Destabilization of Adversarial Organizations with Strategic Interventions

Il-Chul Moon

CMU-ISR-08-124

June 2008

School of Computer Science
Institute for Software Research International
Carnegie Mellon University
Pittsburgh, PA

Thesis Committee

Kathleen M. Carley, Chair
Alexander H. Levis (George Mason University)
James D. Herbsleb
John M. Graham (United States Military Academy)

Submitted in partial fulfillment of the requirements
for the Degree of Doctor of Philosophy

This research was sponsored by CAPES project (FA8650-07-C-6769) of Air Force Office of Scientific Research (AFOSR), MURI project (FA9550-05-1-0388) of Air Force Office of Scientific Research (AFOSR), DNA project (N00014-06-1-0921, N00014-06-0104) of Office of Naval Research (ONR), Geospatial analysis project (W911NF0710317) of ERDC-TEC, Army Research Institute (ARI), and SPAWAR project (N0016403D6623) of Naval Warfare Center. Additional support came from Carnegie Mellon University's Center for Computational Analysis of Social and Organizational Systems (CMU CASOS). Finally, George Mason University's System Architectures Laboratory (GMU SAL) provided valuable support. The views and conclusions in this thesis should not be interpreted as representing the official policies, either expressed or implied, of AFOSR, ONR, ARI or the U.S. government.

Abstract

Destabilization of adversarial organizations is crucial to combating terrorism. The adversarial organizations are complex adaptive systems, which include different types of entities and links to perform complex tasks and evolve over-time to adapt to changing situations. Both the complexity and the adaptivity of the adversary make it difficult for friendly forces to destabilize the adversary and to damage the performance of the adversary's organization. The commander desires to identify the terrorists command structure, key leader; assess their capability; and identify weaknesses; current technologies do not support these desires. At best, the commander might know historic activities, and most of the web of connections among known terrorists.

By taking a dynamic network analytic approach and focusing on how to identify, reason about, and break 1) the adversary's decision making structure, 2) the likelihood that the adversary can engage in key tasks; and 3) the adversary's over-time social and geospatial behavior, we can begin to make headway in reasoning about this complexity and adaptivity. I develop four different, interoperable approaches supporting this assessment and estimation on adversarial organizations. These four approaches analyze different aspects of an organization, i.e. the core decision making structure, the high level assessment of task completion likelihood and the micro level simulation of the behavior of adversaries. By unifying these approaches, we can grasp a complete picture of the target as well as the destabilization strategies against it. First, I estimate the decision making structure of the organization, apply dynamic analysis metrics to it, and identify critical terrorists to be removed. This decision making structure is a trimmed organizational structure expected to be the critical command structure of the adversaries. Second, I extract an influence network for the key tasks. This is an assessment about the organizational support for the adversaries' mission. Third, I use a multi-agent simulation (JDynet) to analyze organizational change. I simulate the

adversaries' social interactions and task execution behavior. Also, I create and test simulation scenarios of removing key adversaries over the course of simulations. This estimates the damage that we can inflict on the adversarial organization with interventions. Fourth, I augment a geospatial component to JDynet, so the relocations of personnel and resources are included in the destabilization analysis. I use the geo-spatial-JDynet to simulate the strategic intervention effects with a joint picture from adversaries' social and geospatial behavior.

To ground and demonstrate this research, I use, primarily, three adversarial organizations, the terrorist networks responsible for 1998 US embassy bombing in Tanzania and Kenya; 1998 US embassy bombing in Kenya; and a global terrorist network. These are adversarial organizational structures including a task dependency network for mission execution; geospatial terrorist, resource and expertise distributions; and terrorist social networks. I regard these datasets as an observed target adversarial structure and provide analyses results that are basis for destabilization strategies.

My research makes contribution at theoretical, technical and empirical levels. First, I provide a theory of how to create a joint picture from different organizational and computational theories. I create theories to merge various existing theories, i.e. merging multi-agent simulations and dynamic network analysis, dynamic network analysis and Bayesian network, dynamic network analysis and decision making structure, etc. This theoretical advancement provides a joint thought and analysis process about reasoning organizational behavior to managers, commanders and intelligence analysts. Second, I develop and test an interoperable analysis framework supported by the suggested joint theory. This analysis framework is realized by expanding an analysis system (*Organization Risk Analyzer)*, so that real world analysts can apply the suggested theory to their target organizations. Third, I empirically analyze three adversarial organizations to demonstrate the usage of this framework and the newly enabled analysis results. For example, the newly enabled analysis approaches estimate *Bin Laden* considered as a non-critical terrorist in *the U.S. Embassy Bombing in Tanzania and Kenya* based on the existing dataset and approach is an actual critical contributor over the mission execution.

This unifying theory and framework for adversarial destabilization, a partially automated intelligence analysis capability, 1) provide intelligence analysis results that can meet the operation tempo in the real world, 2) bridge dynamic network analysis and various inference theories, and 3) provide a better tool that human analysts may use to reduce their time and cost of destabilization analysis.

Acknowledgement

I thank God for allowing me to complete this thesis.

Supports for this work came in part from the below research funding of various agencies.

- CAPES project of Air Force Office of Scientific Research (AFOSR, FA8650-07-C-6769)
- MURI project of Air Force Office of Scientific Research (AFOSR, FA9550-05-1-0388)
- DNA project of Office of Naval Research (ONR, N00014-06-1-0921, N00014-06-0104)
- Geospatial analysis project of ERDC-TEC, Army Research Institute (ARI, W911NF0710317)
- SPARWAR project of Naval Warfare Center (N0016403D6623)

Additional support came from Carnegie Mellon University's Center for Computational Analysis of Social and Organizational Systems (CMU CASOS). Finally, George Mason University's System Architectures Laboratory (GMU SAL) provided valuable support. The views and conclusions in this thesis should not be interpreted as representing the official policies, either expressed or implied, of AFOSR, ONR, ARI or the U.S. government.

This thesis is completed because I was able to get help from three predecessors. Dr. Kathleen M. Carley is my academic advisor, and she enabled this work by her previous work on the multi-agent social modeling, the dynamic network analysis approach, the meta-network concept, etc. She is also a mentor who I will thank during my life time. I thank her for her advice on various matters, academic, research, job, etc. Time-to-time, i.e. a long drive from DC to Pittsburgh, early morning at a hotel lobby or meetings in her office, I had chances to talk to her about research, personal life, etc. She is a very enthusiastic researcher and advisor with a warm heart. Dr. Alexander H. Levis is another predecessor who developed many models that I used in this thesis. I met him when the MURI project started about three years ago. He makes comments and questions that go directly to the center of a problem or a task. I am glad to have his comments and questions about my works because those improve my research a lot. Dr. Lee Wagenhals is the one who developed the Influence Network Analysis approach, which is used heavily in this thesis. He is also a nice researcher who reviewed my work and advised me with potential usages. I enjoyed working with him.

I want to thank Dr. John Graham and Dr. Jim Herbsleb. They are my thesis committee members and provided me valuable comments. Dr. John Graham gave me good comments about the domain that I discuss in this thesis. Dr. Jim Herbsleb gave me unbiased comments that enabled me to think about the potential applications of my work to industries.

I thank CASOS members for every support that they gave to me. They have been great work colleagues, team mates, reviewers, and friends.

I thank for my family and friends. I know that they know that I love them. Also, they know that I know that they love me.

Table of Contents

1. Introduction

Adversarial organizations are prolific around the world. For instance, terrorist organizations are globalized (Elledge, 2003; Urry, 2002; Sageman, 2004), forming alliances (Cragin, 2007) and getting stronger. It appears that they are becoming more complex in their structures (Elliott and Kiel, 2003), more adaptive to changing situations (Goolsby, 2006), and larger in the number of their organizational elements. Assessing these large, amorphous, and adaptive organization is difficult for the human analyst, even those with extensive subject matter knowledge and experience.

To counter these growing adversarial organizations, friendly forces, first, try to reduce the growth of, degrade the performance of, dismantle, or destabilize these organizations. In this thesis, destabilization analysis is a process of strategizing courses of action to induce the above organizational destabilization effect. Such strategies should be built with careful assessments of the adversary's decision-making structure, operational environment and organizational behavior. Therefore, the major part of destabilization analysis consists of estimating the decision-making structure, understanding the operational environment, and reasoning the organizational behavior. Finally, the destabilization analysis should include an estimation of the impact of the composed courses of action toward the target organization.

In industry, this type of destabilization analysis is regarded as a risk analysis of a company. How to appropriately observe and manage employees if they do not exactly follow the specified work relations? Would my company be better off or worse off by reassigning employees to different tasks? Would my company operate without damage if some employees leave? These questions can be addressed in a destabilization analysis.

While destabilization analyses are used by military commanders, managers, and policy makers, traditional approaches are often limited to be biased and not robust. Therefore, the analysis users need a new approach to perform a more complete destabilization analysis. Traditional destabilization analysts are often subject matter experts about target regions, organizations, religions, markets, and so on. The analyses from theses analysts have limitations in several aspects. First, the analysis results are often qualitative and rarely rely on a quantitative and statistical approach. Hence, the results are not free from their prejudices or their partially specialized areas. Second, the organizations of interests are getting much more complex, bigger, and being adapted more quickly. Therefore, human analysts cannot intuitively analyze the targets without help from computational analyses and tools. Third, the traditional analyses take a long time to complete and cannot meet the current tempo of changing situations. Fourth, the traditional analyses cannot handle various data, i.e. large volumes of open source documents, complex social networks, etc. Fifth, the traditional analyses separately perform the cultural, social, and geographical analyses whose combinations can suggest better insights into the organization. These limitations motivated the emergence of various computational destabilization analysis approaches.

The emerged computational analysis approaches address some of the above limitations. There are four outstanding such approaches. Dynamic network analysis (Carley, 2006a), decision making structure analysis (Levis, 2005), influence network analysis (Wagenhals and Levis, 2007), and multi-agent simulation (Moon and Carley, 2007) have emerged as the computational tools that can aid analysts in characterizing, assessing, and examining these organizations. Significant advances in analytic capabilities, a reduction in time to process data for analysis, and he incorporation of various data, such as open source documents, are achieved by some of these approaches. However, these tools cannot handle the target organizations' complexity and adaptation in a complete manner.

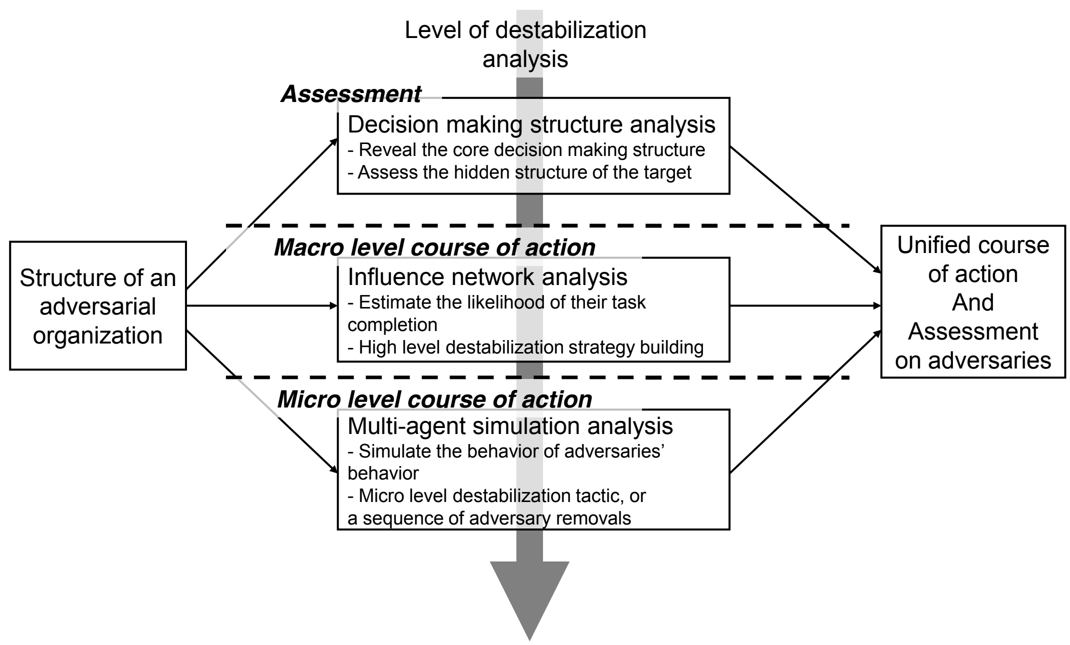


Figure 1-1 a conceptual destabilization analysis

Analyzing an adversarial organization is difficult because such organizations are complex adaptive systems (Elliott and Kiel, 2003; Marion and Uhl-Bien, 2003; Fellman et al, 2003). They are networks with many entities and different types of links. Hence, determining the key personnel, information, and resources on which to intervene is often beyond the scope of human intuition because of the diversity and scale of the structure. In addition, the adversarial organizations are adaptive (Basile, 2004; Rabasa et al, 2006). They restructure themselves over time and adjust to minimize their risks and vulnerabilities (Chagrin et al, 2007). Though we may build an intervention plan based on a snapshot of their structure, it might be obsolete due to the adaptive nature of the target. Thus, the objective of this study is to facilitate intelligence analysis, to identify the weaknesses of the adversarial organizations, and to decrease the time needed time to evaluate courses of action. To achieve this, I have developed, tested, and illustrated an analytic framework that can, given historic data and current communication network data, identify command structures for tasks, assess the capability of the organization to perform these tasks, and then, given these data points, identify critical personnel and resources that serve as targets,. Once this has been completed, one can then evaluate a course of action implied by the removal of these targets with and without geo-spatial considerations (See Figure 1-1 for the conceptual destabilization analysis framework that I suggest).

This study has theoretical, technical and empirical components. The theoretical focus expands the current organization theories by integrating them with computational modeling theories. For instance, organization theory has evaluated organizations' structures in terms of connectedness or closeness among entities. Also, these evaluations are vaguely linked to high-level and abstract organizational performances, such as social capital. However, neither abstract high-level performances nor relations between the structure and the performance predict organizations' actual task completion probability. Estimating actual task performance with an organizational structure can advance the organization management and organization behavior fields. This estimation is possible because this study integrates the organizational structure analysis with computational models, i.e. Bayesian network or multi-agent models.

The study's technical approach develops a new integrated framework to support destabilization analyses. This integrated framework enables us to drill down, assess and simulate an organizational structure, and the framework eventually provides better destabilization analysis results. The integrated framework may seem to be just an aggregation of existing analysis approaches at the software level, but while the interoperability of the software is an outcome, it is a byproduct and not the focus of this research. Each key step is a dramatic enabler of improved analysis of terrorist organizations. Being able to infer task-based decision making structures from general historic data and communication networks is a new capability that affords improved identification of key actors and a better understanding of how adversaries are organized. Being able to assess the organizational support for key tasks with a computational model, such as influence networks, from the historic data and communication structures affords improved capability assessments and the identification of critical resources and tasks, reduces the time needed to generate influence networks, and enables a closer to real-time evaluation of the adversary. However, each of the approaches must first be extended theoretically. These are key steps to identifying courses of action for analysis. The final aspect of the thesis, the simulation, enables the analyst to consider more courses of action, faster, and with less bias. By extending this simulation activity to the geospatial realm, the ability of the resultant analysis to be actionable has increased.

This study develops and expands four different methods of analysis: decision-making structure extraction (Kansal et al, 2007; Dekker, 2002), influence network generation (Wagenhals and Levis, 2007), multi-agent simulation (Schreiber and Carley, 2004a), and geo-space enabled multi-agent simulation (Moon and Carley, 2007a; Moon and Carley, 2007b). First, decision making structure extraction trims a given organizational network to a core decision making structure, so an analyst can observe important relations among the entities. This trimmed structure can also be analyzed by a standard network analysis technique, and the analysis tells the critical entities to be removed. This is comparable to the other results of analysis to a certain extent. Through influence networks (Vego, 2006; Wagenhals et al, 2003), the study evaluates the likelihood of a certain event happening. This influence network analysis describes what to do to intervene in the organization at an event planning stage by showing the level of organizational supports to an adversary's tasks. Lastly, multi-agent simulation and its geo-space enabled version will estimate the impact of implementing a strategic intervention, such as entity removals, on a target organization by imitating the behavior of adversaries (Backus and Glass, 2006) and approximating the developing situation in social and geospatial dimensions. The four analysis methods originated from different fields, but they are all prominent methods applicable to the destabilization analysis. This study's major methodological contribution is in integrating and developing these methods so they can be used as an integrated framework for analysis in this domain.

The study's empirical contribution is an analysis of three terrorist organizations. The organizations were chosen to use the three datasets because they 1) have the necessary components to apply the introduced approaches; 2) are stored in a well-formatted XML; and 3) are about adversarial organizations. One is the terrorist network responsible for the 1998 U.S. embassy bombing in Tanzania and Kenya. The second dataset is the terrorist network responsible for the 1998 US embassy bombing in Kenya (excluding organizational elements related to the Tanzania bombing from the first dataset) (Rosenau, 2005; Carley and Kamneva, 2004). These are small, but they have been well validated by subject-matter experts. The third dataset, a global terrorist network, is a collection of adversarial organizations collected by Computational Analysis of Social and Organizational Systems (CASOS) center at Carnegie Mellon University (CMU). This empirical study applies the framework to each of the datasets, finding their weaknesses and configuring a best strategic intervention. This will illustrate how the framework can be used in real world analyses. This is a premature validation analysis in this framework.

1.1. Integrated framework and potential applications

The above analysis methods, decision making structure analyses, influence network analyses, multi-agent simulations, and geospatial simulation analyses have been supported by various software packages. However, one challenge in this community is how to streamline and process analysis datasets and results among the packages. For example, tools such as *SIAM* and *Pythia* are well-known computer programs for influence network analysis. However, the influence network analysts have to create their own influence network by observing the complex structure of the target organization and conditions in performing a particular task. Also, whereas there are various social network analysis programs, few support the trimming of a network to uncover the decision-making structure of an organization. Then, decision-making structure analysts have to create the target decision-making structure without any help from the observed target social network. This is like a broken analysis chain that the analysis community tries to make seamless. Therefore, there is a growing demand to deliver an integrated and interoperable analysis suite that prepares inputs to other key software packages, integrates the output of the analysis, and implements various analysis approaches. This study explores creating such an analysis suite by supporting the interoperability of outside analysis packages and incorporating various types of analysis results to create a summary analysis result.

1.2. Illustration of usages of integrated framework

We can gain greater value by integrating the approaches that have not been used in such a manner. This section provides three scenarios for how analysts can find the value of this framework and why the value is coming from the integration of analysis approaches. These scenarios are not limited to the adversarial organization analysis because the two scenarios included herein are designed to show how this destabilization framework can be applied to the management of global enterprises and the open source development community. The section also shows how organization theory can be used with network analysis to generate the beginnings of a theory of task through task-based reasoning capabilities. The investigators of these organizations can be managers, commanders, or human analysts who want to understand their operational structure, organizational support of tasks, and changes over time. Therefore, the investigators could be the general managers of an organization, not limited to human analysts interested in adversarial organizations.

> *Scenario 1.* The Center of Computational Analysis on Social and Organizational Systems (CASOS) at Carnegie Mellon University produced a global terrorist network dataset that is an aggregate of multiple relational datasets. These networks come from network text analyses, subject matter experts, databases, and so on. One problem is that the dataset includes a huge number of irrelevant people and events, so the analysts have to find out who, what, or where the focuses of investigation should be. While the analysts have to limit the investigation scope to a set of relevant people, they also have to produce a model describing the impact of the friendly forces' interventions as well as a forecast of the evolution of this terrorist organization. The analysts must estimate how the operational environment of friendly forces or adversaries will change if leaders are captured or sabotage affects their resources or hinders their missions. Additionally, the analysts hope to discover detailed action plans over a period of time, such as when one side acts to remove another. This detailed action plan should be incorporated with estimations of organizational performance of the adversaries.

> *Scenario 2.* Imagine a global investment bank. Its organizational chart is a tree-like hierarchy, in which employees belong to a division . However, some employees (e.g. those deployed to the Hong Kong branch working on an IT project in the financial sector and belonging to the financial division) have multiple superiors to whom they report (e.g. the managers in the Hong Kong branch, IT project and financial division). Additionally, the bank has employees with different types ad levels of expertise. To perform their analytical tasks, the employees with diverse expertise should work together. The CEO of this bank needs an assessment of this organization from any different perspectives and asks whether the organizational chart supports the actual work relations effectively and how to change the operational structure to facilitate informal yet important and efficient work relations. He also wants to evaluate the operational environment of this bank in terms of logistical, personnel, information, and resource supports. Finally, he needs to evaluate the

impact of employees' resignations and the subsequent loss of resources or information on the organization's performance.

Scenario 3. Managing an open source development team is another potential application for this framework. These types of organizations do not have an operational organizational chart, and even the boundary of membership is often unclear. To analyze these organizations, we need to identify the active members and the relationships among them. Since the members are not formally organized, it is unlikely that they would be appropriately and efficiently assigned to the tasks in a way that maximizes a team's success. Thus, it is important to evaluate the personnel assignments, who will code this with what expertise and why, and task distribution, who will debug these errors with which previous implementation assignment and why. Finally, the researchers in this domain are often interested in knowing how the team will evolve over the period of development. This team structure evolution will be driven by the personal expertise, task assignment, work relations, etc.

The above three scenarios have similar analysis questions. First, actual and significant work relations are different from organizational charts while such actual work relations are the focus of analysis. We must investigate how to identify the actual and informal work relationships and how to support them with an operational structure or an organizational system. This is a critical question in terms of organizational management, and we can apply the decision-making structure extraction analysis to address this question. Furthermore, when we take the organizational structure's evolution into account, this informal structural analysis requires more than decision-making structure extraction. Since the evolution will change the informal work relationships, we need a model to estimate the structure's evolution as well as the decision-making structure extractor. We interoperate these two functions and create snapshots of inferred structures over time. This cannot be done if the two functions are not interoperable,. This study allows for this further analysis by integrating the analysis approaches.

Second, the assessment of the overall operational environment is always concerned with the investigators and leaders of these organizations. How can they revise the organizational structures to accommodate the task performance? This can be analyzed by an influence network model that estimates task completion likelihoods. The present study's influence network generation model can expedite such an analysis. Moreover, when it is combined with a multi-agent simulation, we can generate a sequence of influence networks that displays the increase or decrease of the task completion probability over time, whose change is driven by the organizational evolution. On the other hand, if this influence network analysis is used with the decision-making structure extraction technique, it will result in the analysis of the inferred operational environment, rather than the observed environment.

Third, the estimation of the evolution of the organizational performance and structure is another question of interest. How can we forecast the future of this organization? If today we have a picture of the organization and the behavior specifics of the individuals, we may be able to predict the evolution path of the organization. Multi-agent simulations stem from such an idea. However, this is not the only use for of the simulation. Simulations are another way to assess organizational status, particularly about forecasts. Then, we can feed the obtained organizational structure to the other approaches, thereby adding the evolution concept to the approaches.

These newly enabled approaches are made possible by establishing links among the various analyses. These analyses and interoperation links are conceptualized in Figure 1-2.

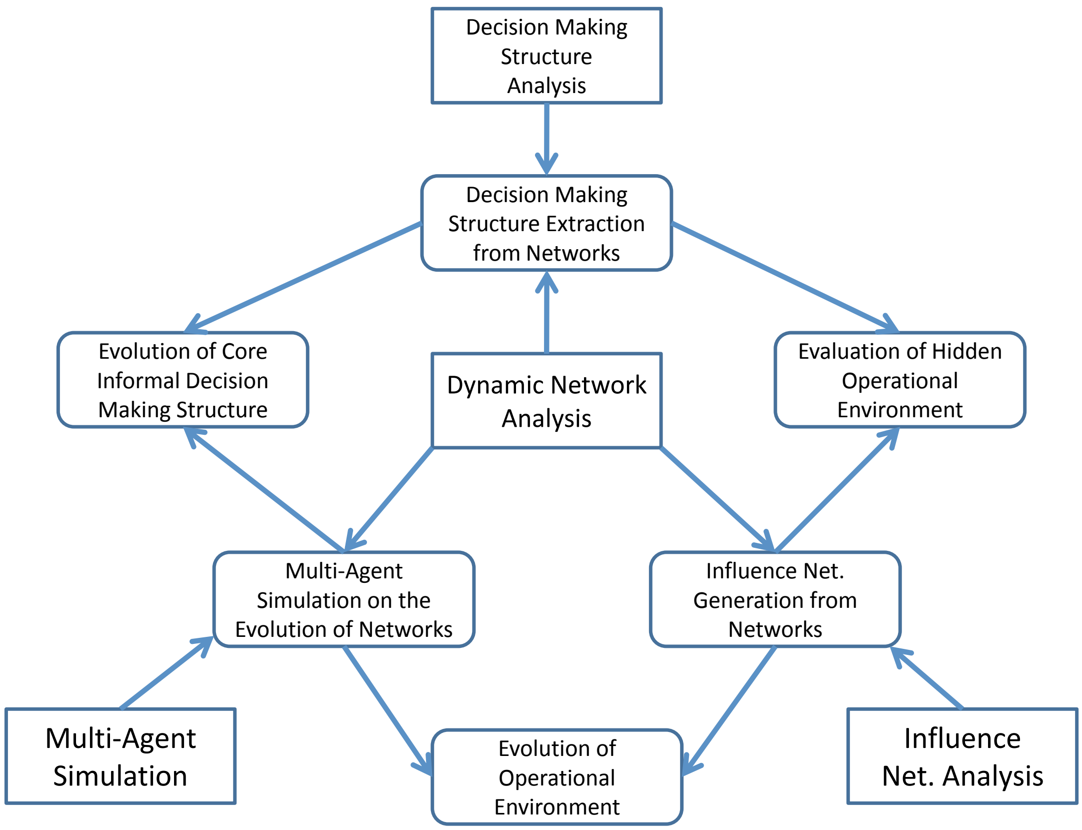


Figure 1-2 a network of interoperable analysis approaches

1.3. Complex adaptive organization and adversarial organizations

Adversarial organizations exhibit the characteristics of complex adaptive system (Mathews, 1999). According to Morel and Ramanujam (Morel and Ramanuham, 1999), there are two commonly observed characteristics of a complex system: having a large number of interacting elements and emergent properties. A terrorist network is a collection of heterogeneous entities interacting with and assigned to each other (Urry, 2002). Though a terrorist network has traditionally been regarded as a simple human network (Krebs, 2002; Mayntz, 2004), recent observations and analyses assert that these networks include resources, information, tasks, locations, and the human component. Hence, the assignment between terrorists and tasks or resources can be regarded as an interaction between two heterogeneous entities.

Adversarial organizations are also adaptive. They evolve over time and hone their organizations to perform better (Fulmer, 2000; Goolsby, 2006) in their perspective. This evolution occurs in two ways, through knowledge management and organizational learning. First, an organization redistributes or diffuses information or resources to the most appropriate personnel as the organization executes its tasks multiple times. This can be seen as an evolution of an agent-to-knowledge network or a knowledge network (Nonaka, 1994; Grant, 1996). Second, an organization changes its social network into an evolved form to perform its tasks or diffuse the necessary elements for task execution (Moon and Carley, 2007c; Child, 1972; Keck and Tushman, 1993). These two evolutions proceed simultaneously and are dependent on each other.

The adaptation in this work follows the logic in JDynet introduced in Chapters 7 and 8. JDynet inherits some of adversarial behavior logic in Construct (Carley, 1991). The logic has been applied and verified by some of the case studies in the domain of small companies (Schreiber and Carley, 2004b) and counter-terrorism (Carley, 2004). On top of the Construct behavior model, this study adds information seeking behavior to the social and geospatial dimensions of agent interactions. There may be other adaptation logics that are more nuanced, but this work limits the adaptation of this logic to make the destabilization analysis tractable by not including all the possible logics.

1.4. Representation of Organizations of Interests: Meta-Networks

Because these organizations exhibit complex systems, we use the meta-network format (Krackhardt and Carley, 1998) to represent and analyze target organizations. Meta-networks are an extended version of social network and include various types of nodes and heterogeneous links that follow the nature of complex systems. Basically, it is a big adjacency matrix among nodes from various types, and parts of the adjacency matrix correspond to the network with specific interpretations. For instance, the adjacency matrix between agents and agents is a social network that we ordinarily imagine.

1.5. Analysis Component 1: Decision Making Structure Analysis

Identifying the decision making structure (Alberts and Hayes, 2006) of an adversarial group is critical when we attempt to understand, intervene, and counter the group (Arquilla and Ronfeldt, 2001; Kansal et al, 2007; Jenkins, 2002). However, real world adversarial decision-making structures often differ from their known operational decision-making structures, and sometimes the members of the decision making structure hide the structure with various types of social interactions and communication channels. Furthermore, when we observe their command relations, the dataset is often noisy, containing misleading and uncertain information. For instance, the decision-making structure of a terrorist network may not have an operational hierarchy, but rather a task force team that does not have a clear cooperation structure. Also, this structure is usually hidden in friendly civilian communities (Raab and Milward, 2003; Allanach et al, 2004; Sageman, 2004). The community may include individuals who are not relevant to the terrorist network or their tasks, yet they have interactions with each other. Finally, the nature of relations among terrorists is various and range from sharing information to reporting results and commanding orders. If we could identify the decision-making structure for specific tasks from this wealth of messy data we would: a) have a better understanding of who the local, on-scene leaders are; b) be better able to destabilize the terrorist network; and c) have decision making patterns that, in the future, we could reason against to determine when and where those patterns are popping up again in order to prevent future terror events. To date, however, the only approach to identifying the decision-making structure is to assume that the entire communication network is the said structure. As noted, this is highly inadequate and overstates the importance of potentially peripheral individuals who play a role in many tasks.

This study introduces a framework that largely consists of two steps to identify the decision-making structure of an adversarial group. First, we use a *decision-making structure extractor* in *Organization Risk Analyzer* (ORA) (Reminga and Carley, 2004) to extract the command structure from a target organization's social network. The extraction is based on social network theories and from organization literature regarding task performance and group management. A social network has different types of social interactions, including decision-making relationships. .Organization theories provide the basis of how to infer the decision-making relationships from a social network. It can be argued that the extracted decision-making structure provides better evidence for assessing key actors to serve as targets for destabilization than does the entire communication structure.

This decision-making structure extraction will benefit a number of relevant or subsequent analyses. Rabasa et al (2006) think that al-Qaeda relies more on loose networks of operatives to conduct operations than before, which means that the operatives may be embedded in a social network of a community populated largely by civilians. Although they co-exist in the social network, it is certain that the group needs decision-making activities among the operatives. Hence, the decision-making structure extraction will reduce or limit the relevant personnel in the social network and help set the scope for investigation and a destabilization analysis.

1.6. Analysis Component 2: Influence network analysis

A key goal of counter-terrorism analysis is to prevent future life-threatening events. However, the core evidence available to assess the capability of a terror group is information on historic events and scattered and incomplete data on current activities. Influence networks are the key approach for assessing these capabilities. Generating these influence networks is generally done by subject matter experts and takes an immense amount of time – weeks and months are not uncommon. From an intervention perspective, there is a need to do such analyses more quickly.

This study proposes a technique for generating task capabilities and event likelihood influenced networks from the historic and network data automatically. The result is a closer to real time generation of data.

An influence network is a directed graph extensively used to estimate the likelihood for an Effects-Based Operation (Wagenhals et al, 2003). It contains nodes that represent events and links that encode causal relationships among events and propagates the likelihood of each event through promotion or inhibition by its parents. Influence network technology is valuable, as knowing how to influence and redirect a situation's changes is becoming important. For example, influence network analysis has been used to analyze the IED attacks in Diyala, Iraq. The influence network contains belief statements related to political, military, social, economic, information and infrastructure, so called PMESII, in military planning (Silverman, 2007; DARPA, 2005). The network helps analysts to evaluate in which sector friendly forces should act to lower the IED attack frequencies (Hufbauer et al, 2001). This approach is different from the traditional action-based operation, which focuses on sweeping regions, setting up multiple checkpoints, and ignoring the consequences of such actions from cultural and sociological perspectives (Vego, 2006).

In the terrorism context, personnel sufficiency, resource availability, information accessibility, organizational support, and so on are the belief statements influencing the completion of a certain task. In addition to this single task analysis, these tasks are interwoven with others in a task network. Therefore, the result of a major and final task (e.g. bombing) is influenced by a set of subtasks. Thus, the prior tasks in the task network and accompanying belief statements for each create a whole influence network resulting in the event occurrence likelihood of the major task. On the other hand, we already have an organization structure in meta-network format where we can infer the above task completion factors and a task network. Thus, we create a function that generates an influence network from a social network in the task completion assessment perspective. This generated network can be used to figure out which task or accompanying belief statement is crucial and should be adjusted in terms of lowering the likelihood. The changes resulting in the lower likelihoods are the strategies that friendly forces should take to disrupt the target organization's performance.

1.7. Analysis Component 3 and 4: Multi-agent simulation and its geo-space enabled version

As noted, the extraction of decision-making structures enables improved identification of key actors, while the extraction of the influence networks enables the identification of key resources/tasks. Each of these key nodes is, in essence, a target. A course of action would be to remove one or more of these targets. Multi-agent simulations can be used to assess these alternative courses of action. This study proposes the development and testing of a multi-agent simulation for evaluating these identified courses of action. While such multi-agent simulations exist, they are limited from a military perspective as they do not consider location. Hence, the key focus here will be on how to include geo-spatial factors and whether the addition of this feature substantially impacts the results of the course of action analysis.

It is important to note that, currently, when a commander evaluates courses of action, only a few are evaluated. These evaluations are done by subject matter experts discussing the course of action. Consequently, these evaluations are prone to all the decision biases to which humans are prone. By using simulations, more courses of action can be considered, it will take less time to consider them, and the analyses will be less biased. As a result, simulations are a key factor in the real-time destabilization of terrorist organizations.

A multi-agent simulation (MAS) has been used to analyze the interactions and emergent behavior of a complex system and to estimate the impact of situation changes in the system (Moon and Carley, 2006). For example, an interesting question for corporate managers is, "What would happen when an important employee decides to leave the company?" The managers want to know the impact of deterioration on the company's performance and structure afterward (Schreiber and Carley, 2004b). Similarly, some military officers encounter a threat scenario and ask a question, "What if we remove some terrorists?" (Moon and Carley, 2007d). Based on the scenario, they try to estimate whether the terrorist network would respond. To answer these questions, the ideal method is to replicate the target domain and organization many times in the real world and to test the scenarios in the replicated environments. Such experiments described above are approximated by the organization science community and the social science community wherein researchers perform field studies or collect experimental data in labs. However, these techniques are very expensive, unethical, or impossible, as opposed to simulation studies. Furthermore, there are many real world scenarios that are too complicated to replicate. MAS has a number of benefits. First, the feature of the MAS draws a nice analogy to human organizations and actors, so in some policy domains, such as civil violence (Epstein, 2001) or the transportation of goods (Bergkvist, 2004; Louie and Carley, 2006), the MAS is used (Davis et al, 2006; Cohen et al, 1972; March, 1991).

This destabilization study applies an existing simulation model, JDynet, to a target organization, observes the internal dynamics, and implements virtual experiments with strategic interventions. Construct, a predecessor model of JDynet, has been applied to many different domains, from corporate management to counter-terrorism. Its simulation results suggest insights into how information is diffused and tasks are performed within an organization. This study augments a geospatial component to JDynet. This new version of JDynet has another layer for agent geospatial relocation behavior that mimics the existing agent behavior to be more nuanced considering real world agent behaviors. Especially in counter-terrorism and decision-making structure research, the physical location of entities often matters because adversarial organizations are aiming to trigger events at specific geospatial locations. Therefore, estimating the whereabouts of the members and critical resources is as important as approximating to what degree a piece of information would be diffused in a network.

1.8. Strategic intervention and destabilization

Finding successful tactics (Carley, 2004; Carley et al, 2002; Morris, 2005; Jenkins, 2002; Cragin and Gerwehr, 2005) to attack a network is critical in organizational destabilization, since most of our target organizations are in network formation. To elaborate this destabilization effort onto a network, we need to define two terms: strategic intervention and the destabilization of a network. A *strategic intervention* in a network means to intervene in the existence of entities or links of a network. For instance, a node can be added or removed, and so can be a link (Borgatti et al, 2006; Albert et al, 2000). While this addition or removal may look as a simple change of a network, in the real world, it can represent removing an agent, disrupting communication links through an electronic warfare, sabotaging a task or a resource, or planting an agent in a target organization. Therefore, in this thesis, most of the intended network changes by outsiders can be regarded as interventions on a network. Particularly, the study limits the interventions to the removal of adversaries, which leads analysts' common question, "What if we remove this person from the organization?" he study creates, evaluates, and optimizes a set of interventions with a specific purpose that is network destabilization, thus, such an intervention can be seen as an intervention with a strategic intention.

In this paper, network destabilization refers to the amount of damage incurred over time to a target organization's performance. Traditionally, destabilization has meant fragmenting a network into several pieces (Cohen et al, 2000; Borgatti, 2003), so the communication between entities is broken. This study adds the evaluation of a group's performance and its historic adaptation to a given situation to this fragmentation idea. While the old fragmentation concept regarded having a sparse or disconnected network as an indication of diminished collaboration, adversarial organizations may intentionally reduce the number of links and create an effective yet sparse topology in their network. This is particularly true when an organization is covert (Carley, 2006a). Therefore, only measuring the density or fragmentation is not a true evaluation of destabilization in this domain. Instead of measuring fragmentation, this study measures the number of completed tasks by providing the required information and resources to agents, the accuracy of task related resource distribution (Schreiber, 2006), and the extent of information diffusion within a group (Ren et al, 2001). These are more practical metrics coupled with real world intuition and more direct measurements from a destabilization viewpoint. On top of these realistic measures, we can add an historic component for the following reasons: there are instances when friendly forces intervene in a target organization and significantly damage the target's task performance, yet the target may be able to restructure and rebound its performance. However, in some other instances, the target would suffer from the damage, which could persist for a long period of time. These two events should be measured differently due to the temporal differences in the reaction of the target. Therefore, the study includes historic changes to track the rebound performance and/or sustained damage.

In addition to the above fragmentation idea, there are many different tactics possible when attacking an organization. For example, recent phishing attacks are a good example of how adversaries try to destabilize and manipulate organizations (Jagatic et al., 2007). Phishing attacks can be represented as changing the nature of links or planting misinformation in the links. Therefore, these interventions are at the link level, rather than the node level. Furthermore, these interventions may be designed to be implicit, compared to the explicit node or link removal tactics. Actually, such implicit and link-level interventions have already researched as the usage of misinformation in the organizational context (Hutchinson and Warren, 2002; Covacio, 2003). This study makes some headway to analyze such link-level interventions by differentiating the communication links according to their nature. However, an overall link-related analysis is beyond the scope of this thesis.

1.9. Thesis organization

This thesis consists of nine major chapters. Chapter 2 explains the concept of *adversarial organization*, *destabilization* and *strategic intervention*. Afterwards, Chapter 3 describes the overall structure of the analysis framework and also describes the datasets used for in the empirical research in Chapter 4. As the framework herein is comprised by four different approaches (consider a multi-agent simulation not considering the geospatial dimension as one approach, and the geospatial analysis enabled version as another approach), the methods are introduced in detail in Chapters 5, 6, 7 and 8. The method introduction chapters have been ordered particularly so that the chapter order follows the natural destabilization analysis flow of an assessment of the core network of an adversarial organization, a macro-level intervention strategy and a micro-level intervention strategy. After the chapters about analysis approaches, Chapter 9 describes how one could use this new framework in the real world. Chapter 10 serves as a concluding document.

2. Requirements of Integrated Destabilization Analysis

Human analysts can better perform destabilization analysis by using this integrated approach. This integrated approach captures target organizations' diverse aspects. Capturing diverse aspects is important because these aspects can help generate more comprehensive lists of key individuals, resources, expertise or tasks, whose removal can induce the destabilizing of the organization. Thus, in the first section, I survey the key aspects of an adversarial organization, derive key requirements of the integrated approach, and find computational analysis providing means to address the requirements. In the second section, I define destabilization in this thesis and survey the existing destabilization analysis approaches that can satisfy the key requirements identified in the first section. In the third section, I summarize which key adversarial organizations' characteristics and destabilization analysis requirements are addressed by which analysis approach.

2.1. Critical aspects of an adversarial organization in destabilization analysis

In the following, firstly, the traditional organization theories are introduced. Then, recent analyses of adversarial organizations are surveyed. The surveyed recent analyses have focused on a few organizational types, i.e. terrorist networks and IED networks, and there are important characteristics of such focused organizational types. These characteristics are important factors in deciding what factors the integrated destabilization analysis approach should be able to analyze. Finally, I derive requirements from the common assessments.

2.1.1. The nature of traditional organizations and their destabilization

In *Organization Design* (Galbraith, 1973), Galbraith said that people believe that they understand the term, organization and organizational structure, until they are asked to define the terms. Galbraith defines organization by suggesting a simple comparison. He compares 50 randomly picked individuals from an airport to 50 individuals from a football team. He claims that the latter is an organization because of their unified goal, or an organizational objective, which the first group does not have. This claim can also be applied to my problem domain by saying that an adversarial organization is a group of individuals with hostile and unified goals against friendly forces. For instance, a terrorist network should be a type of organizations with a clear boundary of its membership and a unified goal. In deeper theory, this argument resembles Weber (Weber, 1978) and classical management theorists who treat an organization as an institution to control individuals in the interest of the organization leaders' goals. If this definition and characteristic are true, the destabilization effort should be about hindering its leader's command and disrupting its unified goal and accompanying actions.

While the above definition about organizations regards the organization as a top-down command passing instrument, there are other ideas about the formation of an organization. In *Organizations in Action* (Thompson, 1967), Thompson argued that an organization emerges around pre-designated offices when an event happens. He illustrated an example of disaster management. If a hurricane hit a town, an organization for managing the disaster will arise. The disaster management organizations are formed around the town leaders and emergency services, but the organization members would not be limited to those. The members will cooperate with each other, and the cooperation will show an emerging organizational structure. The members of this organization have their own specific goals though there is a high level goal, managing the disaster. Also, the operational head of this organization would not be able to enforce his will to the rest of the group because the structure would not be strictly hierarchical. He calls this type of organizations as *synthetic organizations*. If I apply this idea to my domain, the destabilization will be much harder than the previous case since removing the head would not relatively affect to the organizational behavior.

In *The Social Psychological of Organizations*, Katz and Kahn (1966) suggest another definition. They define an organization as a special class of open systems, which means that an organization is a system that takes inputs, transforms the inputs, outputs the transformation, and renews the inputs. While they focus on the relation between organizations and organizations' environment, they also discuss organizational rule enforcement, organizational power and authority, the flow of information, and the leadership. Organizations enforce roles to individuals, organizations have authority structures for the enforcement, and organizations have leadership structures. These discussions imply that there are deeper psychological aspects in organizational operations. We have to identify such underlying psychological structure and destabilization this underlying structure to really impact the targets.

In *Complex Organizations: A Critical Essary*, Perrow (1986) think that an organization has a synergic effect emerging from the interaction of members. This synergic effect may be a key aspect of why the group members work together. The synergic effect enables that the output of the organization is better than its input, which means that a work accomplished by two members would be better than the combination of works done by two separate individuals. If we accept such nature of an organization, we must reduce the synergic effect to destabilize an organization. To reduce the synergic effect, we have to intervene in the interactions among the organizations' members because Perrow pointed out that the interactions are where the synergy is coming from.

In *Designing stress resistant organizations*, Lin and Carley (2003) argued how to create a robust organizations that can withstand stressful situations. In detail, they enumerate three different stress types, such as external stress, internal stress and time pressure. These aspects ask organizations to prepare the countermeasure for such stresses, and this leads to some inefficient structure to some extent. Many of organizations will prepare their structures against these threats, and their sub-optimal structures will look different than we expect from the ideal organizational structures in the context. Furthermore, Carley and Lin (1997) identified information distortion cases within an organization. Personnel in an organization may suffer from the information distortion if 1) information is missed, 2) information becomes wrong, 3) the person with the information is not available, 4) a communication channel breaks down, and 5) the person with the information is turned over. An organization may show adaptation against these information distortion threats and become more robust against the threats. Carley et al (1998) shows the importance of the organizational structure from the organizational performance perspective. They used simulated, experimental and archival data to analyze the relation between the structure and the performance. Their analysis indicates 1) the structure partially dictates the organization performance evolution and 2) cognitive multi-agent social simulations can, to some extent, regenerate the observed real world organizational performance.

The definitions from the traditional organization theories outline the critical points of destabilization efforts toward the organizations of the definitions. I summarize the findings from the surveys below.

- *Literature review finding about organizations 1: If an organization emerged from an event spontaneously around pre-designated offices, the emerging organizations would not share a unified goal. Therefore, only removing a leader would not destabilize the organization.*

- *Literature review finding about organizations 2: If an organization has internal energy, such as rule enforcement; organizational power and authority; and leadership, the strategic interventions should be made with consideration of the above factors.*

- *Literature review finding about organizations 3: If an organization is complex and collective, and if an organization performs better than just sum of its individual members, the destabilization should focus on decreasing such a synergic effect of the group.*

2.1.2. The nature of adversarial organizations of interest and their destabilization

Burton (2003) argues that there are three categories of questions that we can ask in organization science. We can ask questions about 'what is', 'what should be' and 'what might be'. Analysis on the nature of adversarial organizations is very close to asking questions about 'what might be,' because of the covert nature of adversarial organizations. Thus, the following literatures are mostly a series of thoughts about 'what might be' with partially observed evidences.

Current proliferation of terrorist organizations (Sageman, 2004) has led analysts to focus on such organizations (Stern, 1999). Originally, terror organizations have been existed since French revolution (Reich, 1990), and in U.S., domestic terror organizations (Zhou, 2005) are also organizations of interest. However, many recent analyses concentrate on global or middle-east terrorist organizations like al-Qaeda, Hamas, or Hezbolah (Midlarsky et al., 1980). These global or middle-east terrorist organizations have differences in their nature (Atran, 2008), but their one common aspect is that these organizations are based on Islam extremism (Stern, 2003). I limit the adversarial organizations to these current, Islamic extreme, middle-east concentrated terrorist organizations. This limitation enables this work to be more focused on the current critical issues while the computational approaches are still applicable to the other types of organizations. This section shows the traditional qualitative analyses, first, and the movements from the traditional qualitative analyses to the recent computational analyses, next.

Traditionally, analyses of these specific terrorist organizations have been about three questions: why terrorism occurs, how the process of terrorism works, and what its social and political effects are (Crenshaw, 1981). By answering why terrorism occurs, analysts shape the terrorists' demographics and motivations. Felter and Fishman (2007) survey the demographics of recruited al-Qaeda members. Many Saudi-national activists become al-Qaeda members, and many of them are born around 1984 averagely. However, their survey also reveals large portion of transnational recruitments. These surveys are valuable in designing the destabilization framework because the survey tells that the framework should estimate such transnational movements. As another analysis to answer why terrorism occurs, Stern (2003b; 2000) identifies the motivation of terrorists from five aspects: alienation, humiliation, demographics, history, and territory. Each of these aspects invokes the terror activities, and if the aspects are subdued, the activities may fade away. This implies that the integrated framework should consider the cultural, the demographic and the geographic aspects of the terrorists and their organizations. Unlike the above committed motivations and demographics, Grant (2005) has observed that the members of more recent terrorist networks are not entirely committed to their networks based on their unified goal, rather than they do their jobs on an individual contract basis. In the recent adversarial organizations, there is neither individual commitment to their organizations' goals nor organizational method to unify the individual members' goals into one goal considering the observed decentralized structure. Hence, some analysts say that a terrorist network is a decentralized network with a single task oriented affiliation, rather than an ultimate goal based affiliation.

- *Literature review finding about adversarial organizations 1: The adversarial organizations show multi-national recruitments and trans-national movements.*

- *Literature review finding about adversarial organizations 2: The members of adversarial organizations have motivations in alienations, humiliation, demographics, history, or territory.*

- *Literature review finding about adversarial organizations 3: Some terrorists are not entirely* ***committed to their organizations' goals, and they interacted with others in dece****ntralized forms.*

Analyses answering how the process of terrorism works are another major analysis stream. The analyses investigate how the leaders disperse their will to their members (Brachman and McCants, 2006), how the individuals come up with a terrorist organizations (Stern, 2003a), how the organizations are managed (Stern, 2003b), or how the organizations operate and accomplish their goals (CTC, 2007a; CTC, 2007b; Grant, 2005). These analyses points out several common characteristics of the organizations. First, the organizations are very difficult to observe and impossible to survey. Unlike the organizational studies on corporate or friendly militaries, these organizations are only observable through their explicit announcements, captured documents or arrested members. Combating terrorism center (CTC) has translated their documents and letters (Brachman and McCants, 2006), and the center partially uncovered many important organizational aspects (CTC, 2007c), but these findings are still partial and limited. Second, the organizations are very adaptive. They change their missions, so that the missions can be achievable (Stern, 2003a). They transform their organizational structure to more decentralized forms, so that the structures can survive against the friendly forces' efforts (Stern, 2003a; McFate, 2005a; Burke, 2004; Hoffman, 1998). They adapt to their changing operational environments by relocating their bases or approaching locals with different propagandas (McFate, 2005a). Third, the organizations are decentralized. McCants et al. (2006) drew a social network of prominent terrorist individuals. The network was a citation network among documents related to terror ideology, strategy and tactics. When analysts observe the citation network, they recognize that even Usama Bin Laden does not control every ideology groups.

- *Literature review finding about adversarial organizations 4: Analysts cannot survey the adversarial organizations, and they only can observe the organizations partially.*

- *Literature review finding about adversarial organizations 5: The adversarial organizations are hidden in social communities and are distributed geospatially.*

- *Literature review finding about adversarial organizations 6: The adversarial organizations operate in cultural, regional, organizational complex environments and challenging situations.*

- *Literature review finding about adversarial organizations 7: The adversarial organizations are adaptive to changing their missions, organizational structures, and changing operational environments.*

- *Literature review finding about adversarial organizations 8: The adversarial organizations are decentralized, so it is harder to infer and recognize the authority structure compared to the centralized, hierarchical organizations.*

Analyses answering how to destabilize the organizations are parts of answers about what the terrorism activities social and political effects are. Only these destabilization parts are surveyed because these are very relevant to this thesis, and because the other parts are more relevant to the impact on friendly organizations, not the adversarial organizations. CTC has been very active in suggesting the qualitative destabilization policy recommendations. CTC (2007a) asserts that friendly forces should exploit the cracks among the al-Qaeda leadership. The al-Qaeda leaders have internally gone through long struggles and discussions in setting their strategies and larger goals. This means that there are factions in al-Qaeda that can be fragmented if friendlies exploit the chasm between factions. CTC (2007b) analyzes the al-Qaeda relocation to the eastern Africa, which is the background of this thesis's empirical research. The analysis includes qualitative profiling of individual terrorists, cultural challenges that al-Qaeda had to face, etc. There is an interesting policy recommendation in this analysis. The analysis claims that the friendlies have to maintain the interdiction capability against high value al-Qaeda targets. While this claim is valid in general, there was no discussion how to measure the value of the targets except the qualitative analysis. Another interesting research about destabilization of these groups is the policy recommendation made by a terrorist, Aby Yahya (Brachman, 2008). He points out that friendly forces should focus more on the propaganda war, such as painting a bad picture of jihadists in the Arab world or invoking a fatwa from Islam priests. However, his destabilization plan is not close to any practical recommendations such as how to analyze their organizational structure or what to target. McFate (2005b) is a qualitative destabilization analysis about IED attack groups. She clearly links the organizational structures and the structures' elements: personnel, resource and IED tasks. She promotes use of computational theories and approaches, i.e. social network analysis. Obviously, qualitative destabilization analysts now appreciate the necessity of including quantitative analyses. Furthermore, Fishman (2006a) describes the difficulties of friendlies' destabilization efforts. He discusses the future of al-Qaeda in Iraq after Al Zarqawi's death. Friendly forces were able to track down Al Zarqawi, to attack the house where he was hiding, and to remove him. This report tells that the limitation of friendly forces intervention in terms of time and space because friendlies cannot intervene in every place and every individuals. Also, the intervention frightens remaining terrorists since they acknowledge that friendlies can get to where they are. In this case, friendlies cannot remove or interdict any individuals that they can act on because of possible situation changes after the action. Friendly forces need more estimation what will happen after their action. This estimation may be qualitative as Fishman's report, or it can be quantitative as the products from the integrated destabilization analysis framework.

- *Literature review finding about adversarial organizations 9: Friendly forces should exploit the internal disputes of the adversarial organizations.*

- *Literature review finding about adversarial organizations 10: Friendly forces should anticipate transnational movements of the adversarial organizations.*

- *Literature review finding about adversarial organizations 11: The profiles of adversaries are important in destabilization analysis.*

- *Literature review finding about adversarial organizations 12: The operational environment of adversaries can be worsened through propaganda war.*

- *Literature review finding about adversarial organizations 13: The adversarial organizations composed of various elements: personnel, expertise, resources, tasks, missions, objectives, beliefs, etc. These various elements can be a very diverse collection of organizational items used and perceived in the real world.*

- *Literature review finding about adversarial organizations 14: Some destabilization analysts mentioned that they need more computational approaches such as social network analysis.*

- *Literature review finding about adversarial organizations 15: Friendly forces cannot intervene in freely if they do not have any estimation about what will happen after their actions. This emphasizes the importance of effects assessments on the adversarial organization intervention strategies.*

Recently, analysts have moved from the above traditional qualitative analyses to the computational analyses. These computational analyses are introduced in the next section. There are critical aspects that the above qualitative analyses identified, yet the analyses cannot address fully. On the other hand, these critical aspects can be addressed by incorporating computational analyses. The followings are such four aspects driving computational approaches to be involved in destabilization analysis processes. Table 2-1 illustrates what the four aspects are and what survey findings support the aspects.

Table 2-1 Summary of identified adversarial organizations' critical aspects requiring computational analyses, The identified critical aspects are supported by literature review findings from literature review of qualitative analysis

Adversarial organizations' critical aspect requiring computational analyses	Supporting literature review findings
The adversarial organizations are decentralized and loosely coupled	Literature review finding about organization 1; and Literature review finding about adversarial organization 3, 8, 9, and 11
The adversarial organizations are often hidden in communities, and the organizations hide their significant decision making structures	Literature review finding about organization 2, 3; and Literature review finding about adversarial organization 1, 2, 4, and 5
The adversarial organizations perform complex tasks	Literature review finding about organization 3; and Literature review finding about adversarial organization 6, 12, 13, and 14
The adversarial organizations are adaptive	Literature review finding about organization 1; and Literature review finding about adversarial organization 1, 7, 9, 10 and 15

First, the literature review finding about organization 1; and literature review finding about adversarial organization 3, 8, 9, and 11 support that the adversarial organizations are decentralized and loosely coupled (Burke, 2004; Hoffman, 1998). Therefore, it does not have a strict hierarchy, such as a traditional military unit. This decentralized organizational structure cannot be represented by using the typical, tree-like organizational chart. Rather than such an organizational chart, we need to represent the structure as a network of adversaries. The network representation (Carley, 2006a; Fellman et al., 2003) is better because it can better handle flat team structure, cellular structure, and distributed team structure, which are the characteristics of adversarial groups. Furthermore, applying the network representation to the structure means that we can utilize dynamic network analysis metrics and algorithms that are useful in addressing frequent destabilization analysis questions, i.e. which key personnel or resources are critical, which agents are in the same sub group, and etc.

Second, the literature review finding about organization 2, 3; and literature review finding about adversarial organization 1, 2, 4, and 5 suggest that the adversarial organizations are often hidden in communities, and the organizations hide their significant decision making structures (Raab and Milward, 2003; Sageman, 2004). When we observe the members of adversarial groups, the members interact with people who are not relevant to their groups. In this case, we want to exclude such innocent people from our observations. Furthermore, such organizations' decision making structures may have a task force team that does not have a clear cooperation structure. Finally, the adversaries' interactions imply various hidden purposes ranging from sharing information, or reporting results to commanding orders. The decision making structure analysis (Levis, 2005) community has researched the definitions and nature of different command and control relations. Additionally, the community has enumerated the possible interaction networks like information sharing, result sharing and command interpretation. Also, it supplies models to analyze organizational cognition and decision making processes. Thus, integrating the decision making analysis tools would be beneficial for destabilization analysis.

Third, the literature review finding about organization 3; and literature review finding about adversarial organization 6, 12, 13, and 14 support that the adversarial organizations perform complex tasks. For instance, a terrorist network is a collection of heterogeneous entities interacting with and assigned to each other (Urry, 2002; Marion and Uhl-Bien, 2003). Though a terrorist network was traditionally regarded as a simple human network (Krebs, 2002; Mayntz, 2004), recent observations and analyses assert that the terrorist networks include resources, information, tasks, locations, as well as human components. Moreover, the groups' tasks during an operation demand the distributed resources, expertise, information and personnel. Therefore, the adversarial organization in fact is performing very complicated tasks requiring well considered personnel deployment, information exchange and resource deliveries. Hence, destabilization analysis should include a mean to assess the complex operational environments of the adversaries and task completion likelihood. This assessment identifies a vulnerable task with low completion likelihood. We can prevent this vulnerable task to derail the task dependency network of adversaries.

Finally, the literature review finding about organization 1; and literature review finding about adversarial organization 1, 7, 9, 10 and 15 implies that the adversarial organizations are adaptive. They evolve over-time and hone their organizations to perform better (Goosby, 2006; Fulmer, 2000). This evolution occurs in two ways: in knowledge management and organizational learning. First, an organization redistributes or diffuses information or resources to the most appropriate personnel as the organization executes its tasks multiple times. This can be seen as an evolution of agent-to-knowledge network, or knowledge network (Nonaka, 1994). Second, an organization transforms its social network to perform its tasks or diffuse the necessary elements for task execution (Child, 1972). These two evolutions proceed simultaneously and are dependent on each other. To estimate such evolutions, we utilize a multi-agent simulation. Multi-agent simulations are extensively used in the analyses of military planning, information diffusion or cultural movement. Given the decentralized formation of the adversaries, multi-agent simulation is an appropriate tool for imitating the adversarial behavior and the organizational collective behavior.

2.1.3. Real world destabilization cases of adversarial organizations

We observe the destabilization of adversarial organizations in direct or indirect ways. It is very rare to observe the actual collapse of adversarial organizations, i.e. the Soviet regime collapse (Beissinger, 2002). However, these direct observations were possible because those organizations are overt and clearly bounded, and these organizations are not in my research scope. Since the adversarial organizations in my research scope is more covert, complex and fuzzy-bounded, such a direct destabilization observation is not possible.

What we can notice from the destabilization of the adversarial organizations are indirect effects toward the security of friendly forces and civilians. For example, we can see the increase or decrease of the IED attack frequencies, the number of terrorist activities, or proliferation of internet sites. If we are successful in destabilizing their organizations by disrupting their decision making procedures, operational environments, or actual operation execution process, such attack incidents or attempts should occur less frequently. After the death of Hamas's founder and leader, Yassin, Hamas did not become destabilized; rather Hamas enjoyed a victory from Palestinian parliamentary election (Malka, 2005). In spite of Al Zarqawi's death (Washington Post, 2006), who is believed to be the leader of al-Qaeda in Iraq, the IED attacks in Iraq did not diminish (Riedel, 2007). Byman (2003) even argues that the death of Al Zawahiri or Bin Laden might not destabilize al-Qaeda's operation.

On the other hand, the destabilization history of IRA (Moloney, 2002) may be an insightful example to our current situations dealing with al-Qaeda, Hezbollah, or Hamas. IRA's most of political wings are now inactive after the Northern Ireland peace process (Wikipedia, 2008). Over the course of the peace process, the IRA operational environment became hostile. At the end stage, a small incident finished the operation of IRA. A bar fight between a civilian and an IRA member resulted in the civilian's death, and the death made the regional population not to cooperate with IRA. The incident eventually caused the statement of ending IRA operations by a leader of IRA, Gerry Adams. Surely, there are differences between IRA and Middle Eastern terrorist organizations. However, this destabilization of IRA shows the importance of manipulating their operational environment in contrast to the less-than-expected effectiveness of hard-liners' search and raid tactics.

2.2. Existing destabilization analysis approaches

This section surveys the meaning of destabilization and the existing destabilization analysis approaches. In the beginning, this section introduces various destabilization definitions. One may regard disrupting task performance as destabilization, and another may say that destabilization can only be achieved by breaking the organization into pieces. Next, this section surveys the analysis approaches that can satisfy the identified requirements of the previous section. According to the various destabilization levels, analysts have used different approaches and computational tools to strategize courses of actions that can achieve different destabilization effects. The survey includes theories, i.e. dynamic network analysis, decision making structure analysis, influence network analysis, and multi-agent simulation; and implementing computer tools, i.e. *Organizational Risk Analyzer, Caesar III, Pythia,* and *JDynet*.

2.2.1. The definition of destabilization

In this thesis, destabilization means the decrease of organizational performance over the course of time period. This definition is an opposite concept of stabilization that is defined by Carley (1991). However, there are various destabilization effects, which vary in terms of significance, duration, context, etc. This section also explores these different destabilization effects in this section.

2.2.1.1. The concept of destabilization

The concept and the importance of network destabilization are well described in *Networks and Netwars* (Arquilla and Ronfledt, 2001). Arquilla and Ronfeldt examined many different networks ranging from social activist groups to violent terrorist groups. They found five major aspects of these groups: technological, social, narrative, organizational and doctrinal. Particularly, the discussion about the important social basis for cooperation among the network members is significant in this context. My analysis fundamentally depends on the importance of the organizational structures, and the social basis discussion is about the importance. They argue that a network's effectiveness increases when it has built mutual trust and identity based on strong social ties. In other words, weakening the social ties is the start to undermine the terrorist or criminal networks.

To clarify the concept of *destabilization*, understanding what *stabilization* is important because *destabilization* is an inverse impact of the *stabilization*. In *A Theory Of Group Stability* (Carley, 1991), Carley identified that some organizations sustain longer, are more stable and are better at accepting new members or concepts without loosing their characteristics. She presents an idea, *Constructuralism*. Compared to the old group stability theories, which asserts that favorable contexts are necessary to stabilize a group after changes, she says that a social change and its accompanying stabilization come from changes in knowledge distribution as the organization's members interact and diffuse information. Therefore, we can hinder the stabilization process by disrupting the interaction and diffusion. As the context of this work emphasizes the covert network nature of the target organization, its members are likely to interact with someone who is a neighbor in the social dimension. Hence, only weakening the social ties may not be most efficient in destabilization process. We have to aim the critical interaction and the information diffusion paths and cut them off.

2.2.1.2. Levels of destabilization

The above articles about destabilization articulate the types of destabilization that they expect. For example, *stabilization* in Carley's article means a seamless integration process of new members or ideas, and I flip the concept to define *destabilization* in this work. However, while Carley's *stabilization* is more like sociological concept, other articles define destabilization as a purely mathematical or graph theoretic concept like fragmenting a network into pieces (Cohen et al, 2000; Borgatti, 2003). Additionally, some operational research or counterterrorism experts argue that we can destabilize a network by preventing their work performance (Moon and Carley, 2007d) or making their operational environment unfavorable (Wagenhals and Levis, 2007). Thus, we need to define the concept of *destabilization* before we start building a strategy to induce it.

Breaking the organizational structure: A broken network, or a structure, of an adversarial organization may be the evidence of destabilization process. There are theories and computation tools to support breaking a network. For example, NetAttack is a network analysis and disintegration simulation tool developed by Cohen et al (Cohen et al, 2000). The tool analyzes the network shape, identify key personnel, setup node removal scenario and test the efficiency. The model is not a stochastic simulation model, whose agents try to restore the missing links and isolated agents, generally known as network healing. Therefore, the model is meaningful under the assumption that there will be no adaptation and evolution of the analyzed organization. Furthermore, it does not simulate the overall complex structure of an organization. For example, a terrorist network is not an only agent-to-agent network, represented in a typical social network, but a complex organizational structure where knowledge and resource are exchanged, tasks are assigned to agents, agents are connected to knowledge, resource and perform their tasks with continuous evolution. Additionally, we found that KeyPlayer (Borgatti, 2003) developed by Borgatti is a very similar tool to NetAttack, but the same limitations can also be applied to KeyPlayer. Also, a similar concept has been introduced by Farley (2007). Farley presents such network cut problems in mathematical formulations, rather than developing a tool that calculates the network metrics by comparing before and after the cuts of networks.

Removing key elements to decrease the organizational performance: Given the fact that the adversarial organization is able to heal itself and adapt to a changing situation, breaking the organization with a static analysis would not make much sense. Instead of such a static destabilization, we can aim to make the organization stop functioning. For instance, if the adversarial organization is a task-based group, the organization will be neutralized by preventing the task. Thus, some regarded *destabilization* as inflicting damage on the task performance. For instance, Moon and Carley (Moon and Carley, 2007d) defined the destabilization of a network as the state of network that cannot diffuse knowledge or can do so with very low efficiency. They developed a destabilization test-bed simulation providing a performance measure, knowledge diffusion, over the course of a simulation. Thus, their evaluation of destabilization sequence depends on the movement of the knowledge diffusion.

Changing operational environment: Rather than breaking a network or disrupting communication channels, we can change the operational environment of adversaries (Wagenhals and Levis, 2007; Vego, 2006). For instance, removing a set of terrorists may be viewed as breaking a network or preventing information diffusion, but the removals also induce the changes in the personnel management of the target organization and put it in a difficult operational situation. When we expand the scope of intervention from an intervention on network to an intervention on the environment, the intervention strategy space gets diverse and rich. We identify political, military, economic, social, information and infrastructure (or PMESII) dimensions (DARPA, 2005) that might be crucial in the adversarial operation, and we intervene the dimensions through diplomatic, information, military and economic (or DIME) actions (Elledge, 2003; Thompson, 2005). This intervention idea is not as specific as the above direct network intervention one. This is at the high level strategy telling what friendly forces should do to lower the chance of adversaries' successes.

2.2.2. Existing destabilization analysis approaches

There are different destabilization analysis approaches concerning different levels of destabilization. Literature reviews show that there are four frequently used destabilization approaches. They analyze the target from different perspectives and generate different courses of action recommendations. Particularly, these four selected approaches can address the previously identified destabilization analysis requirements. Thus, integrating these four approaches into one framework is my aim throughout this paper. This section introduces what the selected approaches are and how the approaches are used in the past.

2.2.2.1. Dynamic network analysis

Social network analysis has been used to represent the structure of an adversarial organization and to find its weakness. After 9/11, Krebs (Krebs, 2002) showed the terrorist network from the social network analysis perspective, rather than using a tree-like organizational chart (Farley, 2003). He also computed basic social network metrics, such as degree, betweenness and eigenvector centralities (Freeman, 1979; Bonacich, 1972), to show who critical plan executers are. These basic social network analyses are possible by using *Pajek*, *UCINet*, and *Organizational Risk Analyzer,* etc. However, his analysis remained at only dealing with the decentralized organizational formation. The analysis ignored the complexity and adaptiveness of the organization. Borgatti (2003) introduces a key-player concept and a computer program, *Key Player and UCI-*

Net, which is a social network analysis program that estimates the organizational fragmentation level. His idea is removing a set of members from the adversarial group and dropping the organization integrity measured by the fragmentation level. This is a typical destabilization analysis of an adversarial group, which follows assessing the organization, identifying the target member, and measuring the result after the removal of the target. Whereas he advanced the field of destabilization analysis using social networks, his network is still only about the members of the group.

On the other hand, Carley (2006) developed an extended version of social network analysis, or dynamic network analysis. Dynamic network analysis extends the scope of the organizational structure from only personnel to resources, expertise, tasks as well as people. This is done by a meta-network model (Krackhardt and Carley, 1998). We adopt this organizational structure representation. Moreover, she invented some metrics considering such diverse node types, and we use the metrics. Furthermore, she incorporates a multi-agent model, which is a trial of the integrated analysis between social network and multi-agent simulation. This trial instigated our attempts to unify other approaches, not just stopping at the mixture of social network analysis and multi-agent simulation. These concepts are implemented in *Organization Risk Analyzer* (Carley et al., 2007).

2.2.2.2. Decision making structure analysis

Decision making structure analysis is utilized to identify the critical decision making structure of the adversaries and to estimate the feasible structures under their operational and cultural constraints. Originally, this analysis is heavily used in the command and control (C2) structure analysis (Alberts and Hayes, 2006). This C2 structure analysis is about designing, understanding and evaluating the decision making structures of military units. Thus, the C2 structure analysts applied the concept to the adversarial organizations, as well.

This analysis focuses only on the decision making part of an organization. In other words, the analysis does not concentrate on the non-relevant people in the observed group. This is different from social network analysis that often analyzes the observed networks entirely without trimming. This decision making structure analysis models a cognitive process of an individual (Levis, 2005). Then, the analysis defines a relationship between two people by estimating when the interaction happens over the course of cognitive and decision making processes. From this definition of decision making relationships (Kansal et al., 2007), the analysis is able to classify the relevance of a person in the course of decision making. Eventually, this enables trimming a network by removing non-relevant personnel.

Furthermore, this analysis produces a set of feasible organizational structures under cultural and operational constraints. They have fixed, none, or unknown decision making relation-ships among the members of the decision making structure. Then, a computational tool permutes the links among the decision makers and finds organizational structures that satisfy the relationship specifications and the user defined link density. These decision making structure analyses are done often qualitatively or with help of social network analysis. *Caesar III* is a computer program dedicated to perform the computational analyses of decision making structure.

2.2.2.3. Influence network analysis

Evaluating complex operational environments is often done by utilizing an influence network model. Influence network (Wagenhals and Levis, 2007; Wagenhals et al., 1998) is a semi-Bayesian network including belief statement nodes and causal links among the statement nodes. It has parameters enough to regenerate a conditional probability table for each belief statement node, and it propagates the marginal probabilities of the nodes from the bottom nodes to the root node. It has mainly used in anticipating the break-out of a rare event when we do not have enough observations to create a normal Bayesian network. Therefore, its applications are not commonly observable events, but military planning and counter-terrorism. For instance, Wagenhals and Levis (2007) designed an influence model about subduing IED attacks in Iraq. Hudson et al. (2001) introduces potential usages on counterterrorism, and Rosen and Smith (1996) show an influence network model of building a military and diplomatic strategy. There are a couple of computer programs supporting this analysis, i.e. *SIAM* and *Pythia*.

Traditionally, influence network has been produced by hands of subject matter experts. They have knowledge of the target situation and organization, assess belief statements related to a target event or effect, and draw an influence network by setting up its nodes, links and parameters based on their own knowledge. However, this creates a number of problems in real usages of this inference tool (Vego, 2006). First, the generation takes a long time. It has been reported that a trained intelligence analyst was able to generate a network that correctly estimated what would happen in the next phase of a war game, but he could not deliver the model on time. If there had been an automatic support tool generating an influence network model, he must have used it to deliver his analysis model. Thus, it would be a good contribution if we can automatically generate an influence network from an organizational structure and with human analysts' opinion.

2.2.2.4. Multi-agent simulation

Estimating the evolution of an organizational structure is from multi-agent simulations (Moon and Carley, 2007). Particularly, considering that the adversarial organization is hardly observable constantly and almost impossible to survey, we cannot estimate the evolution of the structure in traditional ways. We need to have a model that imitates their behavior computationally.

Among the simulation models for vulnerability analysis, the *Virtual Design Team* (Kunz et al., 1998) project aims at developing computational tools to analyze and simulate decision making and communication behavior to support organizational reengineering. Also, by using a simulation, Lin and Carley (1997) identify strong factors of an organization's performance and weakness. In their paper, they simulated an organization's performance based on a model of agents' information processing and an organization's resource dependency. Finally, Moon and Carley (2007) estimates the social and geospatial distribution change over-time with a simulation model. They use a global terrorist network to build up a virtual reality for agent interactions and relocations. The model produces the expected future terrorists' geospatial distributions and social criticalities.

2.2.2.5. Problems in using these approaches

Analysts tend to specialize in specific tools, and each specific tool captures only part of the analysis problem. These partial analyses of targets result in very different policy recommendations or vulnerability assessments. For instance, one analyst only using the static social network analysis approach will identify some terrorists as the critical personnel in a terrorist network. However, another analyst only using the influence networks will select some political, military, social, economic, information or infrastructure (PMESII) areas (Snyder and Tolk, 2006) that friendly forces can work on to make the targets' operational environments unfavorable. The two analyses focus on how to damage the targets' performances, but they have very different and incompatible implications and results.

Each of these techniques has a key strength and suffers a key limitation; consequently, while valuable, the results might be biased, not robust against the complexity and the size of the targets, or may require a massive amount of subject matter experts' time. Also, it should be noted that there tend to be large databases with relational information on who interacted with who, was seen where, took part in what activity, etc. Thus, there is data for these tools. Dynamic social network techniques make use of most of the empirical data; but have no way of drilling down and focusing on just those actors critical relative to a particular problem. Techniques to assess the decision making structure, require human analysts to come up with a decision making structure from their subject knowledge or qualitative reports (Kansal et al. 2007; Levis, 2005). Drilling down to just what is relevant to the problem being assessed is problematic. The structures are often built on a small sample of the data used by the dynamic social network techniques; but the focus is exclusively on the problem being assessed. Similarly, an influence network model built by human analysts is subject to the analysts' prejudice (Vego, 2006); but, it allows the analyst to assess probabilistic changes in the likelihood of events under diverse scenarios. Both decision making structures and influence networks require the analyst to spend a large amount of time, weeks or even months is not uncommon, and resources to generate a single model. Consequently, these techniques are under-utilized and their use saved for critical situations where there is a long lead time for analysis. If the input to these techniques could be derived from the data used by dynamic social network programs, in an automated or semi-automated fashion more models could be produced in less time, with less bias, thus enabling the decision making and influence network tools to be more widely used. In other words, a key point of integration is to use dynamic social network techniques to generate decision structures and influence net-works. The decision making and influence networks could in turn be used to provide focus to the network data and enable the analyst a systematic approach to drilling down and focusing on the part of the network that is most relevant. Courses of action can be assessed by reading them as inputs to a multi-agent simulation model designed to evolve the adversarial organization through time. Currently to generate the simulation inputs, human analysts have to spend a long time to code a lengthy parameter setting script (Carley et al. 2007). A wide range of virtual experiments need to be done to understand the entire response of the simulation model. However, since each of the network, decision making and influence network techniques enable the analyst to identify courses of action that are likely to influence the adversarial organization in negative ways, if we could use their outputs as inputs to the simulation the time to generate the over time assessments would be reduced. A secondary and technical advantage to integration is that it enables the analyst to not worry about data formats.

2.3. Summary of Identified Requirements and Selected Destabilization Approaches to Satisfy the Requirements

I listed four attributes of adversarial organizations. These four attributes derive requirements for the integrated destabilization analysis. Also, I listed four destabilization analysis approaches. These four analysis approaches have been used in the field separately. One analysis approach cannot cover a single derived requirement alone. To address a single requirement, I need to use multiple approaches in the integrated manner. I summarize the derived requirements and appropriate computational tools to address the requirements below. Additionally, these requirements and corresponding tools are displayed in Table 2-2.

1) The analysis of decentralized organizational structures should be possible.

   This is possible by applying dynamic network analysis to a network structure, a meta-network.

2) The integrated framework should infer hidden critical contacts and communication links to determine implied decision making structures.

   We apply the decision making interaction models to infer the decision making structures. The models include information sharing, result sharing, and command interpretation. Also, the data for the inference should be from the network representation, a meta-network.

3) The framework needs to assess the complex operational environments and to estimate the task success of the targets.

   This is achieved by integrating a prediction model, or an influence network, and a representation model, or a meta-network.

4) The framework should estimate the future changes of the target organizations.

   The integrated framework applies a multi-agent simulation model, JDynet, to the networked organizational structure, a meta-network.

Table 2-2 Summary of adversarial organizations' critical aspects, identified destabilization requirements, and computation approaches to address the requirements

Adversarial organizations' critical aspect requiring computational analyses	Identified requirements	Partial theoretical solutions	Partial analysis tools
The adversarial organizations are decentralized and loosely coupled	The analysis of decentralized organizational structures should be possible.	Dynamic network analysis	ORA, Key Player, UCI-Net, Pajek, DynetML
The adversarial organizations are often hidden in communities, and the organizations hide their significant decision making structures	The integrated framework should infer hidden critical contacts and communication links to determine implied decision making structures.	Decision making structure analysis, Dynamic network analysis	Caesar III ORA
The adversarial organizations perform complex tasks	The framework needs to assess the complex operational environments and to estimate the task success of the targets.	Influence network analysis, Dynamic network analysis	Pythia, SIAM, ORA
The adversarial organizations are adaptive	The framework should estimate the future changes of the target organizations.	Multi-agent simulation, Dynamic network analysis	JDynet, Construct

3. Integrated Destabilization Analysis Framework

This chapter describes an integrated destabilization analysis framework[1] that satisfies the identified requirements in the previous chapter. Particularly, from many literature review findings, four destabilization analysis requirements emerged as primary requirements of the integrated framework.

1) The analysis of decentralized organizational structures should be possible.
2) The integrated framework should infer hidden critical contacts and communication links to determine implied decision making structures.
3) The framework needs to assess the complex operational environments and to estimate the task success of the targets.
4) The framework should estimate the future changes of the target organizations.

These requirements cannot be satisfied with a single existing destabilization analysis approach surveyed in the previous section. Thus, the integrated framework needs to make the approaches interoperable, so that human analysts can use multiple approaches sequentially to address the above requirements. This interoperation should be done at two levels. The theories behind the approaches should be linked, and the tools implementing the approaches should be connected. These relations are summarized in Table 3-1.

Table 3-1 Summary of identified requirements, related existing approaches and computational artifacts supporting the approaches

Requirement	Related approaches	Supporting computational programs or formats
The analysis of decentralized organizational structures should be possible.	Dynamic network analysis	ORA, DynetML
The integrated framework should infer hidden critical contacts and communication links to determine implied decision making structures.	Dynamic network analysis, Decision making structure analysis	ORA, Caesar III, DynetML
The framework needs to assess the complex operational environments and to estimate the task success of the targets.	Dynamic network analysis, Influence network analysis	ORA, Pythia, DynetML

[1] The framework in this thesis refers to the unified software system and the procedure of using the system. The unified software system includes ORA and ORA's functions to interface the other software tools, such as Caesar III, Pythia and Dynet. The analysis procedure of the unified system is described more in Ch. 9. Ch 3.1. is the description of the integrated software system.

The framework should estimate the future changes of the target organizations.	Dynamic network analysis, Multi-agent simulation	ORA, JDynet, DynetML

Table 3-1 suggests three key framework development directions. Firstly, the adversarial organization is regarded as a multi-mode, multi-plex social network, or a decentralized complex adaptive system. Previously, I pointed out that the meta-network model can represent such organizations. Secondly, the destabilization effect is estimated by using four different analysis approaches: dynamic network analysis, decision making structure analysis, influence network analysis, and multi-agent models. According to my survey, there are existing computational tools supporting these different approaches. If I make these computational tools interoperable, then the framework of destabilization analysis is completed. Thirdly, the framework provides a set of assessments about the target organization and recommends a set of courses of action (COA) that destabilizes the target organization.

1) The framework should take a network representation of an adversarial organization.
2) The framework is completed if the above supporting computational artifacts become interoperable through data format exchange or integrated into a single component.
3) The framework should generate an output about the assessments and destabilization of the target organization.

This chapter describes the unified framework in overall. This chapter shows 1) what the input is, 2) what the output is, and 3) what the integrated system looks like. The detailed integration between a pair of approaches is explained in the next three chapters, not in this chapter.

3.1. Overview of the integrated analysis system

This system includes various existing tools and data formats. While a fundamental idea is utilizing the various analysis approaches to build the destabilization analysis results from multiple perspectives, the approaches are implemented in different programs, and they require different input datasets. I explain how to integrate and interoperate these different programs by transforming the programs' input and output from one to another. Figure 3-1 is an outline of the integrated destabilization analysis system. The figure shows how the tools are linked, what inputs are required, and what outputs are expected.

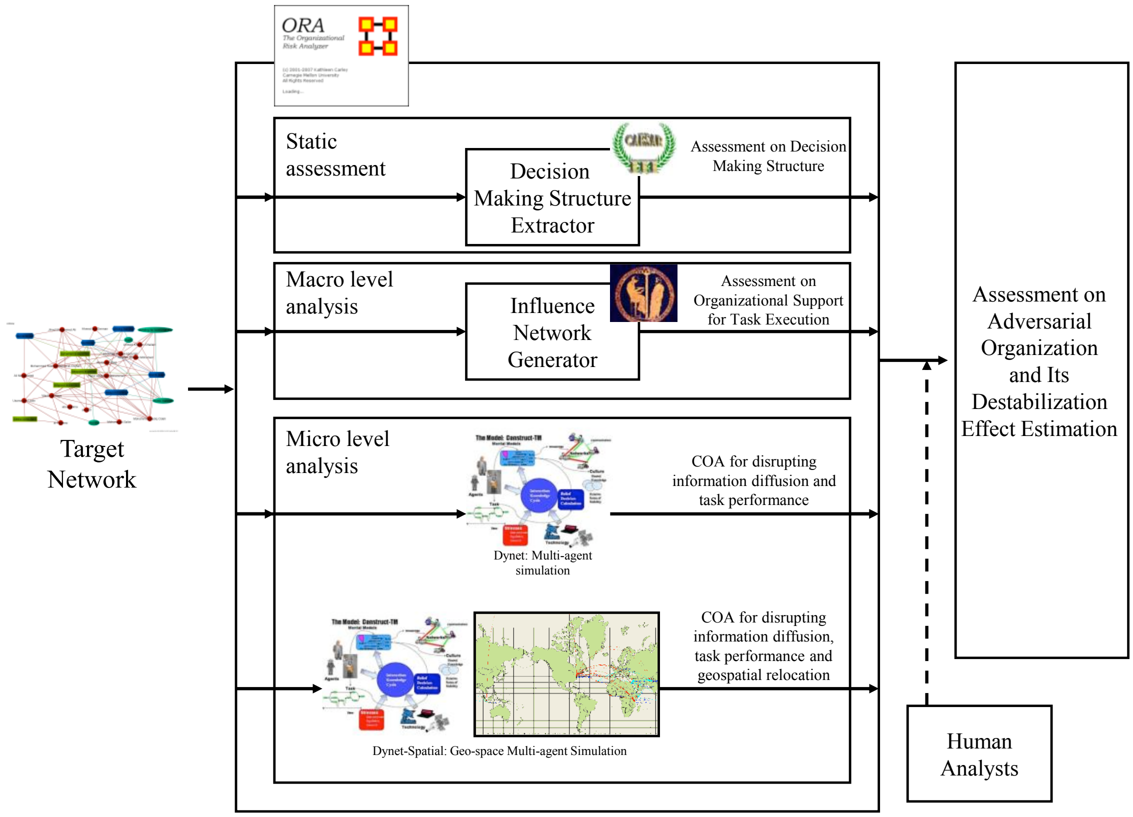


Figure 3-1 the high level abstract of the integrated analysis system

3.2. A type of input dataset – Meta-network of an adversarial organization

As show in Figure 3-1 (find *Target Network* in the figure), an input to this unified system is a network representation of the organizational structure. This organizational structure is in the social dimension as well as the geospatial dimension. Additionally, information on knowledge, tasks and who knows and is doing what are used. Therefore, the input is a large network across a set of different nodes: agents, knowledge, tasks, locations, etc. For instance, if there have been interactions or formal relations between two agents, we assume that there is a link between the two. Similarly, if an agent possesses a knowledge piece, then we link the agent node to the knowledge node. If two locations appear in the same context, we regard the two locations are related. This topological location networks will be the agent relocation dimension. The other sub-networks have their own intuitive interpretations based on the connected node types. We use this multi-mode and multi-link network data as our input to the model with the assumption that it represents the current structural characteristics of the organization. Particularly, the adjacency matrix of the network is called as a meta-network. *DynetML* is an XML type for a meta-network. It saves the meta-network information inclusively and is loadable in ORA.

3.3. A type of output result – Assessment on adversarial organization and its destabilization effect estimation

An output, *An assessment on adversarial organization and its destabilization effect estimation* in Figure 3-1, from this system is a set of assessment results and destabilization estimation regarding the target organization. The assessment results include 1) key personnel in decision making structures, 2) key personnel profiles considering the decision making, 3) key task completion likelihoods, 4) key task completion likelihoods sensitivity analysis from different levels of task difficulties and organization supports, etc. The destabilization effect estimation includes 1) the over-time organizational performance changes, 2) the impact toward the task and the mission completion speeds, 3) the task and mission completion timings, and 4) the social and geospatial organizational changes over-time.

3.4. Interoperability among analysis approaches

The boxes, such as *Decision making Structure Extractor, Influence Network Generator*, etc inside of ORA in Figure 3-1, are the functions enabling interoperations. The key of this integration among analysis approaches is interoperability among analysis tools. I will use *Organization Risk Analyzer* (*ORA*) (Reminga and Carley, 2004) as a main analysis package, which means that the analysis procedure starts by loading the information of an adversarial organization on ORA. However, ORA is a dynamic network analysis package that lacks simulation analysis, influence network analysis and decision making structure analysis capabilities. Therefore, I implement the interoperability functions in ORA to utilize the existing package doing the above analyses. I coded ORA's *Near-Term Analysis* to integrate a simulation model, *JDynet*; similarly, ORA's *Influence Network Generator* for *Pythia*, an influence network analyzer; and ORA's *Command and Control structure extractor* for *Caesar III*, a decision making structure analyzer.

3.5. Dataset transformation to support the interoperations

The interoperation among the above approaches is accomplished by enabling ORA generate the datasets for the approaches and import the outputs from them. Since there are four different analyses, ORA can produce four different datasets. However, since the two simulation analyses will take the same inputs, only three datasets, a dataset for *CAESAR III*, *Pythia* and *JDynet*, will be required. This dataset transformation is from a meta-network to the three data formats. However, this is not a simple XML level conversion though technically it is a transformation from DynetML, or a meta-network XML data structure, to a XML file, i.e. CAE, or an input for *CAESAR III*. This is not simple because the meta-network and the other datasets are not in the relation of one-to-one match. We need to infer a decision making structure, an influence network or a setting for simulations from a meta-network. Thus, the actual work to complete required interoperability and this unified analysis system is establishing functions transforming the datasets and integrating these transformation functions into ORA. Also, the inference for the transformation is the developed theory to enable this unification.

3.6. Enabled destabilization analysis by interoperations

This integrated system enables existing analyses as well as many new analyses that cannot be done by the separate usage of the existing tools. Each of these analyses addresses a part of destabilization analysis requirements above. Table 3-2 lists these analyses, the addressed destabilization analysis requirements, and the required interoperation between approaches and between tools.

Table 3-2 Summary of enabled destabilization analysis by interoperations

Enabled analysis	Addressed requirements	Required interoperation between approaches	Implemented interoperation between tools
Dynamic network analysis	Analysis of decentralized organizational structures	Dynamic network analysis	ORA
Decision making structure analysis	Analysis of decentralized organizational structures	Decision making structure analysis	Caesar III
Influence network analysis	Assessment on the complex operational environments	Influence network analysis	Pythia
Multi-agent simulation	Estimation on the future changes of the target organizations.	Multi-agent simulation	JDynet
Decision making structure extraction from networks	Analysis of decentralized organizational structures, Inference on hidden critical contacts and communication links	Dynamic network analysis, Decision making structure analysis	ORA, Caesar III
Influence network generation from networks	Assessment on the complex operational environments	Dynamic network analysis, Influence network analysis	ORA, Pythia
Multi-agent simulation about the evolution of networks	Analysis of decentralized organizational structures	Dynamic network analysis, Multi-agent simulation	ORA, JDynet
Evolution of core decision making structure	Analysis of decentralized organizational structures, Inference on hidden critical contacts and communication links, Estimation on the future changes of the tar-	Dynamic network analysis, Decision making structure analysis, Multi-agent simulation	ORA, Caesar III, JDynet

Enabled analysis	Addressed requirements	Required interoperation between approaches	Implemented interoperation between tools
	get organizations.		
Evolution of operational environment	Assessment on the complex operational environments, Estimation on the future changes of the target organizations.	Dynamic network analysis, Influence network analysis, Multi-agent simulation	ORA, Pythia, JDynet
Evaluation of hidden operational environment	Analysis of decentralized organizational structures, Inference on hidden critical contacts and communication links, Assessment on the complex operational environments, Estimation on the future changes of the target organizations.	Dynamic network analysis, Decision making structure analysis, Influence network analysis, Multi-agent simulation	ORA, Caesar III, Pythia, JDynet

3.7. Potential challenges in the integration

This integrative approach opens important research questions as well as technical questions. I list some of such questions below. These may not be addressed in this thesis fully, but some questions are negotiated by adjusting levels of integration or limiting the scale of the target organizations.

Overlapping Analysis Assumptions and Parameters: If two models are integrated, care must be taken that the basic assumptions of each model are met and that the theoretical foundations are not undermined. Another critical factor is to make sure that the interpretation of similar parameters is consistent. While these points are obvious, in practice these goals, if they are to be met, may require substantial theoretical and methodological advances.

Scope of Analysis Time-span: This unified system integrates four different tools dealing with a different scope of time. For instance, users of Construct usually assumed that one time-step corresponds to one week in the real world. The message passing time intervals among decision makers in *Caesar III* must be much faster than a week. Also, influence networks regarding a long term strategy will have a longer time span than any other tools. This different time scope issue gets worse because I am treating an adversarial organization as an adaptable system. Adaptation means that it changes over-time, and the time interval between changes should be negotiated among these tools. One ideal solution would be setting up a standard time interval among these models. For example, one time-step in *Construct* is one week in real world, and it should correspond to one time-step in timed influence network. However, this standardized time-step idea should be investigated furthermore to see the feasibility of implementing it among the models.

Different Scalability: This analysis procedure and system is limited to an analysis of a medium size organization, i.e. a group with about hundreds of members. This limitation of scalability is from computational difficulties of analyses. It will take considerable amount of time if we run a simulation analysis with over thousands of agents since the potential social interactions grows as the number of agents to analyze increases. Furthermore, the evaluation logic inside *Pythia*, or CAST algorithm, has a component whose big-O notation grows exponentially. However, this limitation of analysis scalability may be overcome by exploiting the suggested unified approaches. In facts, an analysis that should cover over thousands of people is rare. Often, the scalability problem emerges when analysts have no idea to limit the scope of the investigation. In such a sense, we can use the interoperation between network and decision making structure analyses, limit the organizational structures to a particular core group of interest, and run analyses only on an identified core group. This utilization of this system will ease the difficulties coming from scalability of analysis modules.

Maintenance Problem: This integrated system significantly sophisticates the overall analysis procedures. Eventually, any changes of an involved component will cause changes of other components. This creates a maintenance problem that different software development groups are involved. Therefore, I need to adjust the level of integrations, so that the changes of one model can be contained, and not necessarily influence the other components. This is also critical from the perspective of software errors. I mitigate this maintenance problem by accomplishing the interoperation through data transformations. By not coupling the software components at the source code or program package level, I can avoid source code ownership problem or any serious involvements of developers of *Caesar III, Pythia* and *JDynet.*

4. Dataset for Empirical Analysis

I use three datasets to illustrate the analysis procedure of the integrated framework. The three datasets are 1) an organizational structure of terrorist group responsible for the 1998 U.S. embassy bombing incidents in Tanzania and Kenya, 2) an organizational structure for the 1998 U.S. embassy bombing incident in Kenya, and 3) an aggregated organizational structure for the current global terrorist network. These datasets are chosen because 1) they have been cleaned by a human analysts based on an open-source information; 2) they have required organizational structures, such as task dependency network, for the integrated approach; 3) their sizes ranging from a small task-force team to a global level organization big enough to demonstrate the scalability of this integrated approach; and 4) they are in the same format of other terrorist organizational structures produced by Center for Computational Analysis of Social and Organizational Systems (CASOS).

Some of datasets owned by CASOS are not used because of the following reasons.

- Dataset without any task dependency network component: All of the analysis components in this framework extensively uses a task dependency network of an organization. Therefore, this is an important feature that we cannot run this analysis framework without.
- Dataset without any location information: The location information includes the latitude and longitude of location nodes; agent, resource, expertise, task distributions across the locations; and location-to-location movement network. Even though this information is not included in the dataset, still we can run the analysis until Ch. 8. However, I excluded the datasets without any location information, so that every dataset I test in this work can go through the whole analysis framework.
- Dataset with more than hundreds of agents: The newly developed JDynet logic uses more sophisticated operations research oriented agent behavior logic compared to its predecessor model, Construct. Furthermore, using such operations research oriented simulation model for simulating more than hundreds of agents might be inappropriate because 1) the simulated organization may be actually multiple organizations with different missions, 2) longer time span and larger population can be explained better with sociological model, rather than a task-performance oriented model. Therefore, I excluded such datasets.
- Dataset without any clear resource/expertise requirement to perform task and agent assignment to task: I excluded such datasets because of the same reason why I excluded the dataset without any task dependency network. Resources and expertise requirement and agent assignment of tasks are important in inferring the decision making structure, generating an influence network, and simulating the mission performance of agents.

4.1. Meta-Network for Representing an Organizational Structure

A meta-network (Krackhardt and Carley, 1998; Carley, 2006a) is a multi-mode, multi-relation network that this paper utilizes to represent an organizational structure. We might describe it using a matrix of relations as in Table 4-1. From an organizational task perspective, there are four basic types of nodes of interest: people, expertise, resources, and tasks, and other extensive types of nodes, i.e. location, belief, event, organization, etc, can be included. The relations among these who interacted with whom, who has access to what resources, what has what knowledge or expertise, who can or has done what task, what resources are needed for what task, and what knowledge is needed for what task or to use what resource. Each of these can be observed, with some level of uncertainty, and for many groups only in an "after the fact" fashion. In Table 4-1, for the sake of illustration, we define a possible network for each of the cells.

Table 4-1 Meta-Network component Networks

	People	Expertise	Location	Resources	Tasks
People	Social Network	Expertise Network	Personnel Distribution Network	Resource Network	Assignment Network
Expertise		Information Network	Regional Information Network	Skills Network	Expertise Needs Network
Location			Transnational Passage Network	Regional Resource Network	Regional Task Network
Resources				Substitution Network	Resource Needs Network
Tasks					Task Precedence Network

Meta-network is not just limited to a social network, which is only one part of meta-network. Meta-network covers much broader concepts related to an organizational structure. These concepts are task assignment, resource distribution, information diffusion, resource requirements for tasks, and so on. Since this is not just social relationship information, analysts can store any of their knowledge regarding how the adversarial organizations structured for, prepared for and executed the tasks. For instance, *Task Precedence Network* in Table 4-1 is more commonly analyzed by analysts in the operations research field. *Information Network* in Table 4-1 is a frequent topic for the information scientists researching knowledge management system or knowledge map. However, all of these concepts are critical factors in understanding how an organization operates, and these concepts can be systematically stored in Meta-Network. This additional information of the organizations enable each component of this integrated analysis framework.

Technically, a meta-network is stored as one DynetML file, a technical input to Organization Risk Analyzer. A DynetML file is an XML file designed to store a meta-network flexibly. This file type is much more flexible than the other structures, such as DL file format or UCINet file format. A DynetML file can store a multi-modal and muli-plex network, but a DL file can only store a flat network like a social network showing only one type of relations. Analysts can read a DynetML file even with text editors or XML editors, but a UCINet file is only interoperable with UCINet. The detailed format of a DynetML file can be found in Tsvetovat et al. (2003).

4.2. 1998 US Embassy Bombings in Kenya and Tanzania

1998 US Embassy Bombings in Kenya and Tanzania is a series of incidents executed by al-Qaeda. In Kenya, a bomb in a vehicle adjacent to the embassy building was detonated and resulted in 212 casualties and about 4000 woundeds, and in Tanzania, a vehicle bomb was also detonated simultaneously and resulted in 11 casualties and 85 woundeds. Since the incident, analysts have collected and refined the information on this terror operation (Champagne et al., 2005). The meta-network regarding this incident is the product of such data collection and refinement by the analysts.

The meta-network has five nodesets and 12 graphs. Table 4-2 and Figure 4-1 show the overall structure and basic statistics of the meta-network. This is a relatively small dataset compared to the other dataset, a current global terrorist network. The boundary of this network is almost comprehensive, which means that the analysts put almost all the related entities in the dataset. This aspect is different from the opened boundary of the global terrorist network data, which we do not believe that the dataset is comprehensive and complete. The completeness of the task network in this network particularly stands out. The task network of the bombing procedure is well investigated and reviewed by analysts multiple times, so that the task network is well defined for further analyses such as the decision making structure extraction and influence network analysis.

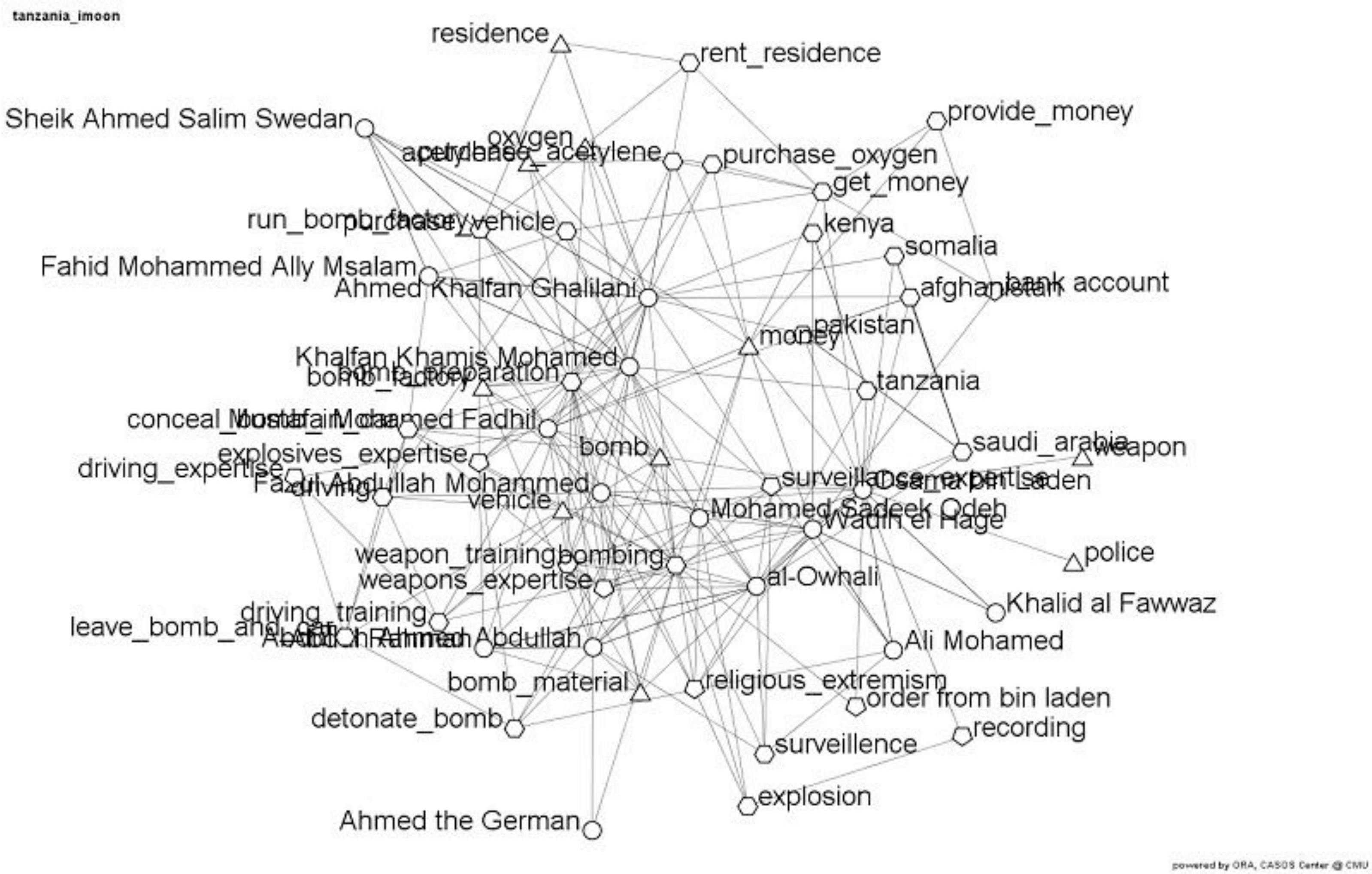


Figure 4-1 the visualization of a terrorist organization responsible for 1998 US Embassy Bombing in Tanzania. This is a complex system, so the different types of entities are shown in different symbols.

Table 4-2 the overall structure of the 1998 US Embassy Bombing in Tanzania and Kenya dataset. 5 nodesets and 12 graphs. Mostly, undirected graphs except the agent-to-agent network and task-to-task network. The density of the existing graphs are specified as the numbers in cells, and the missing densities show that the graphs are not in the dataset

	Agent	Expertise	Location	Resource	Task
Agent (18 terrorists)	0.143	0.126	0.200	0.076	0.142
Expertise (14 expertise)			0.071		0.171
Location (5 locations)			0.500	0.107	0.312
Resource (13 resources)					0.120
Task (25 tasks)					0.055

4.3. 1998 US Embassy Bombing in Kenya

I also created another dataset that only concerns the Kenya bomb detonation, which means that I extracted organizational elements related to Kenya and excluded organizational elements only related to Tanzania. This dataset is generated to analyze the individual bomb detonations of the above series of attacks. Table 4-3 shows the basic statistics of this sub network, and Figure 4-2 is the overall visualization.

Table 4-3 the meta-matrix of the dataset, a terrorist group responsible for 1988 US embassy bombing in Kenya. The density of the existing graphs are specified as the numbers in cells, and the missing densities show that the graphs are not in the dataset

	Agent	Expertise	Location	Resource	Task
Agent (16 terrorists)	0.141	0.070	0.156	0.101	0.139
Expertise (8 Expertise)			0.062		0.048
Location (4 locations)			0.500	0.093	0.230
Resource (8 resources)					0.076
Task (13 tasks)					0.108

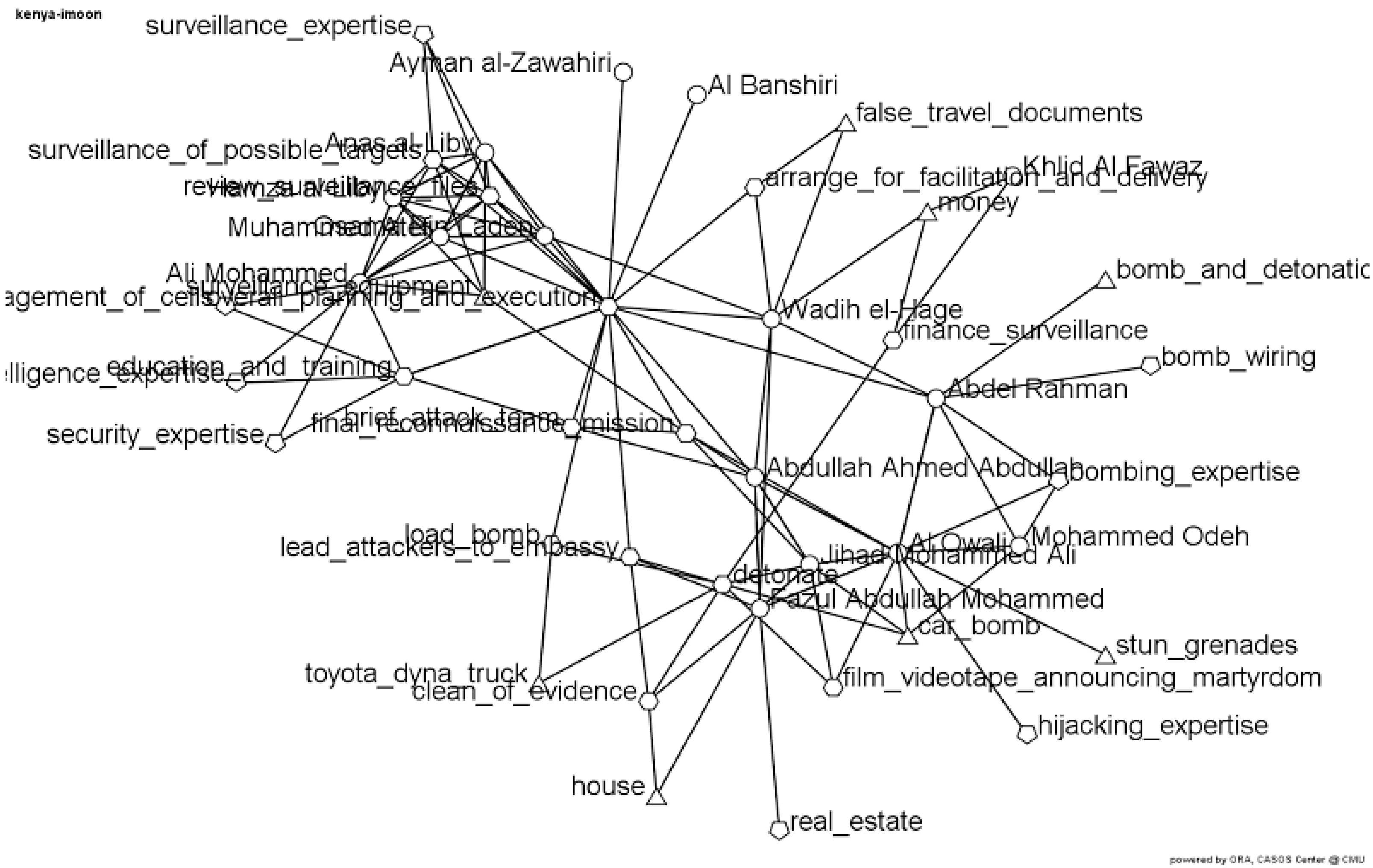


Figure 4-2 the visualization of the meta-matrix of the terrorist group responsible for the 1988 US embassy bombing in Kenya

4.4. Global terrorist network

A current global terrorist network is a dataset aggregating all the available terrorism related datasets at CASOS lab, CMU. Each of the sub datasets is from a single incident or a short time period of a terrorist organization, and a database system merges the nodes and sum up the links. The origins of the sub datasets include human analysts, network text analysis (Carley, 1997) and extracted networks from relational databases. While this dataset covers many of terrorist organizations around the world, this is not precisely validated or confirmed because the generation procedure included multiple automatic data collection routines.

There are pros and cons of this large invalidated dataset. As merits, this dataset approximates the global terrorist social relations and geospatial distributions. Furthermore, the dataset has enough number of nodes and links to test the scalability of introduced framework. As weaknesses, this dataset is not bounded by a mission-oriented structure which this analysis framework aims to analyze the mission and task execution of an organization and to discover better ways to prevent the executions. This dataset might be approached from the sociological perspective, rather than from the operations research perspective. Finally, since the dataset is not validated, the empirical analysis results should be interpreted only to the extent of explaining the capability of the suggested framework, not to the extent of actual global terrorist network analysis.

Figure 4-3 and Table 4-4 are the visualization and basic statistics of the used global terrorist network dataset. Particularly, Figure 4-3 shows the geospatial locations of agents, expertise, location, resources and tasks by matching the coordinates on a world map.

Table 4-4 the meta-matrix of the dataset, a terrorist group responsible for the global terrorist network. The density of the existing graphs are specified as the numbers in cells, and the missing densities show that the graphs are not in the dataset

	Agent	Expertise	Location	Resource	Task
Agent (597 terrorists)	0.00161	0.008989	0.00423	0.00333	0.00835
Expertise (281 Expertise)		0.06134	0.05137	0.05098	0.07050
Location (471 locations)			0.01203	0.06455	0.09216
Resource (381 resources)				0.08768	0.08195
Task (278 tasks)					0.02067

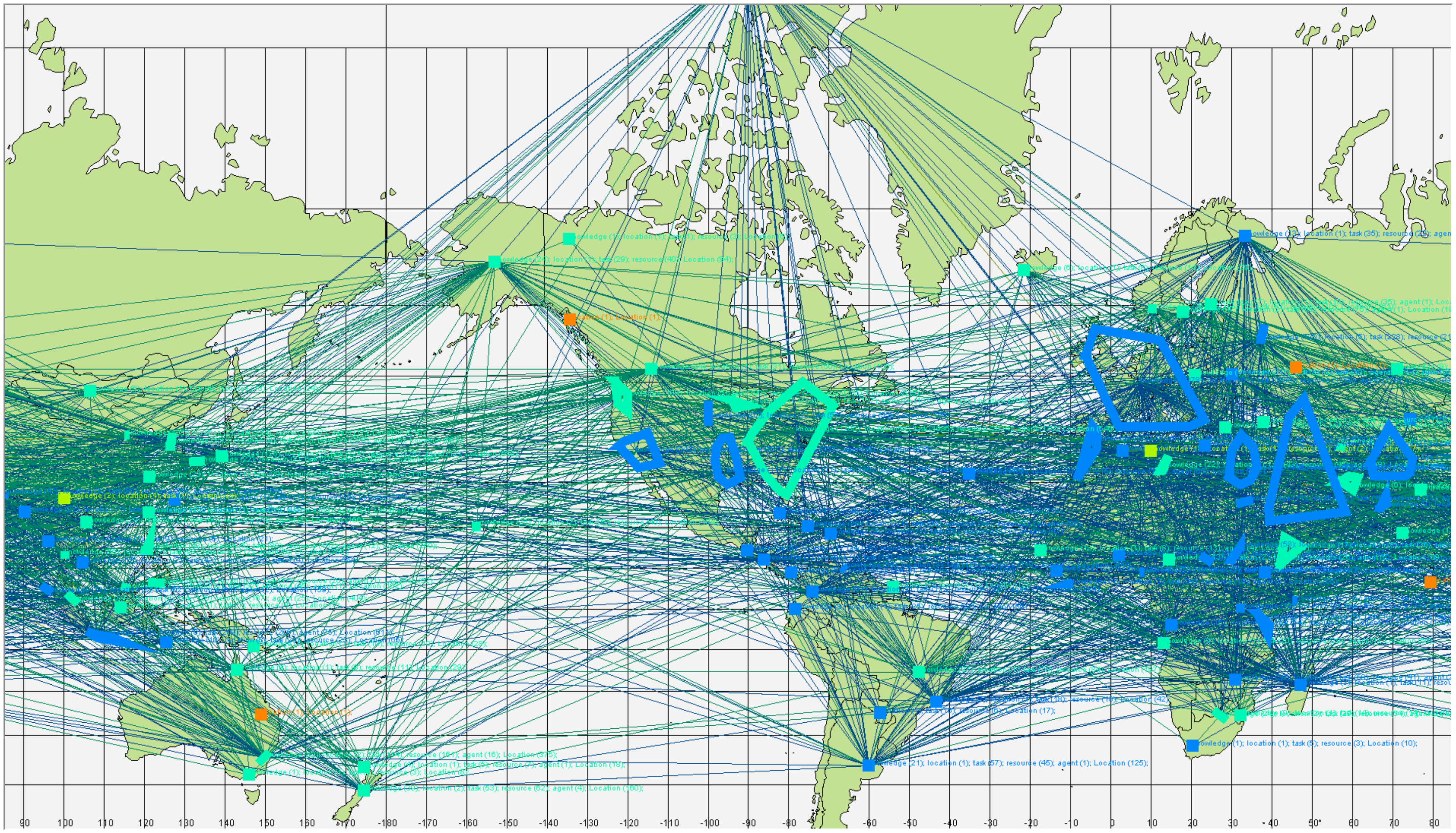


Figure 4-3 the visualization of the meta-matrix by using OraGIS, The clusters of nodes are represented as polygons. The nodes of meta-network are distributed across the geospatial regions.

5. Building Static Destabilization Strategies – Decision making structure Analysis

In today's world there are many organizations or groups that are organized virtually or covertly. Open source project teams, teams in massive multi-player on-line games, and terrorist organizations are just a few examples. For these organizations, what is known is what can be observed. What can be observed are the networks connecting individuals, resources, and activities across many lines and types of communications. Clearly there are many types of relations in this observed structure not all of which are necessarily work related. For these organizations, the organizational chart or the operational structure is likely not to be known apriori. Indeed, it is unlikely that there is an operational structure in the sense of a declaration by the organization about who reports to whom and who is doing what. Nevertheless, it is likely that the operational structure[2] of the organization, who shares information with whom, resolves issues, etc. is embedded in the observed structure. If we could infer this operational structure from the observed structure we would have an improved understanding of how work is done in these groups, their strengths, and their vulnerabilities[3].

I propose an approach for inferring the operational structure from the observed structure. The observed and the operational structure are likely to have distinct profiles, e.g., key personnel and clusters of individuals. This is because the operational is focused only on work related activities whereas the observed is a concatenation of all activities, a snapshot of human endeavors. I illustrate the efficacy of this approach using data collected on a real-world, terrorist organization. The proposed approach expands the horizon of organizational analysis by enabling researchers to identify and assess these operational structures.

Understanding an organization's operational structure is critical when we attempt to understand, intervene in, or manage the organization (Child, 1973). However, organizational structures in the real world often differ from their recognized operational structure (Meyer and Rowan, 1977), and sometimes its membership conceals the operational structure with various types of social interactions and communications (Shetty and Abidi, 2005). Furthermore, when we observe the actual social interactions among the members of the group, the observed social-network data are often noisy, and contain misleading and uncertain links (Borgatti et al., 2006). This is especially true

[2] The definition of *operational structure of an organization* may be different from analysts' viewpoint and used theories in the discussion. I define *an operational structure of an organization* as an organizational structure (including the information processing relations; and the command and control relations) among human actors to complete a specific operation (or a task or a mission).

[3] Human analysts have qualitative ideas about how adversarial organizations might process information, task dependencies or command orders. From these qualitative ideas, I could construct a set of heuristics inferring information processing and decision making structure embedded in an observed social network. The meaning of "an improved understanding of how work is done" is that such qualitative ideas can be improved and updated by reasoning an actual organization with the approach (built upon the current qualitative ideas) introduced in this chapter. Simultaneously, the usage of the approach may improve our empirical understanding of the analyzed organization.

from an organizational task perspective. I described such differences between social relations and operational relations in three scenarios introduced in Chapter 1.2.

In the scenarios in Chapter 1.2., I identify a variety of different structures that vary in their boundaries and explicitness. First, the organizational chart unequivocally outlines the operational hierarchical structure, but the employees have another hierarchical reporting structure (Scenario 2, in Ch. 1.2.) that is not shown in the operational chart. Both of these speak to the organizational tasks but neither is the specific structure for a specific task. I use the term *decision making organizational structure*, to refer to the structure that relates only to a specific organizational task: it includes only task relevant personnel and the related work relationships, relevant to working on, communicating about, and completing that particular task. Second, for example, email accounts show contacts, regardless of the contacts' importance or the nature of the work relations, so the uncovered email transaction structure contains at the same time people with critical work relationships and ones with insignificant relationships from an organizational task perspective. Another observed structure is the social network, or informal structure, the set of observable social interactions among individuals. However, our observations about multiple relationships may look same, but the actual nature of relationships may be different ranging from kinship, friendship, money lending, to work relations. Often, when analysts rely on the observed social interactions between two social entities, they may put the interaction links without any distinction of the nature of the interactions because the interaction motives might not be clear. I use the term *observed structure*, to refer to the structure that is observed and may contain information other than organizational task information.

These different structures can be also seen in diverse organizations, i.e. grass-roots organizations, self-organizing clubs, startup companies, terrorist networks, military command and control structures, and so on. For my purposes, the key is that each of these structures can be represented as a network of implicit relations including significant operational structures as well as insignificant social relations. Then, my approach extracts the operational structures out of mixed observed relations.

For observed structures, the key methodological approach is social network analysis. Social network analysis (Wasserman and Faust, 1994; Borgatti and Everett, 1992) concentrates on finding key personnel, e.g. which boss is more important in Scenario 2 in Ch. 1.2. Or, social network analysis can be used to find clusters, i.e. clusters of developers of the open-source development team in the same scenario. For decision making structures, the key methodological approach is decision making structure analysis. Decision making structure analysis (Levis, 2005; Huber, 1990; Alberts and Hayes, 2003) uncovers the information and response transmissions in members' cognitive processes while a decision is made, i.e. when a employee's report weighs in the operational or informal bosses' decision making processes in Scenario 2 in Ch. 1.2, or to what extent an open source software developer and his discussion partner share the information and when in Scenario 3 in Ch. 1.2. These are distinct methodological approaches each contributing to our understanding of these groups and organizations.

We could enhance our understanding if we could link these two approaches and move easily from one methodology to the other on the same data. We can combine the approaches in many ways, i.e. regarding a critical organizational structure as a decision making structure and applying social network analysis to the structure (applying social network analysis to a decision making structure). Or, we can see the observed network as a decision making structure and estimate the cognitive processes of members of the network (applying decision making structure analysis to a dynamic network). In this chapter, I introduce an integrative approach that is particularly valuable when the decision making structures are never formally defined. First, I extract the decision making organizational structure from an observed meta-network of a target organization. For instance, I extract the only relevant people in the decision making processes among terrorists' contacts in Scenario 1 in Ch.1.2. This extraction is done by considering the work relationships among the members of the group and the work flow of the organizational objective. Next, I analyze the extracted decision making structure with the social network analysis approach. For example, among the three bosses and an employee in Scenario 2 in Ch.1.2, I identify the most important personnel in terms of information delivery, situation cognition, linking to others, by utilizing social network metrics. Then, we can see the different key personnel lists and clustered members between the observed meta-network and the extracted decision making structure. These differences imply that the analysis result can be richer if we investigate not only the observed network, but also the inferred decision making structure. The decision making structure extraction will reduce or limit the relevant personnel in the social network, will help set the scope of investigations, and produce various analysis results from different decision making structure viewpoints. This is particularly valuable when dealing with terrorists, grass roots, or open source groups as those groups can be quite large so that finding a particular organizational task structure, without computational aid, can be rather like finding a needle in a haystack.

I illustrate my approach using data on the terrorist organization responsible for the bombing incidents in Kenya and Tanzania (see Dataset introduction in Chapter 4.2).

5.1. Background about Integration of Dynamic Network and Decision Making Structure Analyses

The key to integrating these two approaches is to move beyond standard social network analysis to a more dynamic network analysis with a focus on not just the social network but the meta-network (Krackhardt and Carley, 1998; Carley, 2006a). The meta-matrix concept is already introduced in Ch. 4.1. This section describes two phases in this integrated framework. Phase 1 is inferring a decision making structure from a meta-network. Phase 2 is using network metrics to assess the extracted structure and identify points of vulnerability. Each of these phases is described in turn afterward.

5.1.1. Inferring a decision making structure from a complex system of an organization

The organizations of interest in this paper exhibit the characteristics of a complex system. According to Morel and Ramanujam (1999), there are two commonly observed characteristics of a complex system: a large number of interacting elements and emergent properties. First, a corporate organizational structure consists of a large number of interacting elements such as workers, information, expertise, and resources (Grant, 1996). These elements should be assigned and distributed properly to perform tasks, and such assignments and distribution relationships are the organizational structure of the corporation. Similarly, a terrorist network is a collection of heterogeneous entities interacting with and assigned to each other. Though a traditionally terrorist network was regarded as a simple terrorist-to-terrorist network (Krebs, 2002; Mayntz, 2004), recent observations and analyses (Carley, 2006; Sageman, 2004) assert that the terrorist network includes bomb materials, reconnaissance on targets, as well as terrorists.

Second, the organizations of interest have emergent properties. According to Thompson (1967), *synthetic organization* is an organization established after a major event, such as a disaster. The organization emerges around operationally designated offices by linking NGOs and relevant groups to the offices. The organization self-organizes the work relationships and seeks a better structure over the course of the event. This emerging structure concept can also be applied to corporate and terrorist network domains. Employees of a corporation have their superiors and take orders from them, as in a hierarchical organization, but they also keep and follow work relationships in practice. Also, it is often seen that a task-force team emerges before or after important events (Nonaka, 1997). This task-force team shows the emergent properties of the organizational structure in a corporation. Additionally, terrorist networks frequently show the emergent properties by adapting their structures to situations (Schilling and Phelps, 2007; Elliot and Kiel, 2003).

If the organizations in focus are complex, we should find a decision making structure by considering the various types of interacting elements and the adaptive nature of the structure. At the same time, since the traditional organizational structure is defined as a structure managing individuals in an organization, the found structure should contain people-to-people relationships. Thus, we focus on developing a model that takes the complex nature into consideration and generates a set of work relationships among the individuals.

CAESAR III (Levis, 2005; Kansal et al., 2007) is a discrete event dynamical model that focuses on the information and decision making processes in organizations. The individual members of the organization interact with other organization members and with the environment through a network of various types of links that differ in content depending on which internal cognitive process generates them. Thus, the model is similar to our approach. Therefore, our major effort in this paper is inferring the links of the cognitive processes among individuals from a meta-network.

5.1.2. Assessing vulnerabilities and criticalities of the organizational structure

There have been a number of approaches in evaluating the organizational structures. For instance, traditional management science developed qualitative evaluation criteria (Smircich, 1983). However, though these qualitative examinations are insightful, the qualitative approaches have problems. They are not scalable to large and complex organizations, nor applicable to various disciplines, and nor designed to assess the complex representation of a meta-network. Therefore, in this paper, we will use a quantitative model.

Social network analysis has been one of the most useful tools in analyzing organizational structures, i.e. corporate structures and terrorist networks (Floyd and Wooldridge 1999; Krebs 2002). It is able to find key personnel (Borgatti and Everett 1992) and embedded clusters. Also, it assesses the characteristics, such as degree of centralization and levels of hierarchy, of the organizations. Gabbay and Leenders (2001) link the social network analysis to the management of social capital of a corporation. Also, Reagans and Zuckerman (2001) investigate the performances of various corporate R&D teams with social network analysis. This analysis is used not only in the corporate domains, but also in the counterterrorism field, and Kreb (2002) visualized the terrorist network responsible for the 9/11 attacks and calculated the social network centrality metrics of terrorists.

In this work, we follow the basic approach of social network analysis, which involves calculating the social network metrics and finding key entities in the structure. However, we are different from the traditional social network analysis in two ways. One way is that we analyze both the observed meta-network and inferred decision making structure. The other way is that we use a couple of metrics, cognitive demand and communication (Carley, 2002)—which are not common in social networks, but insightful in examining a complex organization. Furthermore, we use QAP and MRQAP analysis techniques. These techniques have been used to correlate two networks and regress one network against another. We correlate the inferred structures to the observed structure to examine to what extent the extracted ones are embedded in the observed ones.

5.2. Method

My framework is about extracting a decision making structure from the meta-network of an organization as well as analyzing and comparing the extracted structure and the observed meta-network. In this section, I introduce how to infer a potential decision making structure in the first stage and network metrics in the second stage.

While the analysis procedures are largely in two steps, there are five detailed stages in this analysis framework. The extraction requires three stages. First, I obtain a target organization to analyze and its task of interest. Second, I identify the sub-task network by including only relevant tasks to the completion of the task of interest, and this leads to limiting the personnel involved. Third, the target organization is examined from three perspectives: information sharing, result sharing, and command interpretation. Each of the examinations generates a decision making structure corresponding to the perspective.

The analysis and comparison are done in two steps. First, I compare the extracted structure to the observed network. Additionally, I estimate to what extent I can recreate the observed structure with the extracted ones. These comparisons show the effectiveness and the usefulness of the extraction overall, since I expect the extracted structure to be based on the meta-network, but not be exactly the same structure. Second, we evaluate the network metrics of individuals, identify the key personnel, and see the differences between the key personnel list from the observed and the extracted structures.

This framework is also designed to convert the meta-network into an input dataset for CAESAR III, the software implementation of the information processing and decision making model of an organization. While we discuss and experiment inferring a structure for CAESAR III from a meta-network, we do not utilize CAESAR III to analyze the extracted model from its viewpoint. Our evaluation analysis is limited to social network approaches.

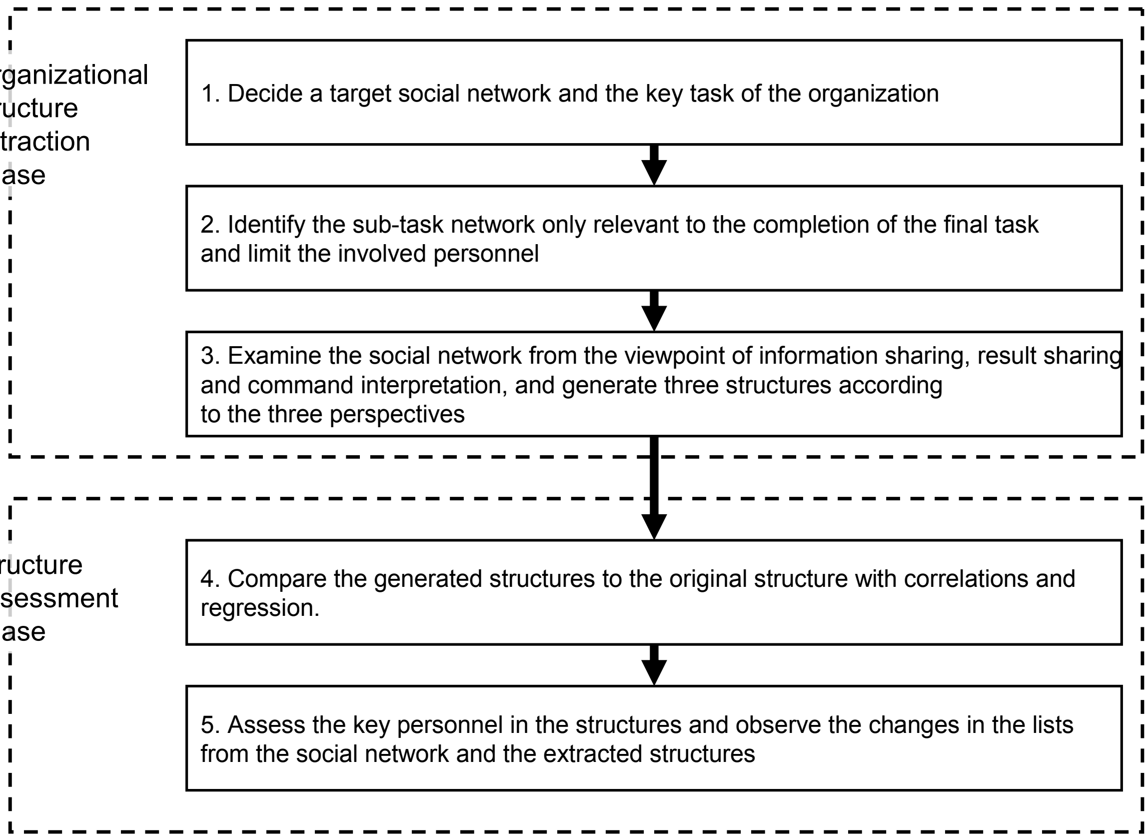


Figure 5-1 The procedure of the introduced analysis framework

5.2.1. Extracting a decision making structure from a meta-network

The scope of the decision making structure is limited by focusing on a single task execution. This way restricts the number of individuals who make up the extracted structure and makes the others as the outside collaborators. As the number of individuals of interests decreases, we can focus on the investigation of the specific task performance and keep the generated structure recognizable to human analysts. Also, in the management science community, these selected individuals are regarded as decision makers, so this limitation differentiates between a social agent and a decision maker in the structure.

After selecting the decision makers, I infer the various management relations by utilizing the social network as well as the task assignment, the information, and the resource distribution networks. For instance, when two members are connected with a communication path and one has expertise required by the other, the shortest path may be the information sharing path in terms of management relationships. With similar methods, in addition to the information sharing relationships, we infer result sharing and command interpretation relationships. These are originated from three different structural links in the CAESAR III model. In the model, information sharing, result sharing, and command interpretation links are different in their timings of message arrival. Information sharing messages are delivered after the sender is aware of the situation and before the receiver performs the information fusion. Result sharing is done after the sender's response selection. Command interpretation occurs before the receiver's response selection. The information fusion, response selection, and command interpretation are the cognitive processes defined in CAESAR III.

5.2.1.1. Limiting a task network and finding decision makers

Since the decision making structure in this paper is task-oriented, our framework aims to extract a structure responsible for completing a certain final task. This task is a user-defined parameter. With the given final task, we can retrace a sub-task network from a meta-network by following the prerequisite tasks repeatedly, starting from the final task. For example, in Figure 5-2, the final task is *lead attackers to embassy*; then, its sub-prerequisite tasks are *provide money, surveillance of possible targets, education and training, etc* (Total 8 tasks). These eight tasks consist of the sub-task network for extraction, and the 8 terrorists (*Abdullah Ahmed Abdullah, Al Owali, Abdel Rahman, etc*) assigned to those tasks are the decision makers of this task-oriented decision making structure.

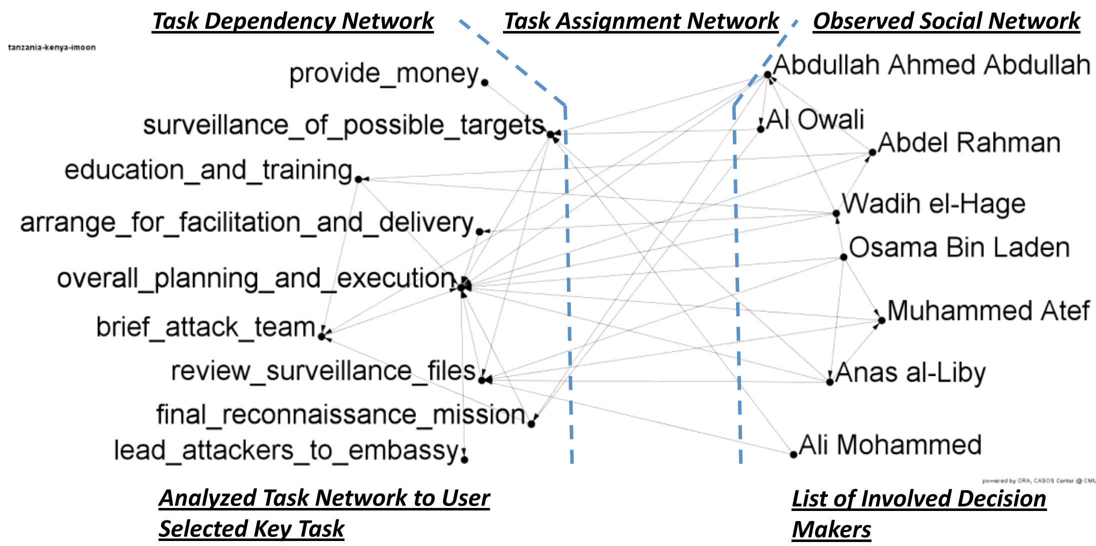


Figure 5-2 The partial visualization of the task precedence network (task-to-task) and the task assignment network (terrorist-to-task). The dashed line represents the separation of the task network and the assigned agents. When users set up lead attackers to embassy as a final task for the extraction, the visualized tasks and the individuals are the components of the sub-task network, and the accompanying decision makers, 65especttively.

After limiting the involved decision makers, I aggregate the uninvolved agents as an outside organization. It is typical to see a decision making structure interacting with outside organizations. If we configure a task-based sub-decision making structure, some of the individuals will be excluded, since they are not doing the tasks in the sub-task network. However, it is still possible that the excluded ones hold required resources or information, and this will require communications between the selected decision makers of the extracted structure and the outside organization, which is the group of the excluded individuals. Thus, finding assigned decision makers does not just limit the personnel of the decision making structure, but also specifies the boundary decision makers interacting with outside entities. In this example, we have a total 18 terrorists, and 16 terrorists are selected as decision makers. Thus, the other 2 terrorists form the outside organization of this decision making structure (It should be noted that these two agents were identified as isolates and had no specific relations with decision makers when we limit our investigations to the *detonate* task).

5.2.1.2. Information sharing structure

In a meta-network, a piece of information, or expertise, is represented as a knowledge node. Thus, we assume that producing information is represented as a link from an agent node to a knowledge node. Also, we infer that one decision maker will acquire information through an information sharing path if 1) he needs the information to perform his assigned tasks, 2) he does not have the information, and 3) the information sharing path is the shortest path from the nearest decision maker holding the information for him. The figures from Figure 5-3 to Figure 5-7 describe the case of information sharing links. According to the sub-network in the figures, *Ali Mohamed* is assigned to *surveillance of possible targets*, which requires *surveillance expertise*. However, *sur-*

veillance expertise is not available to *Ali Mohammed*, but available to *Anas Al-Liby*. Then, *Ali Mohamed* finds shortest paths possible to *Anas Al-Liby*, and he finds the shortest paths with two social links going through *Osama bin Laden* or *Muhammad Atef*. Then, the links in these two shortest paths will be the information sharing links.

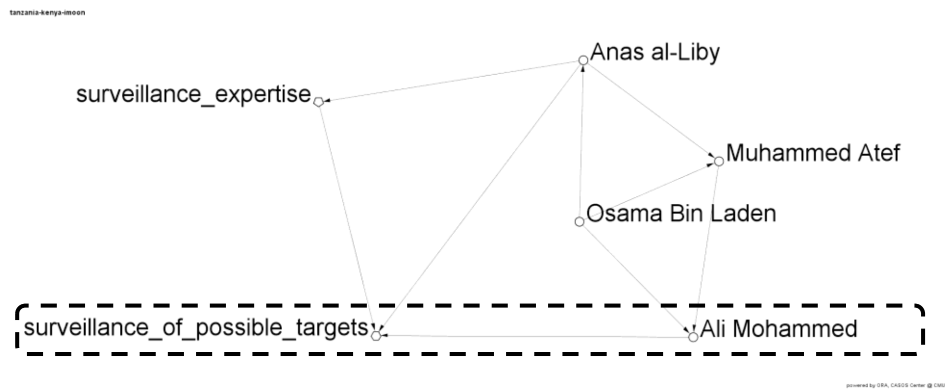


Figure 5-3 A partial visualization explaining the formation of information sharing links: First step, find assigned tasks of an agent

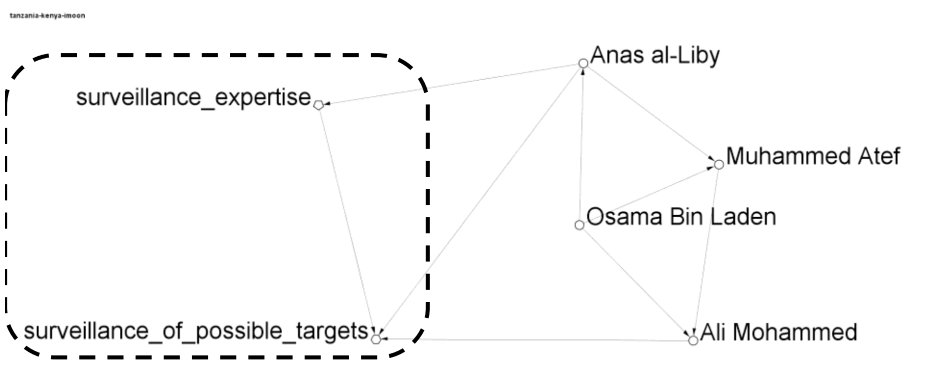


Figure 5-4 Second step, find required expertise or resources that the agent does not have[4]

[4] Recognize that *surveillance expertise* is required to perform the assigned task and A*li Mohamed* doesn't have it

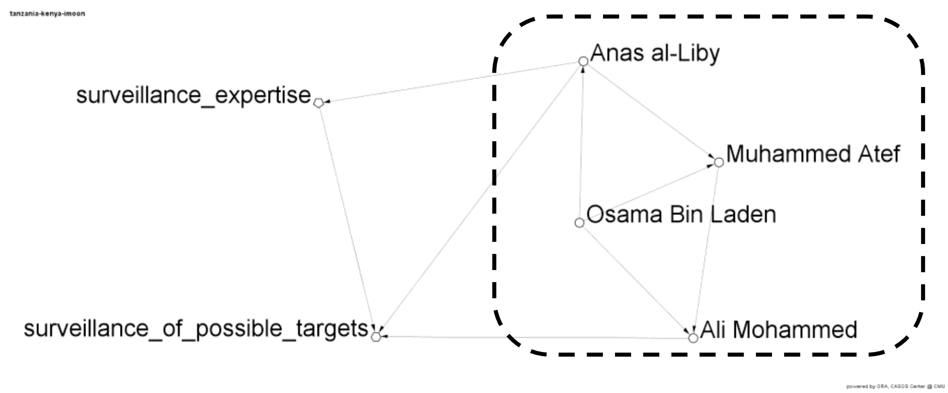


Figure 5-5 Third step, the organization searches an agent with the required expertise or resources from the agents executing the task[5]

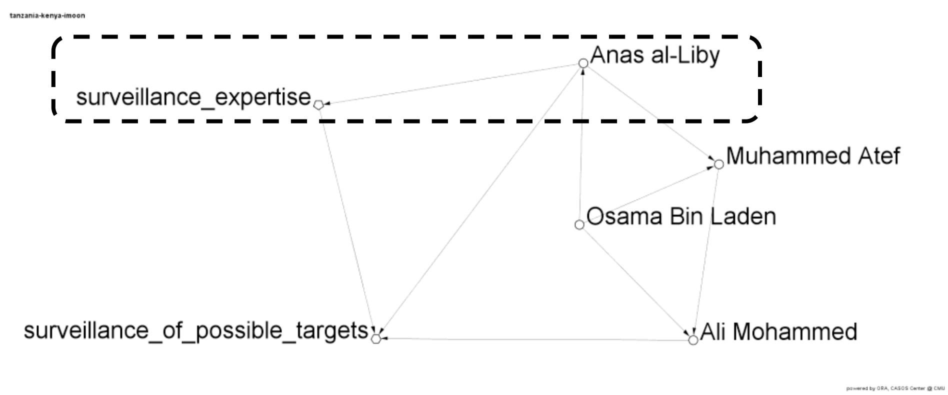


Figure 5-6 Fourth step, the agent with the required resources or expertise has to deliver it to the agent assigned to task without the required elements through the social links[6]

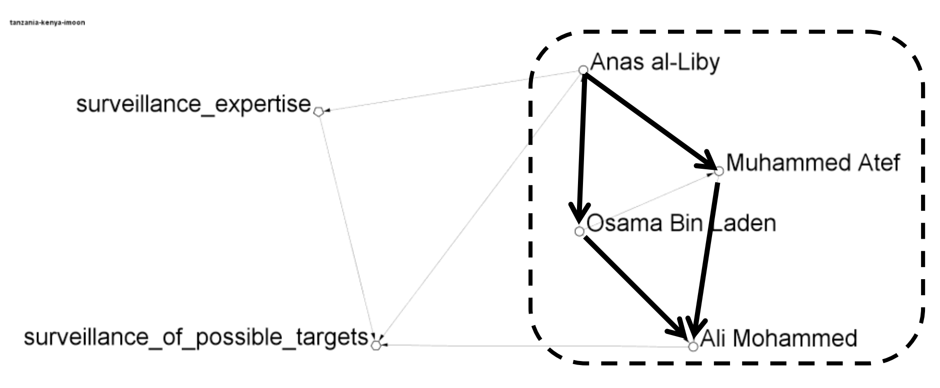


Figure 5-7 Fifth step, the found shortest paths for expertise or resource deliveries there are information sharing links.[7]

---

[5] Search an agent with *surveillance expertise* from the nearest agents through the social network of agents. Stop searching when *Anas al-Liby*, two links away, has it

[6] *Anas al-Liby* has *surveillance expertise*, and he has to provide the expertise through the social network

5.2.1.3. Result sharing structure

Result Sharing (RS) is communication from a decision maker finishing his assigned task to a decision maker with a task that required the previously done task. For instance, there is a RS communication from a terrorist who finished *surveillance of possible targets* to a terrorist who will perform *overall planning and execution*. Figure 5-8 shows the above two tasks and their assigned agents. *Surveillance of possible targets* has three assigned agents, and *overall planning and execution* has eight agents. Then, there will be 16 result sharing links originating from the four agents (*Ali Mohammed, Al Owali, Anas al-Liby, and Abdullah Ahmed Abdullah)* to the four agents (*Abdel Rahman, Wadih el-Hage, Muhammed Atef and Osama Bin Laden*), excluding the agent who is assigned to the next task and already knows the results of the previous task.

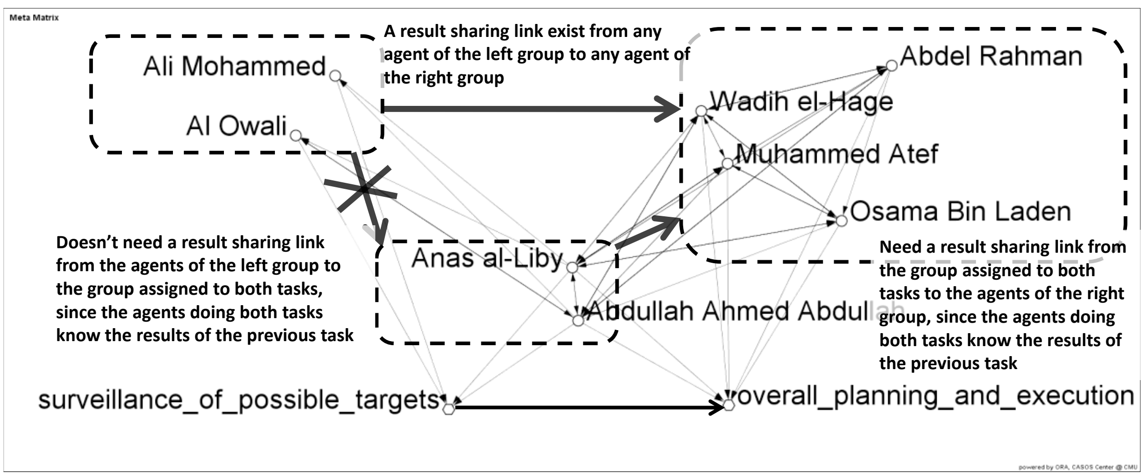


Figure 5-8 A partial visualization of two tasks and ten assigned agents. This precedence task relation will result in 21 result sharing links between the agents doing the prior task and the agents performing the next task. One agent who is doing both does not need any result sharing link.

5.2.1.4. Command interpretation structure

Command Interpretation (CI) is command relation from a decision maker who completed his task and sent an order to a lower ranking decision maker. We infer this relation by reconstructing the hierarchy in the social network based on the direction of agent communication links. We assume that the directions of communications are the representation of who-reports-to-whom relation. Subsequently, the directions will provide a basis for extracting hierarchical structure. For instance, *Ahmed the German* has a one-way link to *Abdullah Ahmed Abdullah*, and *Khalfan Khamis Mohamed* to *Mohammed Odeh.* These one-way social links imply a command chain. On the other

[7] Identify the expertise access paths, all possible shortest path from *Anas al-Liby* to *Ali Mohamed*. Each of the links in the paths are information sharing links.

hand, *Khalfan Khamis Mohamed, Mustafa Mohamed Fadhil and Sheik Ahmed Salim Swedan* has a cycle of communication Report-Ins. This makes no command interpretation relations among the three terrorists. This is because any of the three terrorists can influence the others by using indirect reports. However, the one-way communication ensures that the influence is just one way, not bi-directional.

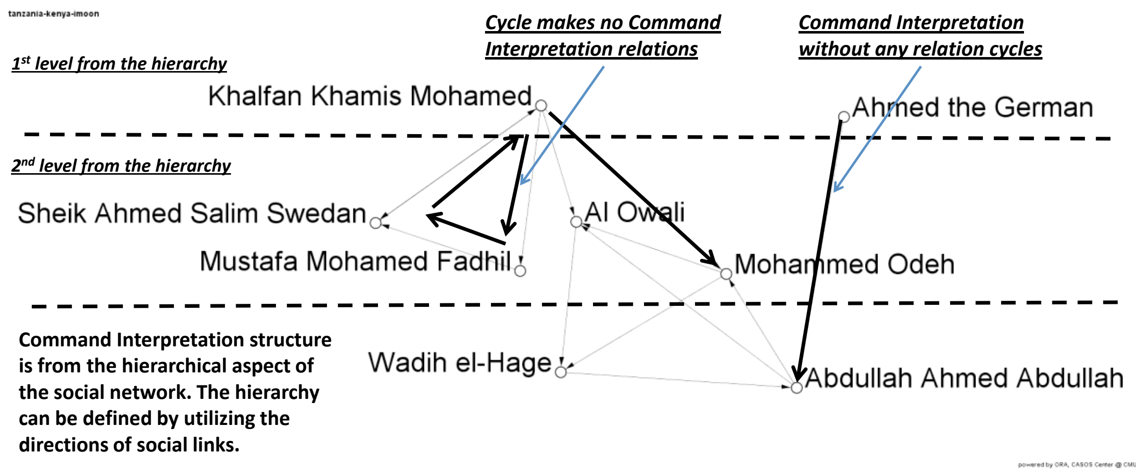


Figure 5-9 a partial visualization of the agent-to-agent network. From the directions of links, we can identify the hierarchy of the network. After configuring the hierarchy, we can see the Command Interpretation relations between two agents at the adjacent level.

5.2.2. Assessing a network structure with measures

The observed meta-network and the inferred decision making structures are all in the meta-matrix format. Therefore, we apply network analysis metrics to assess the criticality of individuals in a network. The metrics are five: *Degree centrality, Betweenness centrality, Eigenvector centrality, Cognitive demand, and Communication*. The detailed interpretation is in Table 5-1.

Table 5-1 Three traditional centrality metrics and two dynamic network metrics used to assess the criticalities of individuals in the structure

Name	Interpretation	Reference
Degree Centrality	Number of in-coming and out-going links from a node, Degree of direct influence to others	Freeman, 1979
Betweenness Centrality	Number of shortest paths passing a node, Degree of information flow control	Freeman, 1979
Eigenvector Centrality	Calculates the eigenvector of the largest positive eigenvalue of the adjacency matrix, Degree of connections to the high-scoring nodes	Bonacich, 1972
Cognitive Demand	Measures the total amount of effort expended by each agent to do his/her tasks, calculation details are elabo-	Carley, 2002

	rated below.	
Communication	Measures the communication need of agents to complete their assigned tasks, calculation details are elaborated below.	Carley, 2002

5.3. Application

The described decision making structure extraction scheme is applied to the datasets introduced in Chapter 4. I outline the application result from the U.S. embassy bombing in the Tanzania and Kenya case in this chapter. The other results can be found in Appendix 11. To analyze the Tanzania and Kenya case, the task of interest was *detonation*. Next, we regress the decision making structures against the observed meta-network structure to find which decision making structure is embedded in the observed network and to what extent. After estimating the overall correlation level between the observed and the extracted structures, we describe and visualize the extracted structure. Next, we calculate five network metrics on the observed meta-network and three different management networks. Comparisons on the calculated metrics provide an insight into who stands out in different settings and why. Also, we identify the clusters based on the factor analysis of the metrics of the four networks.

5.3.1. Initial result and descriptive statistics

Figure 5-10 is the visualization of the extracted decision making structures for the detonation task, and the image is generated by ORA (Reminga and Carley 2004). The collection of these extracted networks is an input dataset for the CAESAR III model, and subsequent cognitive process analysis in decision making structure can be done with the model. However, we leave the analysis as our future work in this paper. Whereas the observed meta-network has 18 members, the extracted structure has only 16. The removed members are not related to the task network of detonation. The topologies of the structures are different. First, the information sharing structure is somewhat similar to the person-to-person network of the meta-network. The inference of the information sharing is done by trimming the links not included in the information passage. Therefore, the base of the information sharing is the person-to-person network (social network), so the inferred network resembles the social network. Second, the result sharing network is very different from the social network. The result sharing is inferred from the task dependency network and task assignment network. Due to the difference between the result sharing structure and the social network, this organization may suffer from the delivery of information about the completion of prerequisites during the task execution period. Finally, the command interpretation structure only includes three individuals. In the observed social network, most of the individuals are linked by a cycle with directed links. Therefore, the inference on the command interpretation is not clear for most of the members. However, we can observe several hierarchical relations such as *Ahmed the German* to *Abdullah Ahmed Abdullah, Khalfan Khamis Mohamed* to *Al Owali, etc.*

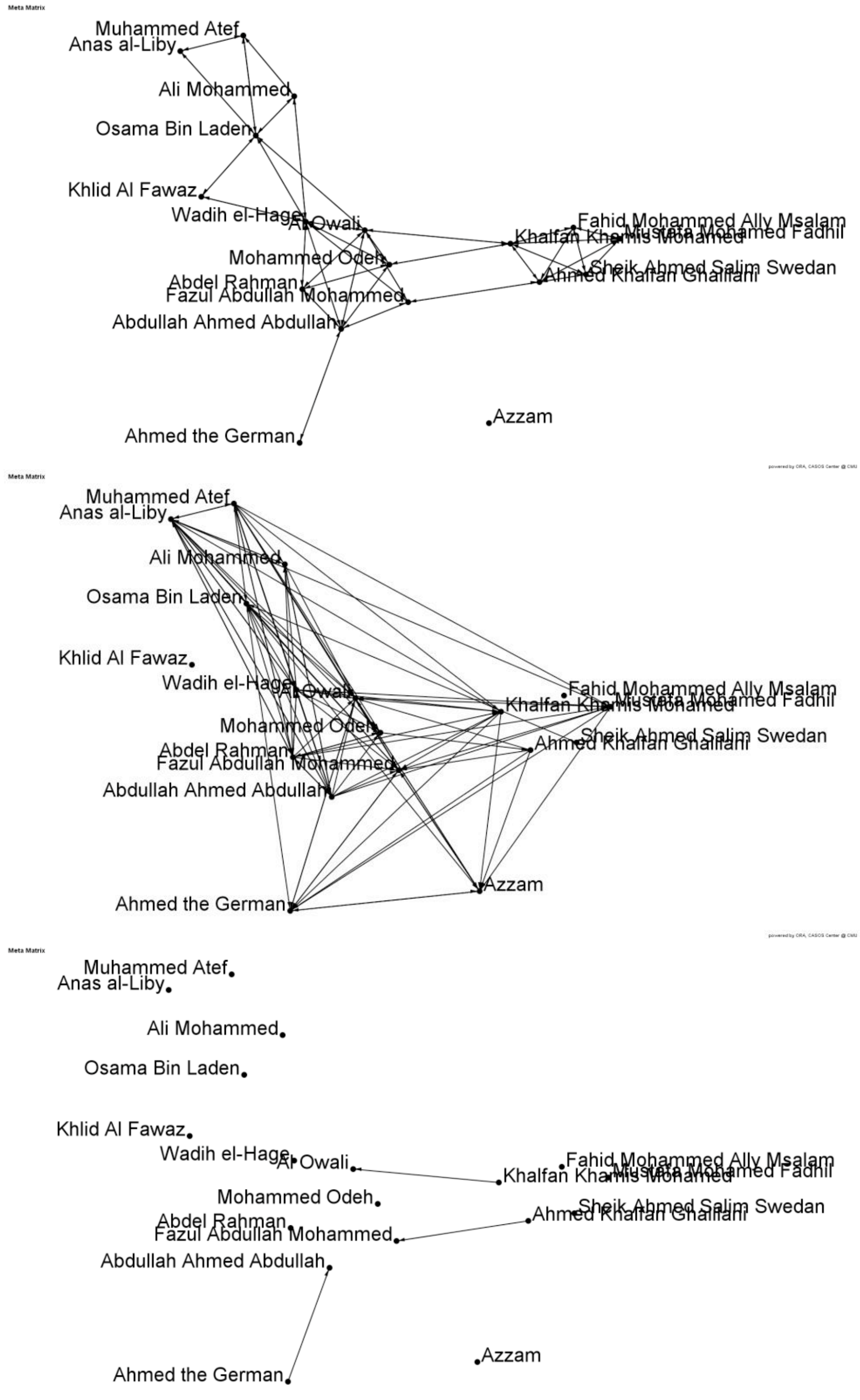


Figure 5-10 Three extracted decision making structures. (Top) Information sharing, (Middle) Result sharing, (Bottom) Command interpretation

5.3.2. Embedded decision making structures in an observed meta-network

We analyze how the extracted decision making structure was embedded in the observed meta-network and to what extent. We use the QAP/MRQAP technique to compare and to regress the extracted decision making structures to the observed network. This is a statistical analysis to support the qualitative findings of Section 5.3.1. If the meta-network implies such decision making structures, the correlation and the R-square of the regression result will be high. Table 5-2 displays the result of QAP correlations between each of the extracted structures and the meta-network. Information sharing is very highly correlated with the observed structure. This high correlation is from the heuristic of the extraction. When we extract the information sharing links, we just trim the existing links, not add ones. However, the high correlation also tells us that there were not many trimmed links, which implies that the observed social links served well as information diffusion paths. The low correlation between the result sharing structure and the meta-network is coming from many additions of links. This means that the network does not adequately support informing the result of the prerequisite tasks to the individuals doing subsequent tasks.

Table 5-2 QAP correlation and other distance metrics between the observed structure and the extracted decision making structures. (IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

	CI	IS	RS
Correlation	0.243	0.726	0.004
Significance	0.000	0.000	0.570
Hamming Distance	41.000	30.000	107.000
Euclidean Distance	6.403	5.477	10.344

The MRQAP analysis in Table 5-3, between the extracted structures as independent variables and the meta-network as a dependent variable, results in a high R-squared value, 0.545. This is a very high value considering the R-squared is usually very low in MRQAP analyses. As the previous correlation indicates, the information sharing structure was the biggest contributor in estimating the link existence in the meta- network. The levels of standard coefficients of the command interpretation and the result sharing structures are similar. However, the result sharing structure was more significant than the command interpretation while the information sharing was far more significant than the other two. From this MRQAP result, we can see that the observed meta-network can be explained by the decision making structures and it embeds those structures. However, the result sharing and the command interpretation are not as well represented as the information sharing.

Table 5-3 regression results. The dependent network is the observed meta-network, and the independent networks are the extracted meta-network. (R-Squared = 0. 545)

Variable	Coef	Std.Coef	Sig.Y-	Sig.Dekker

			Perm	
Constant	0.015		0.000	
CI	0.440	0.124	0.050	0.000
IS	0.582	0.710	0.000	0.000
RS	-0.055	-0.071	0.110	0.000

5.3.3. Personnel with different levels of importance in structures

Table 5-4 shows the top three individuals in the four structures (observed meta-network, information sharing, result sharing, and command interpretation) and by using five metrics (degree centrality, betweenness centrality, eigenvector centrality, cognitive demand, and communication). In overall, *Wadih el-Hage, Al Owali* and *Fazul Abdullah Mohammed* appear frequently in the top 3 critical agent lists. *Fazul Abdullah Mohammed* seems to be the most critical agent from the cognitive demand and the communication perspective. He is the top rank agent by every metric from the result sharing structure. Also, *Wadih el-Hage* shows different important level across the original and information sharing structures. From the betweenness centrality, he is the second most critical agent in the original structure, but his importance is ranked at the third when we consider the information sharing structure. In contrast, *Osama Bin Laden* has the third highest betweenness centrality in the result sharing structure, but his betweenness centrality becomes the second highest when we consider the result sharing structure. These different key actors from different structures suggest that key actors in the observed structure might not be the key actors in the actual decision making structures.

Table 5-4 Top three individuals from five metrics and four structures (OBS=observed meta-network, IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

Measure	Structure	Rank 1	Rank 2	Rank 3
Total Degree Centrality	OBS	Khalfan Khamis Mohamed	Ahmed Khalfan Ghalilani	Wadih el-Hage
	IS	Wadih el-Hage	Al Owali	Osama Bin Laden
	RS	Abdullah Ahmed Abdullah	Anas al-Liby	Al Owali
	CI	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Khalfan Khamis Mohamed
Betweenness Centrality	OBS	Al Owali	Wadih el-Hage	Osama Bin Laden
	IS	Al Owali	Khalfan Khamis Mohamed	Wadih el-Hage
	RS	Abdel Rahman	Osama Bin Laden	Mohammed Odeh
	CI	Muhammed Atef	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah
Eigenvector Cen-	OBS	Wadih el-Hage	Al Owali	Abdullah Ahmed

Measure	Structure	Rank 1	Rank 2	Rank 3
trality				Abdullah
	IS	Wadih el-Hage	Al Owali	Abdullah Ahmed Abdullah
	RS	Al Owali	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah
	CI	Abdullah Ahmed Abdullah	Ahmed the German	Muhammed Atef
Cognitive Demand	OBS	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Al Owali
	IS	Fazul Abdullah Mohammed	Al Owali	Khalfan Khamis Mohamed
	RS	Fazul Abdullah Mohammed	Abdel Rahman	Abdullah Ahmed Abdullah
	CI	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Mustafa Mohamed Fadhil
Communication	OBS	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Mustafa Mohamed Fadhil
	IS	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Mustafa Mohamed Fadhil
	RS	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Mustafa Mohamed Fadhil
	CI	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Mustafa Mohamed Fadhil

Figure 5-11 shows that the difference of metric evaluation results across the observed meta-network and decision making structures. Specifically, we subtract a metric value of a meta-network from the value of a decision making structure. Overall, the differences of the metrics are big, which indicates the inference estimated the levels of individuals' importance quite differently. However, the difference in *Communication* and *Eigenvector Centrality* from the observed network and decision making structures are quite similar except for a few individuals.

Eigenvector centrality and Communication are the two metrics that show not much difference from the original metrics compared to the extracted structures. On the other hand, Degree, Betweenness Centralities and Cognitive Demand show differences between the original and the extracted structures across the most of the agents.

Compared to the original structure, *Anas al-Liby* (A12) has the higher degree centrality and the higher cognitive demand in the result sharing structure. This suggest that he is underestimated in the observed structure regarding the result sharing activity and considering the degree centrality and the cognitive demand. In the information sharing structure, *Wadih el-Hage* (A11) and *Al Owali* (A13) are important. They have higher Degree Centrality in the information sharing structure. Finally, *Al Owali's* (A13) importance is over-estimated from the passing command interpretations. His betweenness centrality becomes lower when we apply the metric to the extracted Command Interpretation structure.

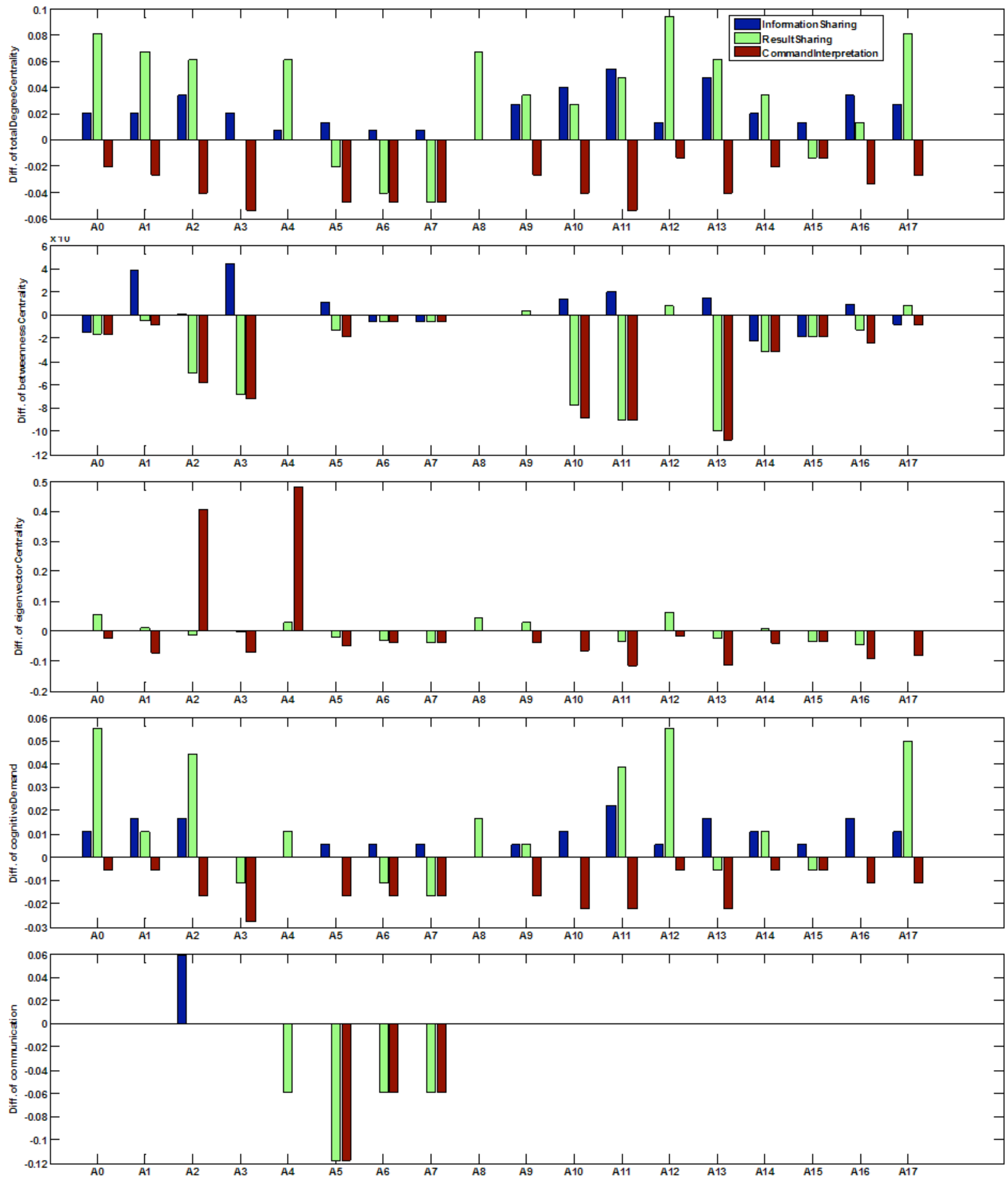


Figure 5-11 Charts displaying the difference of metrics between a meta-network and extracted structures

Table 5-5 I.D. assignments to individuals. I.D.s will be used to distinguish individuals in the later tables. We used some abbreviations for names

ID	A0	A1	A2	A3	A4	A5	A6
Name	Mu-hammed Atef	Fazul Ab-dullah Mo-hammed	Abdullah Ahmed Abdullah	Khalfan Khamis Mohamed	Ahmed the German	Ahmed Khalfan Ghalilani	Sheik Ahmed Salim Swedan
ID	A7	A8	A9	A10	A11	A12	A13
Name	Fahid Mo-hammed Ally Msalam	Azzam	Mustafa Mohamed Fadhil	Osama Bin Laden	Wadih el-Hage	Anas al-Liby	Al Owali
ID	A14	A15	A16	A17			
Name	Ali Mo-hammed	Khlid Al Fawaz	Mo-hammed Odeh	Abdel Rahman			

5.3.4. Personnel clusters with similar characteristics

Since we have four structures and five metrics for each structure, we cannot visualize or cluster the individuals without dimensionality reduction. Therefore, we use principal component analysis (PCA) to project the individuals in two dimensions with highest variances. Table 5-6 shows the coefficients to generate the two components corresponding to the two dimensions, and Figure 5-12 is the projection of the individuals on a two dimensional scatter plot. The clusters in the plots are member profiles according to the criticality. For instance, there may be a group of people with high betweenness and low degree centrality, and PCA will put those individuals close to each other. We apply this analysis to the two structure sets: the observed network and the collection of the three inferred structures. Thus, we can distinguish the different member profiles coming from the observed dataset and the inferred dataset.

According to Table 5-6, we have four sets of coefficients: two principal components for the observed and the inferred. In the observed, the high first principal component value means *high demand in communication to complete the assigned tasks* because it has high coefficient in communication and cognitive demand. The high second principal component value implies *having more connections to other personnel* because it has high coefficients in degree centrality, eigenvector centrality and cognitive demand. In the inferred structures, the meaning of the first principal component, *high demand in communication to complete the assigned tasks,* is similar to the second principal component of the observed, and that of the second component, *having fewer connections to personnel*, is similar to the opposite of the first component in the observed.

Table 5-6 Coefficients of two principal components from the observed structure (top) and the extracted structures (bottom)

	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	OBS	0.031	0.361
Betweenness Centrality	OBS	0.008	0.052
Eigenvector Centrality	OBS	0.105	0.667
Cognitive Demand	OBS	0.279	0.595
Communication	OBS	0.954	-0.260

	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	IS	0.041	0.000
	RS	0.045	-0.073
	CI	0.002	-0.012
Betweenness Centrality	IS	0.007	-0.002
	RS	0.001	0.000
	CI	0.000	0.000
Eigenvector Centrality	IS	0.057	-0.028
	RS	0.049	-0.042
	CI	-0.090	-0.988
Cognitive Demand	IS	0.159	-0.043
	RS	0.149	-0.075
	CI	0.142	-0.047
Communication	IS	0.525	-0.065
	RS	0.571	0.007
	CI	0.560	-0.048

Figure 5-12 displays the clusters of individuals in the projection of the two principal components of the two structures. The observed structure suggests four member profiles: *many connections to personnel and less communication demand to complete their tasks* (A6); *medium or fewer connections to personnel and medium communication demand* (A0, A4, A7, A8, A12, A14, A15); *medium connections to personnel and high communication demand* (A1, A3, A5, A9, A10, A13, A16, A17); *many connections to personnel and medium communication demand* (A2, A11).

The inferred structures provide four profiles: *few connections to personnel and less communication demand to complete their tasks (*A6); *many connections to personnel and medium communication demand (*A2, A4); *fewer connections to personnel and medium communication demand (*A0, A5, A7, A8, A11, A12, A14, A15); and *fewer connections to personnel and high communication demand (*A1, A3, A13, A16, A17, A9, A10).

These profiles tell the groups of individuals well supported in communication to complete their tasks and the groups, which are not. Also, it specifies the groups communicating frequently with other parts of the organizations and groups not communicating that frequently. For example, *Fahid Mohammed Ally Msalam (*A7) and *Azzam* (A8) are grouped in the same cluster in both structures. In the observed structure, their profile indicates that they do not have many links to other personnel, but they have medium communication demand to complete their tasks. The extracted structure shows the same profile for the two terrorists.

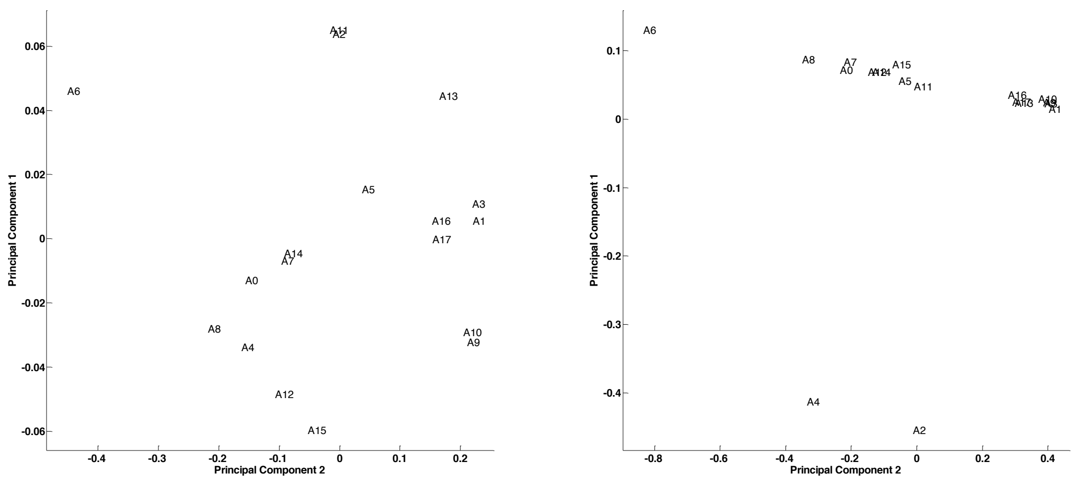


Figure 5-12 Two projections of metrics of individuals using two principal components. The left is using only the observed structure, and the right is from only the extracted structures.

5.4. Conclusion

This chapter demonstrates what can be achieved by integrating social network analysis and an approach for analyzing the information processing and decision making structure of an organization. Social network analysis has been a prominent tool in investigating the structure of observed networks. However, it may mis-estimate the role of individuals vis-a-vis specific tasks, if it is applied only to the observed network particularly where the observed network crosses time periods and tasks. Information processing and decision making structure analysis provides guidance on the fragility and robustness of the operational structure; but requires massive amount of subject matter expertise and time to estimate. By inferring the decision making structure from the observed social network, I am able to focus the analysts or researchers attention on just those parts of the network critical for the tasks of concern. I reduce time and effort to construct the decision making structure and so enable the power of decision making structure analysis to be used on a wider range of problems.

Limitation: I used inference heuristics, so I can extract a decision making structure. These heuristics are well-informed and frequently used by human analysts, and these heuristics are supported by the ontology and semantics of the meta network concept. However, this is the introduction of biases. Without any validation method, introducing more biases may lead analysts into a false result.

Another limitation is in the result interpretation. I come up with a conclusion that there is no significant correlation between the observed organizational structure and the result sharing inferred structure. However, given that the data source is a university research report about the US embassy bombings, this conclusion may be induced by the data collection biases. For example, the data collection activities are more focused on the information sharing than the reporting back. Another possibility is that the adversaries are more adept in hiding result sharing compared to the information sharing. Both possibilities can produce a biased input observation, eventually a biased inferred result sharing or information sharing structure. Therefore, a human analyst using this tool should keep in mind that the inference is based on the observations, so the biases in the observations can influence the inference result. This limitation is difficult to be resolved with the given data. Rather, this analysis will provide an opportunity to check the data observation procedure, so that less biased data can be collected and data collections are done across various interaction intentions.

Theoretic contribution: A by-product of this approach is that each of the components of the decision making structure are inferred including the information, reporting and command structures. This thesis provides a new way to view flat social networks. So far, social network analysts regarded an observed social network as is, and there is no computational tool to infer an embedded structure from the flat observed network. However, since we expanded the observation areas to the resources, expertise, and tasks, we can infer the nature of the interactions based on the additional information. This meta-network level observation and the embedded structure inference tool enables a new way to handle a flat social network as a multi-plex social network.

Technical contribution: Our application results indicate that the point of investigation into the original structure can be reduced by limiting the number of terrorists involved in a specific subtask network (the number of agents are reduced from 18 terrorists to 16 terrorists). Also, an analyst can say whether an organization is well-supported or not by looking into the extracted task-related networks, such as the information sharing and the result sharing structures. These inferred structures suggest different key personnel compared to the original structures. The combination of such key personnel may reveal hidden critical task executors or execution coordinators. I used the principal component analysis (PCA) to show these profiles by using the two structures: the original and the inferred structures.

Empirical contribution: This particular application results found that some key actors who might be over- or under-estimated before[8]. For example, *Anas al-Liby* was the task coordinator who has higher betweenness and degree centralities in the result sharing g structure than in the original structure. Also, this approach enabled different actor profiling by using two different structures: the original structure and the extracted structure. As an example of the actor profiling result, *Fahid Mohammed Ally Msalam and Azzam are* in the same profile suggesting that they are less linked to other personnel and medium communication demand to carry out their assigned tasks.

[8] I do not want this remark to be too definitive statement given that the dataset is a nuanced dataset, not a completely verified dataset. Also, the analysis result is not fully verified and validated. I want to note that this is just a possibility of the over- or under-estimations, not a definite claim.

- *Inferred structure suggests new information such as a different list of critical actors in a networked structure.*
- *Inferred structure suggests more in-depth agent profiles when it is used with the original structure.*
- *Inferred structure limits the size of organizations of interests, so a human analyst can focus on the critical parts related to a key task execution.*

I provide a technical method to extract three decision making structures from an observed social network. This technical implementation is from the theoretical fusion between the decision making structure concept from management, operations research and social network analysis from sociology. Furthermore, by providing different types of links among the same entities, the dynamic network analysis theory can enjoy better multi-plex network datasets.

6. Building Macro-level Destabilization Strategies – Influence Network Analysis

Whether a task will be completed or not is one of managers' critical questions (Scenario 2 and 3 in Ch. 1.2.). The managers estimate the chance of task completion and support their group to increase the chance. Traditionally, they used their past experience, hierarchical structure, or authority to facilitate the completion. However, recent organizational trends, i.e. fast changes, decentralized structures, flat team models, etc, demand more than the old enablers. Thus, we need a new approach for the analysis of task completion of an organization. The approach should be robust against a quickly changing operational environment and complex structures. Additionally, it should be flexible, so that mangers can apply their subject knowledge and experience to the analysis. Thus, this paper introduces such an analysis approach that assesses an organizational structure and estimates its task completion likelihood.

An organizational structure contains factors that are critical for its task success (Malone and Smith, 1988). While traditional structures only display the personnel formation and assignment (Hage et al., 1971), they are not the only component of organizational structure. An alternative view (Galbraith, 1973; Thompson, 1967) is that structures includes social networks as well as the personnel assignment to tasks, the resource and information availability, the task dependency network, etc. This distribution and assignment information suggests how well a task is supported organizationally. I use a meta-network format (Krackhardt and Carley, 1998) to represent this organizational structure. The meta-network is a multi-modal and multi-plex social network including various elements, such as people, expertise, resources and tasks; and various relations, e.g. work relationships, resource distribution, task assignments. I represent an organizational structure with this format and assess the support to the task completion.

I utilize an influence network to evaluate the task completion likelihood. An influence network is a simplification of a Bayesian network. It contains nodes representing events and links encoding causal relationships among events. It propagates the likelihood of each event through promotion or inhibition by its parents. In the real world, the influence network is becoming popular, as knowing how to influence and redirect the change of situation is very important. For example, influence network analysis has been used to analyze the IED attacks over a region of Iraq (Wagenhals and Levis, 2007). This influence network contains belief statements related to politic, military, social, economic, information and infrastructure, so called PMESII (DARPA, 2005; Snyder and Tolk, 2006) in military planning. The network helps evaluate which sectors friendly forces should act upon to lower the IED attack frequencies in the region

I combine these two existing tools, the meta-network and the influence network, and provide task completion likelihood estimations for various organizations, e.g. grass-roots organizations, open source software development teams, corporations, terrorist networks, military units, etc (see Scenarios in Ch. 1.2.). From previous organizational management literatures, I identify six important factors in task completion. Then, I assess the factors with an organizational structure in a meta-network. Then, the assessments on factors become nodes in the influence networks, and I build up the causal links by utilizing a task dependency network. The nodes of assessments and links of task dependencies make up an influence network that we finally use to estimate the task completion likelihood. In this paper, we use the above influence network generation idea and implement a function to carry it out. I test the implemented idea with a terrorism act, the 1998 US Embassy bombing in Tanzania and Kenya (see the introduced dataset in Ch. 4.2). My approach is able to identify the tasks that are well- or ill-supported by the terrorist network, and to find the critical tasks that if prevented will have a significant impact on the probability of overall mission completion based on the key task dependency path.

6.1. Background about the Integration of the Dynamic Network and the Influence Network Analyses

I build a Bayesian network model (an influence network) from a meta-network. This Bayesian network assess the task completion probability by assessing six factors in the task completion from the Operations Research, Management viewpoints. The used Meta-Network concept is already introduced in Ch. 4.1. I outlines the basic of the influence network and the six assessment points over the course of the influence network generation.

6.1.1. Influence network used in the real world

Influence network (Rosen and Smith, 1996; Wagenhals et al. 1998) is a semi-Bayesian network including belief statement nodes and influencing or causal links among the statement nodes. It uses a simplified knowledge elicitation mechanism that heuristically generates a conditional probability table for each belief statement node that has influencing parents, and it computes the marginal probabilities of the nodes with parents given the probability of each of the bottom nodes. Originally developed to support the assessment of political-social influence strategies, their use is most appropriate for modeling situations in which it is difficult to specify conditional probability values especially if their values are subjective and they cannot be estimated by empirical evidence. Applications include military planning at the operational and strategic level and counterterrorism. For instance, Wagenhals and Levis (2007) designed an influence network focused on subduing IED attacks in Iraq. Hudson et al (2001) introduces potential usages for counterterrorism, and Rosen and Smith (1996) show an influence network model for building a military and diplomatic strategy.

Traditionally, influence networks have been produced by subject matter experts. They have knowledge of the target situation and organization, assess belief statements related to a target event or effect, and create an influence network by setting up its nodes, links and parameters based on their own knowledge. However, this creates a number of problems in real usages of this inference tool (Vego, 2006). First, model generation takes a long time. Second, the generation is based on experts' opinions and there may be disagreements and inaccuracies. Currently, experts decide on what the related belief statements are, how the topology shapes the linkage of beliefs, what the baseline probability of the each belief should be, etc. However, without a template or a commonly accepted practice of network generation, the influence network created can be biased by an individual analyst's point of view. Therefore, a potential solution is a tool that creates a blueprint of an influence network with a standardized template that experts can examine and customize based on their expertise.

6.1.2. Traditional management methodologies for task completion and found critical factors

Traditionally, organizational performance management has been based on qualitative analysis and case studies. The management community focused on developing a metric for organizational performance (Dess and Robinson, 1984), but there are no outstanding metrics that researchers frequently utilize. Only some particular fields have several suggested metrics, e.g. shared situation awareness in military command and control structure analysis (Graham, 2005). However, management researchers have been able to identify cases of good group performance based on qualitative assessments and have found reasons for successes. For instance, group efficacy (Silver and Bufanio, 1996) is a critical factor in organizational performance. When group members believe that they can accomplish the mission, then they really complete the mission. In deeper sense, they may be intuitively gauging their ability to perform the task, assessing the situation, and perceiving that they can do the job. Also, work attitudes and satisfaction (Ostroff, 1992) are positively correlated with group performance. In other words, happy workers work better. Whereas these qualitative assessments on the group or individual mental state are important in understanding the group performance, these are not tangible or easily assessable factors, or they are too obvious to apply to the real complex organizational management.

On the other side of aisle, researchers have identified factors derived from the nature of tasks or organizational structure. For example, the operations research domain has developed task precedence network analysis (Eisner, 1962). It suggests better ways to organize the task performance plan or to minimize the impact of completion delays, etc. While the task dependency is one factor considering the links among the tasks, the task complexity and the importance of each task are other factors that affect tasks completion (Campbell, 1991; Forsyth and Schlenker, 1977). Organizational structure suggests the criticality of personnel, resources and information distribution. Human resource management is another approach to enhance the organizational performance by assigning personnel to tasks effectively (Becker and Gerhart, 1996). Furthermore, as organizations perform knowledge-intensive tasks, the diffusion of knowledge or knowledge management becomes another important factor in getting a job done (Argote and Ingram, 2000).

Our objective for this paper is to describe a tool that assesses the organizational structure and situations and estimates the task completion likelihood. Since our approach is based on the current meta-network framework, it does not have enough information to evaluate the psychological aspects of the workers and the group. However, we use the factors from the task natures and the organizational structure since they are represented in the meta-network format. We build heuristics assessing the above factors with a meta-network and use the assessment to generate an influence network, or a tool for estimating task completion likelihood. Sensitivity analysis over the heuristic parameters can provide insight into potential task vulnerabilities indicating potential points of influence, which can support the point of view of task management or task or mission intervention.

6.2. Method – Generating an influence network from a meta-network

I generate an influence network explaining the likelihood of a task completion from a meta- network. Thus, inputs for the generation are 1) a meta- network, 2) a target task to be analyzed in the network and 3) parameters for the generated influence network. Political, Military, Economic, Social, Information and Infrastructure, or PMESII, aspects are the elements of assessing a situation in traditional influence network building. For the task completion assessment, I similarly identify six factors contributing to a task completion, and these six factors come from the literature review of the previous section. The six factors are 1) prior task completion, 2) task importance, 3) task complexity, 4) personnel assignment, 5) accessible expertise and 6) available resources. The below sections explain how we extracted each of the task completion factors and turn them into a node in the influence network. After the generation of an influence network, we evaluate the propagated task completion likelihood using the CAusal STrength (CAST) algorithm developed by Rosen and Smith (1996). The overall procedure of using this method is described in Figure 6-1.

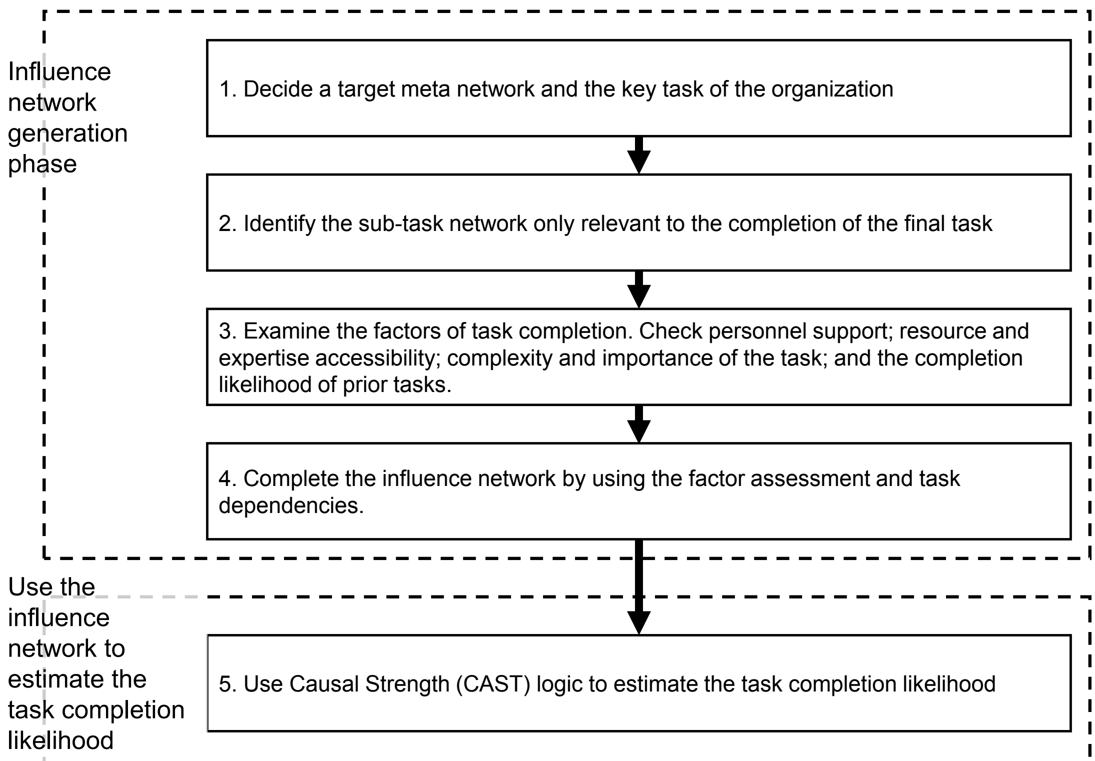


Figure 6-1 The procedure of influence network generation and task completion likelihood estimation

6.2.1. Overall structure of a generated influence network

I describe the overall structure and how the accompanying parameters are determined. The structure of a generated influence network is explained in two steps. First, the skeleton of the influence network is derived from the task network of a particular final task. In the meta- network, there is a task network specifying the prior and the next tasks of a certain task. If an analyst selects a task to be analyzed, I infer a sub-network that only selects the tasks related to the completion of the final task and create a task network for it. That becomes the skeleton of the influence network. After that, we assess the likelihood of success for each task by adding the above six factors as influence network nodes. This becomes the flesh of influence network modeling the success of the each task. With these two parts, I can propagate the estimation of the success likelihood of individual task throughout the influence network with the skeleton of task network, Figure 6-2.

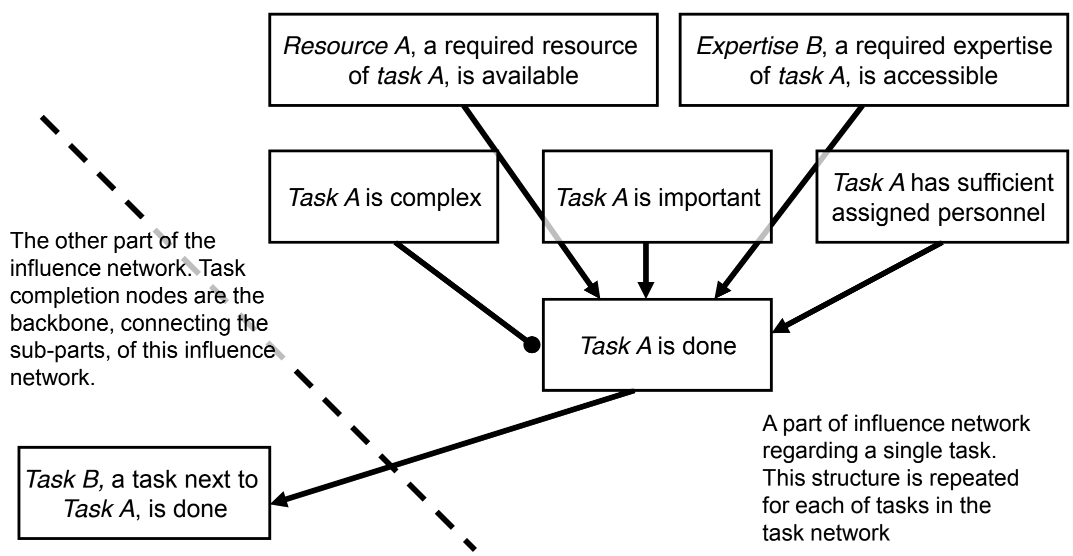


Figure 6-2 A simple diagram displaying how a generated influence network is structured

While we set the topology of the influence network as above, we supply a set of heuristics for determining the accompanying parameters for the network. These heuristics contains our assessment criteria on how to organize personnel, resources and expertise to successfully execute a task.

To use this approach, the user will need to provide a series of marginal probabilities for each factor in Column 1, Table 6-1. To illustrate this use, we provide sample probabilities in Column 2 and the rational we used in choosing the probabilities in Column 3. The use may wish to use probability values other than those we use in this example.

Table 6-1 Assignments of marginal probabilities (or baseline probability for task network nodes) for influence network nodes.

Influence network Node	Illustrative Node Probability	Illustrative rational and organizational structure assessment criteria for assigning the illustrative node probability
Task A is done (Task network)	Medium:0.5	We assume that if there is no external influence, the task has 50% chance of being completed.
Task A is Complex (task complexity)	Very Low: 0, Low: 0.25, Medium:0.5, High: 0.7, Very High: 0.8	We assume that if 1 person and 0 resource/expertise required, then the task has very low complexity. We assume that if 2 persons and 1 resources/expertise required, then the task has low complexity. We assume that if 3 persons and 3 resources/expertise required, then the task has medium complexity. We assume that if 6 persons and 7 resources/expertise required, then the task has high complexity. We assume that the task has very high complexity in the other cases
Task A is important (task importance)	Very Low: 0, Low: 0.25, Medium:0.5, High: 0.7, Very High: 0.8	We assume that if 0 degree or 0 betweenness centrality, then the task has very low importance. We assume that if 0 - 0.25 degree or 0 - 0.25 betweenness centrality, then the task has low importance. We assume that if 0.25 - 0.5 degree or 0.25 - 0.5 betweenness centrality, then the task has medium importance. We assume that if 0.5 - 0.75 degree or 0.5 - 0.75 betweenness centrality, then the task has high importance. We assume that the task has very high importance for the rest of cases.
Task A has sufficient assigned personnel (personnel sufficiency)[9]	Very Low: 0, Low: 0.25, Medium:0.5, High: 0.7[10]	We assume that if 0% of required resources and expertise are covered by the assigned personnel, then the task has very low personnel

[9] Over the course of developing this framework, there was an interesting discussion about measuring personnel sufficiency. We measure personnel sufficiency by counting the number of assigned people with any

Influence network Node	Illustrative Node Probability	Illustrative rational and organizational structure assessment criteria for assigning the illustrative node probability
		support. We assume that if 50% of required resources and expertise are covered by the assigned personnel, then the task has low personnel support. We assume that if 75% of required resources and expertise are covered by the assigned personnel, then the task has medium personnel support. We assume that if 100% of required resources and expertise are covered by the assigned personnel, then the task has high personnel support.
Resource A, a required resource of task A, is available (available resources)	Very Low: 0.25, Low: 0.5, Medium:0.75,	We assume that if the task has 0 assigned personnel with the required resource, then the task has very We assume that if the task has 1 assigned personnel with the required resource, then the task has low resource support. We assume that if the task has 2 or more assigned personnel with the required resource, then the task has medium resource support.
Expertise A, a required expertise of task A, is (accessible expertise)	Very Low: 0.25, Low: 0.5, Medium:0.75,	We assume that if the task has 0 assigned personnel with the required expertise, then the task has very low expertise support We assume that if the task has 1 assigned personnel with the required expertise, then the task has low expertise support. We assume that if the task has 2 or more assigned personnel with the required expertise, then the task has medium expertise support.

of relevant resources or expertise. However, this implies that a person with no proper resource or expertise is not capable of doing the task. This is true in the work environment requiring very specific skills and resources, i.e. surgery. The other way of counting assigned personnel is just counting any assigned people. We take the first way since we felt that our application requires specific mental, knowledge, resource preparations. However, the users can select either way of measuring personnel sufficiency by choosing an option when they use ORA that implements this framework.

[10] Though the organizational structure shows that the 100% of resources and expertise are covered by the assigned people, some analysts may want to assign not 1.0 probability for the assigned personnel because some domains have risks and uncertainties in handling the resources and expertise that are already covered.

While Table 6-1 specifies how we determine the marginal or baseline probabilities of the influence network nodes, each of the influence network links requires two parameters: promotion and inhibition weights. The promotion weight is the strength of the influence toward the destination influence network node when the start node is true. The inhibition is the influence strength to the destination node when the start node is false. Throughout this paper, I use 0.5 for promotion and -0.5 for inhibition weights (except for the task complexity to task completion arc, which is an inhibitor; for this we use -0.5 and 0.5, respectively). These values are selected because we want to balance the causal strengths regardless of the success of the parent nodes. These weights can change as human analysts' qualitative assessment of a target situation. If human analysts feel that the failure of a task facilitates the failure of the subsequent tasks more than the task success promotes the subsequent task successes, they should decrease the promotion weight and increase the inhibition weight.

6.2.2. Task network

Unlike the other five factors, the effect of prior task completion propagates to the child tasks throughout an influence network. For instance, if task A is a prior task of task B, and task B is that of task C, the likelihood of task A affects that of task C. This is different from the other factors, i.e. task complexity of a certain task contributes to the task's completion likelihood in a negative way, but this contribution is limited to that task. This propagation relation can be extracted from the task network in a meta-network. If the task network has directionality, we can see the task flow from the initial, leaf task or tasks to a certain task. For example, Figure 6-3 shows an extracted task network, a task network for detonate task. Because prior task completion is the only factor with a propagation characteristic, we build up an influence network from this task network for a specific task. Then, we can add the other five factors to each of the task in the constructed influence network.

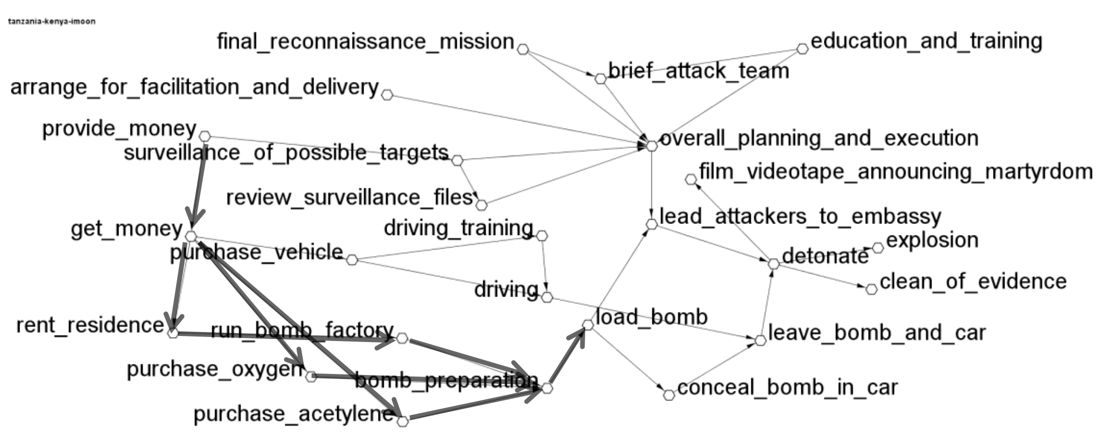


Figure 6-3 An extracted sub-task network (*load bomb* task)

6.2.3. Task importance

A task is more likely to be executed successfully if the task is considered to be important. Therefore, as the task importance of a specific task goes up, the task completion likelihood increases and task importance has a promoting influence on task completion. Then, the question is how to measure the importance of each task in the task network. I gauge the importance based on the number of prior and following task in the task network. If a task has many prior or next tasks, the task is important. This factor can be measured by the degree centrality of a task in a task network. Also, if a task is on many critical paths among two tasks in the task network, the task is important. This is captured by measuring the betweenness centrality of a task. For instance, in the task dependency network of Figure 6-3, the *get money* task is a task with 0.125 degree centrality and 0.020 betweenness centrality, so the task is considered to have low importance, which assigns 0.25 marginal probability to the task importance factor. Each task node in the influence net has the task importance factor node as a parent in the influence network, and the importance node probability is calculated from the heuristics as described in the previous section.

6.2.4. Task complexity

A task is less likely to be performed if the task has high complexity. In a meta-network, 'a task is complex' means that the task requires many personnel involvements and different types of resources and expertise. Thus, we measure the task complexity factor with the number of assigned agents and the number of required resources and expertise. For example, Figure 6-4 shows two tasks, *overall planning and execution* and *clean of evidence*. The former has six associated agent, four required expertise, and two required resources. The latter has two assigned agents, *Mustafa Mohamed Fadhil* and *Fazul Abdullah* Mohamed, one required resources and one required expertise. Therefore, the *overall planning and execution* task is complex than the *clean of evidence* task because the former has more involved agents, resources and expertise. When I assign the marginal probability, the former has 0.5, and the latter has 0.25. This task complexity becomes a node in the influence network and is linked to the task node as described in Ch. 6.2.1.

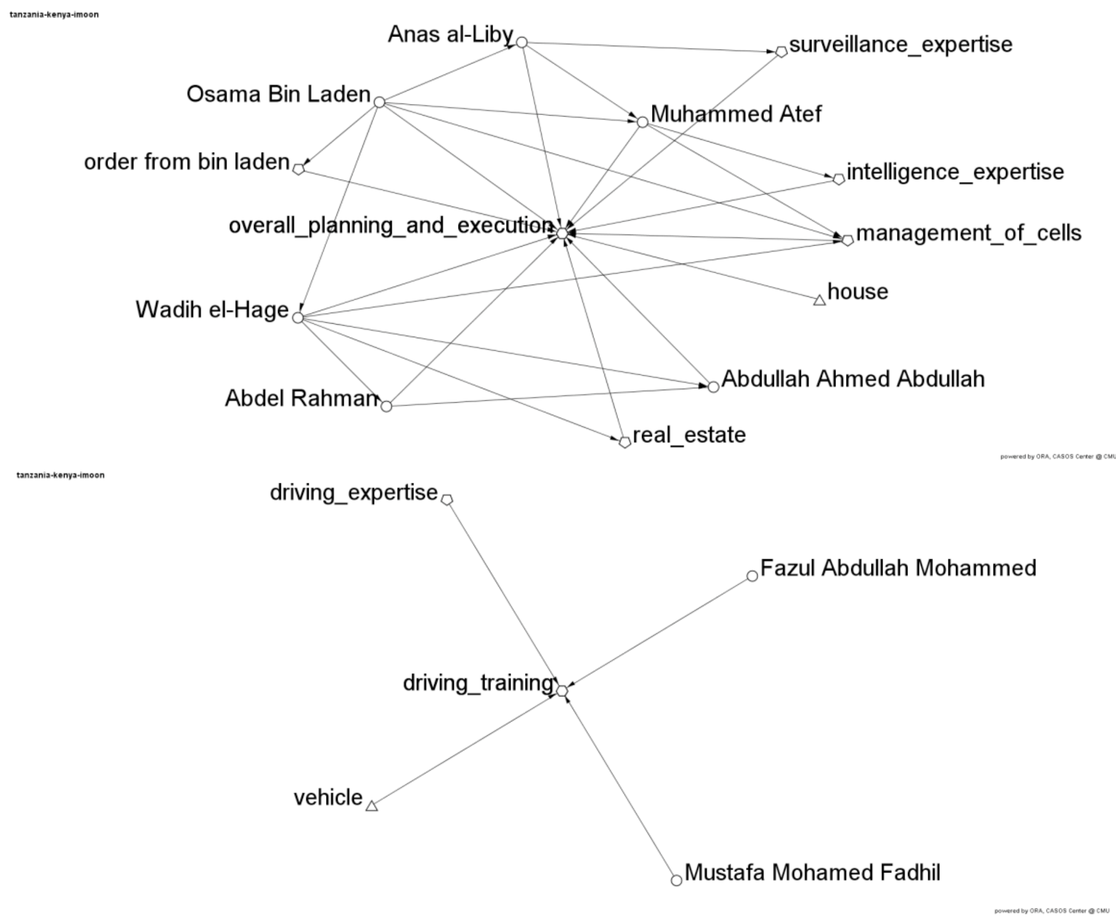


Figure 6-4 (top) A sub meta-network including nodes in one social link distance from *overall planning and execution* task, (bottom) A sub meta-network for the *clean of evidence* task

6.2.5. Personnel sufficiency

A higher probability of personnel sufficiency is a key element in the task completion. However, we have seen that only providing an agent without any proper resources or expertise is not enough. Therefore, when we count the personnel sufficiency, we consider not only the number of agents, but also whether the agent has the required resources or expertise. For instance, as shown in Figure 6-4, the *overall planning and execution* task has four covered expertise by assigned agents and one acquired resource by *Wadih el-Hage.* Thus, 83.3% of required organizational elements are covered. According to Table 6-1, then the personnel sufficiency of this task has 0.5 marginal probability. Personnel count without considering whether or not the assigned person has any relevant resources or expertise is different from counting just assigned persons regardless of their possession of resources and expertise. We further described our rationale in the footnote of Chapter 6.2.1.

6.2.6. Available resources

Providing required resources of a task to assigned agents is an important factor in task completion. Considering the *overall planning and execution* task in Figure 6-4, *real estate* is provided to *Wadih el-Hage*, but the meta-network show that the *house* is assigned to no one doing the task. Therefore, an influence network node, *real estate is available*, has a medium marginal probability, 0.5, compared to that of *house is available*, 0.25.

6.2.7. Accessible expertise

Finally, making expertise accessible through assigned personnel is critical in task completion. The *Review Surveillance Files* task, Figure 6-5, has one required expertise, *surveillance expertise*. *Anas al-Liby* has this expertise, and he is also assigned to the task, as well. However, the expertise is not known to any other assigned personnel. This means that *Anas al-Liby* is the only channel for accessing the required expertise. The heuristic in Table 6-1 assigned a 0.5 marginal probability for this case. If the expertise had been known to one more assigned person, then the probability could be 0.75, but this was not the case in this dataset.

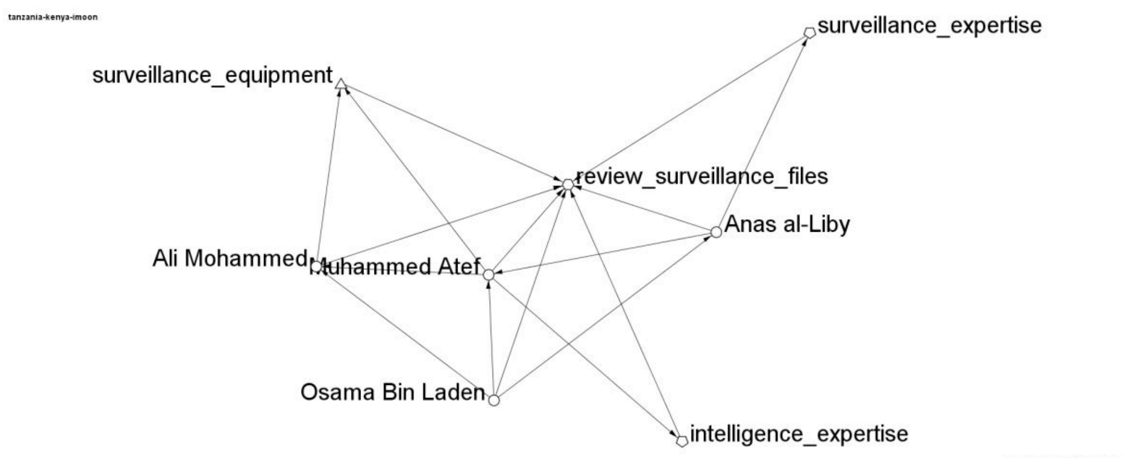


Figure 6-5 A sub meta-network including nodes in one social link distance from *review surveillance files*

6.2.8. Difference among meta-network, traditionally created influence network, and automatically generated influence networks

To illustrate an automatically generated influence network in detail, I compare it to the meta-network and the traditionally created influence network. Through the comparisons, I show what should be inferred and assumed to fill the gap between the meta-network and the influence network. I organized the comparisons in Table 6-2.

As shown in Table 6-2, the meta-network and the influence network have different meanings of their nodes and links. For instance, the nodes in a meta-network are entities while those in an influence network are propositions that may be true or false. Therefore, I interpret the links and the entities in the meta-network and generate a belief statement with the interpretation. If there is a task, or T, with four assigned members, and if the four members have proper expertise or resources, then we generate a proposition "Sufficient actors associated with T" with high marginal probability (considering that T is well supported with four assigned people). This approach is similar to the narrative network representation (Pentland and Feldman, 2007) that stores a story of operations in a network formation.

Additionally, nodes and links in a meta-network do not have parameters except edge weights showing the strength of the link. However, an influence network requires three parameters: baseline probabilities for nodes with parents; and inhibition and promotion parameters for links. Whereas traditionally created influence networks obtain these values from subject matter experts, in the approach in this paper, I supply these values by utilizing a set of heuristics assessing the situation as captured in the meta-network and assigning predefined marginal probabilities. For the inhibition and promotion parameters, I use default values: 0.5 promotion and -0.5 inhibition weights on the promoting arcs and the inverse on the inhibiting arcs (from task complexity to task completion).

Table 6-2 Comparison among meta-network, automatically generated influence network, and traditionally created influence network

	Meta-Network	Automatically generated influence network	Traditionally created influence network
Node	Entities in an organization	Belief statements in a predefined template	Belief statements from subject matter experts
Link	Relations among entities	Influence or Causal link from one belief to another	Influence or Causal link from one belief to another
Node Parameter	None	Predefined baseline probability of a belief becoming true	Expert's baseline probability of a belief becoming true
Link Parameter	Edge weight showing the strength of the relation	Predefined promotion and inhibition parameters	Expert's promotion and inhibition parameters

6.3. Application

We learn more about the task performance in the Tanzania and Kenya Embassy Bombing then we would from the meta network alone when we apply this approach. After creating the influence network using the procedures described in Ch. 6.2., I first use the influence net to estimate the task completion likelihood for each task. This likelihood depends on the assessments on personnel sufficiency, resources and information availability, and task complexity and importance. By ranking the tasks by task completion likelihood, we can identify the tasks that are at risk. Next, we vary the values of the heuristically derived parameters to see the impact on the likelihood of task completion and the effects on the rankings.

6.3.1. Evaluation of task completion likelihoods

Figure 6-6 shows the generated influence network analyzing the completion likelihood of a task, *detonate*. *Pythia* (Wagenhals and Levis, 2007), an influence network analysis program that incorporates the CAST algorithm (Rosen and Smith, 1996), was used to create the influence net. *Pythia* was used to evaluate this influence network.

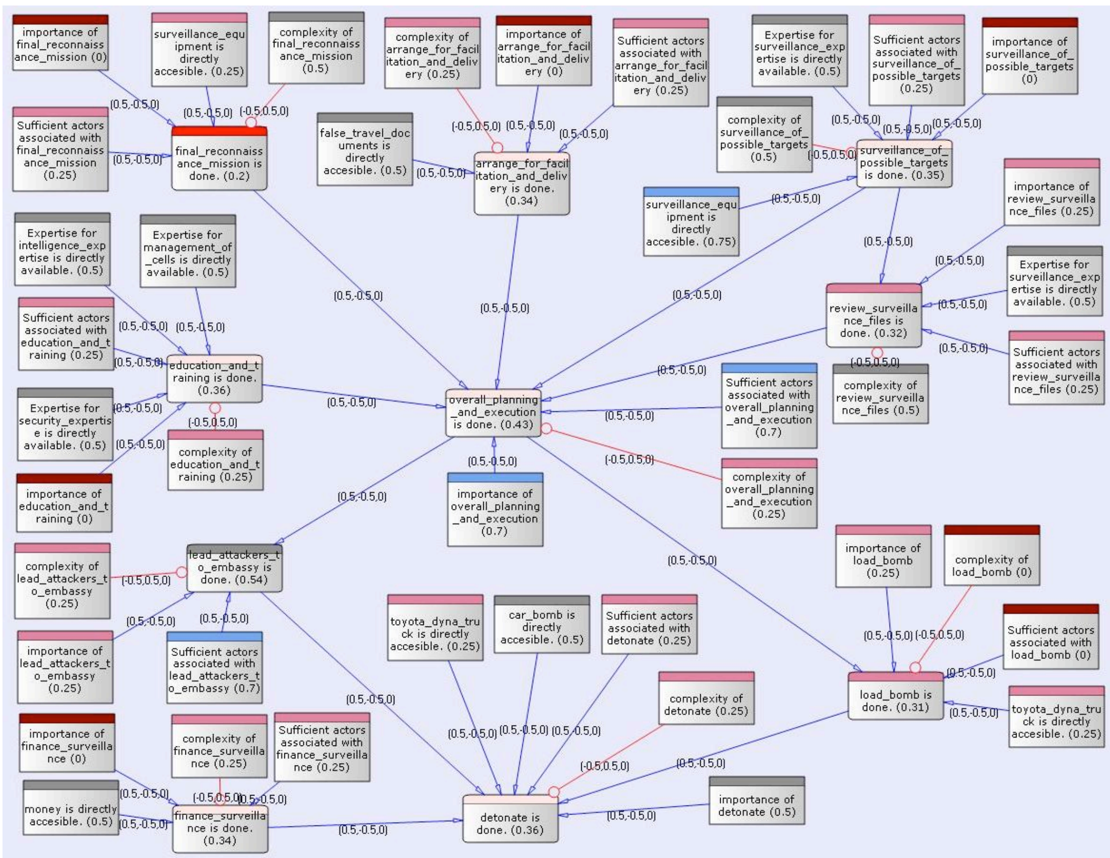


Figure 6-6 The visualization of a generated influence network for analyzing the completion likelihood of *detonate* in the Kenya case (see the dataset introduction in Ch. 4.3.)

Figure 6-7 and Table 6-3 displays the evaluation result of the task nodes. We put each task as the target task to be analyzed and obtained its completion likelihood from the influence net. The node sizes of Figure 6-7 have been adjusted to reflect their likelihood as computed in the influence net; the larger the node, the more likely the task will be completed. Among the tasks, *provide money* is the hardest task to execute (based on the probability of completion). The second hardest task is *conceal bomb in car*. These two tasks are difficult because their initial resources and information distribution was not supportive. For example, *provide money* requires *money, bank account* and *order from bin laden,* but none of these organizational elements were given to assigned terrorists, *Khalid Al Fawaz* and *Wadih el-Hage*. The same reason can be applied to *conceal bomb in car* case, which has four required organizational elements and none of them are acquired by the executing agents.

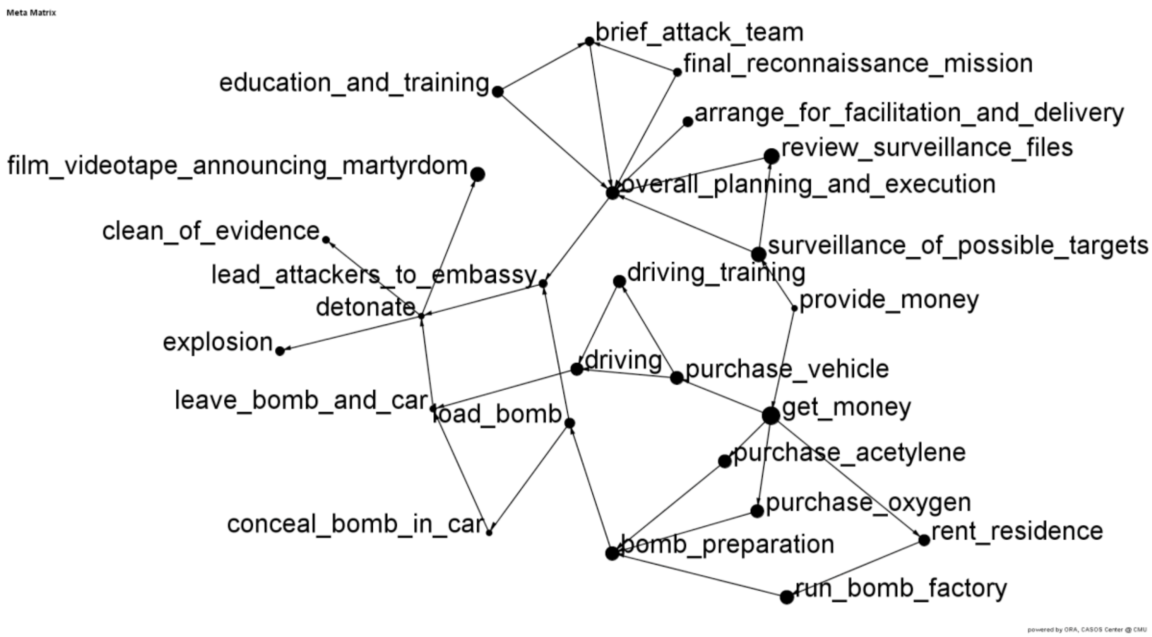


Figure 6-7 The visualization of the task dependency network. The node sizes are adjusted to the completion likelihood of the tasks.

Table 6-3 Task completion likelihoods when evaluated with default (medium) threshold for assessment and default (medium) probability assignment for baseline[11]

Task Name	Completion Likelihood	Task Name	Completion Likelihood
overall planning and execution	0.439	leave bomb and car	0.284
load bomb	0.358	rent residence	0.383
review surveillance files	0.545	run bomb factory	0.466
brief attack team	0.317	purchase vehicle	0.448
final reconnaissance mission	0.304	purchase oxygen	0.448
lead attackers to embassy	0.309	purchase acetylene	0.448
clean of evidence	0.294	get money	0.647
film videotape announcing martyrdom	0.496	explosion	0.317
arrange for facilitation and delivery	0.356	Surveillance of possible targets	0.508
driving training	0.417	detonate	0.259
bomb preparation	0.461	education and training	0.385

[11] While we display the task completion likelihood numbers in Table 6-3, we do not expect that we can estimate the likelihood at the precision level of the numbers. In other words, we expect that the likelihood of *brief attack team* must be significantly higher than that of *final reconnaissance mission*, but we do not think that this can happen with exactly 2.411-times more likelihood.

Task Name	Completion Likelihood	Task Name	Completion Likelihood
driving	0.432	provide money	0.231
conceal bomb in car	0.234		

6.3.2. Design of computational experiments for various settings

I analyze the sensitivity of task completion likelihoods by performing computational experiments. The computational experiments are done by repeatedly generating influence networks modeling the same task, but with different marginal probability parameters in Table 6-4. This marginal probability differentiation imitates human analysts' different viewpoints toward the analysis situation. If human analysts consider that the operational environment is relatively unfavorable, the probability parameters must be low, and vice versa. Therefore, I experiment with the sensitivity of my tool parameters, and the users of this tool will take the sensitivity result into account when they decide the parameters.

I can diversify the setting in two aspects. First, I can change the parameters of the assessment heuristics. For instance, this framework will assign *low* marginal probability if a task needs two persons and one resource or expertise. When I change the parameters of assessment, I change the two-person requirement to a three or four-person requirement, which means that more personnel will be required to regard a task as complex than before. Second, I can change the marginal probability assignment. In default, I assign 0.25 as the marginal probability when we consider the task is complex at the *low* level. If we change the probability assignment, we change the 0.25 value to another value between 0 and 1.

Table 6-4 shows three levels of parameters for assessment heuristics. Table 6-5 displays three levels of baseline or marginal probability assignment. By combining the three heuristic parameter sets and three probability assignments, we have nine computational experiment cells. One may consider changing the parameters for individual influence nodes, but I did not perform this computational experiment by changing the individual node values. Instead of the individual node parameter, I applied the level changes to all the nodes in the influence network.

Table 6-4 A table outlining three levels of heuristic parameters for task assessment

Level	Influence Network Node	Heuristic Parameter Name	Parameter Assignment - alternatives				
			Very Low	Low	Medium	High	Very High
Low threshold for assessment	Task Complexity	Range of req. personnel	0	1	2	3-5	6-∞
		Range of req. expertise	0	0	1-2	3-5	6-∞
	Task Importance	Range of degree centrality	0	0-0.125	0.125-0.25	0.25-0.5	0.5-∞
		Range of betweenness centrality	0	0-0.125	0.125-0.25	0.25-0.5	0.5-∞
	Personnel Sufficiency	Range of assigned personnel and resources level	0	0-25%	25-50%	50-100%	
	Available Resource	Range of assigned personnel with resource level		0	0	1-∞	
Medium threshold for assessment (default)	Task Complexity	Range of req. personnel	0-1	2	3	4-6	7-∞
		Range of req. expertise	0	1	2-3	4-7	8-∞
	Task Importance	Range of degree centrality	0	0-0.25	0.25-0.5	0.5-0.75	0.75-∞
		Range of betweenness centrality	0	0-0.25	0.25-0.5	0.5-0.75	0.75-∞
	Personnel Sufficiency	Range of assigned personnel and resources level	0	0-50%	50-75%	75-100%	
	Available Resource	Range of assigned personnel with resource level		0	1	2-∞	
High threshold for assessment	Task Complexity	Range of req. personnel	0-2	3-4	5-6	7-14	15-∞
		Range of req. expertise	0-1	2-3	4-6	6-9	9-∞
	Task Importance	Range of degree centrality	0	0-0.50	0.50-0.75	0.75-0.90	0.90-∞

Level	Influence Network Node	Heuristic Parameter Name	Parameter Assignment - alternatives				
			Very Low	Low	Medium	High	Very High
		Range of betweenness centrality	0	0-0.50	0.50-0.75	0.75-0.90	0.90-∞
	Personnel Sufficiency	Range of assigned personnel and resources level	0	0-75%	75-90%	90-100%	
	Available Resource	Range of assigned personnel with resource level		1	2-3	4-∞	

Table 6-5 A table outlining three levels of baseline probability assignments

Level	Influence Network Node	Probability Assignment -alternatives				
		Very Low	Low	Medium	High	Very High
Low probability assignment for baseline	Task Complexity	0	0.1	0.25	0.35	0.4
	Task Importance	0	0.1	0.25	0.35	0.4
	Personnel Sufficiency	0	0.125	0.25	0.35	
	Available Resource		0.125	0.25	0.375	
Medium probability assignment for baseline (default)	Task Complexity	0	0.25	0.5	0.7	0.8
	Task Importance	0	0.25	0.5	0.7	0.8
	Personnel Sufficiency	0	0.25	0.5	0.7	
	Available Resource		0.25	0.5	0.75	
High probability assignment for baseline	Task Complexity	0.25	0.5	0.75	0.8	0.9
	Task Importance	0.25	0.5	0.75	0.8	0.9
	Personnel Sufficiency	0.25	0.5	0.75	0.9	
	Available Resource		0.5	0.75	0.9	

6.3.3. Task completion likelihoods under computational experiment settings

The change of heuristic parameters and baseline probability assignment differentiates the completion likelihood values (see Table 6-6) and the ranks of the likelihoods (see Table 6-7) become different. This means that the parameter selection will influence prioritizing the tasks to support or prevent by changing the rank orders of the completion likelihoods. Under the default setting, medium threshold and probability, *get money* has the highest completion likelihood, but it becomes the sixth highest one under the high probability and low threshold assignment. Therefore, if an analyst thinks that the assessment on the task support should be less strict and the task itself has high completion probability, *get money* would be less likely to be completed. On the other hand, *overall planning and execution* and *lead attackers to embassy* are the tasks that would be more likely to be accomplished under the less strict assessment and high completion probability. Since the completion rank changes according to the assumptions of the analysts, the qualitative interpretations of the analysts' parameter setting should be provided when they present the results.

These rank and likelihood value changes can be explained more by the standard deviations of the likelihoods. *Provide money, driving training,* and *purchase vehicle* have low standard deviation across the computational experiment (ranging from 0.149 and 0.204). However, tasks such as *overall planning and execution* and *bomb preparation* are the tasks with high standard deviation (ranging from 0.389 to 0.390). They are inherently complex tasks with many resources and expertise are involved. Therefore, the changes of assessment threshold will change the marginal probability dramatically.

These standard deviation or average of marginal probability suggests valuable information to managers and commanders. These values address their key questions such as which task is significantly volatile so that its completion likelihood swings dramatically when situation changes.

Table 6-6 Task completion likelihoods of tasks under nine different settings

	Low Probability			Medium Probability			High Probability				
Task Name	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Avg.	Std. Dev.
overall planning and execution	0.060	0.023	0.003	0.766	0.439	0.031	0.991	0.960	0.283	0.395	0.389
load bomb	0.113	0.077	0.025	0.493	0.358	0.061	0.812	0.773	0.142	0.317	0.292
review surveillance files	0.293	0.204	0.066	0.741	0.545	0.159	0.898	0.830	0.359	0.455	0.291
brief attack team	0.050	0.047	0.009	0.343	0.317	0.023	0.766	0.792	0.051	0.266	0.298
final reconnaissance mission	0.141	0.116	0.051	0.364	0.304	0.112	0.650	0.631	0.294	0.296	0.209
lead attackers to embassy	0.069	0.045	0.013	0.470	0.309	0.037	0.847	0.815	0.129	0.304	0.315
clean of evidence	0.082	0.087	0.036	0.266	0.294	0.073	0.646	0.697	0.135	0.258	0.237
film videotape announcing martyrdom	0.238	0.217	0.173	0.523	0.496	0.338	0.773	0.782	0.543	0.454	0.216
arrange for facilitation and delivery	0.159	0.125	0.051	0.432	0.356	0.112	0.709	0.694	0.294	0.326	0.232
driving training	0.192	0.188	0.089	0.409	0.417	0.195	0.630	0.686	0.318	0.347	0.195
bomb preparation	0.096	0.047	0.002	0.723	0.461	0.008	0.975	0.938	0.058	0.368	0.390
driving	0.159	0.145	0.056	0.435	0.432	0.147	0.707	0.758	0.278	0.346	0.240
conceal bomb in car	0.056	0.062	0.019	0.204	0.234	0.040	0.564	0.625	0.074	0.209	0.218
leave bomb and car	0.130	0.077	0.040	0.444	0.284	0.130	0.795	0.694	0.335	0.325	0.256
rent residence	0.124	0.108	0.025	0.405	0.383	0.065	0.706	0.744	0.135	0.299	0.259
run bomb factory	0.177	0.126	0.035	0.590	0.466	0.108	0.841	0.825	0.279	0.383	0.293
purchase vehicle	0.215	0.199	0.096	0.466	0.448	0.217	0.671	0.711	0.370	0.377	0.204
purchase oxygen	0.167	0.128	0.034	0.533	0.448	0.103	0.790	0.793	0.253	0.361	0.276
purchase acetylene	0.167	0.128	0.034	0.533	0.448	0.103	0.790	0.793	0.253	0.361	0.276
get money	0.329	0.284	0.199	0.704	0.647	0.457	0.845	0.838	0.655	0.551	0.228
explosion	0.082	0.063	0.017	0.394	0.317	0.054	0.802	0.780	0.173	0.298	0.289
surveillance of possible targets	0.220	0.196	0.083	0.565	0.508	0.191	0.791	0.769	0.295	0.402	0.249

Task Name	Low Probability			Medium Probability			High Probability				
	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Avg.	Std. Dev.
detonate	0.044	0.034	0.007	0.326	0.259	0.029	0.828	0.789	0.132	0.272	0.305
education and training	0.102	0.052	0.004	0.658	0.385	0.019	0.953	0.876	0.136	0.354	0.359
provide money	0.103	0.116	0.055	0.186	0.231	0.078	0.431	0.500	0.144	0.205	0.149

Table 6-7 Ranks of task completion likelihoods of tasks under nine different settings

Task Name	Low Probability			Medium Probability			High Probability		
	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold
overall planning and execution	22	25	24	1	10	21	1	1	10
load bomb	15	16	17	11	15	17	9	14	17
review surveillance files	2	3	6	2	2	6	4	5	4
brief attack team	24	22	21	21	17	23	16	10	25
final reconnaissance mission	12	13	9	20	20	9	21	23	8
lead attackers to embassy	21	23	20	12	19	20	5	7	22
clean of evidence	19	15	12	23	21	15	22	19	20
film videotape announcing martyrdom	3	2	2	10	4	2	15	12	2
arrange for facilitation and delivery	11	11	10	16	16	10	17	21	9
driving training	6	6	4	17	12	4	23	22	6
bomb preparation	18	21	25	3	6	25	2	2	24
driving	10	7	7	15	11	7	18	16	12
conceal bomb in car	23	19	18	24	24	19	24	24	23
leave bomb and car	13	17	11	14	22	8	11	20	5

Task Name	Low Probability			Medium Probability			High Probability		
	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold	Low Thre-shold	Med Thre-shold	High Thre-shold
rent residence	14	14	16	18	14	16	19	17	19
run bomb factory	7	10	13	6	5	11	7	6	11
purchase vehicle	5	4	3	13	7	3	20	18	3
purchase oxygen	8	8	14	8	8	12	14	8	13
purchase acetylene	9	9	15	9	9	13	13	9	14
get money	1	1	1	4	1	1	6	4	1
explosion	20	18	19	19	18	18	10	13	15
surveillance of possible targets	4	5	5	7	3	5	12	15	7
detonate	25	24	22	22	23	22	8	11	21
education and training	17	20	23	5	13	24	3	3	18
provide money	16	12	8	25	25	14	25	25	16

6.4. Conclusion

This influence network generation and analysis with the meta-network concept makes theoretical, technical and empirical contribution as well as has limitations.

Limitation: Some of the assessment factors, such as personnel sufficiency and resource availability, etc might not be independent to each other, which may lead a statistical error in the evaluation period. However, this generation scheme is not a solution for such errors; the errors should be addressed by a more advanced statistical evaluation method of an influence network. Thus, users of this method should aware whether these assessment factors are independent or not. They should not use the CAST logic (Rosen and Smith, 1996) if they believe that the factors are not independent. An alternative statistical evaluation approach is under development by George Mason University.

Another limitation is that we regard an organization as a closed system in this analysis. For example, if assigned personnel do not have a required resource to perform his task, the personnel may purchase the required resource from the outside of the organization. This is particularly true if the needed resource is commonly available. However, this influence network analysis procedure does not consider such addition of outside resources into the organization of interest. Even further, there are resources that are not explicitly mentioned in the meta-network, yet can make the task done. This type of flexible task execution is not also accounted for this analysis.

Finally, this influence network generation scheme can be improved by adding other factors of task completion. For example, being at a specific location to perform a task is an important factor of task completion. However, such a location issue is not discussed in this chapter. Therefore, we may add those additional factors to this influence network generation scheme. For example, we may count the number of assigned agents at required locations where a task will be executed. Then, the human analysts set a threshold for the agent counts at the locations and come up with a baseline probability for a location related factor belief. The location related factor can be named as “Assigned agents are at locations where task X will be executed”. This belief node can be added to an influence network and linked to the belief, “Task X is done.”

Theoretic and technical contribution: I introduced a new approach for estimating task completion likelihoods based on the executing organizational structure and the parameters from analyst. This approach is an interoperation of existing two approaches: meta-network and influence network. A meta-network is used to represent a complex organizational structure, but it does not have an evaluation capability, particularly with regard to task completion. An influence network is a probabilistic model similar to the Bayesian network for evaluating the likelihood of events or effects happening. However, its generation can take a long time, and its results are based on the assumptions made by its creator. To mitigate these challenges, I offer an approach for generating an influence network from a meta-network. This interoperation enables fast delivery of an influence network systematically designed from an organizational structure. This is a new approach that uses an organizational structure to estimate the performance of an organization.

Empirical contribution: I provided an illustrative example of the usage by applying it to the Tanzania and Kenya case dataset. The analysis result identifies tasks that have low completion likelihood, such as *conceal bomb in car* and *provide money*, because the tasks are under-supported by the organization. From an adversarial point of view these tasks with low completion chances are the tasks that managers should provide more support to. On the other hand, if we want to lower the probability of task success, the tasks with low likelihood may be the ones that we should try to prevent. Surely, tasks require the different amounts of effort to prevent them. These different effort requirements mean that some tasks have low completion likelihood, a preferable target task in disrupting the entire task dependency network, but they may require much more effort to prevent. Human analysts will be responsible for this further analysis based on the influence network result.

While this approach enables the computational analysis of the organizational structure and task completion likelihood, human analysts should be careful in the usage of the approach. The parameters for determining marginal probabilities and promotion, inhibition causalities should be determined with analysts' discretion. We provide the sensitivity analysis that shows possible conclusion changes according to parameter settings. Also, human analysts should not consider the computation result to be accurate to the level of the calculation precision. This type of analysis is very prone to errors, and the real world events have many more factors that are not accounted in either meta-network or influence network.

- *Task completion likelihood can be estimated by examining the organization support to complete the tasks.*
- *Human analysts provide their viewpoint toward the situations and organizations, so that the results can be adjusted to their views.*
- *Dynamic network and influence network analyses are combined to add a theoretical component of assessing organizational performance to the organizational structure analysis theories from the task completion perspective.*

So far, intelligence analysts have to spend a long time to create an influence network to represent their subject matter expert viewpoints. This approach provides a better way to generate the influence network by suggesting a machine generated influence network to the analysts. This machine generated influence network will not be adequate enough to be used without any human corrections. However, humans can be much efficient in correcting the generated model and finalize the influence network model ready to be used in the real analysis. This is a human-machine cooperation to use an existing statistical tool that was too complex to be used by only human power.

7. Building Micro-level Destabilization Strategies - Simulating the Social Behavior of Adversaries

In many domains where situations are dynamically changing, 'what-if' analysis is a critical question to prepare for the future. Particularly, some disciplines, such as intelligence, corporate management, military command and control, etc, have some threat scenarios and wonder what will happen if the scenarios become realized. For example, from the perspective of destabilization analysis, an interesting question is what will happen if some key terrorists are removed. Destabilization analysts want to know the deterioration of the adversarial organization's performances and the organizational structure after their removal.

To answer these questions, the ideal method is replicating the target domain and the organization many times in the real world and testing the scenarios in the replicated environments. Such experiments described above are approximated by the organization science community and the social science community where researchers investigate field studies or collect experimental data in labs. However, these techniques are very expensive, unethical or impossible compared to the simulation. Particularly, adversarial organizations are difficult to replicate in the real world because of our limited understanding about the organizations, their complex collective behavior emerging from decentralized structures, etc. Multi-agent simulation (MAS) has a number of benefits. First, the nature of the MAS has a nice analogy to human organizations and actors, so some policy domains, such as civil violence (Epstein, 2001), the transportation of goods (Bergkvist, 2004;Louie and Carley, 2006), used the MAS. Additionally, the growth of computing power allows MAS to run multiple experiments for many times with less cost. For example, Bio-war MAS (Carley, 2006) is a city scale model, and it can be converged in several hours with super computing facilities. Finally, the MAS is now being used for theory building in the organization and strategy literatures (Davis et al, 2006; Cohen et al,1972; March, 1991).

Therefore, in this chapter, I performed the 'what-if' analyses of adversarial organizations under different possible intervention scenarios, and the analyses are done by a MAS system called Dynet. JDynet contains a new agent behavior mechanism and outputs built upon Construct logic, an existing multi-agent simulation. Specifically, I collected a structural datasets in the meta-matrix format, and the datasets are introduced in Chapter 4. Then, I modeled the target organizations' agent behavior, such as task performance, information diffusion, and resource passing. Finally, I created hypotheses with dynamic network analysis from the viewpoint of terrorist removals, and turned the hypotheses into simulation scenarios. With the input organizational structure dataset, agent behavior model, and simulation scenarios, I gauge the impact of the intervention scenarios.

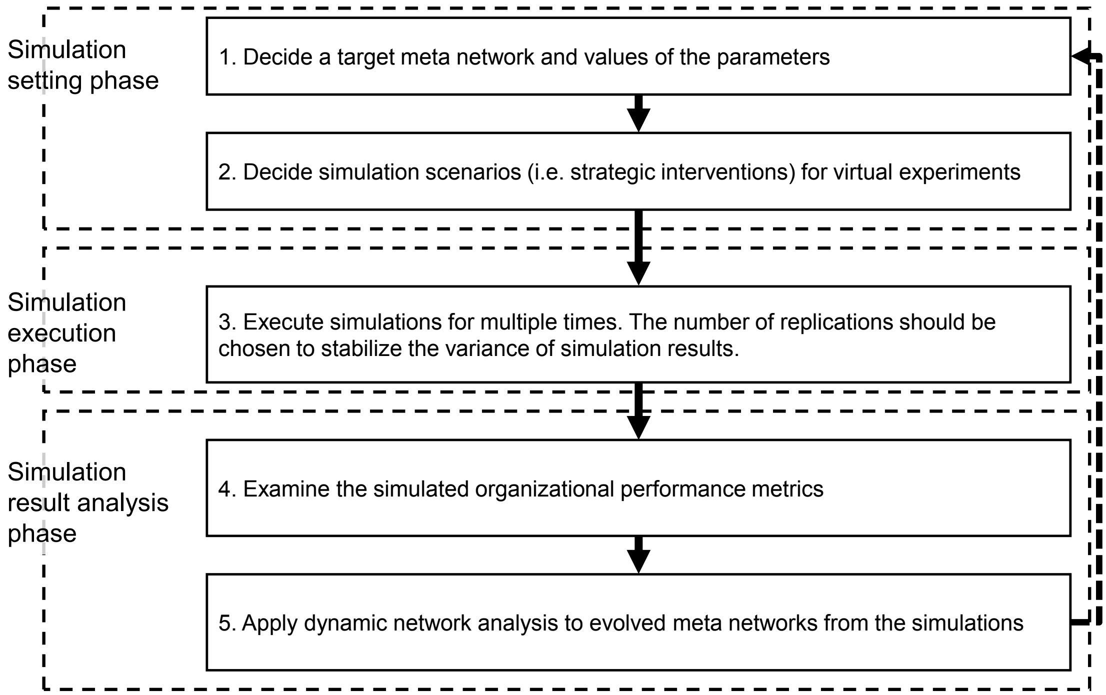


Figure 7-1 an overall analysis procedure of simulations

Before the starts of Ch. 7 and 8, I show a suggested simulation analysis procedure in Figure 7-1. The simulation analysis in Ch. 7 and 8 begins by selecting a target organization to simulate and proper parameter value selections. This is a specification applied to every simulation. In contrast to these general simulation specifications, I can apply different simulation scenarios, i.e. by changing who to remove and when from a simulated organization. Each of these different simulation scenarios forms an experiment cell in a virtual experiment. Then, I replicate each experiment cell with a coded simulation model. After the replications, the simulation model generates 1) organizational performances and general statistics and 2) detailed agent behavior records over the course of simulations. I use regression analysis, analysis of variance, and simple visualizations to analyze the performance values and log records. Particularly, the model generates an estimated organizational structures and element distributions after the mission execution in simulations. The estimated organizational structures can be fed back to the simulation model, and the simulation analysis cycle can starts again.

Throughout this chapter, I illustrate the model and application result by using the Tanzania and Kenya dataset introduced in Ch. 4.2.

7.1. Simulation model description

JDynet is the simulation model that I designed and used to estimate the collective behavior of adversaries throughout this chapter. JDynet takes a number of inputs which are an adversarial organizational structure and parameters. After a simulation run, JDynet produces an expected organizational structure after scenario and various over-time organizational performance scores. During the simulation, JDynet calculates its internal status variables repeatedly and simulate the time flow. This analysis procedure incorporates inputs, outputs and simulation model internal variables. I summarize the variables in Table 7-1.

Table 7-1 Summary of identified requirements, related existing approaches and computational artifacts supporting the approaches

Type	Name (Default value in the parenthesis)	Implication
Input	A networked organizational structure (a meta-matrix)	A network including agents, knowledge bits, tasks, and locations. The network represents the target domain's complex organizational structure.
	Simulation scenario	A sequence of agent removal specification. An element of sequence specifies the removal target agent and the removal timing.
Output	An evolved network organization (a meta-matrix)	A network organization with a recreated agent-to-agent (AA) network and an agent-to-location (AL) network, both of which reflect organizational element transfers, social interactions and geospatial relocations.
	Diffusion	A performance metric showing how fast information can diffuse across the network.
	Energy task accuracy	A performance metric showing how accurately information is distributed to agents who require it to complete their tasks.
	Binary task accuracy	A performance metric showing how accurately agents can classify their binarized assigned tasks with provided information
	Task completion	A performance metric displaying what percentage of the organization's tasks are completed
	Task completion speed	A performance metric displaying how quickly each of tasks can be completed on average. The inverse of the average task completion simulated time-step
	Mission completion speed	A performance metric displaying how quickly the entire task dependency network can be completed. The inverse of the mission completion simulated time-step
	Gantt chart	An estimated mission progress displayed in the Gantt chart format
Parameters	Number of time-step (5000)	The number of simulated time-steps
	Number of replications (30)	The number of replications to stabilize the outputs of this stochastic simulation

Type	Name (Default value in the parenthesis)	Implication
	Weights for requested element delivery (0.33), others' request passing (0.33), or the agent's request passing (0.33)	Only used in task performance agent interaction model. Weights for selecting an agent interaction purpose. An agent selects one purpose out of three, requested organizational element (expertise or resource) delivery, his required element request to others, or passing others' request to different others.
	Correct binary task accuracy threshold (0.5)	When calculating binary task accuracy, the agents have to make guesses on the unknown information. This number specifies the probability of the correct guess
	Interaction count for time-step (3)	An agent cannot interact with another agent after this maximum interaction count.
	Cognitive power for time-step (3)	An agent can only respond to the number of interactions specified by this parameter.
	Exchange success rate (0.75)	If an agent diffuses information or passes a resource to another agent, there is a success rate of such trials.
	Interaction social distance radius (1)	Interaction candidates are limited to agents who are within N social link radius from the interaction initiating agent.
	Task execution success rate (0.5)	When an agent performs a task, the agent can accomplish the task with this success rate. If the task is not ready (the ready state is elaborated later), an agent cannot perform the task.
	Exchange only required elements (true)	If this is true, agents only exchange expertise or resources only the receiving agent needs such elements.
	Treat resource as information (false)	If this is true, resources are duplicated when it is passed, so that the sending and receiving agents have the passed resource.
	Take over removed agent links (true)	If this is true, an agent recognizing that the interacting agent is removed can take over the target agent's various links to organizational elements, other agents and assigned tasks.
	Recognize that interaction partner is removed (0.1)	This is a success rate that an agent recognizes the interaction target agent is actually removed.
	Recover links from the removed agents (0.3)	After an agent recognizes another agent is removed, the agent can recover the links between the agent and the other agent with this probability
	Request decay time (7)	After this number of simulated time-steps, the organizational element request is removed.
	Transactive memory decay time (7)	After this number of simulated time-steps, an agent's transactive memory about other agents is removed.
	Maximum transactive	This is the maximum number of transactive memory

Type	Name (Default value in the parenthesis)	Implication
	memory element (30)	about other agents' links

These inputs, outputs and parameters are introduced in the following sections. The sections explain where the values are used, why the values are selected, and what the values' interpretations are. By varying these parameters or inputs, I design virtual experiments regarding the destabilization of a target organization. A human analyst 1) selects the most appropriate parameter values, 2) strategizes the agent removal sequence, and 3) runs a number of simulations with the specifications. After the runs, the analyst drills down the organizational performance degradation and correlates the impact with his agent removal sequence.

7.1.1. Agent social behavior

JDynet agent behavior is largely in two parts: social interaction and task performance. An agent initiates social interactions to receive expertise or a resource from the interaction partner or to send a request for expertise or resource to the partner. An agent also executes a task that is ready to be performed. A task is ready to be performed if all the prerequisite tasks are done, and if the group of assigned agents has at least one required resource and expertise. More detailed descriptions are in the below sections. Also, Figure 7-2 shows the high level agent behavior flow during the simulations.

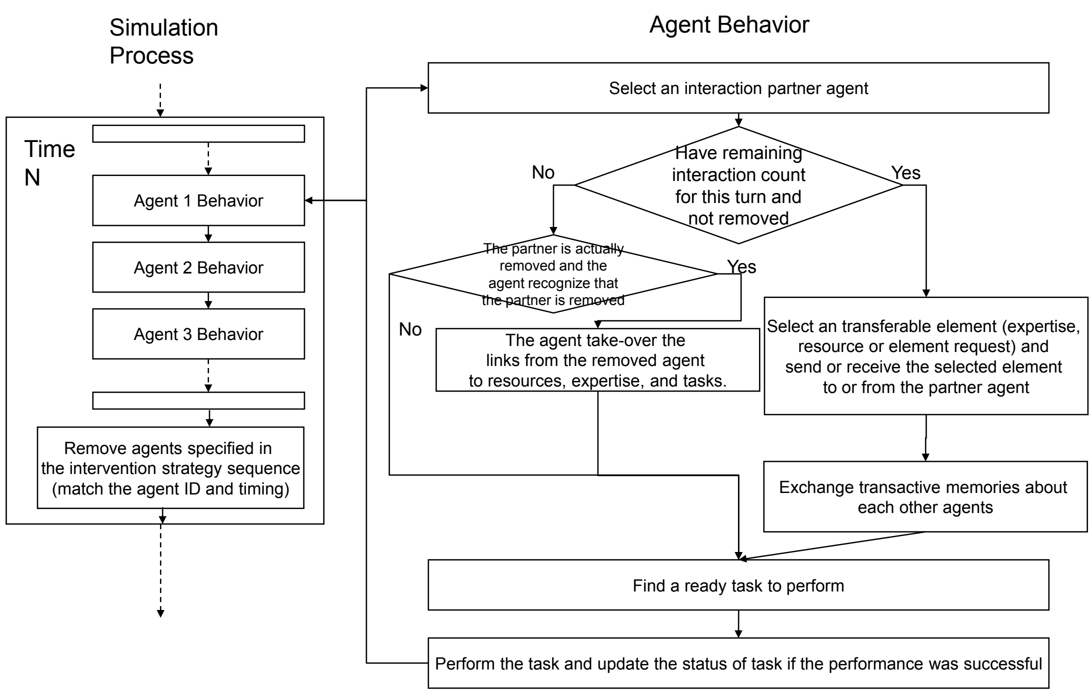


Figure 7-2 the high level agent behavior logic

7.1.2. Selecting an interaction partner agent

This agent behavior model is originated from the operations research domain while the previous Construct model is based on the sociology domain (Carley, 1991). An agent only initiates interactions with others if they need to communicate with them to perform his assigned tasks. They may seek their own necessities, pass the past interaction partner's request for resource or expertise, or pass the acquired resources or expertise to the past partner who needs them.

Agents in this model select an agent as an interaction partner if he can give a necessity to them. Only when there is no agent with any necessity organizational element, the agents choose an interaction partner randomly. Additionally, an agent can pass expertise, a resource as well as an element request that he or another past interaction partner initiated. This model illustrates how the agents will interact when they are goal-oriented. While the sociological model is appropriate for simulating the belief or ideology dispersion, this model is appropriate for simulating the organizational collective behavior to complete the tasks in their task network. This task-completion oriented agent interaction is modeled as three different agent choice motivations below.

1) *Choosing a motivation for interactions:* An agent chooses one interaction motivation out of three motivations: requested element delivery, others' request passing, and the agent's request passing. This is a random weighted selection, and the weights are specified by an analyst, *Weights for requested element delivery, others' request passing, and the agent's request passing* in Table 7-1. After the choice of the motivation, the agents select an agent as the following partner choice mechanisms.

2) *The agent's request passing:* If an agent chose the agent's request passing motivation, the agent finds one required-but-not-acquired expertise or resource to perform his assigned tasks. Then, the agent searches an agent who has the required organizational element, and he initiates an interaction with the searched agent to receive the required element. If there is no agent with the required element, the agent interacts with a randomly chosen agent and leaves a request for element delivery. The possible interaction partners are limited as the sociological limit the interaction candidate set.

3) *Others' request passing:* If an agent chose the others' request passing motivation, the agent finds one requested element among the requests for element delivery from others. Rest of the selection procedure is identical to the agent's request passing motivation. The agent searches an agent who has the requested organizational element, and he initiates an interaction with the searched agent to receive the required element. If there is no agent with the required element, the agent interacts with a randomly chosen agent and leaves a request for element delivery. The possible interaction partners are limited as the sociological limit the interaction candidate set.

4) *Requested element delivery*: If an agent chose the requested element delivery motivation, the agent will find an agent who left a delivery request during the past interactions. The organizational element in the delivery request should be possessed by the agent. Then, the agent initiates an interaction with the found agent to send the organizational element that the interaction partner requested previously.

7.1.3. Transfer an organizational element or a delivery request

The effect of an interaction between two agents is either resource passing, expertise diffusion or delivery request. There are also two ways of modeling organizational elements transfer. Construct, a model that have been used in simulating organizational behavior and evolution, does not differentiate a resource from expertise from the perspective of diffusion. The interaction sender's resource is duplicated and put in both sender's and receiver's possessions. Therefore, Construct way's interaction result is diffusing organizational elements, not passing ore requesting.

On the other hand, I suggest a new way of producing interaction outcomes. First, a resource is not duplicated and just passed from the sender to the receiver. Second, an agent can leave a delivery request for expertise or a resource, so that the interaction partner can remember that the initiating agent needs such elements. Both ways of transferring an organizational element allows only one element transfer for a single interaction. If the agent is already removed or exceeded the number of interactions specified as *maximum interaction count for time-step* in Table 7-1, then the agent cannot transfer any of expertise or resources.

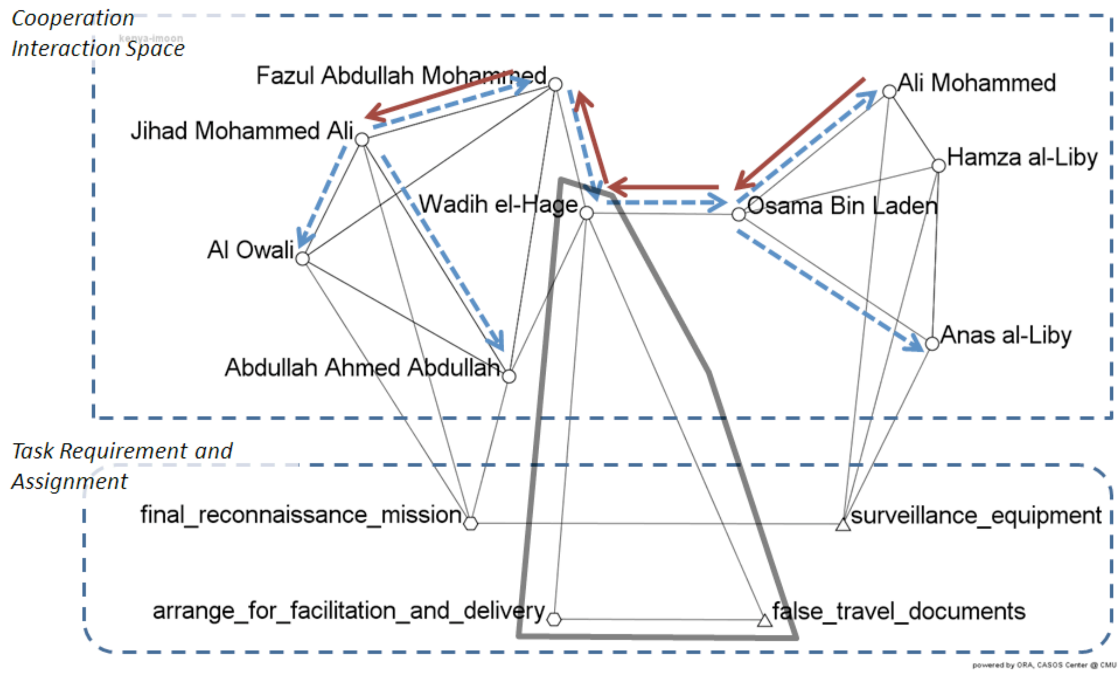


Figure 7-3 An example of agent behavior during the simulation from the Kenya case (See Ch. 4.3. for the dataset introduction). The dashed arrows are the organizational element (*surveillance equipment*) requests to the interaction partner agents. The solid arrows are the actual transfer of the *surveillance equipment*. The solid line polygon includes *Wadih el-Hage*; *arrange for facilitation and delivery*; and *false travel documents*. *Wadih el-Hage* can perform the *arrange for facilitation and delivery* task because he has the required resource, *false travel documents*.

7.1.4. Take-over the removed agent's expertise, resource, task and social contacts

If an agent initiates an interaction with an already-removed agent, the interaction initiating agent may recognize that the partner agent is removed in the past simulation time-step, so he is not responding to the interaction request. This recognition is turned on if an analyst makes *Take-over removed agent links* true. The recognition also depends on the random coin toss whose probability is specified as *Recognize that the interaction partner is removed* in Table 7-1.

After the coin toss, if the agent is allowed to take-over the removed agent's neighbor agents, resources, expertise and tasks, the agent creates a link to those legacies. However, to recover the links from the removed agents, the recovering agents should have prior knowledge about the existence of the link. This is modeled from the transactive memory. Each of the agents has transactive memory storing the link information of other agents. After the link recoveries, he updates the agent-to-agent network space, so that the other agents wouldn't make more interactions to the removed agent.

This take-over mechanism simulates the resilience of an adversarial organization. The adversaries will reassign agents to resources, expertise and tasks, to compensate the removed agents.

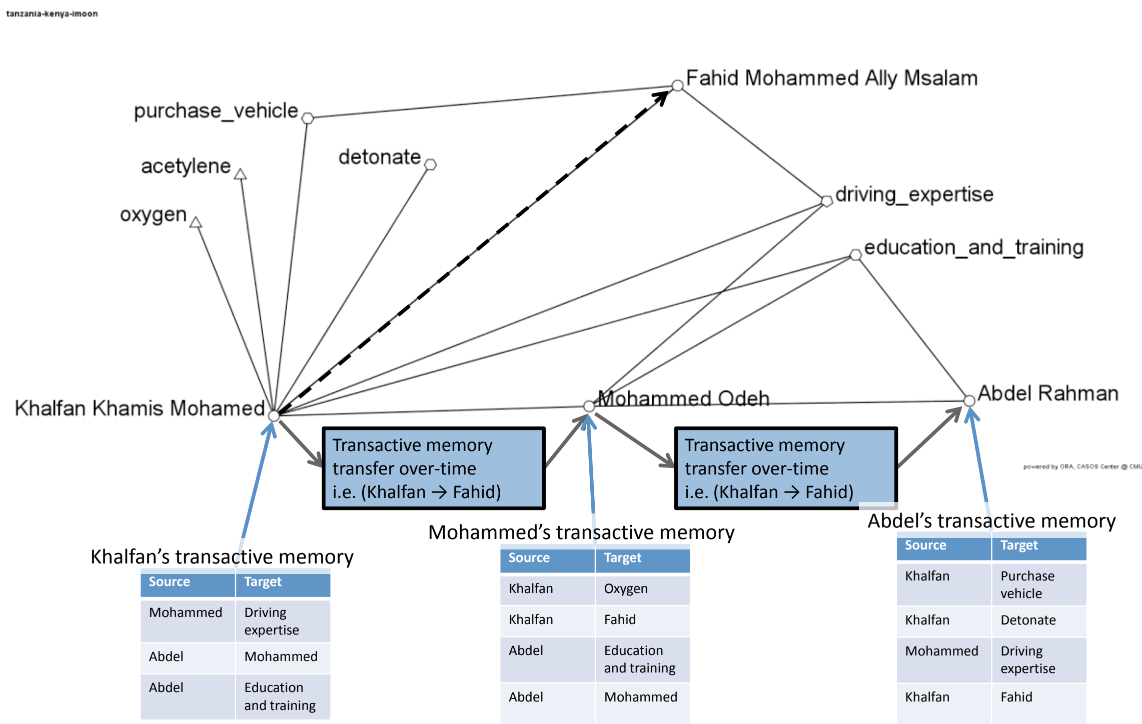


Figure 7-4 A illustrative example of transactive memory transfer, A link information, such as *Khalfan Khamis Mohamed is linked to Fahid Mohammed Ally Msalam,* can be transferred through the interaction network among agents. The transferred transactive memory is stacked in the received agent's transactive memory repository. After transactive memory decay time-steps, the decayed transactive memory element is removed.

7.1.5. Perform an assigned task

An agent performs a task if the task is ready for execution. There are three statuses for a task according to the resource and expertise distribution over the course of simulation.

1) *Not Ready*: A task is not ready if its prerequisite tasks are not completed. The prerequisite tasks are defined in the task dependency network of the input meta-network (see Table 7-1).

2) *Ready:* A task is ready if its prerequisites are done. However, this ready status does not guarantee the task completion. The group of assigned agents has at least one piece of each required element to the task, but the group may not fully equipped with expertise and resources to perform the task. From ready status, an assigned agent can perform the task by coin-tossing with *Task execution success rate probability* in Table 7-1. If the required resources and expertise are not acquired by the group of assigned agents, the task performance will always fail.

3) *Done:* A task is done if the group of assigned agents has the required expertise and resources, at least one piece, and if one of the assigned agents performed the task by successfully coin-tossing whose probability is specified in *Task execution success rate* in Table 7-1.

7.2. Virtual experiment design

Virtual experiment design for destabilization analysis consists of two parts. First, an analyst need to specify the simulation model parameters, such as the number of simulation time-steps, interaction ways (either sociology oriented interaction or operations research oriented interaction), weights for interaction methods, etc. Second, an analyst needs to compose a simulation scenario: who to remove and when. Fundamentally, an analyst can determine the values for the parameters specified in Table 7-1 with his qualitative insights into a target organization.

The presented virtual experiment in this chapter varies simulation scenarios in three ways: removed agent selection scheme, number of removals, and removal timings. The permutation of these three factors and values are listed in Table 7-2. There are 64 different virtual experiment cells that have different simulation environment. For instance, the experiment cells with larger *intervention size* remove more terrorists over the course of simulations. The experiment cells with *later intervention timing* removes agents relatively late phases of simulations. Also, the experiment cells have diverse intervention target selection scheme according to *removal target selection scheme.* This is the manipulation of simulation scenario. Further analyses can be done by changing the simulation parameters, but such experiments are not done in this thesis. Human analysts are free to change the default value that I used here and listed in Table 7-1 and Table 7-2.

Table 7-2 Virtual experiment design for simulation parameters (15 replications, 2500 simulation time steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	1, 5, 9, and 12 agent removals (removing 10%, 30%, 50% and 70% of agents, 4 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	125, 250, 500, and 1000 time-step (removing at after 5%, 10%, 20% and 40% timeflow, 4 cases)	The intervention happens at a specific stage of simulation period.

Total virtual experiment cells	64 cells (4x4x4 cases)

To determine the agents to be removed over the course of simulations, I use dynamic network analysis measures: Degree, Betweenness, Eigenvector centralities and Cognitive Demand. Without such analysis, a human analyst cannot come up with a semi-optimized simulation scenario because of the vast amount of possible simulation scenarios. I added interpretations of the used metrics in Table 7-3.

Table 7-3 Dynamic network metrics used to determine the target agents to remove

Name	Interpretation	Reference
Degree Centrality	Number of in-coming and out-going links from a node, Degree of direct influence to others	Freeman, 1979
Betweenness Centrality	Number of shortest paths passing a node, Degree of information flow control	Freeman, 1979
Eigenvector Centrality	Calculates the eigenvector of the largest positive eigenvalue of the adjacency matrix, Degree of connections to the high-scoring nodes	Bonacich, 1972
Cognitive Demand	Measures the total amount of effort expended by each agent to do his/her tasks, calculation details are elaborated below.	Carley, 2002

7.2.1. Remove an agent specified in the intervention sequence

JDynet is used to assess the impact of intervention strategies, or an agent removal sequence. In Table 7-1, there is an input, *Simulation scenario*. Simulation scenario is a sequence of agent removal specifications. An agent removal specification displays the target agent to be removed and when the target will be removed in the simulation time.

At the end of every time-step, JDynet goes through the agent lists and finds an agent that should be removed at the time-step. If an agent is removed, then the agent cannot make any actions, either social interactions, organizational element transfers, or task performances.

7.2.2. Performance measures

To assess the change of the organization, I implemented four performance metrics: *Diffusion*, *Energy Task Accuracy*, *Binary Task Accuracy* and *Task Completion*. The performance metrics are used to evaluate the performance of the evolving organization over time. Also, I gauge the intervention effectiveness by comparing the performance values to those of non-intervention case (baseline).

1) Diffusion: Diffusion measures the dispersion of expertise and resources across the agents.

$$(Diffusion) = \frac{\sum_{i=0}^{A} \sum_{j=0}^{K} AK_{ij}}{K \times A}$$

2) Energy Task Accuracy: Diffusion only considers who knows or has what. Whereas, energy task accuracy calculates the extent to which the agents have the knowledge they need to do the tasks they are assigned. This is done by introducing the agent-to-task (AT) and knowledge-to-task (KT) network in the formula.

$$ETA = \frac{1}{T} \sum_{t=0}^{T} \frac{\sum_{k=0}^{K} (KT_{kt} \times \sum_{a=0}^{A} AK_{ak})}{\sum_{a=0}^{A} AT_{at} \times \sum_{k=0}^{K} KT_{kt}}$$

3) Binary Task Accuracy: Binary task accuracy measures the agents' binarized, assigned task classification capability with the current information and resource availability. A task classification is performed by classifying N organizational elements required to perform the task. An agent always classifies an organizational element correctly if he has the element. If the agent does not have an element, he can guess the correct answer with 50% of chance. Therefore, if an agent has M (<N) required elements, then he has to guess (N-M) elements to get the result of the binarized task. The task performance is 1 if the agent classifies more than 50% of required elements correctly.

4) Task Completion: Task completion measures the number of completed task over the course of the previous simulation period. A task is completed if the task's status is in *done* status as explained in the previous section. Task completion is a simple ratio calculated from $\frac{(\text{number of completed tasks})}{(\text{number of tasks in the organizational structur})}$.

5) Task Completion Speed: A task duration is the simulated time length between the task's ready status to done status. Then, each task's speed is determined by inversing the task duration. I average each of the task speeds and calculate the organization level task completion speed.

6) Mission Completion Speed: Mission completion speed is the inverse of the number of simulation time-steps over the course of the task dependency network completion. The task dependency network completion means the entire task network completion by completing individual tasks one by one.

7.3. Result

I ran the above virtual experiments with the Tanzania and Kenya embassy bombing case (details are introduced in Chapter 4.2. First, I examine the agent removal impacts toward organizational performances. Second, I observe the delayed task completion timing caused by the agent removals. Third, I enumerate the key individuals over the course of simulations. Finally, I visualize the agents' collective behavior during the simulations.

7.3.1. Impact to performance measures

After running four different simulation scenarios for each of 64 virtual experiment cells, we get 64 simulation results. I regressed the simulation settings to the organizational performance metrics, see Table 7-4. This regression is done by using the two continuous virtual experiment factors (timing and size) and one factor (removal selection scheme) with four categories. There are four categories in the removed agent selection metrics. I represented the four categories by assigning 1 if the metric is used, and 0 if not used. According to the regression result, earlier interventions (smaller intervention timing value) and larger interventions (larger interventions size) are preferable in reducing the performance. In terms of the removal target selection, removing top Degree Centrality terrorists can reduce the mission execution speed, the task execution speed, the binary task accuracy and the level of diffusion. The similar trends can be found in the case of removing top Eigenvector Centrality terrorists.

Table 7-4 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.143*	0.205	-0.021	0.081*	-0.070*	0.369*
Intervention Size	-0.808*	-0.063	-0.263*	-0.978*	0.977*	-0.817*
Degree Cent.	-0.013	-0.192	-0.121	0.044	-0.043	0.033
Betweenness Cent.	0.195	0.074	-0.166	0.041	-0.042	0.132
Eigenvector Cent.	0.014	-0.096	-0.312*	0.018	-0.014	-0.003
Cognitive Demand	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-Square	0.679	0.005	0.046	0.958	0.954	0.797

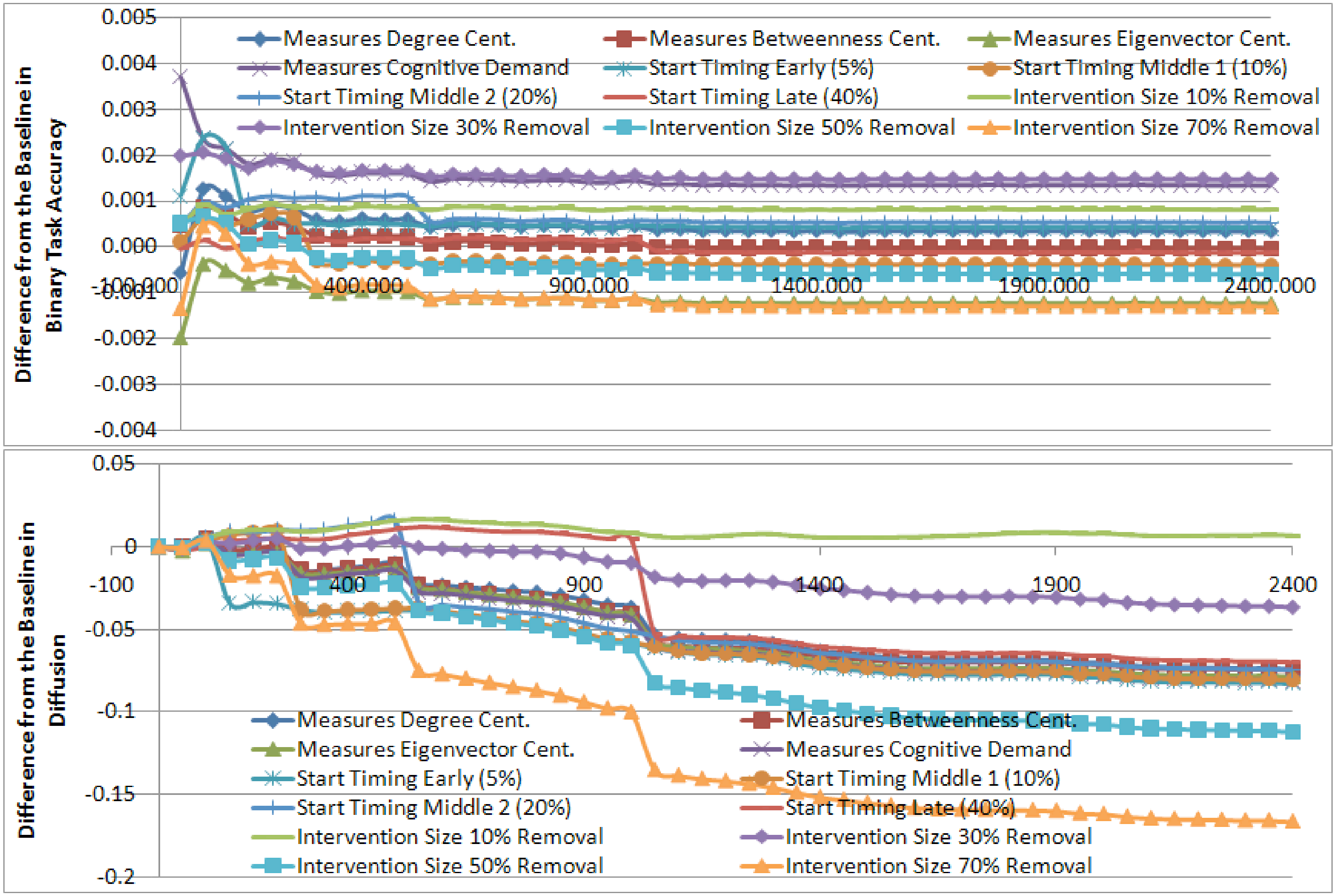
I performed another regression analysis (see Table 7-5) to investigate the characteristics of removed agents. For this regression, I compiled the average network metrics of removed agents and virtual experiment settings. In overall, again, the *intervention size* has significant influence over the mission speed, energy task accuracy, diffusion and task completion. If the intervention size gets larger, the above metrics gets smaller. The *intervention timing* affects somewhat influence over mission speed, binary task accuracy and task completion. If the intervention timing gets earlier, the damage gets larger (and actual performance values decrease). The regression indicates that *Eigenvector centrality* has higher influence and important metrics in predicting the simulated organizational performance. For example, if we choose to remove low *Eigenvector centrality* agents, we can lower the mission execution speed, task execution speed, binary task accuracy, energy task accuracy, and task completion. If we choose to remove high *Degree centrality* agents, we can reduce the mission execution speed, task execution speed, binary task accuracy, energy task accuracy and task completion levels.

Table 7-5 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated metrics of removed agents (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.143*	0.205	-0.021	0.081*	-0.070*	0.369*
Intervention Size	-2.198*	-0.121	-0.857	-0.806*	0.845*	-1.555*
Degree Cent.	-0.251	-0.985	-2.197*	-0.473*	0.542*	-0.614
Betweenness Cent.	0.137	-0.146	0.465	-0.151*	0.142*	0.050
Eigenvector Cent.	1.043*	1.389	2.587*	0.551*	-0.645*	1.104*
Cognitive Demand	0.608*	-0.319	-0.441	-0.184*	0.181*	0.219
Adjusted R-Square	0.814	-0.018	0.102	0.984	0.982	0.851

One thing should be noticed is the high R-square values. In typical cases, agent based social models do not produce high R-square values because inherent randomness and complex agent behavioral models. In contrast, the presented operations research based model shows high R square values in the linear model.

While this is an overall result of the 64 different virtual experiment settings, I grouped the results by their first factors: *target selection scheme*, *intervention size*, and *intervention timing*. Figure 7-5 is the over-time organizational performance evolution of the virtual experiment cell by the first factors.


Difference from the Baseline in Binary Task Accuracy
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (5%)
Start Timing Middle 1 (10%)
Start Timing Middle 2 (20%)
Start Timing Late (40%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal
Difference from the Baseline in Diffusion

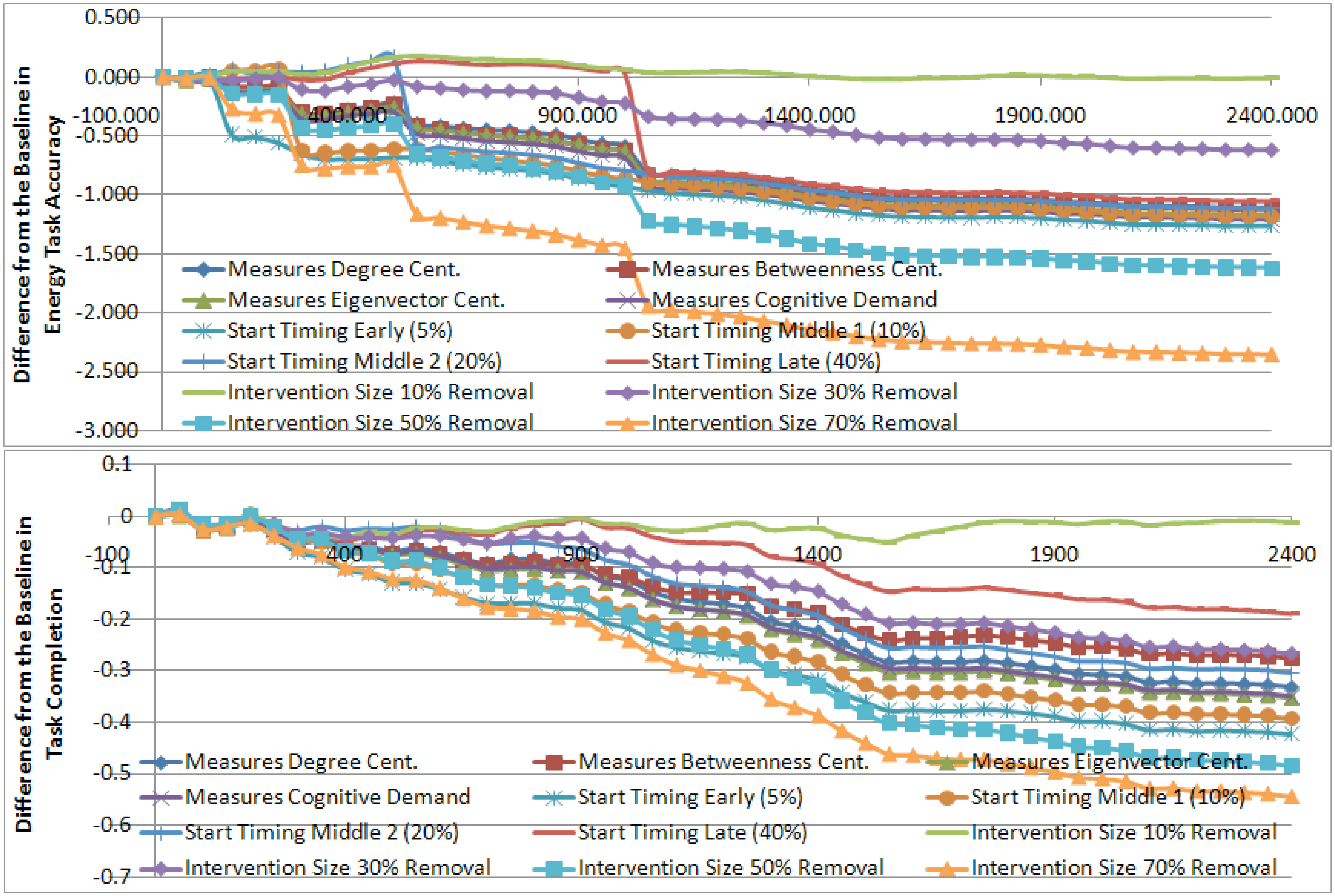


Figure 7-5 Organizational performance over time, aggregated by the first factor

Binary task accuracy converges to the evolved state quickly because I used the modified version of binary task accuracy by averaging the values from the start time up to the measure calculation time. The energy task accuracy and diffusion charts exhibit big drops at the intervention timing: 125, 250, 500 and 1000. On the other hand, the task completion chart shows gradual damages over the course of simulations. If an agent is removed while the agent is not needed right now to execute current tasks, then the agent's removal does not decrease the performance right away. When the agent is needed, the baseline case can perform without serious problems, but the removal cases are damaged when the time comes. In terms of Energy Task Accuracy, large intervention leaves constant and permanent damages while early intervention leaves such damages from the task completion perspective.

7.3.2. Impact to task completion timing

JDynet can perform more in-depth analysis on the task performance of the adversaries compared to the existing Construct model. For example, JDynet regenerates the task completion status over the simulation period, and it generates a task completion speed, a mission completion speed and a Gantt chart. I investigate these task completion timing issues.

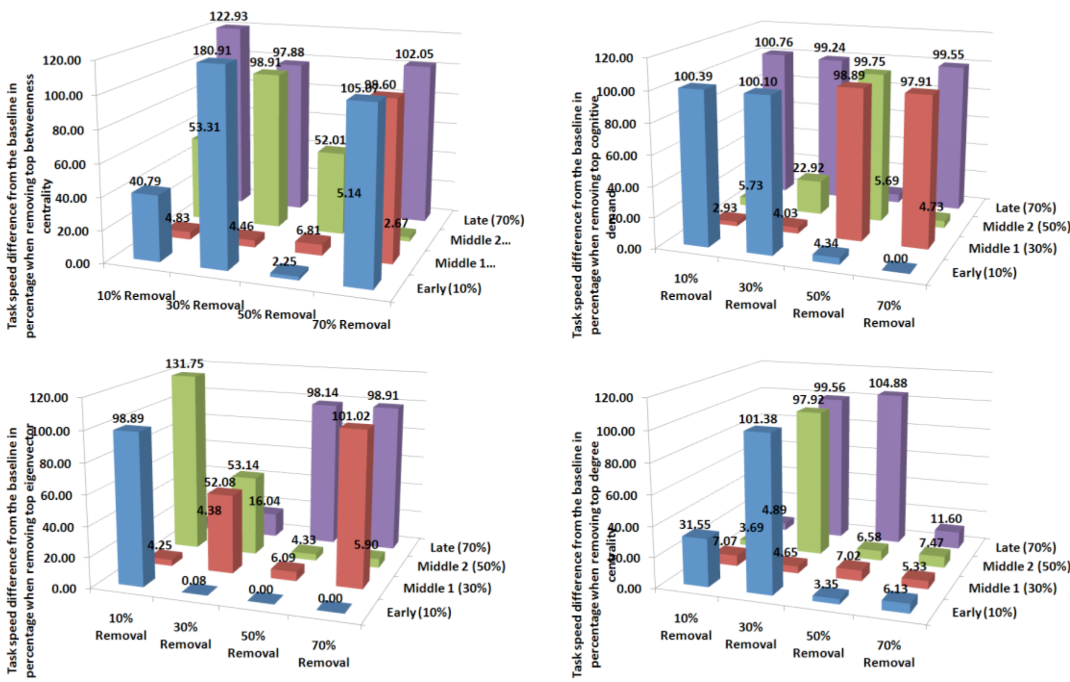


Figure 7-6 Percentage of Task completion speed to the baseline, 64 virtual experiment cells

First, I show the task completion speeds of the 64 virtual experiment cells (See Figure 7-6). The chart value is the percentage value of a specific virtual experiment cell compared to the baseline case. Therefore, if the value is higher than 100, it means the virtual experiment cell has faster task completion speed. If the intervention timing is late, the task completion speed is higher. On the other hand, if the intervention happens earlier, some tasks are impossible to be executed which makes their task completion speed 0.

Figure 7-6 shows that removing the high degree centrality agents is better in reducing the task completion speed. In most of the cases, the degree centrality based removal shows below 32% of the task completion speed compared to the base line (except four cases that show 101.38%, 97.92%, 99.56%, 104.88%). In general, removing a small number of agents at the late simulation timing does not impact any damage or sometimes increase the task execution speed.

Second, I show the mission completion speeds of the 64 virtual experiment cells. Since some removals disabled the organization to execute their entire task dependency network, the cells with successful mission prevention show 0 mission completion speed (infinite execution time). These complete mission disables frequently happen when removing more than 30% of agents at the earlier stage. If the interventions are not successful, some cells show increased mission execution speed (i.e. 103.55% of top cognitive demand agent 10% removal at early stage). Again, large and early removals show better destabilization effect compared to the small and late removals.

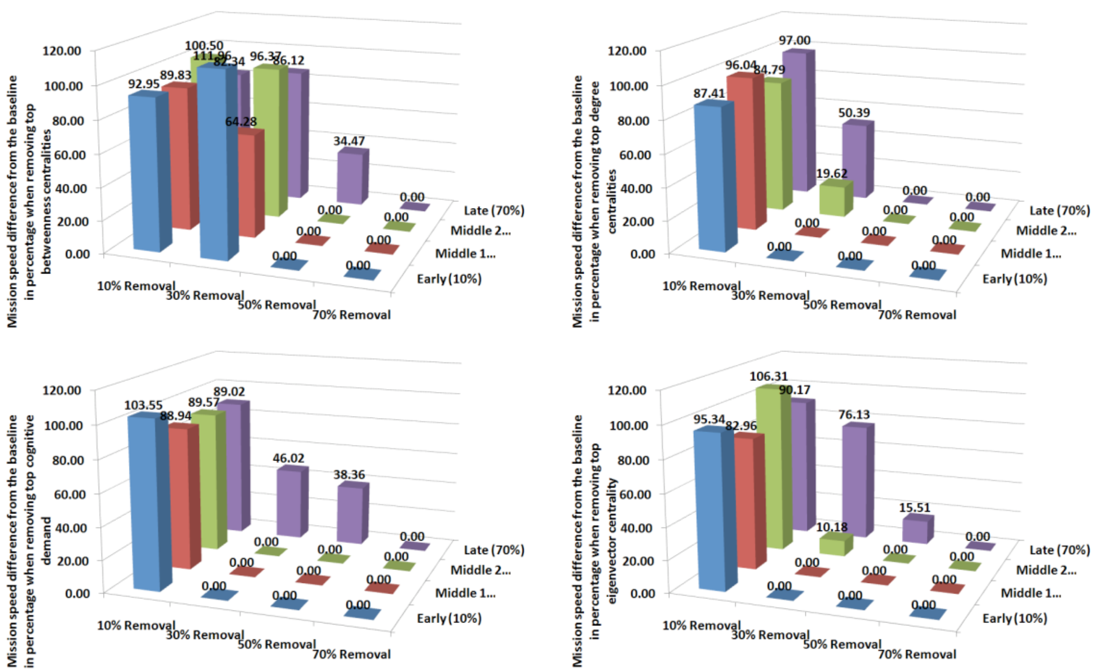


Figure 7-7 Percentage of Mission completion speed to the baseline, 64 virtual experiment cells

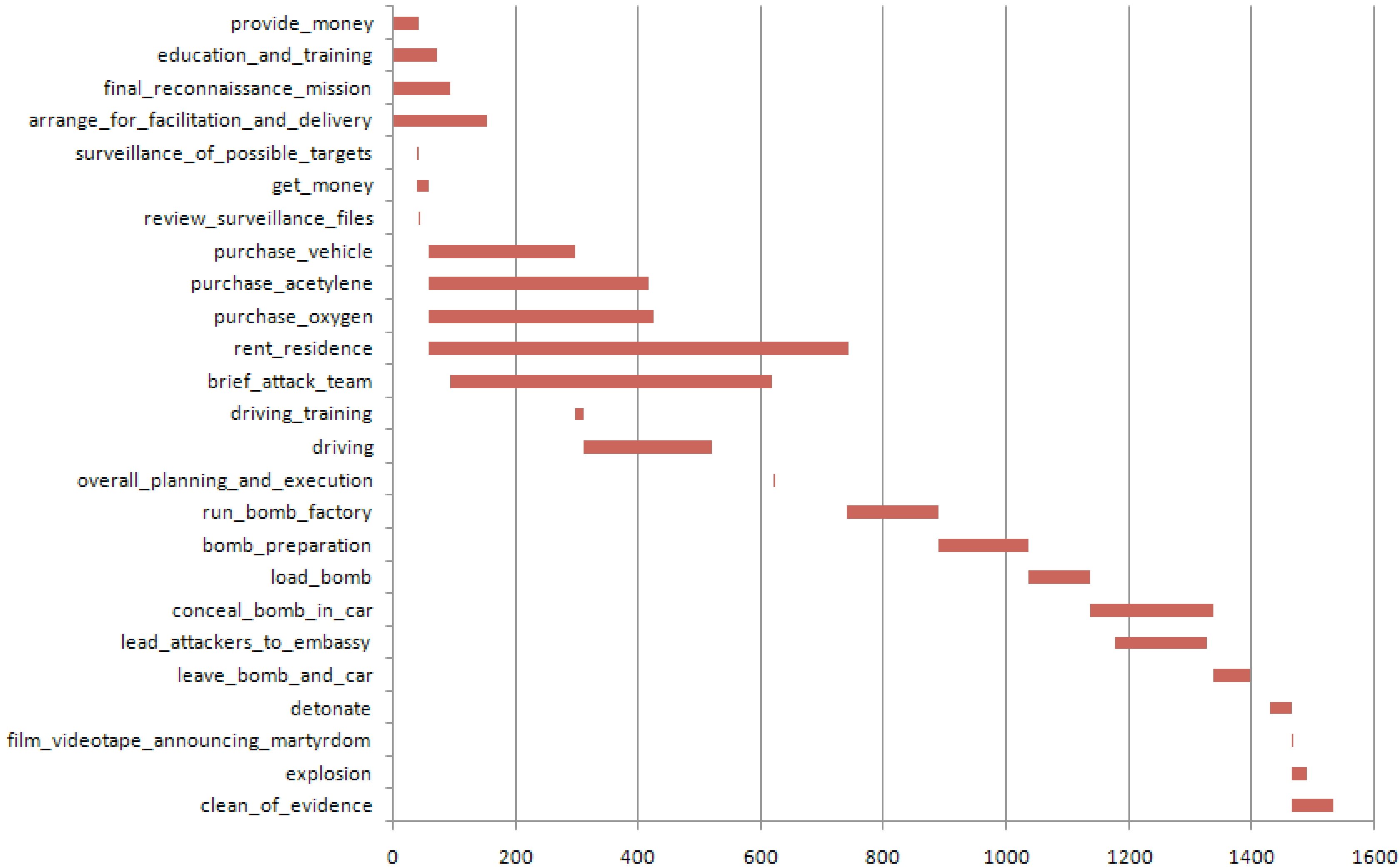


Figure 7-8 The estimated Gantt chart of the baseline case

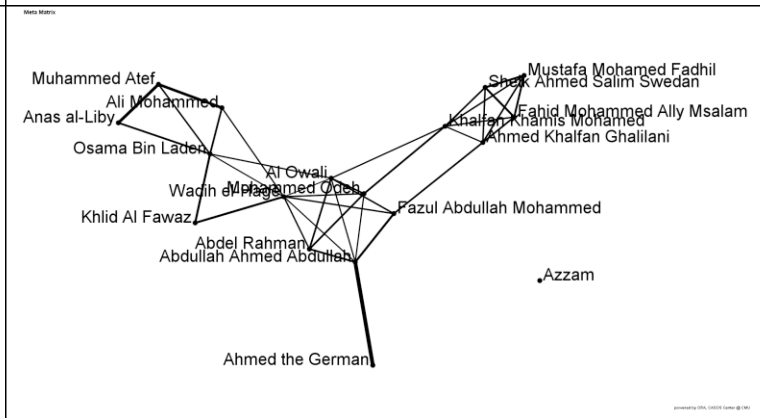
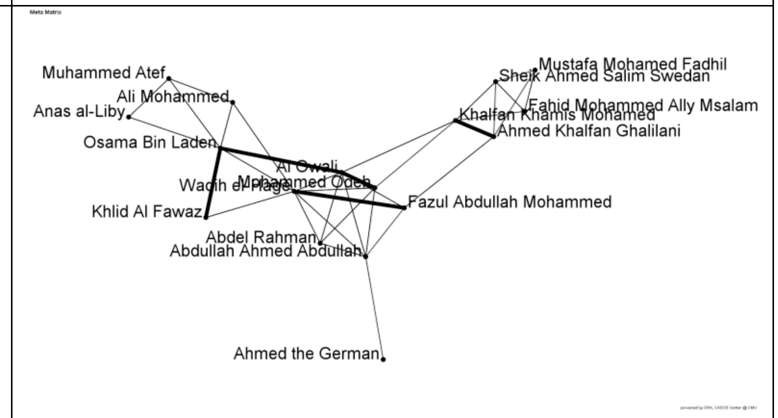
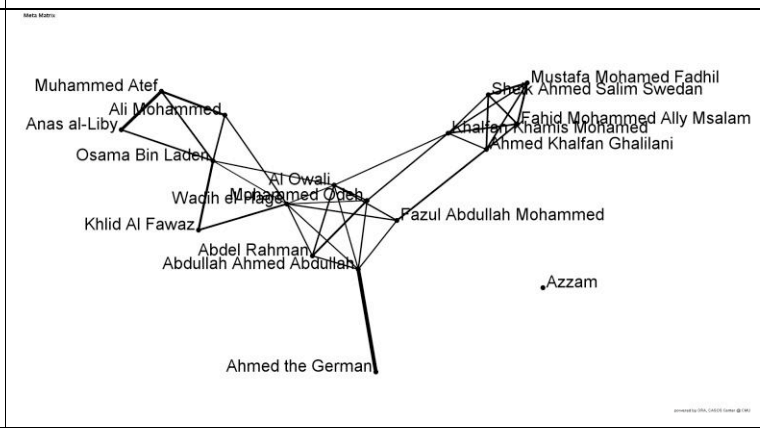
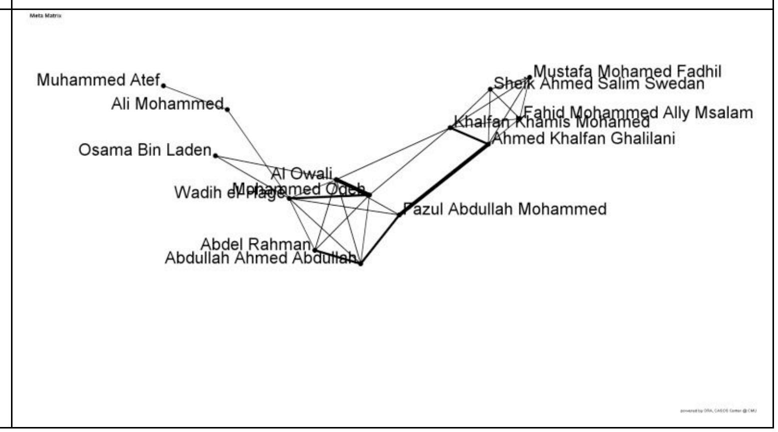
Third I show the Gantt chart (see Figure 7-8) of the baseline to show the bottleneck tasks and the task durations. This demonstrates the JDynet capability to generate such a chart used in the real world and to identify which task are bottleneck tasks that slower the mission execution speed. The *rent residence* task seems to have the longest execution time and seriously damaging the mission execution speed. The *rent residence* is the prerequisite to perform the *run bomb factory* task which leads the later task chains. Because of the *rent residence* task's delay, other tasks executed in the later phase got hold.

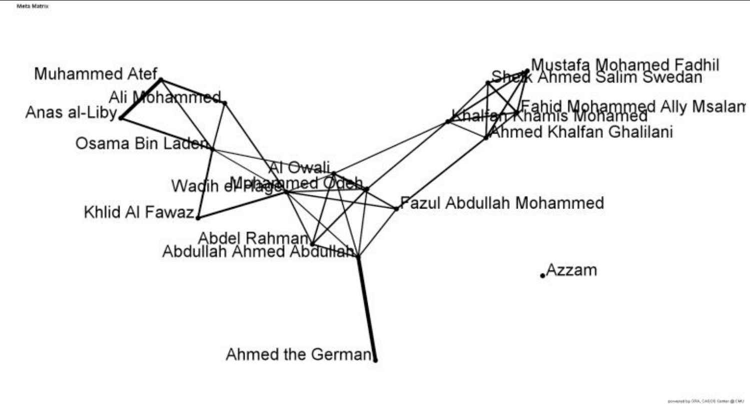
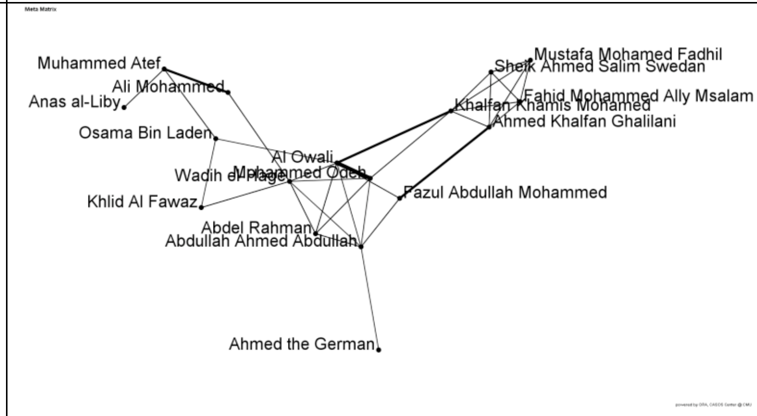
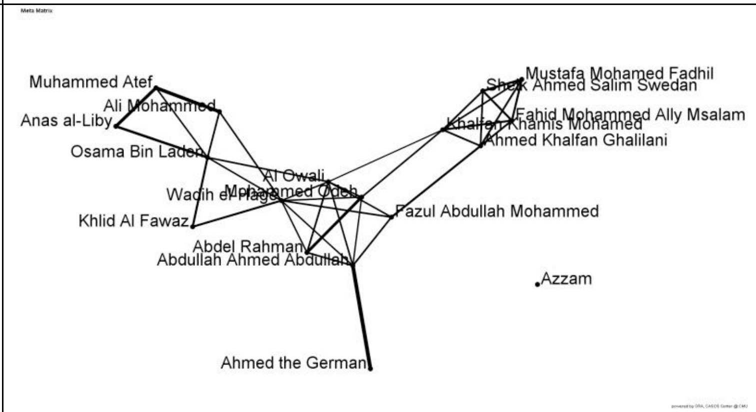
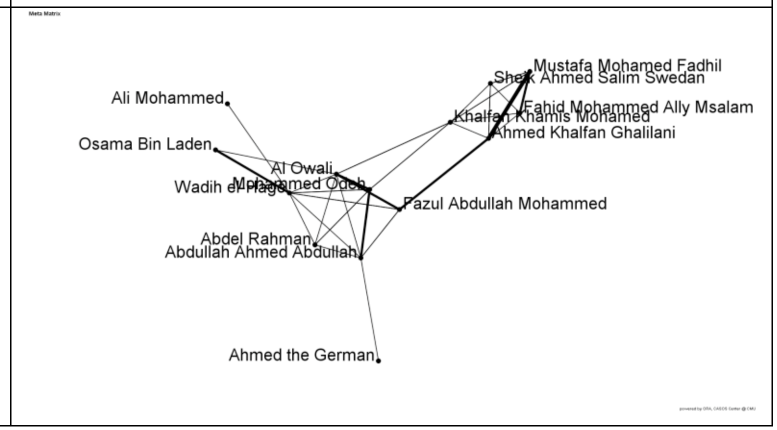
7.3.3. Agent interactions during simulations

I observe the agent interactions and organizational element transfers over the course of the simulation. Figure 7-8 is the Gantt chart of the baseline case over the course of the mission execution. As the Gantt chart displays, the agents focus on different tasks as the mission progresses. Moreover, the agents are assigned different tasks, which makes their interactions and organizational element transfers change over time. Table 7-6 is the collection of the agent interactions and organizational element transfer networks during the course of the simulation.

The agent interaction networks show no significant differences over time. There are minimal changes in the link weights. However, the agent organizational element transfer network changes dramatically, which means that the actual usefulness of the interactions change according to whether the interaction accompanies an organizational element transfer or not. The terrorists are bounded to their cellular network structure, so that the interaction network itself is not an obvious change. We need to see the implied the usefulness of the interactions by looking into whether the link was used to actual resources or expertise transfer. In the transfer networks, there are isolated agents who are not utilized during the particular time period. In this case, a manger may consider reassigning the agents to other tasks which can be executed in parallel. Also, a commander may consider removing heavily utilized agents at a particular time-step when they can figure out which transfer network is going on at the intervention timing. Empirically, *Fazul Abdullah Mohammed, Al Owali* and *Wadih el-Hage* are the agents that consistently appear in the transfer network, which means that their removals would be effective in any of time periods.

Table 7-6 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

<table>
<tr><td></td><td>Agent to Agent network: Interaction</td><td>Agent to Agent network: Transfer resources and expertise</td></tr>
<tr><td>Time 100</td><td>
</td><td>
</td></tr>
<tr><td>Time 500</td><td>
</td><td>
</td></tr>
</table>

<table>
<tr><th></th><th>Agent to Agent network: Interaction</th><th>Agent to Agent network: Transfer resources and expertise</th></tr>
<tr><td>Time 900</td><td>
</td><td>
</td></tr>
<tr><td>Time 1300</td><td>
</td><td>
</td></tr>
</table>

7.3.4. Key individuals over the course of simulations

Since I have the agent interactions and organizational element transfers over the course of the simulation, I can calculate the network metrics for the individuals in the network. Table 7-7 shows the key personnel at the probed time-steps during the simulation. The key individual lists from interaction networks do not change because the interaction networks and the original social network are same. In spite of the weight differences, the network metric values are same because the metrics does not differentiate the link weights (the metrics regard the links as binary values). However, the transfer network shows the difference over the course of simulations. From the degree centrality perspective, *Al Owali* has the highest importance (at time 300, 500, 1300), but the individual with the second highest degree centrality in the transfer network changes over time (*Abdullah Ahmed Abdullah* at time 300, *Khalfan Khamis Mohamed* at time 500, *Mohamed Odeh* at time 1300). This is an example of the individual criticality fluctuation over time. Another example is the betweenness centrality rank of *Wadih el-Hage.* He has the second highest betweenness centrality in the transfer network of the early stage (time 50). However, his betweenness rank fluctuates from the second (time 30), Rank 8 (time 500), third (Time 500), to second (Time 1300). This fluctuation is related to the transfer necessity emerged from the individuals' task execution and element request at the probing time-step.

Table 7-7 Key individual lists over the course of simulations

Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Osama Bin La-den	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Wadih el-Hage
Rank 2	Al Owali	Al Owali	Osama Bin La-den	Wadih el-Hage	Khalfan Khamis Mohamed	Wadih el-Hage	Osama Bin Laden	Al Owali
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Wadih el-Hage	Al Owali	Wadih el-Hage	Khalfan Khamis Mohamed	Wadih el-Hage	Osama Bin Laden
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Muhammed Atef	Khalfan Khamis Mohamed	Osama Bin La-den	Osama Bin Laden	Muhammed Atef	Abdel Rahman
Rank 5	Abdullah Ahmed Abdullah	Abdel Rahman	Al Owali	Mohammed Odeh	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Al Owali	Fazul Abdullah Mohammed
Time 300	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Al Owali	Al Owali	Al Owali	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed
Rank 2	Al Owali	Al Owali	Wadih el-Hage	Abdullah Ahmed Abdullah	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Fahid Mohammed Ally Msalam	Al Owali
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Osama Bin La-den	Khalfan Khamis Mohamed	Wadih el-Hage	Osama Bin Laden	Sheik Ahmed Salim Swedan	Mustafa Mohamed Fadhil
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Khalfan Khamis Mohamed	Mohammed Odeh	Osama Bin La-den	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah	Fahid Mohammed Ally Msalam
Rank 5	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah	Al Owali	Mustafa Mo-hamed Fadhil	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Mustafa Mohamed Fadhil	Ahmed Khalfan Ghalilani

Time 500	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Osama Bin La-den	Al Owali	Al Owali	Khalfan Khamis Mohamed	Ahmed Khalfan Ghalilani	Al Owali
Rank 2	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Al Owali	Fahid Mohammed Ally Msalam	Mohammed Odeh
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Wadih el-Hage	Abdullah Ahmed Abdullah	Wadih el-Hage	Wadih el-Hage	Mustafa Mohamed Fadhil	Abdullah Ahmed Abdullah
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Ahmed Khalfan Ghalilani	Wadih el-Hage	Osama Bin La-den	Fazul Abdullah Mohammed	Khalfan Khamis Mohamed	Wadih el-Hage
Rank 5	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah	Muhammed Atef	Ahmed Khalfan Ghalilani	Abdullah Ahmed Abdullah	Ahmed Khalfan Ghalilani	Sheik Ahmed Salim Swedan	Fazul Abdullah Mohammed
Time 1300	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Al Owali	Al Owali	Khalfan Khamis Mohamed	Wadih el-Hage	Al Owali
Rank 2	Al Owali	Mustafa Mo-hamed Fadhil	Wadih el-Hage	Mohammed Odeh	Khalfan Khamis Mohamed	Wadih el-Hage	Abdullah Ahmed Abdullah	Ahmed Khalfan Ghalilani
Rank 3	Khalfan Khamis Mohamed	Al Owali	Osama Bin La-den	Wadih el-Hage	Wadih el-Hage	Mohammed Odeh	Al Owali	Mohammed Odeh
Rank 4	Mustafa Mo-hamed Fadhil	Khalfan Khamis Mohamed	Ahmed Khalfan Ghalilani	Ahmed Khalfan Ghalilani	Osama Bin La-den	Fazul Abdullah Mohammed	Osama Bin Laden	Fazul Abdullah Mohammed
Rank 5	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah	Muhammed Atef	Mustafa Mo-hamed Fadhil	Abdullah Ahmed Abdullah	Ahmed Khalfan Ghalilani	Mohammed Odeh	Abdullah Ahmed Abdullah

7.4. Implementation of the social simulation model

The simulation model is the agent based simulation model with the social dimension. Therefore, the major focus of the implementation should include the following two points.

1) Simulation model iteration management
2) Social interaction logics
3) Knowledge of space
4) Task execution logics

This subsection describes the implementation of the above four components in this simulation model.

7.4.1. Simulation model iteration management

Simulation iteration is the main loop of the entire model. When a user request a simulation run, the simulation will execute this loop after loading the simulation model inputs (simulation model inputs will be explained later). This simulation model runs a number of iterations to simulate the time flow. These iterations are controlled by a loop controlling individual agent behavior. The following is the pseudo code for coding this big loop in a nutshell.

```
Function main()
        Load simulation inputs;
        Setup simulation inputs;
        Setup random;
        For i = 0 to num_timestep
                simulation_iteration(random,i);
        End;
        Calculate_performance_value_for_entire_simulation();
        Generate_simulation_outputs;
End function;
```

Code 7-8 Geospatial simulation model main loop

As in the above pseudo code, the model runs the number of simulated time-step with a random factor. This random factor makes this simulation stochastic. The reason behind this randomness is explained in the simulated agent behavior.

Just like the simulation input procedure, after the simulation loop finished, the program generates the performance outputs. There are two different types of outputs from this simulation model. First, we get the performance numbers, i.e. task completion rate, knowledge diffusion, task accuracy, etc. These numbers are printed out into files right away. The second output type is the estimated network outputs. These outputs are recorded in a DynetML file, so that the file can be loaded in ORA and visualize the over-time changes. Thus, Generate_simulation_output should handle these two types of outputs.

After coding this big loop wrapping the entire model, we code the individual iteration function that will be invoked over time. The below is the simulation_iteration function.

```
Function simulation_iteration(Random r, int timestep)
        Agent_behavior_order = Randomized_order(1 to num_agent);
        While(Agent_behavior_order)
                i = next(Agent_behavior_order);
                Execute_agent_behavior(i, r);
        End;
        Calculate_performance_value_for_timestep();
End function;
```

Code 7-9 Geospatial simulation iteration for each time-step

By randomizing the agent behavior order, we can simulate the randomness in the action frequency. Also, by executing every agent's behavior for a single time-step, we can guarantee that the agents will execute their actions for the number of time-step throughout the simulation.

The simulation main loop calls the simulation iteration function for the number of time-step times. The simulation iteration function calls the individual agent behavior function in the randomized order. The below is the specification of the individual agent behavior function. As I discussed previously, the agents gather knowledge and resources and perform assigned tasks by using gathered elements.

```
Function Execute_agent_behavior(int agentID, Random r)
        Social_interaction(agentID, r);
        Perform_task(agentID, r);
End function;
```

Code 7-10 High level agent behavior

7.4.2. Social interaction logics

The following pseudo code is the social interaction behavior pattern in the simulation. There are three social interaction motivations as specified in Ch. 7.1.2. The three motivations are 1) requested element (knowledge or resource) delivery, 2) other's element delivery request passing, and 3) the agent's element delivery request generation and passing. When an agent has a chance to make a social interaction, the agent makes a weighted random choice to select one motivation out of three. This weighted random choice represents the gap between the agent's intention and action. For instance, having a higher probability for the agent's element request generation is a representation of the agent's intention to get that element. However, in the simulation, he might have to pass other's element request because of the randomness. Then, his action is different from his intention. Having said this, if he has a far higher probability for a certain motivation, then he is very likely to select the motivation out of the random choice. This reflects the strength of intention and increasing likelihood of his intention realization.

```
Function Social_interaction(int agentID, Random r)
        Neighbor_agents = getSphereOfInfluence(agentID, one social link away, return_only_agent);
        choice = weightedRandomChoice(r, weight_element_delivery, weight_others_request_passing,
        weight_my_request_generation);

        switch(choice)
                case Element_delivery:
                        Element e = find_requested_and_possessing_element(agentID's elements);
                        Request req = find_request_records_specified_by_element(agentID's received
                                delivery request, e);

                        If ( req.sender has done his interaction for this turn) finish this block;

                        If ( req.sender and agentID are at the same location )
                                If ( transferSuccessProbAtSameLocation < r.nextValue )
                                        Unlink(agentID,e);
                                        Link(req.sender,e);
                                End;
                        Else
                                If ( transferSuccessProbAtDifferentLocation < r.nextValue )
                                        Unlink(agentID,e);
                                        Link(req.sender,e);
                                End;
                        End;

                        Remove_request_records(req);

                Case Others_request_passing:
                        Request req = find_request_records(agentID's received delivery request);
                        interactionPartnerID = pick_one_agent_with_the_element
                                        _based_on_the_transactive_memory(agentID, Neighbor_agents);

                        If ( interactionPartnerID has done his interaction for this turn) finish this block;

                        Request newReq = new Request(req.element, agentID);
                        Put_in_the_request_list(interactionPartnerID,newReq);

                Case My_request_generation:
                        Element e = find_required_element_not_in_possession(agentID);
                Request req = new Request(e, null);
                        Put_in_the_request_list(agentID,req);
        End switch;

        transactiveMemoryExchangePartnerID = pick_one_agent_randomly(Neighbor_agents);
        exchangeTransactionMemory(agentID,        transactiveMemoryExchangePartnerID);
End function;
```

Code 7-11 Agent's social interaction implementation pseudo code

7.4.3. Knowledge of space

At the end of the social interaction, the agent exchanges his transactive memory with a randomly selected neighboring agent. This is a simulation of interactions passing the information about the current simulated situation. The transactive memory element exchanges are done as the following pseudo code. This exchanged transactive memory becomes the basis for agent social behavior: finding required elements, finding interaction partners, etc.

```
Function exchangeTransactiveMemory(int agent1ID, int agent2ID)
        Agent1_Neighbor_nodes = getSphereOfInfluence(agent1, one social link away);
        Agent2_Neighbor_nodes = getSphereOfInfluence(agent2, one social link away);
```

```
        N = (number of transactive memory elements exchanged);
        For i = 1 to N
                Agent1_neighbor_node = randomly_pick_one_node(Agent1_Neighbor_nodes);
                Put_transactive_memory_tuple( agent2ID,
                        new TransactiveMemoryElement(agent1ID, Agent1_neighbor_node));
        End;
        For i = 1 to N
                Agent2_neighbor_node = randomly_pick_one_node(Agent2_Neighbor_nodes);
                Put_transactive_memory_tuple( agent1ID,
                        new TransactiveMemoryElement(agent2ID, Agent2_neighbor_node));
        End;
End function;
```

Code 7-12 Agent's transactive management pseudo code

7.4.4. Task execution logics

Finally, the agents perform task execution behavior. A task is not ready to be executed if the task's prerequisite tasks are not done yet. A task is ready to be executed if the task's prerequisite tasks are done. A task is done if the group of assigned agents has all the required resources, knowledge and is placed at required locations. This task execution model is coded as the below pseudo code.

```
Function Perform_task(int agentID, Random r)
        task_list = getSphereOfInfluence(agentID, one social link away, only_task_nodes);
        ready_task_list = select_only_ready_task (task_list);
        task_to_execute = randomly_pick_one_task_that_all_required
                                        _elemets_are_gathered(ready_task);
        If ( taskExecutionSuccessRate < r.nextValue )
                recordTaskIsDone(task_to_execute);
        End;
End function;
```

Code 7-6 Agent's task execution implementation pseudo code

7.4.5. Link to the previous description

Figure 7-9 shows which simulation flowchart components correspond to which pseudo codes in the previous sections. The simulation process is managed by the simulation model main loop, Code 7-1, and the simulation iteration function, Code 7-2. In the simulation iteration function, each agent is called in the randomized order, and the agent executes three aggregated behavior patterns. The first behavior pattern is the social interaction that is implemented as Agent's social interaction implementation pseudo code in Code 7-4. Then, the second pattern is the task execution implemented as Agent's task execution implementation pseudo code in Code 8-6.

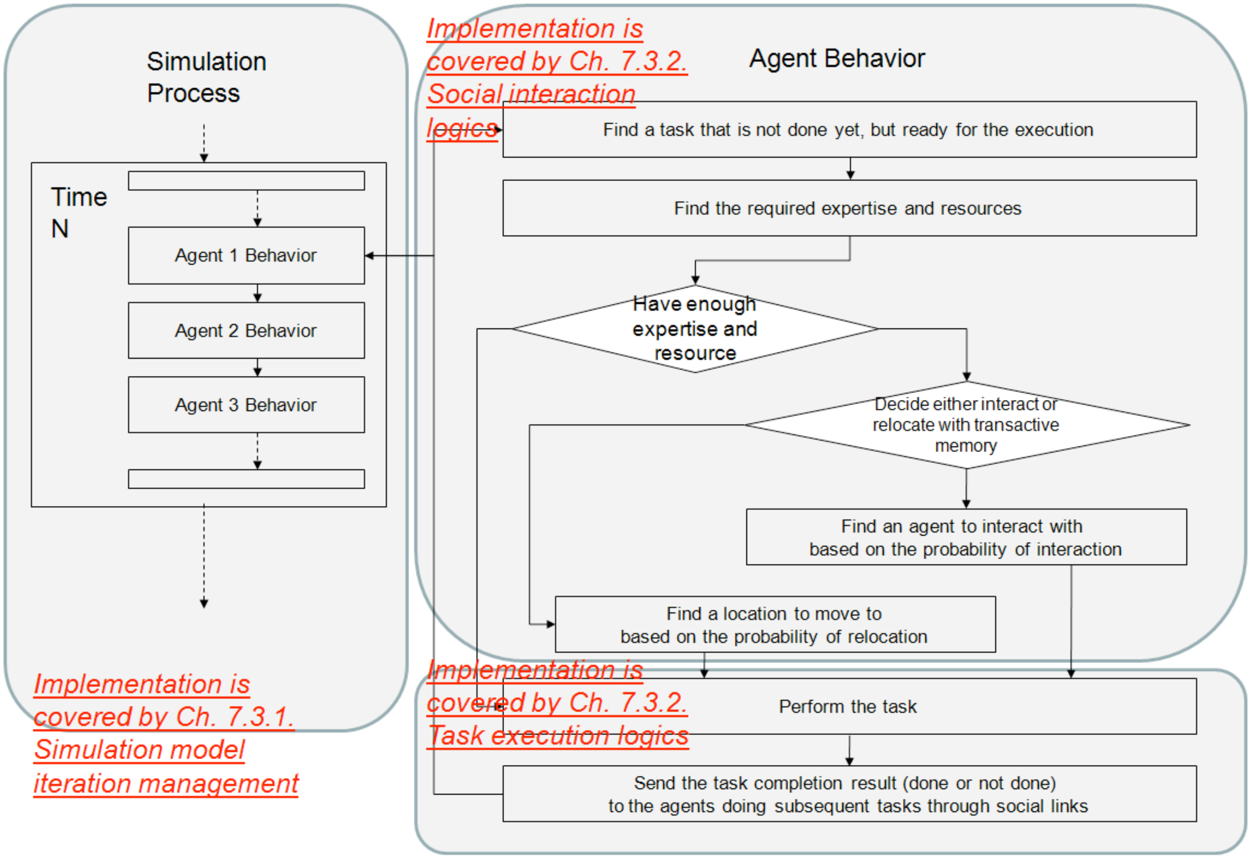


Figure 7-9 Annotated simulation procedure flow chart. The annotation specifies which items in the flow chart correspond to the pseudo code in Ch. 8.5.

Table 7-8 is the list of key parameters. These parameters are introduced earlier in Ch 7.1. However, the earlier introductions were about their types and implications. Table 7-9 provides the links between the pseudo code functions and the used parameters. This table will provide information about where the user parameters are used in which part of the simulation model.

Table 7-8 Annotated simulation key parameter table

Name (Default value in the parenthesis)	Which pseudo code function uses the parameter	Implication
Boost for interaction if two agents are co-located (1.5)	Function Social_interaction (Code 7-4)	If two interacting agents are co-located, the agents will have higher chances of transfer success.
Boost for removal recognition if two agents are co-located (1.5)	Function Social_interaction (Code 7-4)	If an agent tries to recognize one removed agent at the same location, the agent will have higher chance in recognizing the removed agent.
Number of time-step	Function main (Code	The number of simulated time-steps

Name (Default value in the parenthesis)	Which pseudo code function uses the parameter	Implication
(5000)	7-1)	
Weights for requested element delivery (0.33), others' request passing (0.33), or the agent's request passing (0.33)	Function Social_interaction (Code 7-4)	Only used in task performance agent interaction model. Weights for selecting an agent interaction purpose. An agent selects one purpose out of three, requested organizational element (expertise or resource) delivery, his required element request to others, or passing others' request to different others.
Interaction count for time-step (3)	Function Social_interaction (Code 7-4)	An agent cannot interact with another agent after this maximum interaction count.
Cognitive power for time-step (3)	Function Social_interaction (Code 7-4)	An agent can only respond to the number of interactions specified by this parameter.
Exchange success rate (0.75)	Function Social_interaction (Code 7-4)	If an agent diffuses information or passes a resource to another agent, there is a success rate of such trials.
Interaction social distance radius (1)	Function Social_interaction (Code 7-4)	Interaction candidates are limited to agents who are within N social link radius from the interaction initiating agent.
Task execution success rate (0.5)	Function Perform_task (Code 7-6)	When an agent performs a task, the agent can accomplish the task with this success rate. If the task is not ready (the ready state is elaborated later), an agent cannot perform the task.

7.5. Conclusion

An existing model, Construct, is expanded and named JDynet. JDynet includes new behavior mechanisms and outputs. This simulation model has limitations and contributions.

Limitations: JDynet has several issues in validation and scalability. Validating a multi-agent model about adversarial reasoning has been a problem for a long time. Some previous discussions argue that a simulation is not a recreation of the real world, but a computational generation of human behavior identified by previous qualitative analysis. Thus, this validation problem partially depends on the viewpoint of the analysts using the simulation. Scalability is another problem of using this tool. A stochastic multi-agent simulation, just like JDynet, requires a number of replications to stabilize the variance of the results. If the analyzed organization has large size of agents, then the simulation analysis may take long time or impossible depending on the computational capability.

Theoretical contribution: Multi-agent simulation models have a capability to incorporate the agent behavior models and organizational structures. Also, it has an over-time estimation capability, so that it has been used to virtually experiment policies and various social settings. However, the simulation models so far are not closely linked to the nuanced outputs such as a Gantt chart. I show that generations of such outputs are possible and useful in merging operations research and management in the organizational structure analysis.

Technical contribution: I developed a multi-agent simulation model, JDynet, which is based on the operations research oriented agent behavior model. Unlike the sociological Construct mode, which is a predecessor of this model, the agents in this model show actual organizational element transfers and task executions. This more nuanced implementation of agent behavior enables more nuanced simulation outputs. This new model put heavy emphasis on the task execution and its timing, so I supply new metrics such as task completion, task completion speed and mission completion speed. Simulatenously, JDynet inherits important functions of Construct. Agents in JDynet has transactive memories that remember who has what, or who knows who. Also, JDynet takes the networked organizational structure and intervention scenarios that Construct can simulate.

Empirical contribution: I performed virtually experiments with various intervention scenarios and with different settings. I differentiated the target agent selection scheme, intervention size, and intervention timing. I regressed the virtual experiment to the various performance measures considering the information diffusion, task execution capability, task execution speed in Ch. 7.3.1. Removing higher degree agents in large number at the early stage would be effective in the decreasing mission execution speed. However, this may not be achievable in the real world. I also identified bottleneck tasks such as the *rent residence* task that has the longest execution time across the tasks during the mission. It was a prerequisite to the *run bomb factory* task which has many subsequent tasks. You can find the detailed Gantt chart in Ch. 7.3.2. Finally, I identified the organizational element transfer networks among agents. Interactions do not mean that the interactions were utilized. This transfer network only shows the utilized interactions, so that the key players in this transfer network is much meaningful than in the interaction network. There are agents, i.e. *Fazul Abdullah Mohammed, Al Owali*, and *Wadih el-Hage*, who consistently appear in the transfer network over-time.

- *Multi-agent models can be a tool to assess an organizational structure and its evolution over-time.*
- *Building a simulation scenario can be done by using Dynamic Network Analysis.*
- *By incorporating further nuanced agent behavior models, we can generate nuanced outputs that are frequently used in the real world.*

- *Multi-agent simulation models can estimate the actual usefulness of interactions by examining whether the interaction carried any organizational element transfers between the two agents.*

I updated a simulation model by using an operations research idea. This changes the view of the previous simulation model originated from the sociological perspective. The developed mutli-agent model can answer more technical questions with usable outputs. For instance, managers have issues in projecting the project progress, and this simulation model is ready to answer the question with an estimated Gantt chart output. If the managers want to change the behavior mechanism, then the model can be modified and answer the same question with different behavior expectations.

8. Building Micro-level Destabilization Strategies - Simulating the Social and Geospatial Behavior of Adversaries

Sageman's terrorist group profiles (Sageman, 2004), Felter and Fishman's terrorist demographic survey (Felter and Fishman, 2007), and Champaign's terrorist group transnational movement (Champagne et al., 2005) indicate that the transnational movement of adversaries are important. Therefore, we need to include such adversaries' geospatial movement in our adversarial reasoning. I include such behavioral pattern in my reasoning by including another layer of agent movement in JDynet model, so turning JDynet into JDynetSpatial.

The previous chapter introduced a model for simulating adversaries' social behavior. This chapter extends the model by adding adversaries' geospatial behavior. Therefore, every model description in Ch. 7 is implemented in the simulation model in Ch. 8, so that this chapter only explains what is added more than the model in Ch. 7. Mainly, the adversaries' geospatial movements are modeled on top of the operations research based social behavior. The operations research based social behavior aims to simulate the task completion driven agent interactions. Similarly, the agents relocate to other places where they can better perform their assigned tasks. Such a task completion oriented geospatial movements are modeled by this extension. Furthermore, geospatial movements also influence removed agents' link recovery. If an agent is removed, the social model assumes that the neighbors in the social network are able to recognize the agent removal and to recover the removed agents' links. Finally, geospatial movements enable the agents to collect resources or information that are not yet acquired by their organization.

These extensions to the previous model are introduced, and the approach is applied to the 1998 U.S. Embassy bombing incidents in Kenya and Tanzania (see Chatper 4.2. for further introduction). This dataset is different from the Kenya dataset that have been used in this work. Over the course of the incident, the terrorists have to extensively move around regions and cross the borders to align the resources and expertise for the execution. In contrast, the Kenya dataset is limited to the activities within a single state, Kenya.

8.1. Simulation model description

To implement the extensions, I added several parameters to the previous model. The added parameters are listed in Table 8-1. Therefore, the parameters in Table 7-1 should be considered as well as Table 8-1 in this chapter.

Table 8-1 Summary of additional parameters to model the geospatial behavior of adversaries

Type	Name (Default value in the parenthesis)	Implication
Input	Geospatial agent distribution networks in a meta-network	If an agent is located at a certain place, the place should be linked to the agent, and this is an Agent-to-Location network.
	Geospatial organizational element distribution networks in a meta-network	If an organizational element (resource or expertise) is located at a certain place, the place should be linked to the element, and this is a Resource-to-Location network or an Expertise-to-Location network.
	Geospatial task allocation network in a meta-network	If a task has to be done at a specific location, then the task and the location should be linked in a Task-to-Location network.
	Geospatial Transportation network among Locations in a meta-network	If an agent can move from one place to another place, then the two places should be linked in a Location-to-Location network.
Output	An evolved network organization (a meta-matrix)	Estimated Agent-to-Location (AL) networks over-time
	Number of agents at locations	Estimated number of agents in a location at a certain time-step.
Parameters	Probability on successful regional resource and expertise gathering (0.5)	Probability for collecting a location-held expertise and resources by an agent.
	Change timing of the geospatial destination (5)	When an agent selects a place to move, he will cross a location-to-location link for each time-step. In this case, the agent will keep his first selected location as a destination for the number of time-step specified by this parameter.
	Boost for interaction if two agents are co-located (1.5)	If two interacting agents are co-located, the agents will have higher chances of transfer success.
	Boost for removal recognition if two agents are co-located (1.5)	If an agent tries to recognize one removed agent at the same location, the agent will have higher chance in recognizing the removed agent.
	Weights for task performance (0.70), link recovery (0.10), interaction facilitation (0.10), and new resource/expertise acquisition	Weights for selecting a location to move. An agent selects one relocation purpose out of four. An agent may move to a location to execute a task to be done at a specific location. An agent may move to the interaction partner's location to facilitate interactions.

Type	Name (Default value in the parenthesis)	Implication
	(0.10)	An agent may move to the removed agent's location to recover the agent's links. An agent may move to new locations to acquire needed resources and expertise.

8.1.1. Agent social and geospatial behavior

The main point of this agent behavior model is that the agent can perform both social interaction and geospatial movement. An agent has to select an interaction partner agent as well as a relocation destination. Therefore, as the agent chooses an interaction partner in the previous model, the agent chooses a place to move in this model. While an agent decides where to go, the agent has four different intentions for the relocation. Such relocation intentions, regional resource/expertise collections, or various boosting effects toward interactions and removal recognitions are explained in this section. I provide a high level behavior flowchart in Figure 8-1.

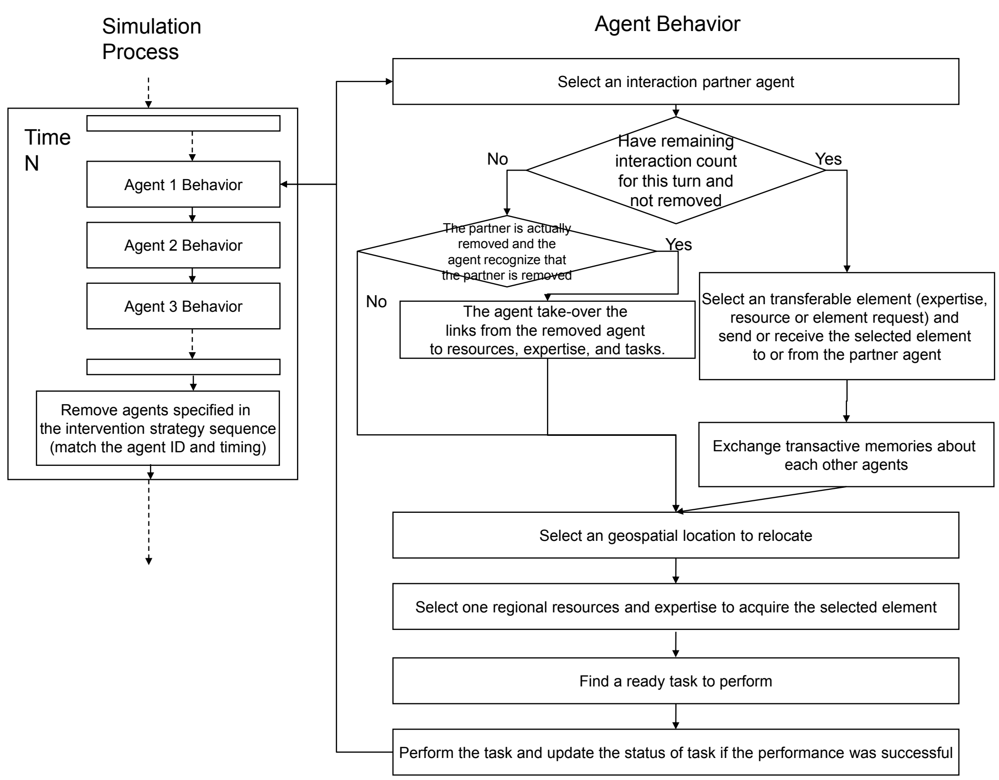


Figure 8-1 Agent behavior logic. Compared to the previous behavior model, the geospatial relocation and the regional resource/expertise acquisitions are added. Furthermore, some of the existing models, such as recognizing the removed agents or transferring organi

8.1.2. Selecting a location to move

As the agent interaction behavior needs to determine an interaction partner, the agent relocation behavior needs to select a destination location. The destination location is determined by a relocating agent's specific intention. There are four possible intentions: to perform an assigned task that has to be carried out at a specific place, to acquire an organizational element that the agent needs to perform his assigned tasks, to recover the removed agents' lost links to organizational elements, social contacts and assigned tasks, and to facilitate the interaction by moving to the place where the interaction partner is. One remaining intention is a random place choice. I explain each of motivations in detail below. Mainly, I use Sageman's and Champagne et al.'s descriptions (Sagemam, 2004; Champagne, 2005) about terrorists' geospatial movements and model the intention of geospatial movement according to their descriptions about terrorists' transnational movement pattern.

Performing assigned tasks at specific places: An agent may move to a specific location to perform tasks that have to be done at the location. On page 5, Champagne et al. (2005) says that "Between 1993 and 1994, members of al Qaeda began to re-locate to Eastern Africa, including Sudan and Kenya." According to them, the relocation reason is training their soldiers and attacking the western targets. These relocations can be modeled as the relocation to perform a specific task. This location requirement in the task execution is represented as the Task-to-Location network in the meta network. For instance, the actual bombing mission of the Kenya and Tanzania incidents should happen in the cities of Kenya and Tanzania where the U.S. embassies are. Therefore, the bombing mission executors, not terrorists for preparation or support, should be actual bombing sites. This motivates the terrorists move to the specific locations, and this motivation is modeled by this simulated motivation.

Acquiring required organizational elements: An agent may move to a location where the agent can acquire expertise and resources required for performing assigned tasks. On page 50, Sageman (2004) describes where the terrorists are trained. Salim al-Hazmi made a transnational movement from his home country, Saudi Arabia, to Afghanistan, where the al-Qaeda training camp is. This is an act of expertise seeking to perform his task. I modeled this movement by using simulated movement intention. In this the Embassy bombing data, the al-Qaeda organization has extensive training facilities in Somalia and Afghanistan, which is also represented in the datasets that I am using. The terrorists may move to the locations to acquire weapons, bomb expertise or import bomb ingredients. This requires the terrorists' relocations, and this requirement is modeled by this relocation motivation.

Facilitating efficient interactions between the interaction partners: An agent may move to a location where his interaction partner is. On page 144, Sageman (2004) explains that the early contribution of Montreal, Milan and Madrid to the Jihad movement is caused by the presence of various terrorists in the locations. He explains that these terrorists' presence in the locations as the geospatial characteristics and the Jihad movement is caused in these cities. Therefore, I assume that the presence of the terrorists will attract more terrorists at a specific location to simulate this trend. Being at the same location often shows more productive interaction outcomes: faster expertise transfer, easier resource movement. This does not mean that the co-location is a requirement for such organizational element transfer, but this means that the co-location makes the transfer success rate higher in the simulation model.

Better recovering a removed agent's links to other agents, resources, expertise and tasks: An agent is able to recover a removed agent's links to organizational elements. On page 56, Champagne et al. (2005) records that Wadih el-Hage and Fazul Abdullah Mohamed went to Lake Victoria to investigate the drowning of Abu Ubaida al Banshiri. This relocation is motivated by an agent removal in their organization. This can be modeled in this order: 1) remember the removed agent's links, 2) try to recover the links that the recovering agent does not have, 3) recovers only parts of links that are selected by the simulation model (some link recoveries are unsuccessful because 1) some resources are only in the recovering agent's transactive memory and not consistent with the simulation status, 2) there is a random factor in the recovery, tossing a coin with a probability of link recovery, specified as *Recover links from the removed agents*, Table 7-1) Being at the same location improves the *Recover links from the removed agents* by boosting the value. This results in more successful link recoveries that the recovering agent tries.

8.1.3. Regional resource and information gathering

An agent performs a regional resource, expertise gathering for each turn of their behavior. This means that the agent has one more chance to acquire a resource and expertise. In the previous social-only model, those acquisitions only happened over the course of an interaction between two agents. This model allows such social link oriented resource, expertise transfer as well as geospatial oriented acquisition. A geospatial location is treated as a social agent except the fact that the location cannot initiates an interaction in spite that the location can hold expertise or resources for giving them to social agents. This is tightly linked to the movement motivation of *acquiring required organizational elements,* explained in Ch. 8.1.2.

Moreover, the social link orient resource, expertise transfer can be more successful by being at the same location with the interaction partner. This is different from the previous case because this social link oriented transfer can happen without being at the same location. The co-location only increases the chance of success, not necessary to the transfer. The increase is done by using the parameter, *exchange success rate* in Table 7-1 and *boost for interaction if two agents are co-located* in Table 8-1 and the below formula.

$$\begin{aligned}&(\text{exchange success rate for two agents at the same location})\\&\qquad = (\text{boost for interaction if two agents are colocated})\\&\qquad \times (\text{exchange success rate})\end{aligned}$$

Because of these effects of better organizational element transfer, the agents has two different motivations for relocation: *acquiring required organizational elements* and *facilitating efficient interactions between the interaction partners*.

8.1.4. Take-over the removed agent's expertise, resource, task and social contacts considering the regional distribution

By being at the same location, an agent has a better chance of recovering the removed agent's links to organizational elements, such as other agents, resources, expertise and tasks. This improvement in link recoveries is modeled as the below formula. The formula uses two parameters: *recover links from the removed agents* in Table 7-1 and *boost for removal recognition if two agents are co-located* in Table 8-1.

$$\begin{aligned}&(\text{Recover links from the removed agent at the same location})\\&\qquad = (\text{Recover links from the removed agents})\\&\qquad \times (\text{Boost for removal recognition if two agents are colocated})\end{aligned}$$

This geospatial effects is related to the geospatial relocation motivation, *better recovering a removed agent's links to other agents, resources, expertise and tasks* in Ch. 8.1.2.

8.1.5. Perform an assigned task considering the geospatial dimension

An agent is required to be a specific location if the task should be done at the location. For example, Figure 8-2 shows a sub-graph of the *detonate* Task. The task should be done at two specific locations, *Kenya* and *Tanzania*. Therefore, at least two agents are required to perform this task because one agent cannot be at two different locations. Two or more agents should be at Kenya and Tanzania, at least one agent for each location. Then, the located agents can toss a coin that determines the success of the particular task. This is not a probabilistic requirement that contributes the task success rate. This is a hard requirement for agent distribution over the geospatial regions. To model this motivation of relocation, I implemented a relocation motivation, *performing assigned tasks at specific places*.

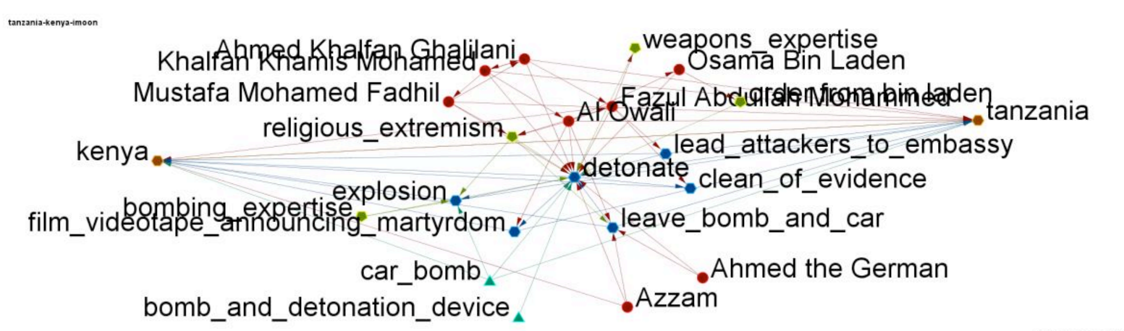


Figure 8-2 A sub-network of the Tanzania and Kenya meta-network, a set of nodes within one social link radius from detonate, The set includes Kenya and Tanzania

8.2. Virtual experiment design

Virtual experiment design for the extended version of JDynetSpatial is same to the experiment design in the previous chapter. In the real world, human analysts qualitatively analyze the given situation and decide the simulation parameters, but this virtual experiment uses an illustrative simulation parameters specified in Table 7-1 and Table 8-1.

The virtual experiment design differentiates three factors: who to remove, when to remove, and how many agents to remove. The virtual experiment selects a set of agents who have high network values as a set of removed agents. To calculate the network values, I use four different network measures: Degree, Betweenness, Eigenvector centralities and Cognitive demand. The set size of the removed agents is another factor in the virtual experiment design. Also, the timing of the removals is another factor in the experiment design.

Table 8-2 Virtual experiment design for simulation parameters (30 replications, 2500 simulation time-steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	1, 5, 9, and 12 agent removals (removing 10%, 30%, 50% and 70% of agents, 4 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	125, 250, 500, and 1000 time-step (removing at after 5%, 10%, 20% and 40% timeflow, 4 cases)	The intervention happens at a specific stage of simulation period.
Total virtual experiment cells	64 cells (4x4x4 cases)	

8.3. Result

I present the simulation results in three sections. First, I analyze the general organizational performance results from strategic interventions. Second, I analyze the timing of task and mission completions. Third, I analyze the estimated agent social and geospatial behavior in detail.

8.3.1. Impact to performance measures

The previously defined organizational performances are examined. Since there are several extended agent behavior mechanisms to include geospatial mechanisms, some organizational performances exhibit different tendencies compared to the results from the social-only model. Table 8-3 is the regression analysis result from the 64 virtual experiments with the virtual experiment settings. Obviously, the *intervention size* is the key factors in explaining the changes in the performance compared to the baseline. The mission speed, task speed, energy task accuracy and task completion goes down as the intervention sizes increases. The earlier intervention is better by looking at the positive standardized coefficients of the coefficient values in the regression model of the mission speed, task speed, energy task accuracy, and task completion. There is no clear trend in the network metrics. However, there are some coefficients which stand out, i.e. removing higher degree centrality terrorists would decrease the mission speed more.

Table 8-3 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.521*	0.355*	0.470*	0.129*	-0.142*	0.602*
Intervention Size	-0.663*	-0.337*	0.013	-0.981*	0.975*	-0.630*
Degree Cent.	-0.058	0.142	0.036	0.040	-0.027	0.002
Betweenness Cent.	0.053	0.073	0.092	0.018	-0.023	0.050
Eigenvector Cent.	-0.008	0.090	0.017	0.013	-0.010	-0.012
Cognitive Demand	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-Square	0.678	0.171	0.144	0.960	0.952	0.725

Moreover, I performed another regression analysis by predicting the organizational performances with removed agents' network position characteristics. I averaged the network measure values of the removed agents and regressed the averaged value to the organizational performance values, which is different from using the categorical value of the virtual experiment setting. Still, earlier interventions (positive intervention timing coefficients), larger intervention sizes (negative intervention size coefficients) and higher betweenness centrality sizes (negative coefficients) are preferable in increasing the amount of damage toward the organizational performances.

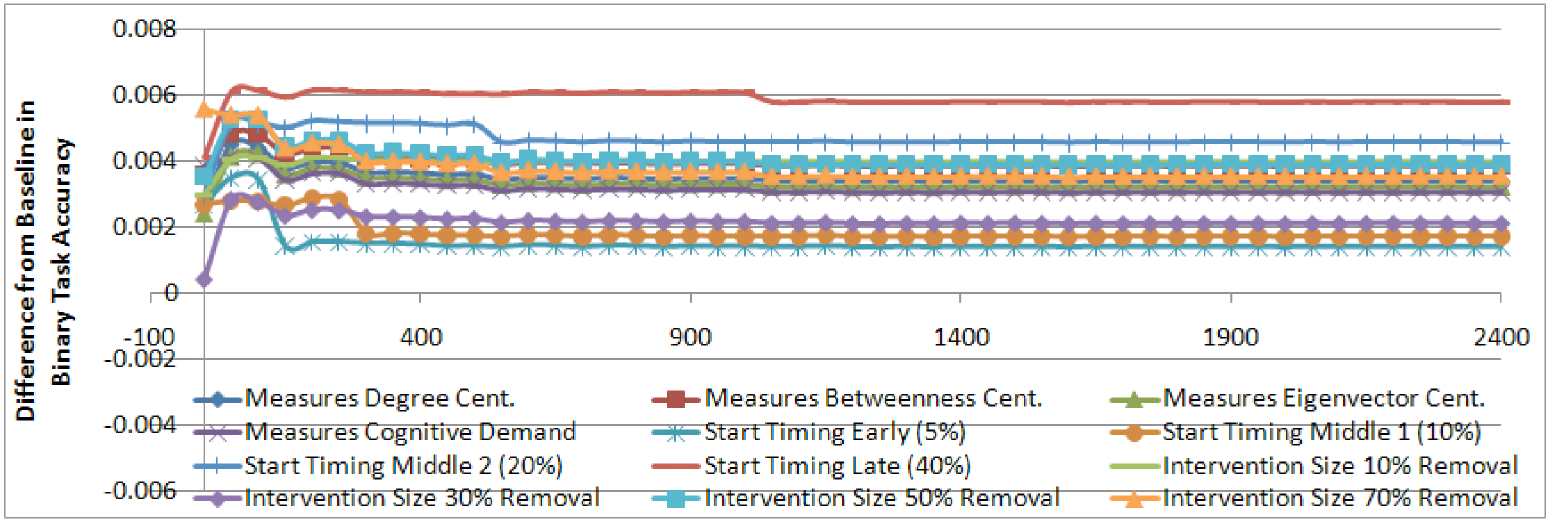
Table 8-4 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated network metrics of the removed agents (N=64 cases) (* for P<0.05)

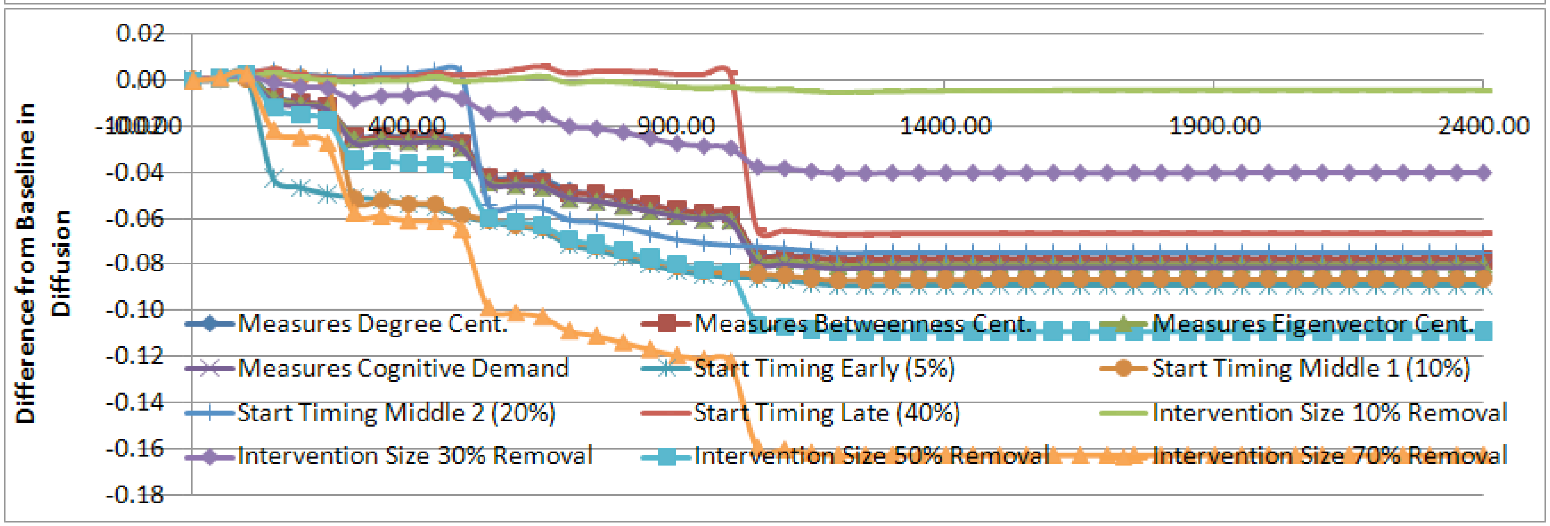
Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Comple-tion
Intervention Timing	0.521*	0.355*	0.470*	0.129*	-0.142*	0.602*
Intervention Size	-1.464*	-0.153	-0.775	-0.773*	0.794*	-1.141*
Degree Cent.	-0.443	0.714	-0.191	-0.494*	0.501*	-0.628
Betweenness Cent.	0.228	-0.074	0.501	-0.133*	0.144*	0.134
Eigenvector Cent.	0.809	-1.118	0.251	0.548*	-0.589*	0.916
Cognitive De-mand	0.263	0.377	0.318	-0.214*	0.209*	0.085
Adjusted R-Square	0.730	0.207	0.199	0.988	0.980	0.761

Figure 8-3 shows the organizational performance over-time. In terms of Energy Task Accuracy and Diffusion, removing more terrorists increase the inflicted damage, i.e. see the curve of intervention size 70%. However, from the task completion perspective, early interventions are more important and leave more prolonged damage to the organizations. This suggests that the intervention tactic should be adjusted according to the objective of the intervention. If a human analyst wants to stop the spread of expertise and aligning resource distributions, then the analyst should focus on removing more agents. If the analyst wants to prevent an event occurring, then the analyst should focus on removing agents earlier.

Additionally, it should be noted that the late interventions (removing agents after 40% of time-steps) and the small interventions (removing only 10% of agents) do not make significant damage in task completion over time. Therefore, such interventions do not result in the disruption of their task performance and should be avoided.

.


Difference from Baseline in Binary Task Accuracy
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-100
400
900
1400
1900
2400
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (5%)
Start Timing Middle 1 (10%)
Start Timing Middle 2 (20%)
Start Timing Late (40%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal


Difference from Baseline in Diffusion
0.02
0.00
-0.04
-0.06
-0.08
-0.10
-0.12
-0.14
-0.16
-0.18
400.00
900.00
1400.00
1900.00
2400.00
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (5%)
Start Timing Middle 1 (10%)
Start Timing Middle 2 (20%)
Start Timing Late (40%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal

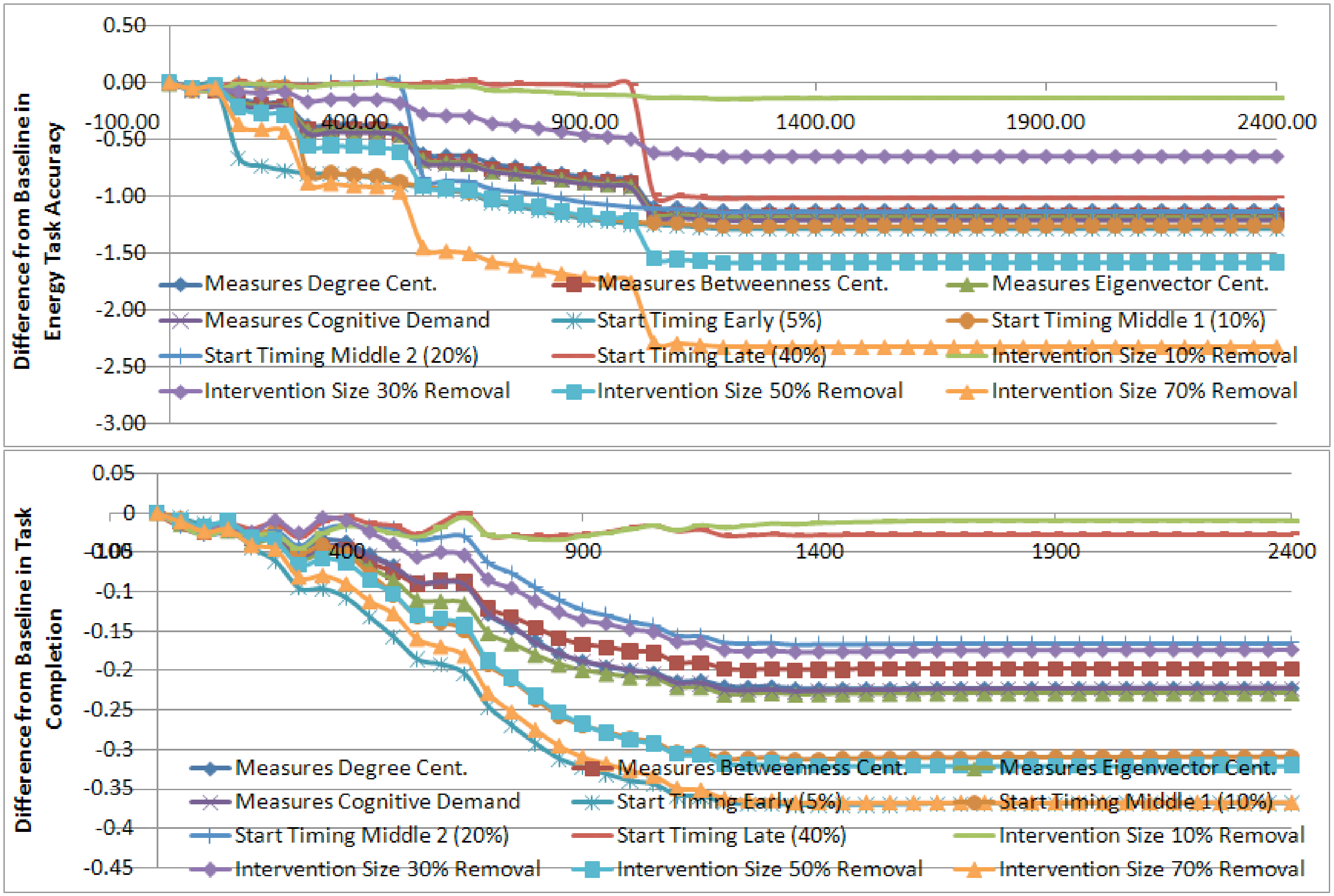


Figure 8-3 Organizational performance over-time

8.3.2. Impact to mission and task completion timing

The strategic interventions impact the mission and task completion timings. Figure 8-4 are two estimated Gantt charts from two virtual experiment cells. One (the upper Gantt chart) is from the baseline, and the other (the bottom Gantt chart) is from the case removing 10% of top degree centrality terrorists at the early stage (after 5% of simulation time passed). Many of other experiment cells show no finishing timing of the mission, which means that the intervention disabled the organization to perform the mission within 2500 simulation time-step. In the baseline case, no interventions, the organization can finish the mission around 859 simulation time-steps, as shown in the upper Gantt chart in Figure 8-4, but the intervention case shows the mission completion around 881 time-steps. From the mission finish time perspective, there is no significant damage from the interventions. However, the individual task completion timings of the two cases become different. The two Gantt charts are similar until the 125 time-step, but after the interventions at the 125 time-step, the task completion timings get different. For instance, after the intervention, it takes more time to finish *lead attackers to embassy, driving,* and *bomb preparation* tasks. At the same time, some tasks, i.e. *run bomb factory, conceal bomb in car* and *clean of evidence, etc,* take shorter time.

These longer task execution times are caused by the rest of agents' spent time for recovering the removed agents contacts, resources and expertise to perform the task. Actually, after recovering the removed agents' organizational elements and social contacts, the rest of the agents can perform the task at the same speed or faster speed in some cases (since the social network gets smaller and agents are tightly connected than before).

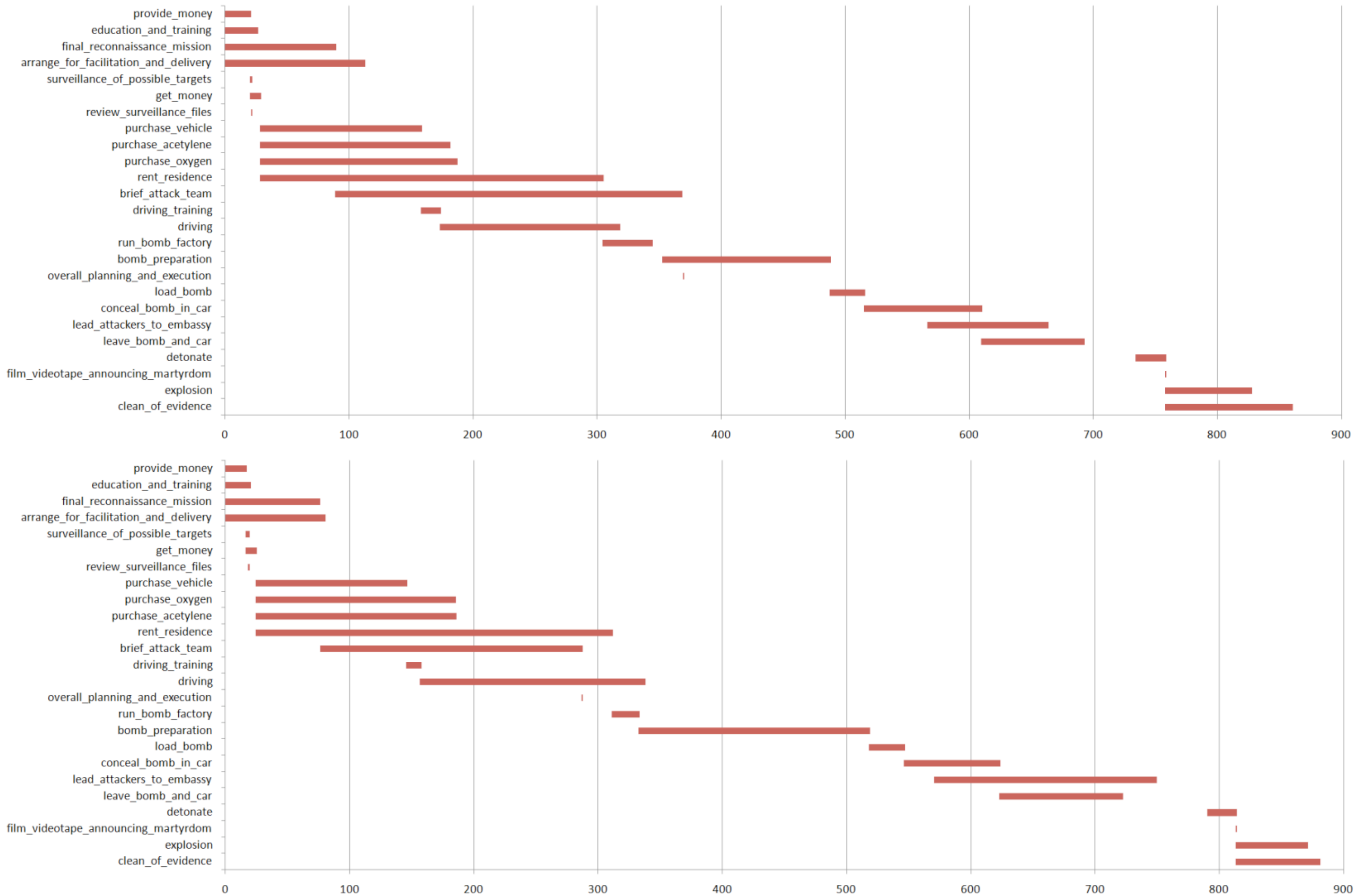


Figure 8-4 Two Gantt charts from Baseline (Upper) and 10% removal of top degree centrality agent removals at the early stage (after % of simulation time step)

Figure 8-5 displays the overall mission completion results across the virtual experiment cells. The measures are bar charts, and there are 4 X 4 X 4 bars corresponding to 4 target decision measures, 4 intervention timings and 4 intervention sizes. If the bar shows 0 mission speed, it means that the experiment cell could not complete the entire task dependency network, or a mission. For example, when removing the top betweenness agents, the 10% and 30% agent removals decrease the mission speed (sometimes, it increases according to timings), but the 50% and 70% agent removals cause complete mission failure unless the intervention happens at the late stage. Actually, the betweenness centrality turned out to be the worst metric in deciding the target in the simulation results because the rest of agents could recover the removed agents' social links and the connections get much tighter. On the other hand, the degree centrality seems to be the best metric in deterring the mission completion. As shown in Figure 8-5, 30%, 50% and 70% interventions at the early (after 5% of simulation time-steps) or early-middle stage (after 10% of simulation time-steps) successfully disrupt the adversaries' mission.

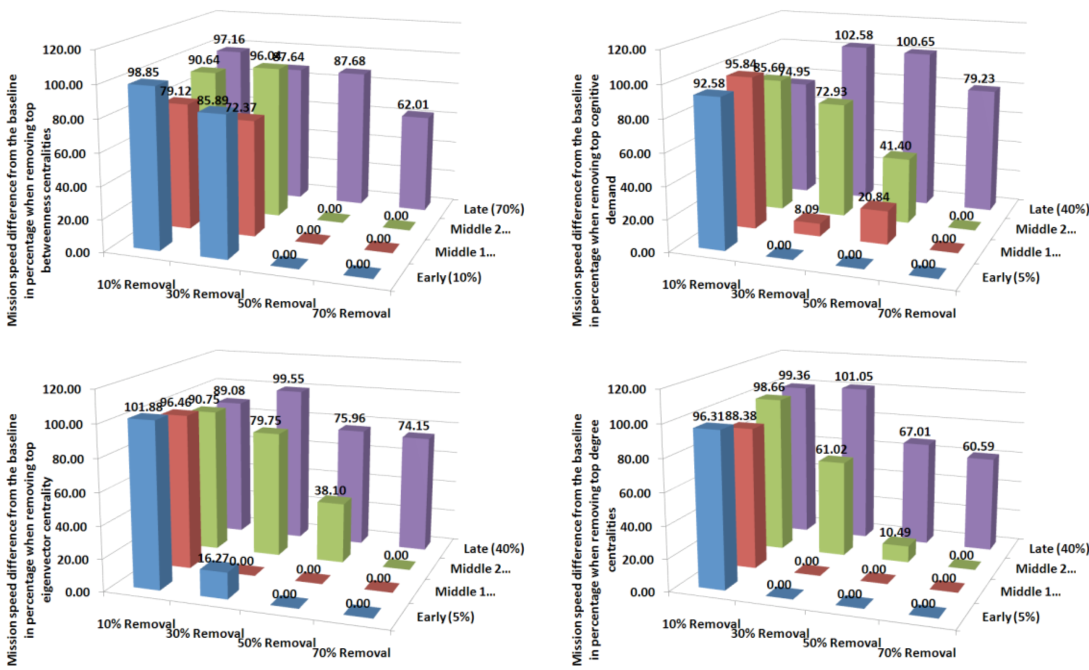


Figure 8-5 Four mission speed bar charts for four intervention strategic schemes (betweenness at top-left, cognitive demand at top-right, eigenverctor at bottom-left, and degree at bottom-right), The number is the percentage of the mission speed compared to the baseline), which means 100% = same as baseline, less than 100% = slower, and more than 100% = faster. If the speed is 0, then the cell could not complete the mission.

Figure 8-6 represents the task speed results across the virtual experiment cells. Given that the mission completion, or the completion of entire task dependency network, is difficult in many of virtual experiment cells, their mission speed are usually zero indifferently. Therefore, task speed is calculated. The task speed is the averages of the inversed task performance durations (See section 7.1.5). Compared to Figure 8-5, Figure 8-6 outlines more differentiated destabilization effect of strategic interventions. Earlier interventions are preferable as the mission speed analysis. However, there is no serious difference effect from differentiating the intervention sizes. Many cases suggest that the late intervention might increase the task execution speed. This is due to the tightened social network after removals if the network was able to recover the social links and re-link adversaries.

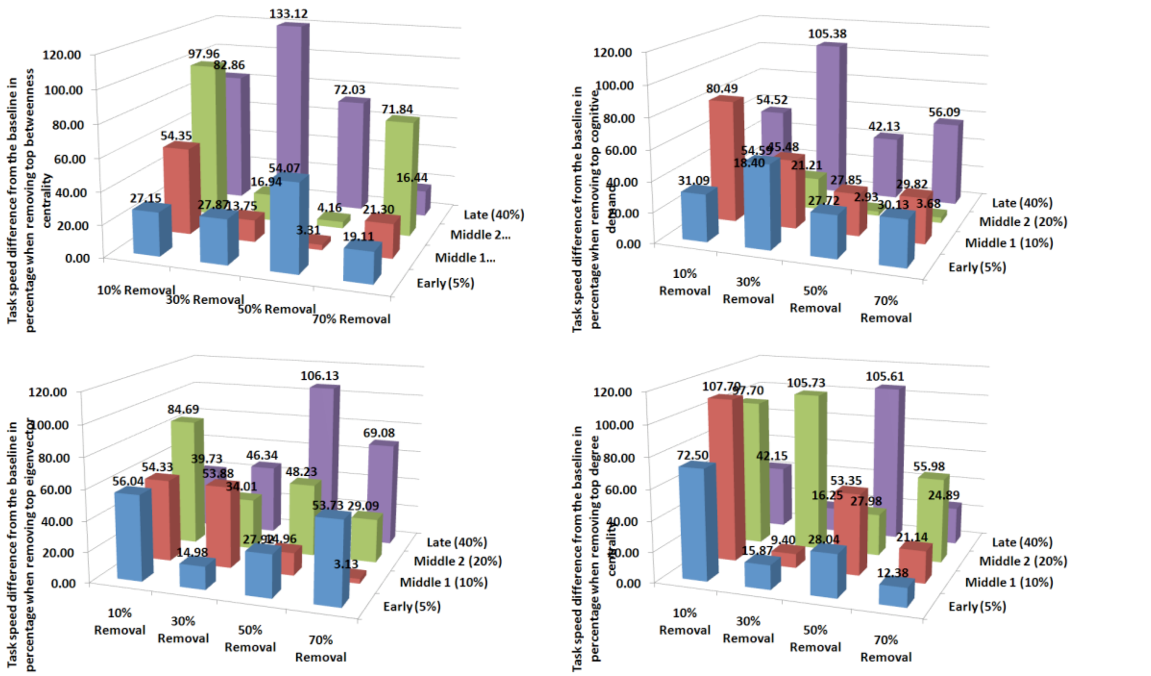


Figure 8-6 Four task speed bar charts for four intervention strategic schemes (betweenness at top-left, cognitive demand at top-right, eigenverctor at bottom-left, and degree at bottom-right), The number is the percentage of the mission speed compared to the baseline), which means 100% = same as baseline, less than 100% = slower, and more than 100% = faster.

8.3.3. Agent movements and interactions during simulations

Compared to the social only model in the previous chapter, the distinct feature of the geospatial and social model is that the agents can move to other locations and collect regional resources and expertise. Therefore, the tool can generate visualizations of the agents' interactions and movements in the baseline case (See Figure 8-7 and Table 8-6). Figure 8-7 is the Gantt chart over the course of the mission execution in the baseline and the line chart showing how many agents were at a certain location and when. Many of training tasks were done at Somalia, and some of resources and resource holding agents were at Afghanistan. Therefore, until 400 time-step, there were noticeable agent presence in Pakistan and Afghanistan. However, as the mission proceeds, and as the Kenya and Tanzania regional tasks increases, the agents move from the training and resource acquisition places to actual bombing places, Kenya and Tanzania. Thus, the later phase of the simulation shows that the agents in Somalia, Afghanistan and Pakistan move to Kenya and Tanzania.

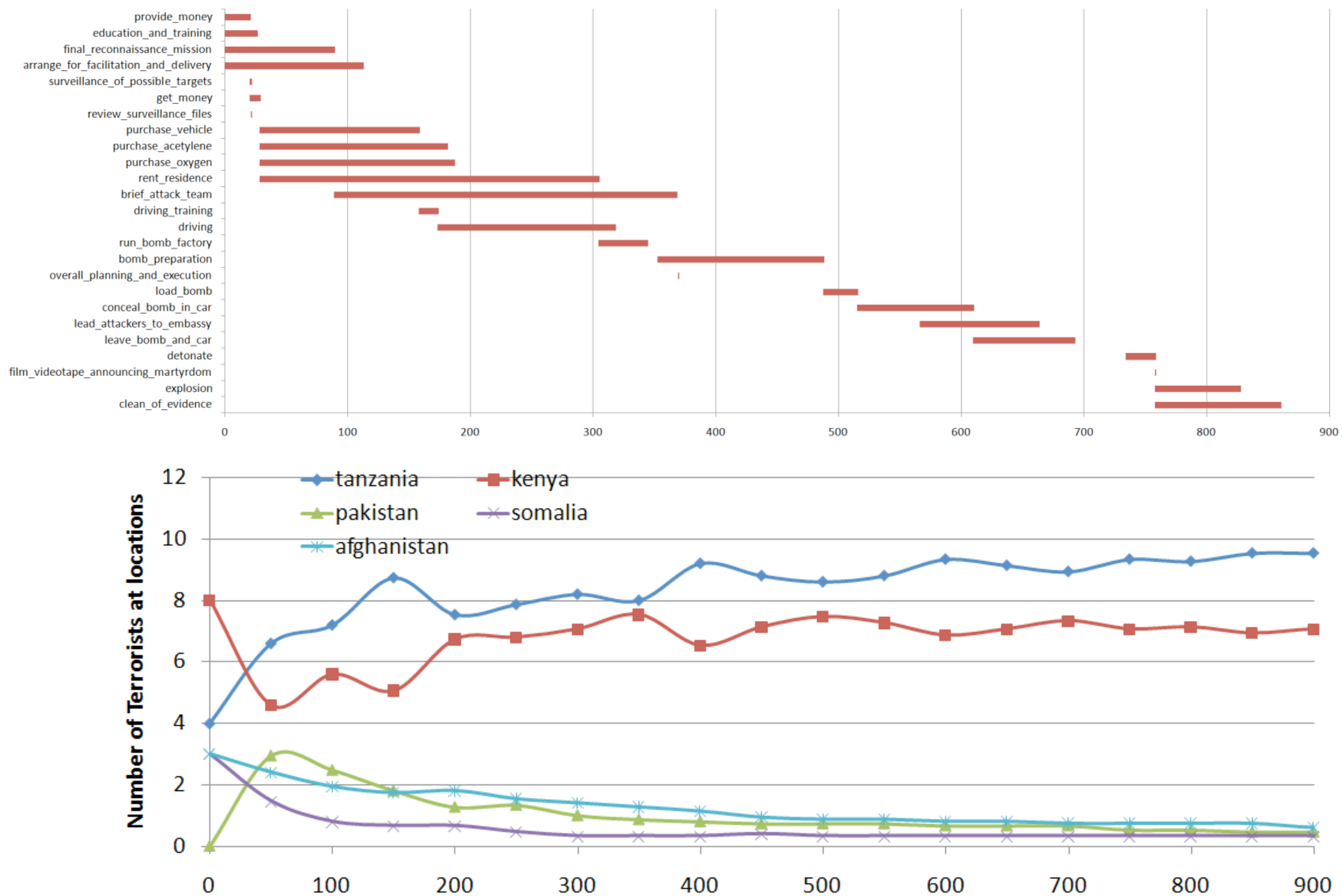
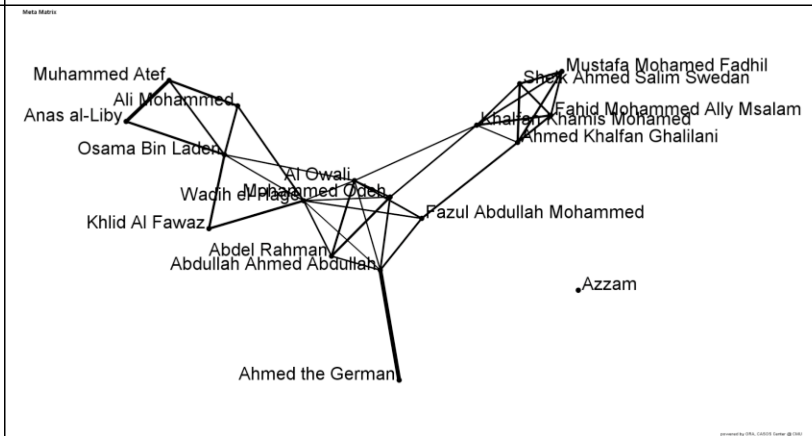
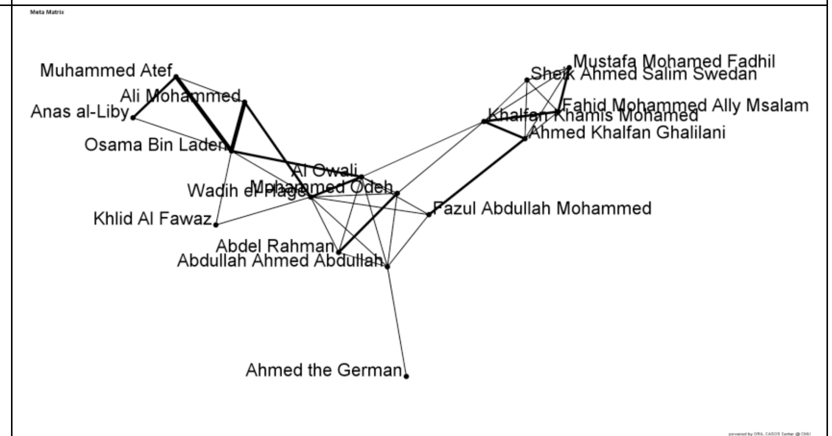
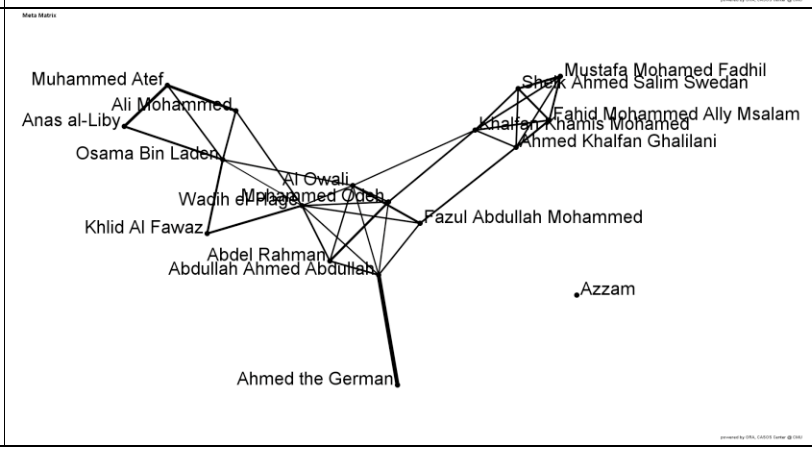
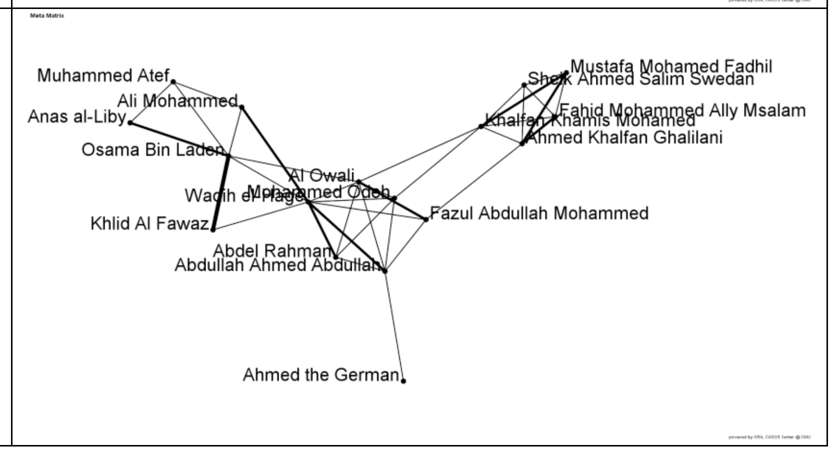


Figure 8-7 A Gantt chart and an agent-geospatial distribution over-time line chart of Baseline. As the task dependency network gets completed, the agents move to new locations where they can perform the next tasks. The initial training center at Somalia and the resource deposit of Afghanistan are attracted agents till the 400 time-steps. After the initial trainings and resource acquisition, the actual bombing tasks in Kenya and Tanzania make the agents to segregate in Kenya and Tanzania

Table 8-5 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

<table>
<tr><td></td><td>Agent to Agent network: Interaction</td><td>Agent to Agent network: Transfer resources and expertise</td></tr>
<tr><td>Time 100</td><td>
</td><td>
</td></tr>
<tr><td>Time 200</td><td>
</td><td>
</td></tr>
</table>

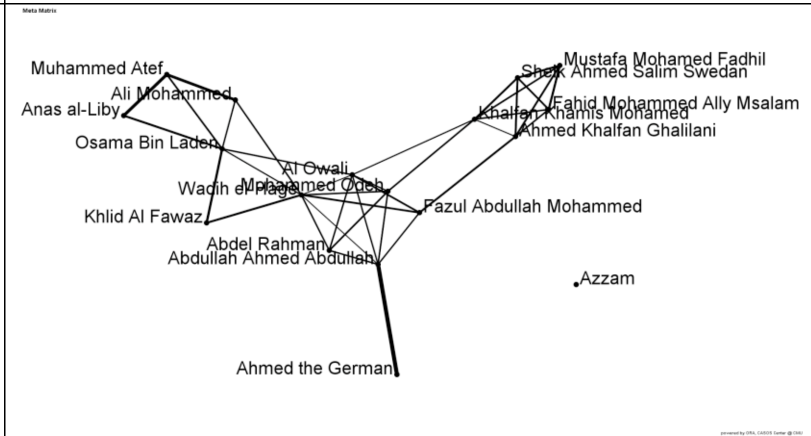
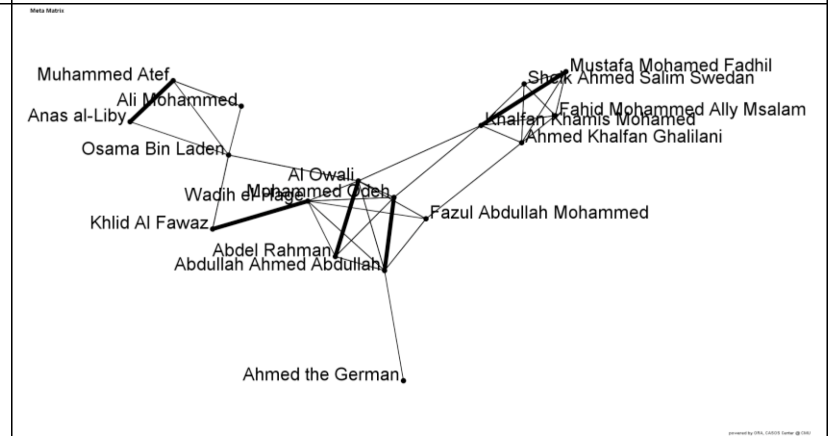
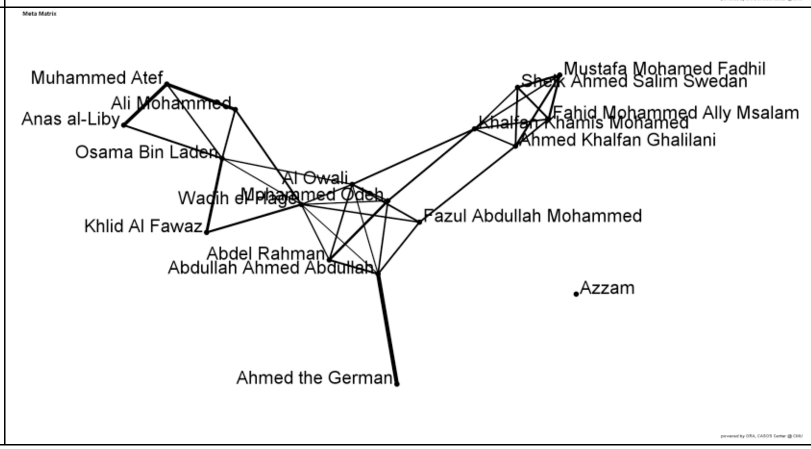
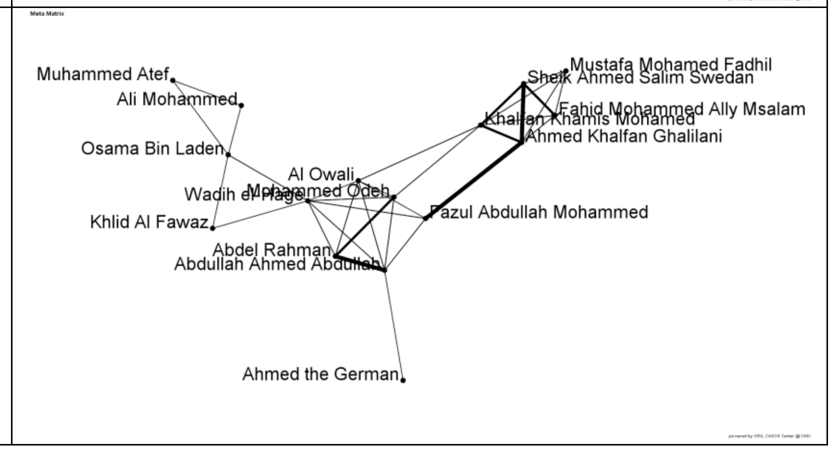
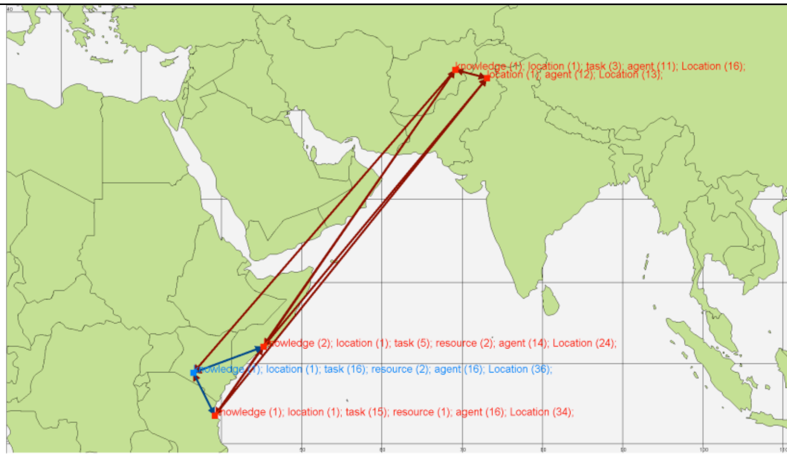
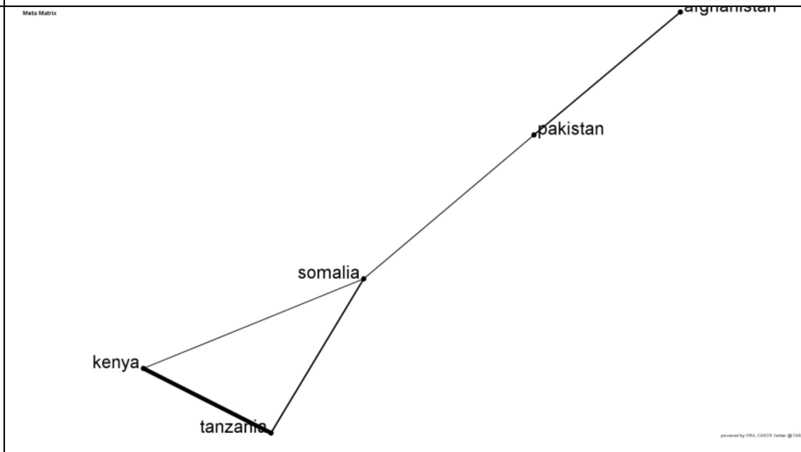
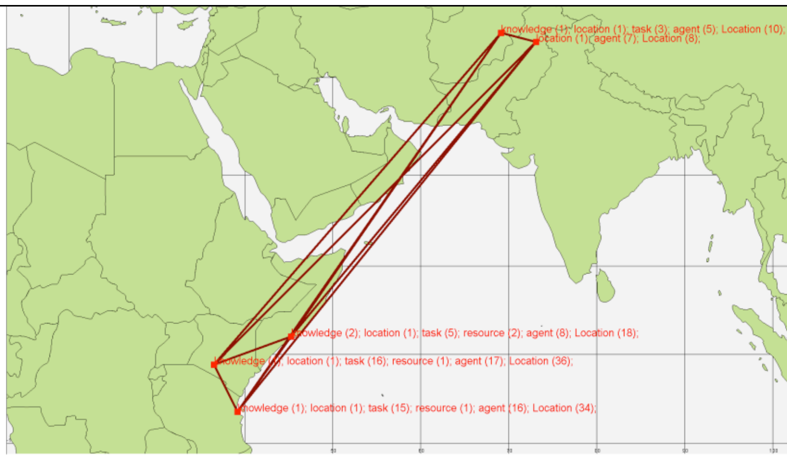
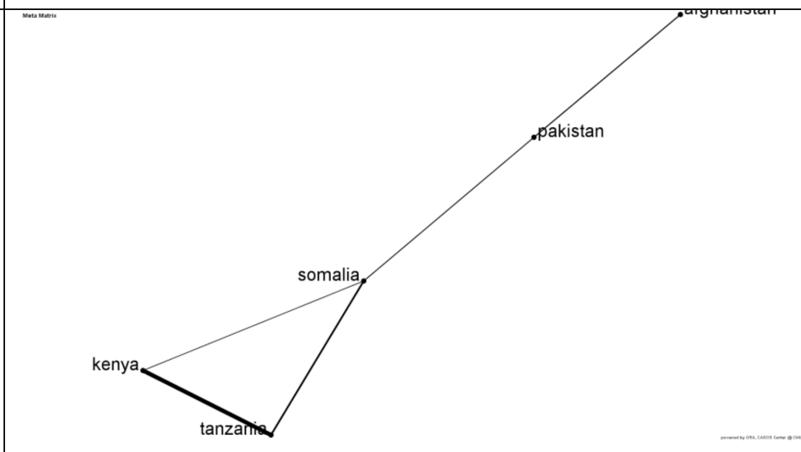
	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 400		
Time 800		

Table 8-6 Collection of agent geospatial movements and transnational movement passage networks over time, link thickness is adjusted to show the frequency of the link usage.

<table>
<tr><th></th><th>Geospatial visualization of meta-network</th><th>Location-to-location transnational movement network</th></tr>
<tr><td>Time 100</td><td>
</td><td>
</td></tr>
<tr><td>Time 200</td><td>
</td><td>
</td></tr>
</table>

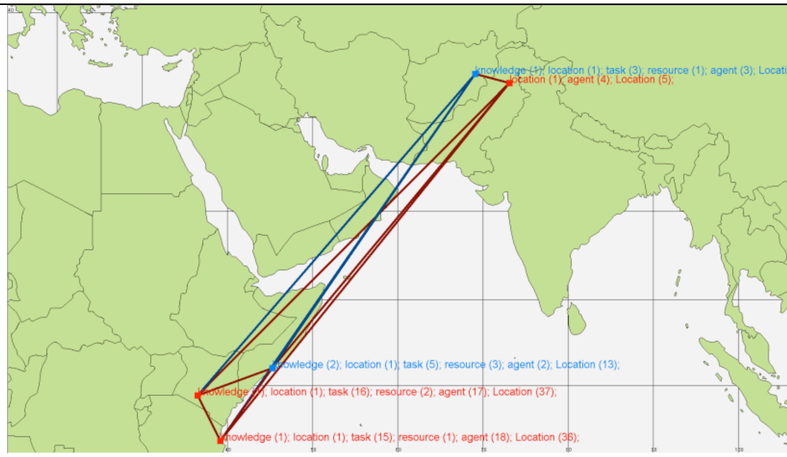
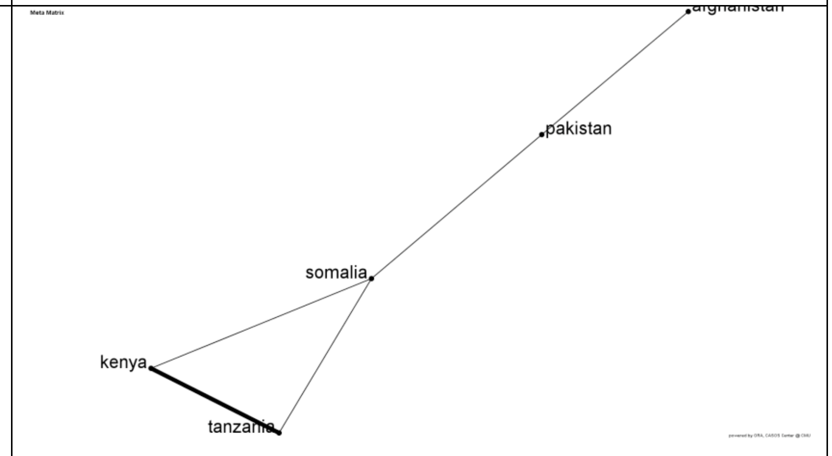
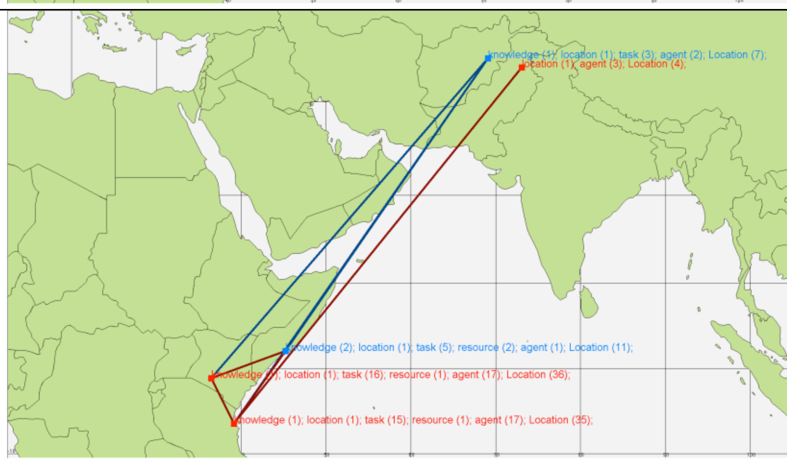
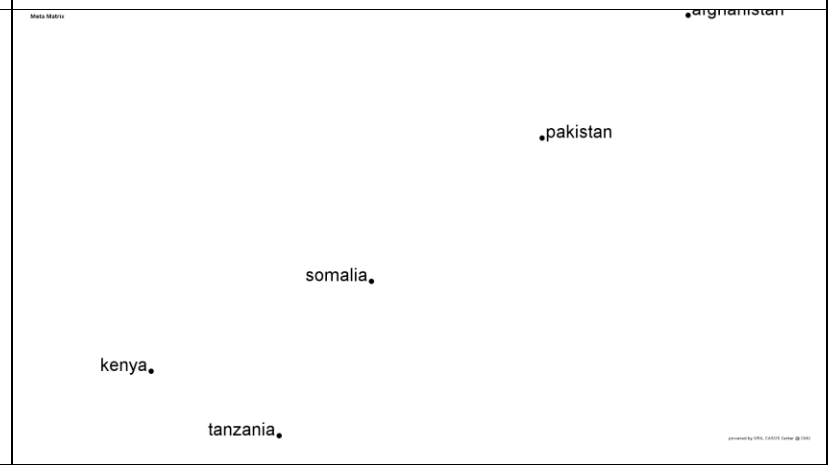
	Geospatial visualization of meta-network	Location-to-location transnational movement network
Time 400		
Time 800		

Table 8-5 shows further details of the agent behavior. First, the interaction network shows which social links are frequently used for interactions. Not all of the social links in the organizational structures are utilized as an interaction channel. Some of social links are much heavily used, i.e. a link between *Ahmed the German* and *Abdullah Ahmed Abdullah*. Moreover, not all of the interactions were effective from the perspective of resources and expertise transfer. The organizational element transfer network shows that only a part of interaction networks were utilized for resources and expertise passing, i.e. a link between *Fazul Abdullah Mohamed* and *Ahmed Khalfan Ghalilani*. Additionally, the agnet-to-agent organizational element transfer network changes over time (particularly, the link weights). This change is driven by the mission process over time.

This adversarial organization had five distinct transnational operational bases (see Table 8-6). To manage the team and to execute the mission, their organizational structure was also international. The geospatial distribution shows the agents segregation levels at the five different regions and the organizational structure laid over the middle-eastern region. This shows the location criticality and the transnational interaction network. Finally, the agents had to move from one base to another base, which require transnational mobility. The geospatial agent-relocation network shows the frequency of such transnational movements between two regions. The edge thickness represents heavy traffic between two location nodes. For instance, Kenya and Tanzania is always linked with heavy edge weights due to extensive agents' transnational movement between the two regions.

8.3.4. Key individuals over the course of simulations

From the baseline case's recorded interaction and transfer networks among agents, I calculate the network metrics to see the adversaries' importance over the course of simulations. There are no big changes in the interaction networks compared to the changes of transfer networks. The interaction networks are more stable because the agents use most of social relations for the interactions during the simulations though the frequencies of the relation usages are different. The used social network metrics only consider the links as a binary value, so the link usage frequency is not reflected in the key individual lists.

The key individual lists of the agnet-to-agent transfer networks show interesting changes in the rosters. *Al Owali's* betweenness centrality in the transfer network is the highest value at time 50 and 300, but he is ranked at the third at time 500 and the fifth at time 1300. This gradual decrease in his betweenness centrality suggests his role change over time. *Wadih el-Hage* is another interesting terrorist. His degree centrality in the interaction network is ranked at top five all the time. However, his degree centrality in the transfer network shows large fluctuation. He is ranked at the top at time 50 and at the third at time 500. At time 300 and time 1300, his degree centrality is ranked out of top five. This suggests that he often becomes the center of interaction, but not the center of organizational element transfer. Therefore, an analyst might think that his shown interaction may not over-reflect his importance from the organizational element transfer.

Table 8-7 Key individual lists over the course of simulations

Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Osama Bin La-den	Wadih el-Hage	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Wadih el-Hage
Rank 2	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Al Owali	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Al Owali	Abdullah Ahmed Abdullah
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Wadih el-Hage	Osama Bin Laden	Wadih el-Hage	Osama Bin Laden	Wadih el-Hage	Al Owali
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Muhammed Atef	Muhammed Atef	Osama Bin La-den	Wadih el-Hage	Mohammed Odeh	Fazul Abdullah Mohammed
Rank 5	Abdullah Ahmed Abdullah	Abdel Rahman	Al Owali	Khalfan Khamis Mohamed	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Osama Bin Laden
Time 300	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Osama Bin La-den	Khalfan Khamis Mohamed	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Mustafa Mohamed Fadhil
Rank 2	Al Owali	Al Owali	Abdullah Ahmed Abdullah	Al Owali	Khalfan Khamis Mohamed	Osama Bin Laden	Wadih el-Hage	Fahid Mohammed Ally Msalam
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Wadih el-Hage	Ahmed Khalfan Ghalilani	Wadih el-Hage	Khalfan Khamis Mohamed	Osama Bin Laden	Khalfan Khamis Mohamed
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Muhammed Atef	Mustafa Mohamed Fadhil	Osama Bin La-den	Wadih el-Hage	Muhammed Atef	Sheik Ahmed Salim Swedan
Rank 5	Abdullah Ahmed Abdullah	Abdel Rahman	Ahmed Khalfan Ghalilani	Fahid Mohammed Ally Msalam	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Ali Mohammed	Ahmed Khalfan Ghalilani

Time 500	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Ahmed Khalfan Ghalilani	Al Owali	Wadih el-Hage	Abdullah Ahmed Abdullah	Ahmed Khalfan Ghalilani
Rank 2	Al Owali	Al Owali	Osama Bin La-den	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Osama Bin La-den	Al Owali	Mustafa Mohamed Fadhil
Rank 3	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Wadih el-Hage	Wadih el-Hage	Wadih el-Hage	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed
Rank 4	Mustafa Mo-hamed Fadhil	Mustafa Mo-hamed Fadhil	Khalfan Khamis Mohamed	Mustafa Mo-hamed Fadhil	Osama Bin La-den	Al Owali	Ahmed Khalfan Ghalilani	Fahid Mohammed Ally Msalam
Rank 5	Abdullah Ahmed Abdullah	Abdel Rahman	Ahmed Khalfan Ghalilani	Al Owali	Abdullah Ahmed Abdullah	Khlid Al Fawaz	Wadih el-Hage	Sheik Ahmed Salim Swedan
Time 1300	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Muhammed Atef	Al Owali	Mustafa Mo-hamed Fadhil	Abdullah Ahmed Abdullah	Anas al-Liby
Rank 2	Al Owali	Mustafa Mo-hamed Fadhil	Wadih el-Hage	Mustafa Mo-hamed Fadhil	Khalfan Khamis Mohamed	Khalfan Khamis Mohamed	Osama Bin La-den	Muhammed Atef
Rank 3	Khalfan Khamis Mohamed	Al Owali	Osama Bin La-den	Anas al-Liby	Wadih el-Hage	Osama Bin La-den	Wadih el-Hage	Osama Bin Laden
Rank 4	Mustafa Mo-hamed Fadhil	Khalfan Khamis Mohamed	Ahmed Khalfan Ghalilani	Osama Bin La-den	Osama Bin La-den	Mohammed Odeh	Muhammed Atef	Al Owali
Rank 5	Abdullah Ahmed Abdullah	Abdel Rahman	Khalfan Khamis Mohamed	Al Owali	Abdullah Ahmed Abdullah	Al Owali	Al Owali	Abdel Rahman

8.4. Simulation result comparison between the social only model and the social and geospatial model

Ch. 7 and 8 shows a multi-agent simulation model only simulating the social dimension and an extended model simulating the social and geospatial dimensions, respectively. The expansion is motivated by the importance of adversaries' geospatial relocation and transnational movement behavior. By adding this additional interaction layer for the simulated agents, we can enable new analyses and obtain different analysis results.

First, I enabled new analysis results that cannot be provided by the social only model. Ch. 8.3.3. shows the impact of adding the additional layer. The similar analysis in Ch 7.3.3. was limited to the visualization of agent interactions at the social dimension. An analyst using the model has no idea about estimations on adversaries' movement. Ch 8.3.3. provides an estimated level of geospatial segregation of adversaries. Furthermore, visualizations of transnational movement passage networks show the importance of transnational movement between two nations, i.e. extensive geospatial movement between Tanzania and Kenya at the end stage, adversaries' segregation in Somalia and Afghanistan at the early simulation stage, etc. These new analysis results provide insights into where the adversaries are segregated and when and why.

Second, adding a new interaction layer changes the existing simulation results. For instance, the key individual lists are different between the social only model and the combined model. *Abdullah Ahmed Abdullah* has the highest degree centrality in the interaction network from the social only model at timg 50. However, the same network from the social and geospatial model at the same timing indicates that *Osama Bin Laden* has the highest degree centrality (see Table 8-8). Additionally, the regression analyses in Ch. 7 and 8 are different. For instance, removing higher cognitive demand agents help decreasing the task speed, binary task accuracy and energy task accuracy level. However, in the social and geospatial model, such removals induce the decrease only in the energy task accuracy. (see Table 8-8).

Table 8-8 Different results from the social only model and the social and geospatial model

Comparison Point	Result from Social Only Model	Result from Social and Geospatial Model	Used simulation results for comparison
Effect of earlier intervention timing to organizational performances	Increased damage in mission speed, task speed, energy task accuracy, and task completion Decreased damage in binary task accuracy and diffusion	Increased damage in mission speed, task speed, binary task accuracy, and task completion Decreased damage in diffusion	Table 7-5 and Table 8-4
Effect of larger intervention size to organizational performance	Increased damage in mission speed, task speed, binary task accuracy, energy task accuracy, and task completion Decreased damage in diffusion	Increased damage in mission speed, task speed, binary task accuracy, energy task accuracy, and task completion Decreased damage in diffusion	Table 7-5 and Table 8-4

Comparison Point	Result from Social Only Model	Result from Social and Geospatial Model	Used simulation results for comparison
Effect of removing higher degree centrality agents to organizational performance	Increased damage in mission speed, task speed, binary task accuracy, and task completion Decreased damage in diffusion	Increased damage in mission speed, binary task accuracy, energy task accuracy, and task completion Decreased damage in task speed and diffusion	Table 7-5 and Table 8-4
Effect of removing higher betweenness centrality agents to organizational performance	Increased damage in task speed and energy task accuracy Decreased damage in mission speed, binary task accuracy, diffusion, and task completion	Increased damage in task speed and energy task accuracy Decreased damage in mission speed, binary task accuracy, diffusion, and task completion	Table 7-5 and Table 8-4
Effect of removing higher eigenvector centrality agents to organizational performance	Increased damage in diffusion Decreased damage in mission speed, task speed, binary task accuracy, energy task accuracy, and task completion	Increased damage in task speed and diffusion Decreased damage in mission speed, binary task accuracy, energy task accuracy, and task completion	Table 7-5 and Table 8-4
Effect of removing higher cognitive demand agents to organizational performance	Increased damage in task speed, binary task accuracy, and energy task accuracy Decreased damage in mission speed, diffusion and task completion	Increased damage in energy task accuracy Decreased damage in mission speed, task speed, binary task accuracy, diffusion and task completion	Table 7-5 and Table 8-4
Top agent in interaction network at the early stage (time 50)	Cognitive Demand: Fazul Abdullah Mohamed Degree Centrality: Abdullah Ahmed Abdullah Betweenness Centrality: Al Owali Eigenvector Centrality: Abdullah Ahmed Abdullah	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Osama Bin Laden Betweenness Centrality: Al Owali Eigenvector Centrality: Abdullah Ahmed Abdullah	Table 7-7 and Table 8-7
Top agent in transfer network at the early stage (time 50)	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Osama Bin Laden Betweenness Centrality: Al Owali Eigenvector Centrality: Wadih el-Hage	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Wadih el-Hage Betweenness Centrality: Al Owali Eigenvector Centrality: Wadih el-Hage	Table 7-7 and Table 8-7
Top agent in interaction network at the middle stage (time 500)	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Osama Bin Laden Betweenness Centrality: Al Owali Eigenvector Centrality: Ahmed Khalfan Ghalilani	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Abdullah Ahmed Abdullah Betweenness Centrality: Al Owali Eigenvector Centrality: Abdullah Ahmed Abdullah	Table 7-7 and Table 8-7
Top agent in transfer network at the middle stage (time 500)	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Al Owali	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Ahmed	Table 7-7 and Table 8-7

Comparison Point	Result from Social Only Model	Result from Social and Geospatial Model	Used simulation results for comparison
	Betweenness Centrality: Khalfan Khamis Mohamed Eigenvector Centrality: Al Owali	Khalfan Ghalilani Betweenness Centrality: Wadih el-Hage Eigenvector Centrality: Ahmed Khalfan Ghalilani	
Top agent in interaction network at the late stage (time 1300)	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Abdullah Ahmed Abdullah Betweenness Centrality: Al Owali Eigenvector Centrality: Wadih el-Hage	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Abdullah Ahmed Abdullah Betweenness Centrality: Al Owali Eigenvector Centrality: Abdullah Ahmed Abdullah	Table 7-7 and Table 8-7
Top agent in transfer network at the late stage (time 1300)	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Al Owali Betweenness Centrality: Khalfan Khamis Mohamed Eigenvector Centrality: Al Owali	Cognitive Demand: Fazul Abdullah Mohammed Degree Centrality: Muhammed Atef Betweenness Centrality: Mustafa Mohamed Fadhil Eigenvector Centrality: Anas al-Liby	Table 7-7 and Table 8-7

8.5. Implementation of the social and geospatial simulation model

I describe the implementation procedure of the introduced simulation model. The simulation model is the agent based simulation model with the social and geospatial dimensions. In other words, this simulation model is an iteration of agents within the four specified interaction spaces. Therefore, the major focus of the implementation should include the following two points.

5) Updated social interaction logic
6) Updated knowledge of space
7) New geospatial movement logic
8) Updated task execution logic

This subsection describes the implementation of the above four components in this simulation model. This social and geospatial model is built on top of the social model, so I only listed the changes in the social model to account for the geospatial dimension.

Before I start explaining the details of updated logics, I show what the big changes are in Code 8-3. In the social and geospatial model, I put the geospatial relocation logic right after the social interaction logic, so that the agent can behave in the two different spaces. Therefore, the geospatial relocation part is completely new compared to the social only model, but the social interaction and task performance parts are updated components.

```
Function Execute_agent_behavior(int agentID, Random r)
        Social_interaction(agentID, r);
        Geospatial_relocation(agentID, r);
        Perform_task(agentID, r);
End function;
```

Code 8-1 High level updated agent behavior

8.5.1. Updated social interaction logic

The following pseudo code is the updated social interaction behavior pattern in the simulation. As you can see, the delivery success rate changes according to whether the interaction happens at the same location or not. This enables new incentive about moving to interaction partners for agent.

```
Function Social_interaction(int agentID, Random r)
        Neighbor_agents = getSphereOfInfluence(agentID, one social link away, return_only_agent);
        choice = weightedRandomChoice(r, weight_element_delivery, weight_others_request_passing,
        weight_my_request_generation);

        switch(choice)
                case Element_delivery:
                        Element e = find_requested_and_possessing_element(agentID's elements);
                        Request req = find_request_records_specified_by_element(agentID's received
                                delivery request, e);

                        If ( req.sender has done his interaction for this turn) finish this block;

                        If ( req.sender and agentID are at the same location )
                                If ( transferSuccessProbAtSameLocation < r.nextValue )
                                        Unlink(agentID,e);
                                        Link(req.sender,e);
                                End;
                        Else
                                If ( transferSuccessProbAtDifferentLocation < r.nextValue )
                                        Unlink(agentID,e);
                                        Link(req.sender,e);
                                End;
                        End;

                        Remove_request_records(req);

                Case Others_request_passing:
                        Request req = find_request_records(agentID's received delivery request);
                        interactionPartnerID = pick_one_agent_with_the_element
                                        _based_on_the_transactive_memory(agentID, Neighbor_agents);

                        If ( interactionPartnerID has done his interaction for this turn) finish this block;

                        Request newReq = new Request(req.element, agentID);
                        Put_in_the_request_list(interactionPartnerID,newReq);

                Case My_request_generation:
                        Element e = find_required_element_not_in_possession(agentID);
                Request req = new Request(e, null);
                        Put_in_the_request_list(agentID,req);
        End switch;

        transactiveMemoryExchangePartnerID = pick_one_agent_randomly(Neighbor_agents);
        exchangeTransactionMemory(agentID,      transactiveMemoryExchangePartnerID);
End function;
```

Code 8-2 Agent's social interaction implementation pseudo code

8.5.2. Updated knowledge of space

Knowledge of space is exchanged and represented as transactive memories held by agents. However, there are no changes to this transactive memory model. I modeled the locations as nodes and distance as networks among location nodes. Therefore, there is no need to make additional changes if the transactive memory is able to transfer the links among any types of nodes. Therefore, the links between locations and agents, knowledge, resources and tasks will be additionally transferred from one agent to another, but such transaction would not need any of transactive model implementation change if you follow the concept of meta-network which treats locations as just a different type of nodes.

8.5.3. New geospatial movement logic

This model specifies the agent movement logics, as well. I described the implement in the below pseudo code. There are four motivations that make agents relocate. The four motivations are 1) performing a task at a certain location, 2) obtaining required resources and knowledge from a certain location, 3) recovering a removed agents' social contacts, knowledge and resources, 4) facilitating the element delivery by co-locating with the interaction partner.

```
Function Geospatial_relocation(int agentID, Random r)
        required_elements = getRequiredElements_consider_agent_task_assignment(agentID);
        visible_areas = getSphereOfInfluence(agentID, vision_range social link away
                                                        , return only location);

        choice = weightedRandomChoice(r, weight_performing_task_at_location
                        , weight_obtaining_required_elements
                        , weight_recovering_removed_agents_contact, weight_facilitating_delivery);

        Place_relocate = null;
        switch(choice)
                case Performing_task_at_location:
                        location_list = findLocationsAttachedToAssginedTasks(agentID);
                        location = randomly_pick_one_location(r, location_list);
                        unLink(agentID, agentID's current location);
                        Link(agentID, location);
                case Obtaining_required_elements:
                        location_list = visible_areas;
                        location = find_location_with_most_required
                                                                _resources_and_knowledge(location_list);
                        If ( path_age != 0 )
                                path = previously_calculated_path;
                                path_age = path_age - 1;
                        Else
                                path = getShortestPasth(agentID's current location
                                                                , location, only_using_location);
                                path_age = path's decay parameter;
                        End;

                        move_location = path.firstInThePath;
```

```
                                        unLink(agentID, agentID's current location);
                                        Link(agentID, move_location);
                              case Recovering_removed_agents_contacts:
                                        location_list = visible_areas;
                                        location_list2 = find_location_with_removed_agents(location_list);
                                        location = randomly_pick_one_location(r, location_list2);
                                        unLink (agentID, agentID's current location);
                                        Link(agentID, location);
                              case Facilitating_element_delivery:
                                        location_list = visiable_areas;
                                        location = find_location_with_most
                                                            _agent_type_neighbors_in_social_network(location_list);
                                        unlink(agentID, agentID's current location);
                                        Link(agentID, location);
                    End switch;

                    obtainable_nodes = getObtainableResourceOrKnowledgeFromLocation(agentID's location);
                    obtainable_node = randomly_pick_one_node(obtainable_nodes, r);
                    if ( geospatial_gathering_threshold < r.nextValue )
                              Link(agentID, obtainable_node);
                    End if;

          End function;
```

Code 8-3 Agent's geospatial relocation implementation pseudo code

8.5.4. Updated task execution logic

The change of the task execution logic is just one line of code. Before an agent tries to execute the task, the agent needs to check whether or not the agent is on the site for the task execution. The codes reflecting this change is placed right after the task requirement checking code.

```
          Function Perform_task(int agentID, Random r)
                    task_list = getSphereOfInfluence(agentID, one social link away, only_task_nodes);
                    ready_task_list = select_only_ready_task (task_list);
                    ready_task_list2 = select_tasks_with_agent_on_site(ready_task_list2);
                    task_to_execute = randomly_pick_one_task_that_all_required
                                                  _elemets_are_gathered(ready_task_list2);
                    If ( taskExecutionSuccessRate < r.nextValue )
                              recordTaskIsDone(task_to_execute);
                    End;
          End function;
```

Code 8-4 Agent's task execution implementation pseudo code

8.5.5. Simulation flow

Figure 8-8 shows which simulation flowchart components correspond to which pseudo codes in the previous sections. The simulation process is managed by the simulation model main loop, Code 7-1, and the simulation iteration function, Code 7-2. In the simulation iteration function, each agent is called in the randomized order, and the agent executes three aggregated behavior patterns. The first behavior pattern is the social interaction that is implemented as Agent's social interaction implementation pseudo code in Code 8-2. The second pattern is the geospatial relocation implemented as Agent's geospatial relocation implementation pseudo code in Code 8-3. Finally, the third pattern is the task execution implemented as Agent's task execution implementation pseudo code in Code 8-4.

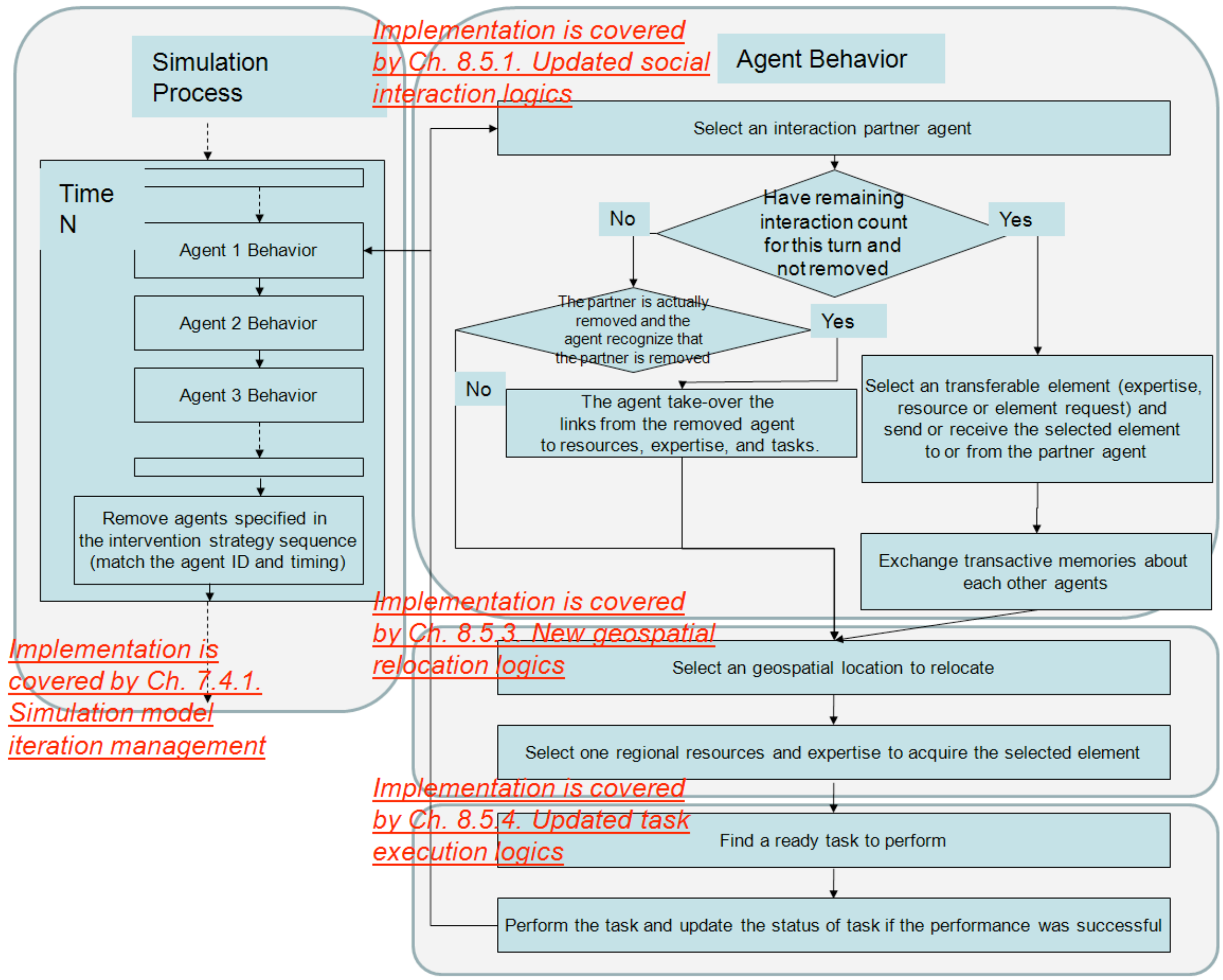


Figure 8-8 Annotated simulation procedure flow chart. The annotation specifies which items in the flow chart correspond to the pseudo code in Ch. 8.5.

Table 8-9 is the list of key parameters. These parameters are introduced earlier in Ch 7.1. and Ch 8.1. However, the earlier introductions were about their types and implications. Table 8-9 provides the links between the pseudo code functions and the used parameters. This table will provide information about where the user parameters are used in which part of the simulation model.

Table 8-9 Annotated simulation key parameter table

Name (Default value in the parenthesis)	Which pseudo code function uses the parameter	Implication
Probability on successful regional resource and ex-	Function Geospatial_relocation (Code 8-	Probability for collecting a location-held expertise and resources

Name (Default value in the parenthesis)	Which pseudo code function uses the parameter	Implication
pertise gathering (0.5)	3)	by an agent.
Change timing of the geospatial destination (5)	Function Geospatial_relocation (Code 8-3)	When an agent selects a place to move, he will cross a location-to-location link for each time-step. In this case, the agent will keep his first selected location as a destination for the number of time-step specified by this parameter.
Weights for task performance (0.70), link recovery (0.10), interaction facilitation (0.10), and new resource/expertise acquisition (0.10)	Function Geospatial_relocation (Code 8-3)	Weights for selecting a location to move. An agent selects one relocation purpose out of four. An agent may move to a location to execute a task to be done at a specific location. An agent may move to the interaction partner's location to facilitate interactions. An agent may move to the removed agent's location to recover the agent's links. An agent may move to new locations to acquire needed resources and expertise.

8.6. Conclusion

This geospatial extension needs further information than usually analysts have. However, from the further information, we can see more detailed expected behavior of adversaries in the social and geospatial dimensions. Particularly, this extension enables new analysis results, i.e. the level of geospatial segregation of agents over-time, and this extension changes the previous analysis results, i.e. newly identified key players, changed standardized coefficient values in the regression models, etc.

Limitations: Analysts often have limited knowledge about the geospatial locations of terrorists, regional resources, and expertise. If they have limited information about the required components, they may obtain only limited results from this model. For example, the Tanzania and Kenya bombing case must have much finer and detailed logistics over the course of incident executions. However, our knowledge about the group is limited, so that the only transnational level simulation was possible. Therefore, the movements may be too obvious or less informative than the level of resolution that a traffic simulation model might generate.

Theoretical contribution: Multi-agent simulation models usually have dealt with a single dimension such as either the spatial dimension or the social network dimension. However, to model the real world in detail, we need to combine multiple interaction dimensions. To perform such a simulation, we need to see the correlation between two or more dimensions to model, which motivations from which dimension dominate the agent intentions, and what the differences are between the multiple dimensions. This chapter introduces such expansion of the multi-agent simulation model. Furthermore, the organization theory domain has not intensively incorporated the geospatial information into their social and organizational dimensions. However, military and corporate logistics, globally distributed software development, global terrorist networks have geospatial components in their model. I show an example of how to model such geospatially distributed organizational structures with an agent based model.

Technical contribution: To visualize this specific multi-dimensional data, I had developed GIS system in ORA. Also, the simulation model, JDynetSpatial, considers discrete geospatial links and transport networks when it decides the agent behavior. The combination of the GIS network visualize and the mutli-agent network simulation model can be powerful in displaying which agents are segregating where and how the segregation stretches command and control or management relations over the geospatial regions.

Empirical contribution: I traced the agent interaction and organizational element transfer network in Ch. 7. This chapter adds the geospatial movements of the simulated agents. When the initial training and education happens, the agents are segregated around the *Somalia, Pakistan, and Afghanistan* regions because these regions are linked to training resources and regional expertise (weapons expertise at the Somalia training base). Afterwards, the agents move from the above regions to actual mission regions, *Tanzania and Kenya*. This geospatial segregation patterns were not discovered by using the social only model. When we match the Gantt chart output to the geospatial segregation chart in Ch. 8.3.3, we can observe which regions are critical and when. Also, the key individual lists in Ch. 8.3.4. are different from the same key individual list in Ch. 7.3.4. For example, this extended model indicates *Al Owali* is more important than the estimation from the social only model in the betweenness centrality perspective of agent-to-agent organizational element transfer networks at the late stage of simulations. To reduce the mission execution speed, the social only model suggests that removing high cognitive demand agents is preferable. On the other hand, the social and geospatial model suggests that removing high degree centrality agents is preferable.

- *A multi-agent model should be able to handle multiple interaction spaces at the same time. The introduced agent model simulates the social and the geospatial co-evolutions over-time.*
- *A successful intervention should consider the geospatial criticality, the task execution timing, as well as the agent interaction and organizational element transfer network.*
- *A combination of the GIS network visualize and the geospatial and social simulation model has a power in displaying which agents are segregating where and how the se-*

gregate stretches command and control or management relationships over the geospatial regions.

This geospatial extension provides the snapshot of organizational behavior in two dimensions: social and geospatial dimensions. This two correlated snapshots provide more sense-making pictures what would be our expected adversarial behavior when their organizational structures and behavior model is assumed. This is more information that analysts can use over the course of building the destabilization strategies.

9. Case Study – How To Use the Integrated Analysis Framework to Analyze the Terrorist Organization Responsible for the U.S. Embassy Bombing Incidents in Kenya and Tanzania

Human analysts need to use an integrated destabilization analysis tools to grasp a more complete picture of a target organization. If they use just a single approach, they may be biases by the used approach because they will not have results generated by the other approaches. Also, one analysis result might be an informative input to other analysis approaches by significantly reducing the input generation for analyses. In such a case, this seamless interoperation may enhance the final analysis results and improve the human analysts' efficiency. However, analysts need to know which analysis approach they can usually start with and how to cycle the analysis result with the other integrated approaches.

This chapter summarizes the analysis procedure of this integrated framework. When a human analyst utilizes this framework for the destabilization analysis of an observed organization, the analyst needs to check whether or not the dataset is usable with adequate inputs. Afterwards, the analyst runs the framework and generates the series of destabilization analysis results. Moreover, when the final simulation analysis is over, the analyst can feed the simulation results back to the decision making structure analysis and influence network analysis.

Since this is a computational procedure using various inference and simulation tools, we need to consider the computational resource required to perform this analysis procedure. For example, the computation cost of evaluating an influence network with the CAST logic grows exponentially. Therefore, I provide the computational cost estimation of each procedure in Appendix Ch. 11. With this estimation, human analysts can get a clue about which procedure will take how much time.

9.1. Summary of the Integrated Framework Usage

The introduced analysis framework is a set of interoperable destabilization analysis modules ranging from the static decision making structure analysis to the dynamic multi-agent simulation analysis (See Figure 9-1). Each of the modules is interoperable, and some of the results can be fed back to the previous or next analysis modules. For example, the arrows, from the decision making structure to the meta network and from the evolved meta network to the meta network, represent that the produced analysis results can be used again for other analysis inputs.

As well as such internal interoperations, the framework supports the interoperation with the existing intelligence analyst's tools, i.e. *Caesar III, Pythia,* and *ArcGIS*, so the analysts can use both the introduced framework and their familiar tools at the same time.

One fundamental feature of this framework is the emphasis on human analysts' inputs. The human analysts play an important role in this analysis procedure by providing various analysis parameters. This is the reuse of their qualitative and subject-matter related expertise, which a machine cannot imitate with this current technology. Also, the outputs of the analysis framework require the interpretation from the human analysts for final course of action recommendations while the outputs provide various refined estimations for such human analysts' conclusions.

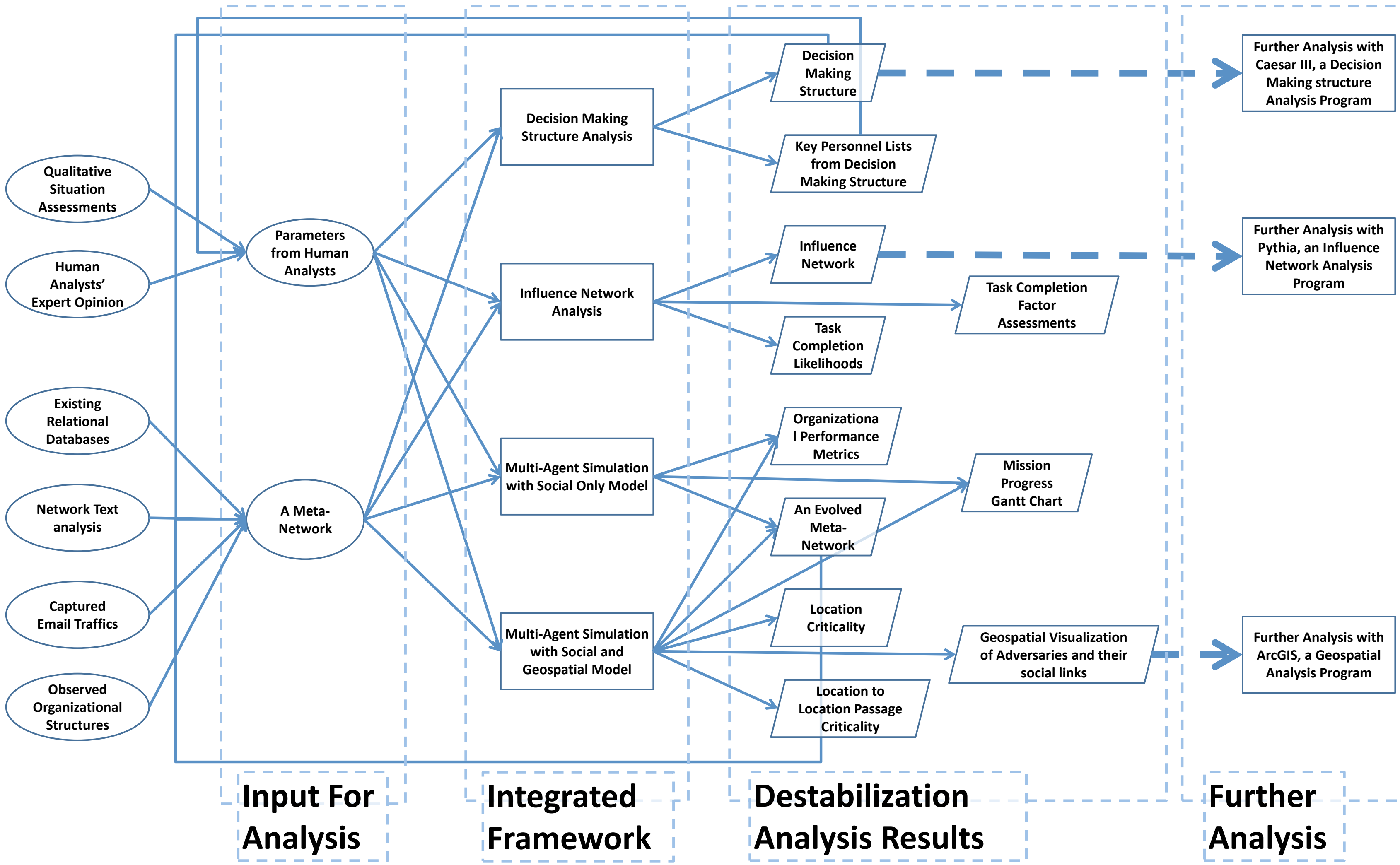


Figure 9-1 The system architecture of the introduced analysis framework

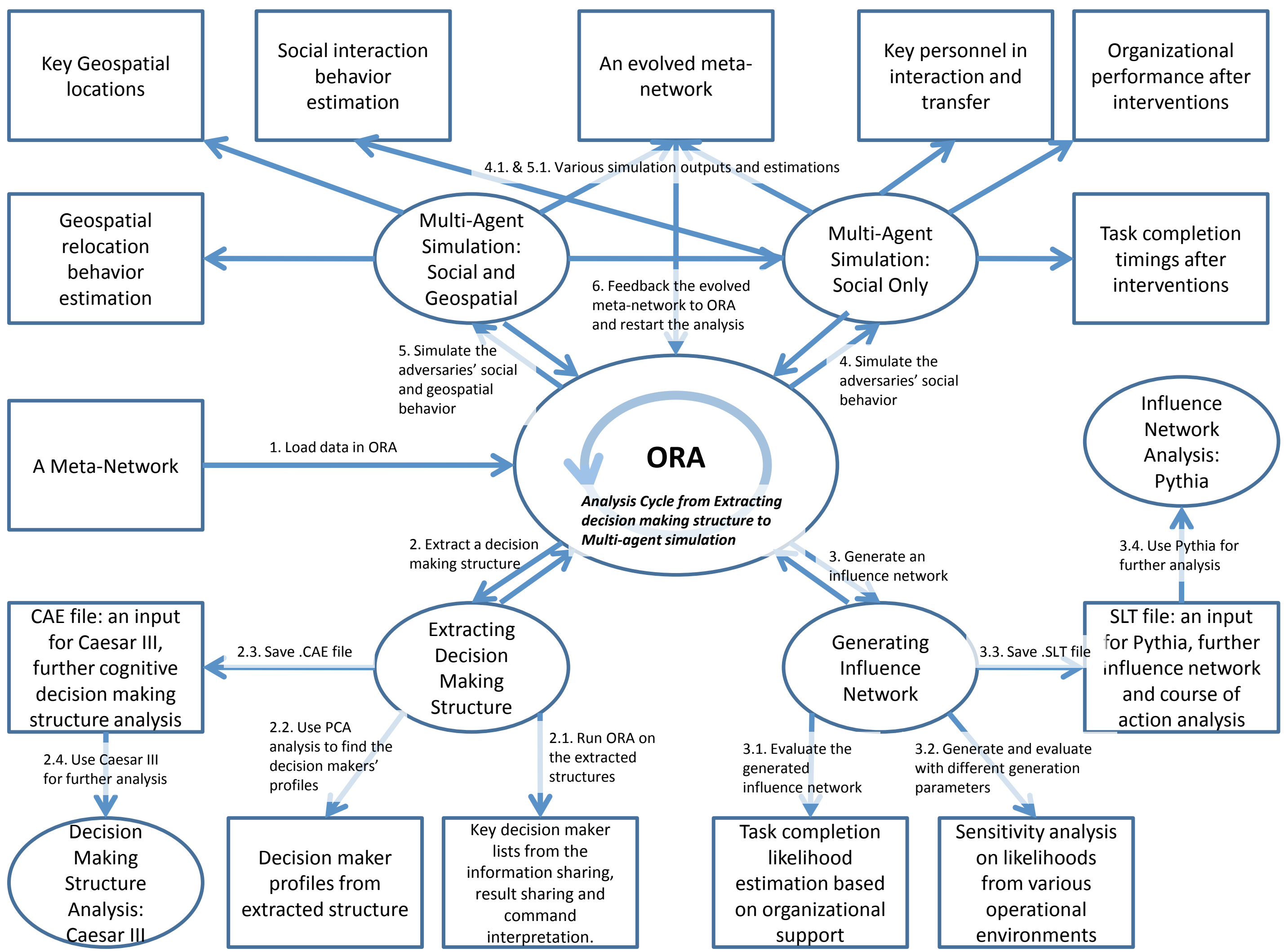


Figure 9-2 A work flow chart describing a suggested analysis procedure

Additionally, Figure 9-2 describes a suggested analysis procedure using the integrated framework (Figure 9-1 is the system architecture of the implemented framework). A human analyst may start using the implemented framework by loading a meta-network in ORA. After loading, the analyst can 1) extract a decision making structure, 2) generate an influence network, and 3) simulate the organizational behavior. Every component generates an estimated network format which can be loaded in ORA again. The analyst may choose to run the same analysis procedure with the estimated network structure again.

9.2. Checking the Dataset Requirement

I have used the 1998 U.S. Embassy Bombing Incidents in Kenya and Tanzania (See Ch. 4.2. for detailed introduction) to describe the detailed analysis components. I will use the same dataset to summarize the analysis procedure of the framework. For readers, I repeat the basic statistics of the dataset in Table 9-1.

Table 9-1 the overall structure of the 1998 US Embassy Bombing in Tanzania and Kenya dataset.

	Agent	Expertise	Location	Resource	Task
Agent (18 terrorists)	(Agent-to-Agent) 0.143	(Agent-to-Expertise) 0.126	(Agent-to-Location) 0.200	(Agent-to-Resource) 0.076	(Agent-to-Task) 0.142
Expertise (14 expertise)		(Expertise-to-Expertise) Doesn’t exist	(Expertise-to-Location) 0.071	(Expertise-to-Resource) Doesn’t exist	(Expertise-to-Task) 0.171
Location (5 locations)			(Location-to-Location) 0.500	(Resource-to-Location) 0.107	(Task-To-Location) 0.312
Resource (13 resources)				(Resource-to-Resource) Doesn’t Exist	(Resource-to-Task) 0.120
Task (25 tasks)					(Task-to-Task) 0.055

The main dataset for this framework is a DynetML file containing a meta network. The meta network is a multi-modal and multi-plex social network that can represent a complex organizational structure (see Ch. 4.1). Since the meta network concept contains different types of nodes and links, Table 9-2 specifies which types of nodes and links are required to perform which analysis component. A human analyst can choose the extent of framework usage based on the dataset that the analyst has.

Table 9-2 the check list to perform an analysis component, Required means that the dataset must have the input component (even it is the blank, it should specify the blank), Optional means that the analysis will take the input into the consideration, but not mandatorily required, Don't Care means that the input component will not be used in the analysis component.

Nodes and Links	Decision Making Structure Analysis	Influence Network Structure Analysis	Multi-Agent Simulation of Social Only Model	Multi-Agent Simulation of Social and Geospatial Model
Agent	Required	Required	Required	Required
Resource	Optional	Required	Required	Required
Expertise	Optional	Required	Required	Required
Task	Required	Required	Required	Required
Location	Doesn't Use	Doesn't Use	Doesn't Use	Required
Agent-to-Agent	Required	Doesn't Use	Required	Required
Agent-to-Resource	Optional	Required	Required	Required
Agent-to-Expertise	Optional	Required	Required	Required
Agent-to-Task	Required	Required	Required	Required
Agent-to-Location	Doesn't Use	Doesn't Use	Doesn't Use	Required
Resource-to-Task	Optional	Required	Required	Required
Resource-to-Location	Doesn't Use	Doesn't Use	Doesn't Use	Required
Expertise-to-Task	Optional	Required	Required	Required
Expertise-to-Location	Doesn't Use	Doesn't Use	Doesn't Use	Required
Task-to-Task	Required	Required	Required	Required
Task-to-Location	Doesn't Use	Doesn't Use	Doesn't Use	Required
Location-to-Location	Doesn't Use	Doesn't Use	Doesn't Use	Required

Additionally, the analyst wants to check the validity of the dataset. In many cases, the observation of the adversarial organizations is noisy and uncertain. Therefore, some input components, such as agent-to-agent, may have false information. However, most of the input components can be verify by humans and existing databases to some extent. For example, the task-to-task network, or task dependency network, can be modified by an analyst if the analyst understands the procedure of terror activities in detail. Also, there are known associations among agents in databases as well as their expertise and available resources, such as whether *Bin Laden* is rich (has the money resource) or not. These are all external supports to build up the appropriate analysis dataset, and the analyst may or may not use those external supports in the dataset preparation.

There are adjunct inputs for the analysis components. These inputs are parameters for analyses. If an analyst has a input meta network in his hand, most of these parameters should be available to the analyst. For example, the interaction partner decision radius should be available when the analyst has the agent-to-agent network. Or, the analyst has his own views toward the operation of the adversaries. Then, his expert views determine the parameters. Or, there are analysis or report requirements that the analyst has to follow, i.e. the possibility of successful *detonation* task execution. Then, these requirements set the parameters. Table 9-3 specifies such parameters.

Table 9-3 Required parameters for analysis components

Decision Making Structure Analysis	Influence Network Structure Analysis	Multi-Agent Simulation of Social Only Model	Multi-Agent Simulation of Social and Geospatial Model
Selection of Task of Interest	Selection of Task of Interest	Agent Removal Scenarios	Agent Removal Scenarios
	Parameters for the Organizational Assessment Heuristics	Parameters Specified in Table 7-1	Parameters Specified in Table 7-1
	Parameters for the Assessment Marginal Probability Assignments		Parameters Specified in Table 8-1

After gathering the meta-network and required parameters for analysis components, the analyst can utilize the integrated framework to the extent that he wants the results and the dataset supports.

9.3. Destabilization analysis procedure

After checking the dataset requirement and human analysts' parameter settings, the analysts start the destabilization analysis. Below sub-sections are in the order of suggested analysis procedure.

9.3.1. Step 1: Decision making structure analysis

The first analysis component is the decision making structure analysis. This is likely to be the first analysis that the analyst may perform because 1) the analyst might want to know the embedded command and control relationships among agents, 2) the analyst might want to limit the scope of the meta network by removing unrelated tasks and agents, 3) the analyst might want to use only the significant social relations in the further investigation.

Analysis objective: The objective of this analysis step is identifying the critical decision making structure from an observed social network. The observed social network does not guarantee that every relation among agents is significant and critical, particularly from the mission or task completion perspective. Therefore, throughout this analysis step, a human analyst aims to drill down and reason possible embedded decision making structure which only contains significant social relations from the organization's operation viewpoint.

Analysis results: Outputs of this analysis are the extracted decision making structures represented as three distinct social networks, *information sharing, result sharing* and *command interpretation*. These networks are different from the original agent-to-agent social network. Additionally, the technical implementation allows the generation of input files for *Caesar III*, which is an cognitive decision making process analysis program. Extracting three further social networks means that the analyst has three more key individual lists from the perspective of each decision making structure. Therefore, the final outputs of this analysis component will be 1) new meta-matrixes with three new social networks (See Figure 5-10), 2) an input to decision making cognitive procedure analysis program, and 3) new key personnel lists (See Table 5-4).

Empirical key lessons learned: This particular application results found that some key actors who are over- or under-estimated before. For example, *Anas al-Liby* was the task coordinator who has higher network metrics in the result sharing g structure than in the original structure. Additionally, *Al Owali* is a newly found critical actor in the information sharing (the second in the degree centrality, the first in the betweenness centrality, the second in the eigenvector centrality, and the second in the cognitive demand). Additionally, actor profiling is done. The profile reveals four actor clusters from the observed network and four other clusters from the extracted network. For example, *Fahid Mohammed Ally Msalam* and *Azzam* are identified as actors with few links to other personnel and medium communication demand to complete their tasks.

Feedback to the analysis framework: Among these outputs, the new meta network can be used in the subsequent analyses. Or, the original meta network can be used consistently. This depends on the intent of the analyst used this decision making structure analysis.

9.3.2. Step 2: Influence network analysis

The next component that the analyst might be interested in is the influence network analysis. The analyst may perform this analysis because 1) the analyst might wants to know well or poorly supported tasks of the adversarial organization, 2) the analyst might wants to know what are the tasks' important factors, i.e. personnel assignment, resource availability, task complexity, etc, 3) the analyst might wants to know the level of task execution likelihood of the adversaries, so that he can evaluate whether the adversaries' mission can be carried out or not under the given circumstances.

Analysis objective: Human analysts aim to find out the organizational supports for tasks of adversaries. With a snapshot of a meta-network, the analysts cannot intuitively distinguish well- or ill-supported tasks of the organizations. As well as the organizational support assessment, the analysts need to see the bottleneck tasks that hinder or promote subsequent tasks. However, these assessments should consider different viewpoints regarding the hostility/easiness of operational environment or the difficulties of tasks. This consideration can be done by adding a sensitivity analysis to the influence network generation and evaluation phases.

Analysis results: Outputs of this analysis are the generated influence network and the evaluation under various parameters that reflect the analysts' perspective. The generated influence network is the input file for *Pythia*, which is an influence network analysis program. The generated influence network shows the marginal probabilities that are determined by the assessment of organizational supports and task inherent difficulties and importance. The assessment is done by using the analyst's selected parameters. The marginal probabilities of tasks are the task completion likelihoods. Examination on these marginal probabilities will suggest tasks of interests and tasks' factors of interests. For example, Figure 6-6 shows the generated influence network. Figure 6-7 and Table 6-3 shows the completion likelihood of each task. Table 6-4 and Table 6-5 are the optional parameters for the analysts' selection. Table 6-6 and Table 6-7 are the completion likelihood changes under various analysts' perspectives. From Figure 6-7 and Table 6-3, the analyst can pick the task of interest based on their well or poor organizational supports.

Empirical key lessons learned: The analysis result identifies tasks that have low completion likelihood, such as *conceal bomb in car* and *provide money*, because the tasks are under-supported by the organization. In contrast, *review surveillance files, film videotape announcing martyrdom,* and *surveillance of possible targets* show high task completion likelihood indicating good organizational supports from adversaries. As the operational environment setting changes, *overall planning and execution* and *bomb preparation* shows big changes in the completion likelihood which means that we can drop the completion likelihood hugely if we are able to change the operation environment of adversaries.

Feedback to the analysis framework: This analysis suggests tasks of interest based on the organizational support for tasks. The tasks of interest can be analyzed again by the previous decision making structure analysis.

9.3.3. Step 3: Multi-agent simulation of social only model

After static analysis on the decision making structure and evaluation on task completion likelihoods, the analyst may want to project what will happen if the analyst strategize the removals of terrorists. Particularly, the analyst may want 1) to see the impact of the removals and whether the impact is negative or not, 2) to see the social interactions and organizational element transfers, and 3) to estimate the timeline of the adversaries' mission.

Analysis objective: Human analysts aim to simulate the adversaries' social interactions, such as resource and expertise transfer through interactions. This simulation considers only the social dimension of the target adversarial organization. From this simulation, the analysts will figure out 1) how long the mission execution would take, 2) what the estimated social behavior of adversaries would be, and 3) what the impact of agent removals (strategic interventions) would be. If the adversarial organization is not ready to execute the mission with only social behavior, this simulation will identify the lack of required expertise and resources which are not acquired by adversaries, yet.

Analysis results: Outputs of this analysis are the estimated meta network from the interaction and transfer perspectives, the organizational performance metric values, the estimated mission completion speed, and the estimated Gantt chart. The estimated meta network is generated by recording the interactions and organizational element transfers among agents (see Table 7-6). Additionally, if some agents are removed over the course of simulations, the recovered organizational structure also can be obtained. To evaluate the impact of interventions, the organizational performance metrics are used. The performance metrics cover how much the expertise is spread and how well the resources and expertise are distributed for correct task executions (see Figure 7-5) Also, the mission completion speeds are calculated by observing when the task dependency network is completed (see Figure 7-6 and Figure 7-7). Finally, the mission execution status is represented by using an estimated Gantt chart (see Figure 7-8).

Empirical key lessons learned: Simulation with the social only model shows that removing higher degree agents in large number at the early stage would be effective. However, this may not be achievable in the real world. The simulation analysis identified bottleneck tasks such as the *rent residence* task that has the longest execution time across the tasks during the mission. The simulations identified the organizational element transfer networks among agents. There are agents, i.e. *Fazul Abdullah Mohammed, Al Owali* and *Wadih el-Hage*, who consistently appear in the transfer network over-time.

Feedback to the analysis framework: This simulation approach generates the estimated organizational structures after removals. Also, the simulation records the estimated interaction and organizational elements transfer networks. These are the new estimated organizational structures in the meta network format. Therefore, the structures can be fed back to the decision making structure analysis and the influence network analysis, so that the two analyses can generate the estimated task completion likelihoods of future or decision making structure after removal.

9.3.4. Step 4: Multi-agent simulation of social and geospatial model

In contrast to the social only model, the social and geospatial model can answer the analyst's geospatial related questions. For example, if the adversarial organizations are spread across regions and if the adversaries exhibit transnational movements, the analysts may want 1) to estimate the level of adversaries' segregation of a specific place, 2) to estimate the importance of transnational movement passages, or 3) to estimate the transnational social and decision making structures that connects two regions.

Analysis objective: Human analysts aim to simulate the social and geospatial movements of adversaries. The analysts need to know 1) where the adversaries will segregate and when; 2) how the social behavior will change if adversaries are able to make transnational movements; and 3) how the intervention effects will be different when we consider geospatial effects. To answer these questions, the analysts will observe the simulation considering the social and geospatial co-evolution with a multi-agent simulation.

Analysis results: Outputs of this analysis include all the outputs of the multi-agent simulation of social only model. On top of the social only model outputs, the social and geospatial model generates the estimated segregation of the agents across regions, the weighted transnational passage networks, and the visualization of the social and decision making structure over the geospatial map. The estimated agent segregation across regions (see Figure 8-7) indicates how many agents are where and when. For instance, some of agents will segregate in Somalia and Afghanistan because they can gain regional expertise and resources by being there. However, after the early stage of the mission, they will move from the training sites to the mission execution sites such as Tanzania and Kenya. Additionally, when agents move to other locations, they use the location-to-location passage networks. Therefore, I show the criticality of the location-to-location links by counting the number of passage uses (See Table 8-6). Finally, I visualize the geospatial distributions of adversaries and their social and decision making structures over a geospatial map (See Table 8-6).

Empirical key lessons learned: The social and geospatial model simulation suggests that the agents are segregated around the *Somalia, Pakistan, and Afghanistan* regions when the initial training and education happens because these regions are linked to training resources and regional expertise (weapons expertise at the Somalia training base). Afterwards, the agents move from the above regions to actual mission regions, *Tanzania and Kenya*. The identified key individual lists are partly different from the list of the social only model. The extended model indicates *Al Owali* is more important than the estimation from the social only model in the betweenness centrality perspective of agent-to-agent organizational element transfer networks.

Feedback to the analysis framework: This simulation approach generates the estimated organizational structures after removals just like the previous simulation model. Hence, the feedback is the same: the newly generates meta network can be fed to the decision making and influence network analyses. On the other hand, the generated geospatial visualizations can be loaded in ArcGIS for further geospatial analyses. The transformation of visualization to ArcGIS can be done by using ORA.

9.4. Summary of key lessons learned

Human analysts are interested in 1) who hidden key actors are in their decision making structure, 2) which tasks are likely done and well supported by the adversaries, 3) whose removals would disrupt their mission execution greatly, 4) geospatially where they are and are heading toward at a particular stage. The above questions are answered by the integrated analysis components.

After running the decision making structure analysis with the observed meta network, human analysts find out that the observed network over- or under-estimate some terrorists in the conventional network analysis. By considering the expected information sharing, result sharing, and command interpretation activities of the adversaries, *Anas al-Liby* is identified as the task coordinator with the high betweenness centrality in the result sharing structure. *Al Owali* is a newly found important actors in the information sharing structure. Furthermore, the observed network and the extracted decision making structure produced actor profiles. For example, *Fahid Mohammed Ally Msalam* and *Azzam* are the actors who are not well connected, but need communications with others to complete their tasks.

While the above answers who hidden key actors are, the human analysts need to know the level of adversarial organization's support to each of tasks in their mission. The influence network analysis with the observed meta network suggests that *provide money* and *conceal bomb in car* are the tasks not well supported. On the other hand, *review surveillance files* is a well supported task. The human analysts have to make a recommendation disrupting the organizational supports to either well- or ill-supported tasks. If they tackle well-supported tasks, they are aiming to lower the overall task completion likelihood of the task network for the adversaries' mission. If they attack ill-supported tasks, they are trying to break the middle of the task network for the mission.

Whereas above assessments are static and macro level, some human analysts want to estimate the individual terrorist behavior and the collective organizational behavior. Furthermore, they want to assess the impact of removing some terrorists over the course of their mission execution. The simulation model about their social behavior indicates that removing high degree terrorists in the large number at the earlier stage would decrease the mission execution time a lot. The model also found that *rent residence* is a bottleneck task of the adversarial mission execution. Some terrorists, such as *Wadih el-Hage, Al Owali,* and *Fazul Abdullah Mohammed,* are estimated to act like the resource and information broker during their mission execution.

Finally, the human analysts want to know where the terrorists would be at a particular mission stage. The estimated Gant chart and the estimated geospatial agent segregation level suggests that there will be terrorist segregation in *Somalia, Pakistan,* and *Afghanistan* at the early stage of mission. However, such segregation will move to *Tanzania* and *Kenya* after the terrorists finish the training. The Gant chart tells the time portion of the training over the course of mission execution time.

The interpretation of the produced results can be basis for the human analysts' destabilization analysis report. However, it should be noted that the results are only the numeric representation of the estimated situation. The human analysts need to include and apply their expertise in the process of interpreting these computational analysis results. With their subject knowledge and estimated computational analysis, the analysts will have a report displaying quantitative and joint picture of adversaries' situation and weaknesses.

9.5. Possible model validation method

Among many possible extensions of this work, I want to point out two validation directions: applying the introduced analysis method to an industrial situation and validating the method with real-world data. These two research directions are, in fact, complementary to each other. While I develop and apply this work to the adversarial organization analysis, I found out that having complete observations about the situation over-time is almost impossible in the given context. I had to rely on a university research report and various open source documents to come up with a meta-network and a qualitative evaluation of the application result. On the other hand, if we apply this method to a general management of research institute or industrial organizations, we have a better chance to have a dataset that can be analyzed with this tool and used to validate this tool.

Thus, I suggest that the first step to expand this research is applying this framework to the industrial context. Particularly, we need to collect the over-time data about the below issues.

- Organizational personnel interactions: Personnel must interact with each other to complete their tasks or to have friendship interactions. The decision making structure inference in this work is partially able to distinguish such nature of interactions. However, to validate such approaches, we need to have more complete observations without biases, i.e. recording information sharing activities, but not reporting-back. Also, human analysts may need to annotate the nature of some interactions, so that they can be used to test the accuracy.

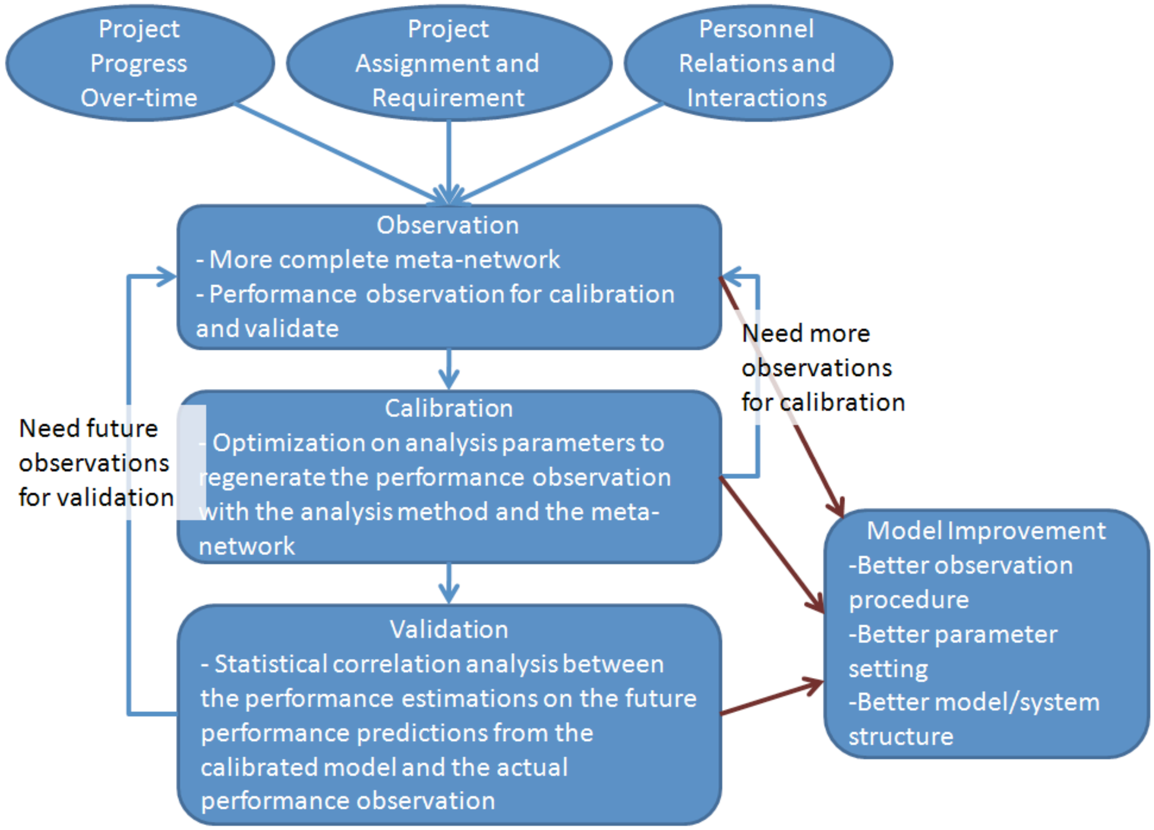


Figure 9-3 A work flow for the possible validation method

- Project requirements and assignments: While the traditional social network analysis focused on personnel interactions, this approach utilizes the dynamic network analysis approach including resources, expertise, tasks as well as personnel. Therefore, the data collection should cover the project-resource, project-personnel, and project-expertise relationships. This extended observation will allow us to have a complete meta-network that we need to run this approach.
- Project progress: Project progress over-time need to be captured. One contribution of my thesis is developing a multi-agent model that estimate the project progress with a given organizational structure. With the above observations about the organizational structure, we have a detailed input deck for the analysis. Then, we need to have the observed project progress, so that we can compare the inferred project progress from my analysis method to the observed project progress.

This observation will provide the basic input deck to run this analysis approach. However, the basic input deck and the analysis result from the default run will not give reliable estimations without calibration. There are number of parameters in this analysis procedure. For example, human analysts have to set the influence network parameters and simulation parameters. These can be calibrated by using the organizational structure and project progress observations. For example, with the early period of organizational structures and organizational performance, we may optimize the parameters to see whether the analysis approach can predict the late period organizational performance. This described procedure is illustrated in Figure 9-3. I believe that this observation, calibration and validation analysis is a big remaining research area that can increase the trust of this analysis framework.

10. Conclusion

This chapter summarizes the limitations and contributions of the introduced destabilization analysis framework. The introduced framework is a new system that 1) provides a joint picture from multiple disjoint pictures from diverse analysis approaches; 2) estimates human organization changes with partial information; and 3) incorporates human wisdom in the process of computational analyses of complex and dynamic problems. Enabling the above outcomes requires the integration of various theories from sociology, statistics, management, and computer science. Therefore, major contributions are made in providing new theoretical, technical grounds to complete the integration of different theories and approaches. However, some inherent problems still exist. For instance, the validation of estimation results, inferring uncovered data, and extensive use of computation powers might be the limitations of this work. In spite of these limitations, this work partially demonstrates, with incomplete datasets, ho on can craft a fusion of computations and organizations/management science to solve real world problems.

10.1. Limitations

This study has three major limitations. First, the framework requires a specific dataset that may not be obtained in the real world situations, and the work assumes that the obtained dataset contains only trustful data. Second, the framework generates estimations without any significant validations. Third, the framework consumes extensive computational power, particularly during the simulation analysis, so there is a limitation in the analysis' scalability.

Dataset requirement: This framework needs specific inputs from analysts. If an analyst does not have such observations, they would have to guess the relationships or use existing databases. These approximations will contribute to noisy analysis results. The required datasets are listed in Chapter 9.1; the type of inputs is described in Chapter 4.1.

Undone validation: This framework generates estimations that are not validated. The analysis results are highly speculative. Sometimes I just implemented human analysts' biases. This framework does not intend to pursue the exact discovery of the relations in past real world or hidden organizations (perhaps the introduced analysis can be an approximation of such hidden relations). A better description of the introduced framework is the computational tool performing human analysts' existing analysis approaches in a more robust manner. From this viewpoint, this analytical approach is different from the data-mining approach that wants to find accurate relationships in the data.

Analysis scalability[12]: This framework is limited to the analysis of a medium-sized adversarial organization. If an organization is a more of a sociological entity than a mission- or task-oriented organization, the organization should be analyzed using more sociological, cultural, and/or belief analysis methods. This approach is highly linked to the concept of task and mission completion, which limits the size of the investigation. According to the scalability results in Chapter 11, this

[12] I made a more extensive discussion and exploratory analysis about the analysis scalability in Chapter 11.

approach can handle more than 500 agents in an organization (in addition to the number of agents, there are many other factors in deciding whether the method is applicable or not). Particularly, the simulation methods require a long time to perform a complete analysis.

10.2. Getting toward more nuanced analysis approaches

This study has attempted to put key aspects of adversarial organizations into an analysis framework. For example, it has combined the social interactions and the geospatial relocations to provide an improved understanding of the impact of strategic interventions. By considering more key aspects of the problem domain, richer analyses should result. Whether the results are more accurate when more key aspects are considered has not been proven. That remains for future research.

Among the earlier works in this domain, Farley (2003) modeled the al-Qaeda organization as a pyramid- or tree-like organizational structure. From this strict hierarchical structure, he computes a set of nodes lists that can disturb the structure. Though this work is a good attempt to formulize a strategic intervention, his model vastly over-simplified the al-Qaeda structure in two ways: it assumed the structure to be strictly hierarchical and treated it as temporarily static. More detailed studies that are closer to the data (Stern, 2003a; McFate, 2005a; Burke, 2004) argue that the al-Qaeda structure is a decentralized network, at least at the below-the-top-leadership level. Other empirical studies demonstrate the evolutionary nature of the adversarial organizational structure (Fulmer, 2000; Goolsby, 2006). A model of al-Qaeda that allows for a distributed and dynamic structure would be more nuanced, closer to empirical reality, and likely to generate different conclusions about how to destabilize al-Qaeda. Indeed, models that allow for a dynamic, distributed structure do suggest different intervention strategies.

Krebs (2002) drew the organization of the 9/11 terrorists as a social network. This network representation can be viewed as an expansion of the previous tree organizational structure. However, it lacks critical information about the attack's execution. For example, resource requirements, task assignments, and task dependency are not represented at all in Krebs' social network visualization. Therefore, the analysis lost the important features in the attack. On the other hand, from the qualitative observations about the adversarial organizations, Sageman (2004) emphasized the importance of social networks as well as the physical movements of terrorists crossing borders, resource seeking, and recruit training. Again, this study has taken the other factors (movements, resources, and expertise) into account.

Carley (2006) provided a tool to consider the multiple types of organizational elements and the multiple types of relations among them. This enabled the representation of the complex organizations that Perrow (1986), Thompson (1967), and Child (1972) identified as the nature of human organizations. Carley's approach produced very informed analysis results by drawing this complex organizational structure idea. Furthermore, she linked this complex organization idea to the evolution of the organizations that Galbraith (1973) emphasized and that Stern (2003a) and Sageman (2004) also observed in the terrorist network domain. However, her work can be improved upon with further integrations of critical aspects (e.g. geospatial movement). Geospatial movement, or transnational movement, has been a focus of counter-terrorism analysis. For example, Sageman (2004), Champagne et al. (2005), and Felter and Fishman (2007) noticed the importance of the geospatial aspects of the terrorist movement. This study builds on this approach to simultaneously look at multiple key factors. Thus, it can generate more nuanced explanations.

This work also expanded upon previous knowledge by including the geospatial dimension in the analysis framework. This addition enables the importance of transnational movements to be discerned. The simulation model implements known terrorist transnational relocations by using relocation logics derived from qualitative and empirical research, mainly from Sageman (2004) and Champagne et al. (2005). This geospatial and relocation model supported by the previous qualitative analysis is expected to produce better and richer results than the analyses resulting from only the social dimension. Thus, in this thesis adds key factors such as spatial relocation that have an empirical basis and expected that the results would be more nuanced, more accurate, and lead to different destabilization strategies. While the study has not been able to prove that the results are more accurate, it has demonstrated that they are more nuanced by accounting for new key factors, as new conclusions have emerged about destabilization.

10.3. Theoretical Contributions

Most of theoretical contributions are made in the process of expanding and interoperating dynamic network analyses, decision-making structure analyses, influence network analyses, and multi-agent simulations. The theoretical expansion is made to interoperate the theories that are not yet interoperable. This interoperation enables new analysis frontiers for human analysts, and these new frontiers enable more in-depth and nuanced assessments and estimations of adversaries. These new assessments and estimations include 1) providing a multi-plex network from a single-relation network; 2) assessing organizational structures to support their tasks with Bayesian network analyses; and 3) modeling human behavior in multiple dimensions.

First, the present study has expanded dynamic network analyses from the only observed network analysis to the inferred network analysis. Human analysts have speculated that there is more than one type of social relations among the adversaries, but many of observed organizational structures are flat social networks without any multi-plex links. Therefore, the use of a dynamic network analysis that can handle a multi-modal and multi-plex social network has been limited. This study has enabled the reasoning of different types of relations from a flat social network. This expands the use and the application of dynamic network analysis by supplying multi-plex networks from flat networks. In detail, by inferring three different decision-making structures from the observed network, we can theorize that the observed social network may contain three different embedded social networks that can be extracted from three different perspectives. From this inference idea, and given adequate multi-modal networks, analysts can now see multi-plex links in three different social networks among agents.

Second, the study expands the dynamic network analysis theory to include the numerical evaluation from a Bayesian network. Human analysts need an answer the question, “Is this organization capable enough to execute this mission?” with direct, task-related performance measures that are not criticality metrics or indirect task performance measures. By using a Bayesian network technique to assess an organizational structure and estimating a task related performance measure, the study allowed for more in-depth analyses of adversaries' task completion probabilities and their ability to execute their mission. Specifically, dynamic network analysis has developed various metrics that evaluates complex organizational structures. However, these metrics are limited to the assessment of network status. On the other hand, the management community has developed various theories in assessing organizational structures from the task completion and organizational support perspectives. Then, the managers familiar with the management science will ask a question about how to numerically assess the organizational support and task completion with a given complex organizational structure in the network format. By using an influence network, a variant of a Bayesian network, the present study theorized an assessment method that answers management questions that are not network status oriented.

Third, the present study expands the multi-agent simulation theories to include more than one interaction dimension. Multi-agent simulation models are often limited to a simulation of a single dimension, (e.g. a two-dimensional grid space with moving dots, a social network space with interacting agents, etc.). However, to model real world situations, the simulation should be able to handle multiple dimensions (e.g. geospatially moving military units with social interactions based on command and control, transnational terrorist movements with internet social interactions, etc.). By using multiple interaction dimensions, analysts can see the adversarial behavior with more complete and nuanced pictures. This study creates a simulation model considering social and geospatial dimensions, thus providing for more complete simulation analyses of adversaries.

10.4. Technical Contributions

I developed and tested this intelligence analysis framework by implementing the theoretical ideas in an existing analysis program, *Organization Risk Analyzer* (ORA). First, the decision-making structure extractor in ORA examines the observed meta-network and generates three inferred social networks among agents (more precisely, decision makers, since the extracted networks are determined by regarding the agents as decision making entities). This function enables the interoperation with *Caesar III*, a decision-making structure and cognitive process analysis application. Also, the extracted structures can further analyzed by ORA's dynamic network analysis capability.

Second, the influence network generator in ORA assesses the organizational supports from the task completion perspective in management. The assessments are represented as an influence network, a type of Bayesian network. The generated influence network is also loadable by using *Pythia*, an influence network analysis program. The influence network and *Pythia* calculate the marginal probabilities of task completion likelihoods. This technical achievement also enables the faster generation of influence network which usually take very long subject matter experts' time.

Third, I developed a multi-agent simulation model, JDynet. JDynet is originally from Construct (Carley, 1991), but JDynet was significantly modified to accommodate the idea of operations research, rather than sociological concepts. With the modification, JDynetSpatial could handle the social and geospatial aspects of an organization. Also, JDynetSpatial could, in the more nuanced manner, estimate the mission completion timeline and organizational element transfers to complete the mission.

10.5. Empirical Contributions

Throughout this work, I applied the developed framework to the datasets about the 1998 U.S. Embassy Bombing Incidents in Kenya and Tanzania. By applying different approaches, I generated more sense-making analysis results compared to previous analysis practices, i.e. simple social network metric calculations.

This particular application results found that some key actors that were over- or under-estimated before. For example, *Anas al-Liby* was the task coordinator who had higher network metrics in the result sharing structure than in the original structure. *Al Owali* was the top critical actor in the observed structure and the information sharing structure. However, in the result sharing structure, *Fazul Abdullah Mohamed* had a higher dynamic network metric value than *Al Owali*.

The analysis results identified tasks that have low completion likelihood, such as *conceal bomb in car* and *provide money*, because the tasks are under-supported by the organization. In contrast, *review surveillance files*, *film videotape announcing martyrdom*, and *surveillance of possible targets* show high task completion likelihoods, indicating good organizational supports from adversaries. As the operational environment setting changes, *overall planning and execution* and *bomb preparation* showed big changes in the completion likelihood, which means that we can drop the completion likelihood by a wide margin if we are able to change the operation environment of the adversaries.

Simulations with only a social model shows that removing higher degree and betweenness agents in large number at the early stage would be effective. However, this may not be achievable in the real world. The simulation analysis identified bottleneck tasks, such as the *rent residence* task, that had the longest execution time across the tasks during the mission. The simulations identified the organizational element transfer networks among agents. There are agents, (e.g. *Wadih el-Hage*) who consistently appeared in the transfer network over time.

The social and geospatial model simulation suggests that the agents are segregated around the *Somalia, Pakistan, and Afghanistan* regions when the initial training and education happens because these regions are linked to training resources and regional expertise (e.g. weapons expertise at the Somalia training base). Afterwards, the agents move from the above regions to actual mission regions, *Tanzania and Kenya*. The identified key individual lists are partly different from the list of the social only model. The extended model indicates *Al Owali* is more important than the estimation from the social only model in the betweenness centrality perspective of agent-to-agent organizational element transfer networks. Previously, *Wadih el-Hage* was considered to be the most critical actor in the transfer network of the social only model.

More empirical analysis results are provided in Chapters 5, 6, 7 and 8. These computational results can be interpreted by human analysts with subject matter expertise, and the analysts can verify the plausibility of the computational results and determine whether or not to include them in their destabilization analysis report.

10.6. Big Picture

As human organizations become more complex and dynamic with technological and management innovations, we need a more sophisticated tool to analyze them. Human analysts can perform an insightful qualitative analysis of an organization, however they demand a computational tool to process their analyses more quickly and broadly. At the same time, they do not want to abandon their subject matter experience, wisdom, and instinct. Therefore, researchers have to provide answers to the following questions: 1) how to create a computational tool for this human oriented, uncertain domain; and 2) how to incorporate human wisdom into the process of computational analysis. Obviously, the researchers have to use the theories from the computational analysis fields (computer science, statistics, etc) as well as the human organization research fields (management, sociology, etc).

Then, the researchers providing such computational tools will have to produce theories and approaches to mitigate and integrate the two types of fields. This work is only a small demonstration of such a research fusion. Throughout this work, I created interfaces that mitigate two or more different analysis practices. Often, I expanded one theory among related theories, so that the chosen theory could take advantage of the other theories' merits. This theoretical expansion from interdisciplinary research 1) enables researchers to meet the real world demand for the computational tools; and 2) offers feedback on the original theories and facilitates the further development of individual theories.

This study helps human analysts in multiple ways. Now, the human analysts can handle bigger and more complex organizations with the support of an integrated computational analysis tool. At the same time, the human analysts can apply their wisdom to the process of the analysis. Finally, the human analysts can get more nuanced analysis results such as the adversaries' more nuanced behavior estimations, organizational supports for task executions, critical decision making structures hidden in an observed social network.

10.7. Future Research

This work still needs further validation, though the analysis models are designed to be rational and follow well-known qualitative analysis results. I suggest that there are two validation approaches for this analysis system and procedure. The first validation approach is validating the usability of this analysis framework[13]. Some analysts will see this system as a computational tool that substitutes their work previously done by hand. In that case, providing good services to the users is an important evaluation point. This can be done by deploying this system to real users

[13] The framework means the overall analysis procedure and system.

and obtaining their feedback. After getting their feedback, we can enhance the procedure and system further. Also, some of models may need to be adjusted according to users' requests. For example, analysts may want more factors to be included in the automated influence network generation. If this is the case, we can increase the value of this contribution by selectively following the analysts' requests.

The second validation approach involves validating the outcome of this analysis framework. This approach is already discussed in Chapter 9.5. Some analysts will see this system as a calibrated and automated prediction tool. First of all, this type of system, particularly analyzing social behavior, would not be accurate as the analysis system of electric circuits. However, human analysts may still want to see that this tool makes estimations that are either 1) observed in the past or 2) reasonable to accept. As discussed in Chapter 9.5, we need to apply this framework to more contained and better observable contexts (e.g. software companies, friendly forces, etc.). Then, we may obtain better datasets that can be input to the framework as well as solution sheet of the analysis answers. This validation will create many interesting research questions: optimizing analysis parameters with partial observation, comparing the simulated data to the real-world data, etc. It is my hope that my colleagues in this community or I will oversee this validation process.

Reference

Albert, R., Jeong, H. and Barabasi, A. L. (2000) Error and attack tolerance of complex networks, Nature, Vol 406, pp 378-382

Alberts, D. S. and Hayes, R. E. (2006) Understanding Command and Control, Department of Defense, CCRP

Allanach, J., Haiying T., Singh, S., Willett, P. and Pattipati, K. (2004) Detecting, tracking, and counteracting terrorist networks via hidden Markov models, Proceedings of IEEE Aerospace Conference, Vol. 5, pp 3246-3257

Arquilla, J. and Ronfeldt, D. (editors) (2001) Networks and Netwars: The Future of Terror, Crime, and Militancy. Santa Monica, Calif.: RAND, MR-1382-OSD. www.rand.org/ publications/ MR/MR1382/

Atran, S. (2008) Who Becomes a Terrorist Today?, Perspectives on Terrorism, Vol. II, Issue 5, pp 3-10

Backus, G. A. and Glass, R. J. (2006) An Agent-Based Model Component to a Framework for the Analysis of Terrorist-Group Dynamics, Sandia Report, SAND2006-0860P

Basile, M. (2004) Going to the Source: Why Al Qaeda's Financial Network Is Likely to Withstand the Current War on Terrorist Financing, Studies in Conflict and Terrorism, Vol. 27, Num. 3, pp. 169-185

Bergkvist, M., Davidson, P., Persson, J. A., and Ramstedt, L. 2004. A Hybrid Micro-Simulator for Determining the Effects of Governmental Control Policies on Transport Chains. Joint Workshop on Multi-Agent and Multi-Agent Based Simulation, New York, NY, Springer

Bernard, H. R., Killworth, P., Kronenfeld, D., and Sailer, L. (1984) The Problem of Informant Accuracy: The Validity of Retrospective Data, Annual Review of Anthropology, Vol. 13, pp. 495-517

Beissinger, M. R. (2002) Nationalist Mobilization and the Collapse of the Soviet State. Cambridge: Cambridge University Press.

Borgatti, S. P., Carley, K. M., and Krackhardt, D. (2006) On the robustness of centrality measures under conditions of imperfect data, Social Networks, Vol. 28, Issue 2, pp 124-136

Borgatti, S.P. (2003) Identifying sets of key players in a network, International Conference on Integration of Knowledge Intensive Multi-Agent Systems, pp 127-131

Brachman, J. (2008) Abu Yahya’s Six Easy Steps for Defeating al-Qaeda, Perspectives on Terrorism, Vol. I, Issue 5

Brachman, J. M. and McCants, W. F. (2006) Stealing Al-Qa'ida's Playbook, Combatting Terrorism Center Reports, US Military Academy at Westpoint, NY

Burke, J. (2004). Al Qaeda. The True Story of Radical Islam. London, Penguin.

Burton, R. M. (2003) Computational laboratories for organization science: Questions, validity and docking. Computational and Mathematical Organization Theory, Vol. 9, No. 2, pp 91-108.

Butts, C. T. (2008) Social network analysis: A methodological introduction, Asian Journal of Social Psychology, Vol. 11, Iss. 1, pp. 13-41

Byman, D. (2003) Al Qaeda as an adversary: Do we understand the enemy?, World Politics, Vol. 56, No. 1, pp. 139-163

Champagne, B., Cobb, W. B., Kaplan, S., and Morrison, D. (eds.) (2005) Anatomy of a Terrorist Attack: An In-Depth Investigation into the 1998 Bombings of the US Embassies in Kenya and Tanzania, Ridgway Center for International Security Studies, Issue 17, University of Pittsburgh, US

Child, J. (1972) Organizational Structure, Environment and Performance: The Role of Strategic Choice, Sociology, Vol. 6, No. 1, pp. 1-22

Cragin, K. and Gerwehr, S. (2005) Dissuading Terror-Strategic Influence and the Struggle Against Terrorism, Santa Monica: RAND

Cragrin, K., Chalk, P., Daly, S. A. and Jackson, B. A. (2007) Sharing the Dragon's Teeth - Terrorist Groups and the Exchange of New Technologies, Rand Corp., pp 11-13

Carley, K. M. (1997) Network Text Analysis: The Network Position of Concepts. Text Analysis for the Social Sciences. Ed. C. W. Roberts. Mahwah, NJ: Lawrence Erlbaum, 79-102.

Carley, K. M. and Lin, Z. (1997) A Theoretical Study of Organizational Performance under Information Distortion, Management Science, Vol. 43, No. 7, (Jul., 1997), pp. 976-997

Carley, K. M., Prietula, M. J. and Lin, Z. (1998) Design Versus Cognition: The interaction of agent cognition and organizational design on organizational performance, Journal of Artificial Societies and Social Simulation, vol. 1, no. 3

Carley, K. M., Lee, J. and Krackhardt, D. (2002) Destabilizing Networks, CONNECTIONS, Vol. 24, Num. 3, pp 79-92

Carley, K. M. and Kamneva, N. Y. (2004) A Network Optimization Approach for Improving Organizational Design, Carnegie Mellon University, School of Computer Science, Institute for Software Research International, CASOS Technical Report CMU-ISRI-04-102.

Carley, K. M. (1991) A Theory of Group Stability, American Sociological Review, Vol. 56, No. 3, pp. 331-354

Carley, K. M. (2004) Estimating Vulnerabilities in Large Covert Networks, In Proceedings of the 9th International Command and Control Research and Technology Symposium, Conference held at Loews Coronado Resort, CA. Evidence Based Research, Vienna, VA.

Carley, K. M. (2006a) Destabilization of covert networks, Computational & Mathematical Organization Theory, Vol. 12, Issue 1, pp 51-66

Carley, K. M. (2006b) A Dynamic Network Approach to the Assessment of Terrorist Groups and The Impact of Alternative Courses of Action, In Visualising Network Information. Meeting Proceedings RTO-MP-IST-063. Neuilly-sur-Seine, France: RTO, 12 - 14. Available from: http://www.vistg.net/documents/IST063_PreProceedings.pdf

Cohen, M. D., March, J., and Olsen, J. P. (1972) A Garbage Can Model of Organizational Choice. Administrative Science Quarterly, 17(1): 1-25.

Cohen, R., Erez, K., Ben-Avraham, D. and Havlin, S. (2000) Resilience of the Internet to Random Breakdowns, Phys. Rev. Lett., Vol. 85, No. 21, pp 4626-4628

Combating Terrorism Center (or CTC) (2007a) CRACKS IN THE FOUNDATION: LEADERSHIP SCHISMS IN AL-QA'IDA FROM 1989-2006, Harmony Project Reports, US Military Academy at Westpoint, NY

Combating Terrorism Center (or CTC) (2007b) Al-Qa'ida's (mis)Adventures in the Horn of Africa, Harmony Project Reports, US Military Academy at Westpoint, NY

Combating Terrorism Center (or CTC) (2007c) Harmony and Disharmony: Exploiting Al-Qa'ida's Organizational Vulnerabilities, Harmony Project Reports, US Military Academy at Westpoint, NY

Crenshaw, M. (1981) The Causes of Terrorism, Comparative Politics, Vol. 13, No. 4., pp. 379-399.

Davis, J. P., Bingham, C. B., and Eisenhardt, K. M. (2006) Developing Theory Through Simulation Methods, Academy of Management Review, forthcoming

Defense Advanced Research Projects Agency (DARPA) (2005) Integrated Battlefield Command (IBC) Program Solicitation Briefing. [Online] Available: http://www.darpa.mil/sto/solicitations/IBC/.

Dekker, A. (2002) Applying Social Network Analysis Concepts to Military C4ISR Architectures, CONNECTIONS, Vol. 24, Num. 3, pp 93-103

Elledge, M. G. (2003) The Global War on Terrorism: A Policy of Containment, ARMY COMMAND AND GENERAL STAFF COLL FORT LEAVENWORTH KS SCHOOL OF ADVANCED MILITARY STUDIES, Report No. A728514, 22 MAY 2003

Elliott, E. and Kiel, L. D. (2003) A complex systems approach for developing public policy toward terrorism: an agent-based approach, Chaos, Solitons & Fractals, Vol. 20, Issue 1, April 2004, pp 63-68

Epstein, J., Steinbruner, J. D., and Parker, M. T. (2001) Modeling Civil Violence: An Agent-Based Computational Approach. Washington, D.C., Center of Social and Economic Dynamics, Brookings Institute.

Farley, J. D. (2003) Breaking Al Qaeda cells: A mathematical analysis of counterterrorism operations (A guide for risk assessment and decision making). Studies in Conflict & Terrorism, 26, pp 399-411.

Farley, J. D. (2007) Toward a Mathematical Theory of Counterterrorism, The Proteus Monograph Series, Vol. 1, Issue 2

Fellman, P. V., Sawyer, D. and Wright, R. (2003) Modeling Terrorist Networks - Complex Systems and First Principles of Counter-Intelligence, Proceedings of the NATO Conference on Central Asia: Enlargement, Civil Military Relations, and Security, Kazach American University/North Atlantic Treaty Organization (NATO) May 14-16, 2003

Felter J. and Fishman, B. (2007) Al-Qai'da's Foreign Fighters in Iraq, Harmony Project Reports, US Military Academy at Westpoint, NY

Fishman, B. (2006a) After Zarqawi: The Dilemmas and Future of Al Qaeda in Iraq, The Washington Quarterly, Vol. 29, Num. 4, pp. 19-32.

Fishman, B. (2006b) Al-Qa'ida's Spymaster Analyzes the U.S. Intelligence Community, Combatting Terrorism Center Reports, US Military Academy at Westpoint, NY

Fulmer W. E. (2000) Shaping the Adaptive Organization: Landscapes, Learning, and Leadership in Volatile Times. AMACOM, New York.

Galbraith, J. R. (1973) Designing Complex Organizations, Addison-Wesley Longman Publishing Co., Inc. Boston, MA, USA

Goolsby, R. (2006) Combating terrorist networks: An evolutionary approach, Computational Mathematical Organizion Theory, Vol. 12, Num. 1, pp 7-20

Grant, G. (2005) Inside Iraqi Insurgent Cells: Captured Terrorist Intel May Help Defeat IED's. Defense News 20:1+ August 1

Grant, R. M. (1996) Prospering in Dynamically-Competitive Environments: Organizational Capability as Knowledge Integration, Organization Science, Vol. 7, No. 4, pp. 375-387

Hoffman, B. (1998) Inside Terrorism, London: St. Andrew's University Press

Hufbauer, G. C., Schott, J. J. and Oegg, B. (2001) Using Sanctions to Fight Terrorism, International Economics Policy Briefs, Vol. 11, Num. 1, pp 1-19

Hutchinson W. & Warren M. (2002) 'Information Warfare: Using the viable system model as a framework to attack organisations', Australian Journal of Information Systems, vol.9, no.2, pp. 67-74.

Jagatic, T., Johnson, N., Jakobsson, M. and Menczer, F. (2007) Social Phishing, Communications of the ACM, Vol 50, Iss 10, pp 94-100

Jenkins, B. (2002) Countering al Qaeda, Santa Monica: RAND, 5.

Kansal, S. K., AbuSharekh, A. M. and Levis, A. H. (2007) Computationally Derived Models of Adversary Organizations, IEEE Symposium on Computational Intelligence in Security and Defense Applications, Apr 1-5, pp 92-99

Keck, S. L. and Tushman, M. L. (1993) Environmental and Organizational Context and Executive Team Structure, The Academy of Management Journal, Vol. 36, No. 6, pp. 1314-1344

Krackhardt, D. and Carley, K. M. (1998) A PCANS Model of Structure in Organization, In Proceedings of the 1998 International Symposium on Command and Control Research and Technology, pp 113-119

Krackhardt, D. (1987) Cognitive Social Structures, Social Networks, Vol. 9, pp. 109-134

Krebs, V. E. (2002) Mapping Networks of Terrorist Cells, CONNECTIONS, Vol. 24, Num. 3, pp 43-52

Levis, A. H. (2005). Executable Models of Decision Making Organizations. in Organizational Simulation. William B. Rouse and Ken Boff. Eds. Wiley. NY

Louie, M. A., and Carley, K. M. (2006) The Role of Multi-Agent Models of Socio-Political Systems in Policy, working paper, CASOS, Carnegie Mello University

Lin, Z. and Carley, K. M. (2003) Designing stress resistant organizations: Computational theorizing and crisis applications. Boston, MA: Kluwer Academic Publishers.

Malka, H. (2005) Forcing Choices: Testing the Transformation of Hamas, The Washington Quaterly, Vol. 28, No. 4, pp. 37-53

March, J. G. (1991) Exploration and Exploitation in Organizational Learning. Organization Science, 2(1): pp 71-87.

Marion, R. and Uhl-Bien, M. (2003) Complexity Theory and Al-Qaeda: Examining Complex Leadership, Emergence, Vol. 5, Issue 1, pp 54-76

Mathews, K. M., White, M. C. and Long, R. G. (1999) Why Study the Complexity Sciences in the Social Sciences?, Human Relations, Vol. 52, Number 4, pp 439-462

Mayntz , R. (2004) Organizational Forms of Terrorism: Hierarchy, Network, or a Type sui generis?, Max-Planck-Institut fur Gesellschaftsforschung Koln, MPIfG Discussion Paper 04/4,

McCants, W., Brachman, J., and Felter, J. (2006) The Militant Ideology Atlas, Combatting Terrorism Center Reports, US Military Academy at Westpoint, NY

McFate, M. (2005a) The Military Utility of Understanding Adversary Culture. Joint Force Quarterly, Issue 38, 2005

McFate, M. (2005b) Iraq: The Social Context of IEDs. Military Review, May-June, 2005.

McIllwain, J. S. (1999) Organized crime: A social network approach, Crime, Law and Social Change, Vol 32. Num 4., pp 301-323

Midlarsky, M. I., Crenshaw, M. and Yoshida, F. (1980) Why Violence Spreads: The Contagion of International Terrorism, International Studies Quarterly, Vol. 24, No. 2., pp. 262-298.

Moon, I. and Carley, K. M. (2006) Estimating the near-term changes of an organization with simulations, AAAI Fall Symposium, Arlington, VA, Oct 12-15

Moon, I. and Carley, K. M. (2007a) Modeling and Simulation of Terrorist Networks in Social and Geospatial dimensions, IEEE Intelligent Systems, Vol. 22, No. 5, pp 40-49

Moon, I. and Carley, K. M. (2007b) Self-Organizing Social and Spatial Networks under What-if Scenarios, AAMAS, Honolulu, Hawaii, May 14-18

Moon, I. and Carley, K. M. (2007c) Evolving Multi-Agent Network Structure with Organizational Learning, SpringSim'07, Norfolk, VA, Mar 25-29

Moon, I. and Carley, K. M. (2007d) Locating Optimal Destabilization Strategies, ICCRTS, Newport, RI, Jun 19-21

Moloney, E. (2002) A secret history of the IRA. New York: Norton.

Morel, B. and Ramanujam, R. (1999) Through the Looking Glass of Complexity: The Dynamics of Organizations as Adaptive and Evolving Systems, Organization Science, Vol. 10, No. 3, Special Issue: Application of Complexity Theory to Organization Science

Morris, M. F. (2005) Al-Qaeda as Insurgency, Strategy Research Project, Carlisle Barracks: U.S. Army War College, 18 March 2005, 14

Nonaka, I. (1994) A Dynamic Theory of Organizational Knowledge Creation, Organization Science, Vol. 5, No. 1, pp. 14-37

Perrow, C. (1967) A Framework for the Comparative Analysis of Organizations, American Sociology Review, Issue. 32, pp 194-208

Raab, J. and Milward, H. B. (2003) Dark networks as problems, Journal of Public Administration Research and Theory, Vol. 13, pp 413-439

Rabasa, A., Chalk, P., Cragin, K., Daly, S., Heather S., Karasik, T. W., O'Brien, K. A. and Rosenau, W. (2006) Beyond al-Qaeda Part 1., Rand Corp., pp 27-29

Reich, W. (1990) The Origins Of Terrorism : Psychologies, Ideologies, Theologies, States Of Mind, New York : Cambridge University Press.

Reminga, J. and Carley, K. M. (2004) ORA:Organization Risk Analyzer, Tech Report, CMU-ISRI-04-106, CASOS. Carnegie Mellon University. Pittsburgh PA, http://www.casos.cs.cmu.edu/projects/ora/index.html

Ren, Y., Carley, K. M. and Argote, L. (2001) Simulating the role of transactive memory in group training and performance. Pittsburgh, PA: Carnegie Mellon University

Riedel, B. (2007) Al Qaeda Strikes Back, Foreign Affairs, May/June, pp. 27

Rosenau, W. (2005) Al Qaida Recruitment Trends in Kenya and Tanzania, Studies in Conflict and Terrorism, Vol. 28, Num. 1, pp 1-10

Sageman, M (2004) Understanding terror networks, Philadelphia: University of Pennsylvania Press

Schreiber, C. (2006) Human and Organizational Risk Modeling: Critical Personnel and Leadership in Network Organizations, PhD Thesis, Carnegie Mellon University, CMU-ISRI-06-120

Schreiber, C. and Carley, K. M. (2004a) Construct - a multi-agent network model for the co-evolution of agents and socio-cultural environments, Carnegie Mellon University, School of Computer Science, Institute for Software Research International, Technical Report CMU-ISRI-04-109

Schreiber, C. and Carley, K. M. (2004b) Going beyond the Data: Empirical Validation Leading to Grounded Theory, Computational and Mathematical Organization Theory, 10, pp 155-164

Shevade, S. K., Keerthi, S. S. , Bhattacharyya, C. and Murthy, K. R. K. (1999) Improvements to SMO Algorithm for SVM Regression. Technical Report CD-99-16, Control Division Dept of Mechanical and Production Engineering, National University of Singapore.

Silverman, B. G., Bharathy, G., Nye, B. and Eidelson, R. J. (2007) Modeling factions for “effects based operations”: part I-leaders and followers, Computational & Mathematical Organization Theory, Vol. 13, Num. 4, pp 379-406

Silvia Covacio (2003) Misinformation: Understanding the Evolution of Deception, Informing Science, June, 2003

Smola, A. J. and Scholkopf, B. (1998) A Tutorial on Support Vector Regression, NeuroCOLT2 Technical Report Series - NC2-TR-1998-030.

Stern, J. (1999) The Ultimate Terrorists, Harvard University Press Cambridge, MA, 1999

Stern, J. (2003a) The Protean Enemy, Foreign Affairs, 82(4), pp 27-40.

Stern, J. (2003b) Terror in the name of God:Why religious militants kill. New York: HarperCollins.

Stern, J. (2000) Pakistan's Jihad Culture, Foreign Affair. November/December, 79:6, pp. 115-26.

Thompson, J. D. (1967) Organizations in action. New York: McGraw-Hill.

Thompson, M. J. (2005) Breaking the Proconsulate: A New Design for National Power, Parameters 35, no. 4, pp 62-75

Urry, J. (2002) The Global Complexities of September 11th, Theory, Culture & Society, Vol. 19, No. 4, pp 57-69

Vego, M. N. (2006) Effects-Based Operation: A Critique, Joint Forces Quarterly, Issue. 41, pp 51-67

WashingtonPost (2006) Insurgent Leader Al-Zarqawi Killed in Iraq, Washington Post Foreign Service, Thursday, Jun. 8, http://www.washingtonpost.com/wp-dyn/content/article/2006/06/08/AR2006060800114.html

Wagenhals, L. W. and Levis, A. H. (2007) Course of Action Analysis in a Cultural Landscape Using Influence Nets, IEEE Symposium on Computational Intelligence in Security and Defense Applications, Apr 1-5, pp 116-123

Wagenhals, L. W., Levis, A. H. and McCrabb, M. (2003) Effects Based Operations: a Historical Perspective for a Way Ahead, Proc. 8th Int'l Command and Control Research and Technology Symposium, NDU

Wikipedia (2008) Nortern Ireland Peace Process, http://en.wikipedia.org/wiki/Northern_Ireland_peace_process

Weber, M. (1978) Economy and society, University of California Press Berkeley

Zhou, Y., Reid, E., Qin, J., Chen, H. and Lai, G. (2005) US domestic extremist groups on the Web: link and content analysis, IEEE Intelligent Systems, Vol. 20, Issue 5, pp. 44-51

11. Appendix - Scalability Analysis

This chapter analyzes the scalability of the introduced approaches. The introduced new approaches utilize various computational components, and these computational parts require more computations as the organizational size grows. For instance, our investigation scope is limited to a task-oriented organization with hundreds of agents. This is a good enough scale for analyzing a medium sized company, a regiment, or a not such a big sized terrorist group. If the organizational sizes are thousands of agents, then the organizational boundary might be defined from the sociological perspective, not from the task oriented perspective. The purpose of this scalability analysis is demonstrating that the approaches can handle task-oriented organizations with hundreds of agents.

11.1. Scalability from the human cognitive perspective

Humans have limitations in recognizing the complex organizational structure. For example, Bernard et al. (1984) points out that humans usually reports inaccurate data when they reports events, relations, assignments, etc. This incorrect perception of social structure is also noted in social networks (Krackhardt, 1987). Therefore, understanding a complex organizational structure in this thesis is very difficult for human analysts without proper tools. Furthermore, designing intervention strategies against this complex structure will make human analysts rely on their instincts if we do not provide proper tools to them. Unfortunately, I could not find a literature that reports how many nodes and which topologies are the boundary of human cognition for understanding the network. However, the above literatures emphasize the necessity of tools for analyzing complex organizations.

On the other hand, there are opinions that the analysis tools become just black boxes when the inputs and models go beyond human analysts' cognition level. For example, a human analyst may understand and design an organization with 10 individuals by his intuition without a computational tool. The analyst may perform his analysis better with a computational tool, so the analyst regards the tool as "a smart calculator" that performs a computational analysis that the analyst can do himself, yet in the faster and more accurate manner. Also, in this case, the human analyst can track down the problem or doubts about the computation result from the input and the tool. However, this problem resolution becomes impossible if his analysis target consisted of 1000 men unless the analyst thoroughly understands the models inside the tool and has confidence that the tool and model is verified.

This discussion leads an interesting question: what is the organization size threshold for a human analyst when the analyst tries to understand the complex organization? To my knowledge, there is no study answering the above question directly. Also, from the computational analysis tool usability perspective, there is another question: when and what point do human analysts feel comfortable for applying this type of computation analysis tools to his analysis? If this usability is dependent on the size of an organizational structure, the size range for maximizing the usability would be the critical organization size range that we make our tools operable within. I think that this issue is often brought upon by analysts actually using this tool. However, my literature review finds that there is no critical and direct study about this issue. I believe that this should be a future research to make this type of tools and approaches more acceptable by actual users.

11.2. Scalability from the technical run time perspective

Particularly, I analyze the scalability from the two viewpoints. First, I run the approaches multiple times and empirically demonstrate the approaches can handle an organization with more than 500 agents. Second, I analyze the worst case run time with a big-Oh notation, which demonstrates the theoretical scalability.

The empirical experiments are done in the below computational environment.

- Intel® Core™2 Duo CPU T9300 @ 2.50GHz
- 4030MB RAM
- 64 Bit Operating System
- Java Virtual Machine 1.6.0
- Non threaded analysis runs

The below analyses regard |A| as the number of agents, |AA| as the number of edges in the Agent-to-Agent social network, |T| as the number of tasks, |AT| as the number of edges in the Agent-to-Task assignment network, |TT| as the number of edges in the Task-to-Task dependency network, |RT| as the number of edges in the Resource-to-Task requirement network, |KT| as the number of edges in the Knowledge-to-Task requirement network, and |MN| as the number of edges in the meta network.

11.3. Scalability of decision making structure analysis

Empirical analysis time: Table 11-1 shows the empirical running time of the decision making structure analyses applied to three different datasets introduced in Ch. 4. With more than 500 agents, it takes only a little more than 7 seconds to generate the structure. However, this analysis time does not include any of subsequent social network analysis. Also, this result depends on the density of social networks and the number of tasks involved.

Table 11-1 Run time of decision making structure analyses (10 replications)

Dataset	Number of Agents	Number of Nodes	Number of Edges	Meta Network Density	Avg. Run Time (Sec)	Std. Run Time (Sec)
Kenya	16	49	148	0.117	1.286	0.077
Tanzania-Kenya	18	75	369	0.127	2.885	0.080
Global	597	2008	77298	0.031	2173.001	67.349

Big-Oh analysis: There are three major components in the decision making structure analysis. The major components are 1) information sharing structure extraction, 2) result sharing structure extraction and 3) command interpretation structure extraction. I analyze the Big-Oh of the three components.

The Big-Oh analysis for the entire decision making structure analysis is the dominant term of the below three Big-Oh analysis results from three sub components.

These Big-Oh analyses are valid under an assumption that 1) the agents do not have any required organizational elements (resources or expertise) to their tasks and 2) the shortest path finding time costs the worst time of Dijkstra algorithm run time.

$$
\begin{aligned}
&(\text{Run Time of Information Sharing Structure Extraction})\\
&\qquad = (\text{Number of Agents}) \times (\text{Assigned Tasks})\\
&\qquad \times (\text{Required Expertise and Resources})\\
&\qquad \times \begin{pmatrix}\text{Run Time of Shortest Path Findings from an Assigned Agent}\\ \text{to the Required Element through social networks}\end{pmatrix}\\
&\qquad = O\left(|A||T|\frac{|RT| + |KT|}{|T|}|AA| \log|A|\right) = O(|A|(|RT| + |KT|)|AA| \log|A|)
\end{aligned}
$$

$$
\begin{aligned}
&(\text{Run Time of Result Sharing Structure Extraction})\\
&\qquad = (\text{Number of Agents}) \times (\text{Assigned Tasks}) \times (\text{Average Num.of Next Tasks})\\
&\qquad \times (\text{Average Num. of Assigned Agents to a Next Task}) = O\left(|A||T|\frac{|TT|}{|T|}\frac{|AT|}{|T|}\right)\\
&\qquad = O\left(\frac{|A||AT||TT|}{|T|}\right)
\end{aligned}
$$

$$
\begin{aligned}
&(\text{Run Time of Command Interpretation Structure Extraction})\\
&= (\text{Number of Agents}) \times (\text{Number of Agnet Neighbor from Outgoing Links})\\
&\times (\text{Run Time of Shortest Path Findings from an Agent to a Outgoing neighbor agent to Check the cycle})\\
&= O\left(|A|\frac{|AA|}{|A|}|AA| \log|A|\right) = O(|AA|^2 \log|A|)
\end{aligned}
$$

11.4. Scalability of influence network analysis

The influence network analysis has two analysis parts. One is generating an influence network, and the other is evaluating an influence network. The run-time of the evaluation can take different amounts of time according to the used evaluation method. I use the CAST algorithm (Rosen and Smith, 1996), so I analyze the run time of the CAST logic.

Empirical analysis time: Table 11-2 shows the empirical running time of the influence network analyses applied to three different datasets introduced in Ch. 4.

Table 11-2 Run time of influence network analyses (10 replications)

Dataset	Influence network generation		Influence network evaluation	
	Avg. Run Time (Sec)	Std. Run Time (Sec)	Avg. Run Time (Sec)	Std. Run Time (Sec)
Kenya	0.076	0.015	0.036	0.029
Tanzania-Kenya	0.373	0.047	0.126	0.040
Global	303.135	48.892	257.666	1.310

Big-Oh analysis: There are two major components in the influence network analysis. The two components are 1) generating an influence network and 2) evaluating an influence network.

The overall Big-Oh analysis result for the influence network analysis is the dominant term of the below two Big-Oh analysis results.

1) Generating an influence network

I use the Dijkstra algorithm to figure out the involvement of a task to a task dependency network for a task of interest. Specifically, I examine the shortest path from a task to the task of interest. Also, the assessment for various factors of a single task takes almost constant time because the function can look up the neighbor of the task nodes in the meta-network in constant time. In this analysis, I assume that every task is involved in the task dependency network of the task of interest.

$$
\begin{aligned}
&(\text{Run Time of Influence Network Generation}) \\
&\quad = (\text{Number of tasks}) \times (\text{Figuring out the involvement of a task}) \\
&\quad + (\text{Number of involved tasks}) \\
&\quad \times \{(\text{Task prerequisite assignment configuration}) \\
&\quad + (\text{Personnel sufficiency configuration for task}) \\
&\quad + (\text{Task complexity assessment}) + (\text{Task importance assessment}) \\
&\quad + (\text{Available expertise assessment}) + (\text{Accessible resource assessment})\} \\
&\quad = O(|T||TT|\log|T|) + O(|T| \times \text{Constant}) = O(|T||TT|\log|T|)
\end{aligned}
$$

2) Evaluating an influence network

When evaluating an influence network, each influence network need an approximated conditional probability table which has 2^X different cases with X number of connected parent nodes.

$$\begin{aligned}&(\text{Run Time of Evaluating an Influence Network})\\&\quad= (\text{Number of task completion node})\\&\quad\times 2^{\{(\text{Previous task completion node})+(5\text{ assessment nodes})\}} = O\left(|T| \times 2^{\left(\frac{|TT|}{|T|}+5\right)}\right)\\&\quad= O(|T| \times 2^{\frac{|TT|}{|T|}})\end{aligned}$$

11.5. Scalability of multi-agent social only model

The run time of a multi-agent simulation model differs a lot depending on users' parameters, i.e. the number of simulation time-step. I simulate for 1000 time steps for empirical analysis. All the other parameters use the default value which is listed in Table 7-1 and Table 8-1.

Empirical analysis time: Table 11-3 shows the empirical running time of the influence network analyses applied to three different datasets introduced in Ch. 4.

Table 11-3 Run time of multi-agent social only model simulations (10 replications)

	Prior Simulation		Actual Simulation		Post Simulation	
Dataset	Avg. Run Time (Sec)	Std. Run Time (Sec)	Avg. Run Time (Sec)	Std. Run Time (Sec)	Avg. Run Time (Sec)	Std. Run Time (Sec)
Kenya (400 time steps)	0.003	0.005	0.728	0.078	0.052	0.011
Tanzania-Kenya (2500 time steps)	0.031	0.002	5.421	0.309	1.082	0.124
Global (2000 time steps)	39.925	7.050	6981.723	1089.270	956.231	108.230

Big-Oh analysis: The agent interaction time is the dominant factor in the run-time of multi-agent simulations. The output configuration and generation takes much longer time than the actual simulation time. However, this output time depends on the performance of file system, XML parsing package performance, etc, so there are variables that I do not have information about. However, I can analyze the actual simulation time (Average Run Time for Actual Simulation). Below is the analysis of the actual simulation time.

$$
\begin{aligned}
&(\text{Run Time of Multiagent Social Only Simulation}) \\
&\quad = (\text{Number of Timestep}) \times (\text{Number of Agents}) \\
&\quad \times (\text{Run Time of Interaction of a single agent}) \\
&\quad = O(|\text{Timestep}||A| \\
&\quad \times \{(\text{Handling transactive memory}) \\
&\quad + (\text{Resource and Expertise Handling considering AR and AK}) \\
&\quad + (\text{Task Execution consider AT, RT, KT and TT})\}) \\
&\quad = O\left(|\text{Timestep}||A| \times (\text{Constant} + \frac{|AR| + |AK| + |AT| + |RT| + |KT| + |TT|}{|A|}\right) \\
&\quad \cong O(|\text{Timestep}||\text{MN without location related nodes and links}|)
\end{aligned}
$$

11.6. Scalability of multi-agent social and geospatial model

The run time of the social and geospatial model takes longer time than the execution of the social only model. Though this addition is just an extension of agent behavior, it changes the characteristic of run time because of more inputs and outputs particularly in the post simulation process time. I simulate for 1000 time steps for empirical analysis. All the other parameters use the default value which is listed in Table 7-1 and Table 8-1.

Empirical analysis time: Table 11-4 shows the empirical running time of the influence network analyses applied to three different datasets introduced in Ch. 4.

Table 11-4 Run time of multi-agent social and geospatial model simulations (10 replications)

	Prior Simulation		Actual Simulation		Post Simulation	
Dataset	Avg. Run Time (Sec)	Std. Run Time (Sec)	Avg. Run Time (Sec)	Std. Run Time (Sec)	Avg. Run Time (Sec)	Std. Run Time (Sec)
Kenya (400 time steps)	0.002	0.001	0.715	0.026	0.061	0.013
Tanzania-Kenya (2500 time steps)	0.049	0.004	5.816	0.334	1.300	0.088
Global (2000 time steps)	63.119	46.628	7491.853	3893.452	1071.200	6420.653

Big-Oh analysis: The agent interaction and relocation time is the dominant factor in the run-time of multi-agent simulations. The output configuration and generation takes much longer time than the actual simulation time as in the run time of the social only model, see Ch. 10.3. I analyze the actual simulation time (Average Run Time for Actual Simulation). Below is the analysis of the actual simulation time.

$$
\begin{aligned}
&(\text{Run Time of Multiagent Social and Geospatial Simulation}) \\
&\qquad = (\text{Number of Timestep}) \times (\text{Number of Agents}) \\
&\qquad \times \{(\text{Run Time of Interaction of a single agent}) \\
&\qquad + (\text{Run Time of Relocation of a single agent}) \\
&\qquad = O(|\text{Timestep}||A| \\
&\qquad \times \{(\text{Handling transactive memory}) \\
&\qquad + (\text{Resource and Expertise Handling considering AR and AK}) \\
&\qquad + (\text{Task Execution consider AT, RT, KT, TLand TT}) \\
&\qquad + (\text{Relocation to a neighbor location}) \\
&\qquad + (\text{Location transactive memory handling}, \text{RL}, \text{KL})\}) \\
&\qquad = O\Bigg(|\text{Timestep}||A| \times (\text{Constant} \\
&\qquad + \frac{|AR| + |AK| + |AT| + |RT| + |KT| + |TT| + |TL| + |RL| + |KL|}{|A|} + \frac{|LL|}{|L|}\Bigg) \\
&\qquad \cong O(|\text{Timestep}||MN| + \frac{|A||LL|}{|L|})
\end{aligned}
$$

11.7. Summary of the technical scalability analysis

I showed the scalability of the analysis components theoretically and empirically. The theoretic big-Oh analysis suggests that the analysis scalability depends on the number of nodes and links in a meta-network. Hence, I summarize the relation between the number of nodes and links and the big-Oh analysis in Table 11-5. While reading Table 11-5, it should be noted that I did not considered a simultaneous change of node and link numbers. For example, if the number of agents increases, it is very likely to see the increase in the number of agent-to-agent network and meta-network. However, such changes are not considered in Table 11-5. This type of changes is subject to the nature, i.e. topology or organizational work relation tightness, of the observed organization.

Table 11-5 Summary of scalability analysis, relation between the number of nodes and links in a meta-network and the big-Oh analysis result, for decision making structure analysis, I show the dominating term out of three sub-components.

Linear increase of number of nodes, links, or parameters	Decision making structure analysis	Influence Network analysis: generation phase	Influence Network analysis: evaluation phase	Multi-agent simulation: social only model	Multi-agent simulation: social and geospatial model
Agents	Linear	Doesn't Change	Doesn't Change	Doesn't Change	Linear
Tasks	Doesn't Change	Linear	Linear	Doesn't Change	Doesn't Change
Locations	Doesn't Change	Doesn't Change	Doesn't Change	Doesn't Change	Doesn't Change

Agent-to-Agents	Square	Doesn't Change	Doesn't Change	Linear	Linear
Agent-to-Tasks	Linear	Doesn't Change	Doesn't Change	Linear	Linear
Resource-to-Tasks	Linear	Doesn't Change	Doesn't Change	Linear	Linear
Expertise-to-Tasks	Linear	Doesn't Change	Doesn't Change	Linear	Linear
Task-to-Tasks	Linear	Linear	Exponential	Linear	Linear
Location-to-Location	Doesn't Change	Doesn't Change	Doesn't Change	Doesn't Change	Linear
Meta-network links	Square	Linear	Exponential	Linear	Linear
Simulation Timestep	Doesn't Change	Doesn't Change	Doesn't Change	Linear	Linear

12. Appendix – the 1998 U.S. Embassy bombing incident in Kenya

I apply the same approach to the 1998 U.S. Embassy bombing incident in Kenay dataset (see Ch. 4.3). Below is the analysis results corresponding to the results of the main chapters.

12.1. Decision making structure analysis

Figure 12-1 visualizes the extracted three decision making structures. As expected, the information sharing looks similar to the original social network, but the result sharing is very different from the original network. The command interpretation structure is very trimmed version of the observed social network.

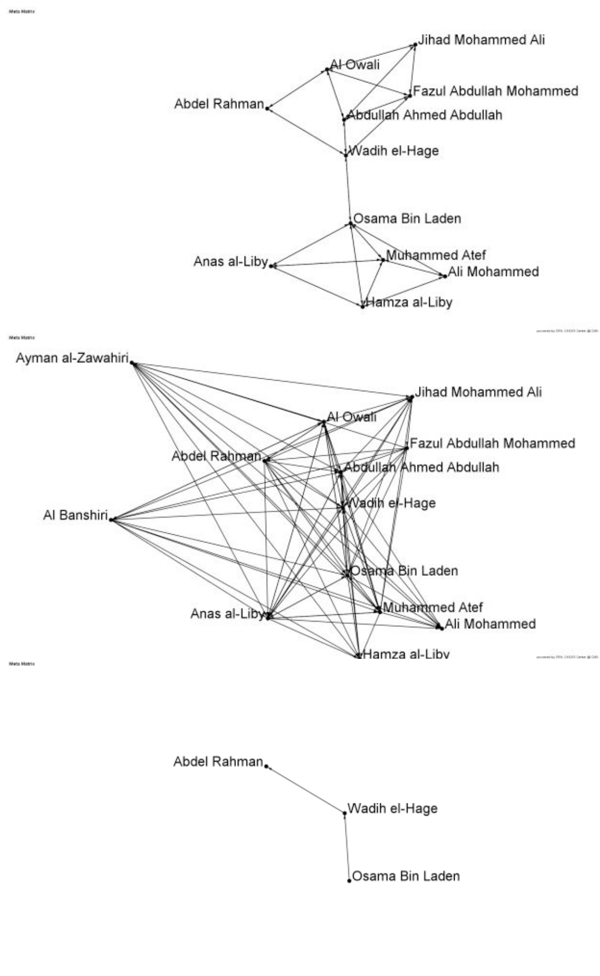


Figure 12-1 Three extracted decision making structures (Top) Information Sharing, (Middle) Result Sharing, (Bottom) Command Interpretation

Table 12-1 and Table 12-2 show the correlation between the observed social network and the decision making structures. The result sharing structure is not close to the observed social network while the information sharing structure is similar to the observed social network. This means that human analysts can obtain a new information by pulling out the result sharing structure.

Table 12-1 QAP correlation and other distance metrics between the observed structure and the extracted decision making structures. (IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

	CI	IS	RS
Correlation	0.226	0.844	0.174
Significance	0.010	0.000	0.070
Hamming Distance	32.000	10.000	81.000
Euclidean Distance	5.657	3.162	9.000

Table 12-2 regression results. The dependent network is the observed meta-network, and the independent networks are the extracted meta-network. (R-Squared = 0. 717)

Variable	Coef	Std.Coef	Sig.Y-Perm	Sig.Dekker
Constant	0.019		0.000	
CI	0.207	0.054	0.310	0.030
IS	0.789	0.844	0.000	0.000
RS	-0.030	-0.041	0.370	0.220

Table 12-3 suggests the top individuals from the observed and the extracted structures. With the observed social network, *Al Owali* seems to have the highest degree centrality. However, when considering the embedded decision making structure, *Osama Bin Laden* (in the information sharing), *Muhammed Atef* (in the result sharing) and *Wadih el-Hage* (in the command interpretation) have the highest degree centrality. These new important actors imply that there are hidden key players in this network if we consider its decision making structure for key task execution.

Table 12-3 Top three individuals from five metrics and four structures (OBS=observed meta-network, IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

Measure	Structure	Rank 1	Rank 2	Rank 3
Total Degree Centrality	OBS	Al Owali	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah
	IS	Osama Bin Laden	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah
	RS	Muhammed Atef	Abdullah Ahmed Abdullah	Osama Bin Laden
	CI	Wadih el-	Osama Bin Laden	Abdel Rahman

Measure	Structure	Rank 1	Rank 2	Rank 3
		Hage		
Betweenness Centrality	OBS	Al Owali	Abdel Rahman	Wadih el-Hage
	IS	Wadih el-Hage	Osama Bin Laden	Fazul Abdullah Mohammed
	RS	Al Owali	Jihad Mohammed Ali	Fazul Abdullah Mohammed
	CI	Wadih el-Hage	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah
Eigenvector Centrality	OBS	Osama Bin Laden	Muhammed Atef	Hamza al-Liby
	IS	Osama Bin Laden	Hamza al-Liby	Muhammed Atef
	RS	Muhammed Atef	Abdullah Ahmed Abdullah	Osama Bin Laden
	CI	Wadih el-Hage	Osama Bin Laden	Abdel Rahman
Cognitive Demand	OBS	Al Owali	Jihad Mohammed Ali	Ali Mohammed
	IS	Al Owali	Ali Mohammed	Wadih el-Hage
	RS	Al Owali	Abdel Rahman	Wadih el-Hage
	CI	Al Owali	Ali Mohammed	Wadih el-Hage
Communication	OBS	Anas al-Liby	Abdel Rahman	Osama Bin Laden
	IS	Anas al-Liby	Abdullah Ahmed Abdullah	Osama Bin Laden
	RS	Anas al-Liby	Abdullah Ahmed Abdullah	Osama Bin Laden
	CI	Anas al-Liby	Abdullah Ahmed Abdullah	Osama Bin Laden

Figure 12-2 displays the discrepancy between the observed social network structure and the extracted decision making structures (See Table 12-4 for ID matching with real names). *Osama Bin Laden* (A3) and *Wadih el-Hage* (A4) are the two terrorists with high betweenness centrality in the information sharing structure. These two actors are not considered as key betweenness centrality players in the observed structure. This means that the two actors are hidden information broker from the mission execution.

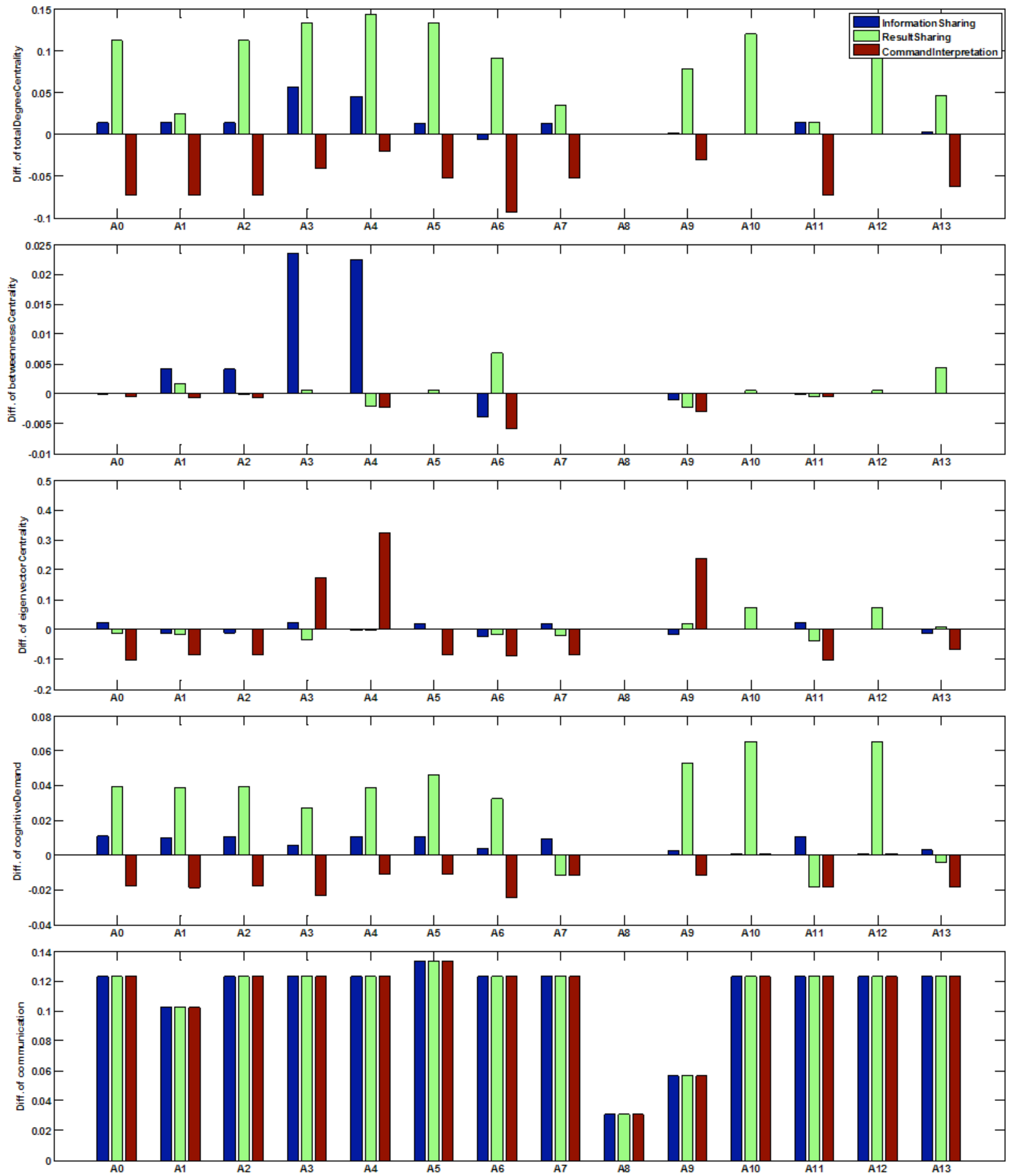


Figure 12-2 Charts displaying the difference of metrics between a meta-network and extracted structures

Table 12-4 I.D. assignments to individuals. I.D.s will be used to distinguish individuals in the later tables. We used some abbreviations for names

ID	A0	A1	A2	A3	A4	A5	A6
Name	Mu-hamme d Atef	Fazul Ab-dullah Mo-Mo-	Abdullah Ahmed Abdullah	Osama Bin Laden	Wadih el-Hage	Anas al-Liby	Al Owali

		hammed					
ID	A7	A8	A9	A10	A11	A12	A13
Name	Ali Mo-hamme d	Khlid Al Fawaz	Abdel Rahman	Ayman al-Zawahiri	Hamza al-Liby	Al Banshi-ri	Jihad Mo-hammed Ali

Table 12-5 shows the two principal components for each of the two structures: the observed structure and the extracted decision making structure. For the observed structure, the higher first principal component means *less communication demand to complete their tasks*. The higher second principal component means that *more connections to other personnel*. For the extracted structure, the higher first component means *less communication demand to complete their tasks*. The higher second principal component means that *more connections to other personnel*.

Table 12-5 Coefficients of two principal components from the observed structure (top) and the extracted structures (bottom)

	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	OBS	-0.079	0.472
Betweenness Centrality	OBS	-0.002	0.013
Eigenvector Centrality	OBS	-0.118	0.608
Cognitive Demand	OBS	-0.104	0.614
Communication	OBS	-0.984	-0.175
	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	IS	-0.051	0.060
	RS	-0.126	0.077
	CI	-0.004	0.044
Betweenness Centrality	IS	-0.005	0.049
	RS	-0.001	-0.004
	CI	0.000	0.001
Eigenvector Centrality	IS	-0.066	0.053
	RS	-0.062	0.015
	CI	-0.088	0.973
Cognitive Demand	IS	-0.055	0.078
	RS	-0.074	0.100
	CI	-0.039	0.073
Communication	IS	-0.564	-0.070
	RS	-0.564	-0.070
	CI	-0.564	-0.070

Figure 12-3 shows the clusters of actors from the two principal component analyses. From the observed network perspective, there are three clusters: *small communication demand and few links to other personnel* (A6, A3, A1, A0, A2, A7, A11, A13, A5, A9), *large communication de-*

mand and few links to other personnel (A10, A12), and *medium communication demand and many links to other personnel* (A8). From the extracted network perspective, there are three clusters: *small communication demand and few links to other personnel* (A3, A4, A9), *large communication demand and few links to other personnel* (A0, A1, A5, A6, A2, A13, A10, A11, A12, A7), and *medium communication demand and many links to other personnel* (A8).

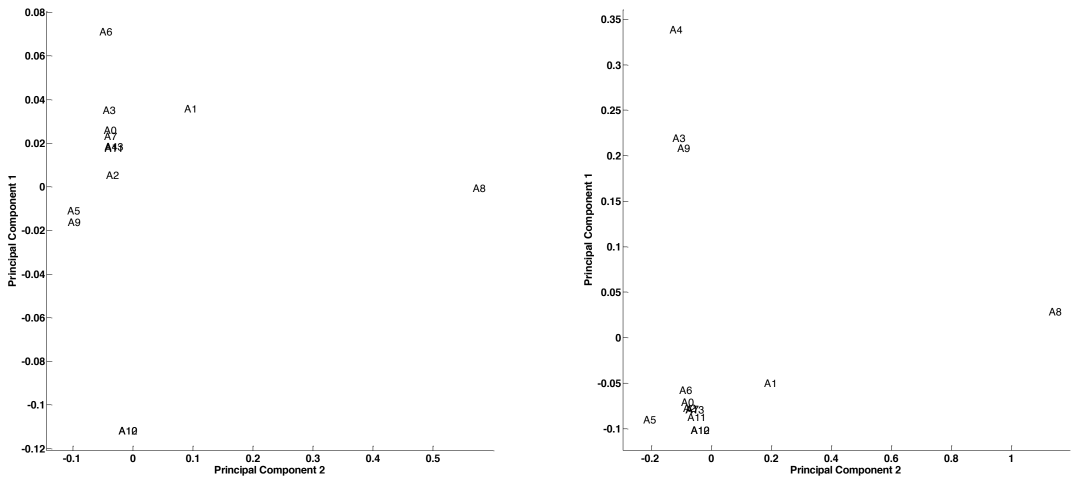


Figure 12-3 Two projections of metrics of individuals using two principal components. The left is using only the observed structure, and the right is from only the extracted structures.

12.2. Influence network analysis

Figure 12-4 and Table 12-6 outline the task completion likelihood. *Brief attack team, surveillance of possible targets,* and *lead attackers to embassy* are the tasks with high completion likelihood, which implies that these tasks are well-supported by the adversarial organization. On the other hand, *education and training, final reconnaissance mission,* and *load bomb* are the tasks which are ill-supported by the organization. Deciding either ill- or well-supported tasks for the intervention target is up to human analysts.

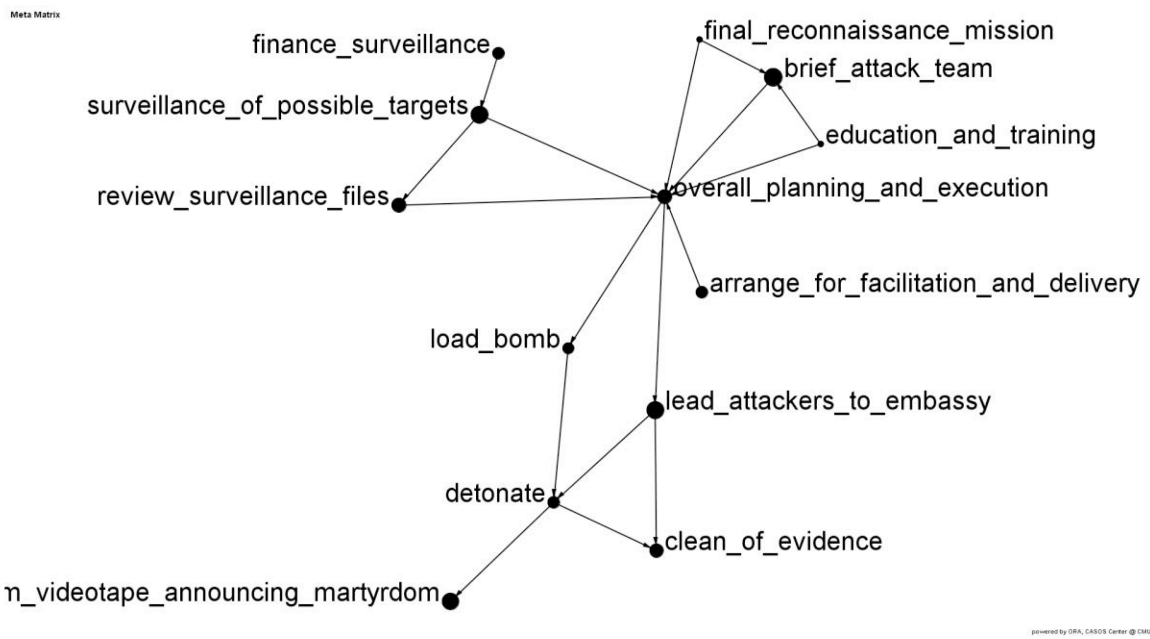


Figure 12-4 The visualization of the task dependency network. The node sizes are adjusted to the completion likelihood of the tasks.

Table 12-6 Task completion likelihoods when evaluated with default (medium) threshold for assessment and default (medium) probability assignment for baseline

Task Name	Completion Likelihood	Task Name	Completion Likelihood
overall planning and execution	0.408	film videotape announcing martyrdom	0.509
load bomb	0.312	arrange for facilitation and delivery	0.339
review surveillance files	0.415	surveillance of possible targets	0.538
brief attack team	0.546	detonate	0.327
final reconnaissance mission	0.204	education and training	0.177
lead attackers to embassy	0.521	finance surveillance	0.339
clean of evidence	0.389		

Table 12-7 and Table 12-8 represent the sensitivity analysis assuming different levels of operational environment (differentiating the completion probability for assessments) and different levels of assessment strictness (differentiating the organizational support assessment). When situation changes, *overall planning and execution* and *detonate* have large fluctuation in the completion likelihood. This means that the disruption of these tasks can induce big drops in their completion likelihood compared to *final reconnaissance mission* and *finance surveillance* whose standard deviations are small.

Table 12-7 Task completion likelihoods of tasks under nine different settings

Task Name	Low Probability			Medium Probability			High Probability				
	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Avg.	Std. Dev.
overall_planning_and_execution	0.147	0.141	0.110	0.395	0.408	0.352	0.658	0.697	0.607	0.391	0.215
load_bomb	0.144	0.162	0.133	0.249	0.312	0.269	0.461	0.545	0.458	0.304	0.144
review_surveillance_files	0.313	0.240	0.170	0.568	0.415	0.297	0.700	0.629	0.519	0.428	0.175
brief_attack_team	0.280	0.316	0.314	0.452	0.546	0.588	0.579	0.673	0.650	0.489	0.144
final_reconnaissance_mission	0.179	0.179	0.159	0.204	0.204	0.178	0.348	0.348	0.271	0.230	0.070
lead_attackers_to_embassy	0.283	0.317	0.330	0.434	0.521	0.581	0.584	0.670	0.724	0.494	0.151
clean_of_evidence	0.220	0.181	0.157	0.441	0.389	0.370	0.664	0.642	0.622	0.410	0.188
film_videotape_announcing_martyrdom	0.292	0.319	0.328	0.438	0.509	0.562	0.584	0.658	0.694	0.487	0.142
arrange_for_facilitation_and_delivery	0.257	0.247	0.219	0.339	0.339	0.313	0.463	0.500	0.500	0.353	0.103
surveillance_of_possible_targets	0.284	0.271	0.227	0.554	0.538	0.460	0.742	0.720	0.672	0.496	0.187
detonate	0.155	0.131	0.093	0.352	0.327	0.249	0.617	0.617	0.486	0.336	0.189
education_and_training	0.084	0.095	0.043	0.141	0.177	0.055	0.367	0.434	0.111	0.167	0.131
finance_surveillance	0.257	0.247	0.219	0.339	0.339	0.313	0.463	0.500	0.500	0.353	0.103

Table 12-8 Ranks of task completion likelihoods of tasks under nine different settings

Task Name	Low Probability			Medium Probability			High Probability		
	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold

	Low Probability			Medium Probability			High Probability		
Task Name	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold
overall_planning_and_execution	11	11	11	7	6	6	4	2	6
load_bomb	12	10	10	11	11	10	11	9	11
review_surveillance_files	1	7	7	1	5	9	2	7	7
brief_attack_team	5	3	3	3	1	1	8	3	4
final_reconnaissance_mission	9	9	8	12	12	12	13	13	12
lead_attackers_to_embassy	4	2	1	6	3	2	7	4	1
clean_of_evidence	8	8	9	4	7	5	3	6	5
film_videotape_announcing_martyrdom	2	1	2	5	4	3	6	5	2
arrange_for_facilitation_and_delivery	6	5	5	9	8	7	9	10	8
surveillance_of_possible_targets	3	4	4	2	2	4	1	1	3
detonate	10	12	12	8	10	11	5	8	10
education_and_training	13	13	13	13	13	13	12	12	13
finance_surveillance	7	6	6	10	9	8	10	11	9

12.3. Simulating the social behavior of adversaries

I design the virtual experiment for the social behavior of adversaries as Table 12-9. I differentiate the removal agent selection scheme (various network metrics to pick a target removal), intervention timing (when to remove over the course of simulations), and intervention size (how many to remove during the simulations).

Table 12-9 Virtual experiment design for simulation parameters (30 replications, 400 simulation time steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	1, 4, 8, and 11 agent removals (removing 10%, 30%, 50% and 70% of agents, 4 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	20, 40, 80, and 160 time-step (removing at after 5%, 10%, 20% and 40% timeflow, 4 cases)	The intervention happens at a specific stage of simulation period.
Total virtual experiment cells	64 cells (4x4x4 cases)	

Table 12-10 shows the regression analysis between the virtual experiment settings (representing the network metric selection as four binary values). Earlier and larger interventions are preferable in reducing the mission speed, task speed, binary task accuracy, energy task accuracy and task completion. Also, removing top betweenness centrality agents is helpful in reducing the mission speed and task speed.

Table 12-10 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.612*	0.272*	0.532*	0.061	-0.079	0.625*
Intervention Size	-0.363*	-0.464*	-0.524*	-0.952*	0.922*	-0.335*
Degree Cent.	-0.014	-0.156	0.205	-0.078	0.150*	-0.030
Betweenness Cent.	-0.166	-0.392*	0.055	-0.131*	0.178*	-0.216

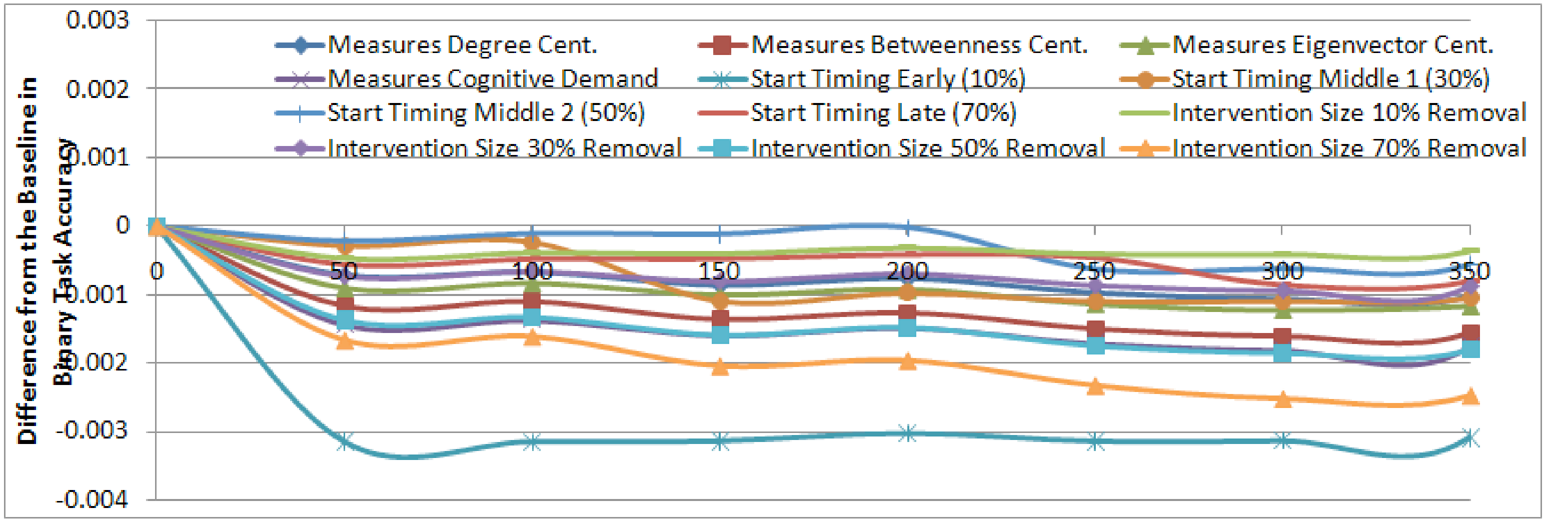
Eigenvector Cent.	-0.047	-0.116	0.161	-0.022	0.115	-0.019
Cognitive Demand	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-Square	0.473	0.331	0.545	0.913	0.865	0.488

Table 12-11 is the collection of regression models between the simulated organizational performance and the virtual experiment settings (this time, the averaged network values from the removed agents are used for regressions). Earlier and larger interventions are preferable in reducing every organizational performance except diffusion. Removing high degree centrality and cognitive demand agents is likely to reduce the mission and task speed.

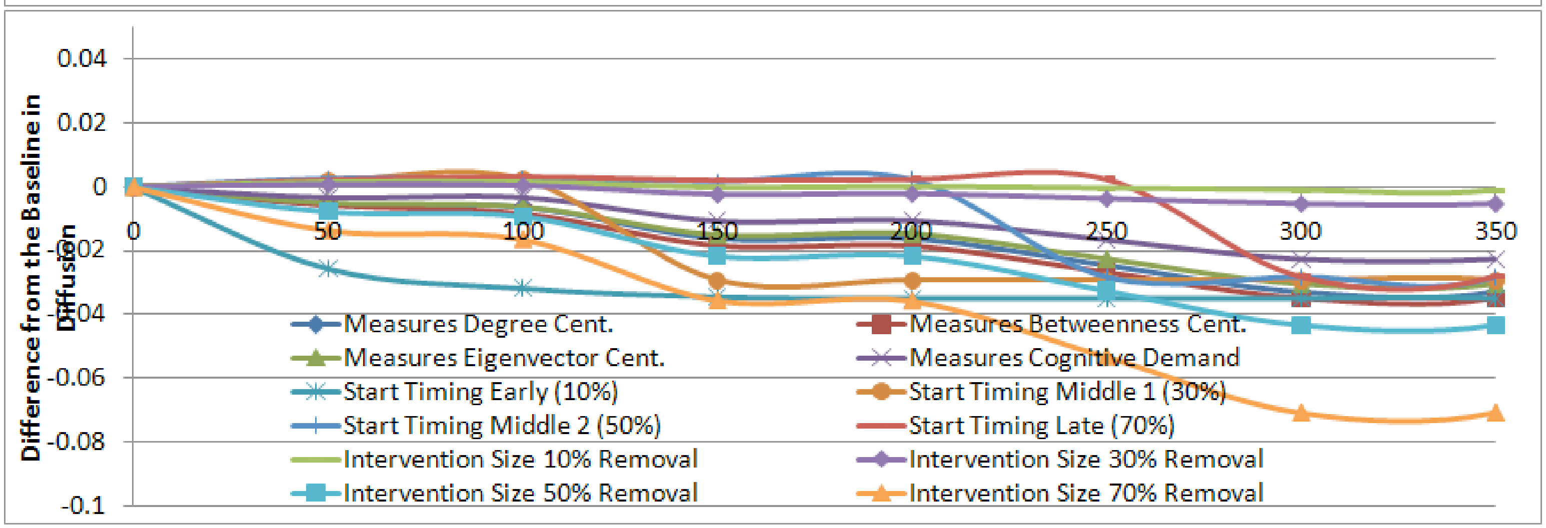
Table 12-11 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated metrics of removed agents (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.612*	0.272*	0.532*	0.061*	-0.079*	0.625*
Intervention Size	-0.167	-0.196	-0.417*	-0.868*	0.796*	-0.186
Degree Cent.	-1.184	-2.867	-0.650	1.253	-1.809*	-0.660
Betweenness Cent.	0.322	0.888	-0.019	-0.413	0.575*	0.231
Eigenvector Cent.	1.213	2.863	-0.270	-1.299*	1.436	0.620
Cognitive Demand	-0.466	-0.820	0.838	0.053	0.346	-0.351
Adjusted R-Square	0.514	0.343	0.542	0.948	0.930	0.514

Figure 12-5 shows the organizational performance over time. The curve of task completion shows the impact of early removals. The early removal shows very significant and prolonged damage from the task completion perspective. On the other hand, the energy task accuracy and the diffusion can be more reduced as more agents are reduced. These two organizational performance is more susceptible to the intervention size than the intervention timing.



Difference from the Baseline in Binary Task Accuracy
0.003
0.002
0.001
0
-0.001
-0.002
-0.003
-0.004
0
50
100
150
200
250
300
350
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (10%)
Start Timing Middle 1 (30%)
Start Timing Middle 2 (50%)
Start Timing Late (70%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal



Difference from the Baseline in Diffusion
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
0
50
100
150
200
250
300
350
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (10%)
Start Timing Middle 1 (30%)
Start Timing Middle 2 (50%)
Start Timing Late (70%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal

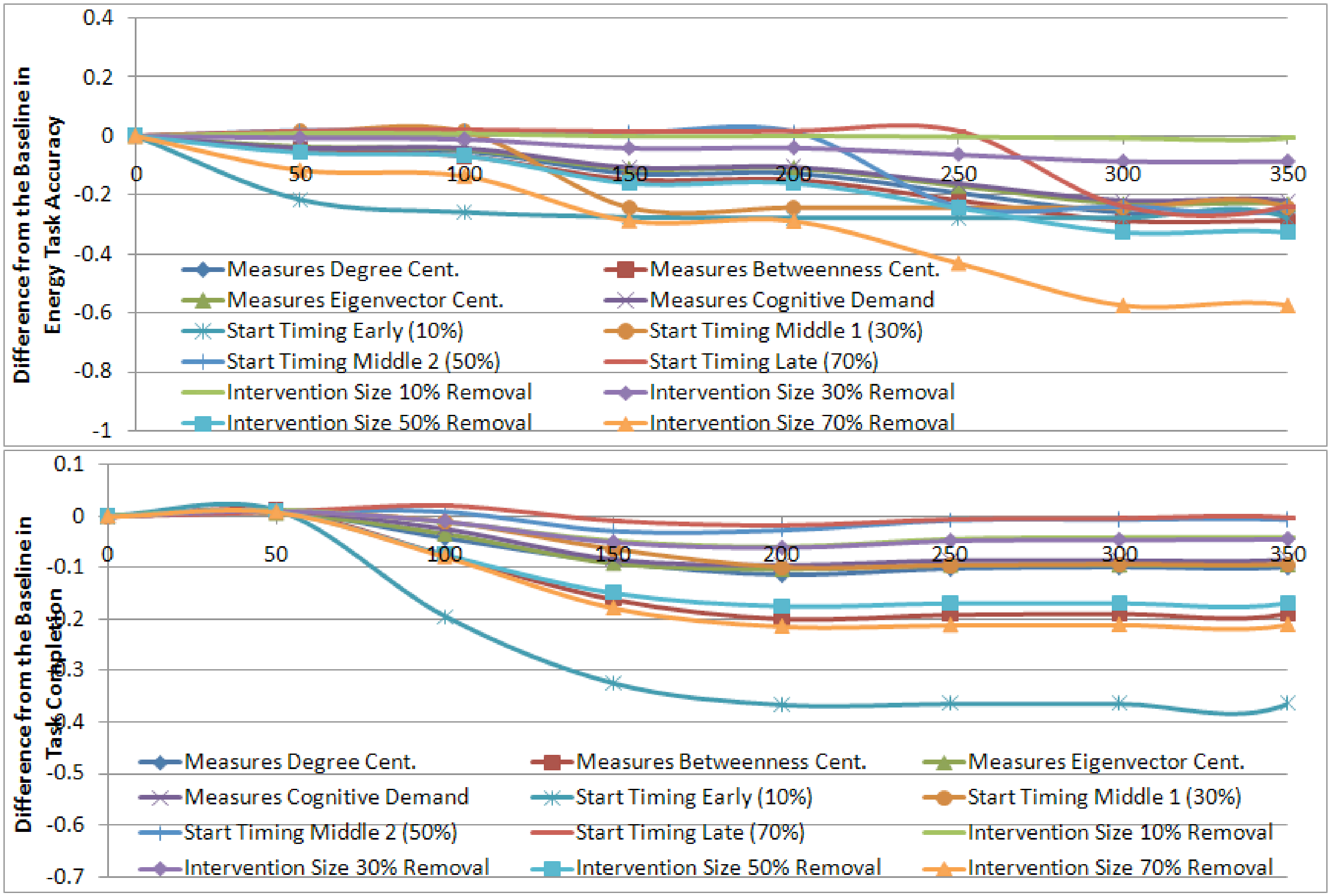


Figure 12-5 Organizational performance over time, aggregated by the first factor

Figure 12-6 outlines the damage of the task speed after removals. Removing the high betweenness centrality agents at the early or early-middle stage reduces the task speed to the 60% of the baseline. The other metrics can reach to the 60% of the baseline, but the other metrics require at least 50% of agent removals (while the betweenness centrality can accomplish the 60% of the baseline task speed with only 10% or 30% of agent removals).

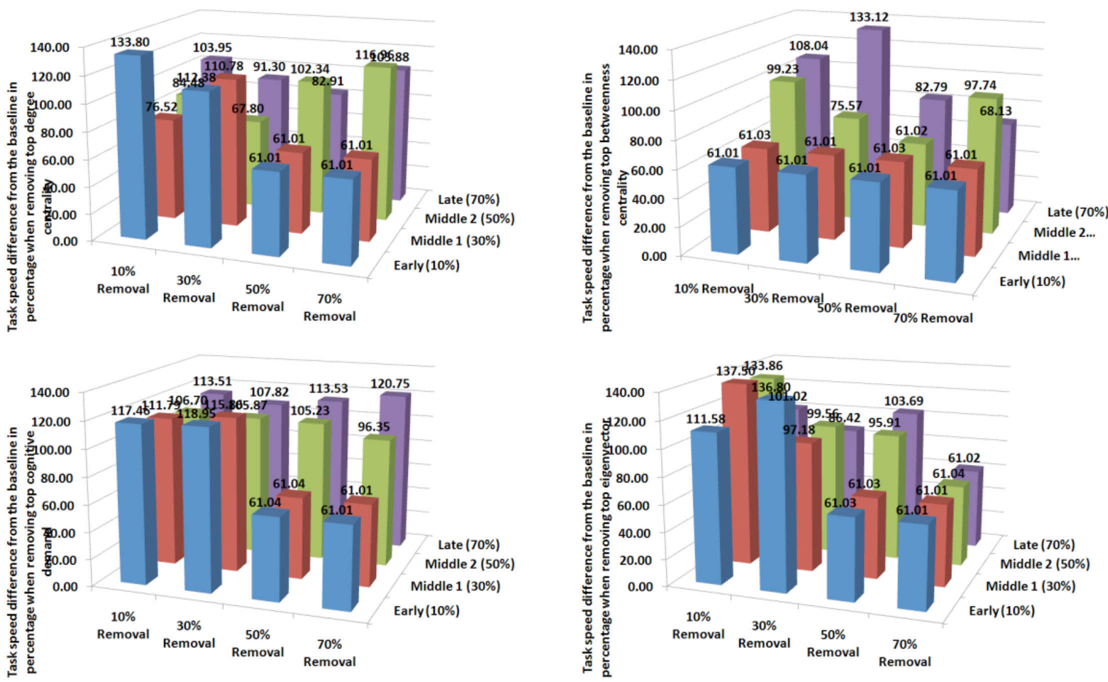


Figure 12-6 Percentage of Task completion speed to the baseline, 64 virtual experiment cells

Figure 12-7 shows the mission speed decrease after the interventions. Same to the task speed result, removing the high betweenness centrality agents is preferable in reducing the mission speed. Unlike the Tanzania and Kenya case (in the main text), it seems that the complete disruption of the mission is unlikely. However, with early intervention on the high betweenness agents, we can reduce the mission speed to the 26% of the baseline. However, the interventions after the early-middle stage seem almost useless.

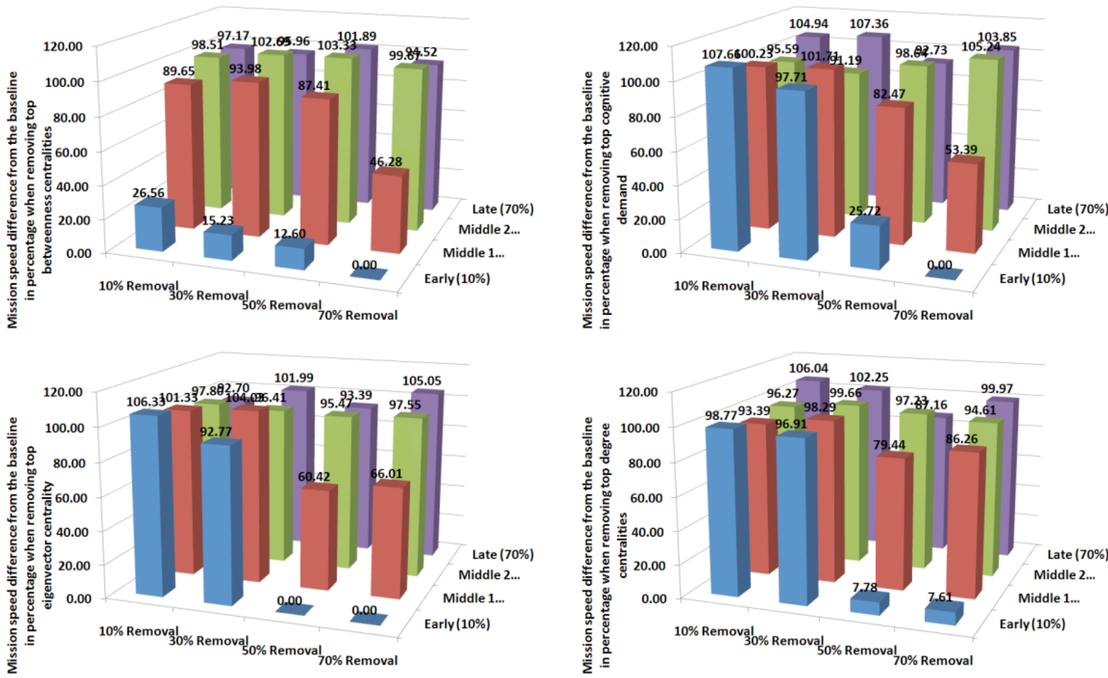


Figure 12-7 Percentage of Mission completion speed to the baseline, 64 virtual experiment cells

Figure 12-8 shows the Gant chart of the mission progress (baseline case). The *final reconnaissance mission* and *education and training* are the bottleneck tasks. The other tasks are quire quickly completed meaning that the adversarial organization is ready to execute such tasks from the initial status or over the course of the other task preparation.

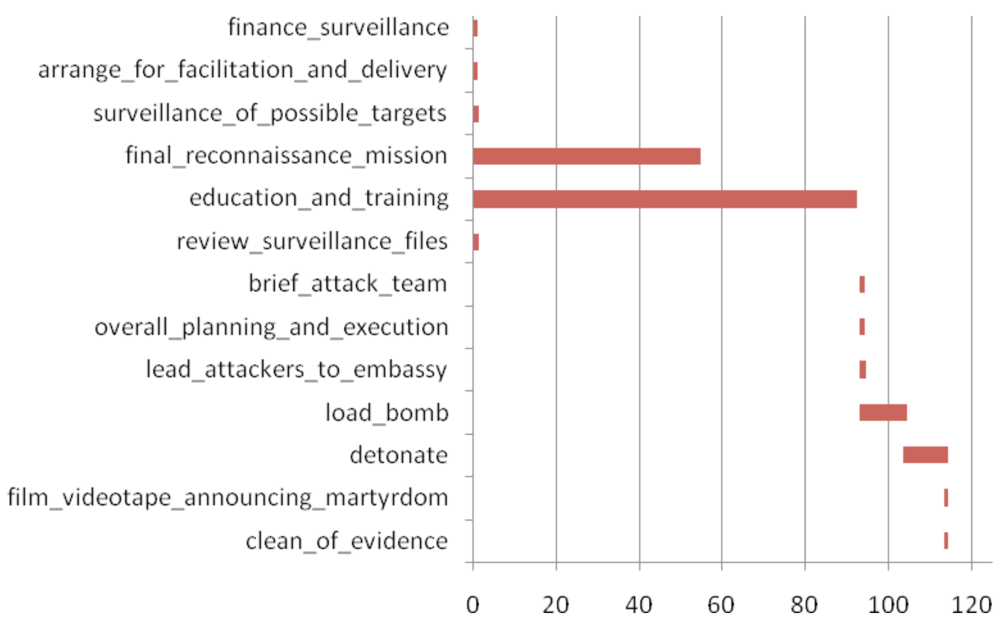
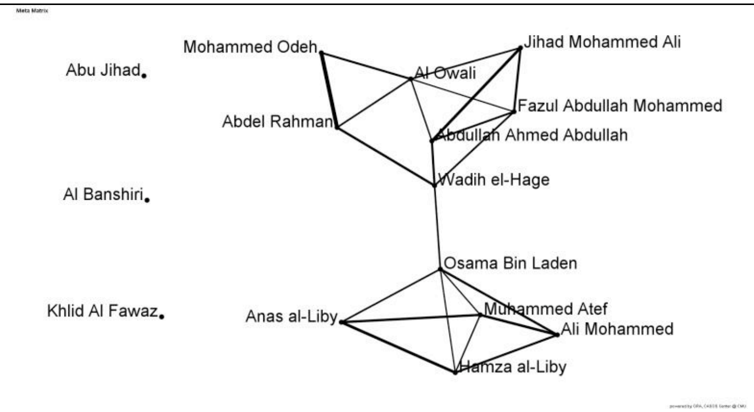
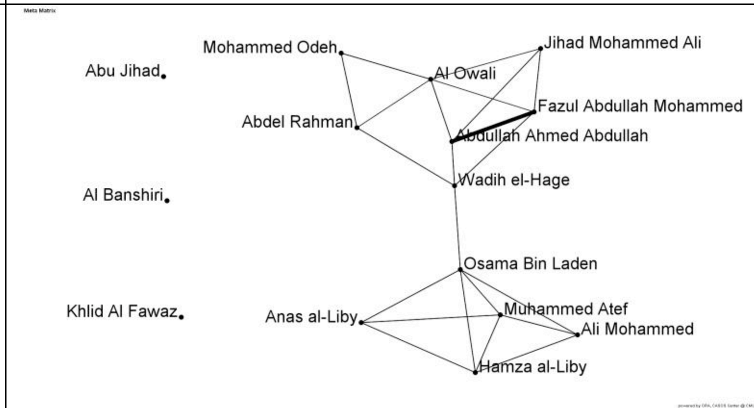
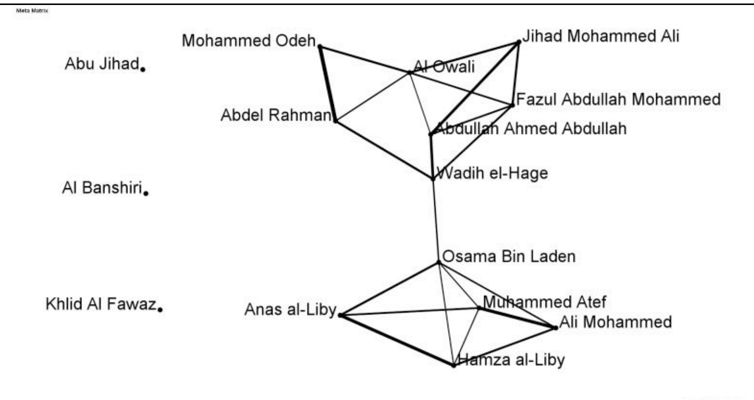
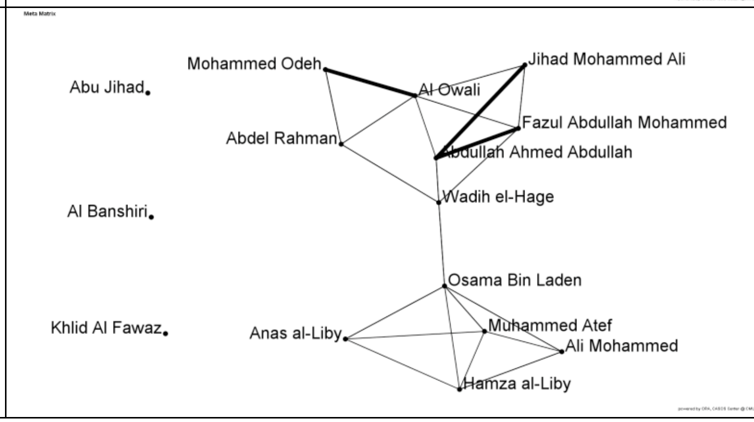


Figure 12-8 The estimated Gantt chart of the baseline case

Table 12-12 visualizes the interaction and the organizational element transfer network among agents over time. The interaction network does not show any change in terms of its topology. However, the interaction frequencies of pairs are different (which are shown as the link thickness in the visualization). The transfer network shows much dynamic changes. These transfer network changes are motivated by the different resources and expertise requirement as the mission progresses. *Fazul Abdullah Mohammed* seems to be the only agent actively engaged in the element transfer at every probing timing.

Table 12-12 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

<table>
<tr><th></th><th>Agent to Agent network: Interaction</th><th>Agent to Agent network: Transfer resources and expertise</th></tr>
<tr><td>Time 50</td><td></td><td></td></tr>
<tr><td>Time 100</td><td></td><td></td></tr>
</table>

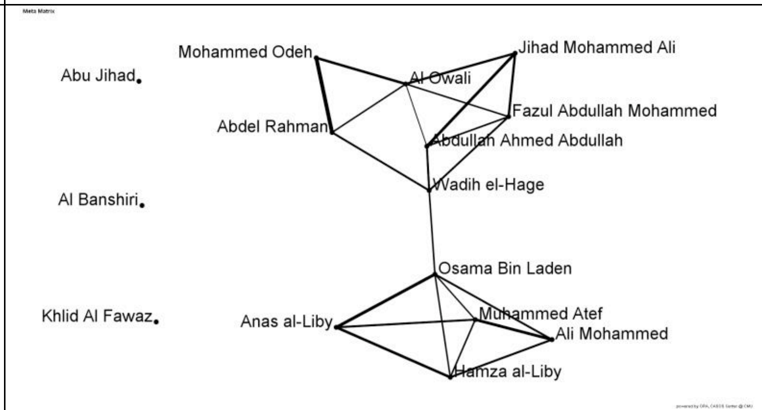
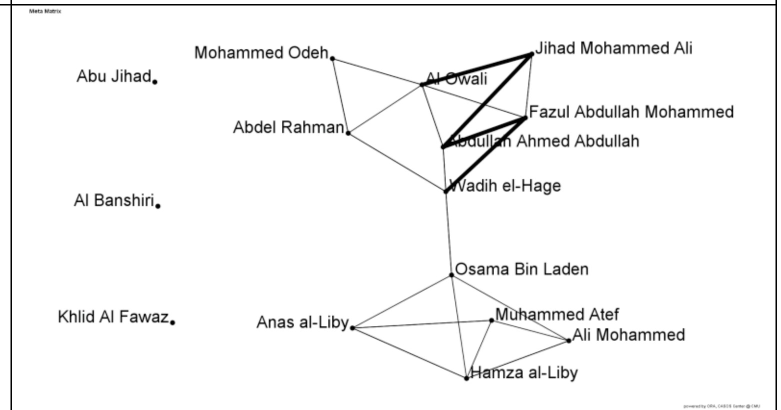
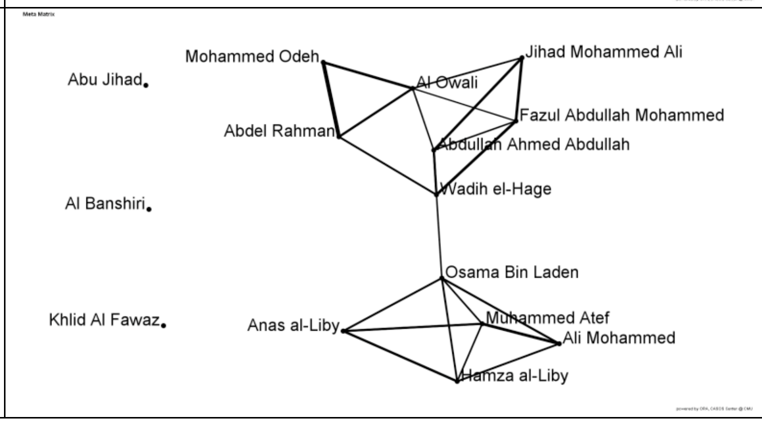
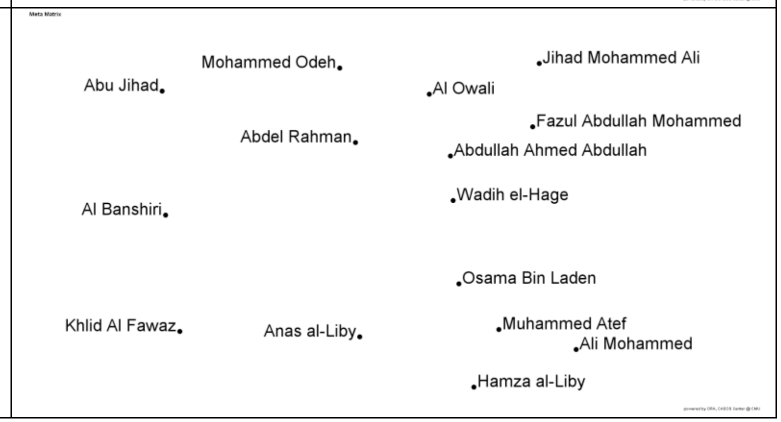
	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 150		
Time 350		

Table 12-13 Key individual lists over the course of simulations

Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank	Al Owali	Al Owali	Osama Bin La-	Osama Bin La-	Wadih el-Hage	Wadih el-Hage	Osama Bin La-	Abdullah Ahmed

1			den	den			den	Abdullah
Rank 2	Ali Mohammed	Ali Mohammed	Al Owali	Abdullah Ahmed Abdullah	Osama Bin Laden	Osama Bin Laden	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed
Rank 3	Jihad Mohammed Ali	Jihad Mohammed Ali	Abdullah Ahmed Abdullah	Hamza al-Liby	Abdel Rahman	Abdullah Ahmed Abdullah	Wadih el-Hage	Al Owali
Rank 4	Wadih el-Hage	Wadih el-Hage	Hamza al-Liby	Wadih el-Hage	Abdullah Ahmed Abdullah	Abdel Rahman	Al Owali	Wadih el-Hage
Rank 5	Abdel Rahman	Abdel Rahman	Wadih el-Hage	Muhammed Atef	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Jihad Mohammed Ali
Time 100	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Al Owali	Al Owali	Wadih el-Hage	Wadih el-Hage	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah
Rank 2	Ali Mohammed	Jihad Mohammed Ali	Osama Bin Laden	Osama Bin Laden	Osama Bin Laden	Osama Bin Laden	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed
Rank 3	Jihad Mohammed Ali	Wadih el-Hage	Hamza al-Liby	Abdullah Ahmed Abdullah	Abdel Rahman	Abdel Rahman	Al Owali	Al Owali
Rank 4	Wadih el-Hage	Ali Mohammed	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Al Owali	Fazul Abdullah Mohammed	Wadih el-Hage	Jihad Mohammed Ali
Rank 5	Abdel Rahman	Abdel Rahman	Wadih el-Hage	Wadih el-Hage	Abdullah Ahmed Abdullah	Al Owali	Jihad Mohammed Ali	Wadih el-Hage

Time 150	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank	Al Owali	Al Owali	Al Owali	Fazul Abdullah	Wadih el-Hage	Wadih el-	Osama Bin Laden	Abdullah Ahmed

1				Mohammed		Hage		Abdullah
Rank 2	Ali Mo-hammed	Jihad Mo-hammed Ali	Osama Bin Laden	Abdullah Ahmed Abdullah	Osama Bin Laden	Osama Bin Laden	Anas al-Liby	Fazul Abdullah Mohammed
Rank 3	Jihad Mo-hammed Ali	Wadih el-Hage	Fazul Abdullah Mohammed	Al Owali	Abdel Rahman	Abdel Rahman	Hamza al-Liby	Jihad Mohammed Ali
Rank 4	Wadih el-Hage	Ali Mo-hammed	Muhammed Atef	Wadih el-Hage	Fazul Abdullah Mohammed	Anas al-Liby	Muhammed Atef	Al Owali
Rank 5	Abdel Rah-man	Abdel Rah-man	Wadih el-Hage	Jihad Mohammed Ali	Abdullah Ahmed Abdullah	Al Owali	Ali Mohammed	Wadih el-Hage
Time 350	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Osama Bin Laden		Wadih el-Hage		Al Owali	
Rank 2	Ali Mo-hammed	Ali Mo-hammed	Al Owali		Osama Bin Laden		Fazul Abdullah Mohammed	
Rank 3	Jihad Mo-hammed Ali	Jihad Mo-hammed Ali	Muhammed Atef		Abdel Rahman		Wadih el-Hage	
Rank 4	Wadih el-Hage	Abdel Rah-man	Abdel Rahman		Al Owali		Abdullah Ahmed Abdullah	
Rank 5	Abdel Rah-man	Wadih el-Hage	Wadih el-Hage		Abdullah Ahmed Abdullah		Abdel Rahman	

12.4. Simulating the social and geospatial behavior of adversaries

Table 12-14 shows the virtual experiment design. This experiment design is identical to the design of the social only model simulation. Three factors are differentiated across the cells. The three factors are 1) the removal agent selection scheme (different network measures), 2) the intervention size and 3) the intervention timing.

Table 12-14 Virtual experiment design for simulation parameters (30 replications, 400 simulation time steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	1, 5, 9, and 12 agent removals (removing 10%, 30%, 50% and 70% of agents, 4 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	125, 250, 500, and 1000 timestep (removing at after 5%, 10%, 20% and 40% timeflow, 4 cases)	The intervention happens at a specific stage of simulation period.
Total virtual experiment cells	64 cells (4x4x4 cases)	

Table 12-15 is the collection of the regression models between the organizational performances and the virtual experiment settings (treating the network metric selection as a categorical vairable). Still, the earlier and larger interventions are preferable in damaging the task speed, binary task accuracy, energy task accuracy, diffusion and task completion. Removing the high betweenness centrality agents is helpful in reducing the task speed, energy task accuracy and task completion.

The mission speed is zero in every virtual experiment cells including the baseline. This suggests that the given organizational structure is not capable of executing the mission when the geospatial requirement is considered. The task execution in this social and geospatial model requires more than one task assigned agent at specified locations by a task to be performed. If there is not enough agent to deploy the specified locations by the task to be executed, then the task cannot be performed. (Imagine that the *detonation* task should be performed at *Tanzania* and *Kenya* simultaneously, and there is only one assigned agent. Then, the task cannot be performed by the organization because the single agent cannot present at two locations at the same time)

This is a new finding of the social and geospatial simulation because the social only model did not considered this geospatial requirement in the task execution. Therefore the social only model generates results supporting this organization can perform the mission, but the social and geospatial model says that the organization cannot perform the mission by generating zero in the mission speed.

Table 12-15 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.000	0.772*	0.767*	0.092	-0.098	0.923*
Intervention Size	0.000	-0.389*	-0.686*	-0.961*	0.935*	-0.299*
Degree Cent.	0.000	0.297*	-0.119	-0.085	0.144*	-0.016
Betweenness Cent.	0.000	-0.332*	-0.123	-0.137*	0.184*	-0.260
Eigenvector Cent.	0.000	-0.020	0.082	-0.031	0.096	0.087
Cognitive Demand	0.000	0.000	0.000	0.000	0.000	0.000
Adjusted R-Square	1.000	0.519	0.621	0.889	0.849	0.419

Table 12-16 is the collection of the regression models between the simulated organizational performances and the virtual experiment settings (for the network values, I averaged the network values of the removed agents instead of using the categorical value as in Table 13-15). Earlier and larger interventions are helpful in reducing the binary task accuracy, energy task accuracy and task completion. Also, removing the high betweenness centrality or high eigenvector centrality agents is better in reducing the binary task accuracy, energy task accuracy and task completion. Removing the high degree centrality or the high cognitive demand agents is good in reducing the task speed.

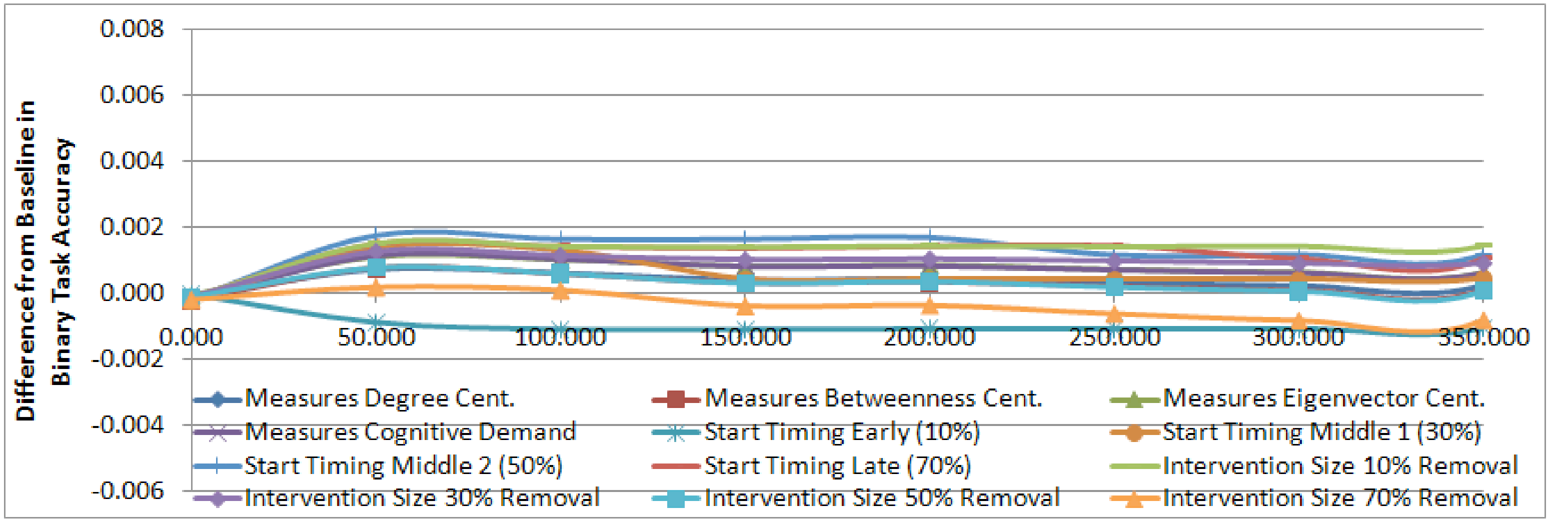
Table 12-16 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated network metrics of the removed agents (N=64 cases) (* for P<0.05)

Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Completion
Intervention Timing	0.000	0.771*	0.752*	0.086	-0.093	0.911*
Intervention Size	0.000	0.067	-0.703*	-0.843*	0.797*	-0.173

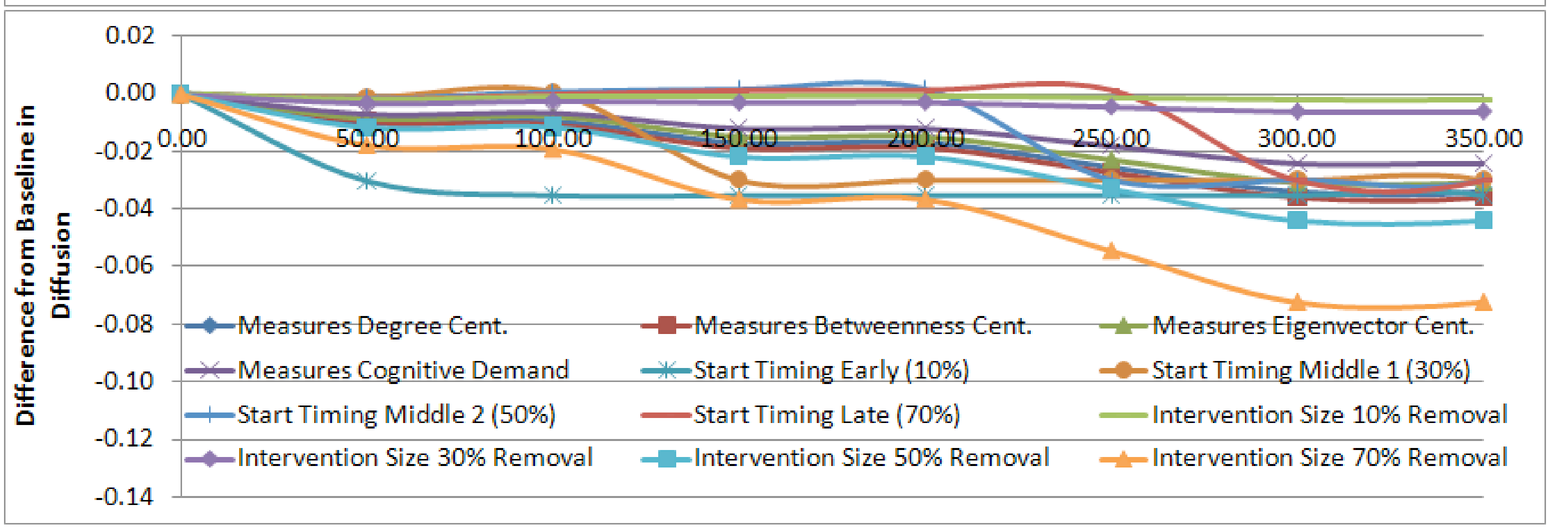
Standardized Coefficient	Mission Speed	Task Speed	BTA	ETA	Diffusion	Task Comple-tion
Degree Cent.	0.000	-4.488	3.652	1.535*	-1.910*	0.372
Betweenness Cent.	0.000	1.186	-1.129	-0.548*	0.622*	-0.096
Eigenvector Cent.	0.000	3.682	-4.159*	-1.641*	1.645	-0.958
Cognitive De-mand	0.000	-0.360	0.879	0.142	0.237	0.297
Adjusted R-Square	1.000	0.487	0.685	0.942	0.926	0.451

Figure 12-9 shows the organizational performance over time. The task completion curve shows the impact of the early interventions. The task completion curve of the early removal cannot re-cover to the baseline level while some other cases can. This means that the early removal left a prolonged damage to the organization while the other interventions could not.

The diffusion and energy task accuracy is more vulnerable to the large interventions rather than the intervention timings. This is caused by the metrics gauge the level of information diffusion and the removal isolated the information from further diffusion.



Difference from Baseline in Binary Task Accuracy
0.008
0.006
0.004
0.002
0.000
-0.002
-0.004
-0.006
0.000
50.000
100.000
150.000
200.000
250.000
300.000
350.000
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (10%)
Start Timing Middle 1 (30%)
Start Timing Middle 2 (50%)
Start Timing Late (70%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal



Difference from Baseline in Diffusion
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10
-0.12
-0.14
0.00
50.00
100.00
150.00
200.00
250.00
300.00
350.00
Measures Degree Cent.
Measures Betweenness Cent.
Measures Eigenvector Cent.
Measures Cognitive Demand
Start Timing Early (10%)
Start Timing Middle 1 (30%)
Start Timing Middle 2 (50%)
Start Timing Late (70%)
Intervention Size 10% Removal
Intervention Size 30% Removal
Intervention Size 50% Removal
Intervention Size 70% Removal

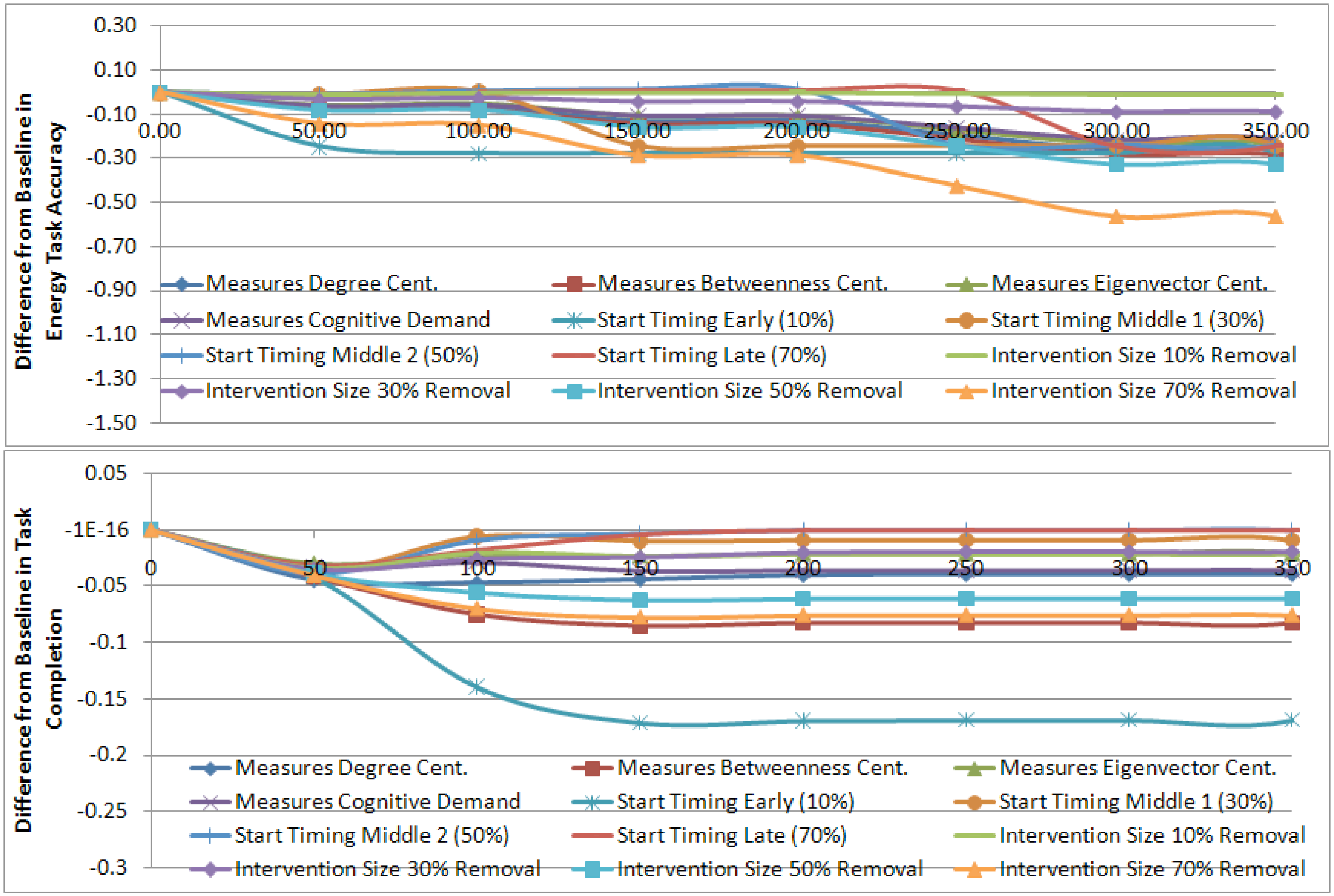


Figure 12-9 Organizational performance over-time

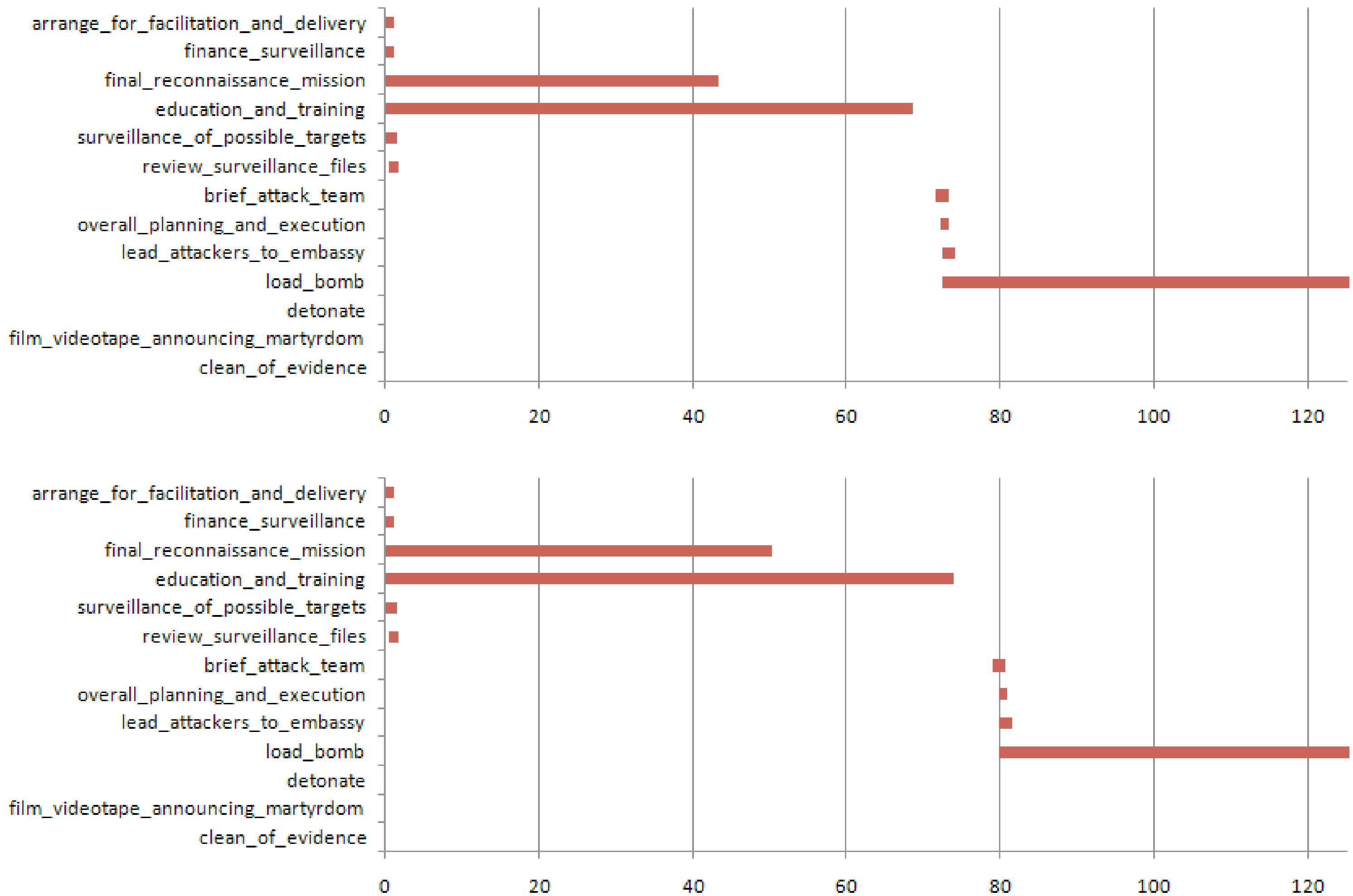


Figure 12-10 Two Gantt charts from Baseline (Upper) and 10% removal of top cognitive demand agents at the early-middle stage (after 10% of time steps)

Figure 12-10 shows two Gant charts: one from the baseline and the other from the 10% top degree centrality agent removals at the early-middle stage (after 10% of simulated time step passed). *Load bomb* is the task that cannot be performed with the current organization settings because it takes infinite time to be completed. Because the *load bomb* task is not completed, the subsequent tasks, such as *detonate, film videotape announcing martyrdom,* and *clean of evidence*, are not done.

Because of the intervention, the two Gant charts are slightly different. The intervention induced longer execution time of *education and training* and *final reconnaissance mission*. Also, the intervention delayed the execution of *brief attack team, overall planning and execution, lead attackers to embassy,* etc.

According to the meta matrix, *load bomb* is assigned to only *Al Owali*. However, *Al Owali*'s location is unknown (no link between *Al Owali* to any of location nodes). On the other hand, *load bomb* needs to be happened at *Kenya*. Thus, the simulator assumed that there is no agent at the scene over the course of the simulation, and it estimated that the *load bomb* cannot be performed. It is possible to assume that *Al Owali* can be present at any of locations if his where-about is unknown, but such assumption is not applied in this social and geospatial model[14].

Figure 12-11 shows the task execution speed of the virtual experiment cells[15]. Early intervention on the high betweenness centrality agents can limit the task execution speed to below 60% of the baseline. However, the interventions after the late-middle stage (20% of the simulated time passed). Then, the interventions can reduce the task speed from 73% to 84% of the baseline (considering the high betweenness centrality agent removals). The effect of removing high eigenvector agents or high cognitive demand agents is very susceptible to the intervention size. The intervention size should be above 50% to avoid the small task speed reduction. If the below 50% of agents are removed, the task speed reduction will be limited only to the 73.17% of the baseline speed at best (30% removal at the early stage with degree centrality oriented interventions). However, with more than 50% of agent removal at the early or early-middle stage using degree centrality, eigenvector centrality or cognitive demand, the task speed can be limited to the 56%.

---

[14] The simulation with the first dataset, the bombing dataset in Tanzania and Kenya, estimated that the mission can be executed. The reason is that *Al Owali* is still the only agent assigned to *Load bomb,* but in the dataset *Al Owali's* where-about is known. He was located at *Tanzania*. This is why the Kenya only dataset estimated that the mission cannot be performed (*Tanzania* node is not included in the Kenya only dataset, neither does *Al Owali*'s link to *Tanzania*).

[15] I exclude the mission execution speed response surface figures because the mission execution speeds for the virtual experiment cells are all zero.

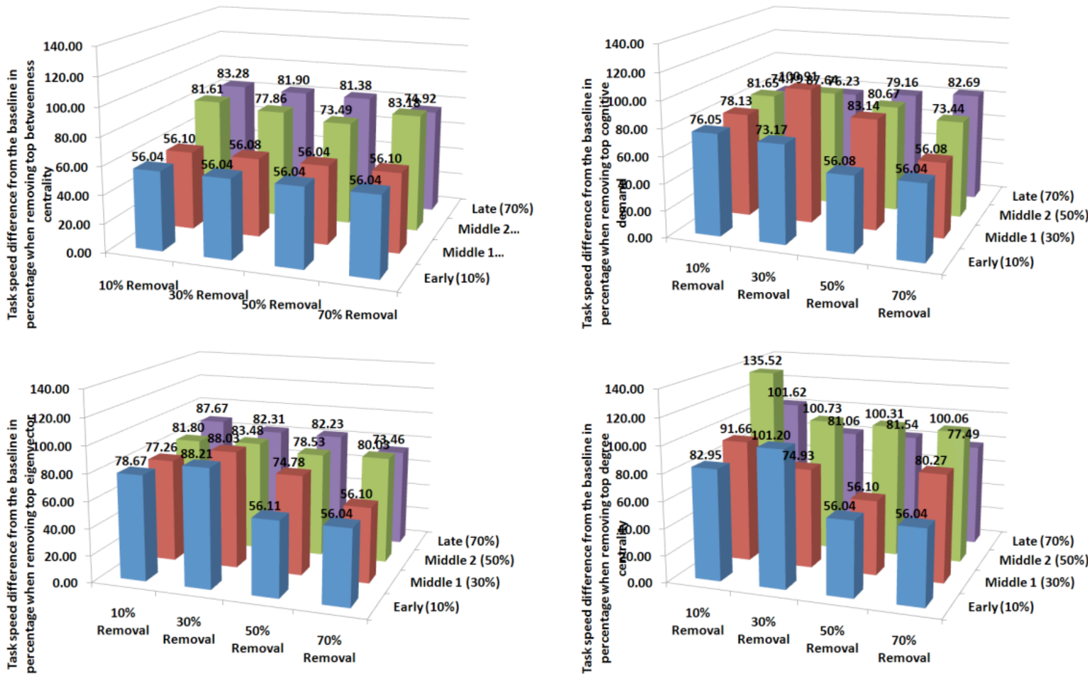


Figure 12-11 Four task speed bar charts for four intervention strategic schemes (betweenness at top-left, cognitive demand at top-right, eigenverctor at bottom-left, and degree at bottom-right), The number is the percentage of the mission speed compared to the baseline), which means 100% = same as baseline, less than 100% = slower, and more than 100% = faster.

Figure 12-12 shows the Gant chart and the agent segregation level from the baseline. According to the Gant chart, the *education and training* task will be done around 70 time steps. The geospatial segregation level of *Afghanistan* and *Pakistan* drops after *education and training* is completed.

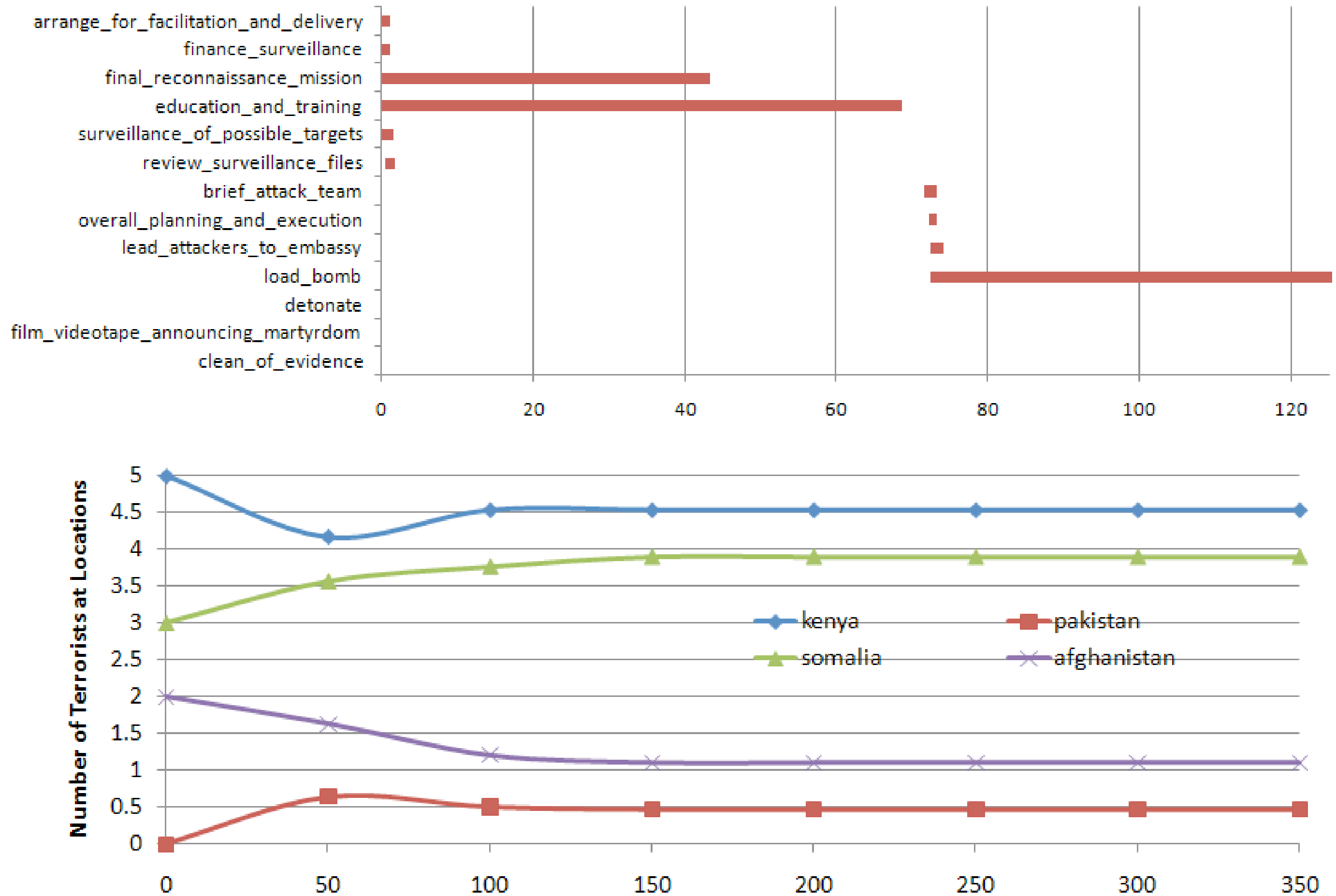
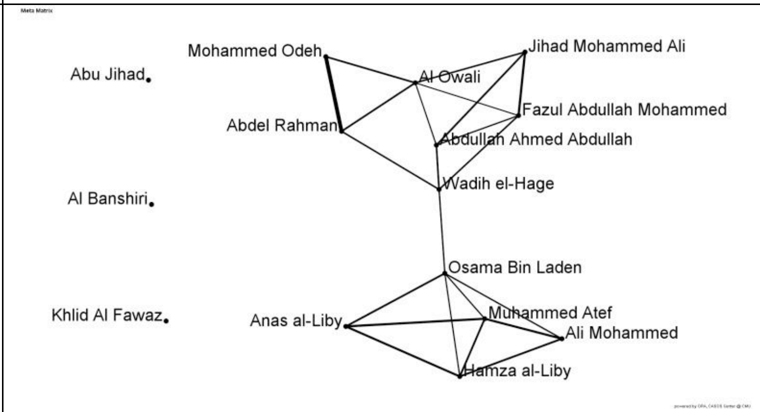
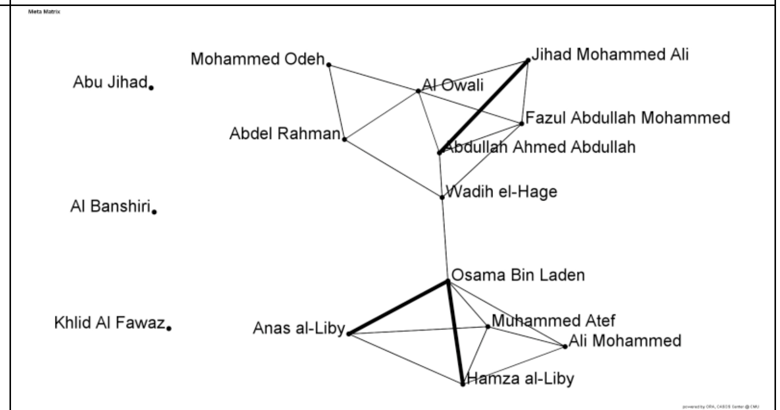
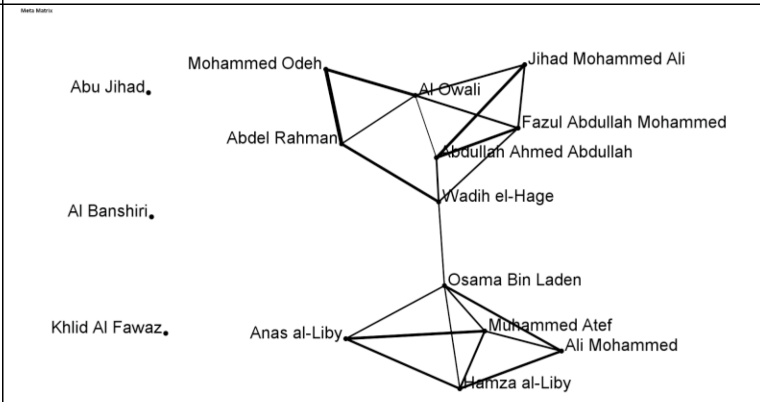
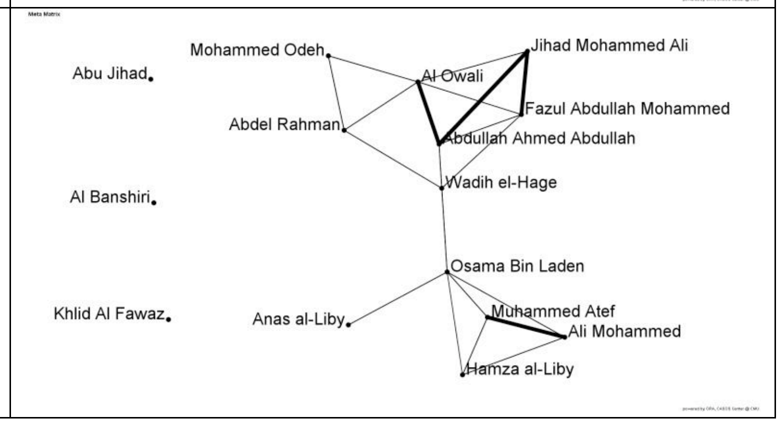


Figure 12-12 A Gantt chart and an agent-geospatial distribution over-time line chart of Baseline. As the task dependency network gets completed, the agents move to new locations where they can perform the next tasks. The initial training center at Afghanistan is attracted agents till around 70 time-steps.

Table 12-17 visualizes the interaction and the organizational element transfer networks among the agents during the simulation. The interaction networks does not change a lot, but the transfer network does change. Particularly, the frequency of the link usages in the transfer network fluctuates greatly because different elements are required at different times and different agents can supply such elements. Over the course of simulation, *Abdullah Ahmed Abdullah* actively engages in the organizational element transfers. According to the transfer network visualizations, he is always a part of heavily used transfer links.

Table 12-18 is the agents' network values in the interaction and the transfer networks during the simulations. *Al Owali* seems to be the most critical agent because he is the top degree centrality and cognitive demand at every probing timing and in both interaction and transfer networks. Also, *Wadih el-Hage* frequently has the highest betweenness centrality in the interaction and the transfer network.

Table 12-17 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 50		
Time 100		

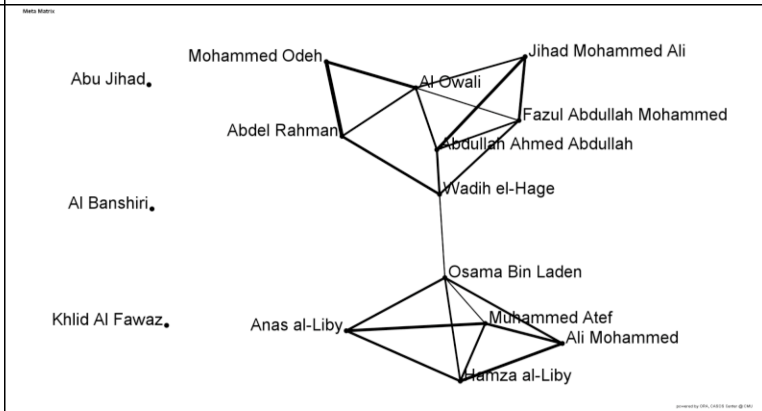
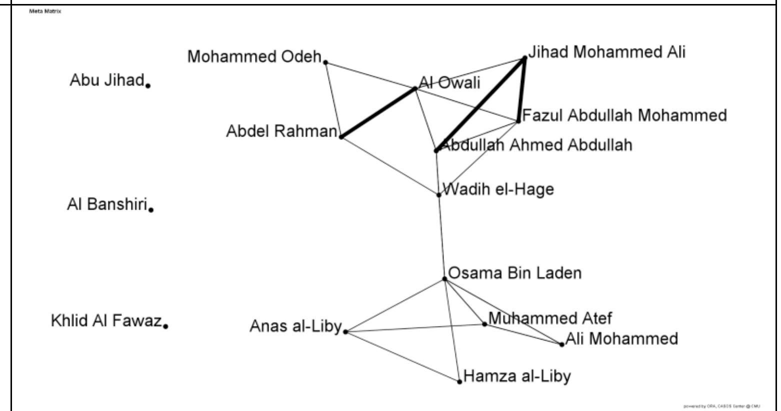
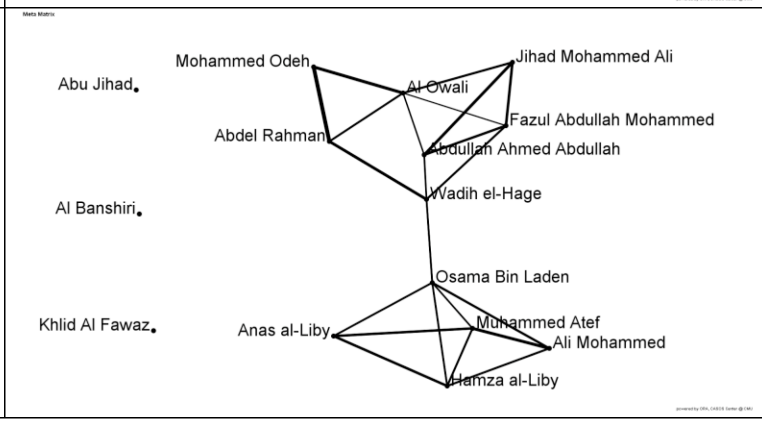
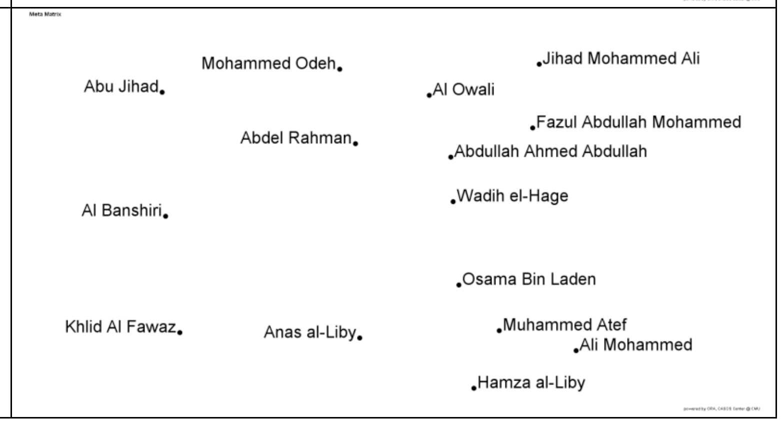
<table>
<tr><th></th><th>Agent to Agent network: Interaction</th><th>Agent to Agent network: Transfer resources and expertise</th></tr>
<tr><td>Time 150</td><td>
</td><td>
</td></tr>
<tr><td>Time 350</td><td>
</td><td>
</td></tr>
</table>

Table 12-18 Key individual lists over the course of simulations

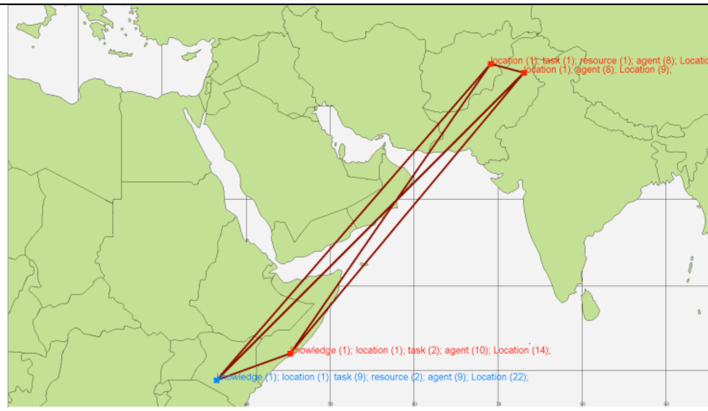
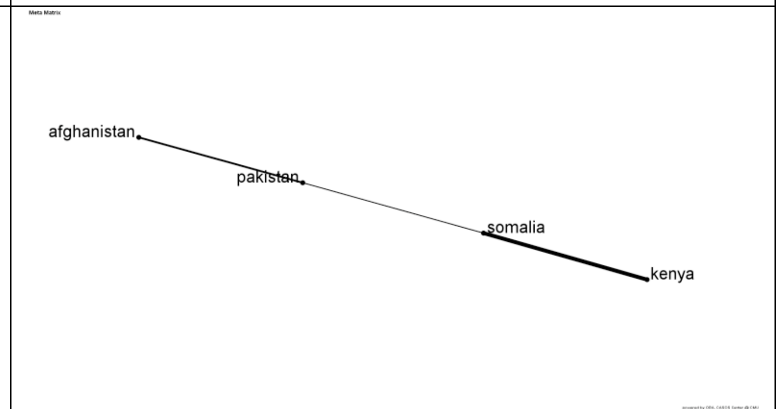
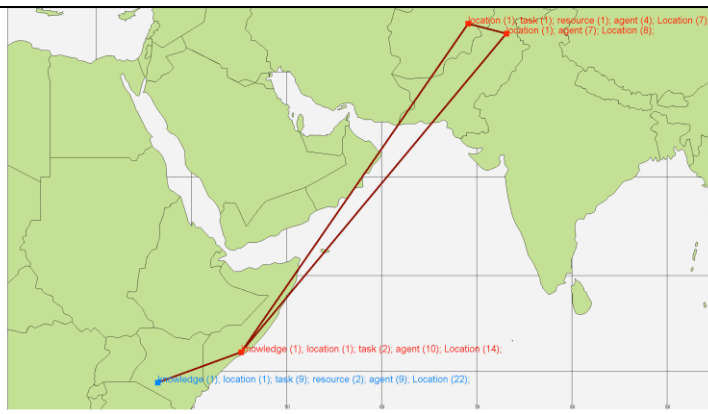
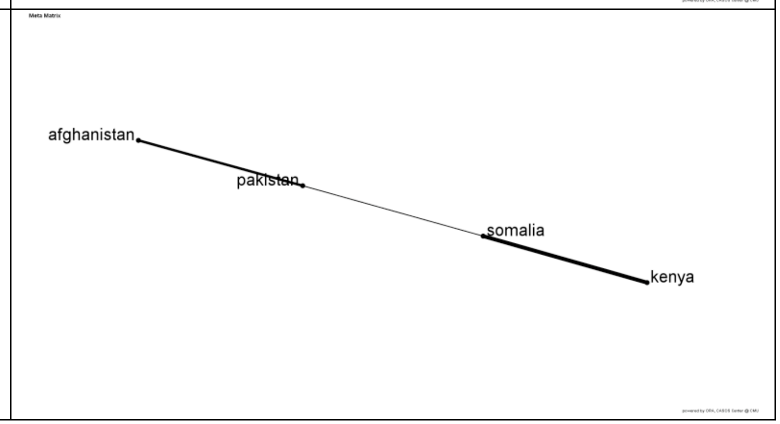
Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Al Owali	Osama Bin Laden	Wadih el-Hage	Wadih el-Hage	Muhammed Atef	Osama Bin Laden
Rank 2	Ali Mo-hammed	Jihad Mo-hammed Ali	Osama Bin Laden	Al Owali	Osama Bin Laden	Osama Bin Laden	Hamza al-Liby	Hamza al-Liby
Rank 3	Jihad Mo-hammed Ali	Wadih el-Hage	Muhammed Atef	Muhammed Atef	Abdel Rahman	Fazul Abdullah Mohammed	Anas al-Liby	Anas al-Liby
Rank 4	Wadih el-Hage	Ali Mo-hammed	Hamza al-Liby	Hamza al-Liby	Al Owali	Abdel Rahman	Osama Bin Laden	Muhammed Atef
Rank 5	Abdel Rahman	Abdel Rahman	Abdel Rahman	Fazul Abdullah Mohammed	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Ali Mohammed	Ali Mohammed
Time 100	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Al Owali	Al Owali	Wadih el-Hage	Wadih el-Hage	Al Owali	Abdullah Ahmed Abdullah
Rank 2	Ali Mo-hammed	Ali Mo-hammed	Muhammed Atef	Abdullah Ahmed Abdullah	Osama Bin Laden	Osama Bin Laden	Fazul Abdullah Mohammed	Jihad Mohammed Ali
Rank 3	Jihad Mo-hammed Ali	Jihad Mo-hammed Ali	Osama Bin Laden	Osama Bin Laden	Abdel Rahman	Abdel Rahman	Abdullah Ahmed Abdullah	Al Owali
Rank 4	Wadih el-Hage	Wadih el-Hage	Hamza al-Liby	Fazul Abdullah Mohammed	Al Owali	Al Owali	Jihad Mohammed Ali	Fazul Abdullah Mohammed
Rank 5	Abdel Rahman	Abdel Rahman	Fazul Abdullah Mohammed	Jihad Mohammed Ali	Abdullah Ahmed Abdullah	Abdullah Ahmed Abdullah	Wadih el-Hage	Wadih el-Hage

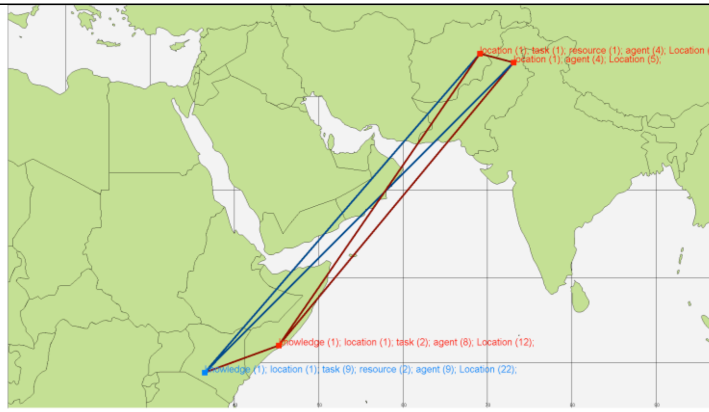
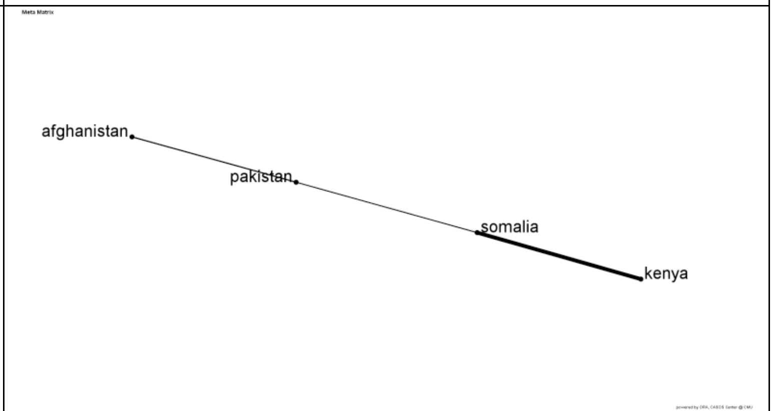
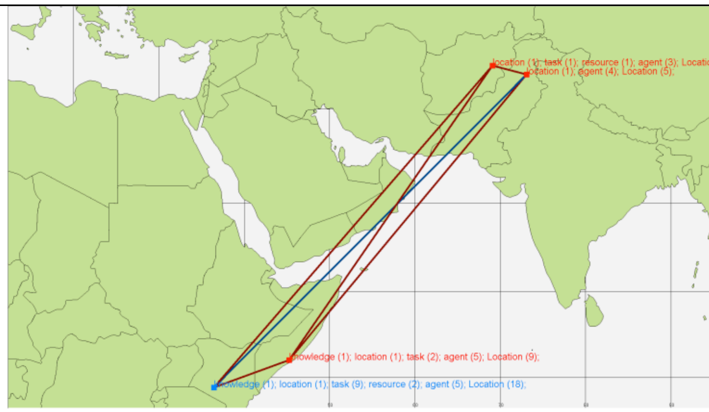
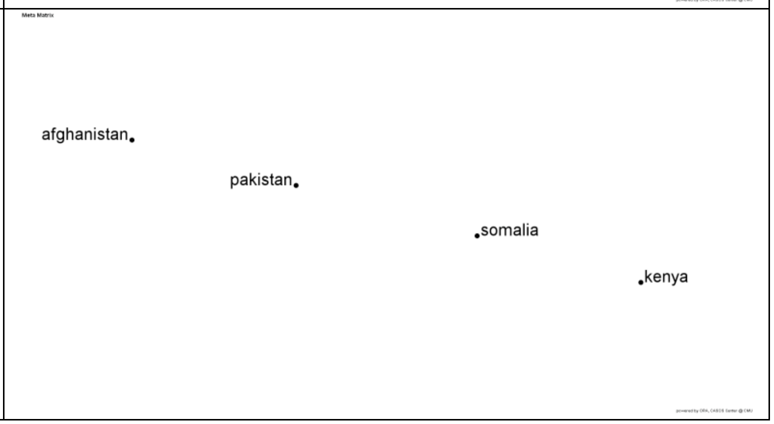
Time 150	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Al Owali	Al Owali	Wadih el-Hage	Wadih el-Hage	Hamza al-Liby	Jihad Mohammed Ali
Rank 2	Ali Mo-hammed	Jihad Mo-hammed Ali	Osama Bin Laden	Abdullah Ahmed Abdullah	Osama Bin Laden	Osama Bin Laden	Muhammed Atef	Abdullah Ahmed Abdullah
Rank 3	Jihad Mo-hammed Ali	Ali Mo-hammed	Muhammed Atef	Jihad Mohammed Ali	Abdel Rahman	Al Owali	Osama Bin Laden	Fazul Abdullah Mohammed
Rank 4	Wadih el-Hage	Wadih el-Hage	Hamza al-Liby	Osama Bin Laden	Al Owali	Abdullah Ahmed Abdullah	Ali Mohammed	Al Owali
Rank 5	Abdel Rahman	Abdel Rahman	Abdel Rah-man	Fazul Abdullah Mohammed	Abdullah Ahmed Abdullah	Fazul Abdullah Mohammed	Anas al-Liby	Abdel Rahman
Time 350	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	Al Owali	Al Owali	Al Owali		Wadih el-Hage		Al Owali	
Rank 2	Ali Mo-hammed	Ali Mo-hammed	Osama Bin Laden		Osama Bin Laden		Abdullah Ahmed Abdullah	
Rank 3	Jihad Mo-hammed Ali	Jihad Mo-hammed Ali	Muhammed Atef		Abdel Rahman		Abdel Rahman	
Rank 4	Wadih el-Hage	Abdel Rahman	Hamza al-Liby		Al Owali		Fazul Abdullah Mohammed	
Rank 5	Abdel Rahman	Wadih el-Hage	Abdel Rah-man		Fazul Abdullah Mohammed		Wadih el-Hage	

Table 12-19 visualizes the geospatial distribution of meta-network. Particularly, the location-to-location passage networks are interesting. There are always intensive transnational movement between *Somalia* and *Kenya.* On the other hand, there are some transnational movement between *Afghanistan* and *Pakistan* at the early stage (time 50 and 100), and such transnational movement exists rarely at the later stage (time 150). Compared to such two intensive transnational movements, the transnational movement link between *Pakistan* and *Somalia* is rarely used (definitely used but not as frequent as the other two links).

From these estimations, human analysts can focus on specific transnational activities that are expected to happen over the course of adversaries' mission execution.

Table 12-19 Collection of agent geospatial movements and transnational movement passage networks over time, link thickness is adjusted to show the frequency of the link usage.

	Geospatial visualization of meta-network	Location-to-location transnational movement network
Time 50		
Time 100		

<table>
<tr><td></td><td>Geospatial visualization of meta-network</td><td>Location-to-location transnational movement network</td></tr>
<tr><td>Time 150</td><td>
</td><td>
</td></tr>
<tr><td>Time 350</td><td>
</td><td>
</td></tr>
</table>

13. Appendix – the Current Global Terrorist Network

I apply the same approach to a global terrorist network (see Ch. 4.4). The followings are the analysis results corresponding to the results of the main chapters.

13.1. Decision making structure analysis

Figure 13-1 visualizes the original and the extracted three decision making structures. As expected, the information sharing looks similar to the original social network, but the result sharing is very different from the original network. The command interpretation structure is very trimmed version of the observed social network. It should be noted that many of the agents are isolates who have no contact links to other agents. Only 143 agents are included in this decision making structures while there are total 597 agents in the observed agents-to-agents network.

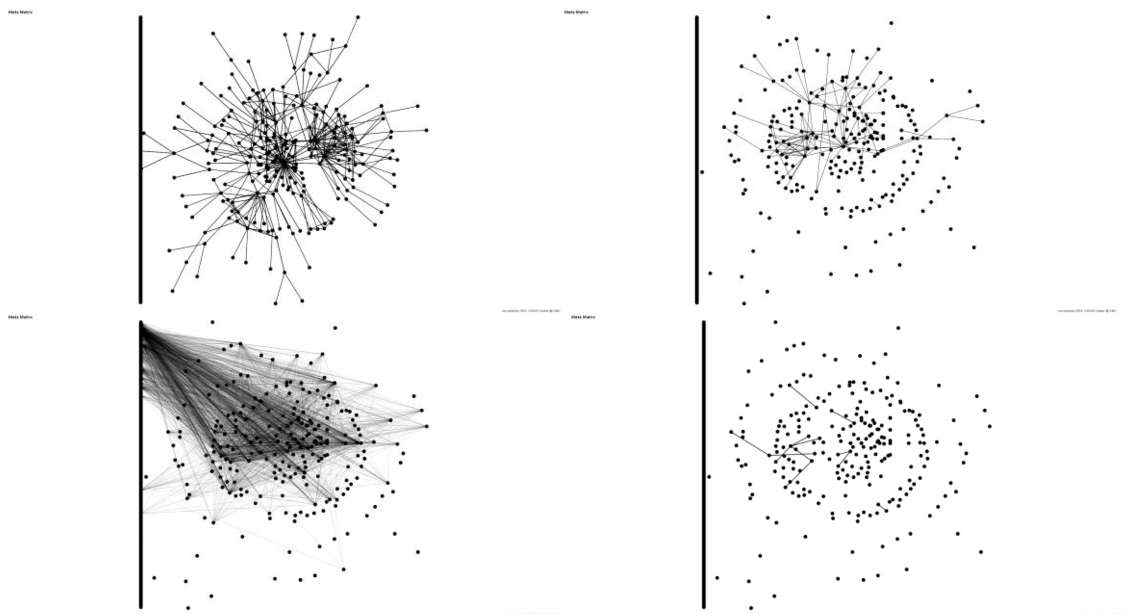


Figure 13-1 One original agent-to-agent network and three extracted decision making structures. (Top-left) the agent-to-agent original network (Top-right) Information Sharing, (Bottom-left) Result Sharing, (Bottom-right) Command Interpretation

Table 13-1 and Table 13-2 show the correlation between the observed social network and the decision making structures from this global terrorist network. The result sharing and the command interpretation structures are not close to the observed social network while the information sharing structure is similar to the observed social network. While the result sharing and the command interpretation have low correlations, their low correlations are resulted by different factors. The result sharing structure has extensive inferred links that are not distributed like the observed structure. The command interpretation has limited inferred links that are distributed like the observed structure among very small population.

Table 13-1 QAP correlation and other distance metrics between the observed structure and the extracted decision making structures. (IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

	CI	IS	RS
Correlation	0.029	0.365	0.022
Significance	0.000	0.000	0.000
Hamming Distance	565.000	517.000	3771.000
Euclidean Distance	137.920	133.154	148.260

Table 13-2 regression results. The dependent network is the observed meta-network, and the independent networks are the extracted meta-network. (R-Squared = 0. 136)

Variable	Coef	Std.Coef	Sig.Y-Perm	Sig.Dekker
Constant	0.003		0.000	
CI	-2.251	-0.057	0.000	0.000
IS	3.422	0.379	0.000	0.000
RS	-0.041	-0.017	0.000	0.000

Table 13-3 suggests the top individuals from the observed and the extracted structures. With the observed social network, *Mohammed Atta* seems to have the highest degree centrality. However, when considering the embedded decision making structure, *Osama Bin Laden* (in the information sharing and result sharing) and *Fathur al-Ghozi* (command interpretation) have the highest degree centrality. These new important actors imply that there are hidden key players in this network if we consider its decision making structure for key task execution.

Table 13-3 Top three individuals from five metrics and four structures (OBS=observed meta-network, IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

Measure	Structure	Rank 1	Rank 2	Rank 3
Total Degree Centrality	OBS	mohammed_atta	marwan_al-shehhi	ziad_jarrah
	IS	bin_laden	bakar_bashir	riduan_isamuddin
	RS	bin_laden	slobodan_milosevic	amrozi_hasyim
	CI	fathur_al-ghozi	bakar_bashir	bin_laden
Betweenness Centrality	OBS	bin_laden	riduan_isamuddin	abdul_aziz
	IS	bin_laden	abdul_aziz	mohammed_atta
	RS	slobodan_milosevic	olusegun_obasanjo	bin_laden

Measure	Structure	Rank 1	Rank 2	Rank 3
	CI	bin_laden	gul_agha	mounir_motassadeq
Eigenvector Centrality	OBS	marwan_al-shehhi	mohammed_atta	ziad_jarrah
	IS	bakar_bashir	imam_samudra	riduan_isamuddin
	RS	hassan_nasrallah	pervez_musharraf	bin_laden
	CI	bakar_bashir	fathur_al-ghozi	azahari_husin
Cognitive Demand	OBS	bin_laden	slobodan_milosevic	pervez_musharraf
	IS	bin_laden	slobodan_milosevic	pervez_musharraf
	RS	bin_laden	slobodan_milosevic	pervez_musharraf
	CI	bin_laden	slobodan_milosevic	pervez_musharraf
Communication	OBS	slobodan_milosevic	silvio_berlusconi	suharto
	IS	marzook	tayyip_erdogan	yassin
	RS	marzook	tayyip_erdogan	yassin
	CI	marzook	tayyip_erdogan	yassin

Figure 13-2 displays the discrepancy between the observed social network structure and the extracted decision making structures. Some agents have large differences from the network measure perspective. For example, there are three agents, *Marwan al-Shehhi*, *Ziad Jarrah*, and *Mohammed Atta*, with very large negative differences when we subtract the original's eigenvector centrality value from the extracted network's eigenvector centrality value. This implies that these three agents have over-estimated network measures from the original structure compared to the decision making structure. Such an example exists in the comparisons of betweenness centrality; *Bin Laden* is an agent shows very large over-estimates in the observed structure.

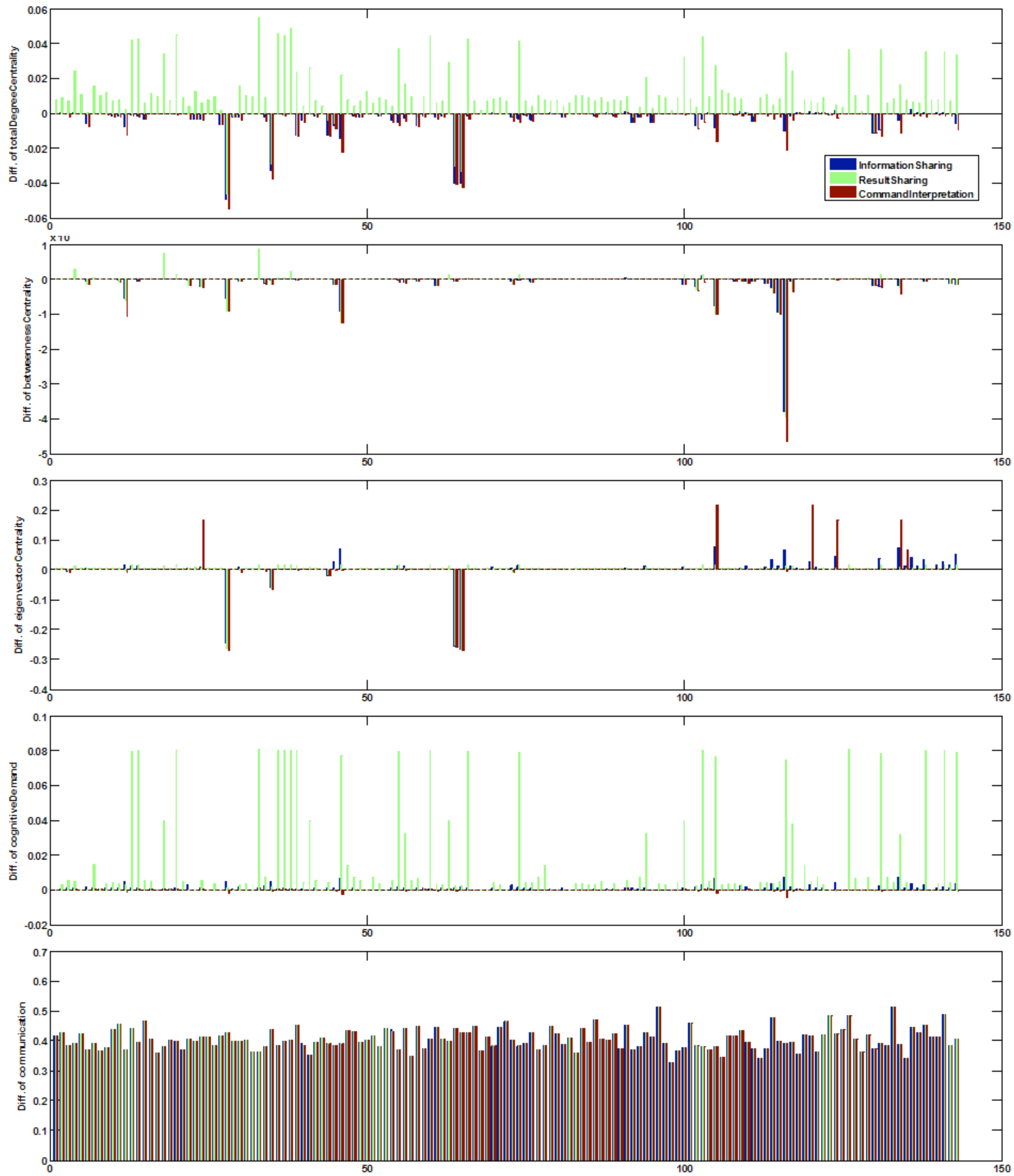


Figure 13-2 Charts displaying the difference of metrics between a meta-network and extracted structures

Table 13-4 shows the two principal components for each of the two structures: the observed structure and the extracted decision making structure. For the observed structure, the higher first principal component means *more communication demand to complete their tasks*. The higher second principal component means that *less connections to other personnel*. For the extracted structure, the higher first component means *mores communication demand to complete their tasks*. The higher second principal component means that *more connections to other personnel.*

Table 13-4 Coefficients of two principal components from the observed structure (top) and the extracted structures (bottom)

	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	OBS	0.009	-0.174
Betweenness Centrality	OBS	0.001	-0.001
Eigenvector Centrality	OBS	-0.032	-0.984
Cognitive Demand	OBS	0.245	0.016
Communication	OBS	0.969	-0.035
	Structure	Prin. Comp. 1	Prin. Comp. 2
Total Degree Centrality	IS	0.003	0.020
	RS	0.034	0.222
	CI	0.000	0.001
Betweenness Centrality	IS	0.000	0.001
	RS	0.000	0.001
	CI	0.000	0.000
Eigenvector Centrality	IS	0.016	0.181
	RS	0.010	0.058
	CI	0.007	0.297
Cognitive Demand	IS	0.131	0.338
	RS	0.185	0.743
	CI	0.128	0.317
Communication	IS	0.557	-0.142
	RS	0.557	-0.141
	CI	0.557	-0.141

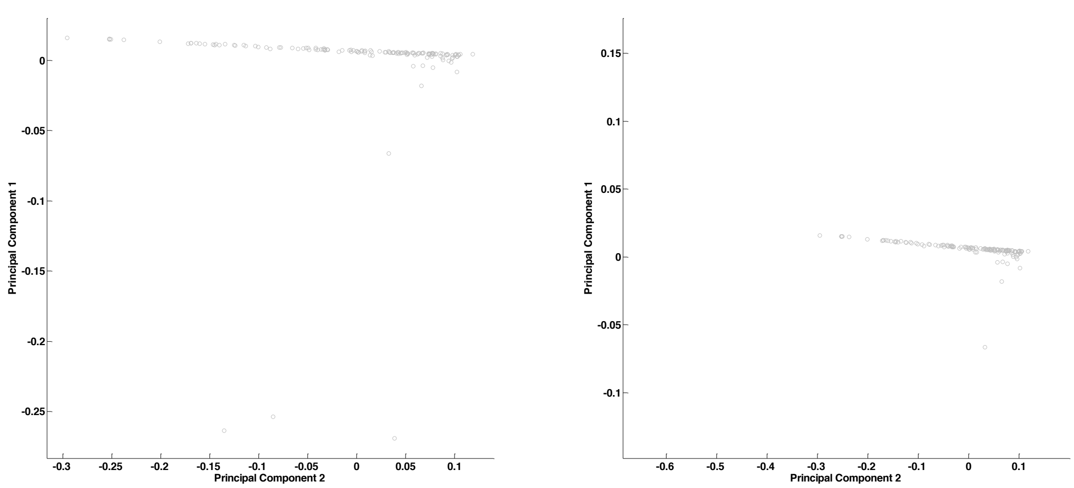


Figure 13-3 Two projections of metrics of individuals using two principal components. The left is using only the observed structure, and the right is from only the extracted structures.

Figure 13-3 shows the clusters of actors from the two principal component analyses. There is no clear cluster except one giant cluster with very high first principal components and with broadly ranging second principal components. This means that most of the agents require communication with others to complete their tasks because they do not have required components while the agents connectivity to other varies a lot. There are few agents with low first principal component values. These agents are *Tariq Aziz, Abu Rusdan, Horst Mahler, Ruhakana Rugunda.* etc.

13.2. Influence network analysis

Figure 13-4 and Table 13-5 show the task completion likelihood. I set the *bombing* task in the dataset as the task of interests. Subsequently, 42 tasks in the datasets are identified that they are involved in the task dependency network of the *bombing* task. However, this influence network analysis estimates that the key task completion likelihood is very minimal. As discovered in the decision making structures, many of the agents do not have their required organizational elements to execute their tasks. Only, few tasks, *commemorate, detonated, counterinsurgency,* and *martyrdom,* are expected to be completed with the limited probability.

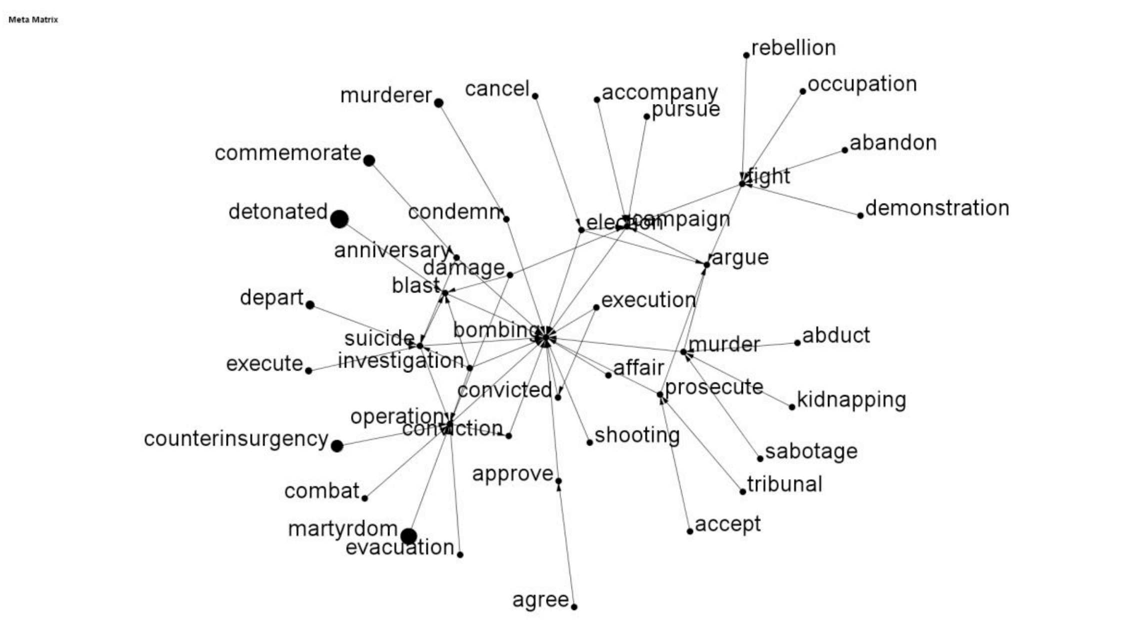


Figure 13-4 The visualization of the task dependency network. The node sizes are adjusted to the completion likelihood of the tasks.

Table 13-5 Task completion likelihoods when evaluated with default (medium) threshold for assessment and default (medium) probability assignment for baseline

Task Name	Completion Likelihood	Task Name	Completion Likelihood
bombing	0.000	accept	0.000

Task Name	Completion Likelihood	Task Name	Completion Likelihood
conviction	0.000	sabotage	0.000
campaign	0.000	kidnapping	0.000
operation	0.006	abduct	0.000
blast	0.000	pursue	0.000
damage	0.000	affair	0.000
argue	0.000	execution	0.000
suicide	0.000	tribunal	0.000
prosecute	0.000	murderer	0.032
investigation	0.000	detonated	0.146
accompany	0.000	anniversary	0.000
execute	0.017	agree	0.000
martyrdom	0.124	cancel	0.000
convicted	0.000	rebellion	0.008
approve	0.000	abandon	0.000
combat	0.000	occupation	0.000
condemn	0.000	shooting	0.000
election	0.000	evacuation	0.000
murder	0.000	demonstration	0.000
depart	0.025	commemorate	0.053
fight	0.000	counterinsurgency	0.062

Table 13-6 and Table 13-7 represent the sensitivity analysis assuming different levels of operational environment (differentiating the completion probability for assessments) and different levels of assessment strictness (differentiating the organizational support assessment). I only listed tasks with higher than zero probabilities in any of the sensitivity analysis cases out of 42 tasks of interests. *Murderer* is a task with the highest completion probability on average. However, its standardized deviation is too large, suggesting that the estimation is volatile according to the parameters that human analysts have to determine. On the other hand, *detonated* is a task with low standardized deviation, implying that its completion probability estimation is stable across the sensitivity analysis parameter setups.

Table 13-6 Task completion likelihoods of tasks under nine different settings

	Low Probability			Medium Probability			High Probability				
Task Name	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Low Threshold	Med Threshold	High Threshold	Avg.	Std. Dev.
murderer	0.001	0.000	0.000	0.093	0.032	0.000	0.816	0.712	0.000	0.184	0.313
detonated	0.057	0.064	0.021	0.116	0.146	0.027	0.373	0.437	0.056	0.144	0.145
execute	0.000	0.000	0.000	0.026	0.017	0.000	0.607	0.575	0.000	0.136	0.243
depart	0.001	0.001	0.000	0.046	0.025	0.000	0.610	0.534	0.000	0.135	0.235
martyrdom	0.040	0.045	0.011	0.099	0.124	0.014	0.381	0.440	0.028	0.131	0.154
counterinsurgency	0.011	0.012	0.001	0.051	0.062	0.001	0.394	0.446	0.002	0.109	0.168
commemorate	0.008	0.008	0.000	0.044	0.053	0.000	0.398	0.448	0.001	0.107	0.170
rebellion	0.000	0.000	0.000	0.006	0.008	0.000	0.425	0.463	0.000	0.100	0.184
operation	0.000	0.000	0.000	0.014	0.006	0.000	0.418	0.326	0.000	0.085	0.155

Table 13-7 Ranks of task completion likelihoods of tasks under nine different settings

	Low Probability			Medium Probability			High Probability		
Task Name	Low Thre shold	Med Thre shold	High Thre shold	Low Thre shold	Med Thre shold	High Thre shold	Low Thre shold	Med Thre shold	High Thre shold
murderer	6	6	8	3	5	6	1	1	6
detonated	1	1	1	1	1	1	9	8	1
execute	7	7	7	7	7	8	3	2	8
depart	5	5	5	5	6	5	2	3	5
martyrdom	2	2	2	2	2	2	8	7	2
counterinsurgency	3	3	3	4	3	3	7	6	3
commemorate	4	4	4	6	4	4	6	5	4
rebellion	9	8	9	9	8	9	4	4	9
operation	8	9	6	8	9	7	5	9	7

13.3. Simulating the social behavior of adversaries

I design the virtual experiment for the social behavior of adversaries as Table 13-8. I differentiate the removal agent selection scheme (various network metrics to pick a target removal), intervention timing (when to remove over the course of simulations), and intervention size (how many to remove during the simulations).

The readers should interpret this analysis results as a covert community structure evolution rather than a project team structure evolution and interactions. While the two other datasets, the US bombing datasets, are about a small project team simulation, this is a community evolution of a larger population. Also, many of the agents are isolates, they do not have required resources to perform their tasks, and their task definitions are sometimes too broad to be interpreted as a single task. Thus, the task related simulation results are not credible as much as the community evolution results, such as diffusion, binary task accuracy, energy task accuracy, etc[16]. In this chapter, I particularly omit the task completion speed, mission completion speed, and Gantt chart because they are project team oriented results. According to the simulation, there are only 12 tasks (out of 278) are done at time 0, meaning that the tasks are ready to be launched without any simulated behavior of the adversaries.

Table 13-8 Virtual experiment design for simulation parameters (3 replications, 1200 simulation time steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	59, 179 and 298 agent removals (removing 10%, 30%, and 50% of agents, 3 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	60, 120, and 240 time-step (removing at after 5%, 10%, and 20%, 3 cases)	The intervention happens at a specific stage of simulation period.
Total virtual experiment cells	36 cells (4x3x3 cases)	

Table 13-9 shows the regression analysis between the virtual experiment settings (representing the network metric selection as four binary values). Larger interventions are preferable in reducing the diffusion level. However, to reduce the binary task accuracy and the energy tsak accuracy, we need to limit the number of interventions. It seems that the population are not properly

[16] Actually, these community (or sociology) oriented metrics are already defined in Construct that is a predecessor of the simulation used in this thesis.

equipped with information and resources, so that having more population helps lowering the average of the task accuracies. Particularly, removing top betweenness centrality agents are helpful in reducing the energy task accuracy while removing top degree centrality agents are better in reducing the diffusion.

Table 13-9 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=36 cases) (* for P<0.05)

Standardized Coefficient	BTA	ETA	Diffusion
Intervention Timing	0.245*	-0.012	0.009
Intervention Size	-0.223*	-0.256*	0.473*
Degree Cent.	-0.023	-0.029	-0.142*
Betweenness Cent.	-0.557*	-0.984*	0.783*
Eigenvector Cent.	0.000	0.000	0.000
Cognitive Demand	0.119	-0.103*	0.035
Adjusted R-Square	0.591	0.963	0.917

Table 13-10 is the collection of regression models between the simulated organizational performance and the virtual experiment settings (this time, the averaged network values from the removed agents are used for regressions). From the intervention size and the timing perspectives, the results are same to the previous table. However, unlike the previous regression result, the removal of high eigenvector centrality agents are preferable in decreasing the task accuracy (the previous regression showed removing the high betweenness centrality agents is better).

Table 13-10 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated metrics of removed agents (N=36 cases) (* for P<0.05)

Standardized Coefficient	BTA	ETA	Diffusion
Intervention Timing	0.245*	-0.012	0.009
Intervention Size	-0.250	-0.649*	0.561*
Degree Cent.	0.378	1.863	-1.160
Betweenness Cent.	0.139	0.057	0.184
Eigenvector	0.412	-2.532*	1.332

Cent.			
Cognitive Demand	-1.258	-0.156	0.571
Adjusted R-Square	0.569	0.778	0.727

Figure 13-5 shows the organizational performance over time. Removing high betweenness centrality agents definitely helps in damaging the three of organization performance metrics. Also, early removals are a good wey to reduce the binary task accuracy and diffusion. Removing high cognitive demand agents, late-middle period removals, and small removals are not preferable because their curves show limited negative difference from the baseline.

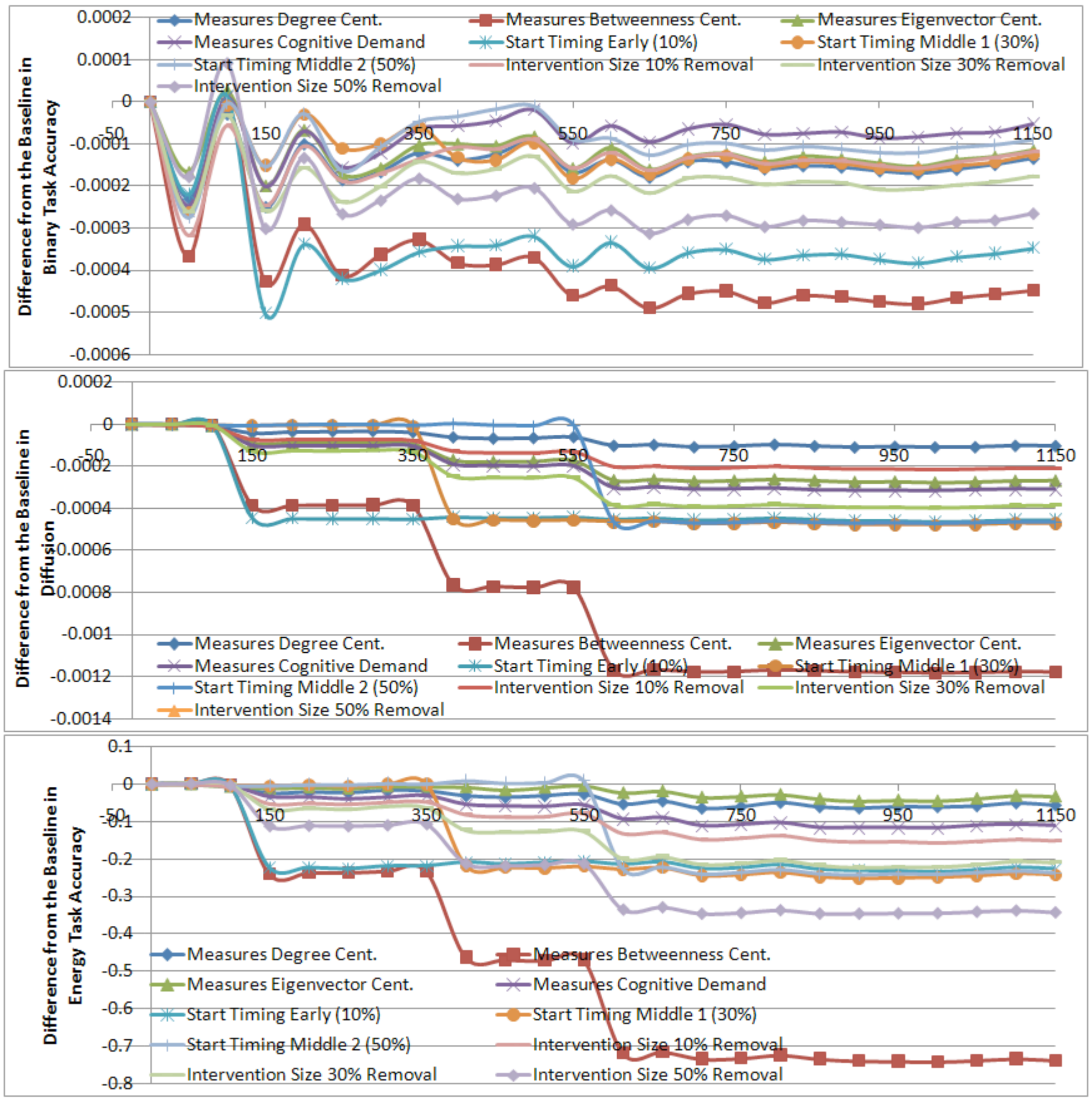
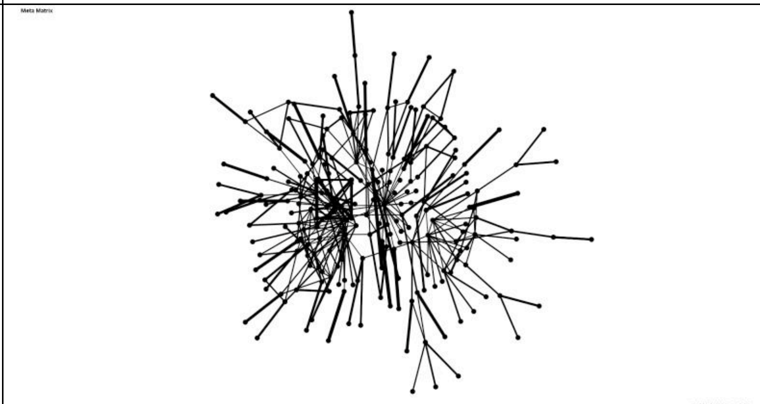
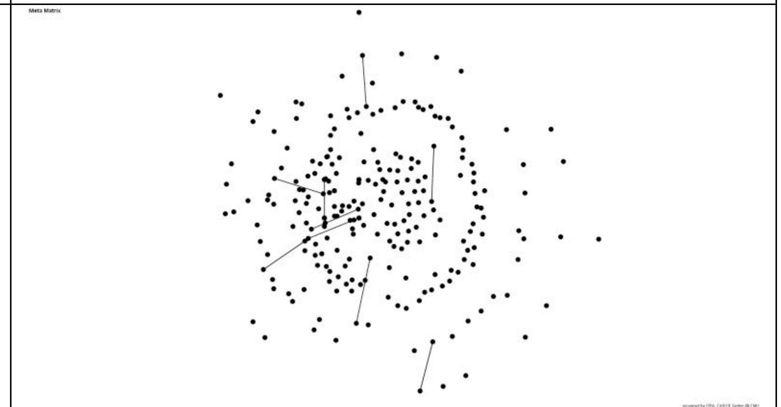
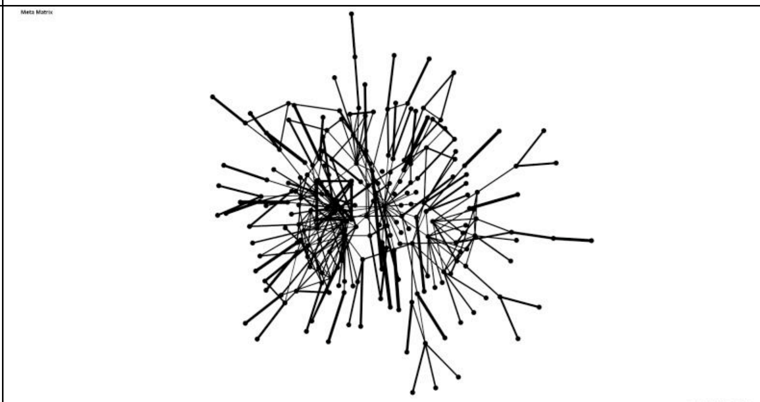
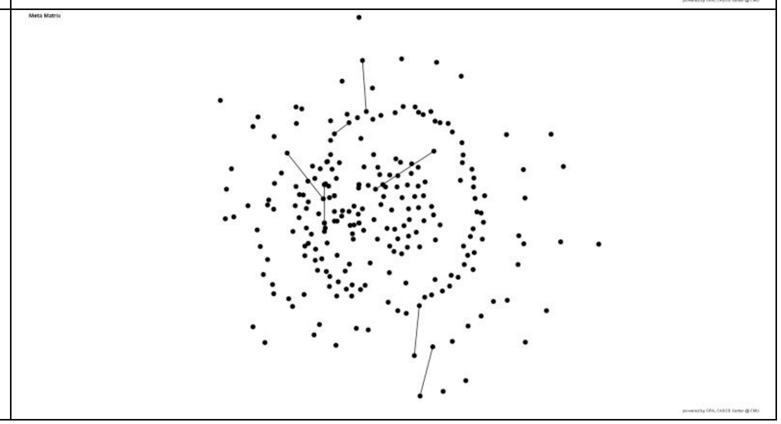


Figure 13-5 Organizational performance over time, aggregated by the first factor

Table 13-11 visualizes the interaction and the organizational element transfer network among agents over time. The interaction network does not show any change in terms of its topology. However, the interaction frequencies of pairs are different (which are shown as the link thickness in the visualization). Unlike the other datasets, This dataset is 1) larger and 2) community oriented data, not a project team. Therefore, the transactive memory of agents are difficult to be diffused due to the large size. Also, the matching required resources and information are hard to be searched through networks. Thus, the organizational transfer happens at minimal frequencies. This is why we see this sparse transfer network compared to the dense transfer network of the other two datasets in the main chapters and the other appendix.

Table 13-12 lists the key agents over the course of the simulations. *Bin Laden* is a name that frequently appears and ranked at the top. He has the highest degree centrality at time 50, 200, and 500. Also, he has the highest betweenness centrality at time 200, 500 and 1150. However, his importance was limited to the interaction network. His name does not appear in the transfer network, which suggests that he was not intensively involved in this limited resource and information transfer.

Table 13-11 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 50		
Time 200		

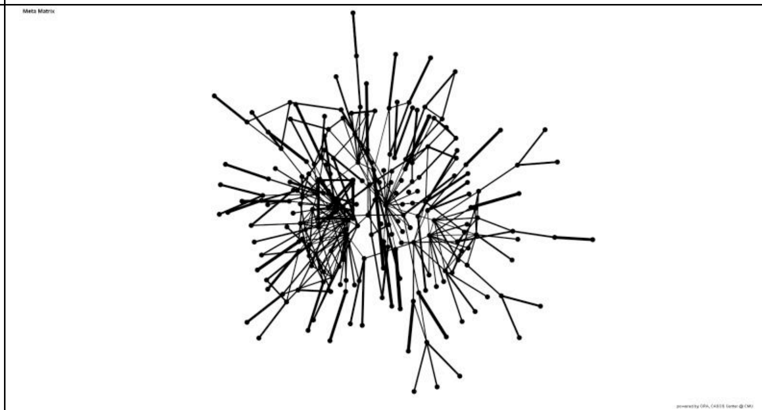
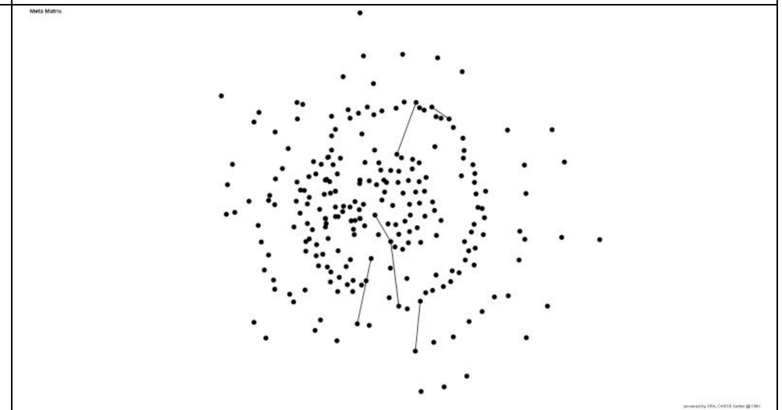
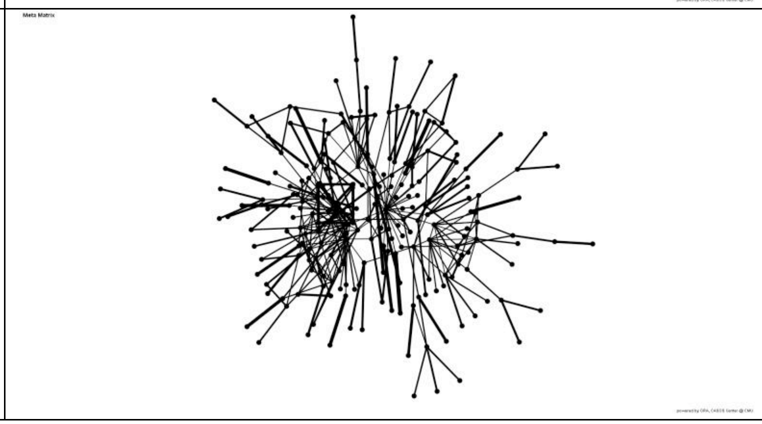
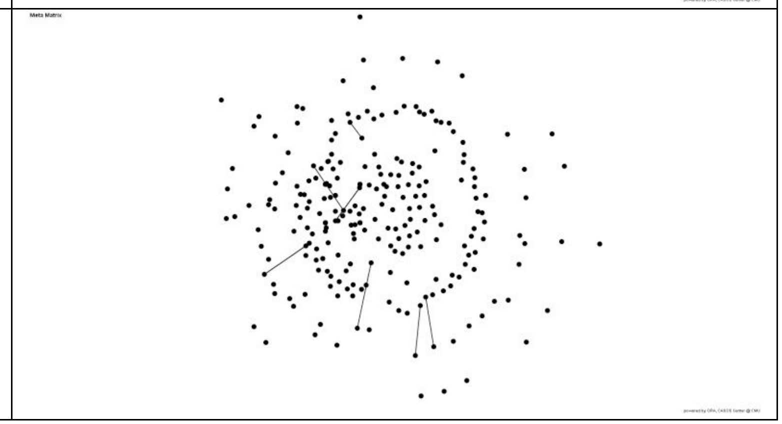
	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 500		
Time 1150		

Table 13-12 Key individual lists over the course of simulations

Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	bin_laden	hamid_karzai	mohammed_atta	Every agent has 0 value for betweenness centrality	marwan_barghouti	hamid_karzai
Rank 2	slobodan_milosevic	slobodan_milosevic	hamid_karzai	suharto	abdul_aziz		muhammad_horani	akram_khakrezwal
Rank 3	pervez_musharraf	pervez_musharraf	riduan_isamuddin	marty_natalegawa	ali_gufron		raanan_gissin	suharto
Rank 4	abu_al-zarqawi	abu_al-zarqawi	ariel_sharon	akram_khakrezwal	bakar_bashir		silvan_shalom	marty_natalegawa
Rank 5	yaacov_perry	yaacov_perry	amrozi_hasyim	amrozi_hasyim	ariel_sharon		ehud_barak	jose_padilla
Time 200	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	bin_laden	mohammed_khatami	bin_laden	Every agent has 0 value for betweenness centrality	salah_shehada	mohammed_khatami
Rank 2	slobodan_milosevic	slobodan_milosevic	aziz_al-rantisi	ali_khamenei	imam_samudra		ismail_abu_shanab	ali_khamenei
Rank 3	pervez_musharraf	pervez_musharraf	amrozi_hasyim	hamid_karzai	abdul_aziz		mohammed_deif	pervez_musharraf
Rank 4	abu_al-zarqawi	abu_al-zarqawi	omar_abu_omar	tayssir_alouni	riduan_isamuddin		mahmoud_al-zahar	abdul_khan
Rank 5	yaacov_perry	yaacov_perry	mohammad_dahlan	ibrahim_bah	bakar_bashir		ismail_haniyeh	abdul_aziz

Time 500	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	bin_laden	l_houssaine_kherchtou	bin_laden	l_houssaine_kherchtou	mamdouh_habib	l_houssaine_kherchtou
Rank 2	slobodan_milosevic	slobodan_milosevic	mohammad_dahlan	crown_prince_abdullah	abdul_aziz	The other agent s have 0 value for betweenness centrality	bin_laden	jamal_al-fadl
Rank 3	pervez_musharraf	pervez_musharraf	bakar_bashir	muhammad_zouaydi	faiz_bafana		tawfiq_attash	mohammed_atef
Rank 4	abu_al-zarqawi	abu_al-zarqawi	hamid_karzai	adnan_ersoz	ahmad_yassin		rahim_al-nashir	qaed_al-harethi
Rank 5	yaacov_perry	yaacov_perry	ramzi_binalshibh	pervez_musharraf	riduan_isamuddin		mohamedou_slahi	muhammad_zouaydi
Time 1150	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	hamid_karzai	suharto	bin_laden	Every agent has 0 value for betweenness centrality	mamdouh_habib	ramzi_binalshibh
Rank 2	slobodan_milosevic	slobodan_milosevic	mokhtar_haouari	zoheir_choulah	abdul_aziz		bin_laden	mullah_omar
Rank 3	pervez_musharraf	pervez_musharraf	mohammad_dahlan	christophe_caze	riduan_isamuddin		tawfiq_attash	pervez_musharraf
Rank 4	abu_al-zarqawi	abu_al-zarqawi	aziz_al-rantisi	marty_natalegawa	ahmad_yassin		abdullah_bin_laden	bakar_bashir
Rank 5	yaacov_perry	yaacov_perry	bin_laden	hamid_karzai	mohammed_atef		rahim_al-nashir	marwan_al-shehhi

13.4. Simulating the social and geospatial behavior of adversaries

Table 13-13 shows the virtual experiment design. This experiment design is identical to the design of the social only model simulation. Three factors are differentiated across the cells. The three factors are 1) the removal agent selection scheme (different network measures), 2) the intervention size and 3) the intervention timing.

Table 13-13 Virtual experiment design for simulation parameters (3 replications, 1200 simulation time steps)

Name	Value	Implication
Removal target selection scheme	Degree, Betweenness, Eigenvector centralities and Cognitive Demand (4 cases)	Agents with high network values are considered critical, and their removal is critical to the organizations. This is how we pick target agents to remove.
Intervention size	59, 179 and 298 agent removals (removing 10%, 30%, and 50% of agents, 3 cases)	The intervention size specifies how many agents to remove with this intervention.
Intervention timing	60, 120, and 240 time-step (removing at after 5%, 10%, and 20%, 3 cases)	The intervention happens at a specific stage of simulation period.
Total virtual experiment cells	36 cells (4x3x3 cases)	

Table 13-14 is the collection of the regression models between the organizational performances and the virtual experiment settings (treating the network metric selection as a categorical vairable). As the previous simulations, the earlier (positive coefficient) and larger interventions (negative coefficient) are preferable in damaging the task speed, binary task accuracy, energy task accuracy, and diffusion.

Table 13-14 Standardized coefficients for regression to the six organizational performance metrics at the end time using the virtual experiment settings (treating removed agent selection scheme with four categorical values) (N=64 cases) (* for P<0.05)

Standardized Coefficient	BTA	ETA	Diffusion
Intervention Timing	0.723*	0.058	0.128*
Intervention Size	-0.592*	-0.873*	-0.724*
Degree Cent.	-0.089	-0.067	0.144
Betweenness Cent.	-0.102	-0.115	0.172

Eigenvector Cent.	0.032	-0.019	0.054
Cognitive Demand	0.000	0.000	0.000
Adjusted R-Square	0.617	0.852	0.835

Table 13-14 is the collection of the regression models between the simulated organizational performances and the virtual experiment settings (for the network values, I averaged the network values of the removed agents instead of using the categorical value as in Table 13-13). Earlier and larger interventions are helpful in reducing the binary task accuracy, energy task accuracy and diffusion. Removing high betweenness centrality agents (negative coefficient) is better in reducing the energy task accuracy and diffusion.

Table 13-15 Standardized coefficients for regression to the six organizational performance metrics at the end time using the calculated network metrics of the removed agents (N=64 cases) (* for P<0.05)

Standardized Coefficient	BTA	ETA	Diffusion
Intervention Timing	0.842*	0.162	0.093*
Intervention Size	-0.872*	-0.921*	-0.697*
Degree Cent.	0.152	0.535	0.910
Betweenness Cent.	0.198	-0.358	-0.479
Eigenvector Cent.	0.157	-0.131	0.697
Cognitive Demand	0.762	0.142	0.205
Adjusted R-Square	0.582	0.917	0.803

Figure 13-6 shows the organizational performance over time. Still removing the top betweenness centrality agents is the best way in decreasing the organizational performance. From the binary task accuracy perspective, while the previous social only simulation showed more damage in the early removals than the damage in the more removals, this simulation prefers more removals than the earlier removals because the rank of the amount of damage is changed between the “Start Timing Early (10%) and “Intervention Size 50% Removal”.

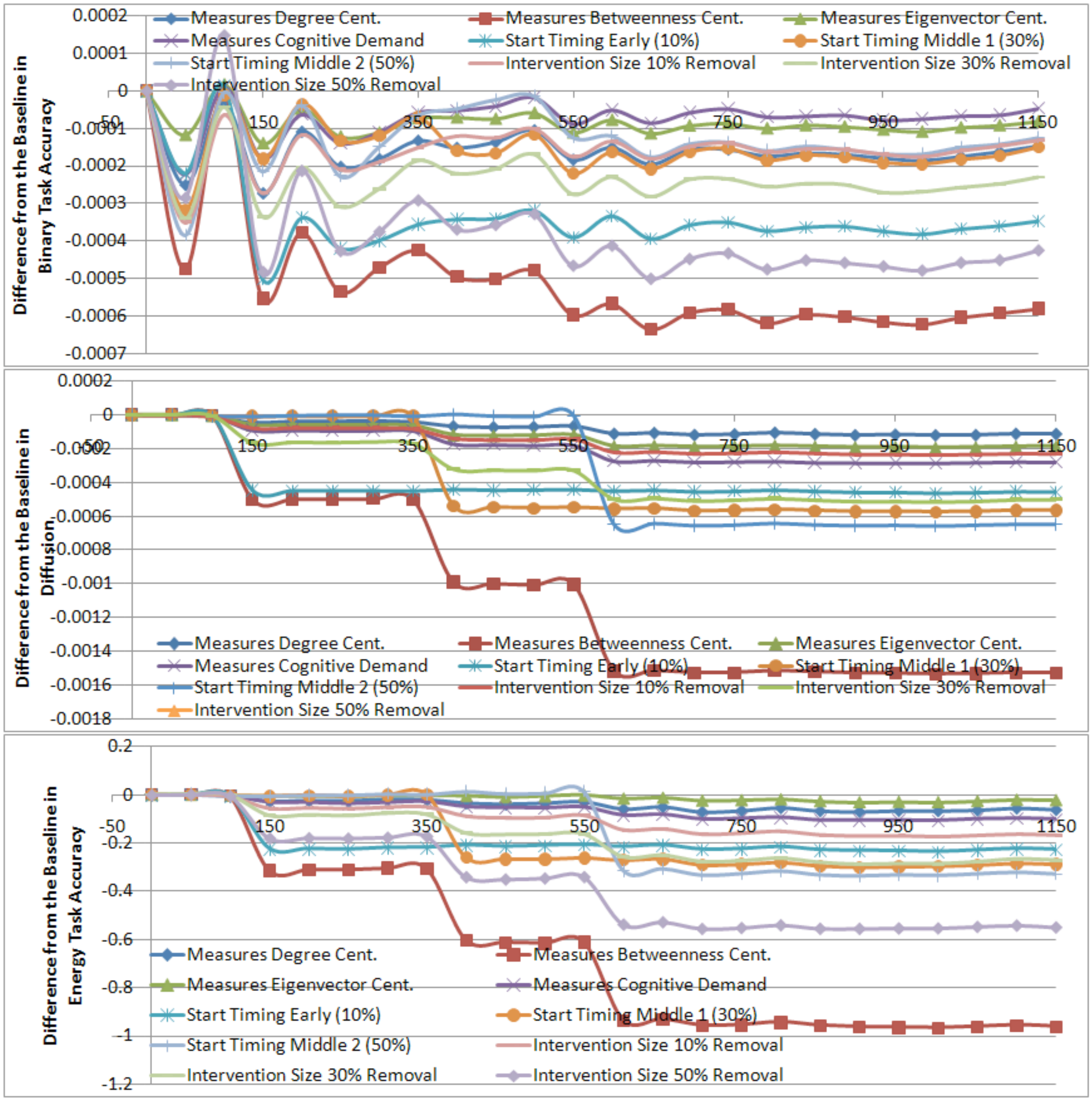


Figure 13-6 Organizational performance over-time

Figure 13-7 shows the agent segregation level from the baseline. *China* and *US* hold larger number of agents over time than any other locations. Also, *Russia* and *London* are the key locations with many agents. This segregation result cannot be well correlated to the task execution of this dataset because this dataset does not complete any of tasks through relocation or interaction (Only tasks ready to be executed from the initial status are done). However, this relocation result suggests general population movement motivated by collecting information and resources.

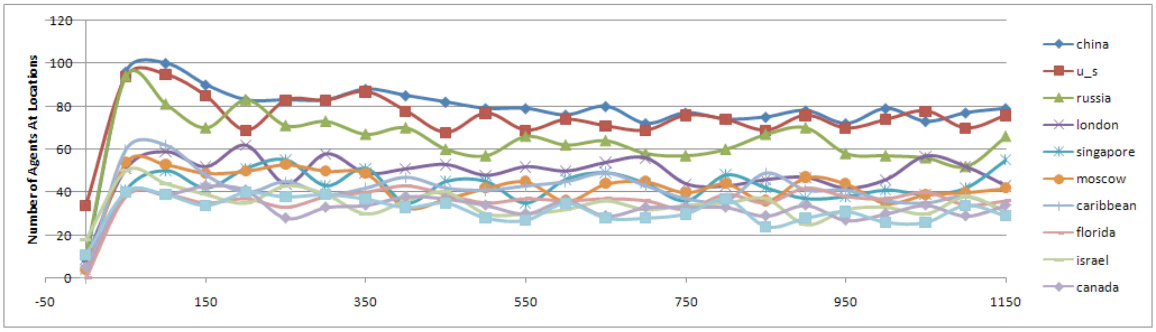
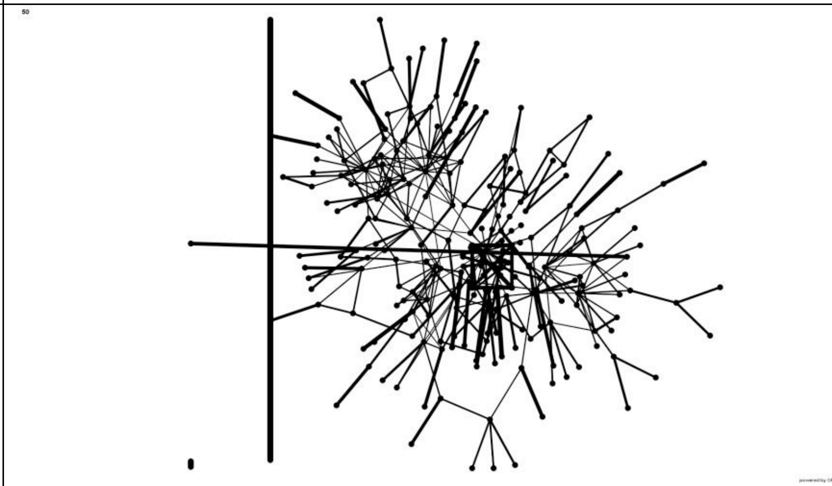
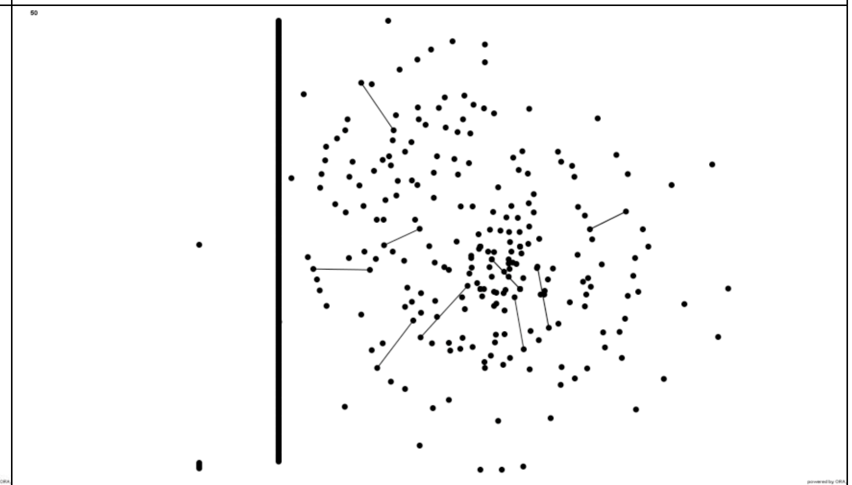
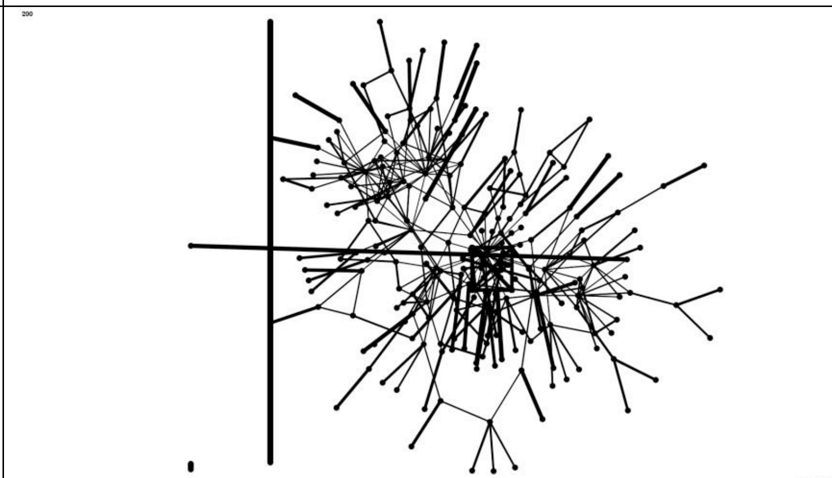
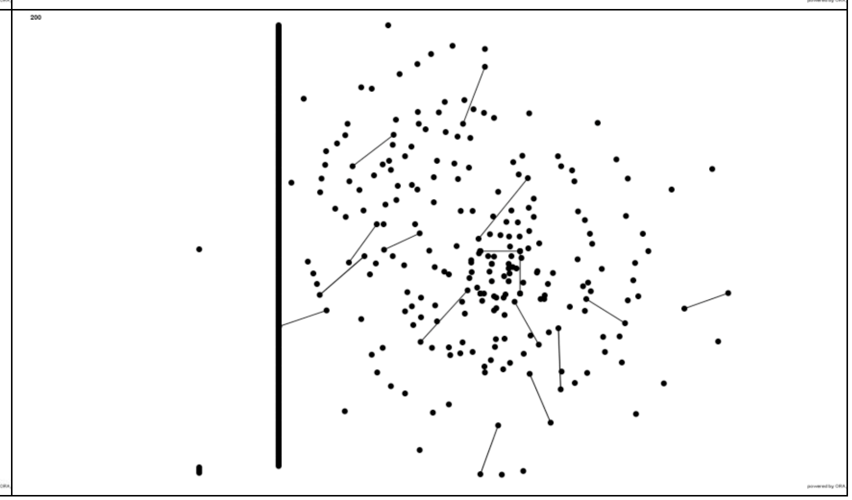


Figure 13-7 An agent-geospatial distribution over-time line chart of Baseline

Table 13-16 shows a collection of interaction and transfer networks among the agents during the simulation. The interaction networks do not change a lot. The transfer networks are very sparse to see a clear pattern. This suggests that the interactions are frequently happening, but resulting transactions of resources and information are very rare.

Table 13-17 is the agents' network values in the interaction and the transfer networks during the simulations. *Bin Laden* is a key actor that appears in the top agent lists of degree centrality, betweenness centrality, and cognitive demand. Also, *Croun Prince Abdullah* is another agent that appears at the top of the betweennes centrality of the transfer network.

Table 13-16 Collection of agent interaction and organizational transfer network over time, link thickness is adjusted to show the frequency of the link usage.

	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Time 50		
Time 100		

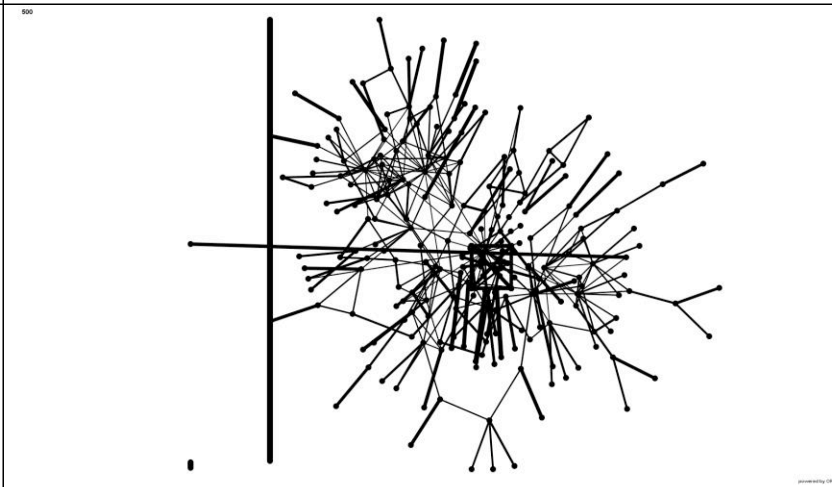
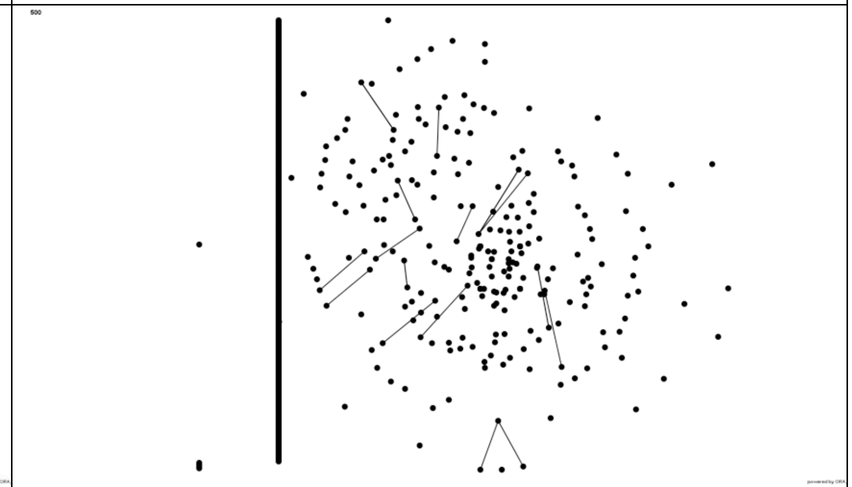
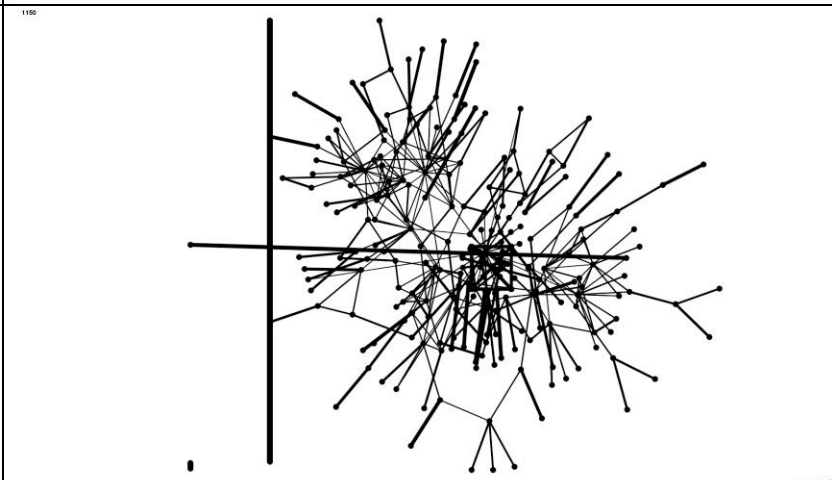
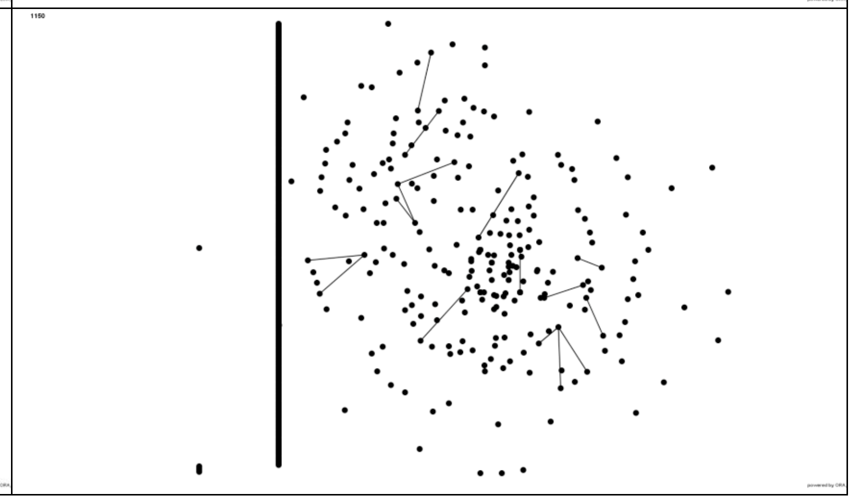
	Agent to Agent network: Interaction	Agent to Agent network: Transfer resources and expertise
Tim e 150		
Tim e 350		

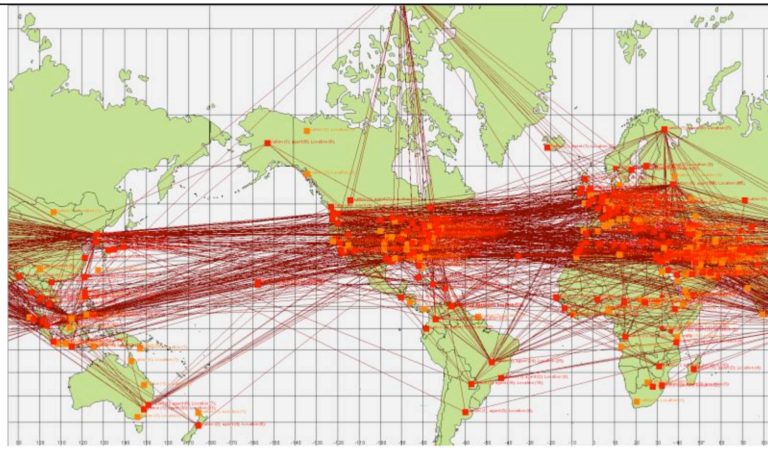
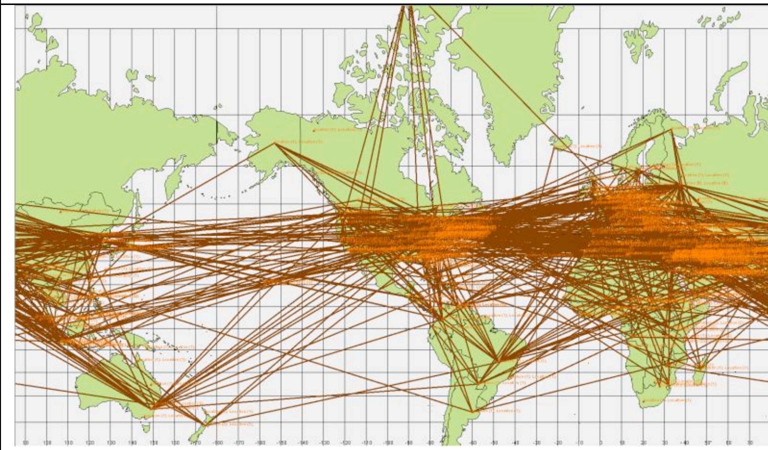
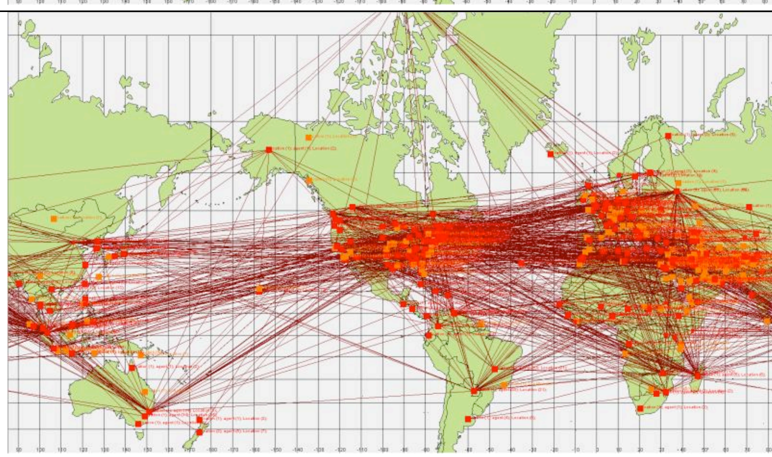
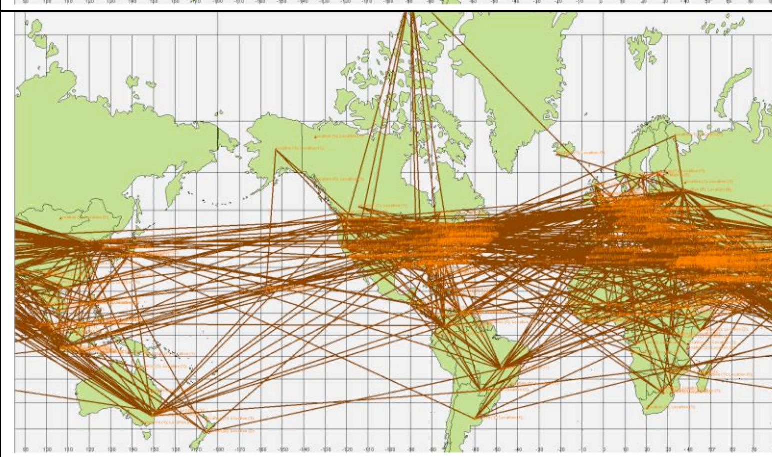
Table 13-17 Key individual lists over the course of simulations

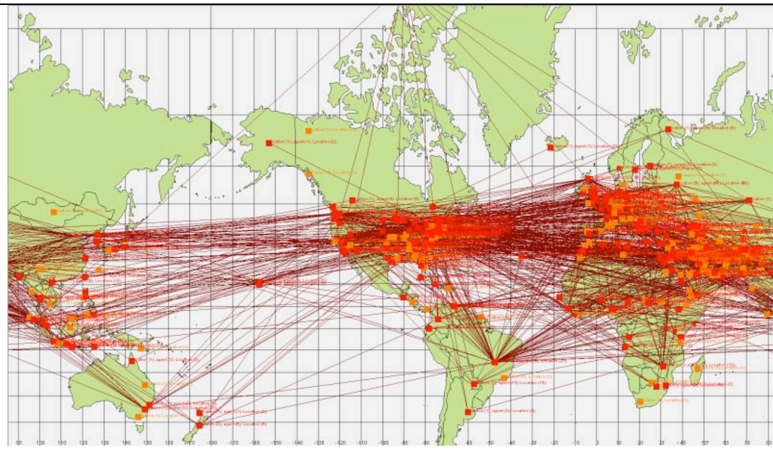
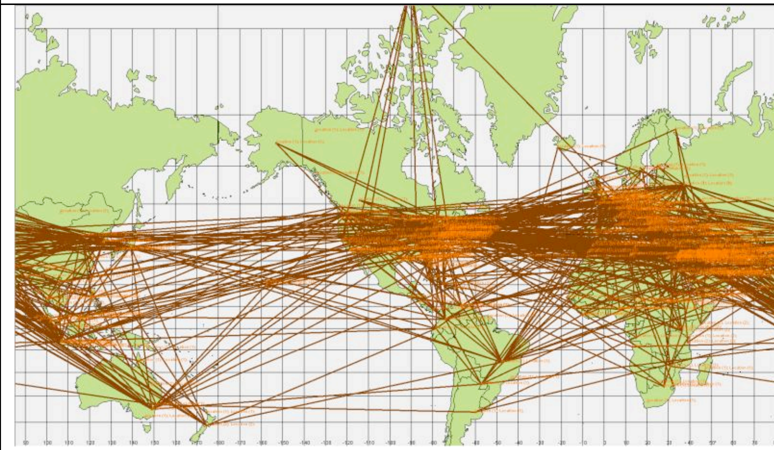
Time 50	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	mokhtar_haouari	aslan_maskhadov	bin_laden		rahim_al-nashir	aslan_maskhadov
Rank 2	riduan_isamuddin	riduan_isamuddin	bin_laden	shamil_basaev	riduan_isamuddin	Every agent has zero value for this measure	tawfiq_attash	shamil_basaev
Rank 3	bakar_bashir	bakar_bashir	bakar_bashir	antonio_martino	jose_padilla		saif_al-adel	antonio_martino
Rank 4	imam_samudra	imam_samudra	omar_abu_omar	saddam_hussein	abdul_aziz		muhsin_atwah	saddam_hussein
Rank 5	abdul_aziz	abdul_aziz	imad_al-alami	ismail_haniyeh	zacarias_moussaoui		saddam_hussein	
Time 200	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	bin_laden	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	hamid_karzai	yassin	bin_laden		muhammad_zouaydi	yassin
Rank 2	bakar_bashir	bakar_bashir	mokhtar_haouari	ali_mohamed	abdul_aziz	Every agent has zero value for this measure	khalaf	ali_mohamed
Rank 3	mohammed_atta	mohammed_atta	aziz_al-rantisi	sharm_sheik	ali_ghufron_nurhasyim		karim_mehdi	sharm_sheik
Rank 4	imam_samudra	imam_samudra	bin_laden	ahmed_hannan	ahmad_yassin		qaed_al-harethi	ahmed_hannan
Rank 5	abdul_aziz	abdul_aziz	abu_marzouk	karim_koubriti	riduan_isamuddin		ahmad_chalabi	karim_koubriti

Time 500	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	bin_laden	crown_prince_abdullah	bin_laden	crown_prince_abdullah	mamdouh_habib	bashar_assad
Rank 2	ri-duan_isamuddin	ri-duan_isamuddin	aziz_al-rantisi	bashar_assad	abdul_aziz	The other agent have zero value for this measure	bin_laden	crown_prince_abdullah
Rank 3	bakar_bashir	bakar_bashir	omar_abu_omar	suharto	zaca-rias_moussaoui		rahim_al-nashir	hosni_mubarak
Rank 4	imam_samudra	imam_samudra	ariel_sharon	marty_natalegawa	faiz_bafana		tawfiq_attash	suharto
Rank 5	abdul_aziz	abdul_aziz	ri-duan_isamuddin	ziad_jarrah	riduan_isamuddin		l_houssaine_kherchtou	marty_natalegawa
Time 1150	CognitiveDemand		Degree Centrality		Betweenness Centrality		Eigenvector Centrality	
ID	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.	Interaction Net.	Transfer Net.
Rank 1	bin_laden	bin_laden	bin_laden	yassin	bin_laden	Every agent has zero value for this measure	mamdouh_habib	sharm_sheik
Rank 2	bakar_bashir	bakar_bashir	amrozi_hasyim	crown_prince_abdullah	abdul_aziz		bin_laden	crown_prince_abdullah
Rank 3	ri-duan_isamuddin	ri-duan_isamuddin	bakar_bashir	bashar_assad	riduan_isamuddin		amar_makhlulif	bashar_assad
Rank 4	abdul_aziz	abdul_aziz	moham-mad_dahlan	fathur_al-ghozi	crown_prince_abdullah		mohammed_abeel	fathur_al-ghozi
Rank 5	amro-zi_hasyim	amro-zi_hasyim	hamid_karzai	faiz_bafana	mohammed_atef		khalid_almihdhar	faiz_bafana

Table 13-18 visualizes the geospatial distribution of meta-network. The agents are heavily populated in *Europe*, *Middle East*, and *US*. Compared to the initial status, the agent presences in *Africa*, *Latin America* and *Southeast Asia* are increasing. These increases indicate that the agents are motivated or preferred to move such new places to collect new resources and information. Also, such a segregation results in more social links connecting two continents, such as *Middle East* and *Latin America*. This may represents the movement of some terrorists heading to *Latin America* for finding new funding sources and dispersing their weapons and terrorism skill.

Table 13-18 Collection of agent geospatial movements and transnational movement passage networks over time, link thickness is adjusted to show the frequency of the link usage.

	Geospatial visualization of meta-network	Location-to-location transnational movement network
Time 50		
Time 200		

	Geospatial visualization of meta-network	Location-to-location transnational movement network
Time 500		
Time 1150