Chapter 2
Modeling and Simulating Command and Control for Terrorist Organization

Keywords Command and control · Organizational goal · Geospace · Global terrorist network · Transactive memory · Dynet · OrgaHead · Construct · Meta-network · AutoMap · Multiagent simulation · Homophily · Knowledge diffusion · Task accuracy · Sensitivity analysis · Gini coefficient · Meta model

2.1 Introduction

As the command and control is an effort to achieve the organizational goal, the command and control structure should be designed to optimize crucial factors affecting the outcome. The interaction structure between the commanders and the units is one of such factors, and their geospatial locations are another critical factor. This is particularly significant when we consider a command and control structure that spans social groups as well as covers large geospace, i.e., a global terrorist network. We analyze the command and control structure of a global terrorist network[1] that we estimate from network text analyses.

Fundamentally, where social agents are influences who the agents know, and vice versa. As the agents move to new cities or countries, their contacts change. For instance, when a company relocates employees, they develop new working relations with others while they perform assigned tasks. In theory, relocation should improve performance. However, we also know that performance is dependent on knowing who to ask about what, i.e., transactive memory (Wegner 1986). Moving disrupts this memory and also the social relations by which information flows. Thus, we ask whether performance can improve when the geospatial and social distribution change simultaneously.

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[1] This case study is introduced by Moon and Carley (2007). This chapter expands the initial publication with additional background, dataset description, and virtual experiment results. Also, at the end of this chapter, we discuss how to interpret the result in the context of the command and control.

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These social and spatial relations evolve over time, so does the command and control structure that the relations imply. Estimating the evolutions is an important issue for management, command and control structure, and intelligence analysis research. By knowing the future social and spatial distributions of agents, an analyst can identify who will be an emergent leader, where will be a hot spot, and what will be the vulnerability of the organization.

Historically, the estimation has heavily depended on qualitative analysis (Arquilla and Ronfeldt 2001) by subject matter experts. A few researchers have approached this issue using multi-agent models and simulation from two perspectives, the impact of change in the social network (Carley et al. 2001; Snijder et al. forthcoming) and the impact of geospatial change (Epstein et al. 2001; Bergkvist et al. 2004). Their models consider the complex nature of the organization and task assignments, resource distributions or the location of the agents. These models were used to simulate the near-term changes of the organizations. Both models are able to project the aspects of future performance and the emerging structure of an organization, but they cannot examine the interaction between physical and social movements.

In this chapter, we develop a simple theoretical multi-agent model that includes the social and the geospatial dimensions at the same time. We expand an existing social simulation model, Dynet (Carley 2003). The agents in the model interact with others as well as relocate themselves to other spatial locations. This model illustrates some of the ways in which group behavior can be affected by the coevolution of social and geospatial relations. Using this model, a theoretical study of the interaction between social and geospatial change is conducted. The focus here is on how changes in the social and geospatial relations, e.g., through the attrition or movement of critical actors defined using social network techniques, influences group behavior. Then, we ground the final results by examining the implications of the model for a real-world organization, a terrorist network. This latter examination is meant to illustrate the potential for reasoning with this type of model. While the results are informative, we note that additional work needs to be done in the field prior to a full validation study, particularly given the weakness of the extant data sets. The data we use are extracted using a network text analysis technique on open source texts.

2.2 Previous Research

The study of the concurrent movement of people through social relations and space has been done mainly using two techniques: data mining and simulation. Data mining has been used to detect the patterns from a large database, and the patterns include the organizational structure network, the entity properties, the clusters of entities, etc. For instance, Jonas and Harper summarized the impact of data mining on the counterterrorism community (Jonas and Harper 2006). First, they claim that the 9/11 attack plan was available to the U.S. Government prior to the attack. The plan could be obtained from an extensive data mining on available databases, and the government might have disrupted the plan if they pursue the available leads. Whereas they introduced the importance of data mining in the field, they also suggest that the high false positive, or incorrect prediction, may waste valuable resources.

Link analysis and discovery is also another data-mining technique used to address counterterrorism. Mooney et al. present a method, inductive logic programming, which can discover implied rules in the multi-relational data (Mooney et al. 2004). When an analyst has an incomplete organizational network, this method will be a powerful tool to approximate the complete network.

On the contrary, modeling and simulation have also been used to analyze real-world problems. For instance, Janeja et al. presented a work focusing on the detection of anomalous geospatial trajectories based on spatio-semantic associations (Janeja et al. 2004). This spatio-semantic association is similar to our correlation between the spatial and the social dimensions. In their chapter, they create basic spatial analysis units, or spatial units. Then, the spatial units are clustered and consist of a micro neighborhood that shares similar characteristics across the sub spatial units. This analysis is interesting because they regard the spatial and the social aspects at the same time.

As another example of computing with social and geospatial issues, Chen et al. wrote a chapter describing the development of the informatics and intelligence model (Chen et al. 2004). They examine three interesting usages, cross-jurisdiction information sharing; terrorism information collection; as well as smart border and bioterrorism application; based on the intelligence and security informatics approach. Their approaches heavily depend on the network and link analysis. Furthermore, one of their models, West Nile Virus-Botulism Portal, has hot spot analysis and prediction function.

Organizational behavior research has benefited from using agent-based modeling techniques. For instance, Carley shows the efforts to model the socio-technical systems as networked multi-agent structures (Carley 2002). She introduces exemplary multi-agent models, such as OrgaHead (Carley and Svoboda 1996) and Construct (Schreiber and Carley 2004). These models take network organizational structure as an input and generate the estimated performance over time as well as the evolved network structures after the simulation. This approach may be difficult to validate, or some may argue that it does not reflect all of the real-world aspects, so the estimation may be misguiding. Meanwhile, this is an effort to create more complex and realistic models that can automatically generate hypotheses forecasting the organizational behavior (Carley 1999). Then, these hypotheses can estimate what the features or trends of interest in the domain, which will lead the validation of hypotheses by other statistical analysis tools, such as data mining.

2.3 Organizational Structure of Terrorist Network

The introduction of this book explains the necessity to expand the simple network or the tree structure between commanders and units to represent the full elements of the command and control. One of the expanded representations is the meta-network. This section explains the meta-network and shows how to apply the meta-network representation to data of organizational elements.

2.3.1 Meta-Network for Organizational Structure

A meta-network (Krackhardt and Carley 1998; Carley 2002) is a multi-mode and multi-relation network that this case study utilizes to represent an organizational structure. We might describe it using a matrix of relations as in Table 2.1. From an organizational task perspective, there are four basic types of nodes of interest: people, knowledge, 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 2.1, for the sake of illustration, we define a possible network for each of the cells.

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 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 2.1 is more commonly analyzed by analysts in the operations research field. Information

Table 2.1 Meta-network component networks

	People	Knowledge	Resources	Tasks
People	Social network	Knowledge network	Resource network	Assignment network
Knowledge		Information network	Skills network	Knowledge needs network
Resources			Substitution network	Resource needs network
Tasks				Task precedence network

Network in Table 2.1 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 a meta-network. This additional information of the organizations enable each component of this integrated analysis framework.

2.3.2 Estimated Terrorist Network in Meta-Network Format

An input to this model is a network representation of the organizational structure in the social and geospatial dimensions. 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, and locations. 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. Our model is applied to a terrorist network that extracted from open source or unclassified documents, such as newspapers and intelligence reports from subject matter experts using the AutoMap software (Diesner and Carley 2005), and then with supplemental hand coding to add latitude and longitude. Additional information on the coding process is provided by Carley

Table 2.2 Meta-network of the organizational structure for this case study

	Agent	Knowledge	Task	Location
Agent (916 agents, *A*)	Social network (*AA*, 0.0024)	Knowledge network (*AK*, 0.0093)	Assignment network (*AT*, 0.0070)	Deploy network (*AL*, 0.0026)
Knowledge (614 knowledge bits, *K*)		Not used	Needs network (*KT*, 0.0961)	Regional knowledge network (*KL*, 0.0692)
Task (258 tasks, *T*)			Not used	Regional task network (*TL*, 0.1042)
Location (387 locations, *L*)				Proximity network (*LL*, 0.0799)

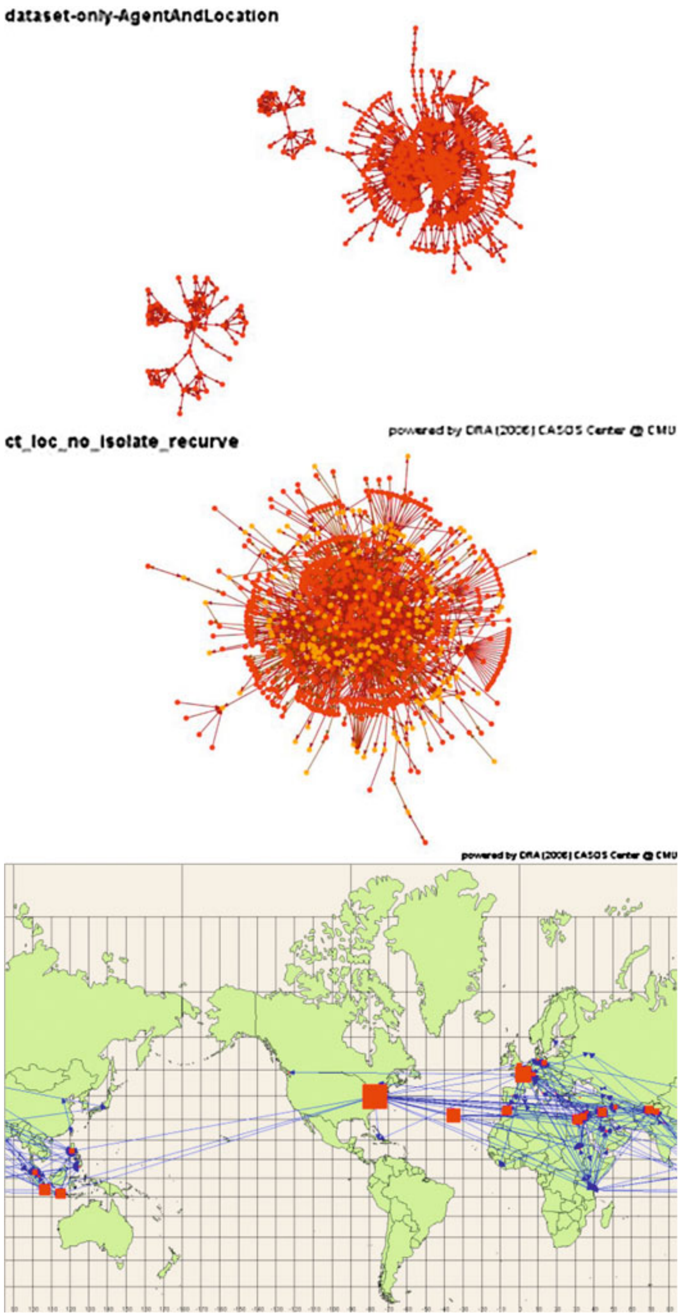

Fig. 2.1 (*Top*) Social network between agents, or AA in Table 2.2, (*Middle*) deploy network of agents, or AL in Table 2.2, (*Bottom*) World map of agent deployments and social interactions between deployed agents

et al. (forthcoming). After the network-text analyses and the dataset cleaning, we display the meta-matrix of the input dataset with descriptive statistics in Table 2.2. The numbers in cells of Table 2.2 represent the network density. Also, Fig. 2.1 visualizes some of the networks in the Table 2.2.

2.4 Modeling Command and Control on Social and Geospatial Dimensions

We introduce a multi-agent simulation model that overcomes the limitations, such as isolated social and geospatial models. To model the social dimension, the agent interaction algorithm specifies the probability of interaction between two agents. Also, for the geospatial dimension, the agent relocation mechanism concerns the agent movement on the geospatial location network in a dataset. The initial social network and geospatial information are drawn from real data for a group. The model output reveals important aspects of the evolved complex organization.

2.4.1 Model Summary

To estimate changes overtime in the performance and structure of organization, the model simulates each individual agent and the agent's interaction with others. As agent interact and learn, their behavior will eventually change the organizational structure and performance. These mechanisms are outlined as a flowchart in Fig. 2.2. Basically, the agents can interact and relocate at each time step. Agents select a location to move and an agent to interact with. The selection is based on the probabilistic values for each interaction and relocation opportunities. Exactly which agent interacts with which, when, what choices they make, and what they communicate and learn are defined probabilistically. Consequently, the model is stochastic, and as such multiple replications are needed to generate stable results and to define the space of outcomes.

Additionally, as listed in Table 2.3, there are several factors, which drive the agent behavior and so the evolution of the network. The parameters concern the interaction radius on the social dimension, the relocation radius on the geospatial dimension, the probability of learning after a knowledge exchange with an agent, or a knowledge gathering at a certain location, etc. Agent behavior also depends on the given input dataset, as this sets their initial environment. The input determines the initial probability of interaction among agents as this is based on what knowledge they have and where they are located. This model has two levels of parameters. Finally, there are factors driving an agent's behavior, calculated from the used defined parameters, inputs, and various formulas.

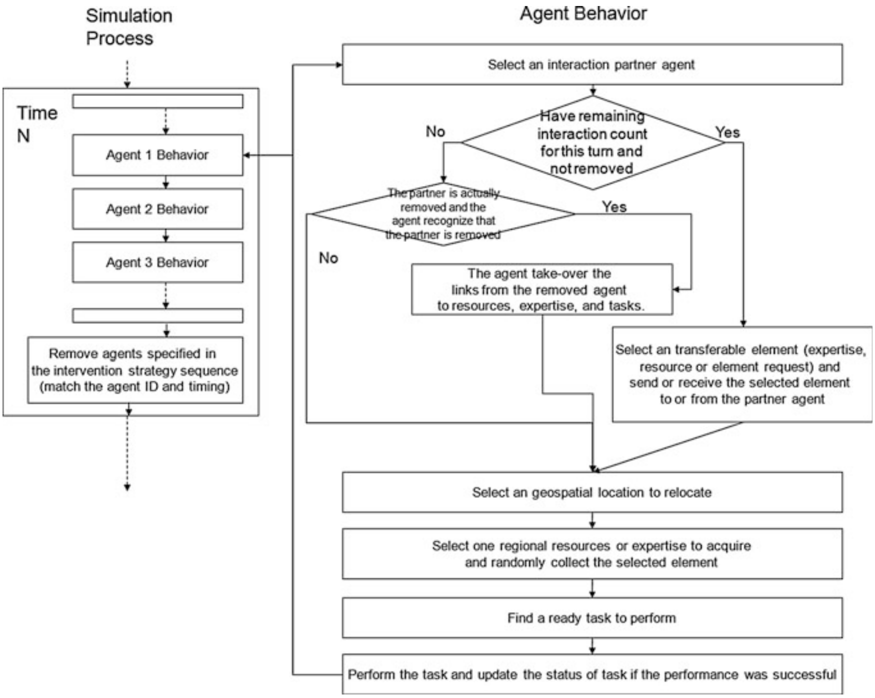

Fig. 2.2 Flowchart describing the simulation progress and the agent behavior

We test this model by varying some important parameters in the agent interactions and relocations. Table 2.4 is the design of such variations, and this provides the sensitivity of the results when exact parameter values are impossible to obtain. First, we change the agent move radius by zero, one, and two. If an agent has zero move radius, then the agent is stationary to his initial location. On the contrary, two move radius means that the agents can search locations linked by two location-to-location links from their initial locations. Next, we vary the weight of relative similarity and expertise contributing to the probability interaction. If the weight of relative similarity is high, the agents mainly interact with agents sharing backgrounds, belief, and knowledge. This imitates that the agents are passive information receivers. In contrast, higher relative expertise weight makes the agents active information seekers. Third, we test the sensitivity of the input data by randomly dropping or adding links in the agent-to-agent network or location-to-location network.

To reason the effect of the parameter variations, we need to describe the details of the agent behavior in the social and the geospatial dimensions. The next section describes such agent behavior.

Table 2.3 List of input variables, output variables, parameters, and major model internal variables of the model

Type	Name	Implication
Input	A networked organizational structure	A network including agents, knowledge pieces, tasks, and locations. The network represents the complex organizational structure of the target domain.
Output	An evolved network organization	An evolved network organization with a recreated agent-to-agent network and a agent-to-location network based on interactions and relocations
	Knowledge diffusion	A performance metric showing how fast the information can be diffused across the network
	Energy task accuracy	A performance metric showing how accurately the information are distributed to the agents who require it for their task completion
	Gini coefficient for *AA* and *AL*	Gini coefficients indicating the extent of unequal distribution of criticalities of agent-to-agent network and agent-to-location network
Parameters	Simulation run time step (default: 30)	Total simulation run time
	Number of replication (default : 3)	Number of model runs, required since this is a stochastic model, not a deterministic model
	Move radius (*MR*)	The radius on the spatial route network specifying an agent's maximum move radius in one time step
	Vision range (*VR*) (default: 1)	The range on the spatial route network specifying an agent ability to gather a knowledge piece or interact with another agent
	Sphere of influence (*SI*) (default: 2)	The number of social links that an agent can cross for an interaction
	Weight for relative similarity (w_1), For relative expertise (w_2), for social distance (w_3) (default: 0.5), for spatial proximity (w_4) (default: 0.5)	Weight for relative similarity when calculating the probability of interaction, for relative expertise when calculating the probability of interaction, for social distance when calculating the probability of interaction, and for spatial proximity when calculating the probability of interaction, respectively
	Learning rate from an agent (default: 0.05)	The possibility that an agent can learn a piece of information from an interaction with another agent
	Learning rate from a location (default: 0.025)	The possibility that an agent can gather a piece of information by observing a knowledge node within vision range
Internal variables	Relative similarity (RS_{ij})	Likelihood of interactions caused by homophily, also can be viewed as passive information seeking
	Relative expertise (RE_{ij})	Likelihood of interactions caused by expertise, also can be viewed as active information seeking
	Social distance (SD_{ij})	Difficulties of interactions over multiple social links
	Spatial proximity (SP_{ij})	Difficulties of interactions from spatial distance
	Interaction candidate set (ICS_i)	A set of agents who agent i can interact with
	Probability of interaction ($P_{ij}^{\mathrm{Interaction}}$)	Likelihood of agent i's interaction with agent j, weighted linear sum of relative similarity, relative expertise, social distance, and spatial proximity
	Probability of Relocation ($P_{il}^{\mathrm{Relocation}}$)	Likelihood of agent i's moving to location l, determined by the number of available knowledge bits required to perform the agents' assigned tasks

Table 2.4 Virtual experiment design to observe the sensitivity of the simulation results and to explore the parameter space

Name	Value	Implication
Move radius (*MR*)	0, 1, or 2 (3 cases)	Parameter space exploration, examining the sensitivity of the result according to the agent movement perimeter
Weights For Relative Similarity (w_1)/Relative Expertise (w_2)	0/1, 0.25/0.75, 0.6/0.4, 0.75/0.25, 1/0 (5 cases)	Parameter space exploration, examining the agent interaction attitudes and its impact to the results, from passive information gathering to active information gathering
Density of the organizational structure network (density of *AA* and *LL*)	75, 100, 125 % (3 cases)	Sensitivity analysis, examining the sensitivity of results according to the density changes of the *AA* and *LL* networks corresponding to the social dimension and geospatial dimension
Total virtual experiment cells	45 cells, (3 × 5 × 3 cases)	

2.4.1.1 Agent Interaction Mechanism

The agents in the model have the opportunity to interact with others each time period. They select an agent to interact with based on the probability of interaction that is a weighted sum of four different factors, relative similarity, relative expertise, social distance, and spatial proximity, explained in the sub-sections. The theory for these factors comes from sociology, communication theory, and counter-terrorism analysis.

As this is a stochastic model, an agent will most of the time interact with those agents whom they have a higher probability of choosing; but, on occasions (as dictated by this probability) will end up with a less likely choice. Like humans, these simulated agents cannot always talk to those they want most. This stochastic model captures this behavior of human intention being distinct from human action and the rare unexpected interaction.

After choosing an agent to interact, the two agents will exchange knowledge pieces. For each exchanged knowledge piece, a number will be drawn from a uniform distribution ranging from 0 to 1. If the number is under the learning rate for that agent, the receiving agent will have a new link to the communicated knowledge piece in the agent-to-knowledge network (AK).

- Relative similarity (RS) and relative expertise (RE): RS is the ratio reflecting the similarity in knowledge of the choosing and chosen agents. This is based on the sociological principle of homophily (McPherson et al. 2001; Kandel 1978; Gavrieli and Scott 2005). Homophily means that a person is likely to interact with another person sharing similar education, beliefs, or race. This represents the phenomena that terrorists often interact with other terrorists sharing the same religion or nationality. (RE) is a ratio reflecting the amount of knowledge the chosen agent has that the chooser does not have. This is based on the transactive memory (Wegner 1986; Hollingshead 2000; Mieg 2001). This captures why a Middle-East terrorist interact with a South American drug Cartel to exchange weapon expertise or information about funding sources. From a glimpse, the two factors may look contradictory, but these are just two metrics capturing different aspects of knowledge acquisition attitudes of terrorists.

$$\mathrm{RS}_{ij} = \frac{\sum_{k=0}^{|K|} \mathrm{AK}_{ik}\mathrm{AK}_{jk}}{\sum_{k=0}^{|K|} \mathrm{AK}_{ik}}, \ \mathrm{RE}_{ij} = \frac{\sum_{k=0}^{|K|} \mathrm{AK}_{jk}(1-\mathrm{AK}_{ik})}{\sum_{k=0}^{|K|} \mathrm{AK}_{ik}} \tag{2.1}$$

- Social distance (SD): The social distance, as shown in Formula 2.2, between the two agents is another factor affecting the probability of interaction. If two agents have to cross many social links, then the probability of interaction should be low, and vice versa (Watts et al. 2002; Friedkin 1983; Akerlof 1997). First, we find the shortest path between the two agents, and then we define SD as one over the number of links in the path. If the SD is larger than the maximum, SI, chosen by the user, it is set to one over the maximum for social interaction perimeter modeling. Agents in the model recognize and distinguish the closeness of other agents in the perimeter of SI, but they cannot differentiate the closeness when the interacting agent is outside of the perimeter. In this case, the agents regard the interacting agents are just SI + 1 links away though the real SD may be different.

$$\begin{aligned} \mathrm{SD}_{ij} &= \frac{1}{|AA_{ij}|} \\ |AA_{ij}| &= \left\{ \begin{array}{r} \text{num. of links on the shortest path from } i \text{ to } j \\ (\#\text{ of links} \leq \mathrm{SI}) \\ \mathrm{SI}+1(\#\text{ of links} > \mathrm{SI}) \end{array} \right\} \end{aligned} \tag{2.2}$$

- Spatial proximity (SP): The spatial proximity, as defined in Formula 2.3, also factors in calculating the probability of interaction. Intuitively, two persons who are at the same location are more likely to talk than are those at different locations (Sorenson and Stuart 2001; Butts 2002; Sageman 2004). Some may argue that the SP is not significantly correlated with the frequency of the interaction in the age of Internet. However, in the terrorism domain, in the same training camp and going the same mosque are critical indicators of interactions (Sageman 2004). The SP model is the inverse of spatial distance and is used as an indicator of the probability of being at the same location. As with social distance, if social proximity is greater than the maximum chosen by user, it is set to one over the maximum for computing convenience.

$$\mathrm{SP}_{ij} = \frac{1}{(|\mathrm{LL}_{l_1 l_2}| + 1)\mathrm{AL}_{il_1}\mathrm{AL}_{jl_2}}$$
$$|\mathrm{LL}_{l_1 l_2}| = \left\{ \begin{array}{r} \text{num. of links on the shortest path from } l_1 \text{ to } l_2 \\ (\# \text{ of links} \leq \mathrm{VR}) \\ \mathrm{VR} + 1(\# \text{ of links} > \mathrm{VR}) \end{array} \right\} \tag{2.3}$$

- Probability of Interaction: The agents select another agent to interact with based on the probability of interaction, as specified in Formula 2.4. The probability is a weighted sum of four different factors explained above. We standardize the factors by dividing them with the maximum value of the interaction candidate sets (defined below).

$$P_{ij}^{\mathrm{Interaction}} = w_1 \mathrm{RS}_{ij} + w_2 \mathrm{RE}_{ij} + w_3 \mathrm{SD}_{ij} + w_4 \mathrm{SP}_{ij} \tag{2.4}$$

Though the probability can be calculated for any pair of two agents, we limit the number of possible interaction candidate agents. The candidate agents are chosen based on two distances, SD and spatial proximity. This is an assumption that a person will interact with others in their neighborhoods—either the social neighborhood or the geographic one. Formally, the candidate agent set is defined using Formula 2.5. An agent can communicate only with his candidate agents, so the probability of interaction is calculated between each agent and that agent's candidate agents.

$$\mathrm{ICS}_i = \{A_j | (|\mathrm{AA}_{ij}| \leq \mathrm{SI}) \vee (|\mathrm{LL}_{l_1 l_2}| \mathrm{AL}_{il_1} \mathrm{AL}_{jl_2} \leq \mathrm{VR})\} \tag{2.5}$$

2.4.1.2 Agent Relocation Mechanism

The agents in the model are capable of relocating themselves to other adjacent locations. The sphere of relocation is determined by a parameter, move radius (MR), but the probability to choose a certain location is calculated by more complicated formula, Formula 2.6. In essence, the agents choose a location which on average guarantees the shortest path to their required knowledge pieces. In other words, the agents try to put themselves at the optimal location to collect the knowledge they want. However, just like the agent-to-agent interaction model, this is a stochastic model with the choice of location determined probabilistically. Hence, it is possible to choose a nonpreferable location with lower probability.

$$
\begin{aligned}
P_{il}^{\text{Reloaction}} &= \frac{1}{\sum_{t=0}^{|T|}\sum_{k=0}^{|K|} \mathrm{AT}_{\mathrm{it}} \times \mathrm{KT}_{\mathrm{kt}} \times |\mathrm{KL}_{\mathrm{kl}}|} \\
|\mathrm{KL}_{\mathrm{kl}}| &= \left\{ \begin{array}{r} \text{num. of links on the shortest path from } l \text{ to } k \\ (\#\ \text{ of links } \leq \mathrm{VR}) \\ \mathrm{VR}+1(\#\ \text{ of links } > \mathrm{VR}) \end{array} \right\}
\end{aligned}
\tag{2.6}
$$

After selecting a location, the model changes the agent-to-location network (AL) by removing the edge from the agent to the old location and adding an edge from the agent to the new location. Additionally, the agent will gather knowledge pieces linked to locations within vision range (VR). This knowledge gathering is similar to the knowledge exchange between agents except using a different learning rate. Some may argue that this regional knowledge acquisition may not be true, especially in the real world where terrorists can learn new knowledge from web sites. However, it should be noted that many terrorists go training sites and headquarters of terrorist organizations to receive specific and detailed training. These terrorists' relocations are an important issue in the counterterrorism field (Sageman 2004), and we are specifically examining such relocations in this chapter.

2.4.1.3 Output Measures

To assess the change of the organization, we have two performance metrics. The performance metrics are used to evaluate the performance of the evolving organization over time. There are two performance metrics, knowledge diffusion and energy task accuracy. Knowledge diffusion (Formula 2.7) gauges the dispersion of the knowledge bits across the agents.

$$
\mathrm{KD} = \frac{\sum_{i=0}^{|A|}\sum_{j=0}^{|K|} \mathrm{AK}_{ij}}{|K| \times |A|}
\tag{2.7}
$$

Knowledge diffusion only considers who knows what. Whereas, energy task accuracy (Formula 2.8) 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. In Formula 2.8, C indicates a constant term.

$$
\mathrm{ETA} = \frac{C}{|T|} \sum_{t=0}^{|T|} \frac{\sum_{k=0}^{|K|} (\mathrm{KT}_{kt} \times \sum_{a=0}^{|A|} \mathrm{AK}_{\mathrm{ak}})}{\sum_{a=0}^{|A|} \mathrm{AT}_{at} \times \sum_{k=0}^{|K|} \mathrm{KT}_{kt}}
\tag{2.8}
$$

Furthermore, we define two criticality metrics for the agents and locations. For agents, we count the number of agents that an agent had interacted with during the simulation. This represents the number of agents that the agents know and influenced. For locations, we count the number of agents in a location at the end time. If the location harbors more agents, the location may have higher terrorist activities.

2.5 Result

The terrorist network in the meta-matrix format is analyzed by the presented agent-based model, and the model generates estimates on the agent relocation, the geospatial clustering, the agent interaction, and the social network evolution. First, we perform a sensitivity analysis. Then, we visualize and analyze the model output in two dimensions.

2.5.1 Sensitivity Analysis

The sensitivity analysis of this model is performed by varying the important input parameters (refer Table 2.3). After running the model with varied parameters, we perform a regression analysis. The independent variables are the varied parameters of a virtual experiment cell. The dependent variables are the two performance metrics and the Gini coefficients of the agent and location criticality distributions.

Table 2.5 is the regression analysis result. First, as MR increases, the performance of the network gets better. This suggests that the terrorists are distributed where they are not receiving the best information from regions and they will relocate to find better places to obtain the information. Furthermore, these relocations will increase their task performance by increasing the information feed. Next, higher MR and higher possible density decreases the Gini coefficient of location criticalities. This illustrates that the terrorists will be dispersed more if they can relocate easier and the input network is denser. Finally, lower RS will induce a more centralized terrorist network. Particularly, the input network density impacts the agent criticality distribution greatly compared to the impact to the location criticality.

2.5.2 Analysis of Location Criticality

The agent movement creates segregation patterns over time, Fig. 2.3. For analysis, we draw an accumulated agent distribution across the locations, Fig. 2.4. The figure implies that the agents will be dispersed more if we increase the move radius. If there are few appropriate places where terrorists can harbor, the increased MR will allow more terrorists to find the places and to be clustered

Table 2.5 Meta-model regression analysis for sensitivity analysis

Dependent variable		Energy task accuracy	Knowledge diffusion	Gini coefficient of location criticality dist.	Gini coefficient of agent crtiicality dist.
Standardized coefficients	Move radius	0.748*	0.780*	−0.956*	−0.088
	Relative similarity	0.008	0.004	0.020	0.131+
	Possible density	0.010	0.009	−0.114*	−0.865*
Adjusted R^2		0.506	0.555	0.925	0.765

+ P value < 0.01, *P value < 0.001

around the places. However, our model indicates the opposite scenario. The terrorists in our model are not able to find the places where they can cluster densely. Rather than gathering in few regions, the terrorists will disperse around the world.

Next, we list the top ten locations harboring terrorists after simulations, Table 2.6. While the accumulated distribution and its Gini coefficient, in Fig. 2.4, illustrate the terrorists will disperse, the listed top ten locations are pretty consistent across three different MR level. This implies that the hot regions with frequent terrorist activities will remain at the top after the relocations though some of the terrorist at the location will move to other non terrorism-intensive regions. In detail, the Northwest African regions, i.e., Morocco and Casablanca, get important as well as some European regions, France and Strasbourg. The south Asian regions, Indonesia and Bali, and the area with frequent activities, US, Iraq, and Israel, will hold status quo.

2.5.3 Analysis of Agent Criticality

We analyze the importance of agents after the simulation. According to the sensitivity analysis, the changes of RS impact the distribution of the agent criticality. Therefore, in Fig. 2.5, we visualize the accumulated agents' social link coverage across the levels of relative similarity. While we can see some slight difference in terms of Gini coefficients, the distribution of link coverage does not change much. This implies that the evolution of the terrorist social network is stable regardless of the parameter change. In spite of the small changes, the increasing Gini coefficient as the higher RS suggest that the social links will be controlled by fewer terrorists, if terrorists gather information more passively. For instance, a group of terrorists often have different backgrounds from another group of terrorists. In that case, under a strong RS interaction weight, only terrorists who have both backgrounds of the two groups will be able to communicate with the members from both groups. This means that there will be fewer agents likely to talk to under strong homophily trend, and these few agents will control more social links.

Like the location criticality analysis, we list the top ten terrorists who control most of links after simulation, Table 2.7. The table shows that the top terrorists, i.e.

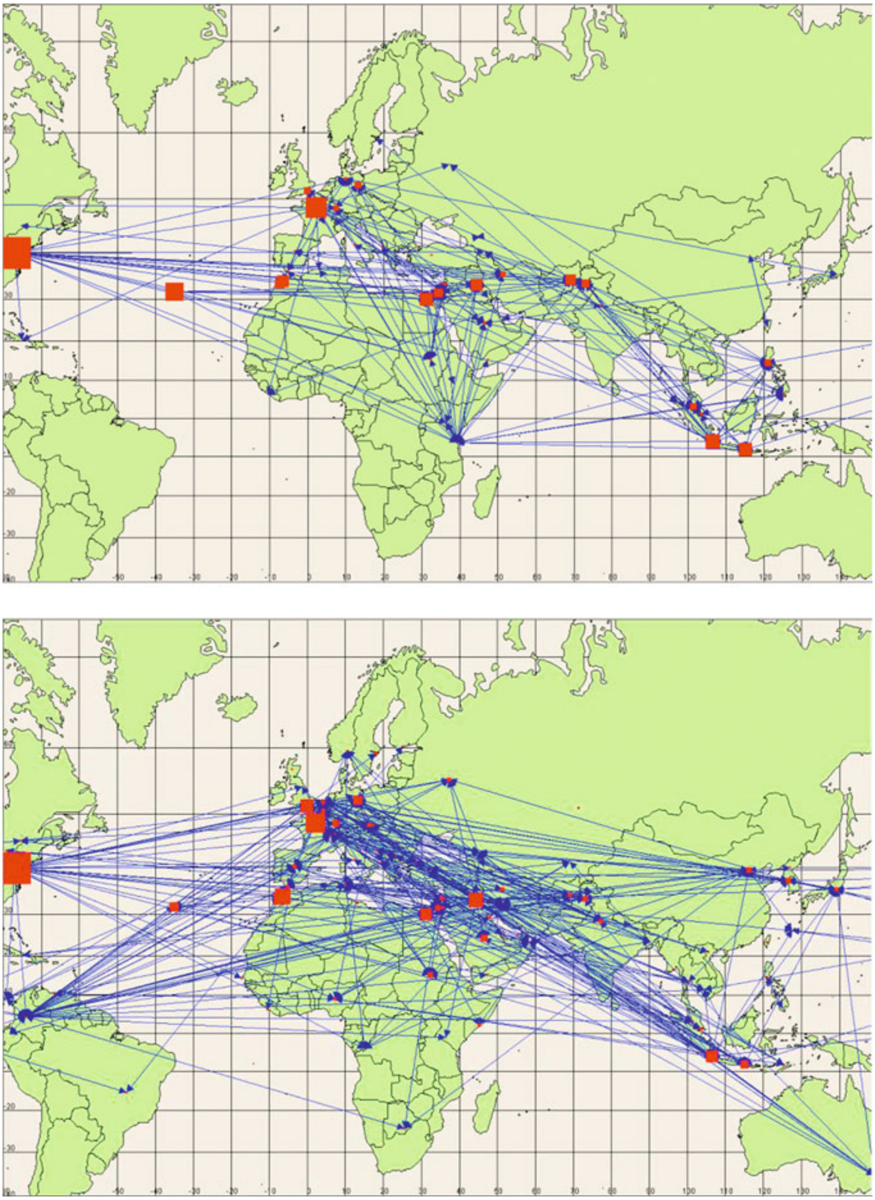

Fig. 2.3 (*Top*) the initial deployment of agents and their social interactions across regions (*Bottom*) the converged deployment of agents and their social interactions when the move radius is set to be one

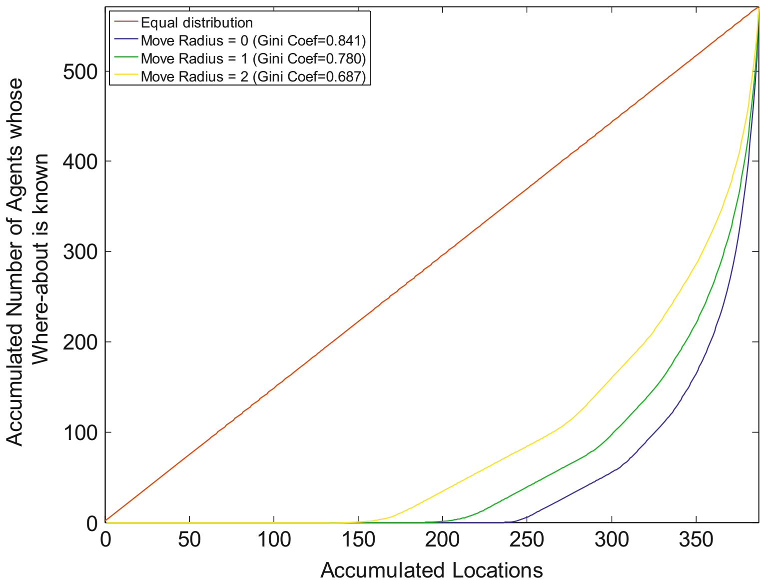

Fig. 2.4 Accumulated distribution of agents across the regions. 570 agents were deployed to 387 locations

Table 2.6 The top ten locations that the agents were deployed to

Rank	Move radius : 0 (Stationary case)	Move radius : 1 (adjacent move)	Move radius : 2 (farther move)
1	u_s	u_s	u_s
2	Israel	France	France
3	France	Morocco	Morocco
4	Bali	Israel	Casablanca
5	Morocco	Bali	Bali
6	Egypt	Casablanca	Egypt
7	Afghanistan	Egypt	Israel
8	Casablanca	Iraq	Strasbourg
9	Iraq	Indonesia	Gaza
10	Indonesia	Strasbourg	Indonesia

Bin Laden or Riduan Isamuddin, will have similar power after simulations in spite of varying parameters. This is because they are already in the center of the social networks among terrorists, so they appear in the interaction candidate sets frequently. Additionally, they have pretty comprehensive backgrounds and knowledge which most of the agents can find high RS and expertise at the same time. On the other hand, Mohammad Atta will have higher ranks under passive information gathering assumption, since his background is common across the agents.

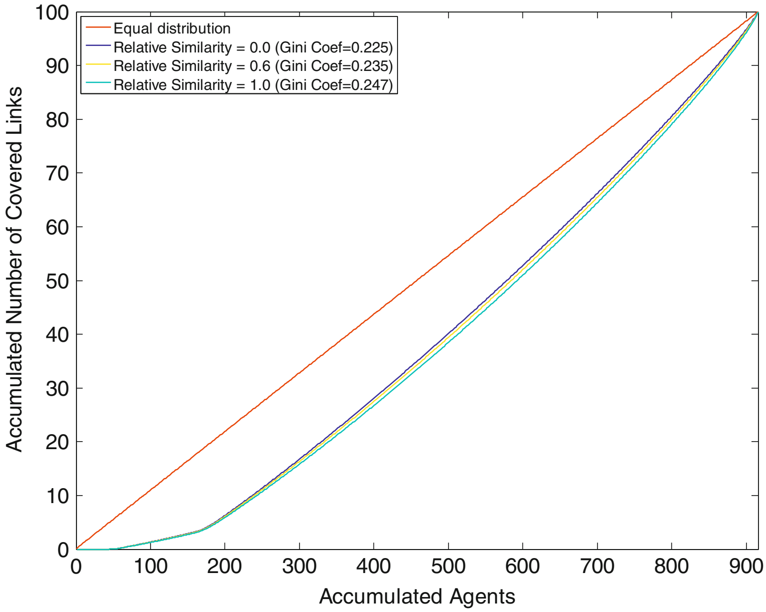

Fig. 2.5 Accumulated distribution of the percentage of covered social links by agents

Table 2.7 The top ten agents that have the highest number of social links to other agents

Rank	Reliative similarity : 0.0 (active information gathering)	Reliative similarity : 0.6	Reliative similarity : 1.0 (passive information gathering)
1	bin_laden	bin_laden	bin_laden
2	riduan_isamuddin	riduan_isamuddin	riduan_isamuddin
3	abdul_aziz	abdul_aziz	mohammed_atta
4	yasser_arafat	yasser_arafat	bakar_bashir
5	bakar_bashir	yaacov_perry	yasser_arafat
6	mohammed_atta	mohammed_atta	zacarias_moussaoi
7	yaacov_perry	bakar_bashir	yaacov_perry
8	imam_samudra	zacarias_moussao	abdul_aziz
9	zacarias_moussao	mohambedou_slah	yazid_sufaat
10	abdullah_sungkar	abdullah_sungkar	mohambedou_slah

2.6 Lessons Learned to Model and Simulate Command and Control

This case study introduces a model and simulation results describing the location criticality and the agent criticality changes over time by using the command and control structure of terrorists discovered from network text analysis on open source documents. The model is a multi-agent simulation model, and we estimate the collective behavior of this networked organization based on our agent behavior mechanism. The agent behavior mechanism consists of two parts, social interaction and geospatial relocation. Based on the input networked organization and the agent behavior, we calculated and analyze the performance, the geospatial distribution, and the interaction log records during the simulation period.

The model and its simulation results indicate the evolution of command and control structure in two modeled dimensions: social and geospatial dimensions. Our analysis indicates that the agents will become more dispersed around the world in the geospatial dimension. In the perspective of location criticality, some regions, such as North America and Middle Eastern Asia, will hold their status quo. On the other hand, some locations, i.e., Europe and North Western Africa, may gain more agents. The critical agents do not change much in the social dimension. Some of the changes are expected according to the agents' information gathering model. If the terrorists gather information passively, Mohammad Atta or Bakar Bashir will gain more power. Meanwhile, well-known key terrorists like Bin Laden or Riduan Isamuddin will hold their powers regardless of agent interaction trend changes. This modeling and simulation result would have limitations in several aspects. First of all, the validity of the results with the given dataset is very limited. The simulation model takes in the limited facet of the real world, and the model would not reflect the reality with the given limitation. Further, the model is very illustrative and simple, so the model would not show the agent behavior with the fine details of the real world.

In spite of this limitation, this case study investigates how the command and control structures rest in multiple dimensions interact with. In the real world, the command and control structure is embedded in multiple spaces that differ in nature. If we redeploy units and commanders in the geospace, we have to readjust the command and control structure in the social space. Similarly, if units and commanders have different chain of commands, this may indicate the units and the commanders have changes in other spaces that are factors of the command and control. Though this case study models only two different spaces, as the modeled behavior of command and control gets complicated, the modelers of command and control should add more dimensions of interests to the simulation model.

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