THE VOLGENAU SCHOOL OF ENGINEERING
DEPT OF ELECTRICAL AND COMPUTER ENGINEERING
SYSTEM ARCHITECTURES LABORATORY

# Computational Modeling of Cultural Dimensions in Adversary Organizations

**Grant Number: FA9550-05-1-0388**

**FINAL TECHNICAL REPORT**

**01 June 2005 to 30 November 2010**

**Submitted to:**
**Air Force Office of Scientific Research**
One Liberty Center
875 North Randolph Street
Arlington, VA 22203-1995

Attn: **Dr. Terence Lyons**
AFOSR/RSL
(703) 696 9542
Fax: (703) 696 7360

**Submitted by:**
**Alexander H. Levis**
George Mason University
System Architectures Lab
ECE Dept., MS 1G5
Fairfax, VA 22030

(703) 993 1619
Fax: (703) 993 1601
email:alevis@gmu.edu

## REPORT CONTRIBUTORS


**George Mason University**

***Alexander H. Levis (PI)***
Lee W. Wagenhals
Abbas K. Zaidi
Claudio Cioffi-Revilla
Robert J. Elder
Tod S. Levitt
Peter Pachowicz
Ashraf AbuSharekh
Smriti K. Kansal
A. Erkin Olmez
Faisal Mansoor
M. Faraz Rafi
Pedro Romero
John Pham

**Carnegie Mellon University**

***Kathleen M. Carley (Co-PI)***
Il-Chul Moon
Geoffrey Morgan
Jesse St. Charles
Brian Hirshman
Michael Lanham

**University of Colorado - Denver**

P. Papantoni-Kazakos

# Table of Contents

## LIST OF FIGURES

## LIST OF TABLES

# PART I: INTRODUCTION

**Chapter 1:** Introduction

# Chapter 1

# Introduction

**Alexander H. Levis**

The initial objectives of the "Computational Modeling of Cultural Dimensions in Adversary Organizations" were:

*(a) To relate an adversary's organizational structure to behavior when both structure and behavior are conditioned by cultural and social characteristics, as they always are in realistic settings.*

*(b) To address basic research questions centered on locating the points of influence and characterizing the processes necessary to influence organizations in diverse cultures.*

*(c) To explore, through a computational modeling framework, the nexus between data and models for individual adversaries (micro level) and data and models for organizations of adversaries (macro level).*

As the project evolved, additional objectives were introduced:

*(d) (d) To explore multi-modeling as a way to model adversary behaviors and research the underlying theory (meta-modeling)*

*(e) (e) Demonstrate the approach through a case study that addresses issues of deterrence*

A set of tasks was defined for achieving the these objectives. They were:

**Task 1: Implement a testbed for computational modeling.**

**Task 2: Expand and enhance the existing models** at George Mason University's System Architectures Laboratory (GMU/SAL) and at Carnegie Mellon University's Center for Computational Analysis of Social and Organizational Systems (CMU/CASOS)

**Task 3: Conduct computational experiments to address the set of research hypotheses**.

**Task 4: Develop and transition theory-based tools to the Air Force**

**Task 5: Provide Education and Training**

**Task 6: Meta-Modeling for Multi-Modeling Integration**

**Task 7: Demonstration of Computational Experiment**

**Task 8: Management and Documentation**

All tasks were carried out during the period of performance. In this report, the research approach taken and results obtained in Tasks 1, 2, 6, and 7 are presented. The many transitions of the tools that have taken place (Task 3) have been reported in detail in the annual productivity reports and in the annual program reviews. Similarly, a substantial education and training effort has been made by both collaborating organizations through the training on many graduate research assistants, the conduct of summer institutes (CMU), the offering of AFCEA sponsored short courses (GMU) to DOD personnel and staff of the Defense Industrial Base, as well as numerous seminars and presentations to Air Force and other defense organizations. Much of the research material is now included in graduate level courses at both universities. Task 8 has also been reported annually to the Air Force office of Scientific Research in accordance with grant requirements.

Since 1992 the nature of military operations has changed. The type of objectives that the military has to address has expanded well beyond those of traditional major combat operations. As military operations became other than conventional war – whether against transnational terrorist threats or conducting stabilization operations – the need to broaden the focus of models that support effects based planning and operations became critical. One major weakness was the absence of socio-cultural attributes in the models used for Course of Action selection and effects based planning. Part II of this report illustrates an approach that enables analysts to evaluate complex situations such as those in which an adversary is embedded in a society from which he is receiving support. In Chapters 2 and 3, a modeling approach is described that enables analysts to examine and explain how actions of the military and other entities may result in desired or undesired effects, both on the adversary and on the population as a whole. First, Timed Influence Nets are described (Ch. 2) and then the theory that underlies them as well as some major extensions of the theory are presented in Chapter 3. A comprehensive theory of Influence Networks is presented that incorporates design constraints for consistency, temporal issues and a dynamic programming evolution of the Influence Constants. A software implementation of Timed Influence nets, a modeling and analysis tool called Pythia, is described in Appendix B. This tool has been distributed widely to military and intelligence organizations. One of the difficulties in using models for new situations is the challenge of starting with a blank screen. In Chapter 4 a novel approach for constructing Influence nets quickly is introduced. One of the main challenges in using TINs has been the difficulty in formulating them. Many Subject Matter Experts have difficulty in expressing their knowledge in the TIN representation. A methodology to develop domain specific Timed Influence Nets (TINs) via the use of an ontological representation of domain data is presented. The meta-model driven ontology based approach provides potential assistance to modelers by enabling them to create quickly new models for new situations through the use of Influence Net Templates. An extension of Timed Influence nets into Activation Timed Influence nets is presented in Appendix D.

In Chapter 5, several case studies are presented that use this approach. First, a power law approach for modeling uncertainty is described and used for analyzing adversary behavior. Data collected in the Diyala province in Iraq is used. Uncertainty is a hallmark of conflict behavior and low-intensity warfare, guerrilla, insurgency, and forms of violence that accompany civil war are no exception. In this case study, aspects of the theory of political uncertainty and complexity theory are applied to the analysis of conflict events during the first three years of the second Iraq war, 2003– 2006, limited to the Diyala province. Findings show that neither the time between attacks T or the severity of attacks S (fatalities) have a normal or log-normal distribution. Instead, both variables showed heavy tails, symptomatic of non-equilibrium dynamics, in some cases approximating a power law with critical or near-critical exponent value of 2. The empirical hazard force analysis in both cases showed that the intensity was high for the first occurrences in both variables, namely between March, 2003, and June, 2004, but even higher in a more recent period.

In the second case study, data from the same province are used to develop Courses of Action that would enable the suppression of IEDs. Two challenges are addressed: (a) the need to understand how actions taken by the military or other elements of national power may affect the behavior of a society that includes an adversary and non adversarial elements, and (b) the need to be able to capture and document data and knowledge about the cultural landscape of an area of operations that can be used to support the understanding of the key issues, beliefs, and reasoning concepts of the local culture so that individuals that are new to the region can quickly assimilate this knowledge and understanding. A Timed Influence Net was developed and analyzed.

The third case study illustrates the implementation of the theoretical developments presented in Chapter 3 to show how it is now possible to relax a number of limiting assumptions regarding causality (such as independence of causes) and include more realistic relationships between causes and effects. An East Timor scenario is used to illustrate the approach.

In Part III, methodologies for modeling adversary and coalition organizations are presented. In Chapter 6, a Petri Net based organization design approach is extended to include cultural constraints. The Lattice algorithm is used to design organizations subject to a number of structural and user defined constraints. These constraints are enhanced by introducing a set of cultural constraints based on Hofstede's dimensions. The approach is applied to an example where both Blue and Red organizations are modeled and the effect of cultural differences is highlighted. Finally, the approach is used to show how cultural attributes can be used in designning effective coalition organizations.

A key issue in modeling adversary organizations is the need to extract pertinent information about the adversary, such as interactions, activities, beliefs, and resources from a wide variety of unstructured textual data. In Chapter 7, a rapid ethnographic assessment procedure was used that moved from data to model through a semi-automated text analysis process. Central to this process is the AutoMap tool. AutoMap is based on network text analysis and so converts texts to networks of relations. Network Text Analysis is a set of methodologies for converting texts to graphs based on the theory that language and knowledge can be modeled as networks of words and relations such that meaning is inherent in the structure of that network. The semantic network is extracted first and then the meta-network composed of agents, resources, expertise, locations, activities, beliefs and organizations was obtained.

Understanding an organization's structure is critical when we attempt to understand, intervene in, or manage the organization. However, organizational structures in the real world often differ from their recognized formal structure, and sometimes its membership conceals the formal structure with various types of social interactions and communications. Furthermore, when the actual social interactions among the members of the group are observed, the observed social-network data are often noisy, and contain misleading and uncertain links. In Chapter 8, an approach for inferring the operational structure from the observed structure is proposed. 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 one is a concatenation of all activities, a snapshot of human endeavors. The approach is illustrated using data collected on a real-world, terrorist organization.

Social network simulation (SNS) is an emergent area of research that combines social network analysis and simulation, typically agent-based simulation. This area is often referred to as dynamic network analysis as much of the focus of the combined modeling approach is on how networks evolve, change, and adapt. Additionally SNS has a focus on how individual and group learning and behavior is impacted by and impacts the changes in the networks in which the individuals are embedded. Frequently, in social network simulations, the social network and other networks, such as the knowledge network, and/or the individuals or "nodes" in the network are co-evolving as agents interact, learn, and engage in various activities. Cognitive and social factors combine to determine the level of information access that individuals/agents may have. Three different information access mechanisms: literacy, internet access, and newspaper readership were examined. In Construct, a dynamic network analysis tool, these access mechanisms affect whether agents can interact with a specific media and get information through a specific form. It is important to note that these mechanisms interact. For example, if an agent is illiterate and has a newspaper subscription, that agent may read the news articles but do so with error. On the other hand, if an agent is literate but does not have access to the internet, they still cannot read web-pages (and the literacy parameter has no effect). Construct and its application to simulating the adversary are described in Chapter 9.

Chapter 10 contains three applications of Dynamic Network Modeling. They illustrate that the key to reasoning about the adversary is taking social networks and embedding them within the spatio-temporal context. Organization theory and task processing analysis facilitate this embedding by providing the constraints and enablers on task-related activity.

In Part III of this report, recent research in multi-modeling and meta-modeling is described. No single model can capture the complexities of human behavior especially when interactions among groups with diverse social and cultural attributes are concerned. Each modeling language offers unique insights and makes specific assumptions about the domain being modeled. For example, social networks describe the interactions (and linkages) among group members but say little about the underlying organization and/or command structure. Similarly, organization models focus on the structure of the organization and the prescribed interactions but say little on the social/behavioral aspects of the members of the organization. Timed Influence net models describe cause-and-effect relationships among groups at a high level. In order to address the modeling and simulation issues that arise when multiple models are to interoperate, four layers need to be addressed. The first layer, Physical, i.e., Hardware and Software, is a platform that enables the concurrent execution of multiple models expressed in different modeling languages and provides the ability to exchange data and also to schedule the events across the different models. The second layer is the syntactic layer which ascertains that the right data are exchanged among the models. The Physical and Syntactic layers have been addressed through the development of two testbeds: C2 Wind Tunnel (C2WT) by Vanderbilt University in collaboration with UC-Berkeley and George Mason University (Appendix E) and SORASCS developed by CASOS at Carnegie Mellon University. Both have been used and developed further in this project.

Once the testbeds became available, a third problem needed to be addressed at the Semantic layer, where the interoperation of different models is examined to ensure that conflicting assumption in different modeling languages are recognized and form constraints to the exchange of data. In the fourth layer, the Workflow layer, valid combinations of interoperating models are considered to address specific applications. Different applications require different workflows. The use of multiple interoperating models is referred to as *multi-modeling* while the analysis of the validity of model interoperation is referred to as *meta-modeling*. Such an approach has been used in simulation mode or to explore the possible outcomes of proposed courses of action; it has not been used to predict outcomes.

In Chapter 11, the focus is on issues relating to the syntactic and semantic layers. In Chapter 12, an ontology based approach is used to analyze (deconstruct) modeling languages and identify common concepts, unique concepts, and contradictory concepts. An enriched ontology is obtained that then guides the interoperation of models by shedding light on which questions can be answered via a valid interoperation of two models and which questions would trigger the use of contradictory concepts. This type of result is key to developing valid workflows for using multiple models in addressing adversary modeling and complex policy issues. This work was not included in the original scope of work; it became apparent in the third year of the research effort that the simulation technology had reached a stage where multi-modeling became practical.

In Part IV, most of the research results were integrated by conducting a complex computational experiment. The issue addressed was deterrence – specifically determining Courses of Action for the US in encouraging de-escalation of an evolving crisis between two states that have strong ties to the US. In Chapter 13, the concept of deterrence, as it is evolving beyond nuclear deterrence between two peer states,  is discussed with emphasis on cyber deterrence policy and strategy. Then in Chapter 14, a detailed case study based on an India-Pakistan crisis scenario is described. Multi-modeling was used extensively to represent India, Pakistan, the US central Command, and the US Pacific Command. Other state actors were also included. The results, presented in a day-long workshop, showed that the approaches taken to adversary modeling have promise and are implementable.

# PART II: TIMED INFLUENCE NETS
# Theory and Applications

# Chapter 2

# Course of Action Analysis in a Cultural Landscape Using Influence Nets

**Lee W. Wagenhals and Alexander H. Levis**

## 2.1 Introduction

In this chapter, two challenges are addressed: (a) the need to understand how actions taken by the military or other elements of national power may affect the behavior of a society that includes an adversary and non adversarial elements, and (b) the need to be able to capture and document data and knowledge about the cultural landscape of an area of operations that can be used to support the understanding of the key issues, beliefs, and reasoning concepts of the local culture so that individuals that are new to the region can quickly assimilate this knowledge and understanding.

The first challenge relates to capabilities that enable the analysis needed to conduct focused effects based planning and effects based operations. Models to support Effects Based Operations developed to date relate actions to effects on the adversary [1]. Such models can be quite effective in informing the comparison of alternative courses of action provided the relationships between potential actions and the effects are well understood. This depends on the ability to model an adversary's intent and his reactions and identifying his vulnerable points of influence. But as the nature of Blue's military operations goes well beyond the traditional major combat operations, there is the need to anticipate the effects of actions not only on the adversary (Red), but also on the local population which may support or oppose that adversary. Such support may depend in part on the actions taken by Blue.

The second challenge involves the need for new personnel to rapidly assimilate the local knowledge needed to analyze the local situation and to analyze and formulate the effects based plans and operations. Data about a culture exists in many forms and from many sources including historical reference documents, observations and reports by intelligence analysts, and unclassified (and unverified) sources such as the internet. The data is often incomplete and partially incorrect and includes contradictions and inconsistencies. Analysts, particularly those new to an area of operation who are responsible for formulating courses of action, are hard pressed to quickly develop the necessary understanding of the cultural factors that will affect the behavior of the adversary and the society in which it is embedded.

## 2.2 Timed Influence Nets

Several modeling techniques are used to relate actions to effects. With respect to effects on physical systems, engineering or physics based models have been developed that can predict the impact of various actions on systems and assess their vulnerabilities. When it comes to the cognitive belief and reasoning domain, engineering models are much less appropriate. The purpose of affecting the physical systems is to convince the leadership of an adversary to change its behavior, that is, to make decisions that it would not otherwise make. However, when an adversary in imbedded within a culture and depends upon elements of that culture for support, the effects of physical actions may influence not only the adversary, but the individuals and organizations within the culture that can choose to support, be neutral, or oppose the adversary. Thus, the effects on the physical systems influence the beliefs and the decision making of the adversary and the cultural environment in which the adversary operates. Because of the subjective nature of belief and reasoning, probabilistic modeling techniques such as Bayesian Nets and their influence net cousin have been applied to these types of problems. Models created using these techniques can relate actions to effects through probabilistic cause and effect relationships. Such probabilistic modeling techniques can be used to analyze how the actions affect the beliefs and thus the support to and decisions by the adversary.

Influence Nets (IN) and their Timed Influence Nets (TIN) extension are abstractions of Probabilistic Belief Nets also called Bayesian Networks (BN) [2, 3], the popular tool among the Artificial Intelligence community for modeling uncertainty. BNs and TINs use a graph theoretic representation that shows the relationships between random variables. These random variables can represent various elements of a situation that can be described in a declarative statement, e.g., X happened, Y likes Z, etc.

Influence Nets are Directed Acyclic Graphs where nodes in the graph represent random variables, while the edges between pairs of variables represent causal relationships. While mathematically Influence Nets are similar to Bayesian Networks, there are some key differences. BNs suffer from the often intractable task of knowledge elicitation of conditional probabilities. To overcome this limitation, INs use CAST Logic [4, 5], a variant of Noisy-OR [6, 7], as a knowledge acquisition interface for eliciting conditional probability tables.

The modeling of the causal relationships in TINs is accomplished by creating a series of cause and effect relationships between some desired effects and the set of actions that might impact their occurrence in the form of an acyclic graph. The actionable events in a TIN are drawn as root nodes (nodes without incoming edges). Generally, desired effects, or objectives the decision maker is interested in, are modeled as leaf nodes (nodes without outgoing edges). In some cases, internal nodes are also effects of interest. Typically, the root nodes are drawn as rectangles while the non-root nodes are drawn as rounded rectangles. Figure 2.1 shows a partially specified TIN. Nodes B and E represent the actionable events (root nodes) while node C represents the objective node (leaf node). The directed edge with an arrowhead between two nodes shows the parent node promoting the chances of a child node being true, while the roundhead edge shows the parent node inhibiting the chances of a child node being true. The inscription associated with each arc shows the corresponding time delay it takes for a parent node to influence a child node. For instance, event B, in Fig. 2.1, influences the occurrence of event A after 5 time units.

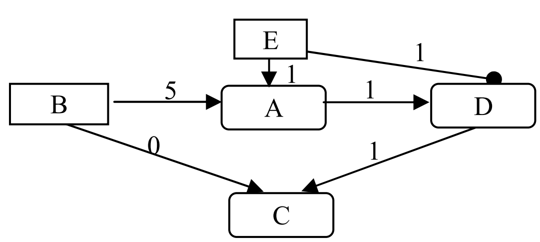



Fig. 2.1 An Example Timed Influence Net (TIN)

Formally, a TIN is described by the following definition.

**Definition 2.1:** ***Timed Influence Net (TIN)***

A TIN is a tuple (V, E, C, B, $D_E$, $D_V$, A) where

V: set of Nodes,

E: set of Edges,

C represents causal strengths:

E → { (h, g) such that $-1 < h, g < 1$ },

B represents Baseline / Prior probability: V → [0,1],

$D_E$ represents Delays on Edges: E → $Z^+$

(where $Z^+$ represent the set of positive integers),

$D_V$ represents Delays on Nodes: V → $Z^+$, and

A (input scenario) represents the probabilities associated with the state of actions and the time associated with them.

A: R → $\{([p_1, p_2,\ldots, p_n],[[t_{11},t_{12}], [t_{21},t_{22}], \ldots,[t_{n1},t_{n2}]] )$

such that $p_i = [0, 1]$, $t_{ij} \rightarrow Z^*$ and $t_{i1} \leq t_{i2}$,

$\forall\ i = 1, 2, \ldots, n$ and $j = 1, 2$ where $R \subset V \}$

(where $Z^*$ represent the set of nonzero positive integers)

The purpose of building a TIN is to evaluate and compare the performance of alternative courses of actions. The impact of a selected course of action on the desired effects is analyzed with the help of a probability profile. Consider the TIN shown in Fig. 2.1. Suppose the following input scenario is decided: actions B and E are taken at times 1 and 7, respectively. Because of the propagation delay associated with each arc, the influences of these actions impact event C over a period of time. As a result, the probability of C changes at different time instants. A probability profile draws these probabilities against the corresponding time line. The probability profile of event C is shown in Fig. 2.2.

To construct and use a TIN to support effects based operations, the following process has been defined.

1. Determine the set of desired and undesired effects expressing each as declarative statement that can be either true or false. For each effect, define one or more observable indicators that the effect has or has not occurred.
2. Build an IN that links, through cause and effect relationships, potential actions to the desired and undesired effects.

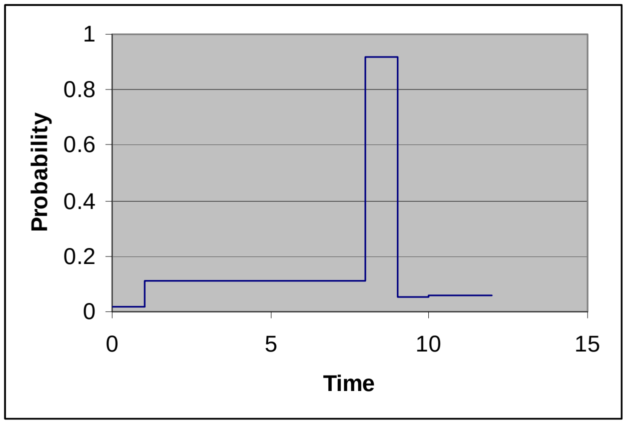


Fig 2.2 Probability Profile for Node C

Note that this may require defining additional intermediate effects and their indicators.

3. Use the IN to compare different sets of actions in terms of the probability of achieving the desired effects and not causing the undesired effects.
4. Transform the IN to a TIN by incorporating temporal information about the time the potential actions will occur and the delays associated with each of the arcs and nodes.
5. Use the TIN to experiment with different timings for the actions to identify the "best" COA based on the probability profiles that each candidate generates. Determine the time windows when observation assets may be able to observe key indicators so that assessment of progress can be made during COA execution.
6. Create a detailed execution plan to use the resources needed to carry out the COA and collect the information on the indicators.
7. Use the indicator data to assess progress toward achieving the desired effects.
8. Repeat steps 2 (or in some cases 1) through 7 as new understanding of the situation is obtained.

In building the IN, the modeler must assign values to the pair of parameters that show the causal strength (usually denoted as g and h values) for each directed link that connects pairs of nodes,. Each non-root node has an associated baseline probability that must be assigned by the modeler (or left at the default value of 0.5). It represents the probability that the random variable will be true in the absence of all modeled influences or causes. Each root node is given a prior probability, which is the initial probability that the random variable associated with the node (usually a potential action) is true.

When the modeler converts the IN into a TIN (step 4), each link is assigned a corresponding delay d (where $d \geq 0$) that represents the communication delay. Each node has a corresponding delay e (where $e \geq 0$) that represents the information processing delay. A pair (p, t) is assigned to each root node, where p is a list of real numbers representing probability values. For each probability value, a corresponding time interval is defined in t. In general, (p, t) is defined as

$([p_1, p_2,\ldots, p_n], [[t_{11}, t_{12}], [t_{21}, t_{22}], \ldots, [t_{n1}, t_{n2}]] ),$

where $t_{i1} < t_{i2}$ and $t_{ij} > 0 \; \forall \; i = 1, 2, \ldots, n$ and $j = 1, 2$

The last item is referred to as an input scenario, or sometimes (informally) as course of action.

To analyze the TIN (Step 5), the analyst selects the nodes that represent the effects of interest and generates probability profiles for these nodes. The probability profiles for different courses of action can then be compared.

# Chapter 3

# Theory of Influence Networks

**Abbas K. Zaidi, Faisal Mansoor, P. Papantoni-Kazakos, Alexander H. Levis**

## 3.1 Introduction

The easy access to domain-specific information and cost-effective availability of high computational power have changed the way people think about complex decision problems in almost all areas of application, ranging from financial markets to regional and global politics. These decision problems often require modeling of informal, uncertain and unstructured domains, to allow the evaluation of alternatives and available courses of actions by a decision maker. The past decade has witnessed an emergence of several modeling and analysis formalisms that target this need, the most popular one being represented by Probabilistic Belief Networks [3, 8], most commonly known as Bayesian Networks (BNs).

BNs model uncertain domains probabilistically, by presenting the network nodes as random variables. The arcs (or directed edges) in the network represent the direct dependency relationships between the random variables. The arrows on the edges depict the *direction* of the dependencies. The strengths of these dependencies are captured as conditional probabilities associated with the connected nodes in a network. A complete BN model requires specification of all conditional probabilities prior to its use. The number of conditional probabilities on a node in a BN grows exponentially with the number of inputs to the node, which presents a computational challenge, at times. A major problem in BNs is the specification of the required conditional probabilities, especially when either objective values of these probabilities cannot be provided by experts or there exist insufficient empirical data to allow for their reliable estimation, or when newly obtain information may change the structural topology of the network. Although a pair-wise cause and effect relationship between two variables of a domain is easier to establish or extract from a domain expert, a BN of the domain requires prior knowledge of all the influencing causes to an effect as well as their aggregate influence on the effect variable, where the measures of influences are conditional probability values. To demonstrate cases where BN modeling may be problematic, we identify the following situations of practical significance: (1) When new, previously unknown, affecting variables to some effect event arise, there are no algorithms allowing easy pertinent adaptation of conditional probabilities. (2) When the need arises to develop a consolidated BN from partial fragments of separate BNs, there are no algorithms that utilize the parameters of the fragments to calculate the parameters of the consolidated structure.

Recognizing the problems in the construction of BNs, especially regarding the specification of the involved conditional probabilities, Chang et al. [4] developed a formalism at George Mason University named Causal Strength (CAST) logic, as an intuitive and approximate language. The logic utilizes a pair of parameter values to represent conditional dependency between a pair of random variables, where these parameter values model assessed (by experts) mutual influences between an affecting and an affected event. The CAST logic approximates conditional probabilities via influence relationships by employing an influence aggregation function. The approach provides the elicitation, update, reuse, and merge interface to an underlying BN, or multiple fragments of a BN, that only requires specification of individual influences between each pair of an affecting and an affected variables. The approach then combines these individual influences to calculate the aggregate effect of multiple affecting variables on an effect variable in terms of conditional probability values of a resulting BN. This pair-wise specification of influences provides us with the, albeit approximate, means to solve the three problems discussed earlier.

The CAST logic approach was later extended to represent relationships between events involved in network interconnections, as in BNs. The extension is basically a BN with conditional probabilities approximated via the use of influence parameters and was named Influence Nets (INs) [5, 9, 10, 11]. INs require an expert who specifies the influence parameter values and their interrelationships, as well as some a priori probabilities, all needed for the approximation of the pertinent conditional probabilities. As basically modified BNs, the objective of INs is to compute the probabilities of occurrence of sequential dependent events, and do not provide recommendations for actions. However, the probabilities of occurrence computed by the INs may be utilized by activation networks towards the evaluation and recommendation of actions [12].

BNs and INs are designed to capture *static* interdependencies among variables in a system. A situation where the impact of a variable takes some *time* to reach the affected variable(s) cannot be modeled by either one. In the last several years, efforts have been made to integrate the notion of time and uncertainty. Wagenhals et al. [12, 13, 14] have added a special set of temporal constructs to the basic formalism of INs. The INs with these additional temporal constructs are called Timed Influence Nets (TINs). TINs have been experimentally used in the area of Effects Based Operations (EBOs) for evaluating alternate courses of actions and their effectiveness to mission objectives in a variety of domains, e.g., war games [1, 15, 16, 17], and coalition peace operations [18], modeling adversarial behaviors [35], to name a few. The provision of time allows for the construction of alternate courses of action as timed sequences of actions or actionable events represented by nodes in a TIN [13, 15, 17]. A number of analysis tools have been developed over the years for TIN models, to help an analyst update beliefs [19, 20, 21, 22, 23] represented as nodes in a TIN, to map a TIN model to a Time Sliced Bayesian Network for incorporating feedback evidence, to determine best course of actions for both timed and un-timed versions of Influence Nets [24, 25] and to assess temporal aspects of the influences on objective nodes [26, 27].

The existing developments of INs and TINs suffer from a number of deficiencies: they do not represent scenarios encompassing dependent conditioning events and they utilize a priori probabilities inconsistently, in violation of the Bayes Rule and the Theory of Total Probability. The motivation behind the work presented in this paper is to address these shortcomings of INs and TINs by developing a correct analytical framework for the design and analysis of influences on some critical effects due to a set of external affecting events. We present a comprehensive theory of Influence Networks, which is free of restrictive independence assumptions, which is consistently observing the Bayes Rule and the Theorem of Total Probability. In this theory, we are concerned with the evaluation of cause-effect relationships between interconnected events. In particular, if the status of some event B is affected by the status of a set of events, $A_1$ to $A_n$, we are interested in a qualification and quantification of this effect. We first graph the relationships between events B and $A_1$ to $A_n$ in a network format, as in Fig. 3.1 below, with each event being a node, with arcs indicating relationships and with arrows representing the cause-effect directions. This graphical representation is identical to that used in BNs.

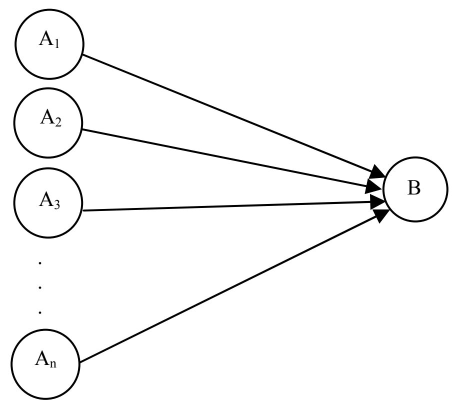



Fig. 3.1 Cause-Effect Relationships

Given the graph of Fig. 3.1, we next decide the metric to be used for the quantification of the effects of events $A_1$ to $A_n$ on event B. As in BNs, modeling each of the involved events as binary random variables, we use conditional probabilities as effect metrics: in particular, we use the probabilities that event B occurs, given each of the $2^n$ scenarios regarding the occurrence or nonoccurrence of each one of the events $A_1$ to $A_n$.

Upon the decision to use conditional probabilities as the effect metrics, the issue of their computation arises. In most realistic scenarios, there exist insufficient amount of data for the reliable estimation of these probabilities. Instead, some influence indicators may be provided by experts. In the example of Fig. 3.1, for instance, for each one of the $2^n$ scenarios regarding the occurrence or nonoccurrence of each on of the events $A_1$ to $A_n$, an expert may provide a number between $-1$ and 1, to reflect his assessment as to the effect of the above scenario on the occurrence of event B. The latter number is named **influence constant**. The objective at this point is to utilize the so provided influence constants for the approximate evaluation and computation of the required conditional probabilities, in a mathematically correct and consistent fashion. These conditional probabilities are subsequently utilized for the probabilistic evaluation of event occurrences in a network of events, giving rise to an Influence Network (IN). In different terms, a IN is a BN whose conditional probabilities are computed via the use of influence constants. The term IN should not be confused with a similarly named formalism called Influence Diagrams [28, 29, 30, 31]. Unlike INs, an Influence Diagram (ID) has different types of nodes (i.e., decision nodes, chance nodes, and utility nodes) and different types of influences (i.e., arcs between the nodes); and the decisions in an ID are assumed to have a certain precedence relationship among them. The IDs can be considered a BN extended with a utility function, while a IN, as noted above, is a special instance of a BN whose conditional probabilities are computed via the use of influence constants and which uses a set of special purpose algorithms for calculating the impact of a set of external affecting events on some desired effect/objective node.

Frequently, in several realistic scenarios, assessments of event occurrences may be needed at times when the status of all affecting events may not be known, while such assessments require sequential adaptation, as the status of more affecting events are revealed. For example, in Fig. 1, the evaluation of the probability of event B may be needed at times when the status of only some of the events A are known, while this probability need to be subsequently adapted when the status of the remaining A events become known. Such sequential adaptations require pertinent sequential computation methodologies for the approximation of conditional probabilities via influence constants and give rise to Time Influence Networks (TINs). We present two different temporal models for the sequential computation of conditional probabilities in a Timed Influence Nets. This enhances the capabilities of the Timed Influence Nets in modeling domains of interest with different time characteristics.

The organization of the paper is as follows: In section 3.2, we present the theoretical formalization and derive initial relationships. In section 3.3, we derive the dynamic programming evolution of the influence constants. In section 3.4, we examine the case where in the generic model, the affecting events are mutually independent, where in section 3.5, the case where the latter events form a Markov chain is examined. In section 3.6, temporal considerations are presented. In section 3.7 we discuss decision model selection and testing. In section 3.8, special forms of the influence constants are discussed. In Section 3.9, we discuss evaluation metrics. In section 3.10, the experimental setup is laid out, while in the final section, 3.11, conclusions are drawn.

### 3.2 Initial Modeling and Relationships

In this section, we formalize our approach for the development of INs and TINs.

Let us consider an event B being potentially affected by events $\{A_i\}_{1 \le i \le n}$. In particular, we are interested in the effect the presence or absence of any of the events in the set $\{A_i\}_{1 \le i \le n}$ may have on the occurrence of event B.

Let us first define:

$X_1^n$: An n-dimensional binary random vector whose $j^{th}$ component is denoted $X_j$, where $X_j = 1$; if the event $A_j$ is present, and $X_j = 0$; if the event $A_j$ is absent.

We will denote by $x_1^n$ realizations or values of the random vector $X_1^n$. A given realization $x_1^n$ of the binary vector $X_1^n$ describes precisely the status of the set $\{A_i\}_{1 \le i \le n}$ of events, regarding which events in the set are present. We name the vector $X_1^n$, the **status vector** of the affecting events. To quantify the effects of the status vector $X_1^n$ on the event B, we define the **influence constant** $h_n(x_1^n)$ via the following quantitative properties:

$$h_n(x_1^n) = \begin{cases} 1 & ;\text{if} \quad \begin{array}{l}\text{given n affecting events, given the status} \\ \text{vector } x_1^n\text{, event B occurs surely}\end{array} \\ -1 & ;\text{if} \quad \begin{array}{l}\text{given n affecting events, given the status} \\ \text{vector } x_1^n\text{, the nonoccurrence of event B is sure}\end{array} \\ 0 & ;\text{if} \quad \begin{array}{l}\text{given n affecting events, given the status} \\ \text{vector } x_1^n\text{, the occurrence of event B is unaffected}\end{array} \end{cases} \tag{3.1}$$

Let $P(B \mid x_1^n)$ denote the probability of occurrence of event B, given the status vector $x_1^n$. Then, the quantitative definition of the influence constant $h_n(x_1^n)$ in (3.1) can be rewritten as follows, where $P(B)$ denotes the unconditional probability of occurrence of the event B.

$$P(B \mid x_1^n) = \begin{cases} 1 \;\; ; \text{ if } & h_n(x_1^n) = 1 \\ P(B); \text{ if } & h_n(x_1^n) = 0 \\ 0 \;\; ; \text{ if } & h_n(x_1^n) = -1 \end{cases} \tag{3.2}$$

We now extend the definition of all values in $[1,-1]$ of the influence constant, via linear interpolation from (3.2). In particular, we define the influence constant via its use to determine the derivation of the conditional probability $P(B \mid x_1^n)$ from the unconditional probabilities $P(B)$, where this derivation is derived via linear interpolation from (3.2). We thus obtain.

$$P(B \mid x_1^n) = \begin{cases} P(B) + h_n(x_1^n)[1 - P(B)]; \text{if } \; h_n(x_1^n) \in [0,1] \\ \quad P(B) + h_n(x_1^n) P(B) \quad ; \text{if } h_n(x_1^n) \in [-1,0] \end{cases} \tag{3.3}$$

Defining $\operatorname{sgn} \gamma = \begin{cases} 1; \text{if } \gamma \geq 0 \\ 0; \text{if } \gamma < 0 \end{cases}$, we can finally write (3.3) as follows

$$P(B \mid x_1^n) = P(B)\{1 + h_n(x_1^n)[1 - P(B)]P^{-1}(B)\}^{\operatorname{sg} n h_n(x_1^n)} \times \{1 + h_n(x_1^n)\}^{1 - \operatorname{sg} n h_n(x_1^n)} \tag{3.4}$$

At this point, we present a formal definition of INs and TINs.

**Definition 3.1:** An Influence Network (IN) is a Bayesian Network mapping conditional probabilities $P(B \mid x_1^n)$ via the utilization of influence constants as in (3.4)**.** Formally, an Influence Net is a tuple (**V**, **E**, **C**, **A**, **B**), with **G** = (**V**, **E**) representing a directed-acyclic graph satisfying the Markov condition (as in BN), where:

- **V**: set of nodes representing binary random variables,
- **E**: set of edges representing causal influences between nodes,
- **C**: set of causal strengths: $E \rightarrow \left\{ \left[ h_1^{(i)}(x_i = 1), h_1^{(i)}(x_i = 0) \right] \text{such that } h_1\text{'s} \in [-1,1] \right\}$**,**
- **A**: a subset of **V** representing *external* affecting events $\{A_i\}_{1 \leq i \leq n}$ and a status of the corresponding vector $X_1^n$,
- **B**: Probability distribution of the status vector $X_1^n$ corresponding to the external affecting events $\{A_i\}_{1 \leq i \leq n}$.

A Timed Influence Network (TIN) adds two temporal parameters to the definition of a IN. Formally, a TIN is a tuple (**V**, **E**, **C**, **D**, $\mathbf{A_T}$, **B**), where **V**, **E**, **C**, and **B** are as defined for INs;

**D**: set of temporal delays on edges: **E** $\rightarrow$ N,

**A**$_T$: same as **A** with the addition that the status of each external affecting event is *time tagged* representing the time of realization of its status. In the IN/TIN literature [12, 13, 15, 16, 17, 18, 25], $A_T$ is also referred to as a Course of Action (COA). A COA is, therefore, a time-sequenced collection of external affecting events and their status.

Returning to the influence constant notion, we note that there exist $2^n$ distinct values of the status vector $x_1^n$; thus, there exist $2^n$ distinct values of the influence constant $h_n(x_1^n)$ as well as of the conditional probabilities in (3.4). In the case where the cardinality of the set $\{A_i\}_{1 \le i \le n}$ is one, the influence constant $h_1(x_1)$ equals the constant $h$ in [5]; if $x_1 = 1$ and equals the constant $g$ in [5]; if $x_1 = 0$.

We now proceed with a definition which will lead to a mathematically correct relationship between influence constants and unconditional probabilities.

**Definition 3.2:** A IN or TIN model is **consistent** if it observes the Bayes Rule.

Let $P(x_1^n)$ denote the probability of the status vector $X_1^n$ at the value $x_1^n$. We can then express the following simple lemma.

**Lemma 3.1**

Let the influence constant $h_n(x_1^n)$ be accepted as reflecting accurately the relationship between the affecting events $\{A_i\}_{1 \le i \le n}$ and event B. Then the IN or TIN model is consistent iff:

$$\sum_{x_1^n} P(x_1^n)\{1 + h_n(x_1^n)[1 - P(B)]P^{-1}(B)\}^{\operatorname{sgn} h_n(x_1^n)}\{1 + h_n(x_1^n)\}^{1-\operatorname{sgn} h_n(x_1^n)} = 1 \tag{3.5}$$

or

$$\sum_{x_1^n} P(x_1^n) h_n(x_1^n)\{[1 - P(B)]P^{-1}(B)\}^{\operatorname{sgn} h_n(x_1^n)} = 0$$

**Proof:** Substituting expression (3.4) in the the Bayes' Rule, $P(B) = \sum_{x_1^n} P(x_1^n) P(B \mid x_1^n)$, we obtain (3.5).

Expression (3.5) relates the influence constant $h_n(x_1^n)$ to the unconditional probabilities of event B and the status vector $X_1^n$. This relationship is necessary if the influence constant is accepted as accurately representing the conditional probability $P(B \mid x_1^n)$ in (3.3). Generally, the influence constant is selected based on a system design assessment provided by experts, while the a priori probabilities $P(x_1^n)$ are accepted to accurately represent the actual model.

**Summary**

Given the events in Fig. 3.1, given well-established a priori probabilities of the cause events, given the influence constants, the cause-effect conditional probabilities are expressed as follows:

$$P\left(B \mid x_1^n\right)=\begin{cases} a+h_n(x_1^n)[1-a]; \text{if } \ h_n(x_1^n)\in[0,1] \\ \ a+h_n(x_1^n)a \quad ; \text{if } h_n(x_1^n)\in[-1,0] \end{cases}$$

where

$$a = P(B) = \left[\sum_{x_1^n : \operatorname{sgn} h_n(x_1^n)=1} P\left(x_1^n\right) h_n(x_1^n)\right]\left[\sum_{x_1^n} P\left(x_1^n\right)\left|h_n(x_1^n)\right|\right]^{-1}$$

*Influence nets thus utilize expert-provided subjective influence constants, in conjunction with well-established objective a priori probabilities of cause events, to generate conditional probabilities of effect events.*

### 3.3 Evolution of the influence Constant

In section 3.2, we derived the relationship between the conditional probability of event B, and the status $x_1^n$ of its affecting events $\{A_i\}_{1 \le i \le n}$, via the influence constant $h_n(x_1^n)$. This relationship is based on the assumption that $\{A_i\}_{1 \le i \le n}$ is the maximum set of events affecting event B and that the value $x_1^n$ of the status vector is given. In this section we investigate the case where the status of some of the affecting events may be unknown. Towards this direction, we derive a dynamic programming relationship between the influence constants $h_n(x_1^n)$ and $h_{n-1}(x_1^{n-1})$, where $h_{n-1}(x_1^{n-1})$ is the constant corresponding to the case where the status of the affecting event $A_n$ is unknown. We express a lemma whose proof is in Appendix A of this report. The proof is based on the observation of the Bayes' Rule and the Theorem of Total Probability.

**Lemma 3.2**

Let the probability $P(B)$ be as in Section II and let $P(x_n \mid x_1^{n-1})$ denote the probability of the value of the last bit in the status vector $X_1^n$ being $x_n$, given that the reduced status vector value is $x_1^{n-1}$. Then, the influence constant $h_{n-1}(x_1^{n-1})$ is given as a function of the influence constant $h_n(x_1^n)$, as shown below.

$$h_{n-1}(x_1^{n-1}) = \begin{cases} Q_n & ; \quad Q_n \in [-1,0] \\ P(B)[1-P(B)]^{-1}Q_n & ; \ Q_n \in [0, P^{-1}(B)-1] \end{cases} \tag{3.6}$$

where

$$Q_n \stackrel{\Delta}{=} \sum_{x_n=0,1} P(x_n \mid x_1^{n-1})\{h_n(x_1^n)\}\{[1-P(B)]P^{-1}(B)\}^{\mathrm{sg}\,n\,\mathrm{h}_x(x_1^n)} \tag{3.7}$$

We note that the influence constants are deduced from the same constants of higher dimensionality, as shown in Lemma 3.2. In accordance, conditional probabilities of the event B are produced from the deduced influence constants, via expression (3.4), as:

$$P(B \mid x_1^{n-1}) = P(B)\{1 + h_{n-1}(x_1^{n-1})[1-P(B)]P^{-1}(B)\}^{\mathrm{sgn}\,h_{n-1}(x_1^{n-1})} \times \{1 + h_{n-1}(x_1^{n-1})\}^{1-\mathrm{sgn}\,h_{n-1}(x_1^{n-1})} \tag{3.8}$$

It is important to note that in the dynamic programming evolution of the influence constants $h_n(x_1^n)$, as well as in the evolution of the conditional probabilities in (3.7), knowledge of the joint probability $P(x_1^n)$ is assumed. This reflects a conjecture by the system designer, based on his /her previous experience regarding the a priori occurrence of the affecting events $\{A_i\}_{1 \le i \le n}$. Thus the probability $P(x_1^n)$ used for the construction exhibited by Lemma 3.2 is a design probability and it may not coincide with the actual probabilities of the status vector $X_1^n$. When full scale dependence of the components of the status vector $X_1^n$ is incorporated within the design probability $P(x_1^n)$, then the relationship between the different dimensionality influence constants is that reflected by Lemma 3.2 and is of dynamic programming nature. In the case where the design probability $P(x_1^n)$ generically reflects either a Markov Chain of events or mutually independent events, then the relationships between the different dimensionality influence constants may be also of recursive nature. The cases of Markovian or independent affecting events, as modeled by the system designer, are examined in sections 3.4 and 3.5.

### 3.4 The Case of Independent Affecting Events

In this section, we consider the special case where the affecting events $\{A_i\}_{1 \le i \le n}$ are assumed to be generically mutually independent. Then, the components of the status vector $X_1^n$ are mutually independent, and:

$$P(x_1^n) = \prod_{i=1}^{n} P(x_i) \quad ; \quad P(x_1^n \mid B) = \prod_{i=1}^{n} P(x_i \mid B) \tag{3.9}$$

Let us denote by $h_1^{(i)}(x_i)$ the influence constant corresponding to the effect of the event $A_i$ on the occurrence of the event B, when event $A_i$ acts in isolation and when the status value of the event is $x_i$. Then, from expression (3.4) in section 3.3, we have:

$$P(B \mid x_i) = P(B)\{1 + h_1^{(i)}(x_i)[1-P(B)]P^{-1}(B)\}^{\mathrm{sg}\,n h_1^{(i)}(x_i)} \bullet \{1 + h_1^{(i)}(x_i)\}^{1-\mathrm{sg}\,n h_1^{(i)}(x_i)} \tag{3.10}$$

We now express a lemma whose proof is in Appendix A.

**Lemma 3.3**

Let the events $\{A_i\}_{1 \le i \le n}$ that affect event B be assumed to be generically mutually independent. Then

$$P\left(B \mid x_1^n\right) = P(B)\prod_{i=1}^{n}\left\{1 + h_1^{(i)}(x_i)\left[1 - P(B)\right]P^{-1}(B)\right\}^{\mathrm{sg}\,n h_1^{(i)}(x_i)} \bullet \left\{1 + h_1^{(i)}(x_i)\right\}^{1-\mathrm{sg}\,n h_1^{(i)}(x_i)} \tag{3.11}$$

Via the same logic as that in the last part in the proof of Lemma 2, we can show the result expressed in the corollary below.

**Corollary 3.1**

When the affecting events are assumed to be generically mutually independent then, the influence constant $h_n(x_1^n)$ is given as a function of the single event influence constants $\{h_1^{(i)}(x_i)\}_{1 \le i \le n}$, as follows:

$$h_n(x_1^n) = \begin{cases} R_n - 1 & ; \quad \text{if } R_n \in [0,1] \\ P(B)\left[1 - P(B)\right]^{-1}\left[R_n - 1\right]; & \text{if } R_n \in \left[1, P^{-1}(B)\right] \end{cases} \tag{3.12}$$

where

$$R_n \stackrel{\Delta}{=} \prod_{i=1}^{n}\left\{1 + h_1^{(i)}(x_i)\left[1 - P(B)\right]P^{-1}(B)\right\}^{\mathrm{sg}\,n h_1^{(i)}(x_i)} \times \left\{1 + h_1^{(i)}(x_i)\right\}^{1-\mathrm{sg}\,n h_1^{(i)}(x_i)} \tag{3.13}$$

The sequence of expressions $\{R_i\}_{1 \le i \le n}$ in (3.13) is clearly recursively generated and the conditional probability $P(B \mid x_1^n)$ is given by $h_n(x_1^n)$ as in (3.4) in section 3.2.

We note that the consistency condition in Lemma 3.1, section 3.2 reduces in a straight forward fashion and by construction to the following condition here:

$$\sum_{x_i = 0,1} P(x_i)\left\{1 + h_1(x_i)\left[1 - P(B)\right]P^{-1}(B)\right\}^{\mathrm{sgn}\, h_1(x_i)}\left[1 + h_1(x_i)\right]^{1-\mathrm{sgn}\, h_1(x_i)} = 1; \forall i$$

or

$$\sum_{x_i = 0,1} P(x_i) h_1(x_i)\left\{\left[1 - P(B)\right]P^{-1}(B)\right\}^{\mathrm{sgn}\, h_1(x_i)} = 0; \forall i$$

### 3.5 The Case of A Markov Chain of Affecting Events

In this section, we consider the case where the affecting events $\{A_i\}_{1 \le i \le n}$ are assumed to form generically a Markov Chain. In particular, we assume that the design probabilities $P(x_1^n \mid B)$ and $P(x_1^n)$ are such that:

$$P(x_1^n \mid B) = \prod_{i=1}^{n} P(x_i \mid x_{i-1}, B)$$
$$P(x_1^n) = \prod_{i=1}^{n} P(x_i \mid x_{i-1}) \tag{3.14}$$
where

$$P(x_1 \mid x_0, B) \stackrel{\Delta}{=} P(x_1 \mid B) \text{ and } P(x_1 \mid x_0) \stackrel{\Delta}{=} P(x_1)$$

We denote by $h_1^{(1)}(x_1)$ the influence constant corresponding to the effect of the event $A_1$ on the occurrence of the event B, when the status value of $A_1$, is given by $x_1$. We denote by $h_2^{(i,i+1)}(x_i, x_{i+1})$ the influence constant corresponding to the effect of the events $A_i$ and $A_{i+1}$ on the occurrence of the event B, when the status values of the $(A_i, A_{i+1})$ pair are given by $(x_i, x_{i+1})$. Then, via (3.4) in section 3.2, we have

$$P(B \mid x_1) = P(B)\left\{1 + h_1^{(1)}(x_1)[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_1^{(1)}(x_1)} \times \left\{1 + h_1^{(1)}(x_1)\right\}^{1-\operatorname{sgn} h_1^{(1)}(x_1)} \tag{3.15}$$

$$P(B \mid x_i, x_{i+1}) = P(B)\left\{1 + h_2^{(i,i+1)}(x_i, x_{i+1})[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_2^{(i,i+1)}(x_i, x_{i+1})} \times \left\{1 + h_2^{(i,i+1)}(x_i, x_{i+1})\right\}^{1-\operatorname{sgn} h_2^{(i,i+1)}(x_i, x_{i+1})}; i = 1 \tag{3.16}$$

We now express a lemma whose proof is in the Appendix.

**Lemma 3.4**

Let the affecting events $\{A_i\}_{1 \le i \le n}$ be assumed to generically form a Markov Chain; thus, $P(x_1^n)$ is assumed to satisfy the equation in (3.14). Then,

$$P(B \mid x_1^n) = P(B)\left\{1 + h_1^{(1)}(x_1)[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_1^{(1)}(x_1)} \times \left\{1 + h_1^{(1)}(x_1)\right\}^{1-\operatorname{sgn} h_1^{(1)}(x_1)} \times$$
$$\prod_{i=2}^{n} \frac{\left\{1 + h_2^{(i,i-1)}(x_i, x_{i-1})[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_2^{(i,i-1)}(x_i, x_{i-1})} \times \left\{1 + h_2^{(i,i-1)}(x_i, x_{i-1})\right\}^{1-\operatorname{sgn} h_2^{(i,i-1)}(x_i, x_{i-1})}}{\left\{1 + h_1^{(i-1)}(x_{i-1})[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_1^{(i-1)}(x_{i-1})} \times \left\{1 + h_1^{(i-1)}(x_{i-1})\right\}^{1-\operatorname{sgn} h_1^{(i-1)}(x_{i-1})}}$$
$$\stackrel{\Delta}{=} P(B)W_n \tag{3.17}$$

where,

$$h_1^{(i)}(x_i) = \begin{cases} Q_{i,i+1} - 1 & ; \quad \text{if } Q_{i,i+1} \in [0,1] \\ P(B)[1 - P(B)]^{-1}[Q_{i,i+1} - 1] & ; \quad \text{if } Q_{i,i+1} \in [1, P^{-1}(B)] \end{cases} \tag{3.18}$$

$$Q_{i,i+1} \stackrel{\Delta}{=} \sum_{x_{i+1}=0,1} P(x_{i+1} \mid x_i)\left\{1+h_2^{(i,i+1)}(x_i,x_{i+1})[1-P(B)]P^{-1}(B)\right\}^{\mathrm{sgn}\, h_2^{(i,i+1)}(x_i,x_{i+1})} \times \left\{1+h_2^{(i,i+1)}(x_i,x_{i+1})[1+P(B)]P^{-1}(B)\right\}^{1-\mathrm{sgn}\, h_2^{(i,i+1)}(x_i,x_{i+1})} \tag{3.19}$$

As with Corollary 3.1 in section 3.4, we can express the corollary below, in a direct fashion.

**Corollary 3.2**

When the affecting events $\{A_i\}_{1 \le i \le n}$ are assumed to generically form a Markov Chain, depicted by the expression in (3.14), then, the influence constant $h_n(x_1^n)$ is given as a function of the influence constants $\{h_1^{(i)}(x_i)\}$ and $\{h_2^{(i,i-1)}(x_i, x_{i-1})\}$, as below, where $W_n$ is defined in (3.17).

$$h_n(x_1^n) = \begin{cases} W_n - 1 & ; \quad \text{if } W_n \in [0,1] \\ P(B)[1-P(B)]^{-1}[W_n - 1]; & \text{if } W_n \in [1, P^{-1}(B)] \end{cases} \tag{3.20}$$

The sequence $\{W_i\}_{1 \le i \le n}$ in (17) is clearly recursively expressed; thus, $h_n(x_1^n)$ is recursively evolving. The consistency condition in Lemma 3.1, section 3.2, takes here the following form, by construction.

$$\sum_{x_i=0,1} \sum_{x_{i-1}=0,1} P(x_i \mid x_{i-1})\left\{1 + h_2^{(i,i-1)}(x_i x_{i-1})[1-P(B)]P^{-1}(B)\right\}^{\mathrm{sgn}\, h_2^{(i,i-1)}(x_i, x_{i-1})}$$

$$\times \left\{1 + h_2^{(i,i-1)}(x_i, x_{i-1})\right\}^{1-\mathrm{sgn}\, h_2^{(i,i-1)}(x_i, x_{i-1})} = 1; \qquad \forall i$$

### 3.6 Temporal Extension

In sections 3.2 and 3.3, we presented our theoretical foundation for the development of INs and TINs, while in sections 3.4 and 3.5, we focused on the special cases of independent and Markovian affecting events. In this section, we focus on the formalization of the temporal issues involved in the development of TINs. In particular, we are investigating the dynamics of the relationship of the affecting events $\{A_i\}_{1 \le i \le n}$ to the affected event B, when the status of the former evens are learned asynchronously in time. Without lack in generality – to avoid cumbersome notation – let the affecting events $\{A_i\}_{1 \le i \le n}$ be ordered in the order representing the time when their status become known. That is, the status of events $A_1$ is first known, then that of event $A_2$, and so on. In general, the status of event $A_k$ becomes known after the status of the events $A_1 \ldots, A_{k-1}$ are known, and this knowledge becomes available one event at the time.

Let us assume that the considered system model implies full dependence of the components of the status vector $X_1^n$. Then, the influence constants $\{h_i(x_1^n)\}_{1 \le i \le n-1}$ are first pre-computed via the dynamic programming expression in Lemma 3.2, section 3.2, utilizing the pre-selected a priori probabilities $P(x_1^n)$ that are part of the given system parameters. The above influence constants can be recursively computed if the adopted system model implies either generically independent affecting events or affecting events that generically form a Markov Chain, as shown in sections 3.4 and 3.5.

Let $T_0$ denote the time when the computation of the system dynamics starts. Let $T_1$ denote the time when the status of event $A_1$, becomes known. Let $T_k$ ; $1 \leq k \leq n$ denote the time when the status of event $A_k$ becomes known. Then at time $T_k$, the conditional probabilities $P(B \mid x_1^k)$ are computed via expression (3.4), Section II, as,

$$P\left(B \mid x_1^k\right)_{i \leq k \leq n} = P(B)\left\{1 + h_k(x_1^k)[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sg} n h_k(x_1^k)} \times \left\{1 + h_k(x_1^k)\right\}^{1 - \operatorname{sg} n h_k(x_1^k)} \tag{3.21}$$

where the probability $P(B)$ is computed via the consistency condition (5).

As the knowledge about the status of the affecting events unravels, the conditional probabilities of event B in (3.21) evolve dynamically in time and finally converge to the probability $P(B \mid x_1^n)$ at time $T_n$, when the status of all the affecting events become known.

It is important to point out that the conditional probability in (3.21) is sensitive to the time ordering of the affecting events. That is, for the same value $x_1^k$ of a partial affecting vector, but different time ordering of events, different conditional probabilities values of the affected event B arise. Thus, the order by which the status of the affecting events become known is crucial in the evaluation of the conditional probabilities of event B.

### 3.7 Selection and Testing of the Decision Model

#### *Model Selection*

As we have discussed earlier, the unconditional probabilities $P(x_1^n)$ as well as the influence constant $h_n(x_1^n)$ are design parameters that may not represent the actual parameters correctly. Furthermore, as discussed in section 3.2, the design parameters must be **consistent**, where consistency is represented by the satisfaction of condition (3.5) in Lemma 3.1. Condition (3.5) can be rewritten as follows, in a straightforward fashion.

$$[1 - P(B)] \sum_{x_1^n : \operatorname{sgn} h_n(x_1^n) = 1} P\left(x_1^n\right) h_n(x_1^n) = P(B) \sum_{x_1^n : \operatorname{sgn} h_n(x_1^n) = 0} P\left(x_1^n\right) \left| h_n(x_1^n) \right| \tag{3.22}$$

which gives:

$$P(B) = \left[\sum_{x_1^n : \operatorname{sgn} h_n(x_1^n) = 1} P\left(x_1^n\right) h_n(x_1^n)\right]\left[\sum_{x_1^n} P\left(x_1^n\right)\left| h_n(x_1^n)\right|\right]^{-1} ; \text{ when } \sum_{x_1^n} P\left(x_1^n\right)\left| h_n(x_1^n)\right| \neq 0 \tag{3.23}$$

**Example:** Let us consider the case where the only affecting event for B is $A_i$.

Let $$P(A_1)\overset{\Delta}{=}P(X_1=1)=p,$$

where then,

$$P(A_1^C)\overset{\Delta}{=}P(X_1=0)=1-p.$$

Define h and g as in [5] and let $P(B)$ be what has been called in [5] base probability for the event B. Then, due to (3.22) the above parameters must satisfy the following equation(s):

$$\begin{array}{ll} either & [1-P(B)]ph = P(B)(1-p)|g| \quad ; \text{ if } h>0 \text{ and } g<0 \\ or & [1-P(B)](1-p)g = P(B)p\,|h| \quad ; \text{ if } h<0 \text{ and } g>0 \end{array}$$

no other h and g combinations are acceptable. Note that parameters h and g in [5] map to $h_1^{(i)}(x_i=1)$ and $h_1^{(i)}(x_i=0)$, respectively, in Definition 3.1, section 3.2.

When new information about the a priori probability $P(x_1^n)$ is obtained, then, $P(B)$ and/or $h_n(x_1^n)$ need to be accordingly adjusted to satisfy the condition in (22). We note that the latter condition involves a number of free parameters; thus even specification of the probabilities $P(B)$ and $P(x_1^n)$ does not specify uniquely the values of the influence constant $h_n(x_1^n)$. Naturally, specification of $P(x_1^n)$ and $h_n(x_1^n)$ uniquely determines the probability $P(B)$, however, as in (3.23).

In the case that the assumed system design model implies generically independent affecting events $\{A_i\}_{1\le i\le n}$, then, for consistency the probability $P(B)$, the probability $P(x_1^n)=\prod_{i=1}^{n}P(x_i)$ of the status vector and the influence constants $\{h_1^{(i)}(x_i)\}$ are constraint to satisfy the condition:

$$\sum_{x_i=0,1}P(x_i)\left\{1+h_1(x_i)[1-P(B)]P^{-1}(B)\right\}^{\operatorname{sgn}h_1(x_i)}\left\{1+h_1(x_i)\right\}^{1-\operatorname{sgn}h_1(x_i)}=1;\forall i \qquad (3.24)$$

Or

$$\sum_{x_i=0,1}P(x_i)h_1(x_i)\left\{[1-P(B)]P^{-1}(B)\right\}^{\operatorname{sgn}h_1(x_i)}=0;\forall i$$

### *Model Testing*

Since the "consistency" constraints allow for a number of free parameters, we will focus on the influence constant $h_n(x_1^n)$ as the constant to be tested, when information about the probabilities of the events $\{A_i\}_{1\le i\le n}$ and B is obtained. Thus, model testing will involve comparison of the $P(x_1^n)$ and $P(B)$ probabilities assumed in the model with those computed, to test the validity of the assumed influence constant. When the computed $P(x_1^n)$ and $P(B)$ values do not satisfy equation (23) for the assumed $h_n(x_1^n)$, then a non valid model is declared and a new influence constant $h_n(x_1^n)$ is sought, in satisfaction of the consistency condition in (3.23).

### 3.8 Some Special Influence Constants

As noted at the end of section 3.7, the influence constant is a important component of the system model: the appropriate choice of this constant needs to be carefully thought out, to accurately reflect the interleaving of partial influences. In this section, we study some specific influence constants, $h_n(x_1^n)$. In particular, we study such constants that are specific analytic functions of the one-dimensional components $h_i(x_i)$; $1 \le i \le n$. We note that we are not mapping the $\{h_i(x_i)\}_{1\le i\le n}$ constants onto conditional probabilities $\{P(B \mid x_i)\}_{1\le i\le n}$. Instead, we are using the constants $\{h_i(x_i)\}_{1\le i\le n}$ to construct a global $h_n(x_1^n)$ influence constant; it is the latter constant which is mapped onto the conditional probability $P(B \mid x_1^n)$, as in section 3.2.

***The $h_n(x_1^n)$ corresponding to the CAST logic***

The influence constant presented below is that used by the CAST logic in [4, 5, 9, 10, 11]. In the present case, given the constants $\{h_i^{(i)}(x_i)\}_{1\le i\le n}$ the global influence constant, $h_n(x_1^n)$, is defined as follows

$$h_n(x_1^n) = \left[\prod_{i:h_1(x_i)<0}\left(1-\left|h_1^{(i)}(x_i)\right|\right) - \prod_{i:h_1(x_i)>0}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right] \times \left[\max\left(\prod_{i:h_1(x_i)<0}\left(1-\left|h_1^{(i)}(x_i)\right|\right), \prod_{i:h_1(x_i)>0}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right)\right]^{-1} \tag{3.25}$$

In agreement with the results in section 3.2, and via (5) in Lemma 1, the global constants $h_n(x_1^n)$ and the probabilities $P(x_1^n)$ and $P(B)$ must satisfy the consistency condition

$$\sum_{x_1^n} P\left(x_1^n\right)\left\{1 + h_n(x_1^n)\left[1 - P\left(B\right)\right]P^{-1}\left(B\right)\right\}^{\operatorname{sgn} h_n(x_1^n)}\left\{1 + h_n(x_1^n)\right\}^{1-\operatorname{sgn} h_n(x_1^n)} = 1 \tag{3.26}$$

Via (4), the conditional probabilities $P(B \mid x_1^n)$ are then given, by the following expression:

$$P\left(B \mid x_1^n\right) = P(B)\left\{1 + h_n(x_1^n)\left[1 - P(B)\right]P^{-1}(B)\right\}^{\operatorname{sg} n h_n(x_1^n)} \times \left\{1 + h_n(x_1^n)\right\}^{1-\operatorname{sg} n h_n(x_1^n)} \tag{3.27}$$

For maintaining the consistency condition in (3.26), the conditional probability $P(B \mid x_1^{n-1})$ is defined via the influence constant $h_{n-1}(x_1^{n-1})$ as in Lemma 3.2, Section 3.2, where,

$$P(B \mid x_1^{n-1}) = P(B)\left\{1 + h_{n-1}(x_1^{n-1})\left[1 - P(B)\right]P^{-1}(B)\right\}^{\operatorname{sgn} h_{n-1}(x_1^{n-1})} \times \left\{1 + h_{n-1}(x_1^{n-1})\right\}^{1-\operatorname{sgn} h_{n-1}(x_1^{n-1})}$$

and

$$h_{n-1}(x_1^{n-1}) = \begin{cases} Q_n - 1 & ; \quad Q_n \in [0,1] \\ P(B)[1-P(B)]^{-1}[Q_n - 1] & ; \quad Q_n \in [1, P^{-1}(B)] \end{cases}$$

$$Q_n \overset{\Delta}{=} \sum_{x_n=0,1} P(x_n \mid x_1^{n-1}) \left\{1 + h_n(x_1^n)[1-P(B)]P^{-1}(B)\right\}^{\mathrm{sgn}\, h_n(x_1^n)} \times \left[1 + h_n(x_1^n)\right]^{1-\mathrm{sgn}\, h_n(x_1^n)}$$

### *A $h_n(x_1^n)$ Constant Representing Extreme Partial Values*

In this part, we first define the effect of the constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$ on the event B as follows:

If at least one of the constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$ equals the value 1, then event B occurs surely, if in addition $\sum_{i=1}^{n} h_1^{(i)}(x_i) > 0$

If at least one of the constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$ equals the value -1, then the nonoccurrence of event B is sure, if in addition $\sum_{i=1}^{n} h_1^{(i)}(x_i) < 0$

The events $\{A_i\}_{1 \le i \le n}$ do not affect the event B if $\sum_{i=1}^{n} h_1^{(i)}(x_i) = 0$

The above conditions translate to the following initial expressions for the conditional probability $P(B \mid x_1^n)$, where $x_1^n$ is the value of the status vector of the affecting events $\{A_i\}_{1 \le i \le n}$:

$$P(B \mid x_1^n) = \begin{cases} 1 & ; \textit{if} \quad \max\limits_{1\le i\le n} h_1^{(i)}(x_i) = 1 \text{ and } \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) > 0 \\ P(B) & ; \textit{if} \quad \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) = 0 \\ 0 & ; \textit{if} \quad \min\limits_{1\le i\le n} h_1^{(i)}(x_i) = -1 \text{ and } \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) < 0 \end{cases} \tag{3.28}$$

Via linear interpolation from the above expression we obtain the general expression of the conditional probability $P(B \mid x_1^n)$, as a function of the influence constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$, as follows:

$$P(B \mid x_1^n) = \begin{cases} P(B) + \max\limits_{1\le i\le n}\left(h_1^{(i)}(x_i)\right)[1-P(B)] & ; \quad \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) > 0 \\ P(B) & ; \quad \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) = 0 \\ P(B) + \min\limits_{1\le i\le n}\left(h_1^{(i)}(x_i)\right)P(B) & ; \quad \sum\limits_{i=1}^{n} h_1^{(i)}(x_i) < 0 \end{cases} \tag{3.29}$$

Defining the operators $O(x) \stackrel{\Delta}{=} \begin{cases} 1 & ; \quad x > 0 \\ 0 & ; \quad x < 0 \end{cases}$ and $U(x) \stackrel{\Delta}{=} \begin{cases} 1 & ; \quad x \geq 0 \\ 0 & ; \quad x < 0 \end{cases}$, we can rewrite equation (29) in a compressed form as follows.

$$P(B \mid x_1^n) = P(B)\left\{1 + P^{-1}(B)\left[1 - P(B)\right]\max_{1 \leq i \leq n} h_1^{(i)}(x_i)\right\}^{O(\sum_{i=1}^{n} h_1^{(i)}(x_i))}\left\{1 + \min_{1 \leq i \leq n} h_1^{(i)}(x_i)\right\}^{1-U(\sum_{i=1}^{n} h_1^{(i)}(x_i))} \quad (3.30)$$

Next, we express a lemma regarding the consistency condition for our present model, evolving from the application of the Bayes' Rule and the Theorem of Total Probability on (3.30). The lemma is the parallel to Lemma 3.1 in section 3.2, for the model in the present case.

**Lemma 3.5**

For the influence model expressed in (3.30), the probabilities $P(B)$, $P(x_1^n)$ and the influence constants $\{h_1^{(i)}(x_i)\}_{1 \leq i \leq n}$ must satisfy the following condition:

$$[1 - P(B)] \sum_{x_1^n : \sum_{i=1}^{n} h_1^{(i)}(x_i) > 0} P\left(x_1^n\right) \max_{1 \leq i \leq n} h_1^{(i)}(x_i) + P(B) \sum_{x_1^n : \sum_{i=1}^{n} h_1^{(i)}(x_i) < 0} P\left(x_1^n\right) \min_{1 \leq i \leq n} h_1^{(i)}(x_i) = 0 \quad (3.31)$$

From the consistency condition in (3.31), we notice that when examining all the values of the status vector $X_1^n$, it is necessary that some $x_1^n$ vector values exist such that $\max_{1 \leq i \leq n} h_1^{(i)}(x_i)$ is positive and that some $x_1^n$ vector values exists such that $\min_{1 \leq i \leq n} h_1^{(i)}(x_i)$ is negative.

***Temporal Issues***

Here, we will assume that the very existence of the affecting events is revealed sequentially. Let then the existence and the status of the events $\{A_i\}_{1 \leq i \leq n}$ be revealed sequentially in time, from $A_1$ to $A_n$, where the status of events $A_1$ to $A_k$ is known at time $T_k$. At time $T_k$, the partial status vector $x_1^k$ is expressed and for each one of its values, the probability $P(x_1^k)$ and the quantities, $S_k(x_1^k) \stackrel{\Delta}{=} \sum_{i=1}^{k} h_1^{(i)}(x_i)$, $F_k(x_1^k) \stackrel{\Delta}{=} \max_{1 \leq i \leq k} h_1^{(i)}(x_i)$ and $G_k(x_1^k) \stackrel{\Delta}{=} \min_{1 \leq i \leq k} h_1^{(i)}(x_i)$ are computed. Next, the probability $P(B)$ is computed from (31) as follows:

$$P(B) \stackrel{\Delta}{=} P_k(B) = \left[\sum_{x_1^k : S_k(x_1^k) > 0} P(x_1^k) F_k(x_1^k) - \sum_{x_1^k : S_k(x_1^k) < 0} P(x_1^k) G_k(x_1^k)\right]^{-1} \sum_{x_1^k : S_k(x_1^k) > 0} P(x_1^k) F_k(x_1^k) \quad (3.32)$$

Given each $x_1^k$ value, the probability $P(B)$ in (3.32) is then used to compute the conditional probability $P(B \mid x_1^k)$, as,

$$P(B \mid x_1^k) = P_k(B)\left\{1 + P_k^{-1}(B)\left[1 - P_k(B)\right]F_k(x_1^k)\right\}^{O(S_k(x_1^k))}\left\{1 + G_k(x_1^k)\right\}^{1-U(S_k(x_1^k))} \quad (3.33)$$

At time $T_{k+1}$, upon the revelation of the existence and the status of the affecting event $A_{k+1}$, for each status vector $x_1^{k+1}$, the quantities, $S_{k+1}(x_1^{k+1}) = S_{k+1}(x_1^k) + x_{k+1}$, $F_{k+1}(x_1^{k+1}) = \max\left(F_k(x_1^k), h(x_{k+1})\right)$, $G_{k+1}(x_1^{k+1}) = \min\left(G_k(x_1^k), h_1(x_{k+1})\right)$ are first recursively computed. Then, the probability $P(B)$ is recomputed as

$$P(B) \stackrel{\Delta}{=} P_{k+1}(B) = \left[\sum_{x_1^{k+1}:S_{k+1}(x_1^{k+1})>0} P(x_1^{k+1})F_{k+1}(x_1^{k+1}) - \sum_{x_1^{k+1}:S_{k+1}(x_1^{k+1})<0} P(x_1^{k+1})G_{k+1}(x_1^{k+1})\right]^{-1} \times \sum_{x_1^{k+1}:S_{k+1}(x_1^{k+1})>0} P(x_1^{k+1})F_{k+1}(x_1^{k+1}) \tag{3.34}$$

The probability in (3.31) is used to compute the conditional probability below.

$$P(B \mid x_1^{k+1}) = P_{k+1}(B)\left\{1 + P_{k+1}^{-1}(B)[1 - P_{k+1}(B)]F_{k+1}(x_1^{k+1})\right\}^{O(S_{k+1}(x_1^{k+1}))}\left\{1 + G_{k+1}(x_1^{k+1})\right\}^{1-U(S_{k+1}(x_1^{k+1}))} \tag{3.35}$$

We note that the time evolution of the conditional probabilities $P(B \mid x_1^k)$ is different for different time orderings of the affecting events $\{A_i\}_{1 \le i \le n}$.

***A linear $h_n(x_1^n)$ Constant***

Here, we assume that the effects of events $\{A_i\}_{1 \le i \le n}$ on event B are weighted by a known set $\{w_i\}_{1 \le i \le n}$ of weights, such that $w_i \ge 0; \forall i$ and $\sum_{i=1}^{n} w_i = 1$. Then, given the constants $\{h_1^{(i)}(x_i)\}_{1 \le i \le n}$, we define $h_n(x_1^n)$ as follows, for some given value $\alpha : 0 \le \alpha < 1$:

$$h_n(x_1^n) = \begin{cases} (1-\alpha)^{-1}\sum_{i=1}^{n} w_i h_1^{(i)}(x_i) & ; \quad \left|\sum_{i=1}^{n} w_i h_1^{(i)}(x_i)\right| \le 1-\alpha \\ 1 & ; \quad \sum_{i=1}^{n} w_i h_1^{(i)}(x_i) \ge 1-\alpha \\ -1 & ; \quad \sum_{i=1}^{n} w_i h_1^{(i)}(x_i) \le -(1-\alpha) \end{cases}$$

A nonzero $\alpha$ value translates to the probability of event B being equal to one, not only when all the $\{h_1^{(i)}(x_i)\}_{1 \le i \le n}$ values equal one, but also when a predefined weighted majority exceeds a total weighted sum of $1-\alpha$. Similarly then, the event B occurs with zero probability when the weighted sum of the $\{h_1^{(i)}(x_i)\}_{1 \le i \le n}$ values is less than $-(1-\alpha)$, rather than only when it equals -1. The relationships between the $h_n(x_1^n)$ and $h_{n-1}(x_1^{n-1})$ influence constants and the probabilities $P(B)$, $P(x_1^n)$ and $P(B \mid x_1^n)$ are as in IX.A.

### *A $h_n(x_1^n)$ constant representing Noisy OR Format*

Given the constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$, we define here $h_n(x_1^n)$ as follows; where $\alpha$ is such that $0 \le \alpha \le 1$:

$$h_n(x_1^n) = \left\{1-(1-\alpha)^{-1}\prod_{i=1}^{n}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right\}^{\operatorname{sgn}\left(h_n(x_1^n)\right)}\left\{-1+\alpha^{-1}-\alpha^{-1}\prod_{i=1}^{n}\left(1-\left|h_1^{(i)}(x_i)\right|\right)\right\}^{1-\operatorname{sgn}\left(h_n(x_1^n)\right)} \quad (3.36)$$

Then, via (3.3) and (3.5) in section 3.2, we obtain:

$$P(B) = \alpha \quad (3.37)$$

$$1 - P(B \mid x_1^n) = \prod_{i=1}^{n}\left(1-\left|h_1^{(i)}(x_i)\right|\right) \quad (3.38)$$

The expression in (3.38) represents the Noisy-OR format [1, 4], where the probabilities in the latter are here substituted by the absolute values of the one-dimensional influence constants $\{h_1^{(i)}(x_i)\}_{1\le i\le n}$.

### *Influence Constant Comparison*

Figure 3.2 shows an example IN with a binary event B known to be affected by the events $\{A_i\}_{1 \le i \le 3}$. The edges connecting the external affecting events $\{A_i\}_{1 \le i \le 3}$ to the event B are shown annotated with the constants $\left[h_1^{(i)}(x_i = 1), h_1^{(i)}(x_i = 0)\right]$ for each i, where $x_i = 0,1$ represents one of the two states of an affecting event $A_i$. A global influence constant $h_3(x_1^3)$ is then designed using all four (i.e., A-D) special influence functions presented in this section. Table 3.1 shows the computed values of $h_3(x_1^3)$ and corresponding $P(B \mid x_1^3); \forall\, x_1^3$ for each of the four cases. For illustration purposes, we also assume that the joint probability $P(x_1^3)$; $\forall\, x_1^3$ values are computed by assigning $P(x_3 = 1) = 0.8, P(x_3 = 0) = 0.2$ and $P(x_i = 1) = P(x_i = 0) = 0.5$; *for* $i = 1,2$ and by assuming $\{A_i\}_{1 \le i \le 3}$ to be mutually independent.

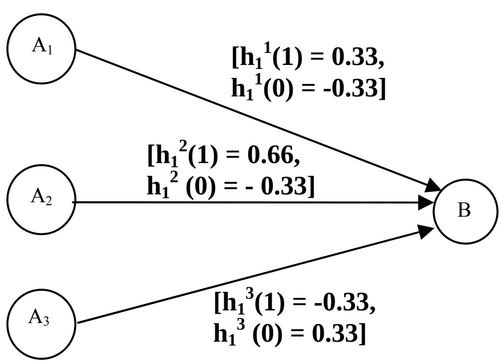



Fig. 3.2 Example TIN

**TABLE 3.1** Comparison of Influence Constants

| $x_1$ | $x_2$ | $x_3$ | $h_3(x_1^3)$ A. CAST Logic Based | $h_3(x_1^3)$ B. Extreme Partials | $h_3(x_1^3)$ C. Linear Constant | $h_3(x_1^3)$ D. Noisy-OR | $P(B \mid x_1^3)$ A. CAST Logic Based | $P(B \mid x_1^3)$ B. Extreme Partials | $P(B \mid x_1^3)$ C. Linear Constant | $P(B \mid x_1^3)$ D. Noisy-OR |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | -0.33 | -0.33 | -0.073 | -0.095 | 0.335 | 0.335 | 0.452 | 0.463 |
| 0 | 0 | 1 | -0.699 | -0.33 | -0.101 | -0.095 | 0.150 | 0.335 | 0.452 | 0.449 |
| 0 | 1 | 0 | 0.66 | 0.66 | 0.498 | 0.326 | 0.83 | 0.83 | 0.663 | 0.749 |
| 0 | 1 | 1 | 0.242 | 0.0 | 0.0 | 0.326 | 0.621 | 0.5 | 0.663 | 0.5 |
| 1 | 0 | 0 | 0.33 | 0.33 | 0.176 | -0.095 | 0.665 | 0.665 | 0.452 | 0.588 |
| 1 | 0 | 1 | -0.33 | -0.33 | -0.044 | -0.095 | 0.335 | 0.335 | 0.452 | 0.478 |
| 1 | 1 | 0 | 0.847 | 0.66 | **1.00** | 0.326 | 0.923 | 0.83 | 0.663 | 1.00 |
| 1 | 1 | 1 | 0.66 | 0.66 | 0.196 | 0.326 | 0.83 | 0.83 | 0.663 | 0.598 |

From the values included in Table 3.1, we notice the sensitivity of the computed probability of event B on the selected structure of the aggregate influence constant. Different such structures reflect different environments and their choice is at the discretion of an expert.

### 3.9 Evaluation Metrics

As already repeatedly stated, the INs and TINs studied in this paper are basically BNs whose conditional probabilities are approximated by expert provided influence constants. Thus, the architectural and computational complexities involved are similar to those in BNs [8, 31, 32, 33, 34], while the complexities involved in the computation of influence constants depend on the specific structure of the latter (see Section VIII). The evolution of lower dimensionality conditional probabilities from high dimensionalities ones, as in Lemma 3.2, section 3.2, is of dynamic programming nature inducing polynomial complexity. As stated in section 3.7, the accuracy of a IN or TIN model is determined by the accuracy of the selected influence constants. The accuracy of the latter may be tested and they may be subsequently adjusted appropriately.

### 3.10 Experimental Setup

In this section, we lay out the steps involved in an experimental setup. Given an event B, determine **all** the events $\{A_i\}_{1 \le i \le n}$ **known** to be affecting its occurrence. Given B, all the known affecting events $\{A_i\}_{1 \le i \le n}$, and the causal strengths $\left[h_1^{(i)}(x_i = 1), h_1^{(i)}(x_i = 0)\right]$ between each $A_i$ and B, design an influence constant $h_n(x_1^n)$, where $x_1^n$ signifies the value of the status vector of the events $\{A_i\}_{1 \le i \le n}$, and where $-1 \le h_n(x_1^n) \le 1$; $\forall\, x_1^n$ values. The $h_n(x_1^n)$ constant may have one of the forms presented in section 3.8. If **all** in (b) is given, then upon a given probability of the status vector $X_1^n$, say $P(x_1^n)$; $\forall\, x_1^n$ values, the probability of event B is given by the following equation, named the consistency equation.

$$\sum_{x_1^n} P(x_1^n)\left\{1 + h_n(x_1^n)[1 - P(B)]P^{-1}(B)\right\}^{\operatorname{sgn} h_n(x_1^n)}\left\{1 + h_n(x_1^n)\right\}^{1-\operatorname{sgn} h_n(x_1^n)} = 1$$

whose equivalent form is:

$$P(B) = \left[\sum_{x_1^n : \operatorname{sgn} h_n(x_1^n) = 1} P\left(x_1^n\right) h_n(x_1^n)\right]\left[\sum_{x_1^n} P\left(x_1^n\right)\left|h_n(x_1^n)\right|\right]^{-1}$$ , if the denominator is non zero

When **all** the affecting events $\{A_i\}_{1 \le i \le n}$ are known, but the status of some of them are unknown, then, the probability $P(B)$, as computed in step (c) is used to compute the conditional probability $P(B \mid x_1^k)$, when the status vector of only k affecting events is known as:

$$P(B \mid x_1^k) = P(B)\{1 + h_k(x_1^k)[1 - P(B)]P^{-1}(B)\}^{\operatorname{sg} n h_k(x_1^k)} \bullet \{1 + h_k(x_1^k)\}^{1 - \operatorname{sg} n h_k(x_1^k)}$$

where $h_k(x_1^k)$ is computed in a dynamic programming fashion from the influence constant $h_n(x_1^n)$ in (b); as follows:

$$h_{n-1}(x_1^{n-1}) = \begin{cases} Q_n - 1 & ; \quad Q_n \in [0,1] \\ P(B)[1 - P(B)]^{-1}[Q_n - 1] & ; \quad Q_n \in [1, P^{-1}(B)] \end{cases}$$

for $$Q_n \stackrel{\Delta}{=} \sum_{x_n = 0,1} P(x_n \mid x_1^{n-1})\left[1 + h_n(x_1^n)[1 - P(B)]P^{-1}(B)\right]^{\operatorname{sg} n \, \mathrm{h}_n(x_1^n)} \bullet \left[1 + h_n(x_1^n)\right]^{1 - \operatorname{sg} n \, \mathrm{h}_n(x_1^n)}$$

We note that in the above expression , the affecting events $\{A_i\}_{1 \le i \le n}$ are assumed ordered as of the revealing of their status in time. Different such ordering results in different evolutions of the conditional probabilities $P(B \mid x_1^k)$.

When the existence as well as the status of the affecting events are sequentially revealed, then at time k, $P_k(B)$ and $P_k(B \mid x_1^k)$ are computed as in (c) and (d) where n is substituted by k in the latter.

**Example 1:** The following example illustrates the steps (a) to (e) with the help of an example TIN. Figure 3.3 shows a IN with a binary event B known to be affected by the events $\{A_i\}_{1 \le i \le 4}$.

The edges connecting the external affecting events $\{A_i\}_{1 \le i \le 4}$ to the event B are shown in Fig. 3, annotated with the constants $\left[h_1^{(i)}\left(x_i = 1\right), h_1^{(i)}\left(x_i = 0\right)\right]$ for each *i*, where $x_i = 0, 1$ represents one of the two states of an affecting event $A_i$. A global influence constant $h_4(x_1^4)$ is then designed using the CAST logic expression (25) in section 3.8. Table 3.2 shows the computed values for $h_4(x_1^4)$; $\forall\, x_1^n$. The joint probability $P(x_1^4)$; $\forall\, x_1^4$ values are computed by assigning $P(x_i = 1) = P(x_i = 0) = 0.5\,; \forall\, i$ and by assuming $\{A_i\}_{1 \le i \le 4}$ to be mutually independent (Lemma 3). The probability of occurrence of event B, i.e., z = 1, is now calculated with the consistency equation, and is given as $P(z = 1) = 0.5$. Assuming the status of all the affecting events to be known, the conditional probabilities $P(B \mid x_1^4); \forall x_1^4$ are calculated via expression (26), and are shown in Table 3.2.

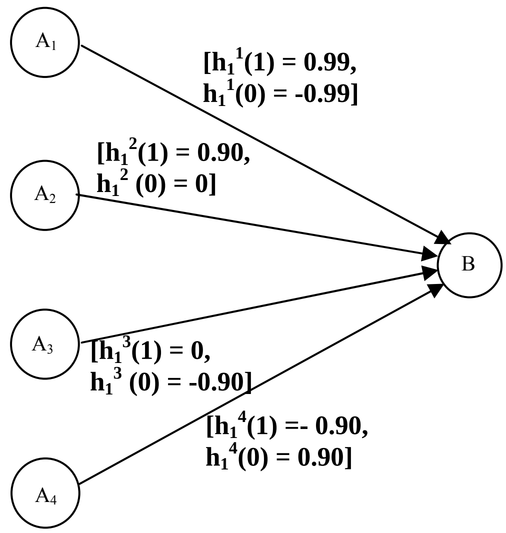



Fig. 3.3 Example TIN

The assumption in step (iii), regarding the knowledge of the status of all the affecting events, may not be valid at times. Such is the case of a TIN with delays on edges (see Definition 3.1), reflecting variations in the times when the status of the affecting events become known. To illustrate this notion, we add temporal information to the IN in Fig. 3.3. The added temporal information together with the underlying graph is shown in Fig. 3.4. The time assigned to an affecting event $A_i$ is the instance at when it assumes a state, i.e., $x_i = 0$ or 1. Prior to that time, the state of the event is assumed unknown. As stated in Definition 3.1, this combination of the external affecting events' status and their timing is also termed a Course of Action (COA), in the TIN literature.

**TABLE 3.2** Conditional Probabilities

| $x_1$ | $x_2$ | $x_3$ | $x_4$ | $h_4(x_1^4)$ | $P(z=1 \mid x_1^4)$ |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | -0.990000 | 0.005000 |
| 0 | 0 | 0 | 1 | -0.999900 | 0.000050 |
| 0 | 0 | 1 | 0 | -0.900000 | 0.050000 |
| 0 | 0 | 1 | 1 | -0.999000 | 0.000500 |
| 0 | 1 | 0 | 0 | -0.900000 | 0.050000 |
| 0 | 1 | 0 | 1 | -0.999000 | 0.000500 |
| 0 | 1 | 1 | 0 | -0.000001 | 0.499999 |
| 0 | 1 | 1 | 1 | -0.990000 | 0.005000 |
| 1 | 0 | 0 | 0 | 0.990000 | 0.995000 |
| 1 | 0 | 0 | 1 | 0.000001 | 0.500001 |
| 1 | 0 | 1 | 0 | 0.999000 | 0.999500 |
| 1 | 0 | 1 | 1 | 0.900000 | 0.950000 |
| 1 | 1 | 0 | 0 | 0.999000 | 0.999500 |
| 1 | 1 | 0 | 1 | 0.900000 | 0.950000 |
| 1 | 1 | 1 | 0 | 0.999900 | 0.999950 |
| 1 | 1 | 1 | 1 | 0.990000 | **0.995000** |

The temporal information in the TIN, Fig. 3.4, determines the dynamics of the relationship between the affecting events and the affected event B; specifically, the times when the status of the affecting events are revealed to B. Figure 3.5 shows a IN equivalent, obtained by mapping the status of the affecting events and their effects on the event B, on a timeline. This mapping determines the number of affecting events 'k' at different time points (or time slices). For the temporal case presented in section VI, the existence of all the affecting events is known to the event B a priori; their status, however, remain unknown until revealed, as determined by the COA and the delays on the edges. The probability $P(B)$, as calculated in step (c), is used to compute the conditional probabilities $P(B \mid x_1^k); k = 1, 2, 4$, i.e., $P(B \mid x_1^1)$, $P(B \mid x_1^2)$, and $P(B \mid x_1^4)$ ,as illustrated in the figure. Table 3.3 shows the values for $P(B \mid x_1^1)$ and $P(B \mid x_1^2)$, as computed by the corresponding $h_1(x_1^1)$ and $h_2(x_1^2)$. The posterior probability of B captures the impact of an affecting event on B and can be plotted as a function of time for a corresponding COA. This plot is called a Probability Profile [12, 27]. Fig. 3.6 shows the resulting probability profile for the illustrative example. The plotted values in the profile are shown with bold letters in Tables 3.3-3.4. The overall complexity is polynomial.

For the temporal case presented in section IX, the existence as well as the status of the affecting events are not known a priori but are determined by the given COA and the delays on the edges. At time k, $P_k(B)$ and $P_k(B \mid x_1^k)$ are computed as in (c) and (d) where n is substituted by k in the latter. Table 3.4 shows the computed values of $P_k(B)$ and $P_k(B \mid x_1^k); k = 1,2,4$ and Fig. 3.6(b) shows the resulting probability profile.

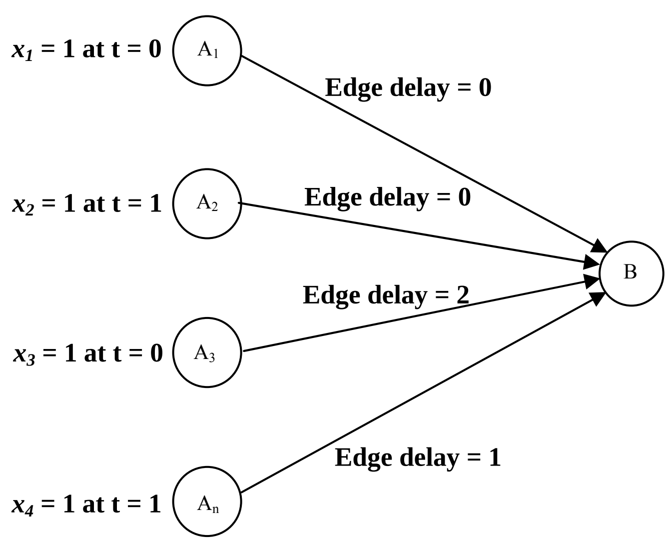



Fig. 3.4. Example TIN with COA and Edge Delays

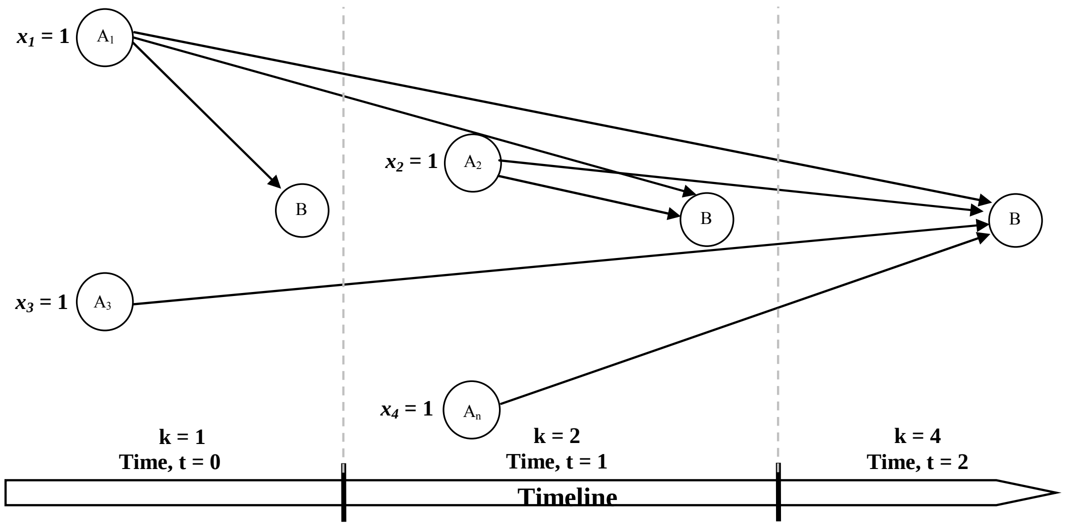


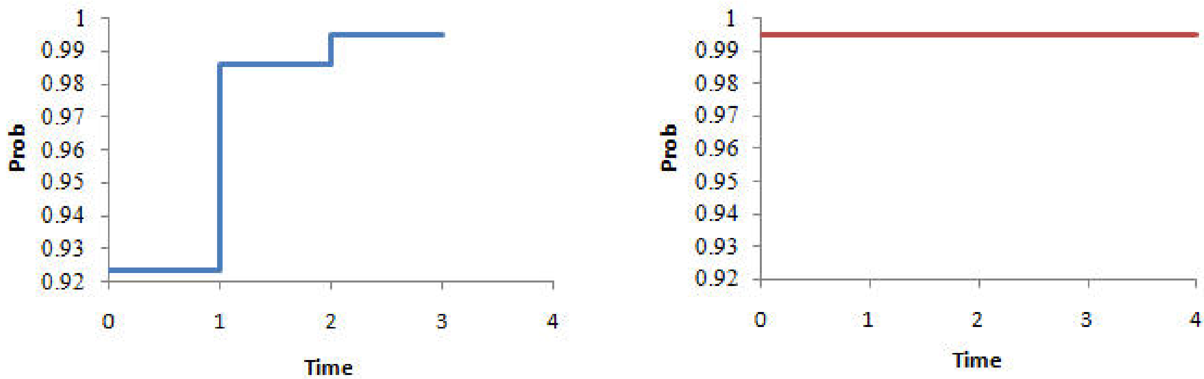

Fig. 3.5. Temporal Model for the Example TIN

**TABLE 3.3** Posterior Probabilities of B

| $x_1$ | $P(z=1 \mid x_1^1)$ | $x_1$ | $x_2$ | $P(z=1 \mid x_1^2)$ |
|---|---|---|---|---|
| 0 | 0.076381 | 0 | 0 | 0.013887 |
| 1 | **0.923619** | 0 | 1 | 0.138875 |
| | | 1 | 0 | 0.861125 |
| | | 1 | 1 | **0.986113** |

**TABLE 3.4** Probability Profile values

| $x_1$ | $P_1(B)$ | $P(z=1 \mid x_1^1)$ | $x_1$ | $x_2$ | $P_2(B)$ | $P(z=1 \mid x_1^2)$ | $x_1$ | $x_1$ | $x_4$ | $x_3$ | $P_4(B)$ | $P(z=1 \mid x_1^4)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | | 0.005 | 0 | 0 | | 0.005 | 0 | 0 | 0 | 0 | | 0.005 |
| 1 | 0.5 | **0.995** | 0 | 1 | | 0.005 | 0 | 0 | 0 | 1 | | 0.005 |
| | | | 1 | 0 | | 0.995 | 0 | 0 | 1 | 0 | | 0.005 |
| | | | 1 | 1 | 0.5 | **0.995** | 0 | 0 | 1 | 1 | | 0.005 |
| | | | | | | | 0 | 1 | 0 | 0 | | 0.005 |
| | | | | | | | 0 | 1 | 0 | 1 | | 0.005 |
| | | | | | | | 0 | 1 | 1 | 0 | | 0.95 |
| | | | | | | | 0 | 1 | 1 | 1 | 0.5 | 0.005 |
| | | | | | | | 1 | 0 | 0 | 0 | | 0.005 |
| | | | | | | | 1 | 0 | 0 | 1 | | 0.995 |
| | | | | | | | 1 | 0 | 1 | 0 | | 0.05 |
| | | | | | | | 1 | 0 | 1 | 1 | | 0.995 |
| | | | | | | | 1 | 1 | 0 | 0 | | 0.995 |
| | | | | | | | 1 | 1 | 0 | 1 | | 0.995 |
| | | | | | | | 1 | 1 | 1 | 0 | | 0.995 |
| | | | | | | | 1 | 1 | 1 | 1 | | **0.995** |




(a). For Temporal Case I (b). For Temporal Case II

Fig. 3.6. Probability Profile for the Example COA

**Example 2:** In multi-node connected network structures, given a set of external unaffected affecting events $\{A_i\}_i$, given influence constants $\{h_n(x_1^k)\}_k$, pertinent conditional probabilities are constructed hierarchically, as the structure of the network dictates. Consider, for example, the network in Fig. 3.7, below. In this network, the affecting events $A_i; i=1,2,3,4$ are external and unaffected by other events, while events B and C are affected, B being affecting as well. Let us denote the status of event $A_i; i=1,2,3,4$; by $x_i$, the status of event B by y and the status of event C by z, where y, z and $\{x_i\}_{1\le i\le 4}$ are 0-1 binary numbers. Let the influence constants $h(x_1,x_2), h(x_3,x_4)$ and $h(y,x_3,x_4)$ be given. Let also the joint probability $P(x_1,x_2,x_3,x_4)$ be given.

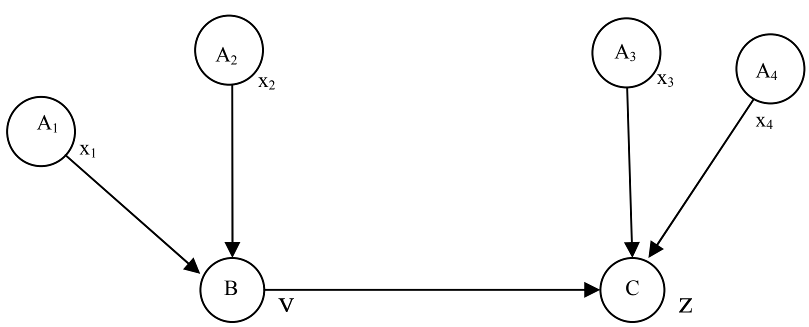



Fig. 3.7. A Multi-node Network

We then compute all the pertinent probabilities in the above network following the steps stated below:

1. Compute the probability $P(y)$ from the consistency condition:

$$\sum_{x_1,x_2} P(x_1,x_2)\{1+h(x_1,x_2)[1-P(y)]P^{-1}(y)\}^{\operatorname{sgn} h(x_1,x_2)}\{1+h(x_1,x_2)\}^{1-\operatorname{sgn} h(x_1,x_2)}=1$$

where,

$$P(x_1, x_2) = \sum_{x_3, x_4} P(x_1, x_2, x_3, x_4)$$

2. Compute $P(y \mid x_1, x_2)$ from,

$$P(y \mid x_1, x_2) = P(y)\{1 + h(x_1, x_2)[1 - P(y)]P^{-1}(y)\}^{\operatorname{sgn} h(x_1, x_2)}\{1 + h(x_1, x_2)\}^{1-\operatorname{sgn} h(x_1, x_2)}$$

3. Compute $P(y, x_3, x_4)$ as:

$$P(y, x_3, x_4) = \sum_{x_1, x_2} P(y \mid x_1, x_2) P(x_1, x_2, x_3, x_4)$$

4. Compute $P(z)$ from the consistency condition

$$\sum_{y, x_3, x_4} P(y, x_3, x_4)\{1 + h(y, x_3, x_4)[1 - P(z)]P^{-1}(z)\}^{\operatorname{sgn} h(y, x_3, x_4)}\{1 + h(y, x_3, x_4)\}^{1-\operatorname{sgn} h(y, x_3, x_4)} = 1$$

5. Compute $P(z \mid y, x_3, x_4)$ from,

$$P(z \mid y, x_3, x_4) = P(z)\{1 + h(y, x_3, x_4)[1 - P(z)]P^{-1}(z)\}^{\operatorname{sgn} h(y, x_3, x_4)}\{1 + h(y, x_3, x_4)\}^{1-\operatorname{sgn} h(y, x_3, x_4)}$$

6. Compute $P(z \mid x_1, x_2, x_3, x_4)$ from,

$$P(z \mid x_1, x_2, x_3, x_4) = \sum_{y} P(z, y \mid x_1, x_2, x_3, x_4) = \sum_{y} P(z \mid y, x_3, x_4) P(y, \mid x_1, x_2)$$

### 3.11 Conclusion

In this chapter, we presented a comprehensive approach to Influence Nets including conditions for model consistency and dynamic programming evolution of the influence constants, as well as temporal issues and model testing methodologies. We revisited the earlier CAST logic [4, 5] based approach to Timed Influence Network (TIN) modeling [13, 15, 17], by redefining the design parameters for a TIN model, reevaluating the cases of independence and (partial) dependence among external affecting events, introducing new methods for aggregating joint influences from design parameters, and by offering new insights into the temporal aspects of causal influences modeled inside a TIN. The presented approach successfully overcomes the deficiencies in the CAST logic based TIN modeling and the inconsistencies therein. It also does not require any additional design information than that already available in a TIN constructed via CAST logic parameters; the entire repository of situational models developed earlier [15, 17, 18] may be simply reanalyzed (without any modifications) using the new set of computational tools introduced in this paper. We analyzed and evaluated our approach and tested it for a specific TIN. This illustrative application is presented in Chapter 5. The approach produces consistent and stable in time results.

# Chapter 4

# Meta-Model Driven Construction of Timed Influence Nets

**Faisal Mansoor, Abbas K. Zaidi, Alexander H. Levis**

## 4.1 Introduction

The analysis and decision problems often require modeling of subjective, informal, and uncertain concepts in a domain in order for an analyst to capture the required behavior of the domain. Influence Net (IN) [36], a variant of Bayesian Networks (BN), is an approach for modeling cause-and-effect relationships among variables of a domain. The construction of an IN requires a subject matter expert (SME) to model the parameters of the domain − random variables − as nodes in a network. The arcs (or directed edges) in the network represent the cause-and-effect relationships between the random variables. The nodes in an IN and their interdependencies may represent the inter effects between political, military, economic, social, infrastructure, and information (PMESII) factors present in an area of interest. The strengths of these dependencies are captured in terms of a small (i.e., linear) number of influence constants (as opposed to an exponential number of conditional probabilities in a BN). The IN approach was developed in recognition of the fact that most domain experts and situation analysts do not think in terms of conditional probabilities (as required for a BN) while relating affecting and effect variables in a domain. The INs provide an intuitive elicitation, update, and merge interface to an underlying BN that only requires specification of qualitatively described individual influences between each pair of an affecting and an affected variables. The approach then combines these individual influences to calculate the aggregate effect of multiple affecting variables on an effect variable in terms of conditional probability values of a resulting BN.

Wagenhals and Levis [13] have added a special set of temporal constructs to the basic formalism of Influence Nets. The Influence Nets with these additional temporal constructs are called Timed Influence Nets (TINs). A fully specified TIN model is characterized by the causal relationships between propositions and the values of the parameters, i.e., strength of influences [22], and temporal delays associated with these relationships. TINs have been experimentally used in the area of Effects Based Operations (EBOs) and Adversarial Modeling for evaluating alternative courses of actions and their effectiveness to mission objectives in a variety of domains, e.g., war games [15] , and coalition peace operations. A number of analysis tools have been developed over the years for TIN models to help an analyst in solving problems of interest [22 - 24]. In this sequel, the term Influence Net (IN) will be used generically to refer to both INs and TINs.

The lack of familiarity with, or enthusiasm for, these analytical representations (i.e., BNs and/or TINs) prevents most domain experts and analysts from developing such models on their own and using them for the analysis tasks assigned. The tools implementing some of these formalisms [37 - 38] require prior knowledge and experience in modeling and, therefore, do not provide any assistance to such users. There is, however, a growing community of analysts who makes use of these analytical and quantitative formalisms resulting in a small, but expanding, repository of models addressing different PMESII aspects of a domain. There is, therefore, a need not only to facilitate the model building task, but also to utilize the existing models for building quick, larger and better domain models without requiring experienced domain experts, at least, in the early stages of a domain modeling exercise.

This chapter introduces a meta-modeling approach that facilitates generalizing an entire class of problem-specific TINs in the form of a meta-model, called Template TIN. For example, a causal relation in an existing TIN might model, "If the Kurd population in the Northern provinces of Iraq finds its rights respected in the new administration, then it will be more cooperative in the new development plans." A simple generalization of this could be, "If an <*ethnic minority*> in a <*geographic administrative unit*> finds its rights respected, then it will <*participate*> in the <*development activity*>." A Template TIN captures such generalized relation using abstract entities characterizing a problem domain. It can be constructed by generalizing several TINs, or can be directly constructed by an expert using the template specification language. A set of stored templates can then be instantiated for a particular situation by substituting abstract entities with concrete instances characterizing a situation.

A Template TIN provides a means for leveraging past, tested TIN models that may have been constructed by other experts or team of experts in addressing a problem similar to the one under consideration. It simplifies the Influence Net construction process by providing an analyst with a repository of templates capturing different fragments of a generalized understanding of the problem domain in terms of possible causal relationships among domain variables. These templates are not intended to prescribe a solution or a model but are a means to enhance an analyst's search for better understanding of the domain and to facilitate the process of building a more pertinent model of the domain. A Template IN identifies a set of concepts that are considered *relevant* by some analyst or a team of analysts for a problem-specific domain. These concepts are described at an abstract level and are required to be instantiated when a model is being constructed for a new domain. Exploring available knowledge bases for information required for instantiating a Template TIN is also a complex and time-consuming task, especially if that information is not implicitly available in the form of an expert of the new domain. With increasing popularity and use of structured knowledge representation and reasoning tools, it is now possible to automate the data exploration and Template TIN instantiation process. In the presented framework, we use an OWL [39] ontology not only as the knowledge representation for domain data, but also as a mechanism to reason about this data while constructing a situational assessment model as a Timed Influence Net. For a fully automated instantiation of a Template TIN with the data in an ontology, the approach proposes a mapping scheme that provides a definition of abstract concepts present in the Template TIN in terms of concepts and properties available in the ontology. These definitions are constructed as a set of mapping rules. The mapping rules are SPARQL (Protocol and RDF Query Language) [40] queries that use the OWL reasoning engine Pellet [41] to identify relevant data in the ontology to be used for TIN instantiation.

The rest of the chapter is organized as follows. In section 4.2, we present the architecture of the developed meta-model driven ontology based TIN construction approach. Section 4.3 presents how this approach can aid in developing situation assessment model for some class of problems. Section 4.4 contains an example while 4.5 concludes the paper with a discussion on future research directions.

## 4.2 The Methodology

Figure 4.1 shows an overview of the meta-model driven ontology based TIN construction approach. The following subsections describe each component of the architecture in Fig. 4.1.

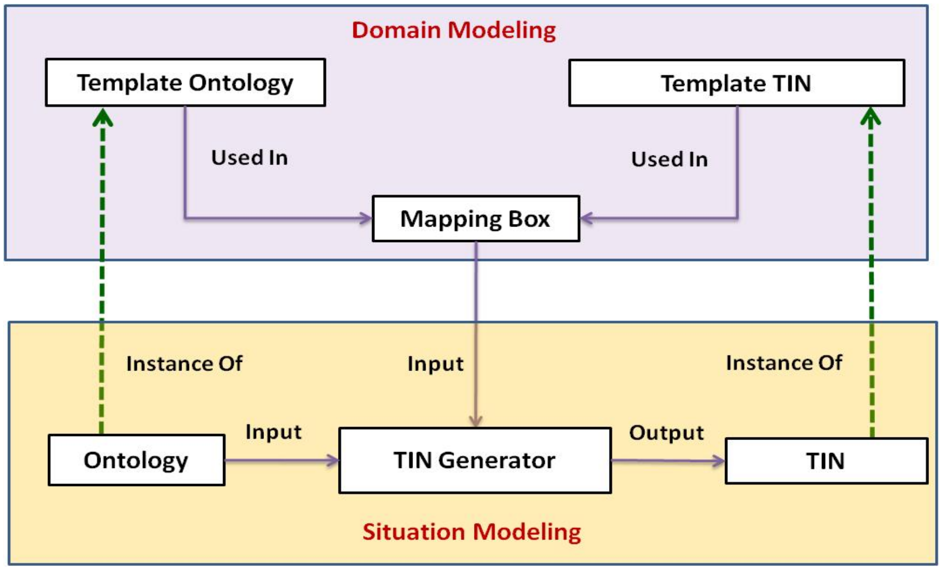



Fig. 4.1 Architecture of the Approach

***Ontology***

Ontology is an explicit conceptualization of some domain of discourse. We can define an ontology as a knowledge base composed of Terminology Box (TBox) and Assertion Box (ABox); K = (TBox, ABox), where:

- TBox is a finite set of concepts and a finite set of relations between the concepts.
- ABox is a finite set of instances, relations between instances and relations between instances and concepts in TBox.

In Fig. 4.1, the terms Template Ontology and Ontology refer to the TBox and the ABox of an ontology, respectively.

***Template Timed Influence Net (TIN)***

An Influence Net for a problem instance involves a pre-specified set of random variables with fixed cause-and-effect relationships. The goal of Template Timed Influence Net is to capture the abstract relationships between classes of causes and effects characterized by a problem domain. Template TINs extend TINs just as first-order logic extends propositional logic.

Template TINs are Influence Nets except that the nodes in them contain labels formed by variables instead of terms representing domain instances. Formally, a Template Influence Net is described as follows:

**Definition 4.1 -** A Template TIN $\mathcal{T}_{\text{IN}}$ is a tuple $(V, E, C, B)$ where $G(V, E)$ is a Directed Acyclic Graph (DAG), and

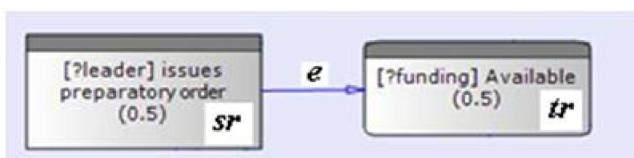
- $V$ is a set of random variables that makes up the nodes of an Timed Influence Net. Where
  - All the variables in the Timed Influence Net have binary states.
  - For each random variable $v \in V$ there exists a set of slot variables $svar(v)$ such that each slot variable in $svar(v)$ represents an abstract domain entity.
- $E$ is a set of directed links that connect pairs of nodes in $V$.
- $C$ is a set of causal strength parameter and the time delay triples. Each triple in $C$ is associated with an edge in $E$ (the causal strength parameters are usually denoted as h and g values).
- $B$ represents a set of baseline and prior probabilities associated with non-root and root nodes respectively.

**Definition 4.2** (Template Influence):- A Template Influence $\mathcal{T}_\mathrm{I}$ in a Template TIN is a tuple $\{sr, tr, e, \mathcal{M}(\mathcal{T}_\mathrm{I})\}$, where $sr, tr \in V, e \in E$, and $sr$ is the source node of $e$ and $tr$ is the target node of $e$. In addition, $\mathcal{M}(\mathcal{T}_\mathrm{I})$ is a function providing a mapping from $svar(sr) \cup svar(tr)$ to situation specific entities.

A Template TIN is a collection of several Template Influences. An example Template Influence is shown in Fig. 2a. The terms [?leader] and [?funding] represent the slot riables $svar(sr)$ and $svar(tr)$, respectively.

**Mapping Box**

Mapping Box defines influences present in a Template TIN in terms of concepts and relation available in a Template Ontology. Specifically, Mapping Box is a set of mappings where each mapping is defined as a pair consisting of a Template Influence and an ontology query (Fig. 2b), the query establishes the link between Template Influence and ontology.




(a) Template Influence


(b) Ontology Query

Fig. 4.2 An Example Mapping

***Timed Influence Net Generator***

Given an ontology (i.e., TBox and ABox both) describing a particular situation, TIN Generator uses the abstract definitions available in the Mapping Box to produce a TIN specialized for the situation described by the input ontology. For the example in Fig. 4.2 this would amount to running the query in Fig. 4.2b for identifying the instances in the ontology that match with the conditions defining the slot variables [?leader] and [?funding] in the Template Influence (Fig. 4.2a). The results of the query are then substituted for the slot variables. The following is a formal definition of this substitution process.

**Definition 4.3** (Substitution):- Let $t_i$ be a term denoting a situation specific entity belonging to a domain of interest. Then a substitution $\theta = \{v_1/t_1, \ldots., v_n/t_n\}$ is an assignment of term $t_i$ to variable $v_i$. Applying a substitution $\theta$ to Template Influence $\mathcal{T}_\mathrm{I}$ yields the instantiated Influence $\mathcal{T}_\mathrm{I}\theta$ where all occurrences of the variable $v_i$ are simultaneously replaced by the term $t_i$.

As shown in Fig. 4.1, the presented TIN construction approach is a two-phase process consisting of a Domain-Modeling phase and a Situation-Modeling phase. In the Domain-Modeling phase, ontology and TIN templates are used to develop a generalized mapping that can be applied to any ontology compatible with the Template Ontology. Domain-Modeling is a process done only once. When a Mapping Box is created, instantiating a TIN from a given instance ontology describing a particular situation becomes a completely automated process.

### 4.3 Castalia

The described meta-model driven ontology based TIN construction process has been implemented as part of the Pythia [38] suite of applications. The implemented software package, called Castalia, takes as input (a) an OWL [39] ontology expressed in Protégé [41], (b) mapping rules expressed in SPARQL [40], and (c) Template TIN developed using Pythia application [38] for instantiating TINs. Pellet [41] is used as the ontology reasoning and query engine by Castalia. The output of Castalia can be imported in Pythia as a Timed Influence Net for subsequent analysis.
An implementation view of the architecture in Fig. 4.1 is shown in Fig. 4.3.

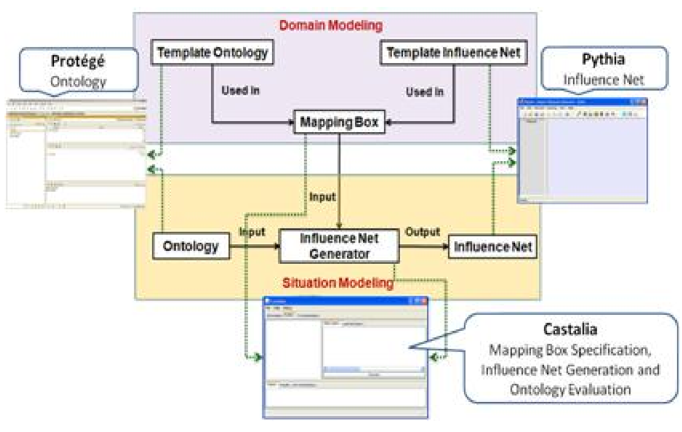



Fig. 4.3 Architecture with Respective Applications

From a procedures point of view, Figs. 4.3 and 4.4 illustrate how a team of analysts and knowledge engineers can use Protégé, Pythia, and Castalia to automate the Influence Net construction process.

The process in Fig. 4.4 comprises of two phases: Domain Modeling and Situation Modeling. In the Domain Modeling phase, Protégé is used to develop the Template Ontology and Pythia is used to develop the Template TIN. The Template Ontology can be developed by a knowledge engineer with technical knowledge of OWL and Protégé , and some understanding of the problem domain. A Template TIN can be developed by a domain expert with no or little help from a knowledge engineer. A Template TIN can also be derived by generalizing already developed TIN models. The derivation of Template TIN in the latter case can be done by a knowledge engineer with no or little help from an analyst. The two meta models are then used to construct the MBox using Castalia, which contains a graphical user interface module for developing the MBox. The construction of MBox requires both the knowledge engineer for SPARQL syntax and the analyst to describe the mapping. Once the MBox is available, it can be used to develop the situation specific Influence Nets during the Situation Modeling phase. It should be noted that the Domain Modeling phase is a one-time effort. Given a new situation described using an ontology which can be automatically constructed using the available text-extraction ontology building tools, the Influence Net Generator module in Castalia automatically generates an Influence Net specialized for the situation. The generated Influence Net is compatible with Pythia and can be opened in Pythia to perform different kind of analyses. The Situation Modeling phase is where the effort put in the Domain Modeling phase pays off: given a repository of such domain models in the form of templates, situation models for new problems can be easily instantiated by an analyst by merely selecting a Template TIN and clicking a button in Castalia to instantiate it with information in an OWL ontology. An analyst using Castalia does not need to know anything about SPARQL, OWL, and/or Protégé. Moreover, Castalia also contains a module for ontology assessment, which computes the TBox and ABox fitness measures during the Influence Net generation process.

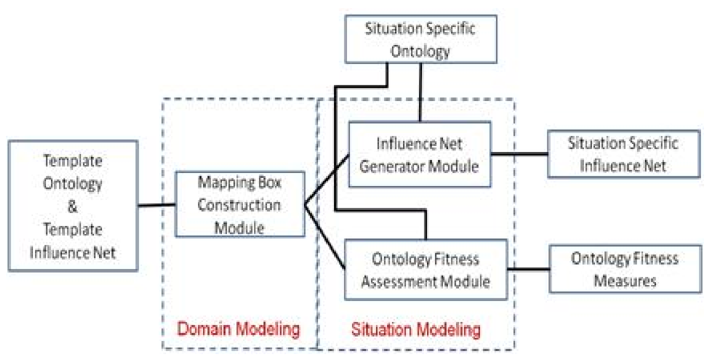



Fig. 4.4 Construction Process

### 4.4 Application

To illustrate the approach described in this paper, a detailed investigative report [42] on the 1998 bombings of the US embassies in Kenya and Tanzania was used to develop and populate an OWL ontology. The class hierarchy of the ontology is shown in Fig. 4.5. The Template Ontology was developed using the concepts derived from an understanding of the general nature of such incidents.

A Timed Influence Net model was constructed for the Kenya incident, using the information in the report, to capture the events leading up to the bombing. The Kenya TIN model was then transformed into a Template TIN to represent a generalized model for a terrorist attack on a US interest abroad. The Template TIN derived from the Kenya based TIN is shown in Fig. 4.6. The Template TIN is a collection of several Template Influences. The nodes in this template represent abstract concepts derived by replacing instances from the Kenya TIN with the slot variables.

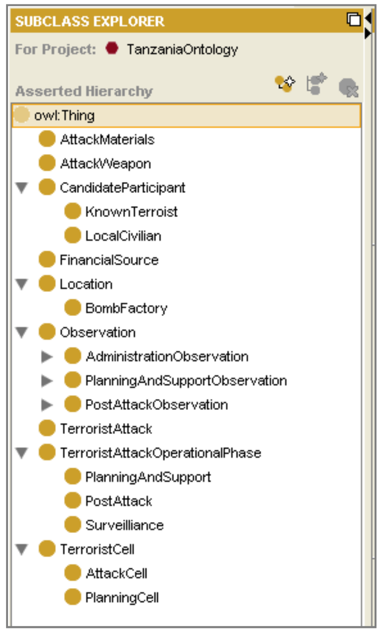



Fig. 4.5 Class Hierarchy of the Kenya and Tanzania Bombing Ontology

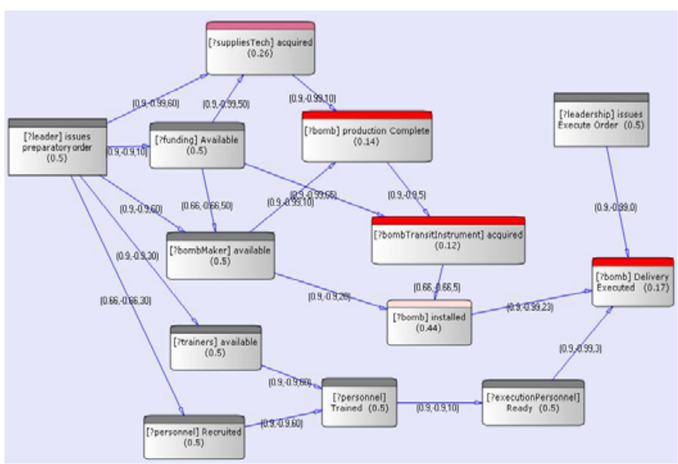



Fig. 4.6 Template TIN used in the Application

A Mapping Box (i.e., MBox) was then constructed with the help of concepts in the Template Ontology (i.e., OWL ontology's TBox) and in the Template TIN. The Following is an example of a mapping rule, expressed in SPARQL, which provides a definition of the relation between a leader and available funding as captured in a Template Influence. The rule states that a leader is a known terrorist and has a high leadership rank. It also states that funding is a financial source and a leader has funding.

```
SELECT  ?leader ?funding
   { ?leader rdf:type  this:KnownTerroist.
   ?leader this:leadershipRank "high"^^xsd:string.
   ?obs1 rdf:type this:C2Observation.
   ?obs1 this:hasParticipant ?leader.
    ?funding rdf:type this:FinancialSource.
    ?obs2 rdf:type this:FinancialAcquisitionObservation.
   ?obs2 this:hasFinancialSource  ?funding.
   }
```

The Template Ontology was populated with information in the OWL ontology's ABox. The ABox used for this illustration contained data from the Tanzania bombing incident only. The Tanzania instance ontology was provided to Castalia that used it and the MBox to generate a TIN specialized for the Tanzania incident. The construction of a new instance TIN was automatically done by Castalia which replaced the variables in each of the Template Influences by the values available in the instance ontology with the help of mapping rules in the MBox. Figure 4.7 shows the generated Timed Influence Net. As can be seen in the generated TIN, not all variables were instantiated with values from the Tanzania ontology. For example, Castalia reasoning engine did not find an instance for the slot variable [?trainer] in the Tanzania data. In other words, the data available for the Tanzania incident had no person identified as the potential trainer of the bomber. The generated TIN, however, succeeded in capturing a number of key elements, i.e., people involved and equipment, used in the bombing.

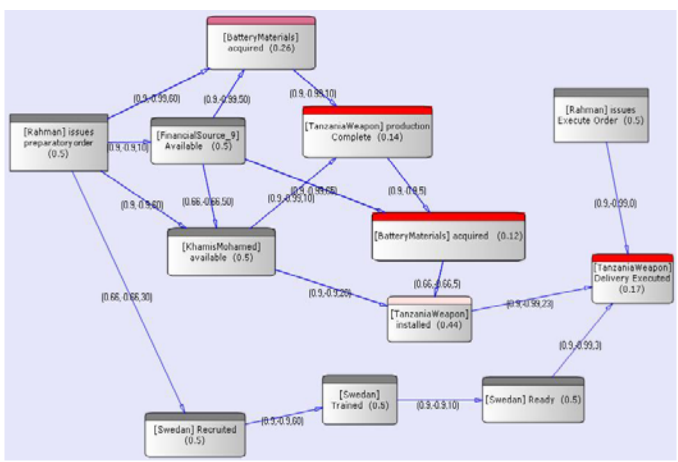



Fig. 4.7  Instantiated Timed Influence Net for Tanzania Bombing

This generated TIN could be used by a SME or analyst as a fragment in a larger domain model that might require it as part of a more complex situation involving vehicle borne explosives or IED attacks. The instantiated TIN can also be used for course of action analysis as well as a host of other analyses provided by the TIN suite of tool. As mentioned earlier, the templates are not prescriptions to be used for building future models, but useful references that a SME/analyst might like to consult either during the process of building a new model or as a starting point for it. The generated TIN can also be used to study temporal aspects of the influences in the TIN and to do a course of action analysis indicating how long it takes for input events to cause some desired or undesired effects on output nodes.

### 4.5 Conclusion

Template TIN models a problem at a generic level using abstract entities characterizing the problem domain, allowing an analyst to model an entire class of Timed Influence Nets using a compact representation**.** However they also lack specialized domain modeling constructs like objects, properties, inheritance etc. that makes it difficult to construct and maintain probabilistic models for complex domains. This limitation of Influence Nets was overcome by using ontologies, which provide a highly expressive language for representing complex domains. The presented approach uses ontologies along with Template TINs to automate the Influence Net construction process. We believe that, given the time and expertise required for Influence Net construction by hand, an automated approach for Influence Net construction would prove vital for Influence Net's widespread adaption and use.

The mapping box used in the approach acts as a bridge between Template TIN and ontologies, and are expressed using SPARQL. In the presented approach, an analyst will have to manually specify the MBox. One possible way to further facilitate an analyst would be to automate the MBox specification using automated inductive learning techniques.

It is assumed that Castalia will benefit a growing community of TIN users that include both government (e.g., NASIC, NPS, JIEDDO, AU) and private (e.g., Raytheon, ANSER, and other corporations supporting DOD and DHS) organizations for rapid construction and deployment of situational influence models for intelligence assessment, course of action planning and assessment in EBO, and adversarial modeling problems. The repository of Template Timed Influence Nets can also be used for training future analysts in different problem domains. The update and the re-use of the templates will also facilitate automated generation of situational models for assessment and planning purposes in a new theatre of operations.

# Chapter 5

# Adversary Modeling Applications

## 5.1 Modeling Uncertainty in Adversary Behavior: Attacks in Diyala Province, Iraq, 2003–2006

**Claudio Cioffi-Revilla and Pedro Romero**

### 5.1.1 Introduction

Uncertainty is a universal characteristic of conflict behavior and low-intensity warfare, guerrilla, insurgency, and other forms of violence that accompany civil war and transnational conflict seem not to be an exception. How can the uncertainty of adversary behavior—its seemingly haphazard nature—be understood or grasped in order to better prepare or mitigate its effects? Which theoretical principles and modeling tools might be tested with available data? How can empirical findings be used to improve simulations, particularly in areas such as validation, verification, and calibration?

Modeling-based analyses can offer new insights for analysts and policymakers, and this study applies well-established concepts, principles, and models from the theory of political uncertainty and from complexity theory—the two core methodological approaches used in this study—to the analysis of conflict events during the first three years of the second Iraq War, 2003–2006, in the province of Diyala. Preliminary findings show that neither the time between attacks $T$ or the severity of attacks $S$ (fatalities) have a "normal" (i.e., bell shaped or Gaussian) or log-normal distribution that is characteristic of equilibrium systems. Instead, both variables showed "heavy tails" in the upper extreme range, symptomatic of non-equilibrium dynamics; in some cases approximating a power law with critical or near critical exponent value of 2. The empirical hazard force analysis in both cases showed that intensity was high for the first epoch in both variables, namely between March 2003 and June 2004, but even higher in the following period ending in March 2006. Moreover, the average empirical hazard rate clearly increased throughout the three epochs, supporting the authors' hypothesis. Although these findings are limited to Diyala province in Iraq, and do not necessarily apply anywhere else in the country or region, Diyala province is linked to several other provinces and neighboring Iran—via the ancient strategic passage linking Khânaqin (Iraq) and Qaş̧r-e Shirin (Iran) across the Zagros mountains.

Analysts and policymakers are always interested in understanding uncertainty, and the uncertainty of warfare continues to dominate much of the scientific modeling literature, consistent with the fundamental nature of this complex phenomenon. This common interest should be developed. In terms of political uncertainty theory applied to the analysis of war [113], [114] - that is, the first methodological approach employed in this study - Fearon [115] and others have applied similar estimation techniques to model the duration of civil wars, classified in five types, arriving at two main results. First, the "sons of soil" and contraband-financed civil war types last longer than other types (coups/popular revolutions, anti-colonial wars, and wars in eastern Europe or former Soviet Union countries). Second, the standard predictors for duration of civil wars (e.g., ethnic diversity, GDP per capita, level of democracy, ideological effects) have a negligible effect on war duration.

In the same tradition, Bennett and Stam [116][1] apply a parametric Weibull regression to predict the duration of the ongoing second U.S.–Iraq war. Based on a set of predictor variables—such as the strategies used and the quality of the terrain, while other factors (e.g., population, military surprise) are held fixed—the Bennett-Stam model predicts a likely duration of 83 months, or almost 7 years since the fall of the Saddam Hussein regime. However, it must be noted that such predictions, based on uncertainty-theoretic models, are probabilistic expectations, not deterministic forecasts.

In terms of complexity theory and power law analysis applied to conflict analysis—the second methodological approach used in this study—the seminal work is by Richardson [118], [119], based on his data set of "deadly quarrels," which included international conflicts and civil wars between 1820 and 1945. An early revision of his work and a discussion of the different theories behind his empirical work is found in Rapoport [120]. Wilkinson [121] and Cioffi-Revilla and Midlarsky [122] present replications of Richardson's results with larger and more diverse data sets.

This chapter proceeds as follows. Section 5.1.2 presents the methods used for data analysis and model testing, based on the theory of political uncertainty and social complexity theory. The essence of these methods is to use events data as signals for understanding latent, underlying dynamics that are causally responsible for observed conflict. Although the methods are statistical, mathematical, and computational, they are essentially information extraction procedures for understanding adversary conflict dynamics. The next section presents the presents the results in technical and non-technical language. The fourth section presents a discussion of the main results and some general conclusions, including discussion of policy significance. The discussion of policy implications is innovative for the integrated multidisciplinary methods used in the analysis, which combined political uncertainty theory and complexity or complex systems theory.

### 5.1.2 Method

Let X denote a conflict-related random variable, such as the time-interval between attacks T (measured in days), the severity S of each attack (measured by fatalities or deaths), distance D from the previous attack, or other variables associated with an attack event. Formally, a conflict process $P(\mathbf{X}_{<\tau>})$ is modeled as an n-tuple of random variables with realizations ordered in historical time $\tau$ (so-called "epochal time" [123]), where each r.v. is defined by its set of associated probability functions $p(x)$ and $\Phi(x)$, or p.d.f. and c.d.f., respectively.

Figure 5.1 illustrates the overall methodological process used in this study, as detailed in the following sections. Empirically, our analysis is based on 2002–2006 high frequency (daily) conflict events data collected independently at the Lawrence Livermore National Laboratory by E. O'Grady [124], [125] as detailed below. We conducted synchronic analyses based on the entire population of data, as well as diachronic analyses based on epochs. In particular, we examined results based on the three data "epochs" proposed by the International Crisis Group (ICG)[2], based on organizational hypotheses.

---

[1] Their model is explained in detail in the earlier paper by Bennett and Stam, [117]

[2] International Crisis Group (ICG). 15 February 2006, available at http://www.crisisgroup.org/home/

The events data were analyzed with two distinct but interrelated types of quantitative/ computational methods: (i) hazard force analysis, founded on the theory of political uncertainty and (ii) power law analysis from complexity theory [126]. Although traditionally autonomous from each another, in this study we exploited the synergy of these two analytical methods to obtain new inferences that advance our understanding of adversary conflict behavior.

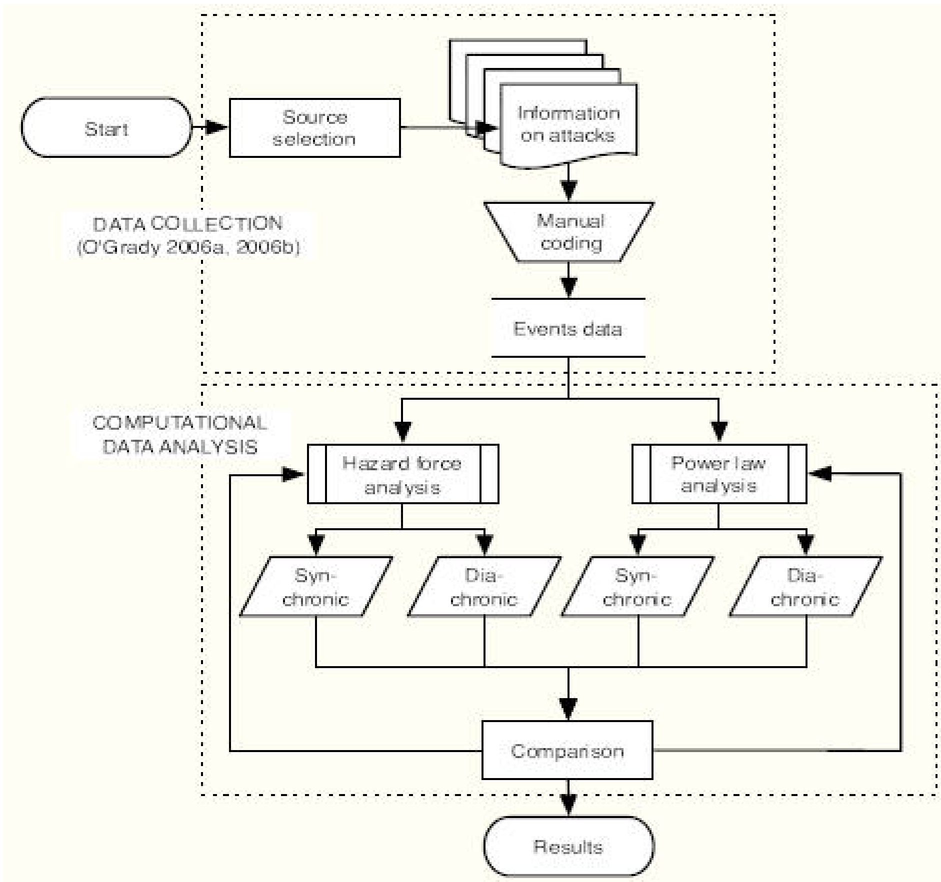



Fig. 5.1 Overall events data analysis process conducted in this study, starting with O'Grady's [124], [125] data on attacks. Hazard force analysis and power law analysis are parallel computational data analysis processes

### 5.1.2.1 Data

This study used the dataset Iraq Event Database: Diyala Province on adversary conflict events recently compiled by O'Grady (2006), which is based on unclassified sources. The data set contains N = 335 attack events that took place in the Province of Diyala, Iraq, between March 2003 and March 2006. The two coded variables used in this study were "date of event", used for computing time between attacks (T) and "total fatalities" (used as proxy for severity S), defined as "the total figure of people killed (includes terrorist/ insurgent and non-terrorist/insurgent)." Moreover: "The fatalities count reports the number killed in situ (in Diyala), not those that were fatally injured and subsequently passed away, e.g., in a hospital in Europe or CONUS [continental United States]." These comprise military and civilian non-terrorist plus terrorist fatalities.

O'Grady's new events dataset is uncommon and scientifically valuable, because— inter alia—it provides a count of high-frequency daily events with fatalities (and other variables not used in this study). Most other conflict data sets that record fatalities contain only low-frequency events (e.g., wars). By contrast, most high-frequency datasets (e.g., COPDAB, WEIS, or KEDS) do not report fatalities. [127]

#### 5.1.2.2 Analyses

As shown in Fig. 5.1 above, we analyzed the conflict events data using two distinct analytical methods, hazard force analysis and power law analysis, as described in the next subsections. Both methods were applied to the same data (N = 335 events) for time-between-attacks T, and severity S. In turn, each analysis was conducted synchronically and diachronically, as explained below.

**Temporal Analyses**

For each variable (time T and severity S) and type of analysis (hazard force and power law) we first conducted an overall synchronic analysis, based on all the data for the entire period (March 2003 to May 2006), followed by a more historically de- tailed diachronic analysis. The latter was based on three epochs of the Iraq conflict hypothesized by the International Crisis Group (ICG):

- "Phase 1": March 2003 to June 2004. According to the ICG, this initial epoch was characterized by "competition" among insurgent groups that had only erratic coordination and little or no organizational capacity. During period I, Iraqi rebel groups were small, not very mobile and many of the first attacks signaled a lack of expertise in handling mortars or other explosive devices. Moreover, they used their small world networks (family, neighbors, mosques) to propagate by means of leaflets their message of resistance and recruit members or, in any case, to foster similar initiatives by other people. Websites —such as iraqresistance.net—were used as a channel to communicate the message to people outside their locality but also outside Iraq. This later strategy was aimed at Muslims willing to fight against the coalition forces.
- "Phase 2": July 2004 to June 2005. During this epoch "consolidation" would have taken place within groups of attackers. During this period, small successful groups merged with others and started to apply more often a strategy of hit- and-run ´a la guerrilla in order to avoid frontal combat. Also, an improvement regarding how to handle explosive devices and the like allowed to them to focus their attacks on specific targets.
- "Phase 3": July 2005 to May 2006. This third epoch would have been characterized by the ICG as having increasing "confidence"—even insurgent optimism— indicative of increased organizational capacity on the part of attackers. This third period would also have been oriented towards justifying religiously their kidnaps and killings of members of the U.S. coalition, foreign civilians, and even Iraqis (mostly Shi'ites) working with the coalition.

The significance of these three "phases" (*epochs*, in quantitative conflict analysis terminology) stems from their application to the overall conflict in Iraq, applying to the whole country; they are not specific to Diyala province. The authors are not aware of any periodization specific to Diyala. The main theoretical motivation for these epochs—and additional reason why epochs matter—is that conflict dynamics, in terms of forces of onset $\mathbf{F}_T$ and forces of severity $\mathbf{F}_S$, which drive the onset and severity of attacks, undergo fundamental changes across epochs due to the increasing organizational capacity of the attackers. Hazard force analysis and power law analysis aim at detecting such latent forces, as described in the next subsections. The ICG epochs should therefore mark significant transitions within an overall politico-military process affected by these forces.

### Hazard Force Analysis

The hazard force or intensity function producing the observed realizations of a conflict process $P(\mathbf{X}_{<\tau>})$ is defined as follows.[3]

**Definition 5.1** (Intensity function) The intensity function H(x) of a c.r.v. X is defined by the ratio of the value of the p.d.f. to the value of the complementary c.d.f.

of X. Formally, H(x) is defined by the equation

$$H(x) = \frac{p(x)}{[1 - \Phi(x)]}, \quad (5.1)$$

where p(x) and Φ(x) are the p.d.f. and c.d.f. of X, respectively.

Note that, although the intensity or hazard force H(x) is a latent or non-observable variable, equation 5.1 renders H(x) measurable, because both p(x) and Φ(x) can be computed from a sufficiently large set of observed realizations $\hat{x}_i \in X$.

Accordingly, by (5.1), the specific qualitative form of H(x) (constant, in- creasing, decreasing, non-monotonic) depends directly on the form of the associated probability functions (c.d.f. or p.d.f.). Specifically, four cases are fundamentally important for analyzing attacks. To illustrate, let X = T, the time interval between attacks, measured—for instance—in days.

*Case 1. Constant intensity*: H(t) = k. In this special or *equilibrium* case the propensity for the next attack to occur— i.e., the hazard rate or event intensity—does not change between realizations, consistent with the notion that escalating and mitigating forces of conflict are in balance. This also corresponds to the Poisson case and simple negative exponential density, with $p(t) = ke^{-kt}$ and $\bar{t} = 1/\hat{k} = \sigma^2(t)$. This case is known to have the strongest empirical support for many types of conflict, both internal and international, following Richardson's [118] pioneering work on wars of all magnitudes. In terms of the ICG epochs mentioned earlier, we expected to detect a constant or slightly decreasing intensity during Period 1 (March 2003 to June 2004), because the attackers were supposed to have been in competition among themselves and attacks were erratic.

*Case 2. Increasing intensity*: dH/dt > 0. In this case the hazard force or event intensity would increase between attacks, symptomatic of a fundamentally unstable situation where attacks occur under rising pressure or increasing propensity. This situation is akin to a driven threshold system that triggers attack event as forces build up. In terms of the ICG epochs, we expected to observe

---

[3] The original interpretation of (5.1) as an intensity or force is probably due to D. R. Cox [128], based on Bartholomew [129]. For a more detailed description of hazard force analysis, including examples from conflict processes and computational issues, see [114] chs. 2–4, containing numerous references. Unfortunately, most of the standard social statistical and econometric literature (e.g., Greene [130]) treats the estimation of $\hat{H}(x)$ as just another case of regression, ignoring the much deeper dynamical implications used in this study.

increasing force intensity during Period 2 and (even more so) in Period 3, given the rising organizational capacity of attackers.

*Case 3. Decreasing intensity*: $dH/dt < 0$. In this case the hazard force or event intensity would decrease between attacks, symptomatic of a stable situation where at- tacks occur under diminishing pressure or decreasing propensity. This situation is akin to a leaky threshold system that dissipates forces as they build up. For example, con- flict resolution mechanisms (nonviolent processes) may be responsible for dissipation and decreasing propensity for attacks. In terms of the ICG epochs, we expected to see this force pattern only in Period 1, if at all.

The above three cases are covered by the two-parameter Weibull model:

$$H(x) = kt^{\beta-1} \tag{5.2}$$

where k and β are the scale and shape parameters, respectively. Thus, the estimated exponent $\hat{\beta}$ computed directly from the data supports the follow inferences concerning the causal conflict dynamics driving the incidence of attacks:

$$\hat{\beta} < 1 : \text{decreasing conflict force} \Rightarrow \text{stable situation} \tag{5.3}$$

$$\hat{\beta} = 1 : \text{constant conflict force} \Rightarrow \text{borderline situation} \tag{5.4}$$

$$\hat{\beta} > 1 : \text{increasing conflict force} \Rightarrow \text{unstable situation} \tag{5.5}$$

Clearly, these three conflict situations are qualitatively distinct, and from a policy perspective they obviously correspond to desirable, indifferent, and undesirable conditions, respectively. Interestingly, the mean or first moment of T is given by

$$\bar{t} = k\Gamma(1 + 1/\beta) \tag{5.6}$$

where Γ is the gamma function. Therefore, commonly used heuristic estimates based of mean values (e.g., "the average time lapsed between attacks") are not generally valid and instead must be computed exactly because $\bar{t}$ is notoriously sensitive to $\hat{\beta}$

Finally, a fourth qualitative case in the qualitative form of the conflict force is also interesting:

*Case 4. Non-monotonic intensity*. After an attack occurs, the conflict force may rise (as in Case 2), but then subside, as in a lognormal function. Alternatively, the conflict force may subside following an attack and then begin to rise again sometime after, as in a so-called "bathtub" function. These non-monotonic situations were also considered in our analysis, given their plausibility. In terms of the ICG epochs, their logic seemed mostly linear, ruling out non-monotonic forces.

Summarizing our hazard force analysis, conflict events data on time intervals between attacks (T) and fatalities produced by each attack (or severity S) were used to compute the corresponding empirical hazard functions, H(t) and H(s), respectively. These empirical functions were then closely examined to determine their qualitative shape and draw inferences concerning conflict conditions. This procedure was repeated for the entire population of data, as well as for each of the three ICG epochs. The initial expectation was that these estimates would yield mostly Case 1 (constant force), consistent with many earlier studies, with rising value of k as the epochs progressed (as argued by the ICG).

## Power Law Analysis

Power law analysis is a complexity-theoretic method for drawing inferences from a set of conflict data. Here we used the so-called type IV power law, which is defined as follows.[4]

**Definition 5.2 (Power law)** *A power law of a conflict process $P(X_{<\tau>})$ is a parametric distribution model where increasing values $x_i \in X$ of the conflict variable X occur with decreasing frequency, or $f(x) / x^{-b}$, with $b > 0$. Formally, f(x) in this case is a p.d.f. given by* (5.7) *where a and b are scale and shape parameters, respectively.*

$$p(x) = \frac{a(b-1)}{x^b} \tag{5.7}$$

From this 2-parameter hyperbolic equation for the p.d.f. it can be easily shown that the complementary cumulative density function (c.c.d.f.), defined as $1 - \Phi(x) \equiv \Pr(X > x)$ (a.k.a. survival function when X = T, or S(x)), has the following form in log-log space:

$$\log[1 - \Phi(x)] = a' - (b-1)\log x \tag{5.8}$$

which, finally, yields

$$\Phi(x) = 1 - \frac{a}{x^{(b-1)}} = 1 - ax^{1-b} \tag{5.9}$$

The penultimate expression is commonly used for empirical analysis, because it can be obtained directly from the set of observed values $\hat{x}_i$.

The empirical estimate $\hat{b}$ is of interest because the first moment of a power law is given by

$$E(x) = \int_{\min\{x\}}^{\infty} xp(x)dx = a(b-1)\int_{\min\{x\}}^{\infty} x^{1-b}dx \tag{5.10}$$

$$= \frac{a(b-1)}{2-b} x^{2-b} \Big|_{\min\{x\}}^{\infty}$$

which goes to infinity as b goes to 2. In other words, there is no mean size (no expected value E(x) exists) for the conflict variable X (such as onset times T or severity S) when X is governed by a power law with exponent b approaching the critical value of 2, or $(b - 1) < 1$ (below unit elasticity). This is an insightful theoretical result for numerous social variables, such as organizational sizes, fatalities in warfare [118], [122] and terrorist attacks. The critical threshold b = 2 marks the dynamical boundary between conflict regimes that have a finite average and computable size (b > 2) and a highly volatile regime that lacks an expected value or mean size ($b \leq 2$). This is a theoretical insight directly derived from the empirically estimated value of the power law exponent b.

---

[4] Other types of power laws include the rank-size law or Zipfian, various algebraic forms, and others [131]. In this study we applied the type IV power law because in the case of conflict data (attacks) it seems to provide the most powerful complexity-theoretic inferences.

Based on previous studies, we expected that (a) T should obey the simple (one parameter) negative exponential p.d.f. of a Poisson process,

$$p(t) = \lambda e^{-\lambda t} \quad (5.11)$$

where $\hat{\lambda} = 1/\bar{t}$; and (b) S should obey a power law. Moreover, with respect to the diachronic epochs (ICG periods) discussed earlier, we expected t to increase across periods (epochal time) and $\hat{b}$ to approach criticality as the attackers gained strength.

Summarizing our power law analysis, conflict events data on time interval between attacks (T) and the severity of attacks (S) were used to compute the corresponding empirical power law functions $\log[1 - \Phi(t)]$ and $\log[1 - \Phi(s)]$, for onsets and severity (fatalities), respectively. These empirical functions were then closely examined to determine their qualitative shape and draw inferences concerning conflict conditions. We also examined the p.d.f.s directly using kernel estimation. This procedure was repeated for the entire population of data (synchronic analysis), as well as for each ICG epoch (diachronic). The initial expectation was that these estimates would yield mostly a poor fit of the power law for the overall synchronic analysis, but increasingly good fit and decreasing exponent (towards criticality) as the epochs progressed and the attackers became more organized.

### 5.1.3 Findings

First are presented the temporal findings for the analysis of time between attacks *T* (the next subsection), including both synchronic and diachronic patterns, followed by a parallel presentation of findings for the severity of attacks *S* (the subsection after). Table 5.1 summarizes the overall descriptive statistics for both processes, *T* and *S*.

**Time Between Atttacks**

*Overall (Synchronic) Patterns.* There were 107 occurrences were T = 0, meaning more than one attack took place in a given day. The large and positive skewness implies that the right tail of the distribution is more pronounced. Kurtosis is substantially larger than zero, implying a leptokurtic feature. These moments suggests a distribution for T with non-normal characteristics.

Another insightful indicator is the ratio of the mean to the standard deviation, which in this case is 0.37 and closer to 0 than to 1. This could imply a hyper-exponential process or a high degree of political uncertainty, because the mean of T is significantly smaller than the variance (by a factor of 24).

Figures 5.2 and 5.3 plot the empirical c.d.f. and p.d.f, respectively, consistent with the non-normal results reported in Table 5.1.

**TABLE 5.1** Onset of attacks T (days between events)

| Descriptive Statistics: Whole Sample | | | | |
|---|---|---|---|---|
| Mean | Variance | Skewness | Kurtosis | Mode |
| 3.25 | 78.15 | 8.13 | 80.65 | 0 |
| Std. Dev | Median | Max | Min | *N* |
| 8.84 | 1 | 104 | 0 | 334 |

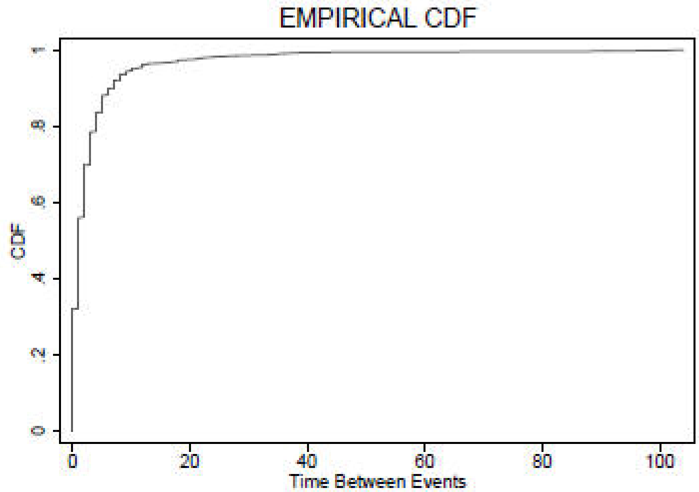



Fig. 5.2 Cumulative probability density for time between attacks T, Diyala Province, Iraq. March, 2003 - March, 2006

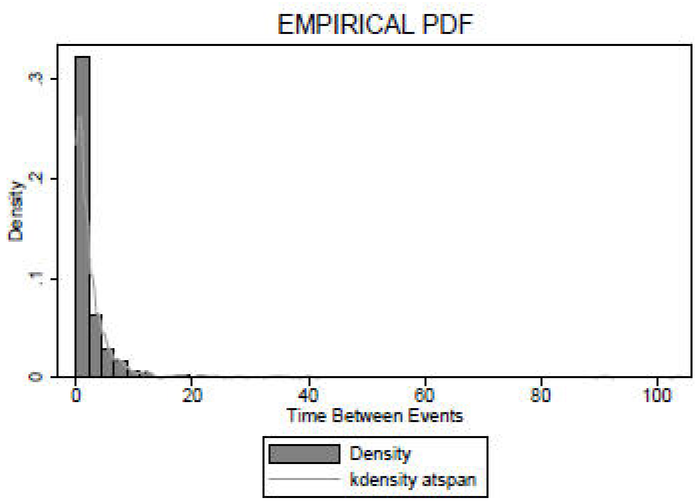



Fig. 5.3 Probability density for time between attacks T, Diyala Province, Iraq. March, 2003 - March, 2006

Both graphs suggest a distribution with a pronounced exponential pattern. Note also that by the 10th day the c.d.f. amounts to 95%, implying that short intervals between attacks are by far the most frequent. In other words, following an attack the probability of another attack is very high within intervals no greater than 10 days. The surprisability of the process, or difference between the mean and the median, yielded 2.3 days, which is another indication of the volatility of attacks.

*Normality Tests*. The results in Table 5.1, showing that the mean of 3.25 days is clearly lower than the standard deviation of 8.84 days, as well as the empirical distributions in Figures 2 and 3, consistently imply that the data might not be normally distributed. A formal test of normality was applied to corroborate these preliminary results. The Shapiro-Wilk test was implemented to test the null hypothesis that the data are normally distributed and the results are reported in Table 5.2.

We also tested the hypothesis of a lognormal distribution, by computing the log-transformation of T. Because the p-value is less than 5% the null hypothesis is rejected in both cases.

In addition, the variable T does not correspond to a lognormal distribution either. In both cases the probability or p-value is very small or close to zero.

**TABLE 5.2** Shapiro-Wilk Test

| Time Between Events | | | | | |
|---|---|---|---|---|---|
| Variable | Obs | W | V | z | p-value>z |
| T | 334 | 0.3571 | 150.67 | 11.83 | 0.0000 |
| Ln(T) | 227 | 0.9425 | 9.56 | 5.23 | 0.0000 |

*Hazard Forces.* We applied the Kaplan-Meier method for estimating the empirical survival function ˆ S(t), and results are shown in Figure 5.4. Recall that the K-M method is non-parametric, so it does not impose a specific structure on the data. In this case the estimated value of the probability of no attack within time t should be interpreted as the product of the probabilities of not attack occurring at t and the preceding periods. In our particular case the K-M estimator tell us that the survival function for attacks drops off sharply in the days following an attack and slowly settling to zero after about 10 days.

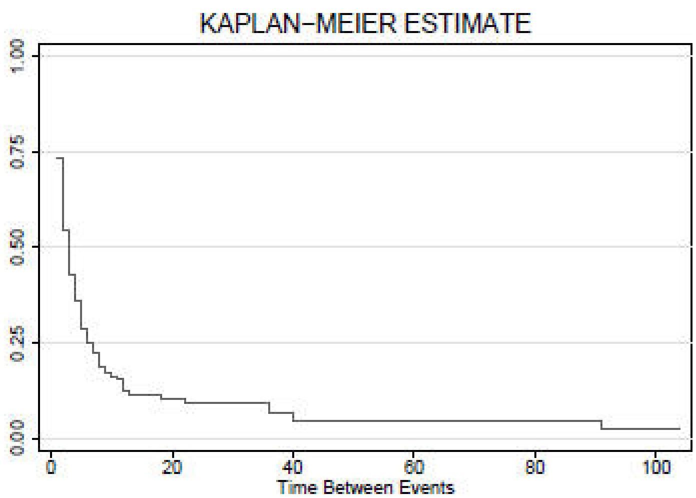



Fig. 5.4 Empirical survival function ˆ S(t), for time between attacks T, Kaplan-Meier estimate, Diyala Province, Iraq. March, 2003 - March, 2006

Figure 5.5 shows the K-M estimate of the hazard force function. In terms of the Weibull hazard model given by (5.2), Figure 5.5 implies that $\hat{\beta} < 1$. Specifically, this empirical hazard force for the complete period is decreasing until approximately the 10th day, after which it shows some volatility around a value of 0.1. The average empirical hazard force is 0.0877, a value that will be more meaningful when we analyze the data within shorter periods (epochal, diachronic analysis).

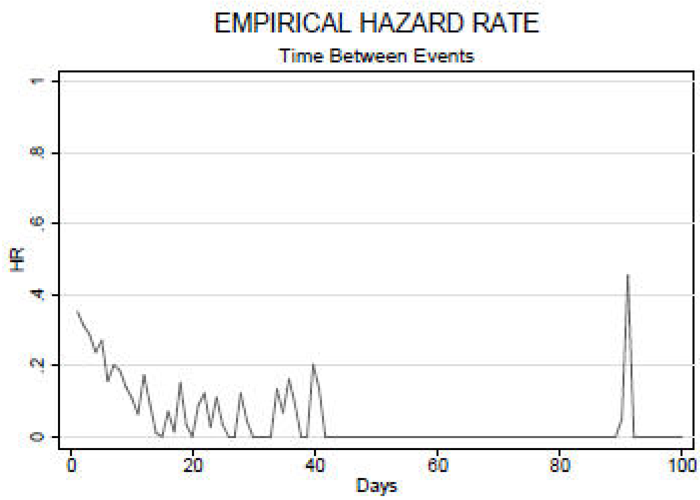



Fig. 5.5 Diyala Province, Iraq. March, 2003 - March, 2006

*Power Laws and Criticality.* Our alternative hypothesis, given the rejection of the normality (or log-normal characteristics) of the data, is that the data follow a power law as defined earlier in the methodological section. A univariate regression model was carried out, in order to test the linearized power law using an ordinary least squares (OLS) procedure. The logarithmic transformation was applied to the complementary c.d.f. (or survival function) and T, as described earlier in the Methods section.

Figure 5.6 shows the scatter plot for both variables, the linear regression fit, and a 95% confident interval. Both point estimates, also inserted in the figure, are statistically significant at the 1% level. The slope estimate is the most relevant in this type of analysis, which is minus 1.03. The $R^2$ is 0.95 and the standard errors for the constant term and the slope are 0.0085 and 0.0153, respectively. Although the overall fit is close, there is clearly some systematic departure in the pattern for the upper range.

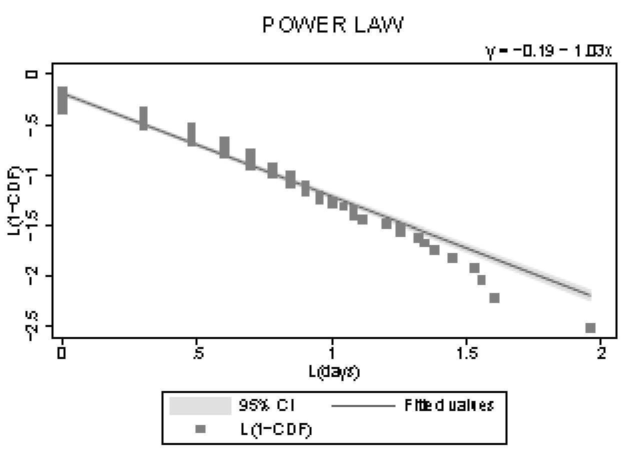



Fig. 5.6 The empirical complementary c.d.f. for time between attacks T in log-log space, Diyala Province, Iraq. March, 2003 - March, 2006

*Epochal (Diachronic) Patterns.* The null hypothesis tested was that the estimates for the hazard force would yield a roughly constant intensity within each epoch with increasing average mean values for the hazard force across epochs. Figures 7 through 9 plot the empirical hazard force functions for the three epochs.

The pattern in Figure 5.7 is not clear-cut or smooth because there are fluctuations starting at zero up to 0.2 for the first forty days, then the hazard rate drops to zero until day 95th where it spikes up to 0.45. The average empirical hazard rate for Period 1 is 0.094. Also, after the twentieth day the pattern is not very different from Figure 5.5, including even the sudden spike around day 95th.

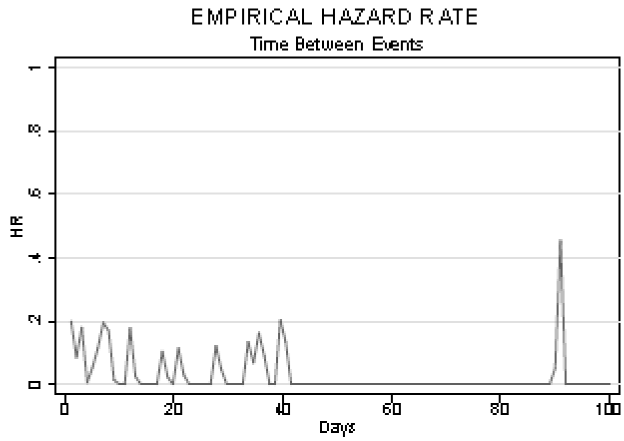



Fig. 5.7 Diyala Province, Iraq. Period 1, March, 2003 - June, 2004. Source: Prepared by the authors based on O'Grady's (2006a, 2006b)

**TABLE 5.3** Severity of attacks S (fatalities data were either normally distributed or belonged to a lognormal distribution)

| Descriptive statistics whole sample | | | | |
|---|---|---|---|---|
| Mean | Variance | Skewness | Kurtosis | Mode |
| 4.17 | 74.0 | 5.19 | 32.66 | 1 |
| Std. Dev | Median | Max | Min | *N* |
| 8.6 | 2 | 71 | 0 | 335 |

In Figure 5.8 for Period 2 we observe a different pattern from the one in Period 1.

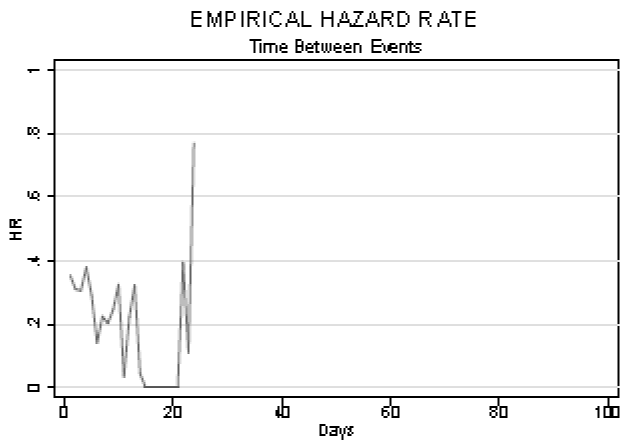



Fig. 5.8  Diyala Province, Iraq. Period 2, July, 2004 - June, 2005. Source: Prepared by the authors based on O'Grady's (2006a, 2006b)

However, before the twentieth day the empirical hazard rate for Period 2 is not very different from the pattern for the empirical hazard rate within the whole period (see synchronic results earlier). That is to say, in Period 2 the hazard rate decreases during the first twenty days and then spikes up beyond 0.5. This last fluctuation of the data, however, might be an artifact of the computation of the data rather than a reflection of the actual intensity of the events. The average empirical hazard rate for Period 2 is 0.212, not counting the last point beyond 0.7. This is twice as high as the average hazard rate for Period 1. Therefore, during this period from June, 2004 until June, 2005, there was a doubling in the hazard force driving attacks in Diyala province.  There is no such a drastic difference between the plot in Figure 5.8 and the one for Period 3 in Figure 5.9, which spans the period from summer 2005 until March, 2006. The average empirical hazard rate in Period 3 was 0.217, not including the last point above 0.8. Thus, during this epoch there was not a substantial increase in relation to what happened in Period 2.

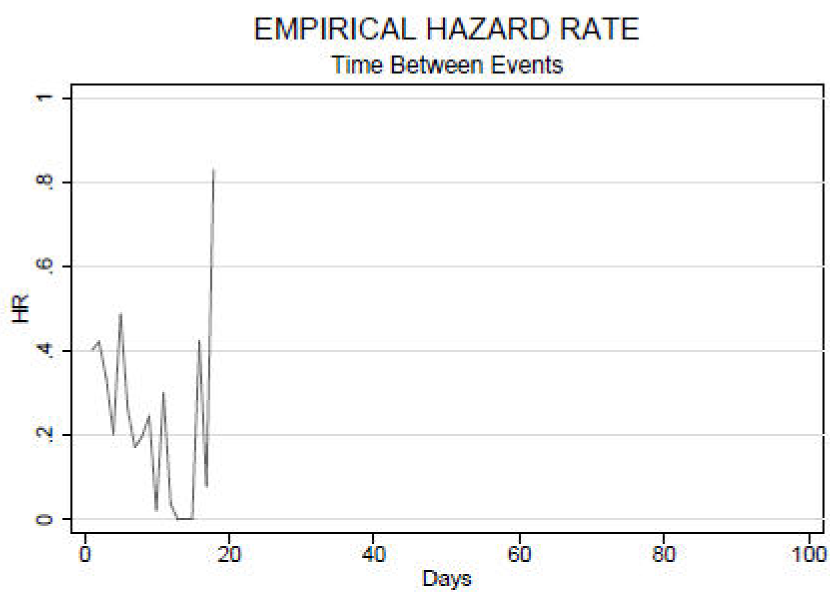



Fig. 5.9  Diyala Province, Iraq. Period 3, July, 2005 - March, 2006

All in all, the analysis of Diyala attacks by epochs is consistent with the increased organizational capacity hypothesized by the ICG in terms of an increase in the average empirical hazard forces.

*Power Laws.* Figures 5.10 through 5.12 report the results of the diachronic power law analysis for individual epochs.

Figure 5.10 for the first epoch shows a linear regression OLS slope estimate of -0.62, which is statistically significant at 1% level of confidence. The standard errors reported for the constant and the slope terms are low: 0.0374 and 0.0399, respectively, with $R^2 = 0.9$. Figure 5.11 shows results for the second epoch, with a steeper slope estimate of -1.15, also statistically significant at 1% level of confidence. The respective standard errors reported for both regression terms are: 0.0179 and 0.0366, $R^2 = 0.9$. Figure 5.12 shows the slope estimate to be -1.25, again statistically significant at 1% level of confidence. The standard errors are 0.0174 and 0.0406, respectively, with $R^2 = 0.92$. Note that the slope becomes increasingly steeper.

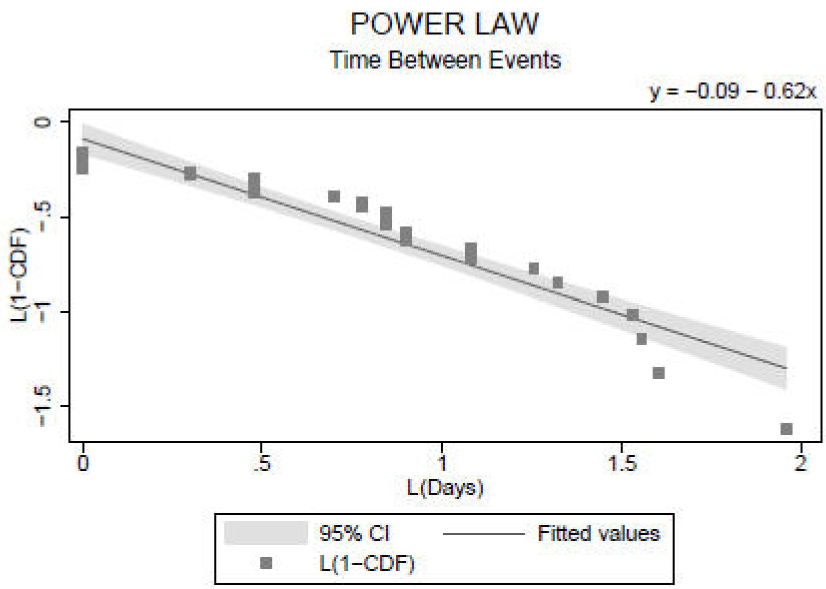



Fig. 5.10 Diyala Province, Iraq. Period 1, March, 2003 - June, 2004

In general, the power law for the whole period is the closest to a linear relationship between the complementary c.d.f. and T. However, all periods show some upper range bending, even if slight in some cases. We cannot make a formal test to determine if the slope coefficients for every linear regression are equal because of the difference in the number of observations.

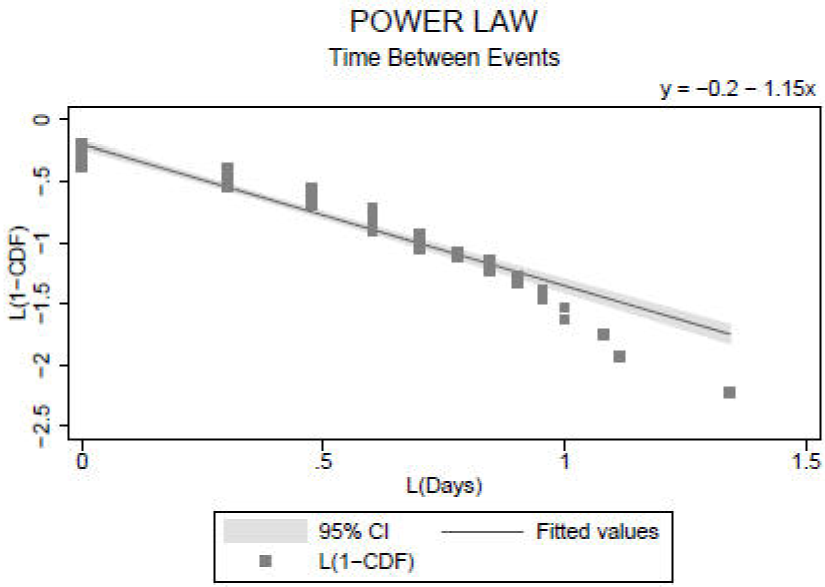



Fig. 5.11 Diyala Province, Iraq. Period 2, July, 2004 - June, 2005

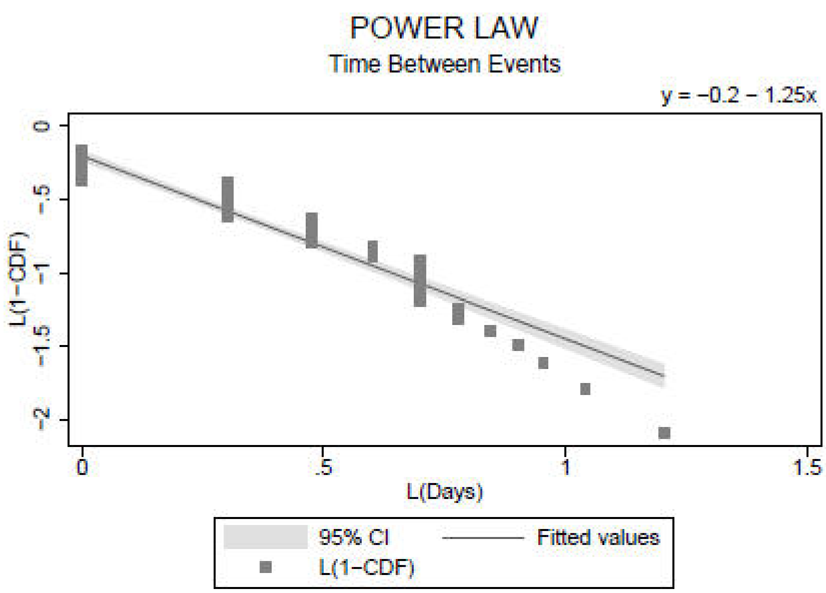



Fig. 5.12 Diyala Province, Iraq. Period 3, July, 2005 - March, 2006

### Severity of Attacks

*Overall (Synchronic) Patterns.* Table 5.3 shows a summary of the descriptive statistics for the severity S of attacks. The statistical properties for S are not very different from those discussed earlier for the time between events (T). We observe positive skewness and kurtosis, again meaning that we should find a pronounced right tail and leptokurtic distribution. The ratio between the mean and the standard deviation is 0.485 which also suggests a non-normal pattern. The mode is 1 and the median is 2. That is to say, the most typical number of fatalities produced by an attack was one death.

The empirical c.d.f. and p.d.f. are plotted in Figs. 5.13 and 5.14 , respectively. We observe the similarity with the respective figures for T. The pronounced right tail with a few values at the end of the distribution, or "dragon tail" indicating the presence of extreme events with unduly high frequency/probability.

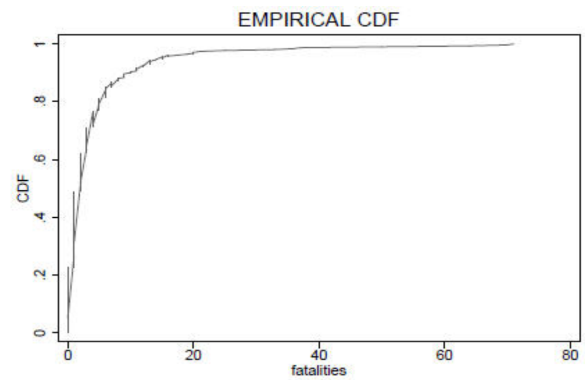



Fig. 5.13 Diyala Province, Iraq. March, 2003 - March, 2006

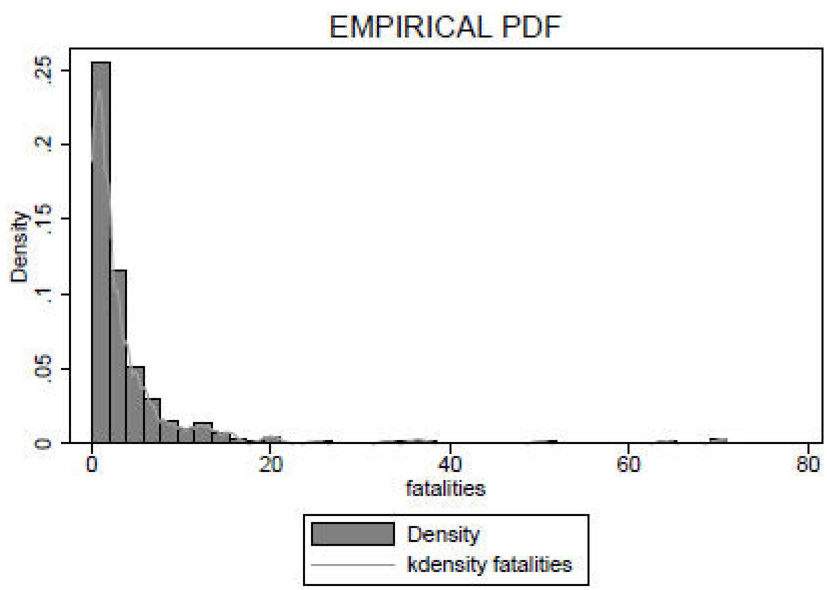



Fig. 5.14 Diyala Province, Iraq. March, 2003 - March, 2006

*Normality Tests.* Table 5.4 shows the results of our Shapiro-Wilk test for the normality of attack severity S (fatalities). As before, the null hypotheses were that the data were either normally distributed or belonged to a lognormal distribution.

Because both p-values are less than 5%, or even 1%, the null hypothesis can be rejected in both tests. These results provide more confident about our previous claim that the data for severity S is not normally distributed or even belong to a lognormal distribution. This provides additional justification for the power law analysis.

**TABLE 5.4** Shapiro-Wilk Test

| Severity of attacks $S$ (fatalities) | | | | | |
|---|---|---|---|---|---|
| Variable | Obs | W | V | z | p-value>z |
| Fatalities | 311 | 0.4846 | 113.37 | 11.12 | 0.0000 |
| Ln(Fatalities) | 241 | 0.9571 | 7.54 | 4.69 | 0.0000 |

*Hazard Forces.* Figures 5.15 and 5.16 show the K-M estimate for the c.c.d.f. and the hazard force, respectively. The K-M estimate for the c.c.d.f. for severity S reflects the cumulative probability of an additional fatality beyond a given level s. For the whole period, that probability is less than 0.25 beyond the first five fatalities and it decreases faster than the Kaplan-Meier curve for the variable time between events T. Beyond S = 20 deaths the probability is very close to zero, although the hazard force highlights the probability of extreme events.

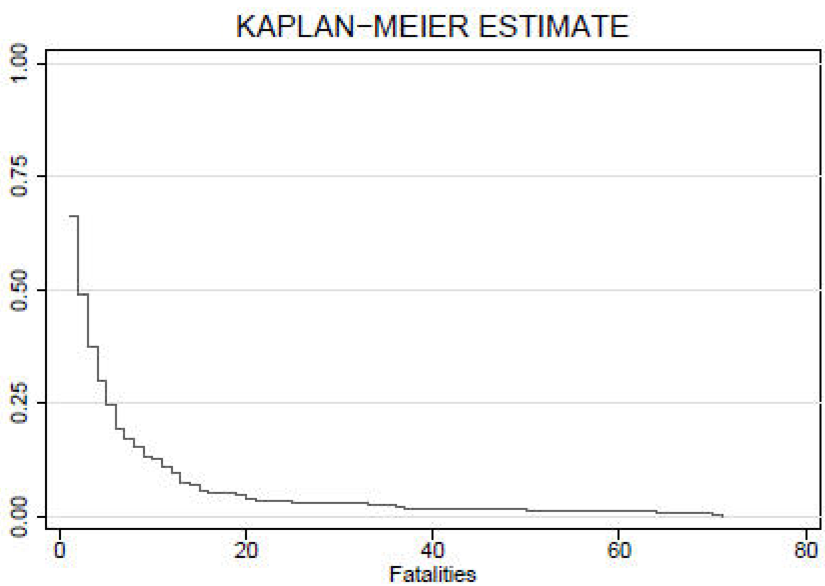



Fig. 5.15 Empirical complementary cumulative probability function for severity of attacks S (fatalities), Kaplan-Meier estimate, Diyala Province, Iraq. March, 2003 - March, 2006

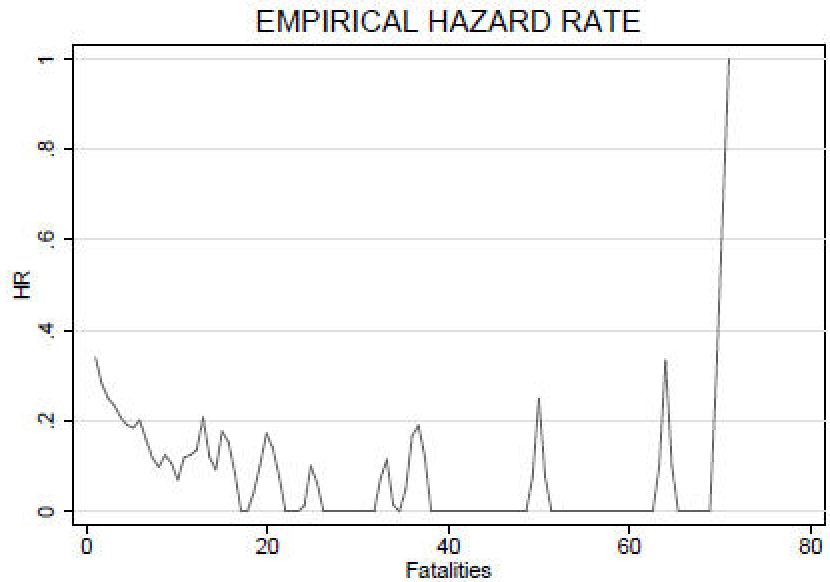



Fig. 5.16  Diyala Province, Iraq. March, 2003 - March, 2006

The empirical hazard rate for severity S, shown in Figure 5.16, starts off at a value close to 0.4 and decreases steadily by the twentieth day, after which it fluctuates around 0.1. The average empirical hazard rate for the whole period is 0.1472. These results have added uncertainty, because in this series there are 24 events with missing data. In general, the intensity in fatalities decreases in Diyala up to a value of around 20 twenty, after which it fluctuates with spikes around 50 and 65—not exactly well-behaved. Power Laws and Criticality Figure 5.17 shows the plot of the empirical c.c.d.f. of S in log-log space, including the observed data points, the best-fitting OLS line, and 95% confidence intervals.

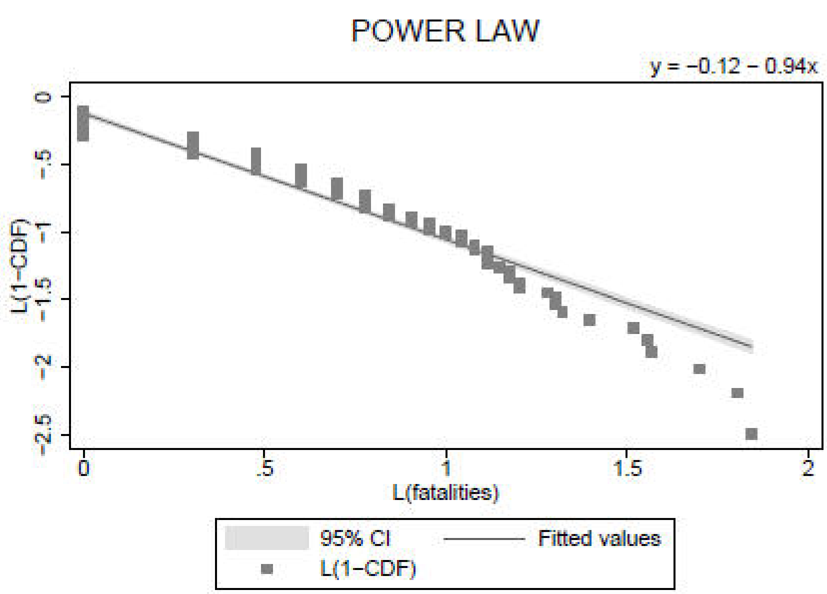



Fig. 5.17  Empirical c.c.d.f. of severity S (fatalities) in log-log space, Diyala Province, Iraq. March, 2003 - March, 2006

The linear regression fitted curve through the OLS approach yields a slope estimate of −0.94, which is statistically significant at the 1% level of confidence. Unfortunately, once again, the upper range falls off exponentially. Nonetheless, the standard errors reported are: 0.0098 and 0.0158 for the constant and slope coefficients, respectively; and the $R^2$ is 0.94. Overall, while the data are not normally-distributed, they also fall short of a perfect fit to a power law, indicating perhaps another fat-tailed distribution.

*Epochal (Diachronic) Patterns.* In Figures 5.18, 5.19, and 5.20 we report results the three epochs, in a similar way as for time between attacks (T). We observe a generally decreasing and fluctuating pattern from approximately 0.4 to 0 in Period 1 (without taking into account the last computed value that climbs to almost 1 due to rounding errors). The average in this first epoch was 0.3737 (omitting the last point). This pattern is quite different from the empirical hazard rate for the complete period in Diyala, but it could be due to fewer observations. On the other hand, a similar pattern in Period 2 to the empirical hazard rate of the whole series is observed in Figure 5.16. Its average hazard rate was 0.1719, again higher than the value for the whole series. And lastly, in Period 3 the average hazard rate is 0.1852, slightly higher than in the second epoch. Therefore, the average hazard force for severity S (fatalities) dropped substantially from Period 1 to Period 2, but then increased slightly in Period 3—a pattern not consistent with the organizational dynamics hypothesized by the ICG. This pattern in overall force mitigation may have been due to increased effectiveness of the coalition forces in Periods 2 and 3 relative to Period 1.

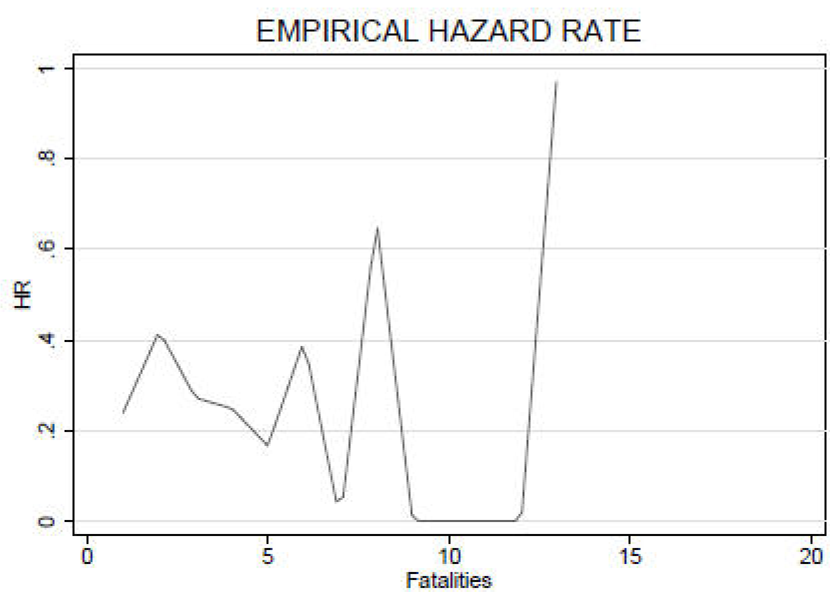



Fig. 5.18 Diyala Province, Iraq. Period 1, March, 2003 - June, 2004

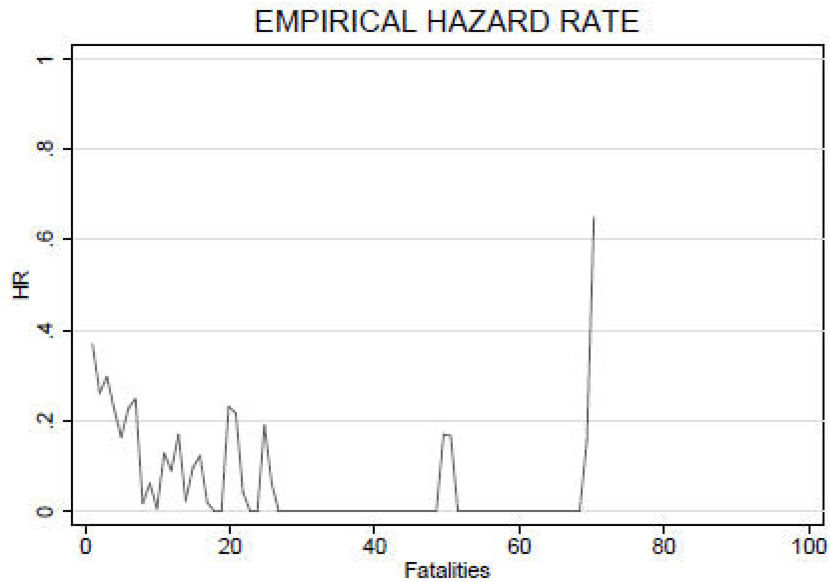



Fig. 5.19 Diyala Province, Iraq. Period 2, July, 2004 - June, 2005

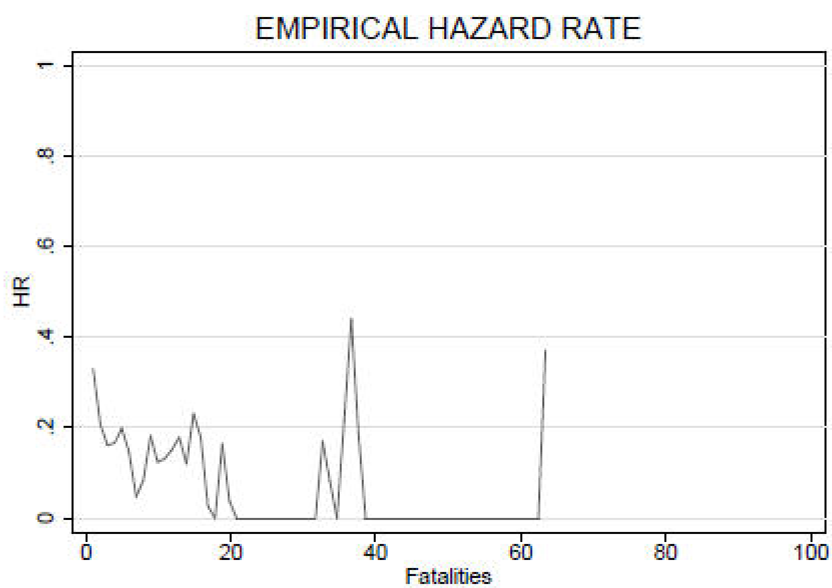



Fig. 5.20 Diyala Province, Iraq. Period 3, July, 2005 - March, 2006

*Power Laws and Criticality.* Figure 5.21 shows the results for the power law analysis in Period 1: the slope estimate is −1.15, which is statistically significant at the 1% level of confidence. Standard errors reported for the constant and slope coefficients are: 0.0427 and 0.0895, respectively; and the $R^2$ is 0.88. In Fig. 5.22 for Period 2 the slope estimate is -0.95, also statistically significant at 1% level of confidence. Standard errors reported for the constant and slope coefficients are: 0.0108 and 0.0185, respectively; and the $R^2$ is 0.96. In Figure 5.23 the slope came to -0.85, again statistically significant at 1% level of confidence, standard errors for the constant and slope were 0.0198 and 0.0299, respectively, and the $R^2$ is 0.9. In general, Periods 1 and 2 clearly show the best fits to a power law, although here again the very highest values tend to deviate. Thus, these two epochs might be reflecting a similar evolution to the one observed for the complete period previously. It is not feasible to make a formal test to compare the slope coefficients across epochs and the whole period due to the difference in the number of observations, however, they indicate a general movement toward a flatter and hence more lethal extreme range.

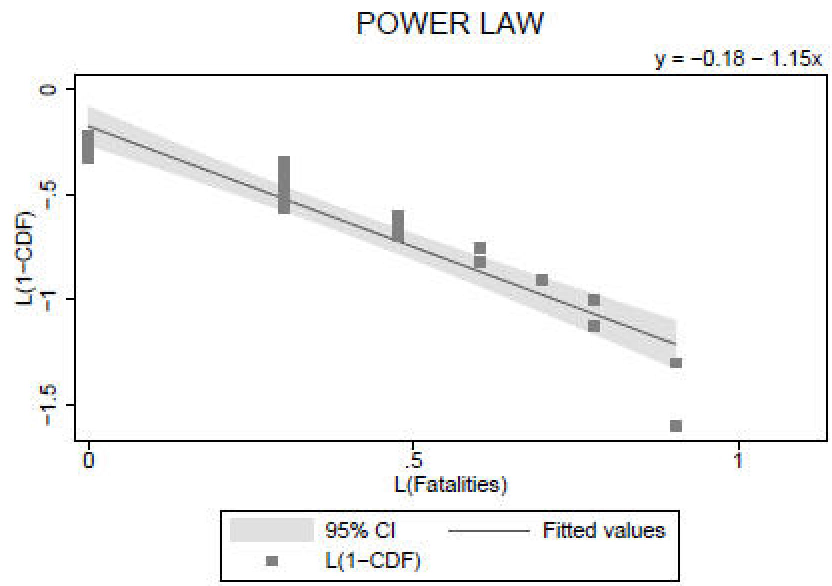



Fig. 5.21  Diyala Province, Iraq. March, 2003 - June, 2004

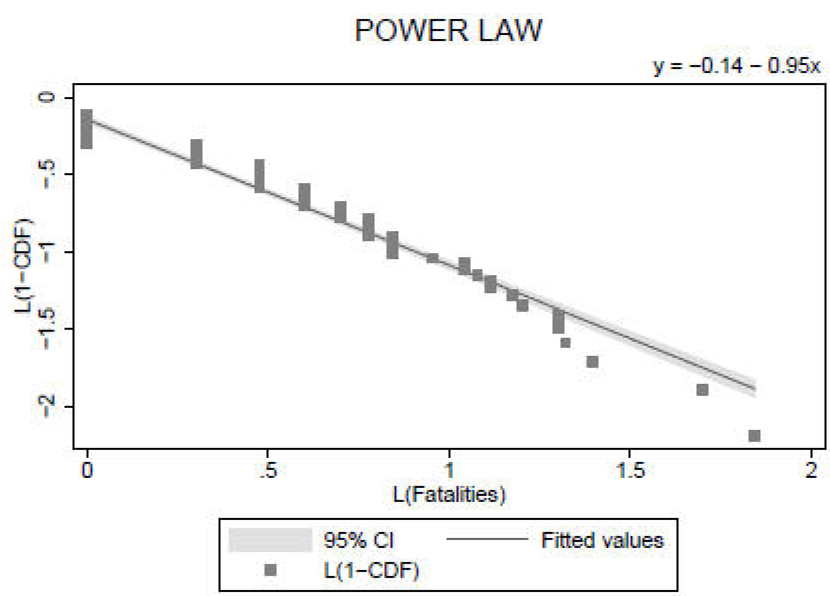



Fig. 5.22  Diyala Province, Iraq. July, 2004 - June, 2005

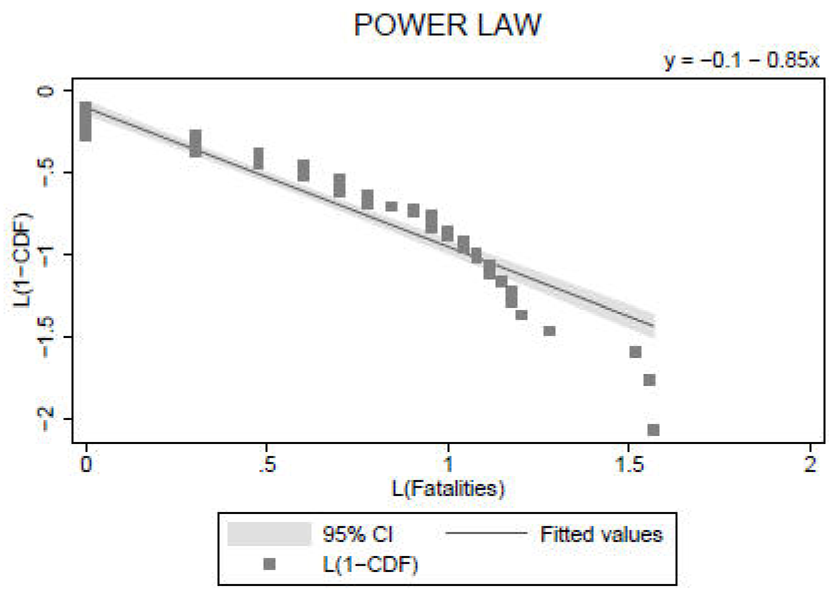



Fig. 5.23 Diyala Province, Iraq. July, 2005 - March, 2006

### 5.1.4 Discussion

The findings reported in this article suggest new insights and implications for research and policy. The utility of these findings is to illuminate the political and military context of conflict, and to address the questions raised in the introduction. The following discussion focuses on the main findings and selected policy implications.

***Main Empirical Findings***

The results for the onset of attacks $T$ (time between events) in the analysis of overall synchronic patterns showed a non-normal distribution with a heavy right tail. The formal normality tests (Shapiro-Wilk) also rejected the null hypothesis for the presence of a lognormal distribution in the data. The empirical c.d.f. and p.d.f. both allow one to visualize this non-normal pattern in the distribution of $T$ . These statistical properties suggest a high degree of political uncertainty, far from the equilibrium conditions of normality with marked central tendency. The Kaplan-Meier estimate of the survival function $\hat{S}(t)$ demonstrated that $T$ has a higher probability of realizing very short time spans between attacks, with rapidly increasing cumulative probability (much faster than Poisson). In addition, the empirical hazard force function showed that the intensity of the force for attacks to take place decreased up to approximately the tenth day, after which this intensity fluctuated below 0.1. The average hazard rate for the complete period was 0.088 attacks/day, but varied across epochs.

The power law analysis of onset times $T$ yielded a point estimate for the slope of the inverse relationship between the c.c.d.f. and $T$ of 1.03, with a statistically significant 1% chance of being wrong. This is basically a perfect inverse relation between these two logarithmic variables. More importantly, the exponent is therefore 2.03, which is critical given the usual level of imprecision in these data. The complexity-theoretic implication of this finding is that, for the overall period, extreme time spans are far more likely than would be normally assumed, and (by Equation 5.12) the first moment is practically nonexistent from a theoretical perspective.

For the *epochal diachronic patterns* the authors found that for the first epoch of $T$ the empirical hazard rate did not evolve in a clear-cut fashion, fluctuating basically around 0.1 until the fortieth day and going to zero thereafter. During Period 1 the average empirical hazard rate was 0.094, which is close to the level for the overall period. For the second and third epochs, however, this average increased to around 0.21, which is at least twice as the early period. In both epochs the hazard rates were decreasing until the twentieth day. In terms of the initial hypotheses, these results are generally supportive.

All the slope estimates of the power law analyses of $T$ for the three epochs were statistically significant at the 1% level of confidence, with high values of $R^2$ and—more importantly—very small standard errors. For the first epoch the slope estimate was –0.62, which is critical, –1.15 for the second epoch, and –1.25, or away from criticality for the third and last epoch. However, the authors also note the occurrence of systematic deviations of the highest values, down from the theoretically expected fit of the power law. Most likely, the upper tail for the distribution of $T$ was exponential, consistent with earlier literature, not power law.

Results for the severity of attacks $S$ (fatalities) also resemble in some ways the nonnormality characteristics of $T$ for the analysis of *overall synchronic patterns*. Severity showed a pronounced right tail according to its skewness (5.19) and the empirical p.d.f. plot confirmed such a pattern. The mode of severity was one casualty per attack in Diyala. Furthermore, according to the Shapiro-Wilk test the statistical distribution of $S$ did not belong either to a normal or log-normal distribution, which is also consistent with the fat tail. A Kaplan-Meier estimate constructed for $S$ also showed an overall similar pattern as that found for $T$ . However, in this case the c.c.d.f. decreased even faster and was less than 25% after the first five fatalities. The corresponding empirical hazard force of $S$ for the whole period started at 0.4 and decreased steadily until about the twentieth day, after which it fluctuated below 0.1 with an average value of 0.1472.

The power law analysis of $S$ for the whole period yielded a slope estimate of –0.94, which was also statistically significant at 1% level of confidence with a high $R^2$ value of 0.94. This demonstrated an almost perfect inverse relationship between the c.c.d.f. and $S$. The *epochal diachronic patterns* for the three epochs of $S$ showed a decreasing and fluctuating pattern from 0.4 to zero in Period 1. This pattern was different from the empirical hazard rate for the complete period in Diyala. However, a similar development in Period 2 to the empirical hazard force of the whole series was observed in the middle panel of Table 4. And, lastly, Period 3 also showed a somewhat similar process to Period 2 but with higher values at points close to 40 fatalities. All in all, the respective averages in these epochs for $S$ were higher than for the overall period.

Finally, the slope estimates for each of the three epochs in the power law analysis of the severity of attacks hovered around the critical value of 2.0 (2.15, 1.95, and 1.85, in chronological order). All of them are statistically significant at 1% level of confidence and high fit. Compared to the whole period, epochs 1 and 2 seemed to be closer to the process of the overall period.

None of these findings are available through plain observation or even field visits to Iraq. Although more traditional methods provide significant information of a different nature, these analytical results provide reliable insights concerning conflict dynamics. Such insights shed new light on insurgent activity and underlying processes. As such, these insights can help inform policymakers on the effectiveness of policies implemented or under consideration.

### *Policy Implications*

The following discussion of policy implications moves from some basic aspects of theoretical science in applied domains to institutional issues. Throughout, the science–policy nexus dominates the discussion, but several important themes are only summarized due to space limitations.

To begin, the scientific principle according to which "*there is nothing more practical than a good theory*" (Lewin, [132]) is or should be as valid for conflict analysis as it has been for social psychology—a science that evolved from humanistic origins dating back to Aristotle. In fact, as Vansteenkiste and Sheldon [133] have noted, Lewin intended to convey a two-way relationship between scientists and practitioners, such that the two would gain from each others' insights and specialized familiarity with information, issues, and methods—as well as toolkits. Whereas computational conflict scientists could and should develop research that yields more actionable results, practitioners could and should make greater use of available scientific progress, including viable areas of social science. The difficulties for each are many but the potential payoff is significant.

*Kline's thesis* is as true for conflict scientists as it is for physicists—some of whom, such as L. F. Richardson (founder of scientific conflict analysis) have made contributions to the science of conflict. Another way to appreciate the power of scientific approaches to conflict analysis is by recalling a thesis formulated by the late mathematician Morris Kline [134] that scientists do not learn mathematics for its own sake, but because mathematics provides a unique and powerful method for discovering fundamental features of the real empirical world that are not accessible through other methods—including direct observation, measurement, or experience. Gravity, pressure, and radiation are among the many natural phenomena that are understood through the exclusive medium of mathematics, even when one can observe their effects. Much the same is true of the conflict features revealed by the medium of theories such as those applied in this study. Conflict hazard rates (the latent intensity for attacks), half-life (the greater-than-even-odds tipping point for attacks to occur), and criticality (the phase transition to an extreme threat environment) are specific features of adversarial attacks that are known exclusively through the medium of mathematics, not through direct experience or plain observation.

Within a politico-military context, the *situational awareness dashboard* of conflict analysts and policymakers could be significantly enriched by adding newpanels for viewing computational indicators, such as those applied in this analysis or others with comparable theoretical foundation. For example, application of these methods soon after the ICG Phase I (i.e., after March 2003) would have revealed the gathering momentum of the insurgency (at least in Diyala), perhaps in time to have avoided the entrenchment and maturation of effective insurgent networks by reformulating an appropriate policy.5 To use an analogy, such latent indicators—based on political uncertainty theory, social complexity theory, and other mathematical or computational social science theories—are akin to measuring pressure changes before the onset of a storm, or radiation prior to blast pressure. Further testing of such indicators is necessary, now that theoretical and methodological foundations exist. A better dashboard—or "computational radar screen"—could help policy analysts and practitioners navigate with reduced risk through complex threat environments where traditional assessments have proven to be insufficient.

Although this study was conducted post-hoc, by necessity, *real-time or near real-time analysis* of uncertainty and complexity models is becoming increasingly feasible. This is also significant within a politico-military context. Already the increased interest in open source data and analysis on the part of the intelligence community is stimulating a new generation of information processing tools that will one day provide real-time capabilities in events analysis and related methodologies [135]. In addition, the merging of real-time facilities with advanced data visualization and cartographic tools (e.g., social GIS, spatial social science models)—combined with Moore's Law—will soon render feasible information awareness environments that would have been close to unthinkable just a few years ago. Real-time events data analysis will provide significant support not just for intelligence analysts but also for planners, decision makers, and others that can benefit from feedback.

Besides these improvements, *sequential event process modeling of attacks*—such as for suicide bombings or Improvised Explosive Device (IED) attacks—could prove helpful for practitioners, as well as challenging from a scientific perspective. For instance, a detailed empirically based event process model (sometimes known as a "business model" in organizational theory) of IED attacks could shed significant light on the attackers' vulnerabilities, by revealing actionable information that a defender could exploit to prevent attacks or mitigate their effects. Models like this already exist for weapons of mass destruction ([136], chap. 15); they should be developed for a broad variety of insurgency and irregular warfare attacks. More specifically, event process models should focus on phases in the overall life cycle of an attack:

1. Decision making: Attackers deciding to act, including cognitive processes and alternative choice mechanisms;
2. Planning: Attackers organizing the schedule for implementing the attack, including operational security;
3. Preparation: Attackers coordinating the tasks necessary to execute the attack;
4. Execution: Attackers carrying out the attack that causes undesirable effects for the defender;
5. Effects: Consequences affecting the defender;
6. Recovery: Defenders restoring partially or fully restoring their condition, including socio-psychological aspects;
7. Investigation: Defenders engaging in a fact-finding campaign to apprehend attackers and their confederates; and, last but not least;
8. Prosecution: Defenders apprehending and processing attackers through the criminal justice system.

The simple fact that the operational causal structure of an attack's processes is serialized—not parallelized—holds fundamental and inescapable policy and practical implications: all serialized behavior is vulnerable to disruption by elimination of one or more necessary conjunctions. Effective defenders must therefore learn how to exploit the inescapable serialization of an attacker's process—by making the difficult life of insurgents almost impossible or as difficult as possible.

Of course, when it comes to the complex conflict dynamics of insurgency and asymmetric warfare, another important consideration within a politico-military context is that *not all the ne-*

*cessary conflict science is known*—not even for selected regions of the world or for subsets of actors—and much will remain unknown for a long time, even as better data and better theories are developed and become available to the policy community. But this situation in the politico-military domain of national security is not different from what occurs in medicine, engineering, or economics; and yet, public policy in these areas does attempt to draw on the best existing scientific understanding. Understanding what one does not know is as important as mastering what one does know.

It is important to increase the *availability and desirability of scientific knowledge on conflict*. The main findings from this study—summarized in the previous section—offer some new insights that are worth considering in the domain of policy analysis and planning. This study—and others like it that apply computational social science approaches to the analysis of real-world conflict events [137], [138], [139], [140], [141] —begin to indicate that some new systematic approaches could eventually become available to policy analysts and practitioners. Much remains to be demonstrated, but some evidence of increasing relevance is already available.

The *specific policy relevance of findings* such as those reported in this study of uncertainty and complexity patterns in adversary behavior must be judged directly in terms of new and testable insights and understanding. These may eventually permit different courses of action, or validation of policies that have been enacted on the basis of different criteria. For example, the hazard force analysis is capable of illuminating the conflict process by revealing phases of stability and instability that are otherwise not directly observable, even through the direct measurement of trends in attack frequencies or fatalities. Likewise, power law analysis can extract signals—such as the trajectory of the exponent in Equation (5.2)— capable of detecting the transformation of a threat environment or the increased likelihood of extreme attacks. Again, the application of these methods on a real-time or near real-time basis soon after March 2003 would have revealed the same gathering momentum as this study—conducted several years later. *The deteriorating conditions detected by power law exponents on the right-hand panels of Tables 5.5 and 5.6 provide unambiguous signals of an increasingly dangerous threat environment, indicating the increasing need for a counterinsurgency campaign that should have begun back in early 2004 at the latest—as opposed to three years later*. Moreover, such policy-relevant indicators could have been scrutinized by the scientific community, just like scientists discuss indicators and other metrics in numerous fields of public policy ranging from environment to health.

Besides anticipating the rise of the insurgency in Iraq, deteriorating hazard forces and increasing criticality could have anticipated the process of *ethno-sectarian segregation and humanitarian crisis with refugee flows* within Iraq as well as to neighboring countries. This is because, based on well-established concepts and principles of social science, social segregation—not just in situations like those in Iraq, but also in many urban areas—is an emergent collective phenomenon that is driven by many individual localized decisions that depend on tolerance for ethnic or sectarian diversity. In turn, such tolerance depends on trust and social bonds of reciprocity, collaboration, and expectations in terms of time horizon. When violence increases—as it did with incipient insurgency—fear in the populace also increased, leading to mistrust (ethnically diverse but formerly trusted neighbors can no longer be trusted), which leads to movement to regain security, which results in a collective pattern of segregation. Although the long chain of events may give the appearance of a Rube Goldberg process, the social scientific understanding of segregation processes has solid foundations in the pioneering work of Thomas Schelling [142] and others. Today, agent-based models of segregation offer unique and powerful computational tools for understanding ethno-sectarian segregation in irregular conflicts and—with added necessary refinements—for exploring and designing better preventive and mitigating policies. Some [135] have recently argued that one desirable course of action would be a comprehensive thrust to increase the policy relevance of scientific conflict analysis to increase national capability in this area—and in a timely fashion consistent with due scientific processes concerning testing, replication, peer review, publication, and other quality control mechanisms. This too, like Lewin's adage, is a *two way interaction between science and policy*: The computational social science of conflict can benefit from greater exposure to policy concerns (not limited to national security), and policy analysts and practitioners can benefit from new insights and understanding derived from science. The science of conflict (and peace) will always benefit from direct challenges originating from the policy community, and—vice versa—the national security policy community will benefit from advances in the relevant areas of social science that investigate conflict.

Admittedly, *practical policy solutions unfounded in science can sometimes suffice*, assuming some luck. Indeed, the Romans were able to build bridges that were sufficiently reliable to advance their military and strategic purposes—and indeed many Roman bridges are still intact and fully operable today—without any scientific understanding of the true laws of mechanics. Although this is certainly true—one does not need a complete science of conflict to improve current performance against adversaries—there is no denying that modern bridges built by modern science and engineering have vastly superior performance characteristics than their earlier Roman counterparts. The same is true for designing more effective counterinsurgency policies: much can be gained in terms of experience and other practical data, but a great deal more can be attained by exploiting scientific knowledge based on testable ideas and valid theories.

Ultimately, *scientific analysis of adversary threat environments can provide alternative views and insights that add value*, based on replicable methods and inter-subjective standards that are less personal or affected by biases. As well, the growing body of scientific knowledge about conflicts of many kinds—not just the insurgency and irregular warfare type of attacks examined in this study—might yet find its way into the policy process, much in the same way as knowledge from the economic sciences and the biological sciences has contributed to better economic policies and public health policies, respectively. Such a prospect leads to a final point concerning policy dimensions of scientific approaches to conflict analysis.

From an *institutional perspective*, the national security policy of the American polity— comprised of foreign and defense policies—is distributed across a number of departments and agencies; components of the national system of government. However, the distribution of science and engineering expertise or receptivity across these components, or even within them, is far from even. Some government institutions are more appreciative of science than others. The result of this uneven landscape is not only a differential appreciation for science across departments and agencies, but cultural and attitudinal differences that render the adoption of scientific methods and greater systematic rationality problematic in some quarters—especially those affected by ideology. C. P. Snow's "two cultures" coexist, often under considerable stress, throughout many areas of the national security establishment— including the legislative branch. Advancing the role of science in the area of national security policy is a complex organizational process that involves not only scientists and practitioners, but the institutions and norms within which they operate. The same is true in allied countries that share similar concerns to America's.

### 5.1.5 Summary

Neither time between attacks *T* or severity of attacks *S* (fatalities) have a normal or log-normal distribution. Instead, both variables showed heavy tails, symptomatic of non-equilibrium dynamics, in some cases coming close to approximating a power law with critical or near critical exponent value of 2. The empirical hazard force analysis in both cases showed that the intensity was high for the first occurrences in both variables, namely between March 2003 and June 2004. Moreover, the average empirical hazard rate clearly increased throughout the three epochs, supporting the article's main hypotheses. These findings—and the underlying theoretical approach and methodology— demonstrate the potential value of adversarial models for conflict analysis. From an applied policy perspective, the article highlighted the additional knowledge contributed by these kinds of analysis, including the fact that real-time or near real-time implementation of these methods could have revealed the surge of insurgents in Diyala, Iraq, relatively soon after March 2003. These and related methods from the computational social science of conflict should be viewed within the broader context of science and policy.

## 5.2 Timed Influence Nets Applied to the Suppression of IEDs in Diyala, Iraq

**Lee W. Wagenhals and Alexander H. Levis**

### 5.2.1 Introduction

A case study was developed to demonstrate the capability of Timed InfluenceN to develop and analyze courses of action. The specific issue that the case study addressed was stated as follows: given a military objective and a set of desired effects derived from statements of commander's intent, develop and analyze alternative courses of actions (COAs) that will cause those desired effects to occur and thus achieve the military objective. Specifically, the case study demonstrated the use of a TIN tool called Pythia that has been developed at George Mason University. This demonstrated the use of the tool to create knowledge about an adversary and the population that potentially supports or resists that adversary and the use of the TIN to analyze various COAs.

A scenario was chosen based on the problem of suppressing the use of Improvised Explosive Devices (IEDs) in a specific province of Iraq, denoted as province D in the year 2005. Specifically, it is assumed that IED incidents have increased along two main east-west routes between the capital town C of the province and a neighboring country M. Both roads are historically significant smuggling routes.

There were hundreds of documents about Iraq in general and D province in particular that were reviewed to get a better understanding of the situation. The province includes substantial fractions of Kurdish, Shia, and Sunni populations as well as other minorities. It was noted that the northern route was in the predominantly Kurdish region and the southern route was in a predominantly Shia region. A dynamic tension existed between these regions particularly with regard to the flow of commerce (overt and covert) because of the revenue the flow generated. It was noted that some revenue was legitimate, but a significant amount was not and was considered covert. Increased IEDs in one region tended to suppress the trade flow in that region and caused the flow to shift to the other. Consequently, each region would have preferred to have the IEDs suppressed in its region, but not necessarily in the neighboring region. The IED perpetrators needed support from the local and regional populations as well as outside help to carry out their attacks. The support was needed for recruiting various individuals to help manufacture the IEDs and to carry out the operations necessary to plant them and set them off. It was postulated that improving the local economy and the quality of the infrastructure services would reduce the local and regional support to the insurgents. Of course, this required effective governance and willingness on the part of the workers to repair and maintain the infrastructure that in turn required protection by the Iraqi security and coalition forces.

### 5.2.2 Model Development

With this basic understanding, the following steps were taken to create the TIN. First the overall key effects were determined to be:

1) IED attacks are suppressed on routes A and B (note these were modeled as separate effects because it may be possible that only one of the routes may have the IED attacks suppressed),

2) Covert economic activity improves along each of the two routes.

3) Overall overt economic activity increases in the region.

4) Insurgent fires are suppressed,

5) Local support for the insurgents exist and

6) Regional support for the insurgents exists.

Nodes for each of these effects were created in the Pythia TIN modeling tool. It was noted that suppression of IED attacks on one route could have an inverse effect on the covert economic activity on the other, but each could improve the overall overt economic activity. The suppression of the insurgent fires positively affected both covert and overt economic activity.

The next step was to identify the key coalition force (Blue) actions that would be evaluated as part of the potential overall COA. To be consistent with the level of model abstraction the follow high level actions were considered: 1) Blue coalition forces (CF) exercise their standard Tactics, Techniques, and Procedures (TPPs) (including patrols, searches, presence operations, and the like). 2) Blue Coalition Forces actively conduct surveillance operations. 3) Blue CF actively conduct Information Operations. 4) Blue CF continue to train the local Iraqi security forces and police. 5. Blue CF broker meetings and discussions between various Iraqi factions (Green).

Of course, it is not possible to just connect these actions to the key effects and, therefore, several other sub-models were constructed and then linked together to produce the final model. These models include a model of the process the insurgents must use to conduct IED operations, a sub-model for the infrastructure and economic activity, and a sub model of the political and ethno-religious activities. In addition, it was recognized that the region was being influenced by outside sources, so these also were added to the model.

The sub model of the insurgent IED activities was based on the concept of how the insurgents develop an IED capability. They must have the IEDs, the personnel to carry out the IED operation, the communication systems to coordinate the operation and the surveillance capability to determine where to place the IED and when to set it off. Each of these in turn requires additional activities. For example, the personnel must be recruited and trained. The IEDs must be manufactured, and this requires material and expertise. Furthermore, the insurgents must be motivated to use their capability. Much of this capability relies on support by the local and regional population and funding and material from outside sources. The nodes and the directed links between them were added to the TIN model to reflect the Insurgents' Activities.

The economic and infrastructure sub-model included nodes for each of the main essential services: water, electricity, sewage, health, and education. It also included financial institutions (banks, etc.) and economic activities such as commerce and retail sales of goods. The nodes for the economic and infrastructure aspect of the situation were linked to the local and regional support as well as to the overall effect on the overt economic activity.

Of course, the economic and infrastructure services will not function properly without the support of the Political and Ethno-Religious entities in the region. Thus a sub-model for these factors was also included. To do this, three facets of the region were considered: the religious activities including Shia, Sunni, and Kurdish (who are either Shia or Sunni) groups, political party activities (Shia, Sunni, and Kurdish), and the Shia, Sunni, and Kurdish activities within the government structure including the civil service and the police and law enforcement institutions. The nodes for all of these activities were created and appropriate links were created between them. Links were also created to other nodes in the model such as local and regional support of the insurgents, economic activity and infrastructure development.

Finally, the outside influences were added to the model. These include external support for the insurgents, anti-coalition influences from neighboring countries, and external financial support for the local government and the commercial enterprises of the region. All of these nodes were modeled as actions nodes with no input links. With this model design, analysts could experiment with the effects of different levels of external support, both positive and negative, on the overall outcomes and effects.

The complete model is shown in Fig. 5.24. The model has 62 nodes, including 16 nodes with no parents, and 155 links.

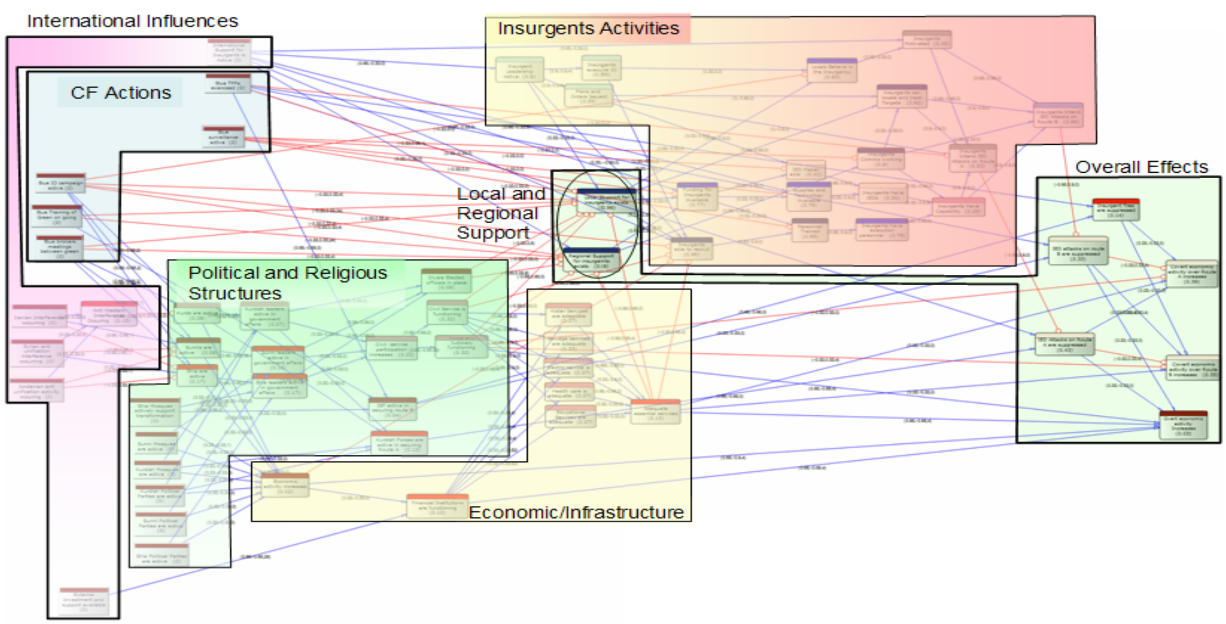



Fig. 5.24 Complete model of the case study TIN

Once the structure of the models was completed, the next step was to assign the values to the parameters in the model. This was done in two steps. First, the strengths of the influences (the g and h parameters on each link) and the baseline probability of each node were selected. This may seem like a daunting task given the subjective nature of the problem and the number of links and nodes. However, TINs and the Pythia tool limit the choices that can be made for these parameters. For each link, the model determines the impact of a parent node on a child node first if the parent is true and then if the parent is false. The choices range from very strongly promoting (meaning nearly 100%), strong (quite likely, but not 100%), moderate (50% or greater, but less than strong), slight (greater than 0% but not likely), or no effect. The modeler can also select a similar set of inhibiting strengths ranging from very strongly inhibiting to no effect. The second set of parameters is the baseline probabilities of the node. These are set to a default value of 0.5 meaning that the probability of the node being true is 0.5 given no other influences or causes (we don't know). In many cases, the default value was selected.

At this point it is possible, if not prudent, to perform some analysis on the model to observe its behavior. We will describe this in detail shortly. The final step in creating the TIN model was to assign the temporal parameter values to the nodes and the links. The default value for these is 0. With all values set to 0 the model is identical to an ordinary Influence Net. The process for assigning the time delay values is similar to that for assigning the strengths of the influences and the baseline probabilities. For each link, the modeler determines how long it will take for the child node to respond to a change in the probability of the parent node. In some cases the change is instantaneous, so the default value of 0 is appropriate. In others, a time delay may be expected. Part of this process requires that the modeler establish the time scale that will be used in the model and thus what actual time length of one unit of delay is. Any unit of measure can be selected from seconds to days, weeks, months or even years. In this particular model each time delay unit was set to be one week. In setting the time delay of the arcs, it may also be useful to set the time delay of the nodes. Again the default value for this delay is 0. This delay represents processing delay. It reflects the concept that if there is a change in one or more of the parent nodes, once the child node realizes that the change has occurred, there may be some time delay before it processes this new input and changes its probability value.

### 5.2.3 Model Validation

Once the complete TIN was created, a validation of the model was undertaken. This was done by consulting with several subject matter experts who had been in the region and were familiar with the situation. Each node and link was checked to see if the node and the relationships to and from that node made sense. In short, we were confirming that the overall structure of the model made sense. Several suggestions were made and the changes were incorporated. Once the structure had been vetted, then the parameters were checked. This was done link by link and node by node. First the strengths of the influences were checked, then the baseline probabilities, and finally the time delays.

### 5.2.4 Analysis

Once the TIN model was finished and validated, two levels of analysis were accomplished to demonstrate the utility of the approach. The first level is the logical level. This can be done without using the parameters because it only requires the structure of the model. At this level of analysis the model shows the complex causal and influencing interrelationships between Blue CF, the external influence, the religious and political factions, the adversary (Red), and the local and regional population (Green). This particular model shows that while Blue CF has some leverage, there are many other outside influences that also can affect the outcome of any actions that Blue may take. The model identifies these influences and how they may help inhibit the progress that is made as a result of Blue CF actions. Furthermore, the model shows relationships between the actions and activities of major religious and ethnic groups and effects on government activities (police, judiciary, public works and service, etc.). It shows the impact of the adequacy of government and public services on support of the insurgency. It captures the IED development, planning, and employment processes and the impact of the other activities, the status of public services, and coalition interventions on those processes. Finally the model captures interaction of IED attack suppression on two major trade routes (suppressing one route increases attacks on the other). In short, the model has captured Blue's understanding of a very complex situation and can help articulate concepts and concerns involved in COA analysis and selection.

The second level of analysis involves the behavior of the model. It is divided into a static quantitative and a dynamic temporal analysis. The static quantitative analysis requires the structure of the model and the non temporal parameters to be set. The temporal, time delay parameters should be set to the default value of 0. This analysis enables one to compare COAs based on the end result of taking the actions in the COA. In the Province D model, four major COAs were assessed as shown in Fig. 5.25. This table has four parts, an Action stub in the upper left corner, the Action or COA matrix to the right of the Action stub, an Effects stub below the Action stub, and the Effects matrix adjacent to the Effects stub. In the COA matrix, the set of COAs that have been evaluated are listed with an X showing the actions that comprise the COA. The Effects matrix shows the corresponding effects as the probability of each effect.

| Actions | Situation (COA) 1 | Situation (COA) 2 | Situation (COA) 3 | Situation (COA) 4 |
|---|---|---|---|---|
| International Interference | X | X | X | X |
| External Financial Support | | X | X | X |
| CF TTPs and Surveillance | | X | X | X |
| CF IO, training, brokering | | | X | X |
| Iraqi political and religious group participation | | | | X |
| EFFECTS | | | | |
| Local and Region Support for Insurgents Exists | 0.97 | 0.92 | 0.26/0.36 | 0.22/0.14 |
| IED Attacks Suppressed on Route A / B | 0.17/0.15 | 0.31/0.34 | 0.67/0.68 | 0.85/0.74 |
| Insurgent's fires suppressed | 0.14 | 0.65 | 0.9 | 0.93 |
| Public services adequate | 0.12 | 0.39 | 0.39 | 0.55 |
| Overt Economic Activity Increasing | 0.02 | 0.08 | 0.31 | 0.89 |
| Covert Economic Activity Increasing along routes A and B | 0.37 | 0.50 | 0.56 | 0.57 |

Fig. 5.25 Static Quantitative COA Comparison

COA 1 was a baseline case in which only international interference and support to the insurgency occurs. There is no action from the Blue CF, no external financial support to the infrastructure and the economy, and the religious and political factions are not participating in the governance of the area. The overall effects are shown in the lower part of the matrix. The results for this COA are very poor. There is support for the insurgency and it is very unlikely that the IED attacks will be suppressed on either route. With an ineffective local government, the basic services are inadequate which encourages the support to the insurgency and there is little chance for economic increase.

COA 2 represents the case where external financial support is provided and the coalition forces are active both in presence operations and in conducting surveillance. However, Information Operations, training of Iraqi forces and workers, and brokering of meetings and agreement between Iraqi factions are not occurring. In addition, the political and religious groups are not participating in positive governance and support to civil service. In this case, there is some improvement compared to COA 1, but still there are many problems. Local support for the insurgents is still very strong, although there is some suppression of the IED attacks and insurgent fires due to the activities of the coalition forces. As a result there is some improvement in public services and an increase in covert and overt economic activity, due in part to the reduction in IED attacks and insurgent fires.

The third COA contains all of the actions of COA 2 plus the addition of coalition force information operations, training of Iraqi security and police forces as well as civilian infrastructure operations and significant brokering of meetings and agreements between the various Iraqi agencies and factions. The result is a significant improvement in the suppression of the IED attacks and insurgent fires due to the improved capabilities of the Iraqi security and police forces and the significant drop in the local and regional support of the insurgents. There is also a significant improvement in the covert and overt economic activity. However, there is little change in the adequacy of the public services, due primarily to the lack of effective participation of the Iraqi governance function.

The last COA has all actions occurring. In addition to the activities of the previous three COAs, COA 4 includes the active participation of the Iraqi religious and political groups in the governance activities. It results in the highest probabilities of achieving the desired effects. While there is still some likelihood or local and regional support for the insurgents (0.22 and 0.14, respectively), many of the IED attacks are suppressed as are the insurgent fires. The result is significant increases in overt economic activity and moderate increase in the covert economic activity. Public services are still only moderately adequate, with room for improvement.

While the static quantitative analysis provides a lot of insight into the potential results of various COAs, it does not address the questions of how long it will take for the results to unfold or what should the timing of the actions be. The dynamic temporal analysis can provide answers to these types of questions.

Having created the TIN model with the time delay information, it is possible to experiment with various COAs and input scenarios. Figure 5.26 shows an example of COA and input scenarios that illustrate such an experiment. The second column of the Table in Fig. 6 shows a summary of the input nodes that were used in the experiment. They are divided into two types, those listed as Scenario and those listed as COA Actions. The scenario portion contains actions that may take place over which limited control is available. These set the context for the experiment. The second group contains the actions over which control exists, that is the selection of the actions and when to take them is a choice that can be made. The last column shows the scenario/action combinations that comprise the COA/Scenario to be examined. The column provides a list of ordered pairs for each Scenario Action or COA Action. Each pair provides a probability (of the action) and a time when that action starts. For example, the listing for the second scenario actions is [0.5, 0] [1.0, 1] which means that the probability of Country M and Country L interfering is 0.5 at the start of the scenario and changes to 1.0 at time = 1. In this analysis, time is measured in weeks.

The entries under the column labeled “COA 4a” mean that the scenario/under which the COA being tested is one in which there is immediate and full support for the insurgency (financial, material, and personnel) from international sources, and it is expected to exist throughout the scenario. The same is true for support from Country S. Countries M and L are modeled with the probability of providing support at 0.5 initially, but it immediately increases to 1.0 at week 1. All of the COA actions are assumed to not have occurred at the start of the scenario, thus the first entry of each is [0, 0]. The coalition force (Blue) actions start at week 1 with a probability of 1.0, meaning that all of the elements of Blue actions start at the beginning. With regard to religious activities, the Kurds begin at week 1 with probability 1.0. The Shia and Sunni have a probability of 0.5 starting at week 10 and then increase to 1.0, becoming fully engaged at week 20. In terms of political activity, the Kurds and Shia become fully active at week 1. The Shia become more likely to be active at week 10, fully active at week 20, then become less likely to be active at week 30 (probability 0.5) and then become fully active again at week 40. Finally, the External Financial support begins at week 26.

| | Action | COA 4a: List [p, t] |
|---|---|---|
| Scenario | Int'l Support to Insurgents | [1.0, 0] |
| Actions | Interference by countries M and L | [0.5, 0], [1.0, 1] |
| | Interference by country S | [1.0, 0] |
| COA | Blue TTPs activated | [0, 0], [1.0, 1] |
| Actions | Blue Surveillance, IO, Training, Brokering | [0, 0], [1.0, 1] |
| | Shia and Sunni Religious Activity | [0, 0], [0.5, 10], [1.0, 20] |
| | Kurd Religious Activity | [0, 0], [1.0, 1] |
| | Kurd and Shia Political Activity | [0, 0], [1.0, 1] |
| | Sunni Political Activity | [0, 0], [1.0, 20], [0.5, 30], [1.0, 40] |
| | International Investment | [0, 0], [1.0, 26] |

Fig. 5.26 Dynamic Temporal Analysis Input

To see what the effect of this input scenario on several key effects, the model is executed and the probabilities of the key effects as a function of time are plotted as shown in Fig. 5.27. In the figure, the probability profiles of four effects are shown: IEDs are suppressed on Routes A and B and Local and Regional support for the Insurgents exists.

Figure 5.27 shows that the probability of suppression of the IED attacks on the two routes increases significantly under this scenario. This means that the number of IED attacks should decrease, more on Route A than on Route B. The improvement can be expected to occur more rapidly along Route A than along Route B by about 35 weeks or 8 months. Route A is the northern route that is controlled by the Kurds and Route B is the southern route controlled by the Shia and Sunni. This can be attributed to the rapid and steadfast political and religious activities of the Kurds as opposed to the more erratic activities of the others as modeled in the input scenario (Fig. 5.26). Also note that it is expected to take 80 to 100 weeks (nearly 2 years) for the full effect to occur. Fig. 5.27 also shows a significant decline in support for the insurgents both by the local and the regional populace with the local support decreasing more as the situation with respect to governance and services improves.

Of course it is possible to examine the behavior of any of the nodes in the model, by plotting their probability profiles. This can increase the understanding of the complex interactions and dependencies that in the situation that have been expressed in the TIN model. The TIN model provides a mechanism to experiment with many different scenarios and COAs. Questions like what will happen if some of the Blue CF actions are delayed or what will happen if the Shia or Sunni decide not to participate after some period of time can be explored. By creating plots of the probability profile of key effects under different scenarios, it is possible to explore the differences in expected outcomes under different scenarios. This can be illustrated by changing the input scenario. Suppose that it is believed to be possible to get other countries or external organizations to reduce the support to the insurgents by some means, for example diplomatic or military action. It is postulated that we could reduce the likelihood of such support to about 50% but it will take 6 months to do this. The results can be modeled by changing the input scenario of Fig. 5.26. In this case the first line of Fig. 5.26 is changed from [1.0, 0] to [1.0, 0] [0.5, 26]. All of the other inputs remain the same. Figure 5.28 shows a comparison of effect of this change on the suppression on IED attacks along Route B. The reduction in international support for the insurgents at week 26 can cause a significant improvement in the suppression of the IED attacks along Route B (and a corresponding improvement along Route A, not shown). The improvement begins about 6 months after the reduction in international support or about 1 year into the scenario. Thus, decision makers may wish to pursue this option.

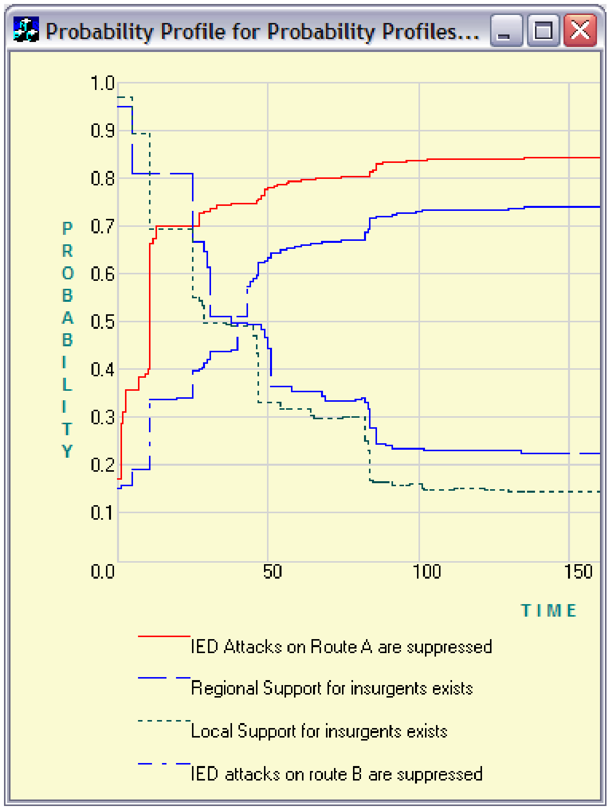



Fig. 5.27 Probability Profiles of Scenario (COA) of Fig. 5.26

### 5.2.5 Observations and Conclusions

Creating TIN models of situations provides a representation of knowledge about a situation that is derived from an understanding of the capabilities of an adversary and the interactions and dependencies of that adversary with the local and regional social, religious, and economic condition. Once created, the TIN model can be used to conduct computational experiments with different scenarios and COAs. In a sense, it provides a mechanism to assess various COAs based upon comparisons of the change in the probability of key effects over time

It is important to emphasize that the purpose of these models is to assist analysts in understanding the potential interactions that can take place in a region based on actions taken by one or perhaps many parties. It is not appropriate to say that these models are predictive. They are more like weather forecasts, which help us to make decisions, but are rarely 100% accurate and are sometimes wrong. To help deal with this uncertainty, weather forecasts are continually updated and changed as new data become available from the many sensors that make a variety of observations in many locations. Since these models cannot be validated formally, the appropriate concept is that of credibility. Credibility is a measure of trust in the model that is developed over time through successive use and comparison of the insights developed through the model and the occurrence of actual events and resulting effects.

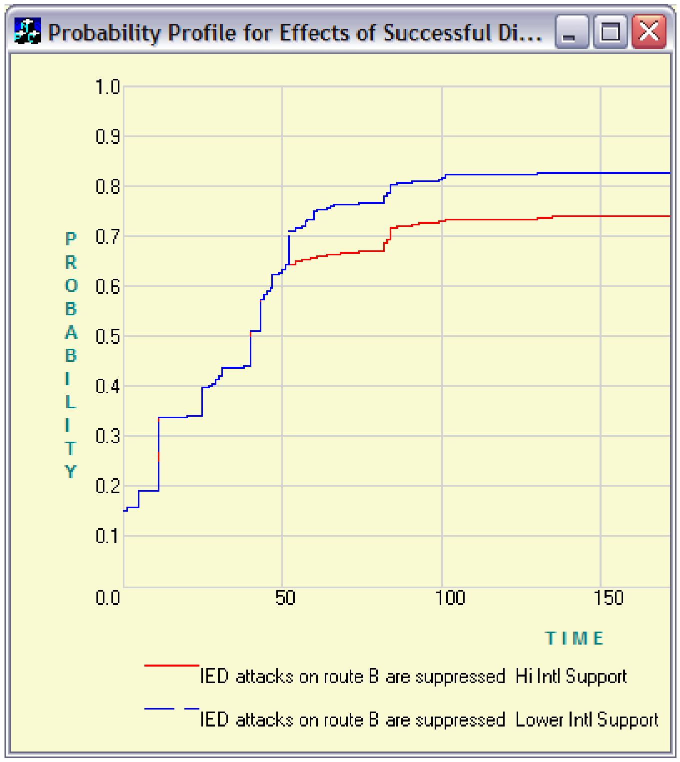



Figure 5.28: Comparison of the Effect of Different Scenarios

The techniques described in this paper can make an important contribution to a variety of communities that need to evaluate complex situations to help make decisions about actions they may take to achieve effects and avoid undesired consequences. The approach offers at least three levels of analysis, a qualitative evaluation of the situation based on the graph that shows the cause and effect relationships that may exist in the environment, and two levels of quantitative evaluation. The first level of quantitative analysis is static, and shows, in a coarse way, what the likelihood of different effects occurring is given different sets of actions. The second quantitative level is dynamic and shows how the scenario may play out over time. The relevant aspect is that the approach allows the inclusion of diplomatic, information, military, and economic (DIME) instruments and highlights their cumulative effects.

The models can be used to illustrate areas of risk including undesired effects, and risks associated *with the amount of time* it will take to achieve desired effects. It should also be noted that these models are not likely to be created on a one time basis. It can be expected that the understanding of the situation will continue to evolve requiring updates or even new models to be created. Perhaps the best contribution is that the technique offers a standardized way to analyze and describe very complex situations.

During the ten years that such models have been applied to different domains and problems, a number of lessons have been noted.

The first lesson is that these models are best suited to addressing issues at the operational/strategic level and are unsuitable for the tactical level. At the tactical level, we need to expand the range of attrition-type combat models to include the influences of the whole spectrum of instruments of national power. A very difficult issue is the determination of the interactions among the various instruments. For example, what is the effect of a diplomatic initiative when coupled with information operations and should the latter precede, be concurrent or follow the former?

The second lesson is that consideration of temporal issues is critical to the understanding of effects based operations applied to transnational terrorist networks. While the results of conventional military operations focused on attrition may be well understood, it is very difficult (not enough data yet) to estimate how some of the non military actions will affect the future recruitment by the terrorist organization. Even issues such as persistence are not well understood and, certainly, not quantified yet.

The third lesson is a critical one. It is much too early to establish general purpose TIN models that can be applied to different circumstances by changing the contained data. It is not even clear that this is a desirable approach or one that is technically sound for this class of problems. Rather, the way the technology and the tools are developing is to provide the analysts the capability to put together models (in a given domain about which the analyst is knowledgeable and for which SMEs are available) to address specific issues in the order of several hours. This approach has been tried successfully at the Global War games at the Naval War College in 2000 and 2001. At this time, the state of the art has taken two directions: (a) the development of template TINs for routine analyses and (b) the extraction directly from unstructured data using ontologies draft TINs that the analyst or modeler can then improve.

## 5.3 Enhanced Influence Nets Case Study

**Abbas K. Zaidi, Faisal Mansoor, Titsa P. Papantoni-Kazakos, Alexander H. Levis**

### 5.3.1 Introduction

In this section, we apply the algorithms developed in Chapter 3 to an illustrative TIN. We also provide a comparison of the latter results with those previously obtained via the use of the CAST logic. The model used in this section was presented by Wagenhals et al. in 2001 [18] to address the following scenario: As described in [18], internal political instabilities in Indonesia have deteriorated and ethnic tensions between the multiple groups that comprise Indonesia have increased. Religion has been a major factor in these conflicts. Members of one of the minority (2%) religious groups have banded together to combat disenfranchisement. These members have formed a rebel militia group. Armed conflicts recently occurred between those rebels and the Indonesian military. The rebels fled to eastern Java where they have secured an enclave of land. This has resulted in a large number of Indonesian citizens being within the rebel-secured territory. Many of these people are unsympathetic to the rebels and are considered to be at risk. It is feared that they may be used as hostages if ongoing negotiations break down with the Indonesian government. The food and water supply and sanitation facilities are very limited within the rebel-secured territory.

Several humanitarian assistance (HA) organizations are on the island, having been involved with food distribution and the delivery of public health services to the urban poor for several years. So far, the rebels have not prevented HA personnel from entering the territory to take supplies to the citizens. The U.S. and Australian embassies in Jakarta are closely monitoring the situation for any indications of increasing rebel activity. In addition, Thailand, which has sent several hundred citizens to staff numerous capital investment projects on Java, is known to be closely monitoring the situation.

### 5.3.2 Modeling

To reflect the situation stated above, a TIN was first created in [18] and is shown in Fig. 5.29. This TIN models the causal and influencing relationships between (external) affecting events (on the left side and along the top of the model in Fig. 5.29) and the overall effect of concern which is the single node with no parents on the right-hand side of the model. In this case, the effect is "Rebels decide to avoid violence". The actionable (external) events in this model include a combination of potential coalition, UN, and rebel actions. The coalition actions include actions by the US government, its military instrument of national power, actions by the Government of Indonesia, and actions by Thailand.

For purposes of illustration and comparison of results, we have selected a part of this network, as shown in Fig. 5.30.

The (external) affecting events in the TIN of Fig. 5.30 are drawn as root nodes (nodes without incoming edges). The text in each node, e.g., "1—Coalition Deploys Forces to Indonesia," represents a node ID and a statement describing the binary proposition. In Fig. 5.30, $\{A_i\}_{0 \le i \le 4}$ represents the set of the external affecting events, where the index 'i' depicts the node ID. The marginal probabilities for the external affecting events are also shown inside each node. In this illustration, we assume all external affecting events to be mutually independent (Section 3.4.)

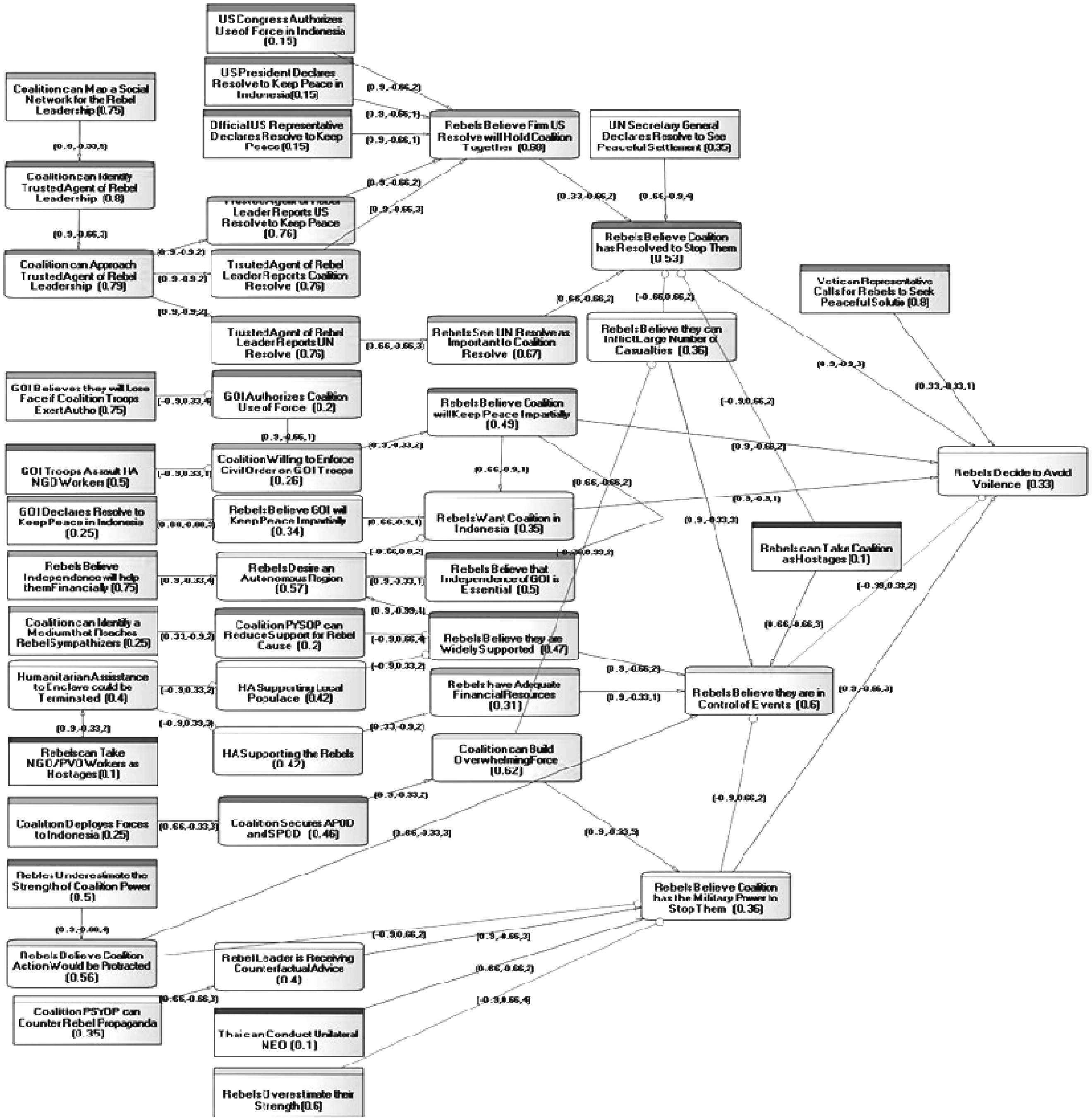



Fig. 5.29 Timed Influence Net of East Timor Situation [18]

A desired effect, or an objective which a decision maker is interested in, is modeled as a leaf node (node without outgoing edges). The node with ID '10' in Fig. 5.30 represents the objective for the illustration. In both Figs. 5.29 and 5.30, the root nodes are drawn as rectangles while the non-root nodes are drawn as rounded rectangles. A directed edge with an arrowhead between two nodes shows the parent node promoting the chances of a child node being true, while the roundhead edge shows the parent node inhibiting the chances of a child node being true. The first two elements in the inscription associated with each arc quantify the corresponding strengths of the influence of a parent node's state (as being either true or false) on its child node. The third element in the inscription depicts the time it takes for a parent node to influence a child node. For instance, in Fig. 5.30, event "1—Coalition Deploys Forces to Indonesia" influences the occurrence of event "7—Coalition Secures APOD and SPOD" after 3 time units.

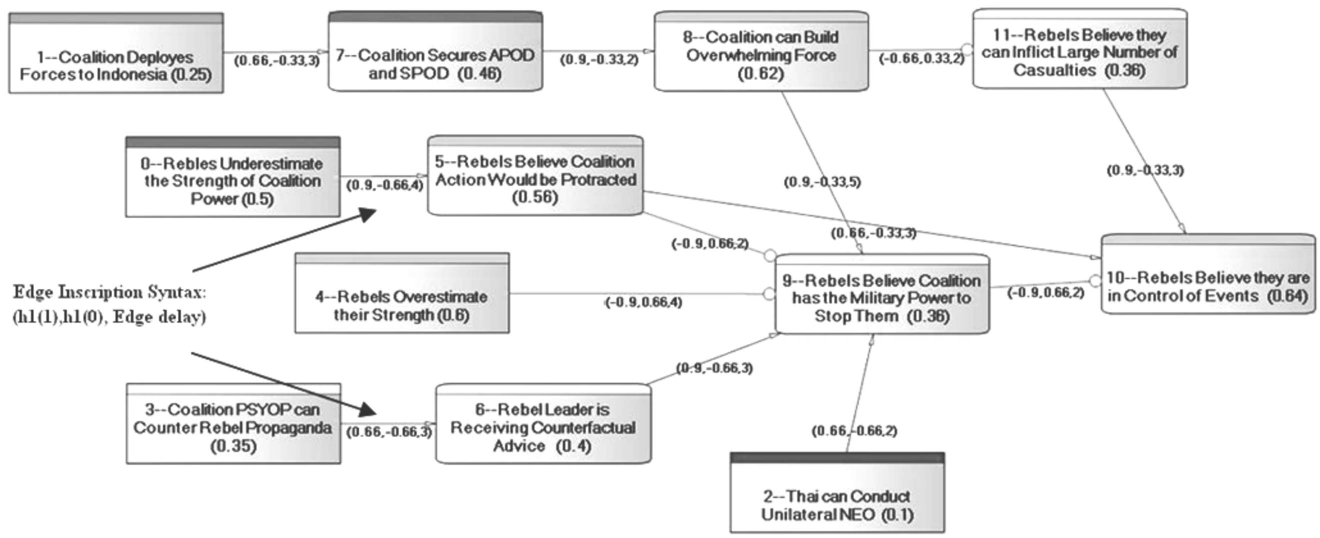



Fig. 5.30 Sample TIN for Analysis

*The purpose of building a TIN is to evaluate and compare the performances of alternative courses of actions described by the set* $\mathbf{A_T}$ *in the definition of TINs.* The impact of a selected course of action on the desired effect is analyzed with the help of a *probability profile*. The following is an illustration of such an analysis with the help of two COAs, given below:

**COA1**: *All external affecting events are taken simultaneously at time 1 and are mutually independent.*

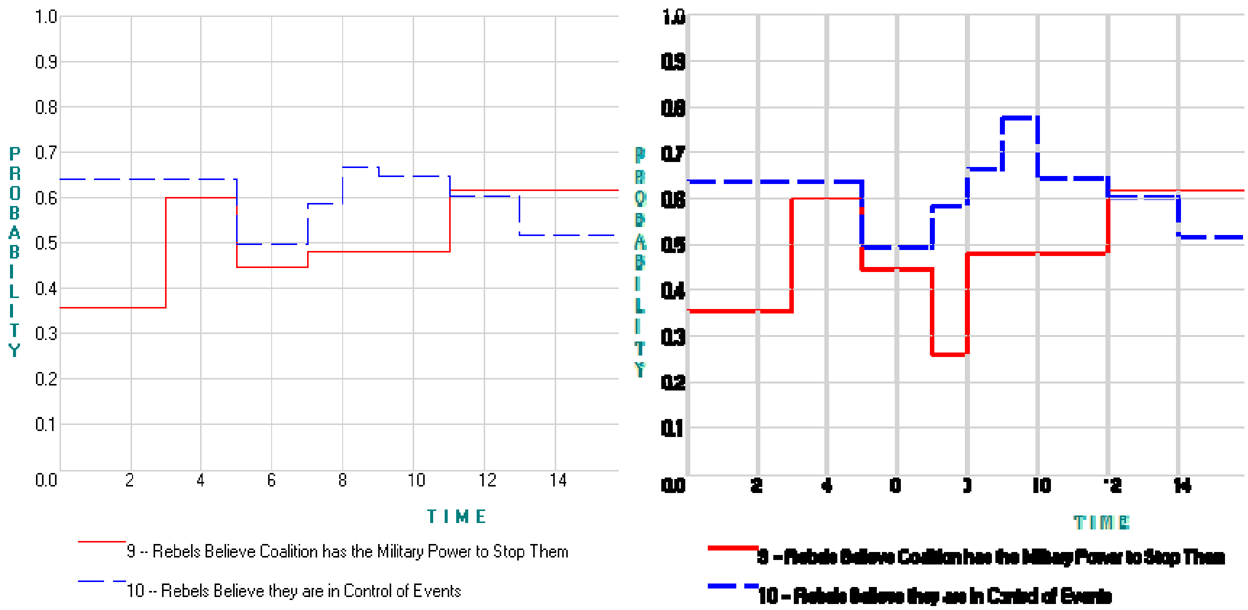
**COA2**: *Events {0, 2, 4} are taken at time 1, simultaneously, and events {1, 3} are taken at time 2, simultaneously.*

The two COAs can also be described as in Table 5.5.

**TABLE 5.5** The two Courses of Action

| Event | COA1 | | COA2 | |
|---|---|---|---|---|
| | **Time** | **Status** | **Time** | **Status** |
| 0 -- Rebels Underestimate the Strength of Coalition Power | 1 | 1 (= True) | 1 | 1 |
| 1 -- Coalition Deploys Forces to Indonesia | 1 | 1 | 2 | 1 |
| 2 -- Thai can Conduct Unilateral NEO | 1 | 1 | 1 | 1 |
| 3 -- Coalition PSYOP can Counter Rebel Propaganda | 1 | 1 | 2 | 1 |
| 4 -- Rebels Overestimate their Strength | 1 | 1 | 1 | 1 |

Note that the simultaneous occurrence of external affecting events does not necessarily imply simultaneous revealing of their status on an affected node; the time sequence of revealed affecting events is determined by both the time stamp on each affecting event and the delays on edges. Because of the propagation delay associated with each edge, influences of actions impact the affected event progressively in time. As a result, the probability of the affected event changes as time evolves. A probability profile draws these probabilities against the corresponding time line. In Fig. 5.31, probability profiles generated for nodes "9—Rebels Believe Coalition has the Military Power to Stop Them" and "10—Rebels Believe they are in Control of Events," using the CAST logic based approach in [4, 5, 13, 15, 17] are shown.



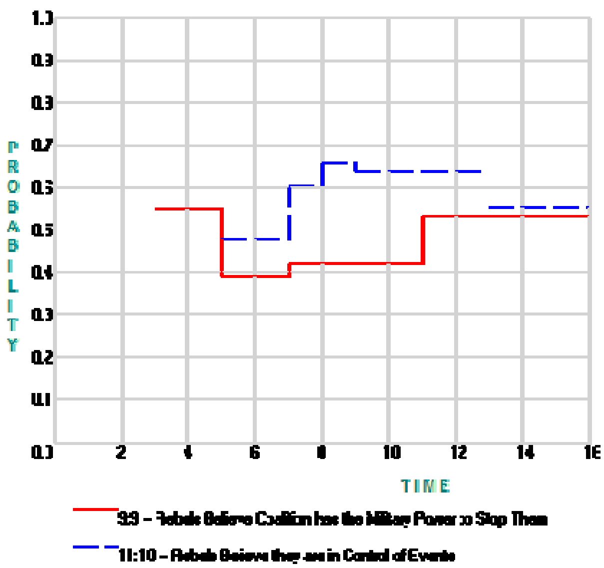

COA1 COA2

Fig. 5.31 Probability Profiles Generated by the CAST Logic Approach

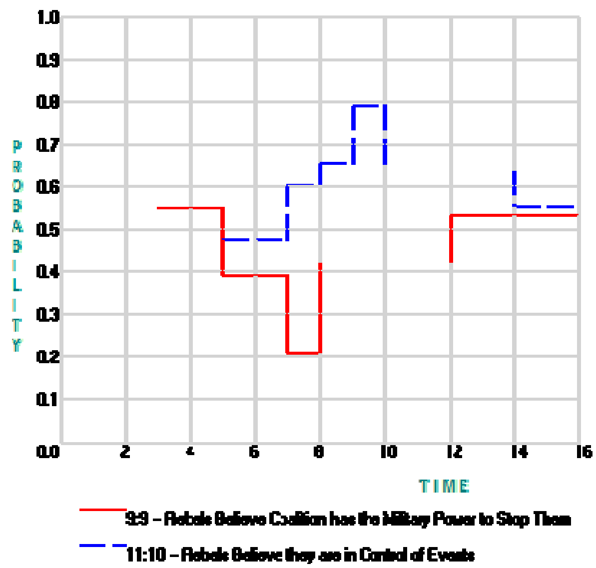
For the same TIN model as in Fig. 5.30 and the corresponding course of actions, we used the approach presented in this paper and produced pertinent results for the following two cases:

**Case I**

For this illustration, we utilize the influence constant model presented in section 3.8. A and the temporal case presented in section 3.6. The influence constants $\{h_i(x_1^n)\}_{1 \le i \le n-1}$ are first pre-computed via the dynamic programming expression in Lemma 3.2, section 3.3. The resulting probability profiles for the two affected events/propositions in the TIN are shown in Fig. 5.32.




COA1



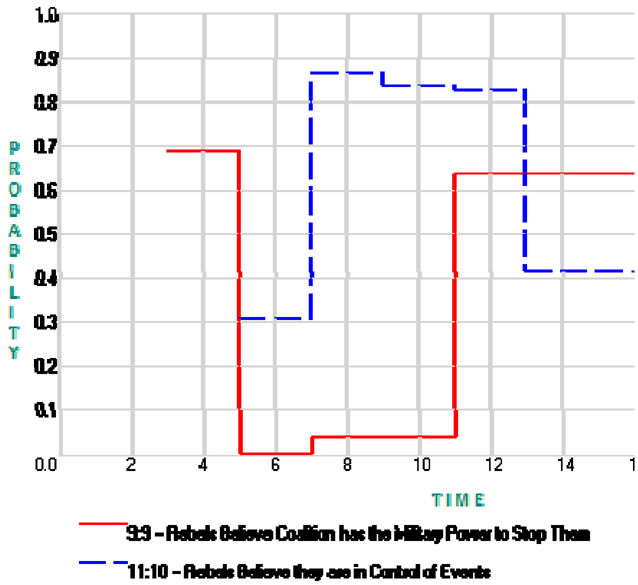

COA2

Fig. 5.32 Probability Profiles for Case I

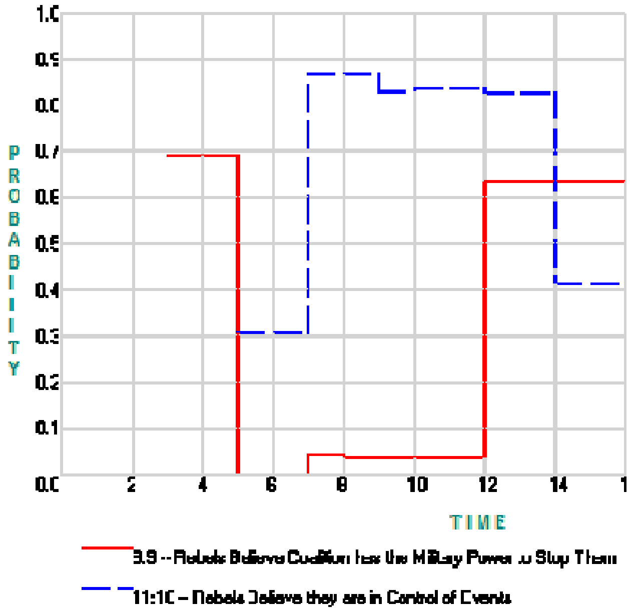
**Case II**

For this illustration, we utilize the influence constant model presented in section 3.8. A and the temporal case where the existence of an affecting event is assumed unknown to an affected event unless it reveals itself and makes its status known to the affected event. The conditional probabilities, in this case, are computed real-time by eq. (3.33). The resulting probability profiles for the two affected events/propositions in the TIN are shown in Fig. 5.33.

Comparing Figs. 5.31 and 5.32, we note that when the existence of all the external affecting events are initially known, then the approach in this paper produces results that are more accurate and consistent than those produced by the CAST logic based approach. This was expected, since the present approach has eliminated the inconsistencies that the CAST logic based approach suffers from. Unlike the CAST logic based approach, the probability profiles generated by the new approach only record the posterior probabilities resulting from the impacts of the external affecting events and do not assume any default initial values; in profiles of Figs. 5.31 and 5.32 the first impact is recorded at time '3'. Comparing Figs. 5.32 and 5.33, we note that, as expected, when the existence of the external affecting events are revealed sequentially in time then, there is a relatively high level of instability in time evolution, as compared to the case where the existence of all the external affecting events is initially known. The selection of a influence constant and of temporal models for a TIN under construction/analysis is a design issue and is reflected by the differences in the resulting probability profiles.




COA1




COA2

Fig. 5.33. Probability Profiles for Case II

## 5.4 Conclusion

In this chapter, several applications were presented. The first one dealt with the analysis of the data regarding the placement and effect of IEDs in the Diyala province of Iraq. The second case, illustrated the application of Timed Influence nets to the development and evaluation of potential Courses of Action for suppressing IEDs in Diyala. The thirds case illustrated how the expanded theory of Influence Nets relaxes the assumptions regarding causality while producing the same results with the original model when the restrictive assumptions apply.

# PART III: MODELS OF ORGANIZATIONS

# Chapter 6

# Computationally Derived Models of Adversary Organizations

**Ashraf M. AbuSharekh, Smriti K. Kansal, A. Erkin Olmez, and Alexander H. Levis**

## 6.1 Introduction

The effort to model organizational behavior with mathematical models has a long history. The groundbreaking work of Marshak & Radner [43] looked at the communications between organization members; today we would call this connectivity and associated information flows. Drenick [44] proposed a mathematical theory of organization in which a number of fundamental system theoretic ideas were exploited to draw insights for the design of organizations consisting of members who process tasks under time constraints – a form of Simon's [45] bounded rationality. Levis [46] and his students developed a discrete event dynamical model and a set of rules that governed the allowed interactions – whether they represented forms of information sharing or of commands. This model, expressed mathematically in the language of Colored Petri Nets [47], allowed the design of organizational architectures that could meet accuracy and timeliness constraints while not exceeding the workload limitations of the decision makers. Essentially, the organization members conducted information processing and decision making tasks, often supported by decision support systems in order to reduce workload, while increasing accuracy and timeliness of the organizational response [48].

The basic model of the single decision maker evolved over time in order to accommodate more complex interactions and allow for different types of internal processing by the organization members [49]. The early focus was on small teams in which several members needed to be organized to perform a demanding, time-sensitive task. The objective was to achieve organizational performance without causing excessive workload that would lead to performance degradation.

A key objective, relating structure to behavior, meant that the structure and attributes of the simulation models must be traceable, in a formal way, to the architecture design. Hence the use of the term "executable" model which denotes that there is a formal mathematical model used for simulation with characteristics that are traceable to the static designs. The mathematical model can also be used for analysis, i.e., properties of the model and performance characteristics can be determined from the mathematical description. A wealth of theoretical results on discrete event dynamical systems, in general, and Colored Petri nets, in particular, can be applied to the executable model.

More recently, the problem of modeling adversary organizations about which we may have limited information has received renewed attention. Adversaries may have differences in equipment or materiel, differences in command structures, differences in constraints under which they can operate, and, last but not least, differences in culture. The differences in equipment and in operational constraints can be handled easily in the existing modeling framework. Differences in command structures require some additional work to express these differences in structural and quantitative ways. The real challenge is how to express cultural differences in these, primarily mechanistic, models of organizations.

Other considerations that drive the design problem are the tempo of operations and whether the adversary has an explicit organization, as a military force would have, or an implicit one, as a loosely coupled terrorist organization may have. This work focuses on the ability to introduce attributes that characterize cultural differences into the mechanistic model for organization design and use simulation to see whether these parameters result in significant changes in structure. The objective, therefore, is to relate performance to structural features but add attributes that characterize cultural differences. Specifically, the attributes or dimensions defined by Hofstede [50] are introduced in the design process in the form of constraints on the allowable interactions within the organization.

In sections 6.2 and 6.3, the modeling approach is described briefly since it has been documented extensively in the literature. In sections 6.4 and 6.5, the Hofstede dimensions are introduced and then applied to the organization design algorithm. In sections 6.6 and 6.7, two illustrative examples are presented – one focuses on the design of adversary organizations and one on coalition organizations. In the final section, 6.8, advantages and shortcomings of this approach are discussed.

### 6.2 The Decision Maker Model And Organizational Design

The five-stage interacting decision maker model [49] had its roots in the investigation of tactical decision making in a distributed environment with efforts to understand cognitive workload, task allocation, and decision making. The five-stage model allows the algorithm in each stage to be defined and makes explicit the input and output interactions of the decision maker with other organization members or the external environment. It also has a well-defined algorithm for characterizing workload. This model has been used for fixed as well as variable structure organizations [51].

The five-stage decision maker (DM) model is shown in Fig. 6.1. The DM receives signals from the external environment or from another decision maker. The Situation Assessment (SA) stage represents the processing of the incoming signal to obtain the assessed situation that may be shared with other DMs. The decision maker can also receive situation assessment signals from other decision makers within the organization; these signals are then fused together in the Information Fusion (IF) stage to produce the fused situation assessment. The fused information is then processed at the Task Processing (TP) stage to produce a signal that contains the task information necessary to select a response. Command input from superiors is also received. The Command Interpretation (CI) stage then combines internal and external guidance to produce the input to the Response Selection (RS) stage. The RS stage then produces the output to the environment or to other organization members.

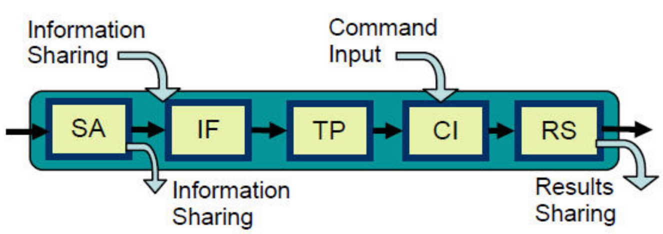



Fig. 6.1 Model of the Five-Stage Decision Maker

The key feature of the model is the explicit depiction of the interactions with other organization members and the environment. These interactions follow a set of rules designed to avoid deadlock in the information flow. A decision maker can receive inputs from the external environment only at the SA stage. However, this input can also be another decision maker's output. A decision maker can share his assessed input with another organization member; this is depicted as an input to the IF stage when the decision maker is receiving a second input. This input must be generated from another decision maker and can be the output of the SA or RS stage. In the CI stage, the decision maker can receive commands. This is also internally generated and must originate from another decision maker's RS stage. Thus the interactions between two decision makers are limited by the constraints enumerated above: the output from the SA stage, can only be an internal input to another decision maker's IF stage, and an internal output from the RS stage can only be input to another decision maker's SA stage, IF stage, or CI stage.

The mathematical representation of the interactions between DMs is based on the connector labels $\mathbf{e}_i$, $\mathbf{s}_i$, $\mathbf{F}_{ij}$, $\mathbf{G}_{ij}$, $\mathbf{H}_{ij}$ and $\mathbf{C}_{ij}$ of Fig. 6.2; they are integer variables taking values in {0, 1} where 1 indicates that the corresponding directed link is actually present in the organization, while 0 reflects the absence of the link. These variables can be aggregated into two vectors **e** and **s**, and four matrices **F**, **G**, **H** and **C**. The interaction structure of an n-decision-maker organization may be represented by the following six arrays: two n x 1 vectors **e** and **s**, representing the interactions between the external environment and the organization:

$\mathbf{e} = [e_i]$, $\mathbf{s} = [s_i]$ for i 1, 2, …, n

and four n x n matrices **F**, **G**, **H** and **C** representing the interactions between decision makers inside the organization. Since there are four possible links between any two different DMs, the maximum number of interconnecting links that an n decision- maker organization can have is

$$k_{max} = 4n^2 - 2n$$

Consequently, if no other considerations were taken into account, there could be $2^{k_{max}}$ alternative organizational forms. This is a very large number: 290 for a five-person organization.

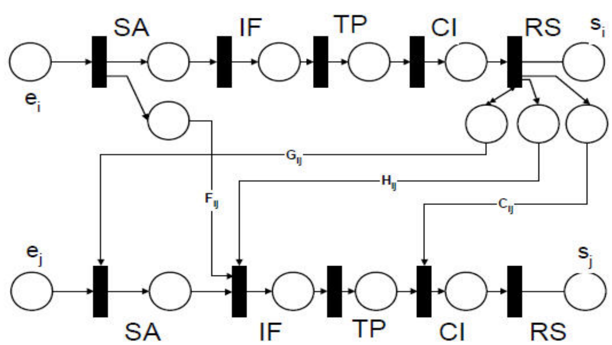



Fig. 6.2 One-sided Interactions Between Decision Maker i and Decision Maker j

In the Petri net representation of the DM model, the transitions stand for the algorithms, the connectors for the precedence relations between these algorithms, and tokens for the messages that flow between the DMs. If the tokens need to be distinct, i.e., carry information, then a Colored Petri net representation is used. Other organization components can be modeled using the same basic five-stage model, but eliminating one or more of the stages. For example, a processor that receives sensor data and converts it to an estimate of a vector variable can be modeled by a single SA transition, while a data fusion algorithm can be modeled by an IF transition. With this model of the organization member and its variants used to model other components, it is now possible to formulate the problem of designing decision-making organizations.

### 6.3. The Lattice Algorithm

The analytical description of the possible interactions between organization members forms the basis for an algorithm that generates all the architectures that meet some structural constraints as well as application-specific constraints that may be present. The set of structural constraints rules out a large number of architectures. The most important constraint addresses the connectivity of the organization - it eliminates information structures that do not represent a single integrated organization. Remy and Levis [52] developed an algorithm, named the Lattice algorithm, that determines the maximal and minimal elements of the set of designs that satisfy all the constraints; the entire set can then be generated from its boundaries. The algorithm is based on the notion of a simple path - a directed path without loops from the source to the sink. Feasible architectures are obtained as unions of simple paths. Consequently, they constitute a partially ordered set. The algorithm receives as input the matrix tuple {**e, s, F, G, H, C**} of dimension n, where n is the number of organization members.

There are some structures corresponding to combinations of interactions between components that do not have a physical interpretation; e.g., DMs can exchange information - $\mathbf{F}_{ij}$ and $\mathbf{F}_{ji}$ can coexist - but commands are unilateral- either $\mathbf{C}_{ij}$ or $\mathbf{C}_{ji}$ or none, but not both. Those structures should be eliminated, if realistic organizational forms are to be generated. The structural constraints define what kinds of combinations of interactions need to be ruled out. A set of four different structural constraints is formulated that applies to all organizational structures being considered.

- R1 A directed path should exist from the source to every node of the structure and from every node to the sink.
- R2 The structure should have no loops; i.e., the organizational structures should be acyclical.
- R3 There can be at most one link from the RS stage of a DM to each one of the other DMs; i.e., for each i and j, only one element of the triplet {$\mathbf{G}_{ij}$, $\mathbf{H}_{ij}$, $\mathbf{C}_{ij}$} can be nonzero.
- R4 Information fusion can take place only at the IF and CI stages. Consequently, the SA and RS stages of each DM can have only one input.

Constraint R1 eliminates structures that do not represent a single integrated organization and ensures that the flow of information is continuous within an organization. Constraint R2, allows acyclical organizations only[1]. Constraint R3 states that the output of the RS stage of one DM or component can be transmitted to another DM or component only once: it does not make much sense to send the same information to the same decision maker at several different stages. Constraint R4 prevents a decision maker from receiving more than one input at the SA stage. The rationale behind this limitation is that information cannot be merged at the SA stage; the IF stage has been specifically introduced to perform such a fusion.

---

[1] This restriction is made to avoid deadlock and circulation of messages within the organization.

Any realistic design procedure should allow the designer to introduce specific structural characteristics appropriate to the particular design problem. To introduce user-defined constraints that will reflect the specific application the organization designer is considering, appropriate 0s and ls can be placed in the arrays {**e, s, F, G, H, C**. The other elements will remain unspecified and will constitute the degrees of freedom of the design. The complete set of constraints is denoted by **R**.

A feasible structure is one that satisfies both the structural and the user-defined constraints. The design problem is to determine the set of all feasible structures corresponding to a specific set of constraints. Note that this approach is not, by design, concerned with the optimal organizational structure, but with the design of a whole family of feasible structures. At this stage, we are only concerned with the structure and information flows, i.e., the development of the set of feasible organizational forms. This set will become the admissible set in the problem of incorporating cultural constraints.

The notion of subnet defines an order (denoted <) on the set of all well defined nets of dimension n. The concepts of maximal and minimal elements can therefore be defined. A maximal element of the set of all feasible structures is called a maximally connected organization (MAXO). Similarly, a minimal element is called a minimally connected organization (MINO). Maximally and minimally connected organizations can be interpreted as follows. A MAXO is a well defined net such that it is not possible to add a single link without violating the set of constraints **R**. Similarly, a MINO is a well defined net such that it is not possible to remove a single link without violating the set of constraints **R**. The following proposition is a direct consequence of the definition of maximal and minimal elements: For any given feasible structure P, there is at least one MINO Pmin and one MAXO Pmax such that Pmin < P < Pmax. Note that the net P need not be a feasible. There is indeed no guarantee that a well-defined net located between a MAXO and a MINO will fulfill the constraints **R**, since such a net need not be connected. To address this problem, the concept of a simple path is used.

The following proposition characterizes the set of all feasible organizational structures: P is a feasible structure if and only if P is a union of simple paths, i.e., P is bounded by at least one MINO and one MAXO. Note that in this approach the incremental unit leading from a feasible structure to its immediate super-ordinate is a simple path and not an individual link. In generating organizational structures with simple paths, the connectivity constraint R1 is automatically satisfied.

The Lattice algorithm generates, once the set of constraints R is specified, the MINOs and the MAXOs that characterize the set of all organizational structures that satisfy the designer's requirements. The next step of the analysis consists of putting the MINOs and the MAXOs in their actual context to give them a physical instantiation. If the organization designer is interested in a particular (MINO, MAXO) pair because it contains interactions that are deemed desirable for the specific application, he can further investigate the intermediate nets by considering the chain of nets that is obtained by adding simple paths to the MINO until the MAXO is reached.

This methodology provides the designer of organizational structures with a rational way to handle a problem whose combinatorial complexity is very large. Having developed a set of organizational structures that meets the set of logical constraints and is, by construction, free of structural problems, we can now address the problem of incorporating attributes that characterize cultures.

## 6.4. Modeling Cultural Attributes

Hofstede [50] distinguishes dimensions of culture that can be used as an instrument to make comparisons between cultures and to cluster cultures according to behavioral characteristics. Culture is not a characteristic of individuals; it encompasses a number of people who have been conditioned by the same education and life experience. Culture, whether it is based on nationality or group membership such as the military, is what the individual members of a group have in common [53].

To compare cultures, Hofstede originally differentiated them according to four dimensions: *uncertainty avoidance (UAI)*, *power distance (PDI), masculinity-femininity (MAS),* and *individualism-collectivism (IND).* The dimensions were measured on an index scale from 0 to 100, although some countries may have a score below 0 or above 100 because they were measured after the original scale was defined in the 70's. The original data were from an extensive IBM database for which 116,000 questionnaires were used in 72 countries and in 20 languages over a six-year period. The hypothesis here is that these dimensions may affect the interconnections between decision makers working together in an organization.

The power distance dimension can be defined as "the extent to which less powerful members of a society accept and expect that power is distributed unequally" [50]. An organization with a high power distance value will likely have many levels in its hierarchy and convey decisions from the top of the command structure to personnel lower in the command structure; centralized decision making. Organizations with low power distance values are likely to have decentralized decision making characterized by a flatter organizational structure; personnel at all levels can make decisions when unexpected events occur with no time for additional input from above.

Uncertainty avoidance can be defined as "the extent to which people feel threatened by uncertainty and ambiguity and try to avoid these situations"[50]. An organization which scores high on un- certainty avoidance will have standardized and formal procedures; clearly defined rules are preferred to unstructured situations. In organizations with low scores on uncertainty avoidance, procedures will be less formal and plans will be continually reassessed for needed modifications. Klein et al. [54] hypothesized that during complex operations, it may not be possible to specify all possible contingencies in advance and to take into account all complicating factors.

The trade-off between time and accuracy can be used to study the affect of both power distance and uncertainty avoidance in the model [55]. Messages exchanged between decision makers can be classified according to three different message types: information, control, and command ones [56]. Information messages include inputs, outputs, and data; control messages are the enabling signals for the initiation of a subtask; and command messages affect the choice of subtask or of response. The messages exchanged between decision makers can be classified according to these different types and each message type can be associated with a subjective parameter. For example, uncertainty avoidance can be associated with control signals that are used to initiate subtasks according to a standard operating procedure. A decision maker with high uncertainty avoidance is likely to follow the procedure regardless of circumstances, while a decision maker with low uncertainty avoidance may be more innovative. Power distance can be associated with command signals. A command center with a high power distance value will respond promptly to a command signal, while in a command center with a low power distance value this signal may not always be acted on or be present.

## 6.5 Using Cultural Constraints

Cultural constraints help a designer determine classes of similar feasible organizations by setting specific conditions that limit the number of various types of interactions between decision makers. Cultural constraints are simply represented as interactional constraint statements. Four types of interactions have previously been defined (information sharing represented by matrix **F**, control represented by matrix **G**, result sharing represented by matrix **H**, and command represented by matrix **C**). The upper bounds, lower bounds and constants of an interactional constraint statement can take a value between 0 or the number of fixed-type interactions allowed by user-defined requirements (whichever is higher) and the maximum number of interactions allowed by user-defined requirements for a given problem, and are formulated using a group's cultural score. An approach for determining the values of these constraints has been developed by Olmez [57]. The constraints are obtained using a linear regression on the four dimensions to determine the change in the range of the number of each type of interaction that is allowed.

$$dY = c + \alpha(PDI) + \beta(UAI) + \gamma(MAS) + \delta\,(IND)$$

where Y is #F or #G or #H or #C

Example:

$\#\mathbf{F} \leq 2, \quad \#\mathbf{G} = 0, \quad 1 \leq \#\mathbf{H} \leq 3, \quad \#\mathbf{C} = 3$

The methodology to obtain the solution space given a set of user-defined constraints and cultural constraints using an extended lattice algorithm called C-Lattice is presented next.

**C-Lattice Algorithm:** The Lattice Algorithm allows the automatic generation of candidate structures based on a set of user and structural constraints. If the cultural constraints can be included in the problem statement in a manner similar to the structural constraints, then the lattice structure of the solution space will be preserved and an extended version of the Lattice algorithm may be used to generate structures that satisfy the additional cultural attributes. Since the cultural constraints impose limits on the number of interactions between the decision makers, they are placing additional structural constraints on the solution space. Hence the constraints R1 to R4 specified in [52] can be extended to include the cultural constraints R5 to R8. For example, for the cultural constraint statement give earlier, they become:

- R5: The number of **F** type interactions must be between 0 and 2
- R6: The number of **G** type interactions must equal 0
- R7: The number of **H** type interactions must lie between 1 and 3
- R8: The number of **C** type interactions must equal 3.

The flowchart in Fig. 6.3 explains the generation of the culturally constrained solution space.

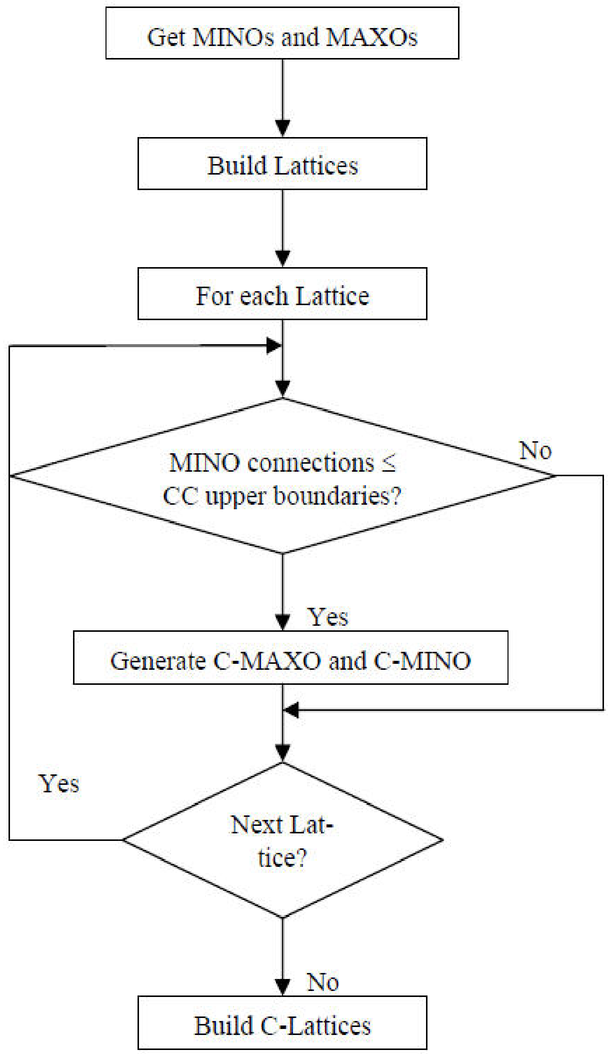



Fig. 6.3 Flowchart for culturally constrained solution space

MAXOs and MINOs are generated using the same algorithm described in [52]. The "Build Lattices" step checks if a MINO is contained within a MAXO. If it is, then the MINO is connected to that MAXO and forms a lattice. For each lattice in the solution space, we check the MINO to see if it violates the cultural boundaries. For example, if the number of **F** type interactions in the MINO is two and the maximum allowable by the cultural constraints is only one, then the MINO does not satisfy the cultural attributes and since the MINO is the minimally connected structure in that lattice, no other structure will satisfy the constraints. Hence the lattice can be discarded. If the MINO does pass the boundary test, then simple paths are added to it to satisfy the cultural constraints R5 to R8. The corresponding minimally connected organization(s) is now called the C-MINO(s) (culturally bound MINO). Similarly, by subtracting simple paths from the MAXO, C-MAXO(s) can be reached. The step "Build C-Lattices" connects the C-MINOs to the C-MAXOs. The advantage of using this approach is that the designer does not have to know the cultural attributes at the start of the analysis. He can add them at a later stage. This also enables him to study the same organization structure under different cultures. Also previously designed organization structures can now be analyzed in new light using cultural attributes.

### 6.6 Adversarial Modeling Using CAESAR III

The design approach and the algorithm are illustrated using a hypothetical example of an adversarial organization. The simulations were performed using a new application called CAESAR III developed in System Architectures Lab at GMU. CAESAR III is used for the design of information processing and decision making organizations at the operational and tactical levels; it takes into consideration cultural differences as required by the designer.

The scenario reads as follows: Intelligence from the field has informed Blue that the adversary (RedD) has organized a force to conduct operations in a distinct part (a province) of the Area of Responsibility. Intelligence has also indicated that the leadership consists of six persons with the command structure as shown in Fig. 6.4. The Field Intelligence Officers have different areas of responsibility.

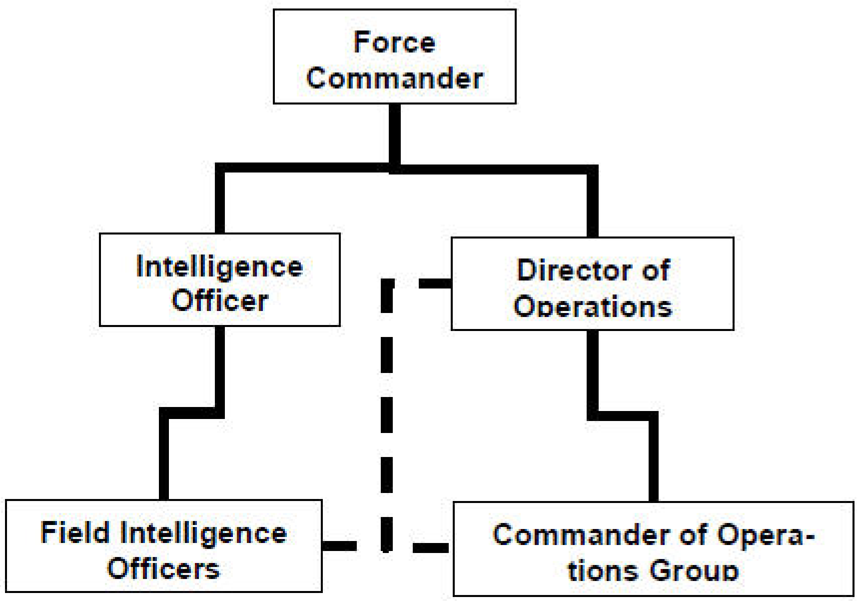



Fig. 6.4 Command Relationship Chart for Red

The cultural constraints for the two countries are also known.

**TABLE 6.1** Cultural Constraints

| | #F | #G | #H | #C |
|---|---|---|---|---|
| Blue | 2 | 0 | 1-3 | 2-3 |
| Red | 2-4 | 0 | 1-5 | 2-4 |

Given the scenario and the cultural attributes of Red and Blue, can one infer the possible organizational structure of the Red Force and its information exchanges so that Blue can focus its ISR assets to the right targets?

Based on the command relationship chart, one can deduce the number of decision makers (six in this case) and also specify the interactions between them;

- The Field Intelligence Officers interact with the environment and send their Situation Assessment to the Intelligence Officer.
- The Intelligence Officer fuses this information and sends his Assessment to the Force Commander.
- Based on the information received, the Force Commander directs the Director of Operations to develop a Course of Action
- The Director of Operations in turn directs the Commander of Operations to develop a plan based on the COA and execute it.
- The variable links have been introduced into the problem based on the type of interactions that usually exist in command and control organizations. They may or may not exist in the Red group. Cultural attributes will be used to determine probable links.

This can be represented in block diagram form as shown in Fig. 6.5. This information can also be represented in matrices form as shown below where ‘1’ represents a fixed type interaction and ‘x’ represents a variable type interaction (Fig. 6.6).

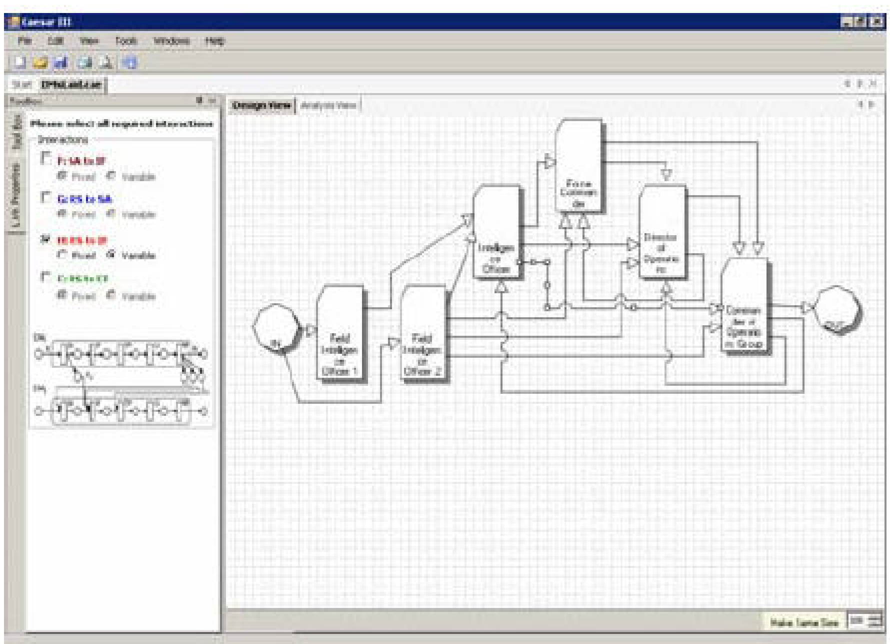


Fig. 6.5 Block Diagram of the Organization as seen in the CAESAR III GUI

The resulting universal net is shown in Fig. 6.7. Running the lattice algorithm without introducing the cultural attributes at this point helps design all feasible organizational structures that meet the specific constraints of the problem. The resulting solution space has a single lattice bounded by one MINO and one MAXO. Figure 6.8 shows the partially expanded solution space.

Applying Red's cultural attributes to the solution space places further constraints on the number of allowable interactions and helps determine the (plausible) organizational structures that Red may be employing. The resulting solution consists of one MINO and 3 MAXOs and is shown in Fig. 6.9.

$$e = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad s = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$F = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & x & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad G = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & 0 & 0 \\ 0 & 0 & x & 0 & x & 0 \end{bmatrix} \quad C = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & x \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 6.6 Matrix representation of the design problem

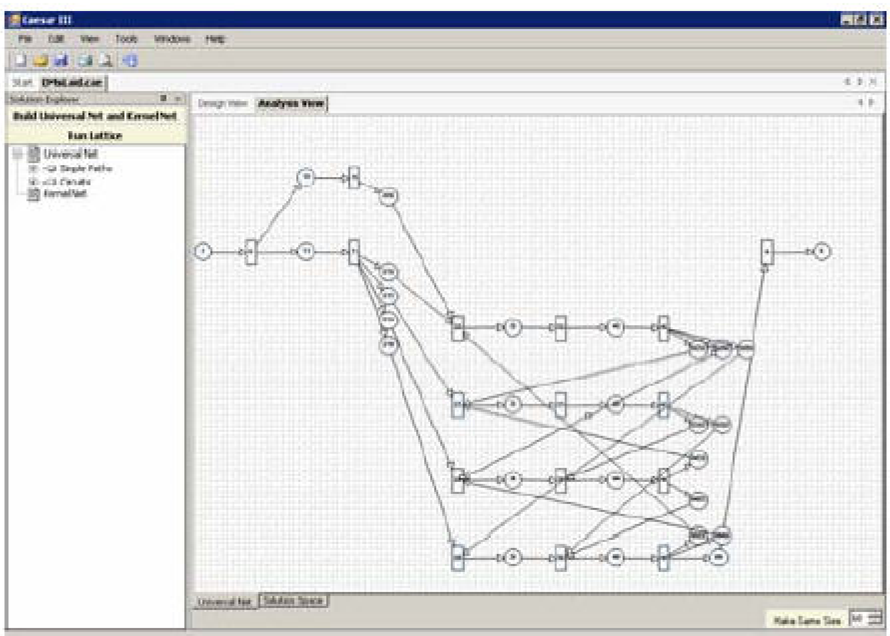



Fig. 6.7 Universal Net

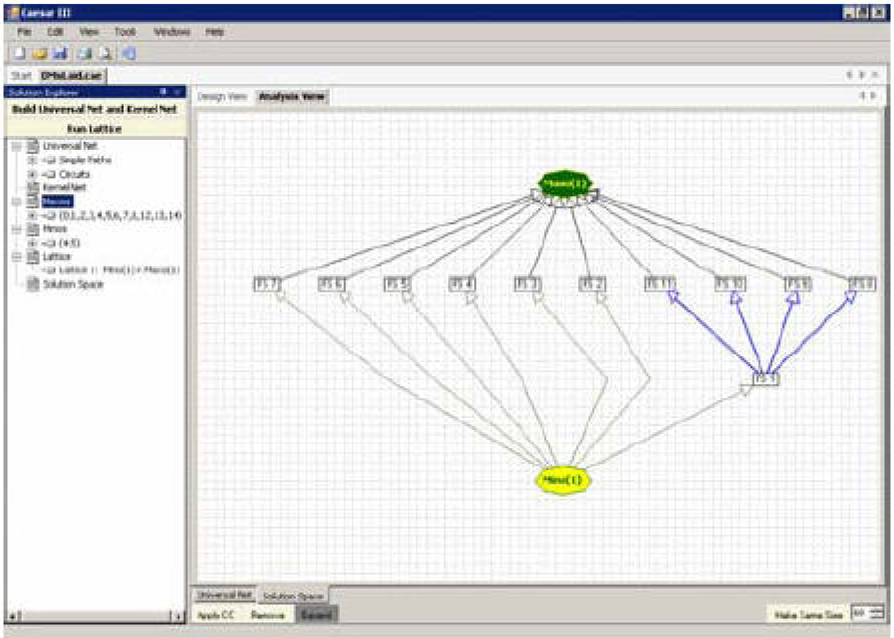


Fig. 6.8 Partially expanded solution space

The C-MAXOs and the C-MINOs lie within the MAXOs and the MINOs, i.e., the culturally bound solution space is contained in the un-constrained solution space.

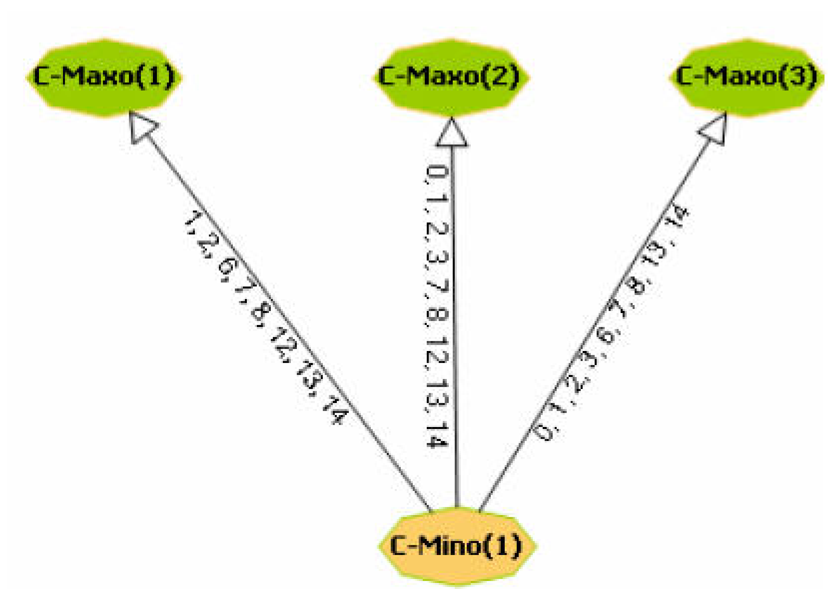



Fig. 6.9 Culturally Constrained Solution Space for Red

An expanded lattice is shown in Fig. 6.10. All the structures that lie between a C-MINO and a C-MAXO satisfy the cultural constraints. The actual Petri nets corresponding to the CMINO and C-MAXOs are shown in Figs. 6.11 to 6.14.

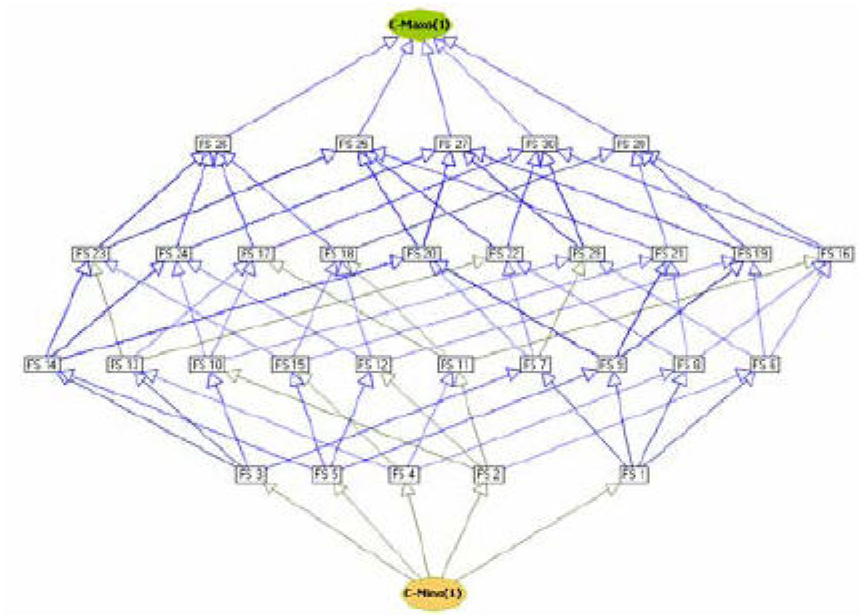



Fig. 6.10 Expanded Lattice Structure from C-MINO(1) to CMAXO( 1) for Red

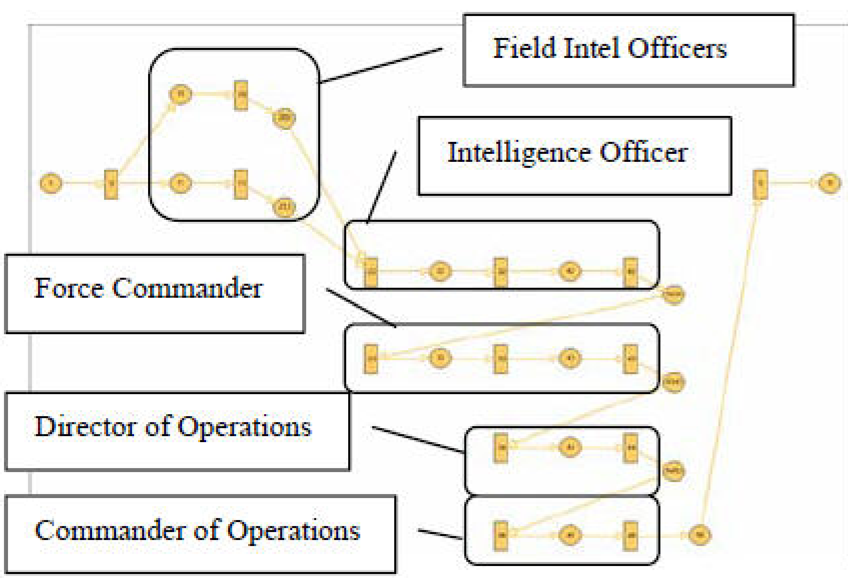



Fig. 6.11 C-MINO(1) for Red

Fig. 6.12 C-MAXO(1) for Red

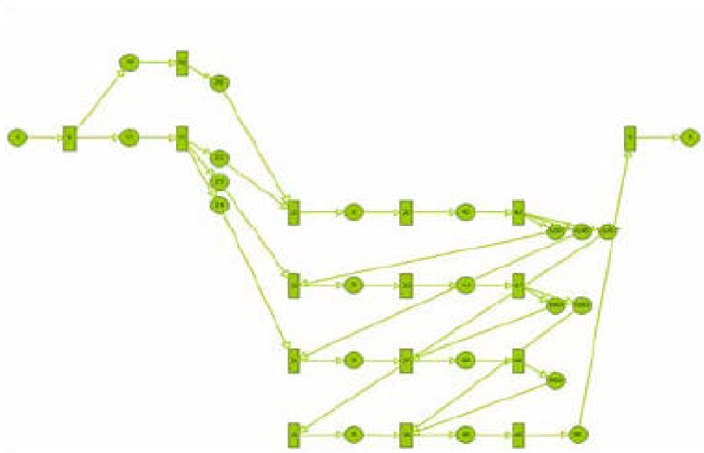


Fig. 6.13 C-MAXO(2) for Red

Fig. 6.14 C-MAXO(3) for Red

Applying Blue's cultural attributes to the original problem results in only one C-MINO and one C-MAXO. The corresponding expanded lattice is as shown in Fig. 6.15.

The actual Petri net corresponding to the C-MAXO is shown in Figure 6.16. The C-MINO for Blue is the same as the C-MINO for Red.

Since the constrained solution space for Red has only one C-MINO, which is connected to all the three C-MAXOs, the C-MINO represents the set of interactions that must be present in all the structures that satisfy the cultural attributes of Red. Further analysis of this structure can help identify the high value ISR targets. In cases where there are more than one MINOs, identifying the interactions that are common to all the C-MINOs will indicate which areas to target for ISR activities.

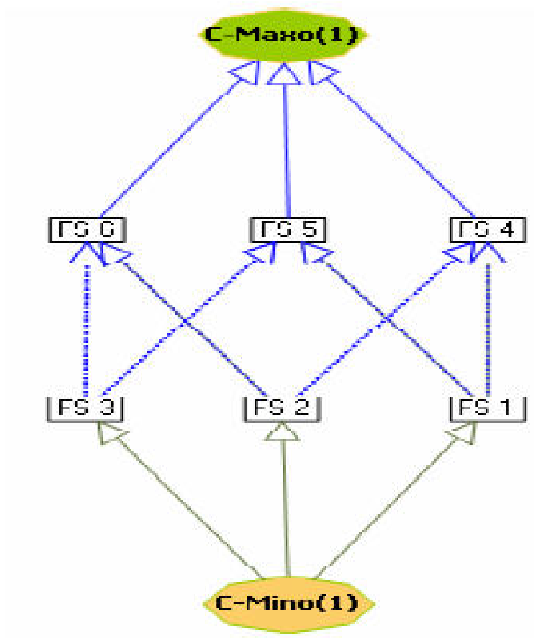



Fig. 6.15 Expanded Lattice Structure from C-MINO(1) to CMAXO(1) for Blue

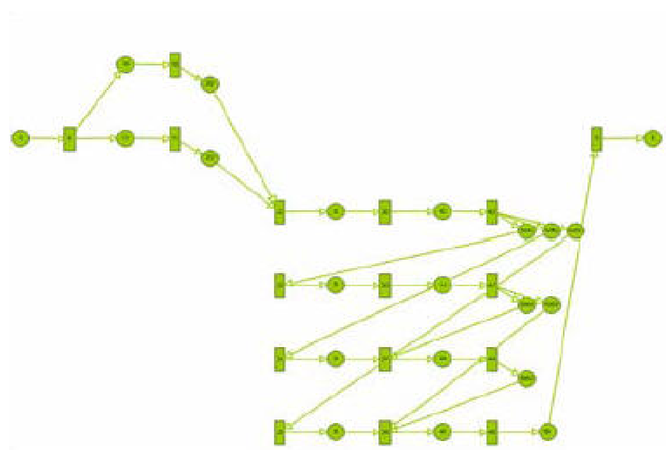


Fig. 6.16 C-MAXO(1) for Blue

Looking at the solution spaces for the two cases, it is easy to see that the cultural attributes do play a role in the final structure of the decision-making organizations and can provide valuable insight into possible structures that may be used by an adversary.

### 6.7 Coalition Modeling Using CAESAR III

The computational approach for the design of adversary organizations can also be applied to coalition operations. This is illustrated using a hypothetical example in which an emergency situation in an island nation requires rapid humanitarian assistance and disaster relief as well as securing military assets. The alternative architecture designs and the associated simulations to evaluate performance were carried out using CAESAR III.

The scenario depicts a situation in which anarchy has risen on an island due to a recent earthquake that caused substantial damage. The infrastructure and many of the government buildings are destroyed in the island's capital. The US maintains a ground station that receives data from space assets. It is concerned about the rising tensions, as there has been opposition to its presence on the island. As a result, US decides to send an Expeditionary Strike Group (ESG) to the island to: (1) provide timely Humanitarian Aid/ Disaster Relief (HA/DR) to three sectors of the island; and (2) counteract the effects of any hostile attacks which impede the normal operation of the HA/DR mission and the security of the ground station. As the ESG is away for the first critical day of the operation, countries A and B offer help to support the mission and agree to take part in a Coalition Force that would be commanded remotely by the US ESG commander. It is assumed that, close to the island, both countries hold different elements for an ESG compatible Coalition Force, which can be deployed in a matter of hours, while the ESG rushes to the island.

A team of five decision-making units carries out the HA/DR mission. The team is organized in the divisional structure and each unit under the team has its sub-organizations and staff to perform the tasks allocated to it. The five units are:

(1) ESGC: Commander;

(2) MEUC-Commander of the Marine Expeditionary Unit;

(3) ACE-Air Combat Element with its Commander and sub-organizations;

(4) GCE-Ground Combat Element with its Commander and sub-organizations; and

(5) CSSE-Combat Service Support Element with its Commander and sub-organizations.

It is assumed that country A can provide support as ACE, GCE and CSSE while country B can only provide support as GCE and CSSE. The roles of ESGC and MEUC remain with the US. The countries are able to provide rapid assistance in coordination with each other and the design question becomes the allocation of different tasks to partners in this ad-hoc coalition.

This is a multi-level design problem in which interactions between different decision making units need to be determined both at the higher level (Level-1) as well as at the lower level (Level-2). The top level interactions correspond to interactions between culturally homogenous subunits, while the bottom level design problem consists of designing the internal structure of these homogenous subunits based on a defined set of interactional constraints and culture. Based on the structure of the ESG, one can impose user constraints to design the level-1 organization.

Figure 6.17 shows the block diagram of this organization as designed in CAESAR III; the matrices describing the interactions are shown in Fig. 6.18.

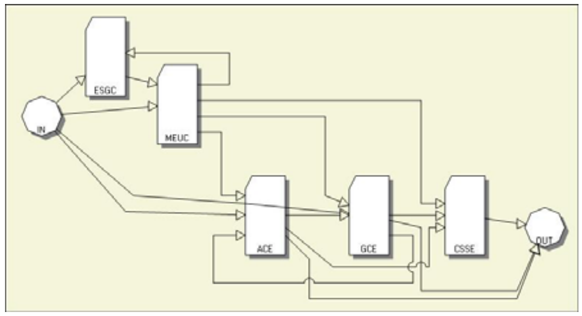



Fig. 6.17 Level-1 organizational block diagram.

$$e=\begin{bmatrix}x & 1 & 1 & 1 & 0\end{bmatrix} s=\begin{bmatrix}0 & 0 & 1 & 1 & 1\end{bmatrix}$$

$$F=\begin{bmatrix}0&0&0&0&0\\1&0&0&0&0\\0&0&0&1&1\\0&0&x&0&x\\0&0&0&0&0\end{bmatrix} G=\begin{bmatrix}0&0&0&0&0\\0&0&0&0&1\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$

$$H=\begin{bmatrix}0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix} C=\begin{bmatrix}0&1&0&0&0\\0&0&1&1&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\end{bmatrix}$$

Fig. 6.18 Matrix Representation corresponding to Fig. 6.17

Figure 6.19 shows the result of running the lattice algorithm on level-1 organization. The solution space contains one MINO, Fig. 6.20, and one MAXO, Fig. 6.21. The designer can pick a structure from this space and use it to design the sub-organizations at level-2.

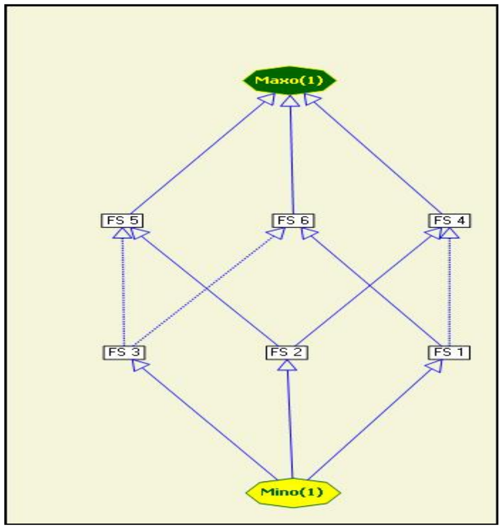



Fig. 6.19. Solution space for Level-1 organization design as seen in CAESAR III

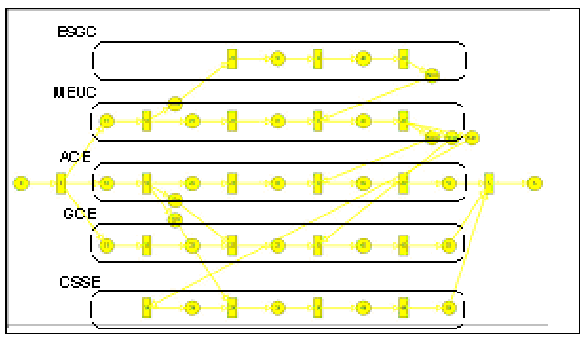



Fig. 6.20  MINO of Level-1 design

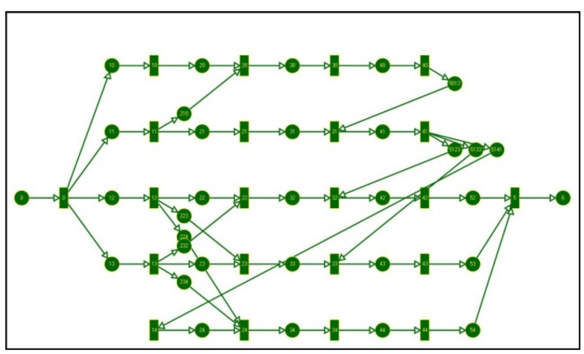
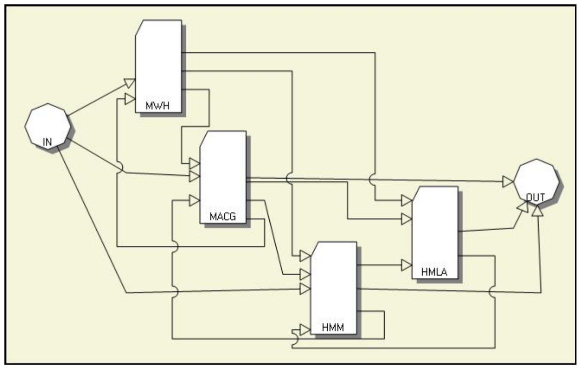


Fig. 6.21  MAXO of Level-1 design

Level-1 design is free of cultural constraints. However Level-2 design uses the C-Lattice algorithm to include cultural attributes to form the various coalition options. The sub-organizations of ACE, GCE and CSSE are designed using CAESAR III. Figures 6.22, 6.23 and 6.24 show the respective block diagrams along with the matrices specifying the user constraints. Since the US always performs the roles of ESGC and MEUC, these sub-organizations are not decomposed further.

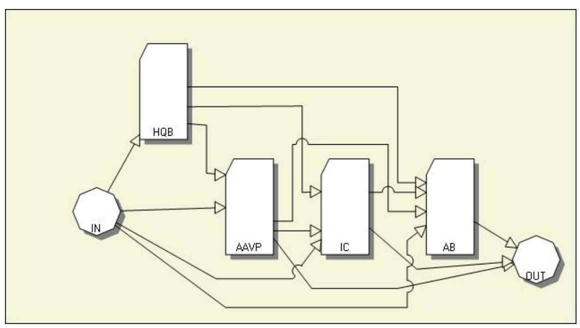



$$e=\begin{bmatrix}x & 1 & 1 & 0\end{bmatrix} s=\begin{bmatrix}0 & x & 1 & 1\end{bmatrix}$$

$$F=\begin{bmatrix}0&0&0&0\\x&0&0&x\\0&x&0&x\\0&0&0&0\end{bmatrix} G=\begin{bmatrix}0&0&0&0\\0&0&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix}$$

$$H=\begin{bmatrix}0&0&0&0\\0&0&0&0\\0&x&0&x\\0&0&x&0\end{bmatrix} C=\begin{bmatrix}0&1&x&x\\0&0&1&x\\0&0&0&0\\0&0&0&0\end{bmatrix}$$

Fig. 6.22 Block diagram and matrix representation for ACE

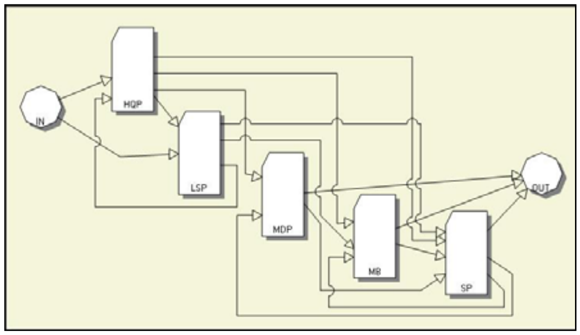



$$e=\begin{bmatrix}1 & x & x & x\end{bmatrix} s=\begin{bmatrix}0 & 1 & 1 & 1\end{bmatrix}$$

$$F=\begin{bmatrix}0&0&0&0\\0&0&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix} G=\begin{bmatrix}0&x&x&x\\0&0&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix}$$

$$H=\begin{bmatrix}0&0&0&0\\0&0&x&x\\0&0&0&x\\0&0&0&0\end{bmatrix} C=\begin{bmatrix}0&x&x&x\\0&0&0&0\\0&0&0&0\\0&0&0&0\end{bmatrix}$$

Fig. 6.23 Block diagram and matrix representation for GCE




$$e = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 \end{bmatrix} s = \begin{bmatrix} 0 & 0 & 1 & 1 & x \end{bmatrix}$$

$$F = \begin{bmatrix} 0 & x & 1 & 0 & 0 \\ x & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} G = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & x \\ 0 & 0 & 0 & 0 & x \\ 0 & 0 & x & x & 0 \end{bmatrix} C = \begin{bmatrix} 0 & 1 & 0 & x & x \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 6.24 Block diagram and matrix representation for CSSE

Table 6.2 gives the Hofstede's scores for US, Country A and Country B. Using a multiple linear regression model, these scores are converted into limits to be placed on allowable interactions based on culture. These are imposed as additional structural constraints on the solution space of the sub-organizations. The cultural constraints for the three sub-organizations are shown in tables 6.3, 6.4 and 6.5. Maximum indicates the limit placed on the number of interactions by user constraints.

**TABLE 6.2** Hofstede's scores for the three countries

| Country | PDI | IND | MAS | UAI |
|---|---|---|---|---|
| US | 40 | 91 | 62 | 46 |
| A | 38 | 80 | 14 | 53 |
| B | 66 | 37 | 45 | 85 |

**TABLE 6.3** Cultural Constraints corresponding to ACE

| Country | #F | #G | #H | #C |
|---|---|---|---|---|
| Maximum | 0≤F≤4 | 0 | 0≤H≤3 | 2≤C≤5 |
| US | 3≤F≤4 | 0 | 2≤H≤3 | 3 |
| A | 2 | 0 | 2≤H≤3 | 3 |
| B | 2 | 0 | 1 | 4≤C≤5 |

**TABLE 6.4** Cultural Constraints corresponding to GCE

| Country | #F | #G | #H | #C |
|---|---|---|---|---|
| Maximum | 0 | 0≤G≤3 | 0≤H≤3 | 0≤C≤3 |
| US | 0 | 2 | 2≤H≤3 | 2 |
| A | 0 | 2 | 2≤H≤3 | 1 |
| B | 0 | 2≤G≤3 | 2 | 2≤C≤3 |

**TABLE 6.5** Cultural Constraints corresponding to CSSE

| Country | #F | #G | #H | #C |
|---|---|---|---|---|
| Maximum | 1≤F≤3 | 0 | 0≤H≤4 | 3≤C≤5 |
| US | 2≤F≤4 | 0 | 3≤H≤4 | 3 |
| A | 2 | 0 | 3≤H≤4 | 3 |
| B | 2 | 0 | 2 | 4≤C≤5 |

Using the C-Lattice algorithm, the solution space for each sub-organization is computed for each culture and a suitable structure is selected by the user. These structures are then used to form the different coalition options and analyze the performance. In view of the limited space, the complete solution spaces are not shown here. Figures 6.25-6.27 show the structures selected by the user for each country for CSSE. A similar approach can be use to select different structures to be used for ACE and GCE.

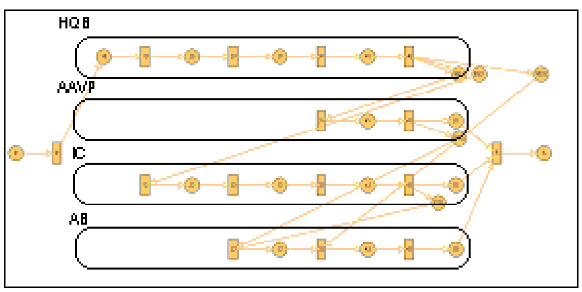



Fig. 6.25 GCE structure selected for US

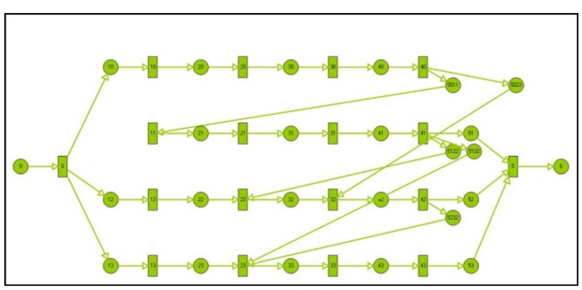


Fig. 6.26 GCE structure selected for Country A

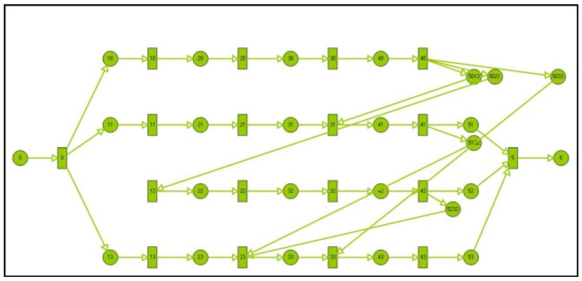


Fig. 6.27  GCE structure selected for Country B

Once the structure is selected, CAESAR III has the functionality of exporting it as a Colored Petri net to *CPN Tools* where it can be simulated to analyze performance. For the given scenario, based on the availability of support from the two countries, eight coalition options are possible, excluding the homogeneous option of all US. The five sub-organizations are combined together using Level-1 MINO and the eight options were simulated to study performance in terms of tasks served. The following assumptions are made. Each process (transition) needs 50 units of processing time. Each additional incoming link increases this time by 50 units. The reasoning is that the additional input(s) will require more processing. Hence, structures that have more interactions will take more time to process the tasks, which will affect the overall performance. Figure 6.28 shows the results of this analysis for all combinations. The x-axis shows the percentage of tasks **un-served**.

Based on these results, US-US-US-B-A performs best. Most options with country B in the CSSE role perform badly. This is because country B needs a high number of command relationships and the structure of CSSE allows for this to occur, thereby increasing the processing delay. User constraints on GCE allow for very similar cultural constraints for all countries and hence changing the ordering in this role does not change the performance very much. Similar results were obtained when the coalition options were simulated using a Level-1 MAXO organization.

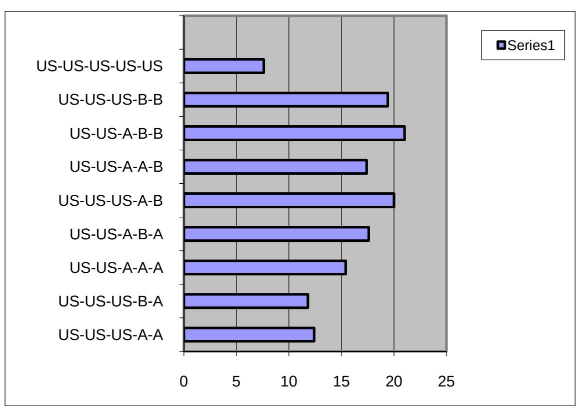



Fig. 6.28 Percent of tasks un-served for coalition options.

A previously developed methodology for the computational design of information processing and decision making organizations has been enhanced to include cultural constraints that affect the choice of organizational structures. While the Hofstede cultural dimensions have been used, other cultural metrics can be used to derive the cultural constrains. A simple example illustrates the approach for designing coalition organizations and analysing their performance. The results indicate that culture does affect the structure and working of organizations thereby affecting the overall performance. This could aid in the allocation of different tasks to partners in an ad-hoc coalition.

### 6.8 Conclusion

A previously developed methodology for the computational design of information processing and decision making organizations has been enhanced to include cultural constraints that affect the choice of organizational structures. While the Hofstede cultural dimensions have been used, other cultural metrics can be used to derive the cultural constrains R5 to R8. Two examples illustrates the approach: one for adversary organizations and one for coalition organizations. The results indicate that culture does affect the structure and working of organizations thereby affecting the overall performance.

# Chapter 7

## Extracting Adversarial Relations from Texts

**Kathleen M. Carley**

### 7.1 Introduction

There is a need to identify texts and extract from them various information about the adversary, their interactions, activities, beliefs, resources and so on. We used in this project a rapid ethnographic assessment procedure that moved from data to model using a semi-automated text analysis process. Key data used was newspaper reports. Over the course of the project this procedure became increasingly automated and the ability to identify agents and their activities improved dramatically. Central to this process is the AutoMap tool. AutoMap is based on network text analysis and so converts texts to networks of relations. We found it useful to first extract the semantic network and then the meta-network composed of agents, resources, expertise, locations, activities, beliefs and organizations. We note that beliefs are the most difficult to extract.

Data mining is commonly used to identify and extract entities. Named Entity Recognition is used to classify items such as people or locations [142]. Machine Learning is used widely to aid in the classification. Aspects of the data that give clues as to classification category are word length, part-of-speech, and external sources such as gazetteers and ontologies. Some algorithms parse at the shallow level of words only, and other parse deeply with machine understanding of part of speech and sentence semantics. Spatiotemporal knowledge discovery techniques are described by Roddick and Lees [143], and location techniques by Buttenfield et al. [144].

Reliance on a gazetteer may improve the computer's ability to recognize locations. Gazetteers differ in scope, coverage and balance, accuracy, and entry specificity. Choice of gazetteer influences match results. The gazetteer can supply additional background knowledge that is helpful in data analysis. Some researchers use existing gazetteers such as the National Geospatial Intelligence Agency gazetteer[1] or GeoNames,[2] while others generate them automatically [145] or derive them from Wikipedia [146]. Semantic technologies have been used to identify network data in texts before [147], [148]. Workshops such as the Data Mining WebKDD/SNAKDD 2007 [149] and conference presentations [150] have been devoted specifically to mining data for social network analysis.

---

[1] National Geospatial Intelligence Agency gazetteer for download at http://earthinfo.nga.mil/gns/html/

[2] http://www.geonames.org

### 7.1.1 Network Text Analysis (NTA)

Network Text Analysis is a set of methodologies for converting texts to graphs based on the theory that language and knowledge can be modeled as networks of words and relations such that meaning is inherent in the structure of that network. NTA encodes links among words to construct a network of linkages. Specifically, this method analyzes the existence, frequencies, and covariance of terms and themes, thus subsuming classical Content Analysis.

### 7.1.2 Semantic Network Analysis

In map analysis, a concept is a single idea, or ideational kernel, represented by one or more words. Concepts are equivalent to nodes in Social Network Analysis (SNA). The link between two concepts is referred to as a statement, which corresponds with an edge in SNA. The relation between two concepts can differ in strength, directionality, and type. The union of all statements per texts forms a semantic map. Maps are equivalent to networks

## 7.2 AutoMap

Texts, e.g., newspaper articles, blogs, and the stories told by people, are a key source of cultural and ethnographic information. AutoMap [151] is a text mining tool that enables the extraction of information from texts using Network Text Analysis methods. AutoMap supports the extraction of several types of data from unstructured texts. The type of data that can be extracted includes: content analytic data (words and frequencies), semantic network data (the network of concepts), meta-network data (the cross classification of concepts into their ontological category such as people, places and things and the connections among these classified concepts), and sentiment data (attitudes, beliefs). Each of these modes assumes the foregoing.

Coding in AutoMap is computer-assisted; the software applies a set of coding rules specified by the user in order to code the texts as networks of concepts. Coding texts as maps focuses the user on investigating meaning among texts by finding relationships among words and themes. The coding rules in AutoMap involve text pre-processing, statement formation, and post-processing which together form the coding scheme. AutoMap exists as part of a text mining suite that includes a series of pre-processors for cleaning the raw texts so that they can be processed and a set of post-processor that employ semantic inferencing to improve the coding and deduce missing information. These pre-processors include such sub-tools as a .pdf to .txt converters, non-printing character removal, and limited types of de-duplication. Text pre-processing condenses data into concepts, which capture the features of the texts relevant to the user. Statement formation rules determine how to link concepts into statements. The postprocessors include such tools procedures that link to gazetteers and augment the coding with latitude and longitude, belief inference procedures, and data secondary data cleaning tools. In addition there are a series of support tools for creating, maintaining, and editing delete lists and thesauri. AutoMap exports data in DyNetML and can be used interoperably with *ORA.

AutoMap is focused around the idea that meaning is carried in the way in which concepts are linked [148]. Concepts are words or phrases that represent a single ideational kernel; e.g., hope or United_States_of_America are both concepts. To identify the concepts, non-content bearing words are often deleted and thesauri are used to map alternative spellings and phrasing into a single concept. Syntactic clues are used to define connections among concepts leading to stronger linkages being built among concepts within the same phrase, than in the same sentence, than in the same paragraph. In its simplest form, a semantic network is built by building a network where two concepts are linked just in case they are within so many words of each other or occur in the same sentence. Ontological thesauri that map concepts into categories are then used to cross-classify concepts into agents, organizations, knowledge, resources, locations, beliefs, tasks and events. This cross-classification results in a set of networks – i.e., a meta-network [152].

AutoMap is first used to extract entities (the nodes), then links, then to cross-classify entities into ontological categories. Entity extraction involves locating and classifying terms that represent instances of entity classes of the meta-network that deviate from the classical set of entities in text data. Unlike traditional text mining, which focuses only on named entities (people, places, organizations), we also extract more fuzzy entities, such as tasks (e.g. signing a contract) and resources (e.g. vehicles), which are not necessarily referred to by a name. The following excerpt from an UN News Service (New York) article released on 12-28-2004 illustrates the EE task:

*Jan Pronk, the Special Representative of Secretary-General Kofi Annan to Sudan, today called for the immediate return of the vehicles to World Food Programme (WFP) and NGOs.*

The underlined concepts are the entities in the meta-network. The quality and accuracy of the extracted network depends on the quality of the entities extracted. AutoMap uses a combination of sub-models to extract these entities. These sub-models include utilization of thesauri and the use of Conditional Random Fields for entity identification. Conditional Random Fields allow for modeling the relationship among $y_i$ and $y_i$-1 as a Markov Random Field (MRF) that is conditioned on x. MRF are a general framework for representing undirected, graphical models. In CRF, the conditional distribution of an entity sequence y given an observation sequence (string of text data) x is computed as the normalized product of potential functions $M_i$ [153], [154].

The resulting entity extraction process using Conditional Random Fields consists of two steps. First, the Conditional Random Field is used to locate the terms that are relevant entities. These terms are then marked as being a part of a relevant entity. Second, the Conditional Random Field is used to classify the identified relevant entities. In order to do this, consecutive words that have been identified as belonging to entities are merged into one concept. This concept is represented as a concatenation of the consecutive entity words.

When using AutoMap to identify adversarial networks, the following features were particularly useful: anaphora resolution, deletion of stop words, thesaurus generalization, and meta-network thesauri (ontological cross-classification). In general, a windowing technique was used for placing links and links were placed among entities occurring within a window defined as two contiguous sentences. Finally, gazetteers were used to add latitude and longitude for locations terms.

### 7.2.1 Anaphora resolution

Anaphora resolution identifies the social entities that pronouns refer to. Co-reference resolution identifies multiple instances of unique real-world entities that multiple text phrases reference. The application of these preprocessing steps in the process of extracting relational data from unstructured text data can impact the entity frequency count, identity of entities and of the identification of relations between entities. It is not uncommon for these steps to modify 15 percent of the edges.

### 7.2.2 Deletion of stop words

Stop words are those words whose presence has little content of value to the analysis. Often, words such as a, an, the, to, for will fall in this category. Lists of common stop words exist in the machine learning community. We used these and augmented them with a set of commonly unused concepts in assessing adversarial relations. We have found it efficacious to remove most articles, prepositions, numbers, terms referring to temporal indicators such as days of the week, and terms referring to intensity such as more or fewer.

These stop words are collected into a delete list. These concepts are then removed before additional work on thesaurus construction is done. In general, you should create a cut-off limit (e.g. a word needs to be used at least three times. Concepts used less than that would be placed in the Delete List.

### 7.2.3 Thesauri generalization

One of the key issues in assessing texts is that different words are used to describe the same thing. For people, we might think of these alternatives as aliases. Thesauri are generally used to take multiple concepts, in different forms, and compile them under one key concept. The purpose of a generalization thesaurus is to cluster together all those concepts that refer to the same entity effectively forming a set of coding rules for translating those concepts into the general term. This generalization process can be used for aliases, to remove alternative ending, decrease the impacts of plurals, and combine concepts where differences in nuance are not relevant to the analysis.

Standard stemmers, which reduce words to their base such as farming and farmed to farm tend to over generalize and do not retain part-of-speech distinction. This we prefer to use specially design stemmers that preserve part-of-speech thus enabling auto-identification of tasks/activities and generic actors. These specialized stemmers are part of the automatically constructed generalization thesauri.

For adversarial reasoning, the key effort in thesaurus construction needs to go into the construction of alias files for organizations and people. These tend to be specific to adversarial group when referring to names entities and so specific people and groups. In contrast, other thesauri referring to activities or "generic" people, e.g., farmers, can be used across studies.

### 7.2.4 Meta-network thesauri

The meta-network is an ontological categorization of nodes in this case concepts into the who, what, when, where, how why needed to assess groups [152]. The meta-network is a multi-mode, multiplex model that reifies these entity classes as: agent, knowledge, resource, task, event, organization, location, belief, time.

Instance of an entity class can have attributes, e.g. the attribute of agent *John* might be *age, 42* and *gender, male*. The relations among the elements within and across any entity classes form certain types of networks. For example, a social network is composed of relations among agents, and a membership network consists of connections among agents and organizations. The meta-network model allows for analyzing socio-cultural systems as a whole or in terms of one or more of the networks contained in the model. This ontological schema has been used to empirically assess power, vulnerability, and organizational change in a diversity of contexts such as situational awareness in distributed work teams, email communication in business corporations and counter terrorism [155], [156], [157].

## 7.5 Data to Model Processing

Each text is processed to remove noise and clean the text, to combine multi-word concepts into a single concept, to normalize the concepts into a reduced vocabulary, and to categorize concepts into the meta-network ontology [152]. The meta-network ontology includes agents, organizations, locations, events, knowledge, resources, and tasks (i.e. activities).

Initial cleaning of the texts involves reformatting as well as a generic cleaning. The generic activities include preprocessing used to correct the text. Examples include typo correction, the expansion of contractions and abbreviations. Pronoun resolution should be done and unidentified pronouns removed. Identification of compound concepts is done by applying a list of concept-changing n-grams. While typically the use of an n-gram is to identify words that are most commonly used together, in this context an n-gram is a multi-word concept whose definition changes when the concepts are reviewed individually versus as a single compound entity. Examples of concept-changing n-grams are "first aid" and "black market".

Concepts are segmented into specific and general types. The specific concepts identify instances of items, such as George W. Bush for agent, UNICEF for organization, and Pittsburgh for location. General concepts include soldier (agent), tank (resource), and base (location). Many of the general concepts in the ontology can be pre-established. Some minor adaptation needs to be done based on the domain as "front" is different for a military domain as opposed to "front" when speaking about weather forecasting. Some specific entities can be pre-established from existing lists such as a list of all countries or major cities, or a list of world leaders.

The processing material requires project-based modifications beyond what can be pre-established. Project-based specific entities can be found by reviewing all proper nouns identified in the corpus by applying part-of-speech analysis. For convenience, proper nouns adjacent to one another can be listed in an n-gram form as many project-based specifics are compound concepts. Alternatively, the approach to finding specific compound concepts would involve the generation of all n-gram possibilities, which is prohibitively large for human review beyond bigrams (n-grams with N=2). The list of possible concepts of interest can be culled by removing all concepts already placed in an ontological category. Using the pre-established material significantly reduces the amount of human involvement.

A base thesaurus is formed from the pre-existing ontologically categorized concepts and augmented with project-based material. The current pre-existing generics material consists of 22,455 entries. The current pre-existing base material (including general and specific entities) consist of 150,749 entries. A number of scenarios were examined including the following:

1. A scenario driven deterrence assessment:  Uses a corpus of 27,000 text files from news sources and government websites. The project-based thesaurus added only an additional 962 entries. The resulting meta-networks contained 7,605 entities.
2. A military multi-actor experiment. Uses a corpus of 3,100 text files from news sources, web sites, and communication logs. The project-based thesaurus added only an addition 500 entries.
3. Open-source information on the Sudan. Uses a corpus of 71,000 text files from news sources, web sites, books, as well as additional information from a wide variety of collected information by scholar experts. The project-based thesaurus includes 38,552 location listings extracted from a gazetteer leaving 16,001 unique entries.

The use of pre-existing thesauri reduced significantly the amount of work needed to extract a meaningful meta-network. The cleaning of the text, extraction of proper nouns and the subsequent removal of pre-existing items for human review, and the generation of the meta-network using pre-existing and project-based thesauri, are all examples of workflows. The workflows are a sequence of common steps used to perform a task, often using different inputs or different thesauri. These web services can be composed into domain-specific workflows that can be used by analysts to automate and manage common sequences of operations. The workflows automate the task management allowing the analyst to focus on the domain and not on keeping track of the individual steps to be taken. By sharing workflows, a consistent approach for data-to-model is established. When advances are made, the workflow can be easily adapted to the new capability and the data-to-model processing re-run.

## 7.6 Limitations and Next Steps

The global learning of features along with their corresponding weights comes at a price: Training the identifier and classifier while using a reasonable iteration rate for the gradient takes a very long time. This limitation can be addressed to some degree by using more powerful hardware, especially by using more memory. Furthermore, an ability to add, change, or remove labels from the used ontology is essential to having a flexible yet robust learning and research process. While the meta-network has many labels of interest, it is likely that the model may be altered as it evolves in the future.

Conditional Random Fields enable us to detect relevant entities along with their corresponding weights without having to have any preliminary or initial guess about what some of those features might be for a particular data set or domain. This means we can let the computer do all the work as long as we provide it with some labeled training data. However, such uninformed global learning approach comes at a price: Additionally, other techniques for improved entity extraction should be considered. These include things such as improved anaphor resolution, entity inference for beliefs and events, and attribute extraction for concepts such as automated cross classification of resources and activities by DIME/PMESII areas.

However key improvements will require improved link identification. Extracting network ties, or relations between entities, is substantially harder than entity recognition. State-of-the-art systems perform less well on this task than on the recognition task. Most research on relation extraction assumes that the entities have been identified correctly. Main methods for extracting relations between entities are to discover verb relations [158], construct concept graphs based on rules [159], or use proximity to find relations within a sentence using a "word window" [160]. These techniques however need to be augmented with syntactic hierarchical parsing; i.e., placing links within clause, then sentence, then paragraph. In additional, machine learning techniques may also be used for improved link identification.

# Chapter 8

# Inferring and Assessing Informal Organizational Structures from an Observed Dynamic Network of an Organization

**Il-Chul Moon, Kathleen M. Carley, Alexander H. Levis**

## 8.1 Introduction

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, the workflow, the formal structure is likely not to be known a priori. Indeed, it is unlikely that there is a formal structure in the sense of a declaration by the organization about who reports to whom and is doing what. Nevertheless, it is likely that the operational structure 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.

We propose and 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. We 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 structure is critical when we attempt to understand, intervene in, or manage the organization [161]. However, organizational structures in the real world often differ from their recognized formal structure [162], and sometimes its membership conceals the formal structure with various types of social interactions and communications [163]. 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 [164]. The following two scenarios exemplify the impending confusion about the identification of an organizational structure.

***Scenario 1:*** *TF is an employee of a global investment bank in Hong Kong. In the formal organizational chart, he reports administratively to the bank's financial division director, who is also the head of the Hong Kong branch. However, because of his assignment to work on a global project, TF also reports to two senior project managers who manage the project from their offices in New York and London. His corporate email activity includes not only personal-activity re-*

*porting emails to the local administrative manager and project status reporting to the two project managers, but also includes information sharing emails to work colleagues.*

***Scenario 2:*** *IC is a developer in a software development team which is informally organized. He has frequent email contact with the users and other team members, including one team leader with whom he often reports his progress. Because there is no formal team structure, there is no membership boundary in the team, so the team involvement is determined by consensus from the active members who are reporting bugs and developing programs.*

In these scenarios, we identify three different types of organizations that vary in their boundaries and explicitness. Firstly, the organizational chart unequivocally outlines the formal hierarchical structure, but the employees have another hierarchical reporting structure that is not shown in the formal chart. Secondly, his email account shows his contacts, regardless of the contacts' importance or the nature of the relations, so the uncovered email transaction structure from his account contains people with critical work relationships and ones with insignificant relationships at the same time. This second organizational structure is a *social network* in this paper. The third structure, our definition of *decision making organizational structure* in this paper, is a social structure including only relevant personnel, or three formal or informal bosses, and work relationships, or reports to the bosses in terms of completing the organization's goal. These different organizational 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, etc. This paper uses a terrorist network as a test dataset.

We focus on the differences in analysis approaches regarding the two above organizational structures: *meta-network* (an extended version of *social network*) and *decision making structure*. Meta-network is a network representation of a complex organizational structure. Its dataset is gathered from email transactions, survey from group members, observations on social interactions, and etc. Meta-network analysts concentrate on finding key personnel, i.e. which boss is more important in Scenario 1. Or, they find clusters, i.e. clusters of developers of open-source development team in Scenario 2. Decision making structure is an organization structure design whose members, or decision makers, interacts with each other in various purposes over the course of decision making. The structure is from organizational charts, survey, or subject-matter experts of the organization. Decision making structure analysis uncovers the information and response transmissions in members' cognitive processes while a decision is made, i.e. when TF's report weigh in the formal or informal bosses' decision making processes in Scenario 1, to what extent IC and his discussion partner share the information and when in Scenario 2.

Considering the above two perspectives, we need the third approach that combines the two. 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 meta-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 paper, we introduce one approach combination. First, we extract the decision making organizational structure from an observed meta-network of a target organization. For instance, we extract the only relevant people in the decision making processes among TF's contacts in Scenario 1. This extraction is done by considering the work relationships among the members of the group and the work flow of the organizational objective. Next, we analyze the extracted decision making structure with the social network analysis approach. For example, among the three bosses and TF in Scenario 1, we 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 original meta-network and the extracted decision making structure. These differences imply that the analysis result can be richer if we investigate not only the existing meta-network, but also the inferred structures from it.

The workers segregate and create clusters socially based on the work flow rather than their formal structure. If this is true, an analyst may find out how well the formal structure supports the current work practices by comparing the formal and informal structures. As another example, Rabasa et al. [165] think that Al-Qaeda operatives may be embedded in a social network of a community including civilians and operatives at the same time. Although they co-exist in the social network, it is certain that management activities occur among the operatives. 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. Finally, this work is an effort linking two different disciplines, social network analysis, and decision making structure analysis. Meta-networks have been gathered from various terrorist networks and military organizations, but these have not been used frequently in the decision making structure analysis domain because the interpretations of the meta-network and decision making structure are different. With the proposed framework, we successfully extract a decision making structure from a meta-network, so that we can use the existing meta-network datasets in further decision making structure analyses.

## 8.2 Background

Our framework is presented in two steps: (a) inferring a decision making structure from a meta-network, and (b) analyzing the extracted structure with social network analysis metrics and algorithms. Thus, the theories behind our approach are twofold. First, we explain the complex nature of a meta-network and how we exploit the complex organizational structure in inferring its decision making structure. Second, we describe the used social network analysis metrics and algorithms.

### 8.2.1 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 [166], 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 [167]. 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 [168], [169], recent observations and analyses [170], [171] assert that the terrorist network includes bomb materials, reconnaissance on targets, as well as terrorists.

Second, the organizations of interest have emergent properties. A *synthetic organization* [172] is an organization established after a major event, such as a disaster. The organization emerges around formally 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 [173]. 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 [174], [175].

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 [176], [96] is a model that we regarded as a base of our developed model. Originally, it was used to analyze the cognition processes of multiple decision makers. The individual cognitive processes are structured as a network of various types of links that differ in terms of inputs and outputs of the cognitions. Thus, the model is similar to our approach. Therefore, our major effort in this paper is inferring the links of cognitive processes among individuals from a meta-network.

### 8.2.2 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 [177]. 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 [168], [178] It is able to find key personnel [186] and embedded clusters. Also, it assesses the characteristics, such as degree of centralization and levels of hierarchy, of the organizations. Gabbay and Leenders [179] link the social network analysis to the management of social capital of a corporation. Also, Reagans and Zuckerman [180] 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 Krebs [168] 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 original meta-network and inferred decision making structure. The other way is that we use a couple of metrics, cognitive demand and communication [181] - 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 original structure to examine to what extent the extracted ones are embedded in the original ones.

## 8.3 Dataset

Throughout this paper, we use a dataset collected from the 1998 U.S. Embassy bombing incident in Kenya. As the organizations of interests exhibit complex organizations, we use a meta-network format [187] to represent and analyze the target organization. Meta-network is an extended version of a social network, including various types of nodes and heterogeneous links, which follow the nature of a complex system. Initially, this dataset is from a network text analysis [182] on open-source documents, but later, the soundness and realism of the dataset were verified by human analysts. This meta-network dataset is appropriate for this analysis for a couple of reasons. First, it has a directed terrorist-to-terrorist network required for inferring a *Command Interpretation* structure, which will be explained later, included in the expected decision making structure. Second, it has a detailed task network. With inputs from human analysts, the dataset has a detailed task procedure of the incident, so it is particularly appropriate when we extract a decision making structure for the completion of a certain task.

As our framework starts with a meta-network, the initial input dataset is a collection of terrorists, information and resources for the bombing and related tasks. Fig 8.1 is the visualization of the meta-network of the Kenya case. Also, we visualized two sub-networks, the terrorist social network in Fig. 8.2 and the task precedence network in Fig. 8.3. The basic statistics of this network is listed in Table 8.1 and Table 8.2. For each of the sub-networks, there is an interpretation for the links. For instance, the link in a social network represents that the two terrorists interacted or communicated with each other, and the link in a task assignment network shows that the terrorist was assigned to completion of the linked task.

**TABLE 8.1** The meta-network of the dataset, a terrorist group responsible for 1998 U.S. embassy bombing in Kenya. The numbers in the cells are the densities of the adjacency matrices.

| | Terrorist | Expertise | Resource | Task |
|---|---|---|---|---|
| Terrorist (17 terrorists) | Social Network (0.147) | Information Distribution Network (0.095) | Resource Distribution Network (0.088) | Task Assignment Network (0.126) |
| Expertise (8 bits) | | Not used | Not used | Required Expertise Network (0.048) |
| Resource (8 resources) | | | Not used | Required Resource Network (0.076) |
| Task (13 tasks) | | | | Task Precedence Network (0.121) |

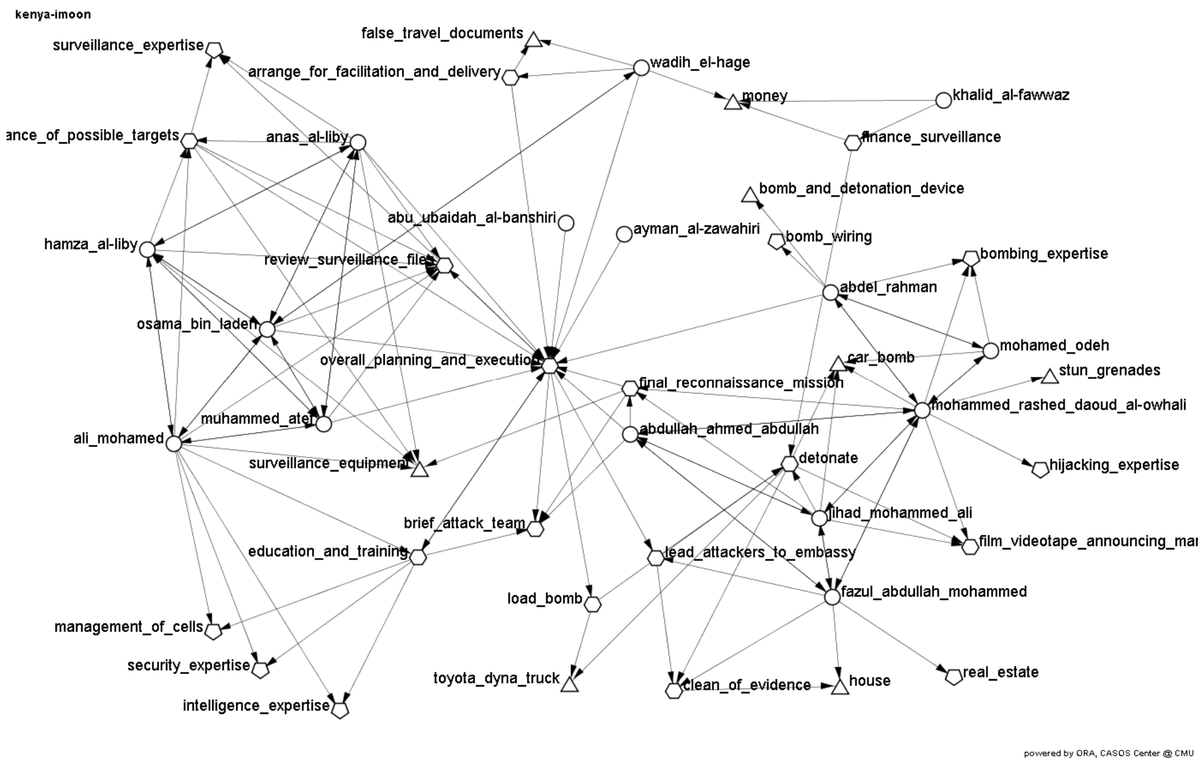



Fig. 8.1 The visualization of the meta-matrix of the terrorist group responsible for the 1988 U.S. embassy bombing in Kenya

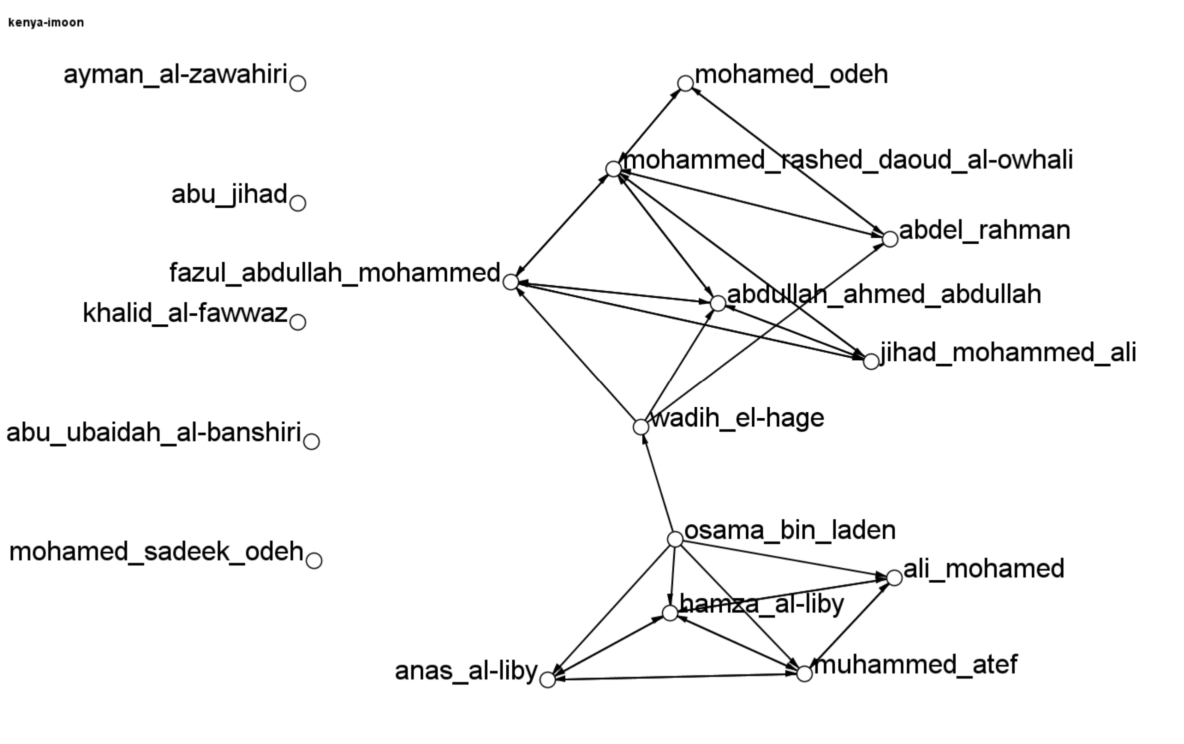



Fig. 8.2 The terrorist social network in the meta-matrix

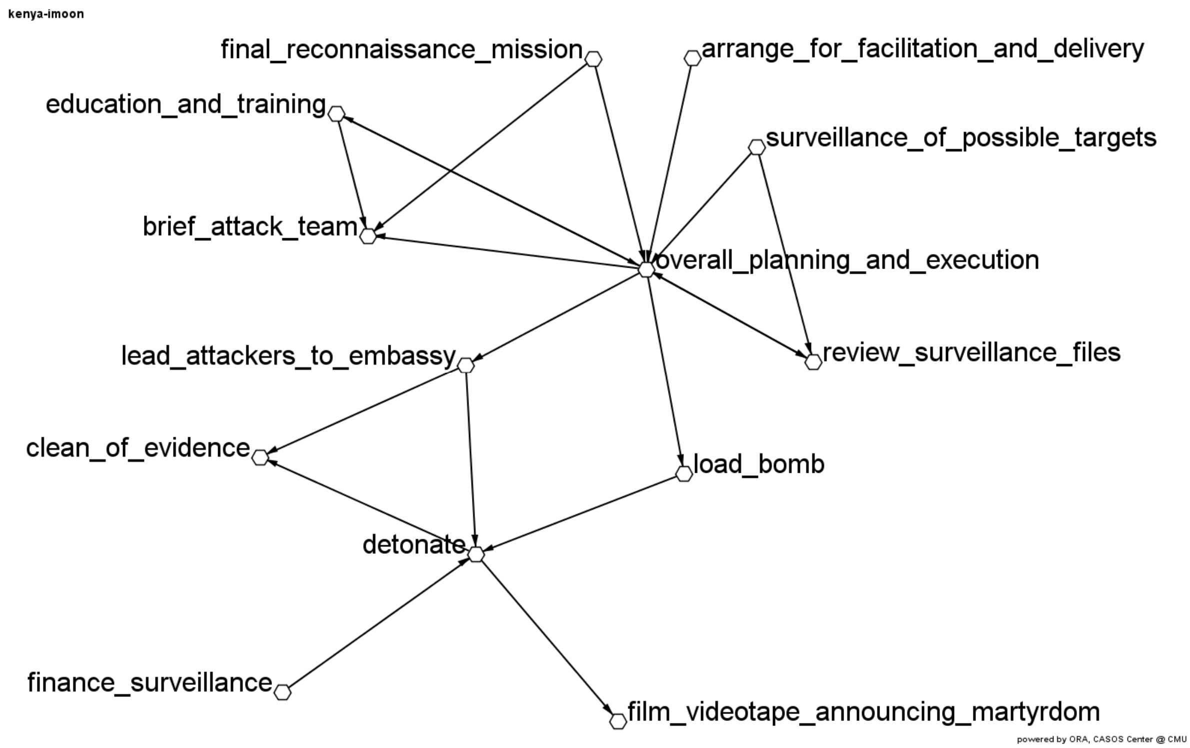



Fig. 8.3 The task network in the meta-matrix

**TABLE 8.2** A table of descriptive statistics for the metrics. This table includes means, standard deviations, and a cross-correlation table.

| | Mean | Std. Dev. | Total Degree Centrality | Betweenness Centrality | Eigenvector Centrality | Cognitive Demand | Communication |
|---|---|---|---|---|---|---|---|
| Total Degree Centrality | 0.0921 | 0.0478 | 1.0000 | 0.7411 | 0.4880 | 0.9113 | 0.4030 |
| Betweenness Centrality | 0.0065 | 0.0073 | 0.7411 | 1.0000 | -0.0650 | 0.8384 | 0.2870 |
| Eigenvector Centrality | 0.0337 | 0.0204 | 0.4880 | -0.0650 | 1.0000 | 0.3087 | 0.3802 |
| Cognitive Demand | 0.0681 | 0.0393 | 0.9113 | 0.8384 | 0.3087 | 1.0000 | 0.3929 |
| Communication | 0.6964 | 0.1897 | 0.4030 | 0.2870 | 0.3802 | 0.3929 | 1.0000 |

## 8.4 Method

Our 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 original meta-network. In this section, we 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, we obtain a target organization to analyze and its task of interest. Second, we 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, we compare the extracted structure to the original network. Additionally, we estimate to what extent we can recreate the original structure with the extracted ones. These comparisons show the effectiveness and the usefulness of the extraction overall, since we 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 original and the extracted structures.

This framework is also designed to convert the meta-network into an input dataset for CAESAR III model, a decision making structure analysis framework. 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.

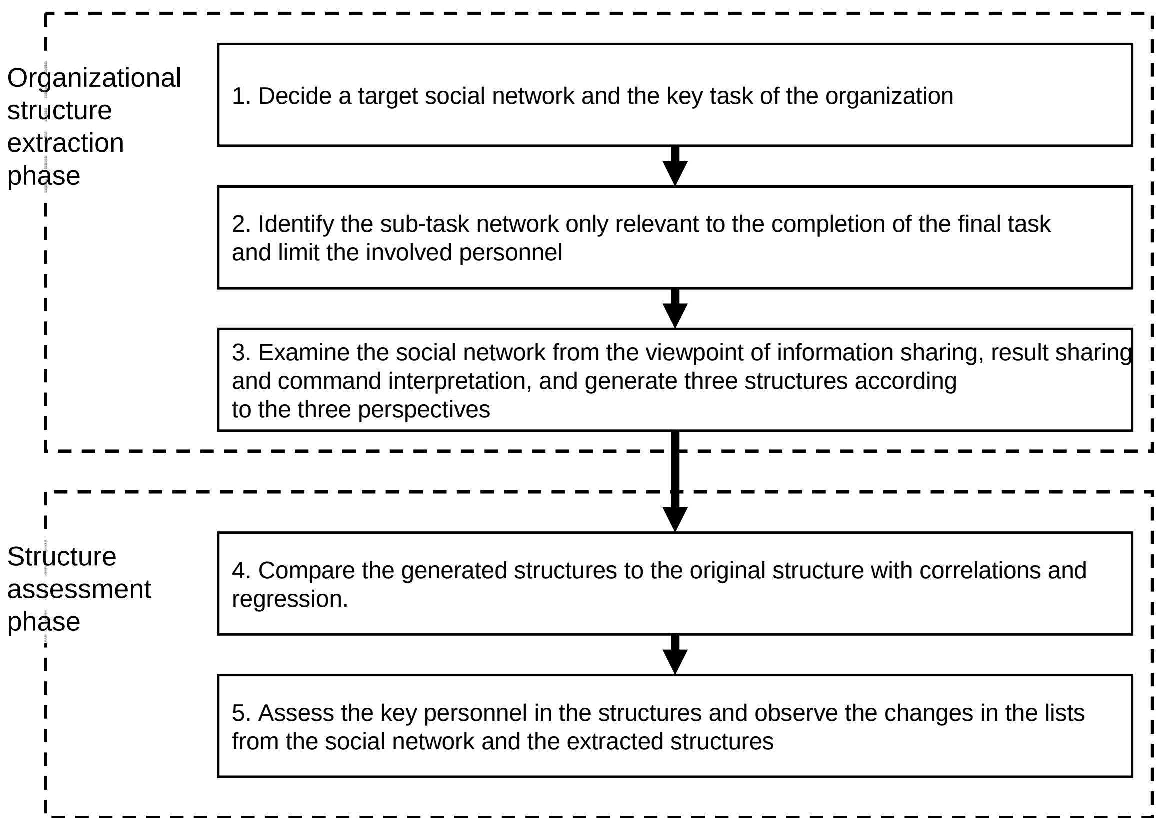



Fig. 8.4 The procedure of the introduced analysis framework

### 8.4.1 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, we 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 for 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.

**Limiting 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 Fig 8.4, the final task is *overall planning and execution*; then, its sub-prerequisite tasks are *surveillance of possible targets*, *final reconnaissance mission* and *arrange for facilitation and delivery*. These four tasks consist of the sub-task network for extraction, and the 12 terrorists assigned to those tasks are the decision makers of this task-oriented decision making structure.

After limiting the involved decision makers, we 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 doesn't 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 17 terrorists, and 12 terrorists are selected as decision makers. Thus, the other 5 terrorists form the outside organization of this decision making structure.

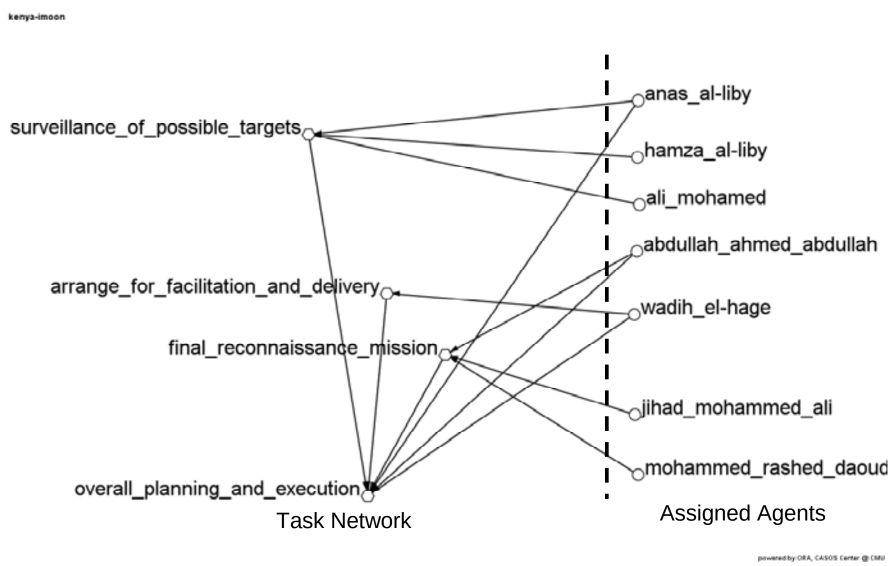



Fig. 8.5 The partial visualization of the task precedence network (task-to-task) and the task assignment network (terrorist-to-task). The dashed line represents the separation of the task network and the assigned agents. When users set up *overall planning and execution* as a final task for the extraction, the visualized tasks and the individuals are the components of the sub-task network, and the accompanying decision makers, respectively.

**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. Figure 8.5 describes the case of information sharing links. According to the sub-network in the figure, *Ali Mohamed* is assigned to *surveillance of possible targets,* which requires *surveillance expertise*. However, *surveillance 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*, *Hamza Al-Liby* or *Muhammad Atef*. Then, the links in these three shortest paths will be the information sharing links.

**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 8.6 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 21 result sharing links originating from the three agents to the seven agents, excluding the agent who is assigned to the next task and already knows the results of the previous task.

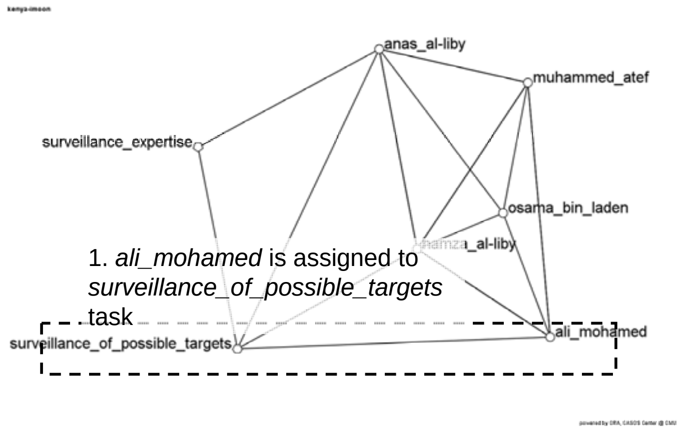



Fig. 8.6a  A partial visualization explaining the formation of information sharing links: First step, *Ali Mohamed* is assigned to *surveillance of possible targets*.

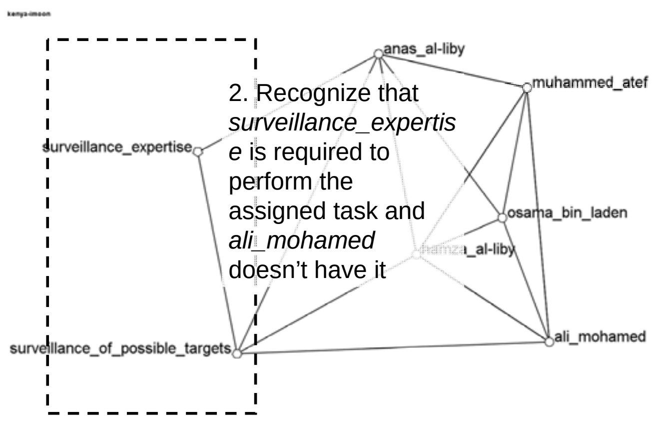



Fig. 8.6b  Second step, *Ali Mohamed* requires *surveillance expertise* to perform his assigned task, but he does not have it.

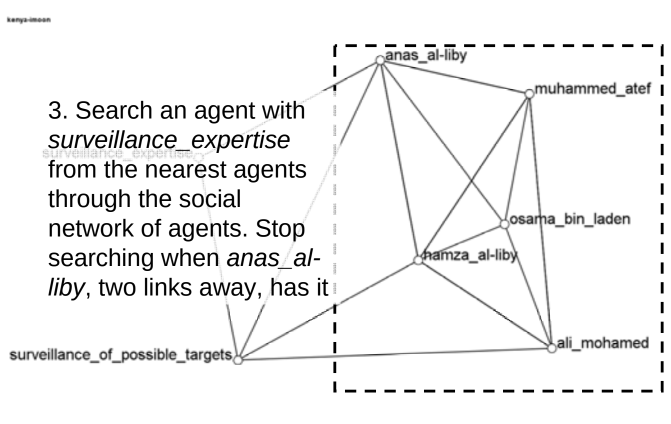



Fig. 8.6c Third step, the organization searches an agent with *surveillance expertise* from the agents near to *Ali Mohamed*. It finds an agent two social links away, *Anas Al-Liby*.

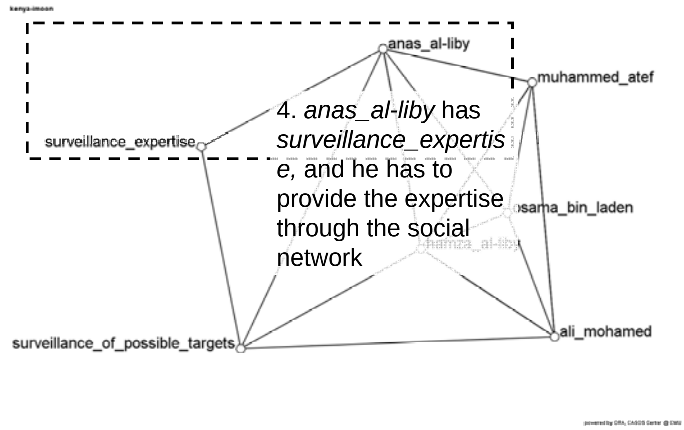



Fig. 8.6d Fourth step, *Anas Al-Liby* has the required expertise and has to deliver the expertise through the social links.

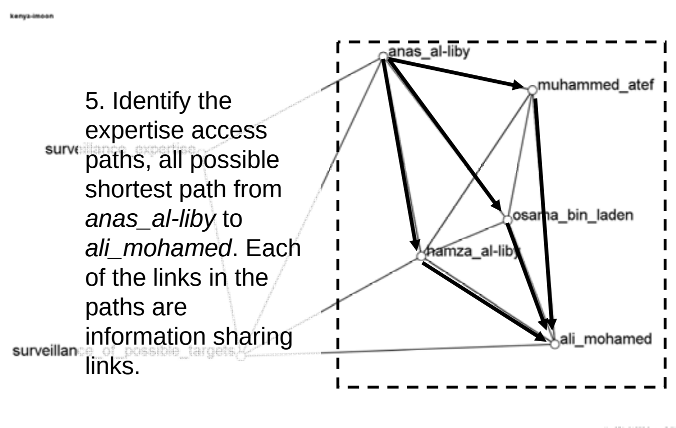



Fig. 8.6e Fifth step, there are three possible shortest paths from *Anas Al-Liby* to *Ali Mohamed*. These paths are information sharing links.

### 8.4.2 Assessing a network structure with measures

The original 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 8.3.

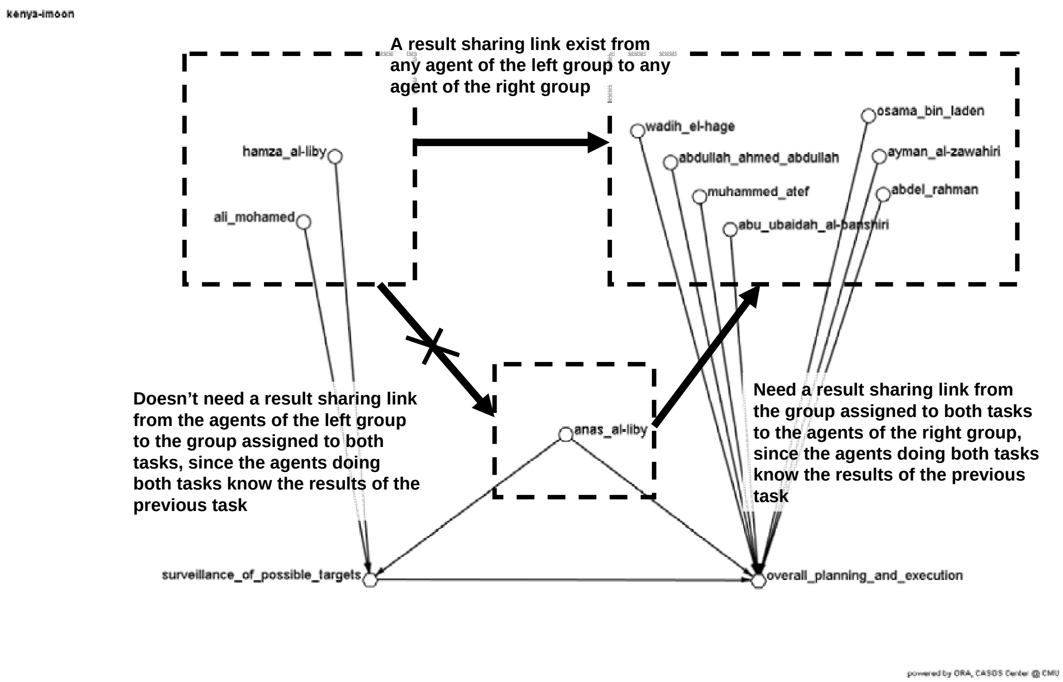



Fig. 8.7 A partial visualization of two tasks and ten assigned agents. This precedence task relation will result in 21 result sharing links between the agents doing the prior task and the agents performing the next task. One agent who is doing both does not need any result sharing link.

**TABLE 8.3** 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 [184] |
| Betweenness Centrality | Number of shortest paths passing a node, Degree of information flow control | Freeman [184] |
| Eigenvector Centrality | Calculates the eigenvector of the largest positive eigenvalue of the adjacency matrix, Degree of connections to the high-scoring nodes | Bonacich [185] |
| Cognitive Demand | Measures the total amount of effort expended by each agent to do his/her tasks, calculation details are elaborated below. | Carley [181] |
| Communication | Measures the communication need of agents to complete their assigned tasks, calculation details are elaborated below. | Carley [181] |

### 8.5. Results

The described decision making structure extraction scheme is applied to the U.S. embassy bombing in Kenya case, and the task of interest was *detonation*. Next, we regress the decision making structures against the original 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 original and the extracted structures, we describe and visualize the extracted structure. Next, we calculate five network metrics on the original 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.

#### 8.5.1 Initial result and descriptive statistics

Figure 8.7 is the visualization of the extracted decision making structures for the detonation task, and the image is generated by ORA [185]. 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 original meta-network has 17 members, the extracted structure has only 14. 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 original social network, most of the individuals are linked as a circle with directed links. Therefore, the inference on the command interpretation is not clear for most of the members. However, *Osama bin Laden, Wadih el-Hage* and *Abdel Rahman* show a clear hierarchy in the social network. We do not believe that the actual command interpretation is as sparse as the inferred structure, but from the observed structure, there is no clear way to infer the hierarchy of the other members.

#### 8.5.2 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 original network. This is a statistical analysis to support the qualitative findings of Section 5.1. If the meta-network implies such decision making structures, the correlation and the R-square of the regression result will be high. Table 4 displays the result of QAP correlations between each of the extracted structures and the meta-network. Information sharing is very highly correlated with the original 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.


Fig. 8.8 Three extracted decision making structures. (Top) Information sharing, (Middle) Result sharing, (Bottom) Command interpretation

**TABLE 8.4** A table of QAP correlation and other distance metrics between the original structure and the extracted decision making structures. (IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

| | CI | IS | RS |
|---|---|---|---|
| Correlation | 0.2204 | 0.8181 | 0.1399 |
| Significance | 0.0200 | 0.0000 | 0.0510 |
| Hamming Distance | 34.0000 | 12.0000 | 81.0000 |
| Euclidean Distance | 5.8310 | 3.4641 | 9.0000 |

The MRQAP analysis in Table 8.5, between the extracted structures as independent variables and the meta-network as a dependent variable, results in a high R-squared value, 0.6759. 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 original 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 8.5** A table of MRQAP regression results. The dependent network is the observed meta-network, and the independent networks are the extracted meta-network. (R-Squared = 0.6759)

| Variable | Coef | Std.Coef | Sig.Y-Perm | Sig.Dekker |
|---|---|---|---|---|
| Constant | 0.0288 | 0.0000 | | |
| CI | 0.2080 | 0.0524 | 0.2250 | 0.0400 |
| IS | 0.7876 | 0.8232 | 0.0000 | 0.0000 |
| RS | -0.0487 | -0.0648 | 0.1790 | 0.0600 |

### 8.5.3 Personnel with different levels of importance in structures

Table 8.6 shows the top three individuals in the four structures (original meta-network, information sharing, result sharing, and command interpretation) and by using five metrics (degree centrality, betweenness centrality, eigenvector centrality, cognitive demand, and communication). When observing the importance of individuals in the extracted structures, *Osama bin Laden* stands out in the information sharing aspect. In the original observed network, he ranked seventh in degree centrality, ninth in cognitive demand, and has zero betweenness centrality, though he ranked second in eigenvector centrality. However, the information sharing network ranks him second in betweenness centrality. Also, *Wadih el-Hage* is an individual with high importance in the extracted structures. He is not ranked in the top three with any metrics of the original network. However, he is ranked second (RS) and third (CI) in degree centrality; first (IS and CI) in betweenness centrality; and third (CI) in eigenvector centrality, etc. Actually, *Wadih el-Hage*, whose alias is *the Manager*, was actively engaged in and even managed this terrorist attack. While the human analyst and the network text analyzer generated a meta-network not reflecting his importance, our inference and the meta-network including expertise, resources, and tasks are able to find his importance in the organizational structure. These over- or under-estimations on the criticality of personnel can be found from the metrics of other individuals, i.e. *Anas al-Liby*.

**TABLE 8.6**: A table of top three individuals from five metrics and four structures (ORI=original meta-network, IS=Information Sharing, RS=Result Sharing, CI=Command Interpretation)

| Measure | Structure | Rank 1 | Rank 2 | Rank 3 |
|---|---|---|---|---|
| Total Degree Centrality | ORI | Mohammed Rashed Daoud al-Owhali | Ali Mohamed | Fazul Abdullah Mohammed |
| | IS | Mohammed Rashed Daoud al-Owhali | Ali Mohamed | Fazul Abdullah Mohammed |
| | RS | Anas Al-Liby | Wadih el-Hage | Abdullah Ahmed Abdullah |
| | CI | Ali Mohamed | Mohammed Rashed Daoud al-Owhali | Wadih el-Hage |
| Betweenness Centrality | ORI | Mohammed Rashed Daoud al-Owhali | Fazul Abdullah Mohammed | Abdel Rahman |
| | IS | Wadih el-Hage | Osama Bin Laden | Fazul Abdullah Mohammed |
| | RS | Jihad Mohammed Ali | Fazul Abdullah Mohammed | Ali Mohamed |
| | CI | Wadih el-Hage | Abdel Rahman | Osama Bin Laden |
| Eigenvector Centrality | ORI | Anas Al-Liby | Osama Bin Laden | Ali Mohamed |
| | IS | Anas Al-Liby | Osama Bin Laden | Ali Mohamed |
| | RS | Anas Al-Liby | Abdullah Ahmed Abdullah | Osama Bin Laden |
| | CI | Anas Al-Liby | Ali Mohamed | Wadih el-Hage |
| Cognitive Demand | ORI | Mohammed Rashed Daoud al-Owhali | Ali Mohamed | Abdel Rahman |
| | IS | Mohammed Rashed Daoud al-Owhali | Ali Mohamed | Abdel Rahman |
| | RS | Abdel Rahman | Mohammed Rashed Daoud al-Owhali | Anas Al-Liby |
| | CI | Mohammed Rashed Daoud al-Owhali | Ali Mohamed | Abdel Rahman |
| Communication | ORI | Abdel Rahman | Mohammed Rashed Daoud al-Owhali | Jihad Mohammed Ali |
| | IS | Jihad Mohammed Ali | Muhammed Atef | Wadih el-Hage |
| | RS | Jihad Mohammed Ali | Muhammed Atef | Wadih el-Hage |
| | CI | Jihad Mohammed Ali | Muhammed Atef | Wadih el-Hage |

Figure 8.9 shows that the difference of metric evaluation results across the original meta-network and decision making structures. Specifically, we subtract a metric value of a meta-network from the value of an 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 betweenness centralities from the original network and decision making structures are quite similar except for a few individuals.

*Osama bin Laden* (A0) and *Wadih el-Hage* (A2) show extreme underestimations in betweenness centrality of the original network compared to that of the information sharing network. When we remember that *betweenness centrality* is specialized in the information diffusion passage and the information sharing network is an inferred information flow network from a meta-network, those two are the key personnel in diffusing information pieces in this network. Also, Abu Ubaidah Al-banshiri (A11) is somewhat underestimated in the result sharing structure. He has a big positive difference in degree centralities, eigenvector centralities, and cognitive demand, which means that he has higher value in result sharing compared to the original observation.

**TABLE 8.7** I.D. assignments to individuals. I.D.s will be used to distinguish individuals in the later tables. We used some abbreviations for names (Fazul= Fazul Abdullah Mohammed, Jihad= Jihad Mohammed Ali, Banshiri= Abu Ubaidah al-Banshiri)

| Name | Osama Bin Laden | Muhammed Atef | Wadih el-Hage | Ayman Al-Zawahiri | Anas Al-Liby | Abdel Rahman | Fazul | Al-Owhali |
|---|---|---|---|---|---|---|---|---|
| ID | A0 | A1 | A2 | A3 | A4 | A5 | A6 | A7 |
| Name | Ali Mohamed | Hamza Al-Liby | Khalid Al-Fawwaz | Banshiri | Abdullah Ahmed Abdullah | Jihad | | |
| ID | A8 | A9 | A10 | A11 | A12 | A13 | | |

### 8.5.4 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 8.8 shows the coefficients to generate the two components corresponding to the two dimensions, and Fig. 8.10 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 original network and the collection of the three inferred structures. Thus, we can distinguish the different member profiles coming from the original dataset and the inferred dataset. Before the interpretation, it should be noted that we disregarded *Khalid al-Fawwaz* (A10) because he is an extreme outlier in PCA. In the original and the inferred networks, he was the only one who had all the necessary resources to execute his assigned task. This makes him unique in the membership profile and disrupts the overall visualization of PCA. Therefore, we perform the PCA without him, but he, himself, forms a cluster whose profile is '*Completely supported to perform his task in terms of provided resource and expertise*'.

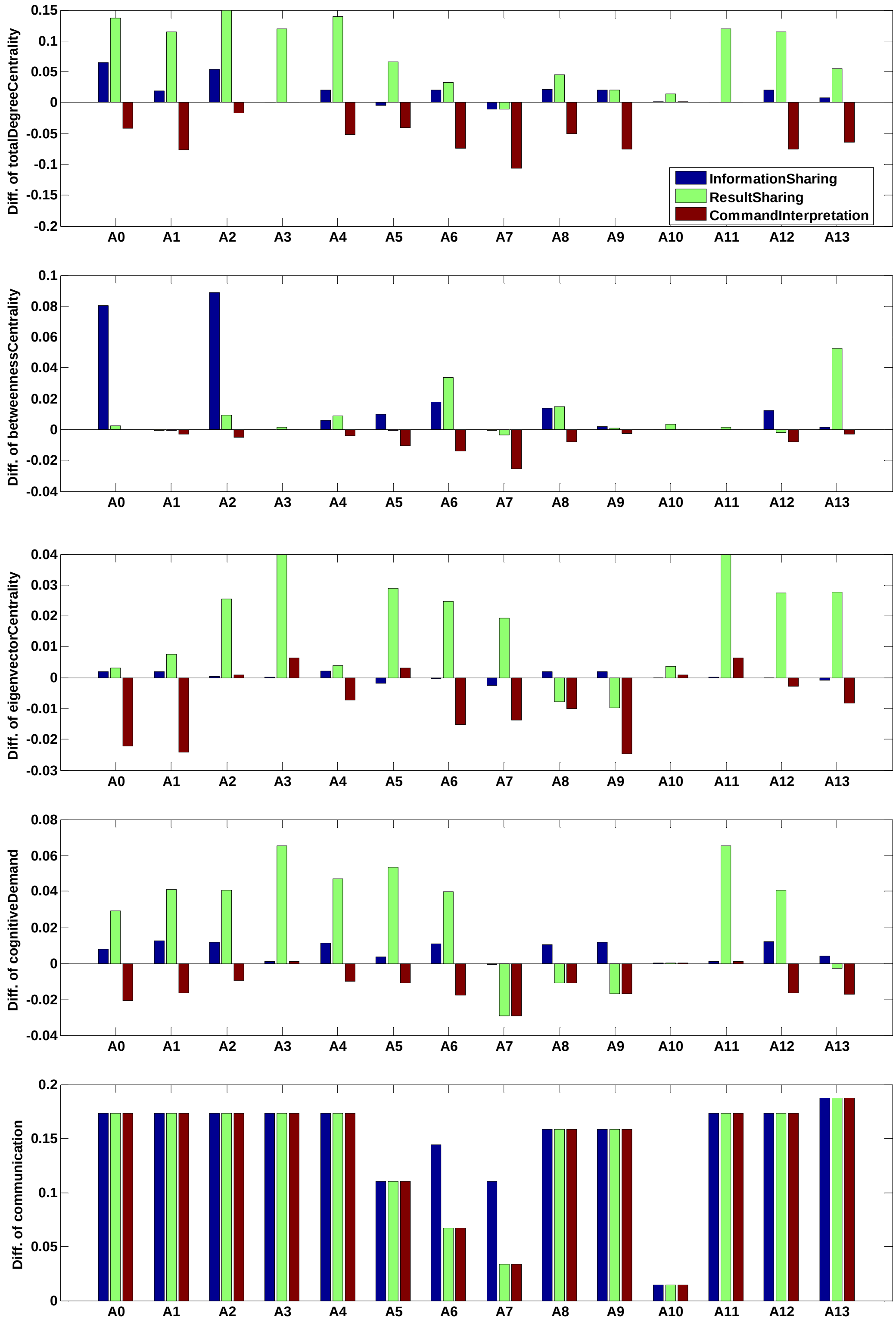



Fig. 8.9 Charts displaying the difference of metrics between a meta-network and extracted structures

According to Table 8.8, we have four sets of coefficients: two principal components for the original and the inferred. In the original, the high first principal component value implies *having more connections to other personnel, resources, and tasks* because it has high coefficients in degree centrality and cognitive demand. The high second principal component value means *high demand in communication to complete the assigned tasks* because it has high coefficient in communication. In the inferred structures, the meaning of the first principal component, *low demand in communication to complete the assigned tasks,* is similar to the opposite of the second principal component of the original, and that of the second component, *having more connections to other elements*, is similar to the first component in the original.

**TABLE 8.8** Coefficients of two principal components from the original structure (top) and the extracted structures (bottom)

| | Structure | Prin. Comp. 1 | Prin. Comp. 2 |
|---|---|---|---|
| Total Degree Centrality | ORI | 0.6473 | -0.4217 |
| Betweenness Centrality | ORI | 0.0920 | -0.0309 |
| Eigenvector Centrality | ORI | 0.0513 | -0.1513 |
| Cognitive Demand | ORI | 0.6088 | -0.1763 |
| Communication | ORI | 0.4463 | 0.8759 |
| | Structure | Prin. Comp. 1 | Prin. Comp. 2 |
| Total Degree Centrality | IS | 0.1672 | 0.5702 |
| | RS | -0.0848 | 0.3977 |
| | CI | 0.0571 | 0.2502 |
| Betweenness Centrality | IS | 0.0214 | 0.2144 |
| | RS | 0.0424 | 0.0664 |
| | CI | -0.0018 | 0.0067 |
| Eigenvector Centrality | IS | 0.0103 | 0.1234 |
| | RS | -0.0286 | 0.0297 |
| | CI | -0.0241 | 0.0805 |
| Cognitive Demand | IS | 0.1114 | 0.4353 |
| | RS | 0.0282 | 0.2082 |
| | CI | 0.0783 | 0.3402 |
| Communication | IS | -0.4370 | 0.1346 |
| | RS | -0.6114 | 0.0850 |
| | CI | -0.6114 | 0.0850 |

Figure 8.10 displays the clusters of individuals in the projection of the two principal components of the two structures. The original structure suggests five member profiles: *many connections to organizational elements and medium communication demand to complete their tasks* (A6, A8, A9); *medium connections and medium communication demand* (A0, A2, A1, A4, A12); *less connections and medium communication demand* (A5, A13); *less connections and high communication demand* (A3, A11); *and medium connections and low communication demand* (A7). The inferred structures provide four profiles: *medium or less connections and low communication demand* (A0, A1, A2, A4, A5, A7, A8, A10, A12, A13); *medium connections and medium communication demand* (A9); *high connections and medium communication demand* (A6); *and less connections and high communication demand* (A3, A11). These profiles tell the groups of indi-

viduals 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. *Al Zawahiri* and *Banshiri* were grouped in the same cluster in both structures. They were suffering from sparse communications to others and high communication needs to complete their tasks.

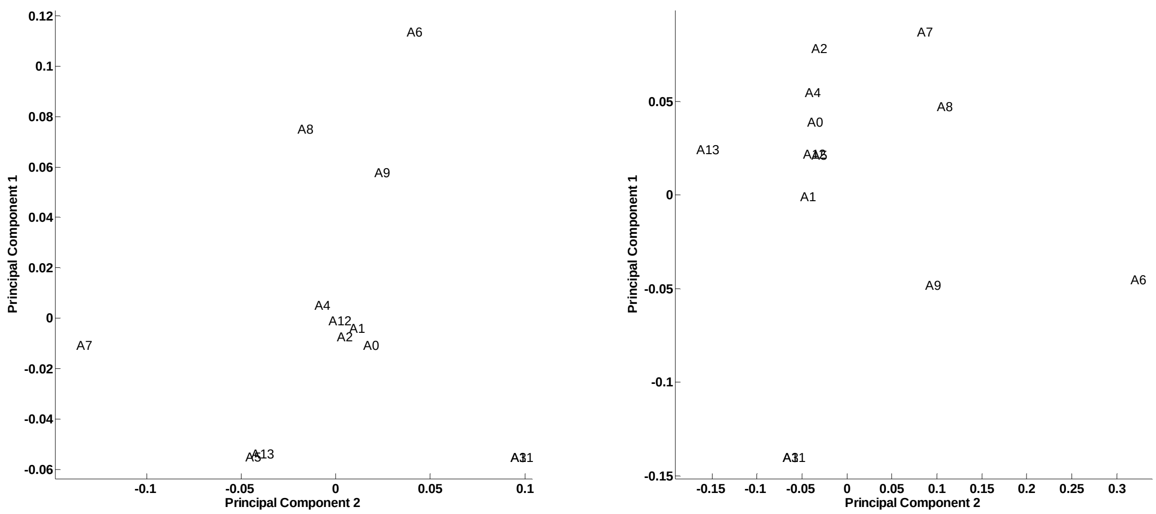



Fig. 8.10 Two projections of metrics of individuals using two principal components. The left is using only the original structure, and the right is from only the extracted structures.

## 8.6. Conclusion

This paper demonstrates what can be achieved by integrating social network analysis and decision making structure analysis. Social network analysis has been a prominent tool in investigating the structure of an organization. However, it is also susceptible to errors embedded in the given network structure. Therefore, reorganizing the links is required to perform analysis correctly. This reorganization is often done by human analysts. We expect to reduce such efforts by utilizing the introduced methods.

Furthermore, the method produces a set of different decision making structures that differ from each other in their natures. For instance, information sharing is a different relation compared to result sharing or command interpretation. When we only used a social network analysis, often the links are single-mode, meaning that the links are not differentiable. Therefore, the above method will enable analysts to think about the different types of links among the same entity types, and the analysts can reason more deeply by asking questions such as why these two agents have a command interpretation without any result sharing.

From the organizational structure perspective, a decision making structure and a meta-network are both network structures. Therefore, the analysis methods are interchangeable to some extent. For instance, we can apply social network metrics to both structures. This interoperability or interchangeability makes the analysis more comprehensive. For instance, we have different sets of critical personnel by analyzing various management relations and an original meta-network. We are not certain which set contains the true personnel of interests, but we can suggest a package of results to human analysts.

Future work on this integration will include two major components. First, we should strengthen the decision making structure extraction heuristics. Currently, the information sharing extraction generates a dense network that is not common in the management science field. Also, we have a too sparse command interpretation that we believe are more in the organization. Therefore, we develop the existing method further or validate the current model by showing that the dense information sharing and the sparse command interpretation are legitimate. Second, we need to include more decision making structure oriented analysis methods in the framework. The result in this paper only comes from social network analysis, though it used the decision making structure for the analysis input. There are several decision making structure analysis methods, e.g. generating a set of feasible decision making structures under certain cultural constraints. In spite of these incomplete developments, this framework still shows its value by showing 1) the trimming process of a noisy meta-network, 2) different criticality analysis results from the extracted decision making structure, and 3) the opening of a unified organization analysis framework integrating social network analysis and decision making structure analysis.

# Chapter 9

# Simulating the Adversary: Agent-Based Dynamic-Network Modeling

**Kathleen M. Carley, Geoff Morgan, Jesse St. Charles, Brian Hirshman**

## 9.1 Social Network Simulation

Social network simulation (SNS) is an emergent area of research that combines social network analysis and simulation, typically agent-based simulation. This area is often referred to as dynamic network analysis as much of the focus of the combined modeling approach is on how networks evolve, change, and adapt. Additionally SNS has a focus on how individual and group learning and behavior is impacted by and impacts the changes in the networks in which the individuals are embedded. Frequently, in social network simulations, the social network and other networks, such as the knowledge network, and/or the individuals or "nodes" in the network are co-evolving as agents interact, learn, and engage in various activities. The need to address complex systems but produce realistic results means that these SNS are typically focusing on many types of networks simultaneously not just the social networks. An example of such a model might be one that explores how communicating new ideas via diverse social-media has differential impact on the movements of ideas and diseases through the population and response to the information and disease by the populace.

There are various types of social network simulation each has a unique perspective on the problem and each has its own collection of strengths and weaknesses. We begin with more formal approaches that rely heavily on statistics and mathematical formalisms and then move on to less formal bottom up approaches. System Dynamics is a top down, aggregate view of networks. Regression or econometric approaches like Quadratic Assignment Procedure provide a non-parametric approach to modeling dynamic social networks. More traditional parametric statistical approaches to SNS will use methods such as Expectation Maximization or Maximum-likelihood estimation to find the optimal (or near optimal) model parameters given the data. Finally, agent based SNS provides an intuitive bottom up approach for investigating social systems. Regardless of the method used for social network simulation, there are unique sets of challenges around validation, analysis, prediction, and computational efficiency that are common to all.

### 9.1.1 System Dynamics

System Dynamics supports top down reasoning about complex systems. Basic variables, system level mechanisms and the relations between them are modeled. System dynamics uses stocks, flows, and feedback loops to describe system behavior but because of its top-down, aggregate perspective it is less useful at the individual level. If we were studying information diffusion in a social network setting, a system dynamics approach might have a stock of people who have the knowledge, and stock of people who don't have the knowledge, with knowledge flowing between them at some rate which is dependent on the percent of the population that already has the information, the density of the social network, and other graph-level network metrics. The approach is perhaps accurate in the aggregate but we lose the subtlety and nuance that explicitly representing complex networks of people provides. For most social network simulation needs, the system dynamics approach is not the modeling framework of choice and is only used to talk about overall change in the structural parameters of networks such as the change in density but does not produce specific new networks of who is interacting with whom.

### 9.1.2 Statistical Network Generation

Both parametric and non-parametric statistical methods have been applied to learning and inferring models of social networks.

For parametric approaches: Random Graph Models provide a statistical, data driven mechanism for social network simulation. These models are derivative from graph theory or have been observed in real world networks. Networks are generated randomly using edge generation functions. Edges in social network do not exist or not exists; rather they have some probability of existence. This probability is modeled by a named parametric distribution like, Poisson, Exponential, or Power Law. Each of these distributions comes with a set of simplifying assumptions that may or may not be appropriate for the phenomenon being modeled. Optimal parameters for these edge models are empirically derived using expectation maximization or maximum likelihood estimation. However, due to the complexity of networks, the state space of these systems is massive making direct solving of the likelihood function intractable. This requires clever heuristic approximations to find near-optimal parameter values rather than the most optimal parameter values. Random graph models have been used to simulate collaboration and affiliation models. It is worth noting that these statistical approaches are typically aimed at the simulation of topological formation and have much less complexity and much less to say from a sociological viewpoint than their agent based counterparts.

For statistical models that have a stronger sociological basis we look toward P* models, otherwise known as Exponential Random Graph Models (ERGM). These models are based upon Markov random graphs and represent a logistic regression of the network parameterized by various network statistics such as reciprocity, transitivity, centralization, connectedness and others. Using a pseudo-likelihood function, P* models are fit to observed networks. This model can then be sampled to produce simulations of the observed social network. Tools like Sienna, developed by Tom Snijders, can be used to fit ERGMs to data.

There are also non-parametric approaches to social network simulation; one example is the Multi-Regression Quadratic Assignment Procedure, or MRQAP. MRQAP uses multiple samples from the social network being studied to perform a regression analysis of dyadic information that is correlated. Since properties of transience, reciprocity, and homophily are generally assumed to exist within social networks, most dyadic links have significant correlation with one another. This autocorrelation would normally be a significant issue for regression analysis but MRQAP uses a permutation procedure to account for the autocorrelation. MRQAP produces a regression model of social relationships that can be useful for running hypothesis tests on networks; this method can be significantly affected by bias learned in the model.

### 9.1.3 Agent Based Models

One of the most commonly used and intuitive approaches to SNS is Agent Based Models (ABM) (see *agent-based models*). ABMs employ a bottom up approach in which a set of heterogeneous agents, their behavioral properties, the "rules" of interaction, the environment and the interaction topology that the agent populates is explicitly modeled. Complex social behavior emerges from simple individual level processes. In ABMs many computational entities, with varying levels of cognitive complexity, interact with one another in a manner similar to the real world entities they represent. These agents are simplified versions of their real life counterparts (e.g., ants, people, robots, or groups), only retaining elements salient to the phenomena being studied. Agents interact in a virtual world and can be constrained and enabled by the network position they occupy.

In most ABMs the topology of the virtual world is a simple 2-D grid and agents form "networks" as they occupy the same or neighboring spaces or the agent's network is prescribed as the set other agents within so many spaces of ego. Networks generated from grid-based interactions or defined in terms of grid-nearness tend not to have the same properties as true social networks; i.e., the distribution of ties, the method of tie formation and dissolution, and the relation of ties to physical space are not realistic. Most ABM toolkits support this type of grid-based modeling of the social topology.

There is, however, a growing interest in and a growing number of ABMs where the agents exist and move in a socio-demographic or network topology rather than a grid topology. An example here is the Construct model. In these models the agents occupy a social network position defined in terms of which other agents ego can interact with. In other words, rather than physical adjacency, social adjacency is used. This network topology may be static or dynamic. This latter type of model where agents exist in dynamic social networks rather than on grids is where most research on SNS is focusing. This is the approach we found to be most valuable for modeling the adversary and it is embodied in Construct.

### 9.1.4 Relational Sources of Complexity in ABM SNS

Social network simulation has a deliberate and expected preoccupation with relational information. The space in which people interact is a social one, there may be geographic motivations for communication, but these considerations merely temper and constrain the social space. As such, for the virtual spaces in the ABM SNS, agents interact in a social space where every agent is potentially adjacent to all others.

Using populations of virtual individuals, network effects emerge from both intended and unintended interaction among agents connected by ties of varying strength. The strength of the tie between two agents is defined in terms of frequency of interaction or strength of social tie or degree of similarity. Agent behavior, when the network is dynamic, can change the strength of this tie. Moreover, these ties may be hierarchically organized; e.g., two agents may interact and that interaction may be a work-based interaction and that interaction may be further characterized as interaction vis a specific task.

The mechanisms that drive interactions in an ABM SNS are typically based in social theory. Theories of human interaction such as homophily, transitivity, reciprocity are coupled with basic or sophisticated cognitive abilities. Theories of interaction take into account both social, emotional, and cognitive processes. Hence the cognitive load on the agent to determine whom to interact with when can be quite high increasing the demand both for more storage and more computational processing power.

Another source of complexity is the over-lapping social circles. Since the agents are socially embedded, the social environment itself may be characterized in multiple ways. For example, agents might be tied by different forms of similarity – age, gender, ethnicity, attendance at common events or co-location, shared resources, shared knowledge or beliefs, various role based relations – kinship, mentorship, leadership, and through diverse media – face-to-face, email, web. The result is that the agents occupy a multi-dimensional topology.

Finally, agents are not just embedded in social networks. Rather, they are connected in trails of who was where when doing what with what information or resources and for what effect. That is underlying any SNS that deals with socio-cognitive actors (hence not the simple statistical models) there will be an ecology of interlinked networks. This is referred to as the Meta-Network – a multi-mode, multi-link, multi-level network of networks at multiple points in time. For most ABM SNS the classes of nodes will include: Who (people, teams, organizations); What (tasks, events); How (knowledge, resources); Why (beliefs); and Where (locations). By formalizing these entities we are able to explicitly get at unique relationships between them implicit in multimodal data. A network of people-to-organizations is an affiliation network, while a network for knowledge-to-tasks is a Needs network, and agent-to-agent networks are the familiar social network formalization. A meta-network approach allows the developer to more fully represent and formalize relationships present in the real world that drive social interaction. For example, if a person is driven to interact with another person because they have to complete a particular task, and this particular task requires they know something specific but they don't have this knowledge then they have to go to a resource (book) or another person to gain the knowledge required.

These five key sources of complexity are completely connected network (full adjacency), hierarchical interaction, cognitive load, high dimensionality of and overlap in the social space, and meta-network considerations. These factors dramatically increase the complexity of social network simulation over many traditional agent based simulations. These factors also reduce the size of populations that can be simulated and increase the computational resources needed to simulate the system. ABMs have been used to model incredibly large populations, e.g., millions of agents. Parallelizing activity makes this possible. However, when accurate network representations are added as in the SNS models rather than just deriving the network from grid-based interactions, standard approaches to parallelization are no longer possible.

### 9.1.5 Common Research Challenges

Two core challenges are reuse and validation. Reuse is the process of taking an existing model and with no change to the internal processes reuse the model with different input data to address a new situation. An example would be to use a model of information diffusion to first explore how best to communicate medical information to effect change in smoking behavior and then reuse it to explore how to intervene in the social network to effect world leader's understanding of global climate change. Currently, most models are one-off model and require sufficient rebuilding and extension for new problems. SNS models, however, are a potential exception. In SNS models, these models can be built to take as input one or more real-world networks. The SNS models can then be used, on any network data set, to identify the probability of alternative futures and the impact of various interventions. A core advance in this area has been the development of support technologies to generate networks from socio-demographic data, such as census data, as import to ABM SNS (see e.g., the work on BioWar). For adversarial modeling we enabled reuse by augmenting Construct so that it could take meta-network data directly from ORA. This is described in the later modeling chapter and was used with the Indo-Pak scenario.

Validation of any socio-cultural simulation is difficult. The core reasons are that these models violate all the assumptions that underlie validation theory due to being comprised of agents that learn. In the SNS area, the challenges are further compounded by the lack of spatio-temporal network data and by the fact that human lab experiments are inappropriate as network effects do not show up without groups greater than 5.

For ABMs the key validation approach is to do validation in parts and to validate each mechanism separately. The hope is that by validating the pieces, some confidence is bestowed to the whole. The problem, is little is known about the conditions under which this is true for a complex non-linear system.

Docking and model-to-model comparison is a key validation strategy. This process involves showing that for two or more models, common inputs produce common outputs. This allows a simulation that has not been formally validated to gain validation from an older simulation which has been validated and sheds light on the elements of the models that are robust. This model-to-model approach is part of the multi-modeling approach used in this MURI.

For the statistical models like ERGM, P* and MRQAP the models have been “trained” on real data. In this case, validation is the process of seeing whether the predictions hold in the future or in other time periods. For these models generalizability is more of a concern if the models learned are ported to other reasonably equivalent systems.

### 9.1.6 Applications

Common uses of SNS range from theoretical investigation to applied analysis and prediction tasks. Researchers can explore the ramifications of sociological principles like homophily and transitivity: are these mechanisms sufficient to produce real networks that we observe? What are the properties of analysis methods and are they robust? In applied settings SNS can assist in predicting how a network will evolve and help analyze the dynamic equilibriums that might arise. Key application areas are the spread of disease, information diffusion, belief formation and diffusion, and activity contagion. SNS are critical for understanding the impact of various interventions where social influence is expected to play a role. Here we use them to assess adversarial groups. In particular we used agent-based dynamic-network models, specifically Construct.

## 9.2 Agent-Based Dynamic-Network Models

Agent-based modeling is a simulation technique which relies on the capabilities of individual actors, called agents, in order to model a global behavior. In an agent-based model (ABMs) complex system level behavior emerges from the local action of, and interaction among, a large number of heterogeneous agents. The relationships between agents, the social and spatial topology in which agents are embedded, and the logic that guides agent behavior play a crucial role in determining the overall behavior of the system. Global outcomes emerge as heterogeneous agents interact and engage in various local activities.

There are a number of advantages to investigating a research problem by building or extending an agent-based model. All simulation techniques, including agent-based modeling, are key tools for theory development as they force researchers to encode their assumptions when writing models and to question previously hidden assumptions in theories. This process allows a researcher or policymaker to realize the limitations of a particular theory or solution, or conversely to develop extensions of a theory into a new domain or to develop a solution that is more robust. When building an agent-based model, the simulation designer will have full control over what types of data will be gathered, and can be modified relatively easily if follow-up virtual experiments are performed. The data gathered will not be subject to the kinds of cognitive or methodological biases found in empirical research. Virtual experiments performed using agent-based models may be more ethical than those using people, especially if the experiment requires radical or harmful reorganization of the actors involved. The size of agent-based virtual experiments can also be much larger than those performed using traditional human subjects, and the marginal cost of adding an extra actor or even an entire replication can be trivial. Simulation can also be used to examine the same starting condition multiple times, allowing the researcher to perform a 'what-if' analysis as random changes build up and cause the simulated population to evolve differently. Simulation can also be used predicatively in order to forecast what would happen to a specific initial condition; when run multiple times, broad trends may be detected and outlying cases and their causes potentially identified. Lastly, by leading the researcher to think about the kinds of local rules that lead to global patterns or by forcing the researcher to confront the unintended consequences of seemingly individual rules, agent-based modeling can help a researcher understand the link between individual and social behavior.

Agent-based modeling, like other technique, has its strengths and limitations. These models are particularly valuable for comparing, contrasting and combing theories about how individuals act and so serve as a virtual world for developing theory by both exploring theory interactions as well as generating and testing hypotheses. They are valuable when there are not strong empirical regularities relating the past to the future as they allow discovery of the space of possibilities. ABMs are tools for gaining intuition about how individual differences can have systemic global consequences. Finally, ABMs enable experimental protocols to be examined and the likely consequences estimated using virtual experiments when the same experiment is too complex, costly, technologically infeasible or unethical to run in the real-world. Agent-based modeling also has a number of weaknesses. These models often have a vast number of parameters and so must be run a large number of times in order to appropriately explore the parameter space. This can create analytic difficulties. Validation, as will be discussed, may be difficult. Many ABMs are built with rules specific to a narrow domain and so have to be significantly rebuilt to be used in a different domain. ABMs can require vast quantities of computational resources, particularly if very high fidelity agents are used.

ABMs are distinct from other mathematical or modeling techniques such as closed-form solutions, discrete event simulations, and system dynamics models. While ABMs are agent focused, the other techniques are population focused. Closed-form solutions are mathematical transformations which attempt to find an exact (and optimal) solution to a particular problem when expressed mathematically; while such solutions may be found for certain simple problems, they are often not applicable for the complex and often inexact problems that agent-based models are used to address. In contrast ABMs are concerned with the process and not on some optimal or final state. Discrete-event simulations focus the design of the model around events, usually organizing the simulation around an event queue; however, these events need not be generated by actors themselves. ABMs can take as input event sequences but add individual rules of behavior to respond to such events. System dynamics models focus on aggregate behaviors in a society, and as such attempt to express the number of agents who have a particular trait without completely specifying the agents themselves. Both system dynamic models and ABMs are complex system models. The key difference is that the logic for social change is that system dynamic models are top-down whereas ABMs are bottom up. From an environment perspective in an ABM, the environment, such as the social network, is represented explicitly; in contrast, the other models represent the environment using summary statistics such as density. As a result, only an ABM can explore the explicit flow of ideas, beliefs, influence, trust, disease, money etc. though the network as agents interact and get as output the specific network and which agent has what when.

### 9.2.1 Agents and Their Environment (and Social Network)

ABMs vary in how the environment is represented. This could be as simple as a single dimension or array and so ego interacts with those other agents that are within so many squares left or right of ego. This is the case in Kaufman's NK model. Traditionally, however, the environment was a grid and the agents interacted with other agents in and/or could move to those squares that surrounded them. Most early studies explored the relative impact of von Neuman (squares left, right, up, down of ego) or Moore (eight squares around ego) or extended Moore neighborhoods (squares within some distance of ego). In these traditional approaches the structure of the social network is directly tied to the physical position of the agents. Examples of such models are the game of life, the original Schelling segregation model and the more recent SugarScape models developed by Epstein and Axtell. In general, it is difficult to get realistic social networks in this representation of the environment. Further, as early results showed, unless the grid is bent into a torus, the resultant social behavior is largely dictated by "edge effects"; i.e., restrictions on activity caused by being at the edge of the physical grid.

More advanced models place agents in a socio-demographic space and separate the physical and the social space. In such models, very few have explicitly modeled the social network. Increasingly, however, researchers are incorporating more realistic network representations, such as small-world, scale-free, or other types of network generators. The most advanced of these models are the dynamic-network ABMs in which the networks and the agents co-evolve (the first model of this type was Construct). In some cases, the models are instantiated with networks that are actually derived from real data. These models will often generate or import an appropriate graph before the simulation agents are initialized, and then assign each agent to a graph position when the simulation starts. Other models use a social network gathered from empirical studies. These networks have the advantage of being as realistic as possible, but may potentially bias the simulation results due to the structure and nature of the particular social network gathered (see *social network simulation*). Correctly specifying the topology of a social network in an agent-based model has important implications for the conclusions drawn. In modeling the adversary it is valuable to use the social network of the adversarial group.

The quality of the social network modeling can have important effects on simulation outcomes. For instance, in the Construct model, the social network topology has a non-linear effect on knowledge and belief diffusion rates in the system. Construct uses sophisticated agents that have the ability to interact and choose partners with which to exchange knowledge and belief. A stylized meta-network, which specifies the pattern of potential partners with which an agent can interact, can be imposed to limit the form of the evolved networks. We use Construct to model the adversary. Our results indicate that the most effective type of intervention depends on how the adversary is structured; e.g., Al Qaeda and Hamas have different structures and the same intervention, such as isolation of the top leader, in the two cases can lead to performance decrements in one and performance improvements in the other.

### 9.2.2 Trade-offs

When building an ABM, particularly an agent-based dynamic-network model, researchers should be aware of the key trade-offs. One important trade off is between simplicity and realism. Simple models, such as Schelling's segregation model, attempt to use a specific principle to describe an important trend in human or social behavior. By keeping the principle narrow, the modeler seeks to illustrate how a particular phenomenon has important explanatory power. Such models are extremely valuable for engaging systematic thinking in an area and for making key points to an audience. However, the results generated by using such models, however, tend to be quite fragile and can change radically as new types of agents, alternative environments, or additional interaction logics are added. In contrast, more expressive models are more veridical and by capturing greater realism are capable of explaining a wider swath of human socio-cultural behavior. The more expressive emulative models often employ multiple modules, as well as an extremely large number of parameters, in order to increase their accuracy and predictive power. This increase in power and fidelity, however, comes at the cost of ease of explanation, time to generate results, and time to analyze model results. Another important trade-off is between the sophistication of each agent and the number of agents in the model. In general, the more sophisticated the cognitive model the fewer the number of agents represented. Models with a larger number of agents typically employ simpler agents with fewer rules such as in the artificial life simulations; in contrast, models with only a few agents typically employ quite sophisticated cognitive agents capable of actually doing tasks, e.g., flying planes, as in tac-air-SOAR. The reason is simple: processing and run-time constraints are such that increasing either the number or the cognitive sophistication of the agents increases computational costs. There are two source of complexity in the agent model: cognitive and social. The more sophisticated the cognitive model the more the ABM can be used to explore behavior on specific tasks, such as buying groceries. The more sophisticated the agent's social model, the more it can be used to address issues of socio-cultural change and information diffusion. Both cognitive and social complexity increase computational processing costs. Historically, ABM designers with more emulative models have either worked with a few (less than a hundred) very realistic cognitive agents, or a moderate number (less than 25,000) of very realistic social agents that are moderately cognitively realistic, or millions of agents that are both cognitively and socially simplistic. A further trade-off occurs between overall model sophistication and speed. Not only will more complex models take longer to run due to their more complex computer logic, but they will also take a substantial amount of time to code, debug, and process results. Simple models, on the other hand, will run faster but may be more limited in their output. As a result, the more sophisticated the model, the more likely it is built, maintained, and extended by a team whereas the simple model may be built by a single research.

### 9.2.3 Validation and Verification

Validation, or the alignment between the model's behavior and actual empirical data, is a major concern and is a criticism often levied against simulation models of socio-cultural systems. Though models are often criticized for insufficient validation, the type, scope, extent, and precision of validation depends on the data available, the type of model built, and the expected use of the model's predictions. More validation is not always better; extremely basic models are rarely validated as their purpose is illustration, and some models need not be validated at all. On the other hand, emulative models rarely can be validated using a single case scenario and consequently the researcher needs to fuse data from a wide variety of sources – often at different time scales and collected for diverse purposes – to obtain a "good enough" dataset for validation.

ABMs of socio-cultural systems present special challenges to validation and analysis. One cannot naively assume that if the basic model of a single agent is validated then the aggregate model is valid, as interaction effects may lead to very different behavior. Typically models are validated at either the individual agent or the collective level but not both. When compared to engineering models of physical systems, these socio-cultural ABMs have more variables, high covariance among variables, discontinuities in variables, and non-stationary processes, interaction effects and temporal variations in the relations among variables often due to learning. As such, the nature of socio-cultural ABMs violates basic assumptions about the nature of simulation models that underlie the traditional formal approaches to analysis and validation developed in engineering and the physical sciences. This means that a new science of validation is needed, and that socio-cultural ABMs should not be used to predict the future but to describe the space of future possibilities. Given these complexities, new approaches to validation in this area have emerged: validation by parts (validating individual sub-modules), validation of inputs, validation of processes, and validation by docking. The process of docking two models, whereby the results of one model are compared to that of another, enables a greater understanding of what factors make the model results robust and identifies common failings. Moreover, common results from divergent models, as we found in the Indo-Pak scenario enhance the likelihood of the overall finding.

## 9.3 Construct

For modeling the adversary we extended and used the Construct model. Key extensions were enabling reusability by allowing the model to be instantiated by ORA, geo-spatial diffusion modeling, and multi-intervention analysis. Over the course of the MURI a large number of studies were done. These included: analysis of basic adversarial forms, impact of alternative COA related to both agent isolation and knowledge promulgation, and assessment of best approach for effecting belief change, i.e., "winning the minds and hearts of the adversary."

Construct 3.5 – hereafter referred to as simply Construct – is a multi-agent dynamic-network simulation model for examining the co-evolution of agents and the socio-cultural environment [109], [188]. Using Construct, one can examine the evolution of networks and the processes by which information moves around a social network [189], [190]. Construct captures dynamic behaviors in groups, organizations and populations with different cultural and technological configurations [191]. In Construct, groups and organizations are complex systems. The variability of human, technological and organizational factors among such systems are captured through heterogeneity in information processing capabilities, knowledge, and resources. Multiple non-linearities in the system generate complex temporal behavior on the part of the agents.

Construct is the embodiment of constructuralism, a mega-theory which states that the socio-cultural environment is continually being constructed and reconstructed through individual cycles of action, adaptation and motivation. Many social science theories and findings are part of the constructural theoretical approach including structuration theory [192], social information processing theory [193], symbolic interactionism [194], [195], social influence theory [196], cognitive dissonance [197], and social comparison [198]. In addition a number of cognitive processes are embedded such as transactive memory [199].

There are three key features of Construct 3.5 that make it ideal for our purposes. First, the experiment designer has complete control over which sub-agent models are used for interaction over the course of a run. Second, Construct contains a suite of agent models which enable diverse socio-technical conditions to be modeled. Third, general agent characteristics can be easily configured *a priori* using empirical data or they can be based on hypothetical data. To use Construct, as we did in this work, the researcher specifies both the relevant agents [200] and the social and knowledge networks [201].

While additional information about the Construct interaction model can be found elsewhere (e.g., [109], [190]), the core Construct agent dynamics are as follows.

Each time period of the simulation, agents take a variety of actions including initiating an interaction, responding, sending messages, engaging in tasks, updating beliefs. For each agent, these action tend to occur cyclically except for responding to media and making decisions which may occur off cycle – see Fig. 9.1. Exactly which actions an agent can take, and how many can be done simultaneously, depends on the agent's socio-cognitive nature. Each action takes a certain amount of time, typically a time period. Human agents use their preference for homophily or expertise, their transactive memory of other agents' knowledge, their beliefs, their socio-demographic characteristics, their availability, and their recommendations from others in order to rank the importance of interacting other agents in their social network. Based on this ranking, the human agent may choose to initiate communication with one or more other agents. The type of agent – human, web-page, etc – will determine whether the agent can initiate interaction and what are the agent's information processing characteristics.

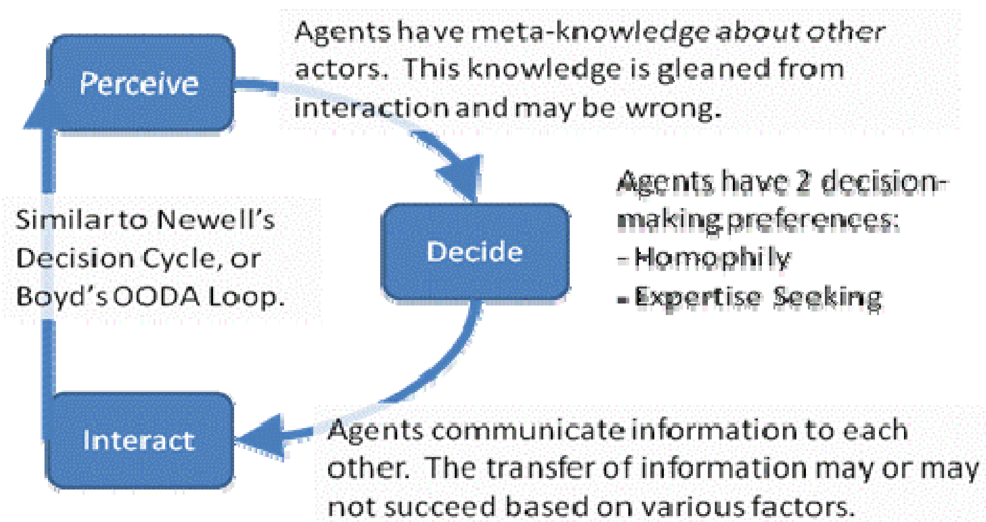



Fig. 9.1 Cycle of Agent Activity

If two agents are able to interact and communicate, then both agents will prepare a message and send it to the other. A message is a set of memes [202], and so consists of one or more instance of any or all of the following: knowledge, beliefs, transactive memory about the knowledge of third parties, or transactive memory about the beliefs of third parties. Once prepared, the message is communicated to the interaction partner, where it may be modified, misinterpreted, or ignored based on the socio-cognitive properties of the receiver. After receiving a message, processing it, and possibly learning from it, both parties may modify their beliefs or make any relevant decisions. This process then repeats for each agent during each time period.

All agents operate in the same "time frame" meaning that interventions and/or interrupts can occur at a particular time and all agents can respond to it – e.g., a news add can come out at time period 3, and agents will respond during that time period and other periods when the interrupt or intervention is active. Statistics, outputs, and decision information are gathered relative to these the time periods, as well as at the end of the simulation.

Although Construct was originally developed as a pure lock-stepped model with each agent interacting each time period and then updating their memory, that is no longer the case. As of version 2.5, Construct includes event driven mechanisms, variable duration interaction, and fixed as well as mutable agent characteristics. In addition to these programming changes to update Construct with newer simulation technology, additional work has performed done on validating the core mechanisms independent of the exact technological mechanism in a variety of settings. Finally, the current version is multi-threaded.

The fundamental mechanisms in Construct have been scientifically validated [188], [203], [204], [205]. It has been used to explain group mobilization [188], the impact of leadership [206], and the impact of the printing press [207]. Directly germane to the current study, Construct has been used to compare and contrast different educational media by socio-demographic feature [208] and the impact media and opinion leaders in real cities [209].

### 9.3.1 Agents

Agents are decision-makers with varying information processing, socio-demographic, and access constraints and as such may or may not be human [152]. Within Construct, agents go about their business interacting, communicating and learning each time period, as described in Fig. 9.1. As agents learn or acquire information, they may change their preferred interaction partners and modify what they are likely to communicate. These factors, in turn, influence what types of decisions are made by each agent. A variety of factors influence who agents select as interaction partners, what they communicate with that partner, how much and how they communicate, whether they learn anything from that partner, and the accuracy and sustainability of that learning. Such factors include the agent's socio-demographic characteristics, information processing characteristics, proximity, and current position in the social and knowledge networks. The agent model has been described in depth in other venues (e.g., [188], [200], [201]; thus, we concentrate here on both a high level description and details of those components used for the simulations reported.

Within Construct, agents both influence and are influenced by others. Agents who have influence over others can use that influence to escalate or de-escalate activity at a societal level by communicating information and/or beliefs. Social influence – as derives from shared attributes such as socio-demographic factors, shared knowledge, beliefs, and proximity – co-evolves with the spread of knowledge and beliefs [109]. Consequently, in more heterogeneous populations where the lines of differentiation line up the chance of self- reinforcing beliefs at the group level is greater [210]. Factors that are not influenced by the diffusion of information and beliefs include the agent's socio-demographic role (e.g., age, race, gender, level of education), the agent's basic cognitive limitations and information processing capabilities (e.g., likelihood of forgetting, risk taking, amount of information and beliefs that can be communicated or processed, and whether the agent has transactive memory), the size of their sphere of influence (at least in the short term), and factors that have resulted from socio-cognitive interactions (e.g., literacy, access to newspapers, radio and the internet).

Within Construct, agents develop likelihoods of interacting with others based on relative similarity (RS) and relative expertise (RE) [211], [200]. Relative similarity is a homophilly based mechanism [212], [109] and derives from the idea that individuals are more likely to interact if they have more in common. Homophilly based interaction is a multi-causal phenomenon due to ease of communication, shared understandings, and comfort. The relative similarity of i and j, from i's perspective, is characterized as

$$RS_{ij} = \frac{\sum_{k<K}(AK_{ik} * AK_{jk})}{\sum_{j<I}\sum_{k<K}(AK_{ik} * AK_{jk})}$$

where individual i's relative similarity to j, is determined in terms of socio-demographics, knowledge, and belief items K in the agent-to-knowledge matrix AK.

Of important note: an individual is most relatively similar to itself, and each period will have a reasonably high probability of choosing to "interact with itself" and to avoid communicating with others. Just because an agent has the highest relative similarity with itself, however, does not mean that an agent will always interact with itself; indeed, due to the large number of other agents in the simulation, such avoidance of communication is relatively rare.

Relative expertise is a search based mechanism and derives from the idea that individuals are more likely to interact if one has information that the other wants. The relative expertise of j as judged by i is characterized as

$$if\ AK_{ik} = 0, then\ X_{jk} = AK_{jk}\ else\ X_{jk} = 0$$

$$RE_{ij} = \frac{\sum_{k<K} X_{jk}}{\sum_{j<I}\sum_{k<K} X_{jk}}$$

where individual i's relative similarity to j, is determined in terms of socio-demographics, knowledge, and belief items K in the agent-to-knowledge matrix AK [213].

Agents are more likely to initiate interaction with another if they think the other has information they need and/or they are similar to them. However, there is a curvilinear relation between this familiarity and expertise; to wit, as agents initially increase in similarity (homophily) they are more likely to realize the other has expertise they need but as they increase still further in similarity they realize that the other is so similar there is no specialized expertise.

The researcher needs to specify the strength of each of these factors for agent-agent interaction. Herein, we set all human agents to use both logics and to at any time create a combined probability of interaction that is based on 60% similarity and 40% expertise. In both cases, individuals are giving and receiving information and the overall tendency to give versus receive is about 60/40 as identified by Valente, Poppe and Merritt [214].

When setting up a virtual experiment in Construct the researcher needs to specify multiple parameters for each agent. This is often facilitated by the used of agent classes to parameterize multiple agents simultaneously. Specifically, the agent needs to specify the number of agents in each of the classes of agents in a virtual experiment, the distribution of socio-demographic parameters for the agents of that class, the distribution of cognitive factors for each class, the sphere of influence for that class, and the access constraints for that class. There are many other factors that can be varied, such as the rate of forgetting. However, we have found that for modeling the adversary the items listed are the core variables that need to be defined.

### 9.3.2 Agent Classes

In this study, we find it helpful to think in terms of two meta-classes of agents – human agents and media agents (which may or may not be human). Each time period, human agents may interact with other members of the general human population or with a media agent. Sometimes, it is useful to further break the general public into subgroups such as red, green and blue, or terrorists, harboring population and US forces.

There are two classes of human agents: the general public, who will make decisions, and the opinion leader, who can help sway decisions. In the experiments performed, the opinion leader attempts to get the general public to act in one way while the media are designed to thwart it.

In this experiment, we consider five classes of media agents: newspaper advertisements (ad), publically accessible web sites (web), centers that have people in them that provide assistance when someone comes in physically or calls in via phone (call), radio advertisements (radio), and letters sent via postal mail (mail). Media agents differ from each other in terms of the time periods they are active and the length of the messages they send. All agents can communicate facts or beliefs, but the particular set transmitted depends on their knowledge or belief at the time. All media agents are passive – they cannot initiate communication with a human agent. Instead, they provide information only when the human agent selects to go to, listen to, or read the information available through the media.

These particular media agents were chosen because they represent distinct forms of access to information. You might ask why we did not use television when it is so prevalent. The reason is that, within the characteristics we were varying television and radio ads are identical. Thus one can think of radio as radio/television ads.

The number of each type of agent, their activity level and length of messages sent needs to be defined. Table 9.1 provides an example.

The initial knowledge and beliefs held by each of the media agents and the general public at the beginning of the simulation need to be defined. See Table 9.2 for an example. Note the user can specify one or more beliefs and for each define the distribution of knowledge. Over the course of the simulation, the general public, i.e., the agents representing humans, learns; however, the knowledge of the opinion leader and the media remains constant. The number of facts in each category, specified in the left-hand column of the table, is proportioned based on subject-matter expert's views of the relative amount of time it takes for the overall meta-concept – such as know-how for a task – to diffuse.

In order for a human agent to make a decision, an agent must recognize that the activity exists, must have sufficient know-how knowledge, and hold a positive view of one of the two beliefs. In order to have sufficient know-how information, agents must learn at least three of the six know how facts; considering that agents do not start with any of this information, they must learn it from, ultimately, the opinion leader or media. Additionally, we have modeled two beliefs here – one where the true belief is that one shouldn't engage in the activity (believe not right), and one that is neutral as to whether there is some benefit to engaging in the activity (believe worth doing). In order to make the decision, agents must hold at least as many positive beliefs as negative beliefs, or they must be subject to social influence from their peers which convinces them that the decision is a good one. Each activity modeled would have a set of beliefs associated with it.

**TABLE 9.1** A table illustrating how a user can characterize different classes of agents by specifying their number, activity, and message capabilities.

| Class | Number | Periodicity | Active Time Periods | Message Length |
|---|---|---|---|---|
| Humans | 3000 | Continuous | 104 | 1 fact, belief, transactive fact or belief, or social information |
| Opinion Leader | 1 | Periodic every other time period | 52 | 1 fact, belief, or transactive fact or belief, or social information |
| Ad | 1 | New news ads are periodic | 26 | 1-2 facts or beliefs |
| Web | 1 | Periodic access every other time | 52 | 4 facts or beliefs |
| Call | 1 | Periodic access every fourth time | 26 | 3 facts or beliefs |
| Radio | 1 | New ads are periodic | 1 (per ad) | 1-2 facts or beliefs |
| Mail | 26 | Periodic new mail | 6 | 3 facts or beliefs |

**TABLE 9.2** A table illustrating how a user can characterize a population by differentially distributing information and beliefs across classes of agents.

| Information and Beliefs | General Human Population | Opinion Leader | Media Agents | | | | |
|---|---|---|---|---|---|---|---|
| | | | Ad | Web | Call | Radio | Mail |
| **Activity exists (1 fact)** | 0% | 100% | 100% | 100% | 100% | 100% | 100% |
| **Activity know-how (6 facts)** | 0% | 100% | 10% | 33% | 10% | 10% | 10% |
| **Believe right (3 facts)** | 1% | 100% | 0% | 0% | 0% | 0% | 0% |
| **Believe not right (4 facts)** | 5% | 0% | 33% | 100% | 100% | 33% | 33% |
| **Believe worth doing (3 facts)** | 1% | 100% | 0% | 0% | 0% | 0% | 0% |
| **Believe not worth doing (3 facts)** | 5% | 0% | 33% | 100% | 100% | 33% | 33% |
| **General knowledge (500 facts)** | 20% | 20% | 10% | 2% | 5% | 10% | 10% |

The more facts per category – and hence the more complex the message – the longer it takes that category as a meta-concept to diffuse. However, it is important to note that all information related to the activity (twenty total facts) is small relative to the amount of simulated general knowledge (five hundred facts) so that most of the time the general population will not be communicating facts about the activity. Furthermore, the ratio of positive and negative facts associated with the belief influences whether the "correct" belief is positive, negative or neutral. We have two beliefs here – one where the true belief is that one shouldn't engage in the activity, and one that is neutral as to whether there is some benefit to engaging in the activity. Finally, the amount of information associated with activity know-how and with any one belief is comparable so that both spread in a comparable amount of time. The more complex the know-how and the more complex the belief the longer that information will take to spread and the lower the fraction of the population that will have the expertise or belief at any one time.

The advertisement is meant to provide a small amount of knowledge and belief while also containing a large amount of general knowledge information to encourage agents to examine it. Such behavior is typical of articles or advertisements in newspapers. Advertisements only exist for a few time periods during the simulation, reflecting relative infrequent publication. Advertisements can be expected to have a small impact on a variety of agents due to the infrequent interaction and small message conveyed; however, they will be among the most common media that human agents access. Since the advertisement is in printed media, it can be subject to two different constraints: a cognitive constraint, literacy, and an access constraint, subscription access.

In contrast to the advertisement, the web site is designed to provide a large amount of belief information by proving a large number of reasons why the activity is inappropriate. In doing so, however, it could potentially be scraped for knowledge information, thus serving a purpose that is contrary to what the designers intended. For this reason, resources such as the website can be two-edged swords. Because the website is frequently available, it will be easily accessed; however, users accessing it may have literacy or internet access issues.

The information-call-center is designed to answer questions about the activity, based on requests for information from those members of the general population who contact the center. Because the information-center represents the actions of humans who work at the center it has associated with it more social knowledge then the web site. Unlike the web-site, though it may be difficult to get to the center as it requires physical movement and thus may not be as favorable an interaction partner to some agents.

The radio advertisement is very similar the print advertisement. It is designed to provide a small amount of information or beliefs but can reach a large number of agents in the general population. Unlike the advertisement, however, the radio advertisement is not affected by the literacy or access constraints as modeled in this experiment.

The postal mailing is designed to represent a piece of mail containing information meant to deter at-risk agents from engaging in the activity in question. It, too, has the same information content as the advertisement, but the way the general population interacts with it is unique. Only some "human" agents receive mail. However, whether or not the "human" agent reads the mail is up to the individual agent. For the next six time periods, the mail message resides in the agent's "mailbox". The general population agent then has a certain probability of checking their mail and learning the information in the letter. Agents who read the letter absorb some of the information contained in the letter.

To date, a large number of media have been modeled. In general, we tended to model media known to be used by the adversary and/or US forces.

### 9.3.3 Agent Socio-Demographics

In Construct, agents can have a set of non-evolving attributes that influence behavior. Herein, we consider those attributes to be socio-demographic characteristics. These attributes can be set based on census data, or based on other considerations. The researcher can in fact define any characteristics as agent attributes and then use these to effect interaction. The critical difference between attributes and knowledge/beliefs is that for an agent the attributes are fixed for the duration of the simulation; in contrast, the agent's knowledge and beliefs may change. Consequently, attribute based interaction tends to be stable, and variations in interaction are due to changes in knowledge and beliefs.

The user can define any attributes that make sense within the socio-cultural context being modeled. One possibility is to base this off of population demographics. The socio-demographic attributes are used to set the baseline interaction that exists independently of agent knowledge. The greater the overlap in agent socio-demographic attributes, the more likely the agents will interact, as part of the homophily effect [215]. Table 9.3 shows an example of attribute setting using a set of ubiquitous general aspects of human behavior.

Two classes of agents, general public human agents and opinion leaders, have these socio-demographic attributes. Media agents could be "targeted" so that they were aimed to "match" and so interact with humans with different attributes. Specifically, media were designed to target the agents who had either the lowest or second-lowest level of income and education. Thus, the opinion leaders and media would match any agent who had one of those two attribute values, but would not match any other agent. These attributes were oversampled in the human agent population relative to the general population of the United States in order to better understand the effects of the cognitive limitations, and information processing capabilities.

**TABLE 9.3:** A table illustrating how the user can differentiate agents by varying the socio-demographics.

| Attribute | Number of Values | Values (% of Human Agent Population) |
|---|---|---|
| Age | 5 | 0-29 (20%); 30-39 (20%); 40-49 (20%), 50-64 (20%), 65+ (20%) |
| Gender | 2 | Male (50%); Female (50%) |
| Race | 5 | White (60%); African-American (15%); Hispanic (10%); Asian (10%); Other (5%) |
| Income | 6 | 0-15k (40%); 15k-30k (35%); 30k-50k (15%); 50k-80k (6%); 80k-120k (3%); 120k+ (1%) |
| Parent | 2 | Yes (50%); No (50%) |
| Education | 4 | Less than high school (40%); High school diploma (35%); College degree (30%); Graduate schooling (1%) |

The correlation between these attributes is also an important consideration. Population level correlations could have been generated in one of three ways: 1) proportional to census data, 2) randomly, or 3) evenly. Results can vary dramatically with the socio-demographic distribution.

### 9.3.4 Agent Cognitive Limitations and Information Processing Capabilities

Construct agents are complex. Two core features of Construct agents are information processing capabilities and transactive memory. Agents are information processing decision makers and so have one or more of these capabilities: initiate interaction, send messages, receive messages, learn from messages. Agents can have both general and transactive memory [199]. An agent's general memory can contain both what information the agent knows – its facts – and what beliefs it agent holds. The transactive memory, on the other hand, contains the agent's understanding of third parties – who knows what and believes what. This transactive memory can be incorrect: the third party might not know the knowledge or hold the belief. Who knows what, as well as who knows who knows what, can be tracked by time period.

Agents make decisions as to whether or not to engage in activities based on their current knowledge and beliefs. These decisions require various information and beliefs, such as: information on how to do the activity, a belief that the agent should do the activity, and a belief that the activity is appropriate. The point here is that there is a mask on information and beliefs such that different information and beliefs are needed for different decisions. In addition, for this study, decisions are made at the final time period based on accumulated information and beliefs.

However, agents differ in their information processing constraints. In this study we use the following factors: amount of information and beliefs that can be communicated or processed at a time, whether the agent has transactive memory, and whether the agent can initiate interaction or learn. These factors are set differently for each agent class. In Table 9.4 illustrative distribution of cognitive capabilities per agent class are described. In Table 9.5 illustrative distribution of the information processing capabilities per agent class are described. Other possible factors that we can consider in the future are forgetting and risk-taking.

**TABLE 9.4** A table illustrating how the user can differentiate agents based on constraints.

| Factors | General Population Human | Opinion Leader | Media Agents | | | | |
|---|---|---|---|---|---|---|---|
| | | | Ad | Web | Call | Radio | Mail |
| Access Constraints | Literacy, Web, Newspaper | None | None | None | None | None | None |
| Number of messages received and processed at the same time | 1 | None | None | None | None | None | None |
| Number of messages sent at same time | 1 | unlimited | unlimited | unlimited | unlimited | unlimited | unlimited |

### 9.3.5 Networks

Construct is a multi-agent dynamic-network simulation system in which the agents are constrained and enabled by their position in a meta-network. A meta-network defines the set of relations among who, what, how why through a set of geo-temporal trails [152], [216]. As such, a meta-network is a multi-mode, multiplex, multi-level network. Consequently, in Construct, agents are embedded in a large number of networks, including formal and informal relations among agents, relationships between agents and knowledge, and assignments of knowledge and beliefs to tasks. From a meta-network perspective the key entity classes in Construct are agents, knowledge or expertise, beliefs, and tasks. Thus the core networks are the social network among agents, the knowledge network (agents to knowledge), the beliefs network (agents to belief), the assignment network (agents to tasks), and the requirements network (knowledge + beliefs to tasks). Within this the social network can be further broken down in to a proximity based network, a socio-demographic based network and a knowledge/belief based network.

**TABLE 9.5** A table illustrating how to define agent classes by varying the information processing capabilities of the agents in that class.

| Factors | General Population Human | Opinion Leader | Media Agents | | | | |
|---|---|---|---|---|---|---|---|
| | | | **Ad** | **Web** | **Call** | **Radio** | **Mail** |
| Initiate | Yes | Yes | No | No | No | No | No |
| Send | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Receive | Yes | Yes | No | No | No | No | No |
| Decide to take action | Yes | No | No | No | No | No | No |
| Learn | Yes | No | No | No | No | No | No |
| Change beliefs | Yes | No | No | No | No | No | No |
| Information Atrophy | No | No | No | No | No | No | Yes |
| Message Complexity | Very Low | Very Low | Low | High | Med | Low | Med |
| Supports multiple searches | Yes | Yes | Yes | Yes | No | No | Few |

Additionally, Construct allows the experiment designer to set networks as fixed or dynamic during the simulation. Moreover, the initial topology of such networks can be specified. This enables the impact of topology to be studied at the same time as the impact of information-based media. In this study, parts of the social network are fixed based on demographics and parts dynamic based on changing expertise. The result is that the overall probability of interaction between each dyad is dynamic. In this paper, both knowledge networks and belief networks, were dynamic and would change over the course of the simulation.

The social network is of particular interest to this study. Empirical studies of social networks often form a network by asking individuals for the names of their interaction partners. The result is a snapshot of a network at a point in time as it is perceived. Based on this perspective it is tempting to think of networks as simple binary relations, two individuals either are or are not connected. Simulation makes it obvious that the idea of a network is more amorphous.

In Construct there are a number of ways to characterize the network of possible agent-agent interactions. All agents exist in a social network, and in this network the links among agents are probabilistic. These probabilities evolve over time, changing as agents increase in similarity and expertise. At any point in time, who is interacting with whom can be extracted in multiple ways:

as a moving average, as probabilities, as a number of interactions in one particular time period , and as whether an interaction occurred from the beginning of the simulation to that point.

In designing the simulation, the sphere of influence – the alters with which an ego's probability of interaction is nonzero – is the set of others who the agent is likely to interact with. In the full Construct model this sphere can grow and shrink; however, in this study we leave it fixed. Agents with greater reach – such as the opinion leader – have a larger sphere of influence, while most human agents have a relatively small one. Constraints on information access, as will be described, can impact the effective size of an agent's sphere of influence by making certain types of agents inaccessible. The size of the sphere of influence per agent class is described in Table 6; both the theoretical maximum is provided and the "in-practice" value determined from the experiments run. Note, the opinion leader is in every general human agent's sphere of influence. Additionally, for each human agent whether or not an media agent is in the human agent's sphere of influence depends on whether or not the human agent has an access constraint that prevents interaction.

In Table 9.6, demonstrates the distinction between the theoretical maximum size of the sphere as well as the in practice value. The network underlying the sphere of influence is designed exogenously by the experimenter prior to the start of the run. However, the actual sphere of influence in practice is the set of partners with whom the individual agent interacts due to homophily, expertise, or socio-demographic similarity. Since agents often do not interact with all of their potential partners, the effective size of the interaction sphere in practice is often much smaller than the theoretical maximum.

**TABLE 9.6** A table illustrating the way in which the user can adapt the agent classes by specifying the size of the sphere of influence per class.

| Factors | General Population Human | Opinion Leader | Media Agents | | | | |
|---|---|---|---|---|---|---|---|
| | | | Ad | Web | Call | Radio | Mail |
| Sphere of Influence Theoretical Maximum | 40±10 | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 |
| Sphere of Influence in Practice | 25±10 | 250±50 | 300±75 | 100±50 | 66±20 | 250±100 | 150±50 |

For each pair of agents, the probability that they interact is a function of proximity, socio-demographics, knowledge, beliefs, and the interaction logic. Since the socio-demographics remained constant in this study, the overall probability of interaction contains both a fixed and a non-fixed component. Since these overall probabilities can change, we say that the social network is evolving as who actually interacts with whom will vary over the simulation run: the interaction partners of the early simulation periods will differ substantially from those of the later periods. This evolution can be observed in the changing likelihoods that the agent has for interacting with those in its sphere of influence; however, the size of the sphere of influence and the topology of the fixed portion of these probabilities do not change. Thus, as the probability of interaction increases for any pair of agents, that increase must come relative to that of other agents in the interaction sphere and must mean that both agents are evolving to become relatively less similar to all other possible interaction partners.

Using Construct a number of different topologies for the fixed portions of these networks can be examined. They can be random [217], cellular [218], or small world [219], [220]. The accuracy of the simulated topology is extremely dependent on number of agents and the overall density. For example, with 10 agents and a density of 0.5 it is not possible to cannot get a cellular network – agents are too interconnected to exhibit cellular structures; similarly, a network with 100 agents and a density of 1.0 is not random, cellular or small world as everyone is uniformly connected to anyone. When the populations have more than 3000 agents, the selected densities and sphere of interaction sizes should be selected to ensure that the topologies examined are good representations of that topology; i.e., truly random, cellular or small world.

The key differences in the random, small-world and cellular network are clustering and the ratio of internal to external ties. In a random network the links are distributed independently and identically. These are the general fixed communication links. In the small-world network, each agent has a few links and a few agents have many links. In contrast, in a cellular network the agents are clustered in to a few cells and mostly communicate with other cell members while only one or two members per cell interact with anyone in another cell. The placement of these ties affects the diffusion of information throughout the society and has the potential to lead to different rates of diffusion among and between different agents.

### 9.3.6 Constraints on Information Access

Cognitive and social factors combine to determine the level of information access that individuals may have. We examine three different information access mechanisms: literacy, internet access, and newspaper readership [221]. Within Construct, these access mechanisms affect whether agents can interact with a specific media and get information through a specific forum. These mechanisms are implemented as “switches” that the researcher can enable or not, depending on the research question.

In Construct, agents can be literate or not, as set by an experimenter-controlled switch. The literacy mechanism affects all media that require reading printed material. This means that printed advertisement in newspapers, web site, and information sent in letters via the postal system are affected. When literacy as an information access parameter is enabled, illiterate agents can still access these media; however, they do not learn all the information and beliefs conveyed in the message and they may even mis-learn information. A small level of mis-learning is implemented as the literature on literacy shows that literacy is in part a matter of degree which often leads the illiterate individual to misinterpret what is being read. Literate agents are unaffected by enabling the literacy mechanism, and receive the full information from these media. When the mechanism is disabled, all agents receive the full information.

In Construct, agents can surf the web or not – and those that do have access to internet-based media. When the internet access constraint is enabled, agents lacking web access cannot read information posted on web sites at all. Agents with internet access can read such information, and use this information to affect subsequent interactions with other non-web agents. When the mechanism is disabled, all agents can read information from web sites.

In Construct, agents also have the ability to read newspapers and access the information contained in them. The newspaper access mechanism affects all media that require physical newsprint such advertisements in newspapers and specialized articles by opinion leaders. When newspaper access is enabled, agents lacking newspaper subscriptions cannot read articles published in the paper. Agents who are newspaper readers, though, can still read such information. When the mechanism is disabled, all agents can read information printed in newspapers.

It is important to note that these mechanisms interact. For example, if an agent is illiterate and has a newspaper subscription, that agent may read the news articles but do so with error. On the other hand, if an agent is literate but does not have access to the internet, they still cannot read web-pages (and the literacy parameter has no effect).

For each agent class, the researcher must exogenously specify whether or not an access constraint applies, and the probability that an agent in that class is constrained. In this study access constraints only apply to general public human agents. That is neither the opinion leader nor the media agents are constrained. In this study, the probability that an agent is illiterate, cannot access the web, or does not read a newspaper was derived from socio-demographic attributes and national averages. A series of formulas, one for each constraint, that determine the probability that the agent is constrained based on age and education were derived from national data (see [221] for details).