Violent Extremist Network Representation and Attack the Network Course of Action Analysis in Social Simulation

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Abstract

The representation of violent extremist networks (VENs) and their behaviors within social simulations is required in order to leverage models and simulations for use in attack the network course of action analysis. VENs appear throughout the world in multiple forms with varying objectives and behaviors. They exist as a subset of society, nested within and leveraging the underlying social network of a culture to further their own ends. The interdiction of these networks to presents a challenging task for law enforcement and military organizations due to their ability to change and adapt to the situation at hand. The use of social simulation with VEN representations and designed simulation experiments can provide decision makers with insights into the potential impact of their actions to attack the threat network to include the likely manner in which the VEN might adapt to counter the attack. This paper discusses the requirements to represent VENs within simulations, provides an overview of the current VEN representation within the Cultural Geography model, and provides a case study analysis of the use of social simulations for the exploration of possible futures in support of course of action analysis.

1. INTRODUCTION

Violent extremist networks are difficult to defeat because they are complex adaptive systems, which exhibit coherence under change and are able to anticipate and adapt without central direction [1-3]. One of the most critical factors in the success of countering violent extremist networks is an understanding of the civilian populace in the area of operations and the underlying factors that influence the population's beliefs, attitudes, intentions and behaviors. Understanding how to achieve desired effects on the civilian populace in relation to their support of these violent extremist groups remains one of the most challenging areas for coalition forces, host nation forces, local police and governments. This problem is compounded by the inherent variance in human attitudes and behaviors, even within what one would consider a homogeneous population segment. Though a population might be homogenous in some dimensions, preferences can be heterogeneous [4]. Even within relatively small population areas, the number of unique population segments that a stabilizing force might have to interact with and understand grows at an alarming rate as does the complexity of the problem. The importance of gaining an understanding of the problem space and creating a transferable framework for modeling the beliefs, attitudes, intentions and behaviors of the civilian populace cannot be overstated. The ability to take a modeling framework, populate it with data from a given region, and gain insight into potential means to influence the populace in relation to these violent extremist networks (VEN) is of great importance. Social simulations present a mechanism to gain insight into this complex problem domain. Viewing violent extremist networks as subsets of the larger social network, moving among the social network structure like fish through the water [5]. The problem for stabilizing forces, whether police or military in nature, is one of identifying the fish within this conflict ecosystem [6]. The representation of violent extremist networks within social simulation requires a more detailed and sophisticated model of cognition than that required for the sea of society through which these sharks swim.

This paper will provide an overview of the requirements to represent violent extremist networks within social simulation, a brief overview of the Cultural Geography (CG) social simulation model, a detailed explanation of the current violent extremist network representation within this model, a case study analysis for attack the network course of action analysis using design of experiments in conjunction with social simulations, and a discussion of the path forward for more sophisticated models for violent extremist networks.

2. VEN REPRESENTATION REQUIREMENTS

In order to represent VENs within social simulations a description of these networks and their behaviors is required. Examining the network and its functions, as they

impact society, is critical to any effort to represent these networks, their effects on an area or issue of interest and their behavior over time. In order to accomplish these tasks data describing VENs must be available or obtainable. In general terms then, the representation of VEN or any other actor requires knowledge of the actor and its behavior, algorithms that are acceptable for representing the phenomena of interest at the desired level of sophistication, and data, both quantitative and qualitative in nature. This section will discuss the ontological requirements for representing VENs, the minimum set of required behaviors, data requirements, and potential approaches for modeling cognition for application.

2.1. VEN Ontology

The requirement to generate an ontology for the object to be represented corresponds to the knowledge development step in the general approach. The identification of this knowledge is required in any effort to gain an understanding about a problem. The development of simulation representations does not differ in this regard. Ontology provides a framework and key for reference reducing the bar to access for the knowledge for others and facilitating collaboration among multiple groups in seeking to expand the body of knowledge [7, 8].

In order to develop an ontology for a VEN we must provide an explicit description of the concepts or classes that make up a VEN, the attributes or roles of these concepts, and the restriction on these roles or constraints on these attributes. This general framework describing the components of the VEN combined with a specific set of instances of these concepts, attributes and restrictions taken together form a knowledge base [7, 8]. It is important to note that the development of ontology for any domain is an iterative process informed by subject matter experts in the domain. An example ontology for VEN groups is included below.

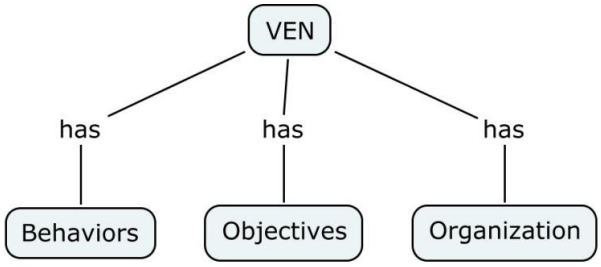

Figure 1. Top level VEN representation for social simulation.

2.1.1. VEN Behaviors

Behaviors are certainly a component of a complete ontology for a VEN, but bear further discussion because of their importance to the intended use of the VEN representation within social simulation for attack the network COA analysis. The intent of this section is to provide a description and justification for the minimum set of behaviors required to gain insight into means of attacking threat networks.

VEN behaviors are related to their objectives and motivation. The specific motivations for these behaviors varies by network type, but the general behavior choices available to these types of organizations seems consistent, whether the VEN is concerned with moving drugs across a border or seeking to overthrow a legitimate government. VEN behaviors are purpose driven to achieve the objectives of the network through influence on the population. VEN behaviors can be categorized by type as illustrated in the diagram below.

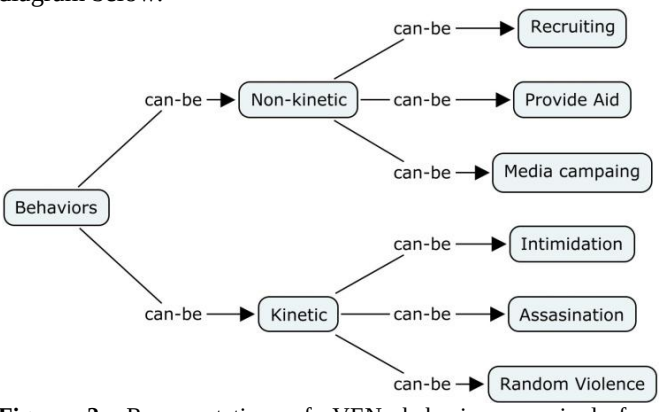

Figure 2. Representation of VEN behaviors required for representation within social simulation.

2.1.2. VEN Objectives

The objectives of VENs vary greatly. The diagram below serves to provide a frame of reference on the problem space, but is not intended to be all inclusive.

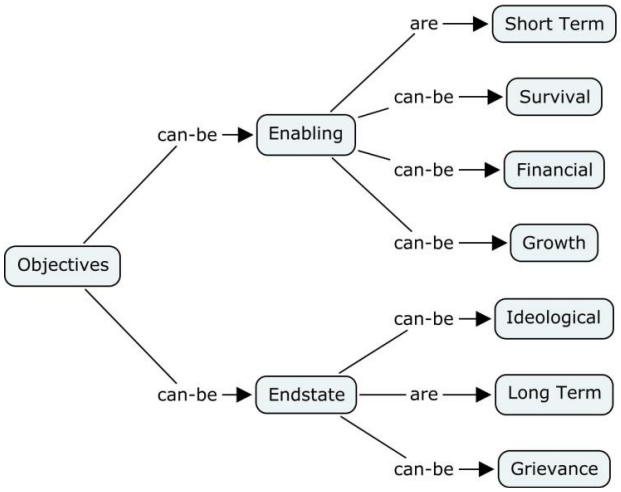

Figure 3. Representation of VEN objectives required for representation within social simulation.

2.1.3. VEN Organization

VENs vary greatly in their organizational structure, and an understanding of this structure is necessary for productive COA analysis [9-13]. Like all organizations, some VENs exhibit a more hierarchical structure, while others have operations that are planned and executed through a more decentralized cellular process. Moreover, VENs have organizational roles that will be filled by one or more individual members of the network, and these roles can be expressed through ontology.

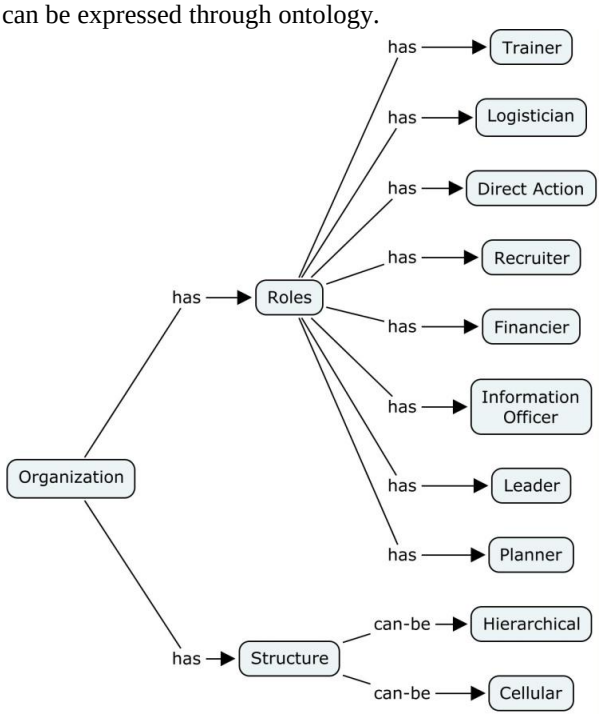

Figure 4. Representation of VEN organization required for representation within social simulation.

2.2. Data Requirements

The data required to populate the representation of VENs within a social simulation mirrors the process of the intelligence preparation of the battlefield familiar to most members of the military intelligence community. All source information characterizing the composition of the threat including the personalities of individual actors within the network, and the networks organization and likely course of action are required to develop a realistic representation of the network and its likely actions. It is important to point out that the model serves as a framework for data management and fusion, common tasks for the intelligence community, and the exploration of future threat courses of action based on this knowledge. The development of these representations is an iterative process.

The population of the model also serves the important function of identifying gaps in knowledge about the network and their activities. As a starting point insight gained from the VEN's ideology and stated opinions is gathered. In some cases this information can be gathered from websites, in others from first person narratives from former members of the group or from individual's with first-hand knowledge of the group's activities. The identification of the group's motivations and beliefs, values and interests is the goal of this stage of data development.

The organizational structure of the group must then be examined and fleshed out based on knowledge available concerning the functional roles that the group must have individual's serving in and the extent to which the identities of the individual's filling those roles is known. Organizational structure can be updated as new information about the VEN and its activity is gained.

Once personalities are identified within the VEN, narrative descriptions of these key individuals must be gathered, again from either existing accounts or from interviews with first person observers if possible. If available documents written by these individuals can provide great insight into the beliefs, values and interests of these key leaders.

2.3. Potential Cognitive Modeling Approaches

Here we discuss the utility of potential agent patterns for the representation of the different roles within the VEN. Agents refer to anything that perceives its environment through sensors and acts on the environment through effectors [14]. Sensors provide the agent with percepts that inform them about the environment depending on the accessibility of the environment and the effectiveness of the sensor. The environment that entities interact with in social simulation typically consists of a social network. The approach required to represent these groups within models and simulations is chosen based on the use case and the data available.

Using the "Direct Action" role as an example, this section will illustrate the application of four agent templates to this domain: simple reflex, model-based reflex, goal-based, and utility-based. In all cases the agent represents a member of a VEN assigned to a direct action role. The agent has access to his environment via messages from other members of the network and that update the percept average population support (APS). *APS* is defined as the average population support for the host nation government and is expressed as a continuous value {0..1}. The direct action agent must choose from three action choices: randomViolence, intimidation, or declareVictory.

2.3.1. Simple Reflex Agents

The simplest agent framework for consideration is a direct action agent is the reflex agent [14]. These agents use the current state of the world to select actions using simple logic statements. These entities have the benefit of simple implementations and typically require little computational

power. Inaccessible environments can challenge reflex agents ability to achieve optimal performance. The importance of this limitation has not been fully explored in this domain. A reflex agent with a direct action role that takes action against a target based on a percept describing the civilian population's support of the government might follow the simple rule-set below.

```
1. Update state. APSt: Average population support for the
government from the portion of the population that the agent has
access to at time t.
2. Conditioned-based rule execution.
if(APS>0.5){
    action = randomViolence; }
3. Return action.
```

This agent pattern might be useful for some entities within the network, but is not likely sophisticated enough to be used throughout the threat network.

2.3.2. Model-Based Reflex Agents

Model-based reflex agents differ from reflex agents in their ability to maintain an internal state based on a sequence of percepts [14]. Agents of this type require information about the state of the world and about how their own actions impact the world. The same direct action agent is described below as a simple model-based reflex agent, which considers information describing the outcome of its last attack and the current state of the population support for the government prior to making an action choice.

```
1. Update state. APS: Average population support for the
government from the portion of the population that the agent has
access to at time t.
2. Model-based rule execution.
if(APS>0.5){
    if(lastAction=randomViolence){
        action = Intimidation; }}
3. Return action.
```

This pattern provides additional flexibility and depending on the resolution of the model can likely accommodate the majority of the roles contained in the VEN in at least a rudimentary fashion. More sophisticated action choice models are possible using this pattern, including those allowing entities to select more actions based on previous success or failure.

2.3.3. Goal-Based Agents

Goal-based agents explicitly represent goal states within the entity [14]. This allows entities to reason backwards from goals to determine actions required to meet achieve these goal states and allows greater flexibility for knowledge representation. This type of pattern might be appropriate for the leader or planner role of the insurgent network. Agents in these roles are planning actions with a goal state in mind in relation to the civilian population's support for the government.

```
1. Update state. APS: Average population support for the
government from the portion of the population that the agent has
access to at time t.
2. Goal check. Goal: Objective state of average population support
for the government from the portion of the environment that the
agent has access to at time t.
if(APS<0.1){
    action = declareVictory;}
3. Estimate distance of future states from Goal as a result of
action selection.
if(action = randomViolence){
    APS = APS - 0.2;}
if(action = Intimidation){
    APS = APS - 0.1;}
if(action = declareVictory){
    APS = APS - 0.05;}
4. Return action that brings the agent closest to its goal state.
```

This framework can provide great flexibility and can be used in conjunction with a variety of search methods and heuristics to facilitate planning to achieve a goal state based on the level of accessibility of information in the environment. The resulting plan in this example is to conduct intimidation operations for two turns, resulting in an achievement of the goal state at the end of turn two.

2.3.4. Utility-Based Agents

Utility based agent frameworks seek to choose behaviors to maximize or minimize the expected value of a utility function [14]. Backwards reasoning is not possible since the goal state is not clearly defined. The concept of utility allows the representation of any number resource constraints and the idea of value. The agents within this construct will choose the action or series of actions with the greatest value based on the defined utility function. In the example below each action has an associated cost along with an expected effect on the APS.

1. Update state. *APS*: Average population support for the government from the portion of the population that the agent has access to at time t.
2. Determine expected utility of next move.

min C+APS {utility of selected action for entity}

ST: $action_i * c_i = C$ {cost function}

$APS - actionEffect_i = APS$ {change in APS caused by action i}

3. Return action.

Decision networks and influence diagrams are useful in expressing the probabilistic nature of expected utility in graphical form for ease of understanding.

3. CULTURAL GEOGRAPHY MODEL FOR SOCIAL SIMULATION

The Cultural Geography (CG) model is a Java based, government owned, open source, agent based multi-agent system (MAS) model for representing social phenomena related to a population within a given geographical area during a specified period of time [15]. The reusable framework, composed of actors, objects and laws, leverages "plug and play" java modules that implement theories from behavioral and social science, facilitating development and testing of theory-based simulations within a conflict ecosystem [16,17]. The data driven model is populated with methodology strongly tied to Mansoor's counter-insurgency intelligence preparation of the battlefield [6]. The framework can be generalized into a cognitive module and a social network structure module.

3.1. Cognitive Module for Population Entities

The foundational social science concept for populating the cognitive identity of each population sub-type within the current CG model is the narrative paradigm. Based on the idea that each human possesses a unique narrative identity derived from their culture and life experiences, this identity encapsulated each entity's world view. The narrative identity is implemented as a Bayesian belief network (BBNs) for each entity in the simulation. Entities possess a unique BBN for each issue about which they hold an opinion that is represented within the model and these BBN constitute the internal state representation of each entity, managing the entity's strength of belief and interpretation of new events. Other models of entity cognition can be used within the framework dependent on the needs of the analysis and the availability of reasonable alternatives to the Bayesian approach. Bayesian networks provide a general approach to representing human cognition which philosophers have used for hundreds of years for this purpose. Note that current theoretical model implementations, such as the theory of planned behavior, within this social simulation also leverage BBN implementations.

The theory of planned behavior (TPB) controls the intention to take action within the simulation. It holds that individuals within a group form an intention execute a behavior based on: 1) their individual attitude toward the behavior, 2) their perception of group norms associated with that behavior, and 3) their perceived level of behavioral control in regard to that behavior.

3.2. Social Network Module

Homophily, the theoretical underpinning for the social network representation of the population within the CG model, states that the likelihood of contact between individuals increases with their similarity among social factors. Social factors include those human traits that affect social interaction, including socio-demographic, socio-cultural, and socio-economic attributes. Homophily has a strong empirical history, and has been well-documented for a wide variety of social factors, including age, sex, birth region, education, religiosity, occupational prestige and socioeconomic status (SES) [18-20].

The current CG model uses a static social network based on ascribed attributes corresponding to the "baseline homophily" [18] or "induced homophily" [19]. The total distance between two entities as determined by their location in the social space defined by these factors is used to determine the strength of the tie connecting these two entities within the social, or homophily, network. This complete network describes the likelihood that any entity within the simulation will communicate with any other entity. The same structure can be informed by attained attributes that change dynamically during run time as actors interact and gain new information. Future implementations of the CG model will use issue stances derived from entity BBNs to inform this portion of the social network structure.

3.3. Current VEN Representation

In the current implementation of the social simulation, the VEN agents do not contain a mechanism for managing beliefs, values and interests. Rather, their behavior is strictly guided by a Bayesian network implementation of TPB [21]. These VEN actions are interpreted by the civilian population as exogenous events. The following case study represents a proof of principle and examines the utility of using this simulation in VEN COA analysis.

4. CASE STUDY: ATTACK THE NETWORK COURSE OF ACTION ANALYSIS WITHIN SOCIAL SIMULATION

Attack the network course of action analysis requires the use of designed experimentation in conjunction with an appropriate social simulation scenario. The scenario must represent the VEN in enough resolution to gain an understanding of how attack the network policies, both kinetic and non-kinetic, might impact the response of the civilian population within the area of the VEN. This is critical in these cases as the civilian population is typically the center of gravity in these types of operations.

4.1. Case Study Description

The scenario for this case study is set in Iraq in 2008 and uses data developed from open sources to describe the population in an urbanized area of approximately 400,000. The case study involves a stabilizing force operating in conjunction with host nation forces to improve the population's perception of security in the area. Following Sageman and others [22][23], we portray the violent extremist network in the simulation as a scale-free social network of 15 agents (Figure 5) where the more central agents generally direct the violent activities of the group,

and the more peripheral agents generally carry out the violent activities (e.g., suicide bombings). In addition, a more centrally located agent was responsible for strategic communications, attempting to influence the population's perception of security through media campaigns (e.g., publicity, propaganda).

The base case actions for the friendly and opposing forces were developed through iterative war-gaming to simulate actions over the course of a six month time period. This analysis will seek to leverage this developed scenario to examine the impact of eight attack the network courses of actions (COAs) on the perceived security in the area.

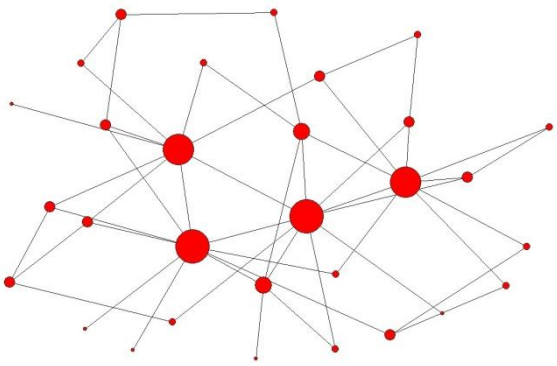

Figure 5. Network representation of VEN, nodes sized by degree.

The VEN was constructed using an algorithm that builds around the "first" person involved in the network, node 1, our nominal leader. Every node in the network will "recruit" new members, and new members are more likely to link to already well-connected members. Through social network analysis (SNA), we identified nodes that are "central" to the operations and information flow across the network. We used simple degree (number of links), betweenness (likeliness to be involved in the passing of information), and closeness (how long it takes their information to reach all other nodes) as our measures of centrality. We also calculated Borgatti's "KeyPlayer" metrics to determine how the removal of one or more agents would fragment the VEN [24]. Agents at the periphery, identified by centrality measures, were linked to the population. Node 10, a somewhat central player, was identified as the "media" node, and also connected to the individuals in the populations, influencing strategic segments of the simulated society.

It's not surprising that there is a high level of correlation between the centrality measures in a network this small, as there would be presumably in most real world VENs. Nodes 2 and 3, each have 10 links, making them the "hubs" of this small network in terms of absolute degree, where the VEN leader, node 1, and node 17 each have 9 links. In terms of betweenness and closeness, node 3 scores the highest, followed by node 2, and then node 1. The removal of node 2 has the greatest impact on network fragmentation.

4.2. Designed Experiment for COA Analysis

In order to leverage social simulations for attack the network course of action analysis, the use of exploratory designs of experiments is required [25,26]. In particular, the use of large exploratory designs of experiments are called for in order to explore the range of potential futures generated not only by potential courses of actions selected by decision makers, but by the noise created by the unpredictable nature of the VEN and its activity and the unknown variance within the human population being modeled. These models, under the best of circumstances, can produce insights into the problem domain and aid in the identification of potentially robust decisions and can aid in decision making under uncertainty. At a minimum they serve as a vehicle through which the decision maker and the analyst gain knowledge about the problem space, identify gaps in required data, and improve their intuition about the problem.

We designed a set of COAs given these statistics that included removing nodes 2, 3, and 10 (media). We removed these nodes individually and in each possible combination resulting in an 8-way design where the first COA was to take no action against the VEN (Figure 6). This base case allows us to develop a benchmark to compare with the subsequent COAs. Removing central nodes (such as 2 and 3) from the VEN roughly equates to the arrest of those "key" individuals, whereas removing the media node from the network, given node 10's relatively low centrality scores, more roughly equates to actions taken to limit the VEN's media campaign.

	Course of Action
1	Take no intervention actions (Base case)
2	Fragment network and interdict media campaign
3	Remove the hub node 3 to disrupt communications
4	Interdict VEN media campaign only
5	Remove hub nodes 2 and 3 to fragment and disrupt
6	Remove hub node 3 and interdict media campaign
7	Fragment the network by removing node 2
8	Remove nodes 2 and 3, and interdict media campaign

Table 1. Eight design points and corresponding COAs.

The results of these design points are explored below, and it is important to note that the simulation does into take in to account the real world dynamics of shifting lines of communication. Networks change structure following the removal of key players, and some evidence points to the idea that central individuals are often quickly replaced. These dynamic features of all VENs are being implemented for the current version of the social simulation.

4.3. Results and COA Analysis

Initial analysis of the model output for the 8 design points (DP) explored for the aggregate population on the issue of security are shown in the figure below. Security is examined since it is the issue within the model most likely impacted by attack the network actions. The base case with no, interdiction of the network is shown by DP 1, in blue below. The subsequent analysis will examine DP 1, DP 3, and DP 8 in further detail.

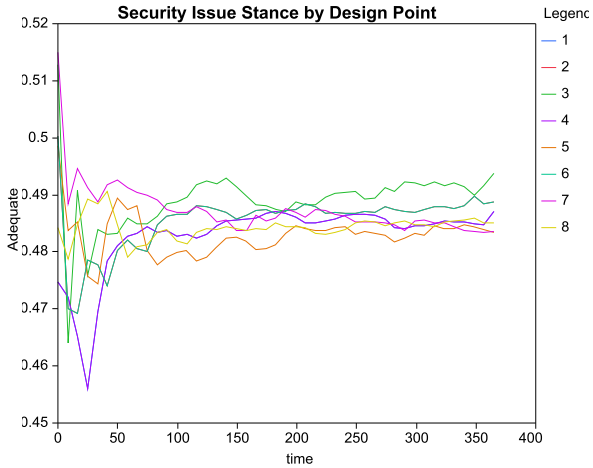

Figure 5. Visualization of potential futures based on COAs 1- 8.

The figures below illustrate the communications network from 10-50 days and volume of communications regarding security over the course of the run for DP 1, the base case.

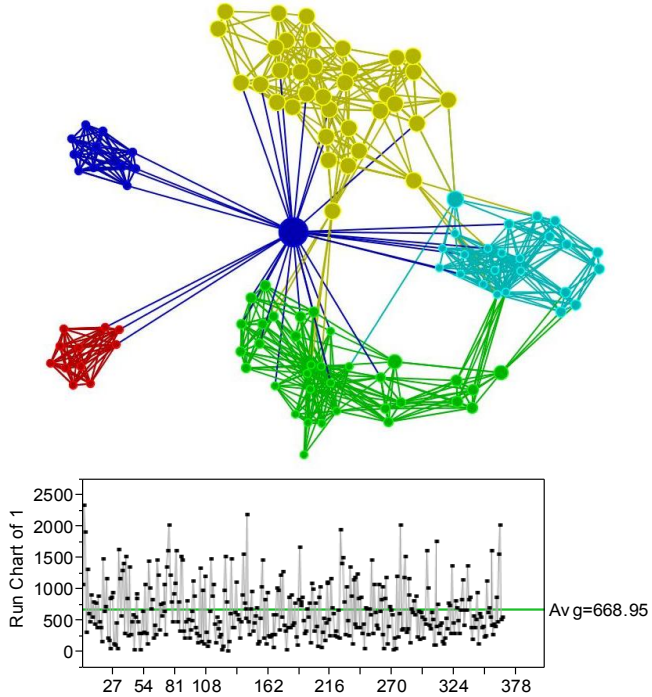

Figure 6. Communication network structure (nodes sized by closeness, color indicates community grouping), t=10-50 & volume DP1.

The same illustrations are shown in subsequent figures for DP 3 and DP 8 below. DP 3 resulted in the highest end of run issue stance while DP 8 resulted in one of the lowest end of run issue stances for security.

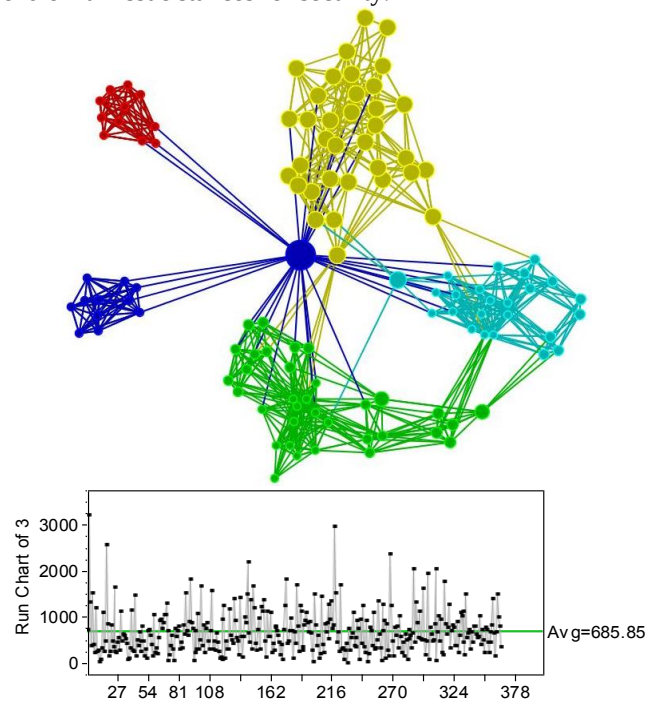

Figure 7. Communication network structure (nodes sized by closeness, color indicates community grouping), t=10-50 & volume DP3.

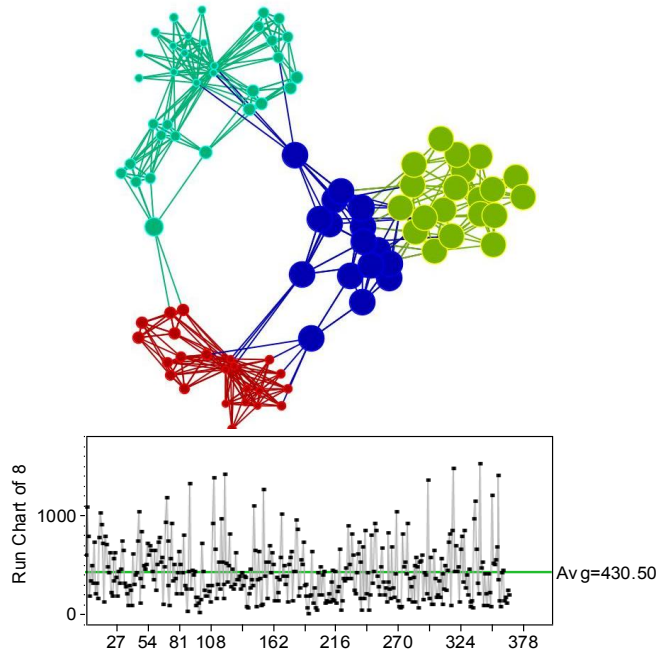

Figure 8. Communication network structure (nodes sized by closeness, color indicates community grouping), t=10-50 & volume DP8.

In the networks above, the nodes are colored according to their community group via the Clauset-Newman-Moore algorithm [27]. Nodes in the same community are expected to interact frequently. As represented in the model, the COA of targeting only the key node in the VEN, DP 3, resulted in a higher level of satisfaction on the issue of security, while the COA targeting multiple nodes in conjunction with an active campaign to interdict the media, resulted in lower aggregate satisfaction and a greatly reduced volume of communications regarding the issue.

5. CONCLUSIONS AND FUTURE WORK

The representation of violent extremist networks within social models and simulations can provide insight to decision makers in a wide variety of domains, add to the realism and robustness of counterinsurgency and stability operations training, and facilitate the analysis of future systems related to Irregular Warfare. Such representations can illuminate the second order and unintended consequences of attack the network courses of action. We addressed the requirements to represent these networks and the data required to develop unique representations of networks of interest. Potential agent frameworks for use in representing individual actors within the VEN were reviewed and a case study analysis was developed as an illustration of the concepts and utility of the approach. Future work is needed to explore the appropriateness of a variety of alternative agent frameworks within the social models and simulations through the use of larger space filling experimental designs in high performance computing environments, as well as continue the theory building process for the accurate and actionable M&S representation of violent extremist networks and civilian populations.

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