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Title**:** Exploring Edge Organization Models for Network-Centric Operations

Topics:

- C2 Modeling and Simulation
- C2 Concepts and Organizations
- Social Domain Issues

Authors:

Adam Forsyth
Referentia Systems Inc.
550 Paiea St., Suite 236
Honolulu, HI, 96734

Susan Sanchez
Naval Postgraduate School
1 University Circle
Monterey, CA, 93943

Hong Wan
Purdue University
315 Grant Street
West Lafayette, IN 47907

Kok Meng Chang
Naval Postgraduate School
1 University Circle
Monterey, CA, 93943

Paul Sanchez
Naval Postgraduate School
1 University Circle
Monterey, CA, 93943

Point of Contact:

Dr. Adam Forsyth
Referentia Systems Incorporated
550 Paiea St., Suite 236
Honolulu, HI, 96819
Ph: (808) 423 1900 xt 119
Cell: (808) 375 4818
Fax: (808) 423 1960
Email: adam@referentia.com

Abstract:

Defense analysts must explore and provide insight into how future network-enabled forces will perform across a range of threat capabilities and scenarios. An emerging approach to this challenging problem is the use of agent-based models (ABMs) and novel experimental designs. When used within a data farming framework, these designs allow rapid exploration of models of network-centric military and non-military operations, and provide insights on the performance of edge structures in combat settings.

ABMs provide a context for discussing and distilling the key aspects of knowledge and power in an organization as well as its impact on an organization's performance (e.g., knowledge flow, power flow, organizational effectiveness). Currently, 'what-if' analyses in computational organizational theory explore a small set of configurations or focus on a handful of factors. Models of edge organizations in network-centric warfare have literally hundreds or thousands of factors that should be investigated. The use of ABMs will enable analysts to build theoretical frameworks from the ground up after investigation of these factors using fast-running simulations and state-of-the-art experimental designs. This paper illustrates an approach for ABMs of edge and hierarchical organizations, and describes ongoing work to extend the experimental design toolkit for exploring organizational structures in network-centric operations.

Background:

Armed forces around the world are considering radical transformations to their structures and strategies because of the information revolution and the changing global environment. Senior leaders continually face decisions on how best to structure, modernize, organize, and employ forces in an increasingly uncertain future. To support their decision-making efforts, defense analysts must explore and provide insight into how future network-enabled forces would perform across a broad range of threat capabilities and scenarios. This is a challenge for the analysis community—traditional models have dealt poorly with issues such as quantifying the effects of C4ISR, or modeling adaptive asymmetric adversaries over an extensive set of possibilities.

One approach to this challenge is the use of agent-based models (ABMs), where multiple entities mimic complex large-scale system behavior by sensing and stochastically responding to conditions in their local environments. The process of constructing an ABM can be a useful way to frame questions and provide a context for discussing and distilling the key aspects (e.g., knowledge flow, power flow, organizational effectiveness) of an organization's performance, and enable theory building (Epstein and Axtell 1996). Asking 'what-if' questions of multi-agent models can improve "our understanding of how different technologies, decisions, and policies influence the performance, effectiveness, flexibility, and survivability of complex social systems" (Carley 2002).

The studies typically done for this 'what-if' analysis in computational organizational theory (COT) explore only a small set of configurations or focus on a handful of factors. Yet it is clear that models of edge organizations in network-centric warfare have literally hundreds or thousands of factors that could be varied. We propose a framework for a much broader exploration, made possible because of new experimental designs for simulation studies (Kleijnen et al. 2005; Wan, Ankenman and Nelson 2006a, Sanchez Wan and Lucas 2005). This leverages the tools and infrastructure developed as part of the USMC's "Project Albert" effort to provide insights to military decision-makers via the use of agent-based models, data farming, and high-performance computing.

The modeling and simulation for this work involves three important concepts: agent-based modeling (ABM) (e.g., Fry and Forsyth 2002, Cioppa, Lucas and Sanchez 2004), data farming (Brandstein and Horne 1998, Horne and Meyer 2004) and an extension to data farming called network farming (Dekker 2003, Dekker 2004, Dekker 2005).

Agent Based Modeling

In recent years there has been a rapid growth in the interdisciplinary field of complex adaptive systems (CAS). A complex system is typically a dynamic system composed of many, simple, interacting parts. The complexity of these systems often comes from the interaction of the component parts, and not from any complexity of the component parts themselves. Indeed, while the behavior exhibited by these systems can be incredibly complex, the components themselves are often incredibly simple. There is a marked similarity between C2 systems and CAS (adapted from Illachinski 1996).

CAS Attribute	Corresponding Agile C2 Requirement
Non-linear interactions	Command and control is a highly non-linear process. More information and longer decision cycles does not necessarily lead to better decisions. Indeed, the 70% solution arrived at in a timely manner is often more effective than the optimal solution too late.
Decentralized control	Due to the dynamic nature of combat, military commanders understand that commanders on the scene often have better and more timely information than those removed from the battle, and are hence better able to modify plans to achieve the overall objective.
Self-organization	Local C2 cells may use substantially different processes to contribute to the overall order of the decision making process.
Non-equilibrium order	Military conflicts, by their nature, proceed far from equilibrium.
Adaptation	Agile C2 systems will by definition adapt to an amorphous environment.
Collectivist Dynamics	There is continuous feedback between the behavior of (low level) combatants and the (high level) command structure.

Table 1: Similarities Between C2 Systems and CAS Attributes

One widely-used method to study such systems is through the use of ABMs. Agent-based distillations take a unique approach to representing reality. The emphasis is on introducing a sufficient degree of abstraction into both the model and input data to gain insights into a specific area of inquiry. This abstraction overcomes some of the shortcomings experienced by traditional constructive simulations (e.g., attempting to model human behavior and decision-making processes) as well as focusing on universal truths rather than situational specifics. The simple and abstract nature of these models makes them very flexible, and applicable to a wide range of military problems, from the investigation of the implications of different C2 architectures to strategic policy decisions such as the effectiveness of trading manpower for advanced technology. In addition to their flexibility, these simulations run extremely rapidly – often on the order of seconds. This makes them the perfect tool with which to data farm.

Data Farming

Data Farming is a meta-technique developed by Dr. Al Brandstein (then Chief Scientist of the USMC) and Dr. Gary Horne (now Director of Project Albert) to examine those areas of combat modeling that were poorly supported by traditional constructive simulation (Brandstein and Horne 1998). Specifically, data farming involves running simulations many hundreds of thousands of times on high performance computers, such as those at the Maui High Performance Computing Center. Data farming allows the modeler to rapidly explore a large parameter space, with sufficient depth to provide valid statistical results. This massive data exploration capacity allows the modeler to quickly focus in on those areas of the parameter landscape that represent potential problems or opportunities to exploit. Due to the large numbers of replications possible with such a technique, not only does the user get an appreciation for the mean and standard deviation of possible outcomes, but those 'one-in-a-million' possibilities that reside in the tails of the distribution can also be discovered. Traditional analysis often discards these anomalies as they do not fit the pattern. Project Albert cherishes these outliers, as they may represent the true threats or opportunities. It is this appreciation of the entire range of possibilities, rather than simply the most likely outcomes, which makes data farming such a powerful tool.

For example, consider a force on force scenario that is run 1000 times with different random seeds. Let us assume that red wins 999 times and blue only once. Often we can learn much more from the one case where blue was successful against what are obviously overwhelming odds than we can from the remaining 999 iterations put together. If we can learn the conditions required for success from this one scenario, then in the field we can begin to shift the odds from one in a thousand to closer to one in one.

Network Farming

Recently, the theory of data farming has been extended to include farming over network topologies (Dekker 2003, Dekker 2004, Dekker 2005). In Network Farming (NF) the underlying network topology is simply another parameter that can be explored. Within the concept of network farming, the network topology need not be explicitly specified, but may be generated by an algorithm. For example, consider the Kawachi Process for generating networks. The generation process begins with a regular network of large diameter and rewires links with a probability p. For small values of p this produces a "Small-World" network, while with $p = 1$, it produces an Erdös-Rényi random network (Bollobás 2001) Within NF, we can specify a particular generation algorithm, and farm over the generation parameters. Hence we can begin to study the effect of network topology in much the same way we would any other factor such as network latency. This is important, as we do not a priori specify any particular network, and can look to see what type of network performs a given task most efficiently. Additionally, for each parameter within the generation algorithm we will study hundreds or thousands of networks. Hence we get a realistic representation of the performance of that type of network topology, not just a point estimate.

Experimental designs for comprehensive exploration of ABMs

Since CAS have many interacting parts, ABMs of CAS have many potential parameters (factors) that can be manipulated by the analyst – even if the individual characteristics of the component parts are simple models. This means experiments on ABMs must investigate a large number of factors simultaneously, if the potential benefits of performing experiments in a virtual world are to be fully realized. Yet, this idea does not appear to be well known in computational organizational theory community, where experimental designs appropriate for field experiments (such as comparing two or three scenarios to a baseline or small factorial experiments) are also the norm for simulation experiments. For example, Nissen (2005) describes the result of a 2x2 experiment using the VDT simulation (Virtual Design Team Research Group, 2006). Here, one factor is the organizational structure (hierarchical or edge) and the other is the mission/scenario (industrial age or 21st century). Nissen finds that each of these factors has significant impacts on one or more of eight performance measures. However, the organizational structures are determined by specifying 26 individual factors and the mission/scenarios by 16 individual factors. The experimental designs we discuss below would allow all these (and more) to be explored to provide insights about their relative importance, the sensitivity of the performance measures to the specified values, and more.

Two broad classes of designs are suitable for exploring CAS: space-filling designs and screening designs. Space-filling designs are beneficial for developing a broad understanding of a simulation model when the factors are quantitative and easily manipulated. By varying the levels of each factor over its range of interest in a smart manner, they allow the analyst to identify significant factors and interactions, and uncover regions, ranges, and thresholds where interesting things occur. Screening designs typically vary each (qualitative or quantitative) factor over two distinct levels and assume that only main effects are important (or that factors with strong interactions can be identified via their main effects). Screening experiments allow the researcher to eliminate factors that are obviously unimportant so that more detailed investigations can focus on the most influential factors. In some cases, the results from screening experiments may indicate that a more compact ABM can be developed for subsequent studies. Screening experiments can also help to reduce a complex system to a simpler one so the analysis becomes more transparent.

One feature of NF we wish to exploit is the ease of applying sequential methods in simulation studies. It is possible for the observations to be collected in stages, where the information collected in one stage will determine which network configurations (or excursions) we want to perform in the next stage. Sequential methods are usually more efficient than single-stage methods. By incorporating efficient sequential procedures into the NF environment, we expect to gain the ability to investigate a much larger number of factors without imposing an unreasonable computational burden.

Among space-filling designs, we have found that Latin hypercubes (McKay et al. 1979) and nearly orthogonal Latin hypercubes (NOLHs) (Cioppa and Lucas 2006) are good general-purpose designs for exploring CAS. The authors have been involved in over 40 studies using these designs, including the oversight of graduate theses at the Naval Postgraduate School, problems addressed in and beyond Project Albert International Workshops, and studies for DoD clients. Using these at several stages during the model development process, as well for the final experiment, has proven beneficial in many ways. Kleijnen et al. (2005) discuss examples illustrating how this approach “can uncover detailed insight into the model’s behavior, cause the modeling team to discuss in detail the implications of various model assumptions, help frame questions when the analysts may not know ahead of time what questions should be asked, challenge or confirm expectations about the direction and relative importance of factor effects, and even uncover problems in the program logic.” An application of these designs to a model of collaborative decision-making in edge and hierarchical organizations is summarized later in this paper.

Many screening methodologies have been developed to identify important factors with an economical number of design points and replications. The most commonly-used ones are fractional factorial, central composite and Plackett-Burman designs (Myers and Montgomery 2002). However, those screening designs were developed for physical experiments: they typically involve less than 25 factors and do not take advantage of the sequential property of the simulation experiments. The methodologies that appear most promising for screening purposes in CAS are the Controlled Sequential Bifurcation (CSB) procedure developed by Wan, Ankenman and Nelson (2006a), and extensions of this procedure (Wan, Ankenman and Nelson 2006b, Sanchez, Wan and Lucas 2005). Since the network ABMs we will explore have many random components, one important characteristic of CSB is its ability to control the probabilities of misclassification errors. Misclassification errors include both classifying a factor as important when it is not (Type I Error), and classifying a factor unimportant when it is important (Type II Error = 1-power). Another benefit of CSB is its validity when the error variances differ across different factor settings, as is commonly the case in simulation experiments. One extension (CSB-X) allows for valid screening of main effects even in the presence of strong two-way interactions (Wan, Ankenman and Nelson 2006b). The two-phase procedure of Sanchez, Wan and Lucas (2005) begins with a fractional factorial design in the first phase of experimentation and uses CSB in the second phase; this does not require a priori knowledge of the direction of any factor effects, and can be substantially more efficient than CSB for screening purposes when factor effects are not sparse.

Both the space-filling designs and the screening designs allow the analyst to investigate a large number of factors simultaneously. To better illustrate the benefits of such an approach, we provide an overview of one such experiment. We finish with a discussion of work currently underway for the Center for Edge Research at the Naval Postgraduate School.

A Framework for Investigations

This section outlines a computational experiment performed as part of a Master of Science Thesis at the Naval Postgraduate School; details can be found in Chang (2005). The ABM is a discrete-event simulation model written in Java using the SIMpleKit simulation library (Sanchez 2004,5). It is flexible, transparent, and easy to use in an automated simulation experiment environment. The discrete-event nature means the simulation runs very quickly even for large models, unlike many of the agent-based simulations that employ a time-step approach. Another discrete-event model for examining edge organizations is the POW-er model described in Ramsey and Leavitt (2005) (or see the Virtual Design Team web page; VDT 2006). The underlying scenario is based on a draft design for a physical experiment intended to investigate an information-gathering task (Evidence Based Research, 2005).

The Organization

Twelve agents are organized in one of two structures. Figure 1 is an example of an edge organization, and Figure 2 depicts the agents in a hierarchical organization (from Chang 2005).

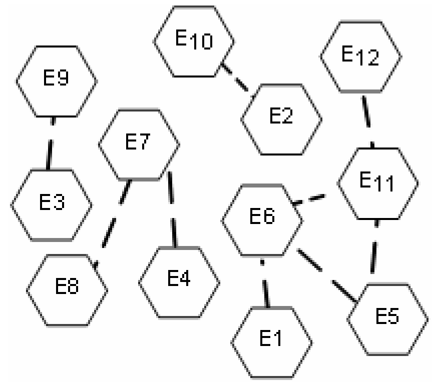

Figure 1 - An Edge Organization with 12 Agents

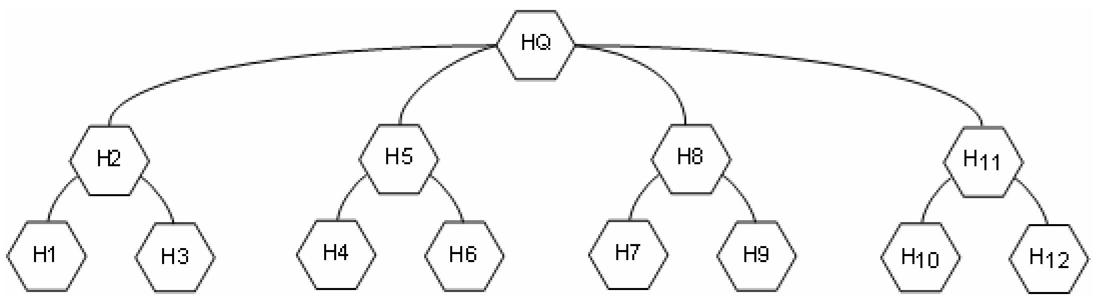

Figure 2 - A Hierarchical Organization with 12 Agents

In the edge organization of Figure 1, the dashed lines indicate possible information links between the agents. Information tends to flow freely from one agent to another, according to the agent's behavior and grouping. Groups can be of different sizes, and agents within a specific group may communicate directly with some members and only indirectly with others.

In the hierarchical organization of Figure 2, the solid lines indicate the fixed information links between the agents. Information tends to flow upwards through the hierarchy. There are four specialized sub-groups of agents, and agents H2, H5, H8 and H11 are the sub-group leaders. These leaders report to a central headquarters.

The Task

The agents are tasked to identify the *who*, *what*, *when* and *where* of an adversary attack by discovering a set of information factoids. Like pieces of a puzzle, each factoid contains a piece of information for one of the four problem types. Collectively, these pieces form the solution to the problem. In the physical experiment that motivated this study, the factoids are written clues that participants logically decipher to determine whether or not they help answer the questions. In the simulation model, factoids are abstracted and modeled as having specific amounts of information. This abstraction also makes it possible to have factoids that are untrue in the simulation experiment, similar to false intelligence in an intelligence-gathering task. The agents discover information by drawing from a set of factoids that represents all potentially available knowledge. Each agent acquires information by drawing (with replacement) from the pool of available factoids according to the discovery rate, so information accrues at random points in time. The intelligence-gathering task can be characterized by the five main attributes shown in Table 2.

Total amount of information available for discovery
Total amount of negative information
Total number of factoids available
Total number of negative factoids
Rate at which the factoids are discovered
Solution threshold

Table 2: Attributes of Intelligence-gathering Task

Clearly, a wide variety of tasks can be investigated by varying these task attributes. Different tasks may have different characteristics even if they have the same total information value. Some tasks may just require a few key factoids to solve while other may require numerous factoids of smaller value. A difficult task is defined as one with low discovery rate; whereas a less difficult task is defined as one with a higher discovery rate.

The solution threshold indicates the amount of information required to solve the problem. When the solution threshold is much lower than the total information available, there is excess factoid information and the discovery rate of new information is generally constant throughout the information discovery process. Conversely, if almost all the available information is required to solve the problem, we have a task that has little excess factoid information; as time progresses, it will be increasingly difficult to discover new information rather than rediscover old information.

The Agent Behaviors

Within Edge Organizations

In the edge organization, there is a common portal where an agent can choose to post factoids he discovers. All agents in the organization can access the common portal to obtain factoid information posted by other agents. This approach of information exchange can be thought of as a 'push and smart-pull approach' inherent to a robustly networked environment (Alberts and Hayes, 2003), made possible by the advancement of information exchange technology. This portal is similar to the shared-awareness of the organization in the context of network centric warfare (Alberts, Garstka, and Stein, 1999).

In the edge organization, the agent may discover different types of factoids. Upon discovering a factoid, the agent can decide to post it to all the members in the organization using the common portal, share the factoid with some of his selected peers, or completely hoard the information. There are factors that might influence the agent's propensities to post, share or hoard the information. For example, by hoarding the information the agent may end up being the first one to solve the problem. This may mean that an agent interested in becoming the 'winner' might withhold necessary information and increase the time required to solve the problem. Other factors like individual agent characteristics, relationship with peers, the organization's reward policy, task criticality, peer pressure, organization culture, etc., will also influence the agent's decision. Note that this ABM models the behavior (i.e., propensities to post, share, or hoard information) without explicit modeling organizational or psychological reasons for this behavior.

Edge organizations have no fixed leaders, but leaders may emerge as the discovery process progresses and evolves. In this intelligence-gathering task, we define a leader as one whose postings in the common portal have a combined information value that exceeds the information posted by any other agent by a specified threshold. The agent must be in this state for a period of time before he will emerge as a leader. The emergent leader will lose his status if at any point in time he fails to meet the above criteria. Another agent may subsequently emerge as a leader if he manages to post more significant factoids and meets the leader's criteria. This definition is analogous to that of an internet forum of special interests. Visitors to the forum for the first time are usually able to identify the 'leader' of the forum by reading through some of the posts. The leader is usually the one that posts more *important* messages and provides the *best* advice to the less well-versed members.

When an agent decides to work in a group and share information with his selected peers, the receiving agent is more likely to reciprocate, provided that the receiving agent decides to share at all. This type of reciprocal sharing is common in our social and working relationships. An agent is also more willing to share his information with a leader, if there is one. The emergent leader assumptions in this scenario are consistent with the hypothesis by Leavitt (Leavitt, 1951) that a centrally–located individual with the greatest access to information will emerge as a leader in an organization with no designated individual as boss (Alberts & Hayes, 2003). The emergent leader also acts as a source for synchronizing the behavior of all the agents towards a common goal, by generating an additional common information flow link (other than the direct link to the common portal) that redirects information from the rest of the agents to the common portal.

In an edge organization, the agent may form sub-groups in solving the problem. The groups can be of different sizes and types. A formal grouping is one where every agent knows and communicates directly with all group members; an informal grouping is a virtual group where the member agents do not know the group members and each agent shares his information only with agents that share with him.

The competency of the agents in an edge organization also plays an important part in the intelligence gathering process. The competency of an agent affects how quickly the agent discovers intelligence, how fast the agent processes and interprets the information, and how the information and false information are interpreted. The more competent agent tends to gather intelligence faster, interpret the information faster, be less affected by the negative information, and require less information to identify the attack.

Within Hierarchical Organizations

In a hierarchical structure, there are also common portals where agents can post factoids they discover. However, each agent can discover only factoids according to their specialized type. For example, an agent who specializes in the *what* problem will only discover the *what* type factoids. This models the specialization and decomposition characteristics of a hierarchical structure. Similarly, an agent can only access the portal belonging to his own specialization group.

Upon discovering a factoid, there are fewer incentives for an agent to hoard or share information, as the primary task of the agent is to discover factoids and pass the information to his leader. There are minimal (if any) interactions between agents of different sub-groups. The reward system of a hierarchical structure also encourages the agents to find as many factoids as possible and pass them up to their leaders.

The leaders in the hierarchical organization are fixed by position, and they are generally considered to be more competent than the group members. The definition of competency here is similar to that in the edge organization. It affects the discovery rate, message processing rate and information interpretation.

Individual Agent Characteristics

The characteristics of an agent in either simulation model are defined by the parameters listed in Table 3.

Post probability	Probability that the agent posts a newly discovered factoid to the common portal.
Share probability	Probability that the agent shares a newly discovered factoid with the members in his group or the emergent leader (if one exists).
Hoard probability	Probability that the agent hoards a newly discovered factoid.
Group	Group to which the agent belongs.
Group type	Formal or informal grouping.
Competency	A value with a maximum of 1.0 representing the agent's competency.
Normalized discovery rate	Rate at which the agent discovers new factoids (a function of the task-specific discovery rate and the agent's competency).
Normalized message processing rate	Rate at which the agent interprets the factoid (a function of the task-specific discovery rate and the agent's competency).
Posting check rate	Rate at which an agent checks the common portal for new information.
Switch task capability	An indicator of whether or not the agent will self-select to work on unsolved tasks.

Table 3: Individual Agent Characteristics

Most of the characteristics in Table 3 are self-explanatory, but a few need additional elaboration. First, note that posting, sharing, and hoarding are mutually exclusive, and their probabilities sum to 1.0. An agent will choose to do one of these actions each time they finish processing a factoid.

The group type affects the agent's sharing actions. When an agent in a formal group receives a new factoid from a peer, he will not re-share the new factoid with the rest of the group members since he knows they will also receive the same factoid. In an informal group, each agent only knows who he intends to share information with. When the agent receives a new factoid from a peer, he may decide to share the factoid with other members in his group list.

Every agent has a competency level. The maximum competency is 1.0, and an agent with a competency of 0.8 is 20% less competent than one with competency of 1.0. Competency affects the rates for two random processes in the intelligence-gathering task: the factoid discovery rate and the message processing rate. Given a normalized factoid discovery rate, *dr*, an agent with a competency level of 0.8 will have a discovery rate of 0.8 * *dr*. Similarly, given a normalized message processing rate, *mpr*, an agent with a competency level of 0.8 will have a message processing rate of 0.8 * *mpr*. The times between successive discoveries, as well as the message processing times, are modeled as exponential distributions.

An agent also extracts information from a factoid according to his competency level. For example, given a factoid with information value of *v*, an agent with a competency of 0.8 is able to extract 0.8 * *v* information value from the factoid. Given a factoid with a (negative) information value of –*v*, an agent with competency of 0.8 is able to extract (1 - 0.8) * (–*v*) information value from the factoid. In essence, a competent agent discovers and processes information faster, extracts more information from a given factoid, and is less affected by negative information.

Our models allow for the analyst to specify average characteristics for a group but allow each agent to have distinct parameter values. For example, the competency levels of individual agents vary according to a uniform distribution. Specifying the mean and half-width of this distribution provides an easy mechanism for examining the effects of diversity among the agents. Similarly, the rates at which agents discover new factoids, process these factoids, and check the common portal for new factoids can differ, as can their probabilities for sharing or hoarding information.

Measures of effectiveness

The problem is solved when sufficient information is accumulated for each of the four categories, so as to correctly identify the attack. Two measures of effectiveness common to both organizational structures are the time required to solve the problem and the information distribution at the completion of the intelligence-gathering task.

The simulation model also reports an extensive list of other indicators of performance. Of particular interest for the edge organization are whether or not a leader emerges, the identities of any emergent leaders, and the identities of the agents that solve any of the four categories of problems, i.e., the ‘winners’ in the scenario.

Experimental design

Chang (2005) ran several experiments involving the edge and hierarchical ABMs. We briefly summarize one of the edge experiments to illustrate the use of state-of-the-art designs for simulation experiments.

Several attributes are fixed for this experiment. These include the number of agents in the organization, the number of subtasks to be solved (4: who, what, when, and where), the total information value per subtask (1800), and the distribution of the number of factoids (uniform between 100 and 140). Agent heterogeneity is modeled by varying individual agent characteristics from the group mean by a uniform distribution with (fixed) range +/- 0.1.

The experimental design is a 3 x 2 x 2 crossed with a 65-run NOLH design. (We remark that seven additional factors could have been incorporated into this NOLH design.) Thirty replications are performed for each of the 3 x 2 x 2 x 65 = 780 distinct design points, yielding 23,400 runs. The first three factors are the solution threshold (3 levels), the type of grouping (formal or informal), and whether or not the agents will focus on tasks that are currently unsolved. The NOLH design specifies the values for 9 additional factors. These include the group means for share probability, hoard probability, competency, discovery rate, message processing rate, and posting check rate (each varied at 65 levels); the number of negative factoids (integers from 18-36); and the total value of the negative factoids (36-360). The final factor in the NOLH design is the group size (1-6). Here, a group size of 1 corresponds to no groups. Group sizes of 2, 3, 4, or 6 divide the agents into 6, 4, 3 or 2 groups, respectively. A group size of 5 corresponds to two groups of size 5 and one group of size 2.

To put the efficiency of the NOLH into perspective, note that a full factorial involving the same numbers of levels for all factors would be impossible to run, because it would require over 6.5×10^{15} design points. Even if all factors in the NOLH other than group size were explored at only their low and high levels, the design would require 3 x 210 x 6 = 18,432 design points.

Because of the designed experiments, a wide variety of statistical and graphical approaches can be used to gain insight into the behavior of the edge model. Chang (2005) uses stepwise regression, multiple comparison procedures, regression trees, box plots, contour plots, and parallel plots to explore how these 12 factors influence several measures of effectiveness. Analyses of solution time give insights on the factors affecting the efficiency of an organization's structure. Examining the 'winner' provides insights on the attributes that identify a winning agent in an edge organization. For example, a winner may be a leader, a hoarder, a sharer, or just a normal agent in an edge organization. The distribution of information among the agents at the completion of the intelligence-gathering task gives insights on how robust the organization is to different agent characteristics and composition.

Next Steps

We plan to adapt our model in such a way that it can vary from a highly centralized network (such as a traditional industrial age C2 network) to a highly decentralized network (such as an edge organization). Rather than say Network A is best for task 1 and Network B is best for task 2, we can begin to examine what influence decentralization has on the efficacy of various networks.

When put into the context of edge organizations in network-centric warfare, additional considerations come into play. For example, key questions faced in military transformation efforts partially revolve around determining which tactics, products, and technologies to employ, where each of these may affect several attributes or behaviors.

So, to provide guidance to senior leadership on how decentralized organizational structures work for network-centric, we also need experimental designs capable of handling hundreds of factors efficiently, when many of those factors might represent the presence or absence of a particular agent, sensor, communication device, tactic or technology. We are currently exploring a hybrid procedure with three phases: an initial phase where a fractional factorial design allows the analyst to gather some initial indication of the signs and magnitude of potential factor effects, a second phase where CSB is employed, and an optional third phase where additional runs are conducted using a controlled sequential factorial design (Shen and Wan 2005) to assist in developing regression models of the ABM's performance. The first two phases are essentially the procedure described in Sanchez, Wan and Lucas (2005) with the added option of classifying clearly influential factors as important without passing them along to the CSB phase. Preliminary empirical investigations indicate this hybrid procedure is both efficient and effective. Additional research is needed to provide theoretical justification for its performance, as Wan, Ankenman and Nelson (2005) did in their initial development of CSB. We also seek a broader understanding of how the procedure's performance is influenced by the patterns of the underlying factor effects and the response variability.

Our longer-term goal is to adapt this adaptive sequential screening procedure and obtain one that allows the analyst to identify important two-way interactions as well as main effects. The simple construction method for obtaining very large 'resolution V' fractional factorial designs (allowing estimation of all main effects and two-way interactions) recently developed by Sanchez and Sanchez (2005) is anticipated to facilitate this effort.

Conclusions

Defense analysts must explore and provide insight into how future network-enabled forces will perform across a broad range of threat capabilities and scenarios. An emerging approach to this challenging problem is the use of agent-based models (ABMs) and novel experimental designs. When used within a data farming framework, these designs allow rapid exploration of models of network-centric military and non-military operations, and provide insights on the performance of edge structures in combat settings. We illustrate this framework by providing an overview of an investigation of ABM models of edge and hierarchical organizations, and discuss ongoing work involving further development of ABMs suitable for examining edge organizations and other organizational structures in network-centric warfare, along with experimental designs that facilitate explorations of these ABMs.

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