14th ICCRTS
"C2 and Agility"

(Cover Page)

Paper ID#: 145

Title:
Entropy and Self Organizing in Edge Organizations

Topic 6: Modeling and Simulation

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Entropy and Self-Organizing in Edge Organizations

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Along with the advance of technologies and evolving variety of military missions, Edge Organization has been proposed to transform C2 from its conventional hierarchical and inflexible structures into more network centric and flexible forms. To develop a better understanding of Edge Organizations, in our research we take a dynamical and adaptive complex systems approach to exploring dynamical features of Edge Organizations and investigate how networking structures and self-organizing mechanisms may impact on the entropy of Edge Organizations and consequently determine their *agility* and performance. After defining the basic concepts, we introduce an agent-based simulation model that captures the interplay among networking structures, self-organization mechanisms, and organization agility and performance with entropy as an intermediate variable. Through simulation-based case studies using the proposed model, important dynamical features of Edge Organizations can be clarified and conditions for avoiding high entropy equilibriums and for achieving high level of agility be identified. In addition to the description of the proposed model, various measures of organizational entropy and organizational agility are discussed. A scenario design for future simulation studies is presented.

1. INTRODUCTION

The advances of technology have led to the transformation of the world from the traditional Industrial Age to the new Information Age. To respond to such transformation, a new organization form, called *Edge Organization*, has been proposed for the military to transform itself for more effectiveness and efficiency in the battlefields (Alberts & Hayes, 2003). To deepen our understanding of, and provide management guidance for, Edge Organizations, we take an dynamical and complex adaptive systems approach to exploring, through theoretical investigation, computer based simulation and practical validation, the dynamical features and agility of Edge Organizations and eventually developing a theoretical understanding that can be applied to explain the interplay between the *structure*, *individual behaviors*, and *agility & performance* of Edge Organizations.

The concept of Edge Organization (EO) is defined based on the following four tenets: 1) a robustly networked force improves information sharing, 2) information sharing and collaboration enhances shared situation awareness, 3) shared situation awareness enables self-synchronization, and 4) these, in turn, drastically increase mission effectiveness (Alberts, 1996, pp. 7-8). Furthermore, the diverse military missions, such as peace keeping, and various forms of operation, such as coalition, have enlarged the phase space of the possible military operations, calling for a *dynamic and emergent* process to approach military affairs in which maintaining a coherent *focus* describing the collective intent and a coordinated *convergence* to that focus is essential (Alberts D. S., 1996). Although the EO concept has been endorsed by the military as an enabler for future warfare, the present understanding of Edge Organization is still at the level of conjecture; little guidance is available for managing such organizations. To make EOs truly practicable, a better understanding is needed that can explain and predict EO behaviors and help military commanders facilitate and manage their Edge Organizations.

The second law of thermodynamics (Clausius, 1865) predicts that a closed system, including life processes in general (Schrödinger, 1944) and human activities in particular (Wiener, 1948), tends to increase its entropy (or disorder) to the maximum. For an EO to maintain its order and therefore its effectiveness and efficiency, it must interact with its environment with efficient mechanisms to keep reducing its entropy. Given that an EO is an open system, the question then is: *what mechanisms an EO can employ to maintain its viability?* We identified two important mechanisms. One is structural: *networking structure* of EO agents, and the other behavioral: *self-organizing behavior* of the agents. The overall goal of our research is to *explore dynamical system features and their relations with agility* in the context of Edge Organizations by focusing on the interplay between *networking structure*, *self-organizing behavio*r and *organization performance*, with *entropy* as an intermediate variable. More specifically, we want to understand what are the macro-level (structural level) and micro-level (individual level) conditions that must be satisfied by EOs in order to attain high level organizational agility and performance, including *shared awareness of situations*, *coordinated decision-making*, and *cohesive actions*, in different task situations. Some of the general research questions we intend to address include:

- *What are the typical network features of Edge Organizations in terms of size, degree of connections, clustering, centrality, and hierarchy?*
- *What are effective self-organizing mechanisms and how do they relate to increasing agility as well as reducing entropy?*
- *What are the enablers and/or conditions of such self-organizing behaviors that are effective for Edge Organizations to achieve their focus and convergence while maintaining maximum agility?*

In the following sections, we first review the related work in Section 2 and then in Section 3 introduce a physical metaphor and associated hypotheses for modeling various organizations including edge organizations. In Section 4, we present our ESO (Entropy and Self-Organizing) model of edge organizations and introduce a set of measures for evaluating the characteristics and effectiveness of edge organizations. Concluding remarks and future work will be described in Section 5.

2. RELATED WORK

Our research is built based on the ideas of entropy and second law of thermodynamics, multi-agent systems, organization theory, network theory, and edge organization research. Entropy in physics is a measure of unavailability of energy. It is also associated with order, disorder and chaos in a thermodynamic system. The second law of thermodynamics dictates the physical world by stating that the spontaneous evolution of an isolated system always leads to an increase of its entropy (or disorder) until it eventually reaches its maximum value, which is equilibrium. The entropy of the universe tends to a maximum (Clausius, 1865). After the works of Shrodinger (1944) and Wiener (1948) and others, there is a consensus that life processes in general and human activities in particular are thermodynamic processes. While the second law does not directly apply to human organizations that often are open systems, it clearly indicates the wind-down tendency of an organization in the absence of effective interactions between the organization and its environment. Researchers have demonstrated that a dissipative system (like an organization) can stabilize its otherwise improbable structure at the expense of the compensative or negative entropy production due to energy and/or information flow through that system (Prigogine & Stengers, 1984). This dissipative system theory has led to the research on the systems featuring self-organizing, a mechanism that facilitates the exchange between the system and its environment and leads to complex, stable and orderly emergent system behaviors. The concept of entropy and the second law together with the notions of dissipative and self-organizing systems provide a strong theoretical basis to model, verify, and evaluate Edge Organizations.

Self-organizing is a mechanism or process that enables a system, either physical, biological or social, to change its organization without explicit external command and/or control during its execution time (Serugendo, Gleizes, & Karageorgos, 2005). It is basically a process of *evolution* where the development of new and complex structures *emerges* primarily in and through the system itself. A self-organizing system must be an open system since the self-organizing processes decrease the system's entropy and must dissipate such entropy to its surroundings (von Foerster, 1960). A system shows self-organizing if its behavior shows increasing *redundancy*, *information*, and *constraint*. In human organizations, self-organizing is a dynamic change within the organization by reinventing new structures and policies in order to survive, grow and develop. One example is organization learning that allows self-organization, rather than attempting to control the bifurcation through planned change (Dooley & Johnson, 1995). The structuration theorists also introduced the self-organizing concept into social systems by interpreting the relationship of social structures and social practices/actions as dialectical (Giddens, 1984; Fuchs, 2003). In such theories social structures enable and constrain social actions and are produced and reproduced by social actions.

In multi-agent systems, agents' local learning mechanism is often a self-organizing process. The research has shown that in a multi-agent system, agents can model the environment in a self-interested way without sharing knowledge, and a game dynamics emerges naturally through environment-mediated interactions (Sato & Crutchfield, 2003). Further, the collective learning dynamics emerged from the local reinforcement learning exhibits a diversity of competitive and cooperative behavior including quasi-periodicity, stable limit cycles, intermittency and deterministic chaos. The behavior can be modeled using a generalized form of coupled replicator equation. Reinforcement learning can be taken as an algorithm for agents to optimize their local policies; the agents can use their learned knowledge about others to undergo a specific self-organizing mechanism so that the global network can be dynamically optimized (Abudallah & Lesser, 2007). The self-organizing behavior of agents has also been studied among the networked agents. The research has shown that in the case of networked prisoner's dilemma game, the ratio of collaborating agents is dependent on the type of the network and the average degree of connections (Tang, Wang, & Wang, 2006). Multi-agent based modeling has also been adopted in studying military combat and warfare situations (Ilachinski, 1997) and various system measures were developed to evaluate the complexity of combat situations (Sprague & Dobias, 2008), although edge organization issues were not explicitly addressed in these studies. Edge organizations feature distributed local control and self-synchronizing (Alberts & Hayes, 2003). Studying the roles and effects of self-organizing in edge organizations and how does it facilitate information flow (Nissen, 2007) is essential for both understanding and practicing edge organizations.

The structure of an organization plays a key role in determining the organization's performance. Organization researchers have examined how the structure of control or decision-making influences the behavior of organizations (Mintzberg, 1992) and how different task dependencies may demand different control and communication structures (Thompson, 1967; Galbraith, 1974). Structuration theorists view both rules and resources as components of structures that both enable, and are reproduced by, human actions (Giddens, 1984). A social system is defined as an "interdependence of action" made up of an established network of relationships and network conditions which moderate any change effort targeted at a subsystem (Giddens, 1979). The research in organizational learning has investigated the roles of individuals' belief and aspiration in determining the decisions of refining current capability or exploring new ones (Levitt & March, 1988; March, 1991). Recent research on complex networks including social network, information network, technological network and biological network, has deepened our understanding of various types of networks, their properties, and the application potential of network analysis (Newman, 2003). It has been recognized that scale free networks with a power-law degree distribution, such as those found in social networks, can be highly resistant to the random attacks to the network nodes, but are quite sensitive to targeted attacks aimed at fracturing the network quickly. Small world networks, as found in many biological systems, are more robust to perturbations than other network architectures. In applying network analysis to organization research, it was found that R&D organizations can enhance their effectiveness by promoting communication outside the formal, hierarchical boundaries (Allen, 1977). In cases of environmental change, organizations are better off if they adopt an organic, nonhierarchical and informal structure (Burns & Stalker, 1961) and maximize strong cross-departmental relationships (Krackardt & Stern, 1988). Dynamically changing environments create uncertainties for the individuals that make them less comfortable to cross subunit boundaries to interact with others; while more cross subunit cooperation is the key to stabilize the whole organizations (McGrath & Krackardt, 2003).

Edge organization research to date has conceptualized numerous C2 (Command and Control) approaches (i.e., organization and management of people and activities) (Nissen, 2008). Alberts and Hayes (2006) introduce the three-dimensional C2 Approach Spaced depicted in Figure 1. As a closely related research work, Gateau et al. (2007) conceptualize and execute computational models for six organizational forms (i.e., each corresponding to an alternate C2 approach), including Mintzberg's (1979) five archetypal configurations and the Edge Organization (Alberts and Hayes 2003, Nissen 2005). Computational model POWer based results were used to reduce the large, multidimensional space into a minimal orthogonal design space (Nissen, 2008). Furthermore, ELICIT (Experimental Laboratory for Investigating Collaboration, Information-sharing and Trust) multiplayer intelligence game was developed to frame testable hypotheses about the relative effectiveness of edge organizations in comparison to other methods of organization through a series of real-world experiments. Numerous ELICIT based experiments have been reported using ELICIT (Leweling and Nissen 2007, Ruddy 2007).

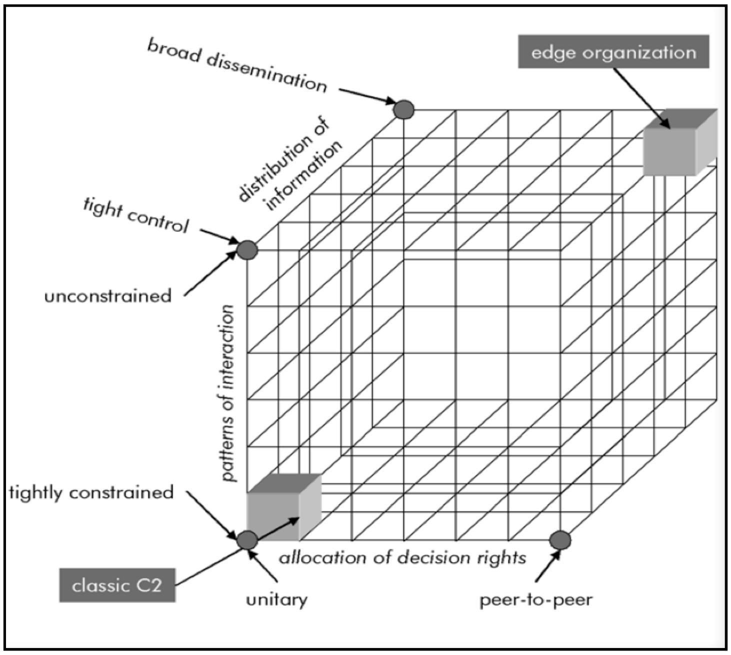


Figure 1: C2 Approach Space (Alberts and Hayes 2006)

3. A PHYSICAL METAPHOR AND HYPOTHESES

Building on previous work, our research attempts to investigate how edge organizations work and why they work in certain ways as compared to conventional C2 organizations. We attempt to understand both endogenous (organizational) and exogenous (environmental or task dependent) conditions for edge organizations to work effectively by examining the interplay between collective characteristics such as *focus* and networking *structure* and self-organizing mechanisms that are needed to *convergence* to the prescribed focus.

The basic idea behind this research is two-fold: 1) the highly dynamical behavior of edge organizations have made it important to treat them as dynamical systems and investigate their dynamic *evolution* process in which no single command or control exists and the *focus* must be shared and the *convergence* to the focus be maintained; and 2) a dynamic system must employ effective self-organizing mechanisms to maintain its productive relationships with its environment so that the system entropy can be kept reduced; it is therefore essential to investigate how both structures and self-organizing mechanisms are related to the tasks and battle environments for their best organizational performances.

Following the basic idea described above, we can speculate how various organization forms may exhibit different dynamical system features, as illustrated in Figure 2. Traditional *hierarchical organizations* have clear control/reporting structures and can be viewed as close to *solid state* of physical matters. In general, this type of systems has high level of informational redundancy (i.e., knowing one node leads to knowing the others) so that the entropy is low. In this case, the system possesses strong capability or energy, due to low entropy, to perform its intended tasks. However, when changes occur, both exogenous and endogenous, the inflexibility due to tight links between the nodes of will impede its functionalities. On the other hand, when an organization is in case of *anarchy*, as shown in Figure 2, it can be viewed as close to *gas state* in which the level of uncertainty (i.e., knowing one node does not increase knowledge of any other node) cannot be higher so that the entropy is at its maximum. While in this case the system can "deal with" any situation invariably, the quality of work will uniformly unacceptably low.

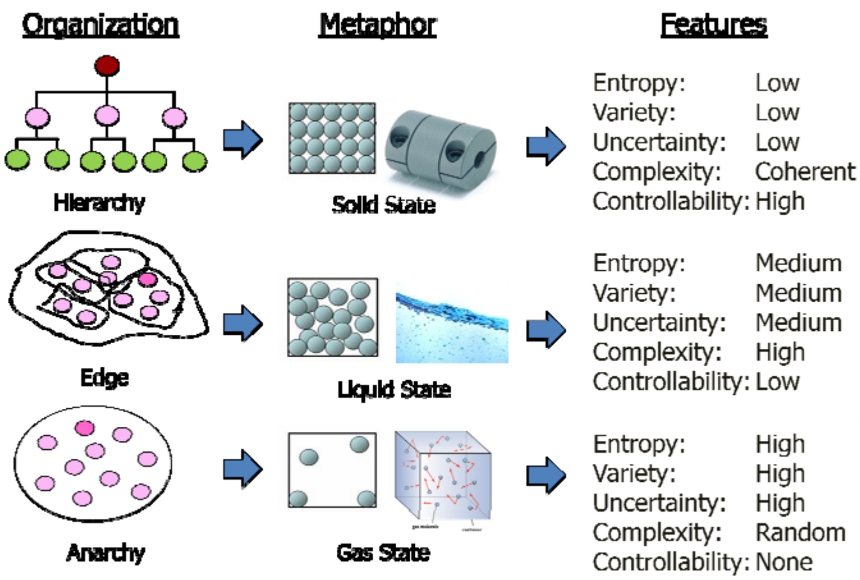


Figure 2: From Hierarchy to Edge: Dynamical Features

Edge organizations can be viewed as in a state in between, *liquid state*, as shown in Figure 2. In this case, the system appears less uncertain (i.e., knowing one node does allow one to know more, but hardly all, of the system) so that the entropy is medium. This medium level entropy provides potential for the system to do both *adapting* and *functioning*. Less constrained, or sometimes even unconstrained, patterns of interaction, decision allocation, and information distribution give rise to innovative possibilities. At the same time, a variety of *distinguishable patterns* of control, communication and action provide momentum for the system to work effectively under various situations. From a complex system's perspective, for an Edge Organization to effectively performing *adapting* and *functioning* through choosing among the innovative possibilities, it requires the intervention of two antagonistic manifestations (Nicolis and Prigogine, 1989): *short-range randomness*, providing *innovative options* to explore the state space; and *long-range order,* enabling an edge organization to sustain a *collective regime*.

Following the same line of thinking, we can establish corresponding relationships between system attributes and system states for different types of organizations including conventional military organizations, companies, professional societies, and social societies, as described in Table 1.

Table 1: System Attributes and Corresponding System States

System Attributes		<----- static **System States** dynamic ----->			
System Entropy & Equilibrium	Entropy	Low	Medium	High	Max
	Distance from Equilibrium	No Equilibrium	Far from Equilibrium	Close to Equilibrium	On Equilibrium
System Behavior	Macro Level Behavior	Designed Order	Emergent Order	Disorder	Chaos
	Micro Level Behavior	Designated Behavior	Weak Self-organizing	Strong Self-organizing	Independent Action
Sample Systems	Physical Systems	Solid or Artifact	Liquid	Liquid-gas	Gas
	Human Organizations	Conventional Military	Companies → Universities (*Garbage Can Model*)	Universities → Societies	Society
System Properties	Structure	Hierarchy	Small World Network	Scale Free Network	Random Network
	Stress	High	Medium	Low	None
	Entropy Production Rate	High	Medium	Low	Zero
	Resilience	Low	Medium	High	Very high
	Robustness	Low	Medium	High	Very high
	Power or Control	Centralized	Middle Edge	Edge	Individual
	Maintenance Cost	High	Medium	Low	Zero

Conventional hierarchical military organizations are more static, have low entropy, but are less robust and less resilient. The move toward Edge Organizations implies the move to more dynamic and “fluid” organizations. It is worth mentioning that the “Garbage Can Model” of organizational choice in universities (Cohen et al, 1972) can be considered as a primitive type of Edge Organization. Our physical metaphor together with our review of the extant literatures has led us to the following hypotheses about edge organizations.

Hypothesis 1:

An Edge Organization must maintain one or more dynamical and changing hierarchical structures in response to the situation change in the battlefield and other military missions. In his seminal work (Simon, 1981), Simon indicated the existence of hierarchy in almost all complex systems and argued the efficiency and robustness of such hierarchical forms. Our intuition is consistent with Simon’s notion and we further hypothesize that the reason to maintain such structures is to keep to the overall entropy of the organization low so that there will be energy for desired actions. We intend to investigate and validate this intuition.

Hypothesis 2:

For an Edge Organization to exhibit “fluidity”, it must generally have low-level (closer to individual) randomness (i.e., unconstrained in any way) and high-level (at a larger scale) order (i.e., somehow constrained in some way). A true complex system, such as an Edge Organization, should have its complexity profile follow the *Power Law* with respect to the level of details. This requirement implies that the system must have high complexity (i.e., uncertainty, disorder) at lower levels for changing and adapting to new situations and low complexity at higher levels for maintaining the *focus* and *convergence*. This hypothesis assumes the Hypothesis 1 and is consistent with the "short-term randomness and long-range order" condition for complex systems discussed in (Nicolis and Prigogine, 1989).

Hypothesis 3:

In order to maintain such dynamic task dependent structures, EOs must possess and exhibit effective and changeable self-organizing mechanisms. The literature (Ashby, 1962; Heylighen & Joslyn, 2001) has shown that self-organizing behavior generally generates negative entropy and introduces order into a system by interacting effectively with the environment. Our hypothesis indicates that this relationship should apply to EOs with respect to dynamic structuring described in Hypothesis 1.

Hypothesis 4:

To sustain the self-organizing dynamics for entropy reduction, EOs must absorb information and/or energy from its environment; thus providing effective information infrastructures for the EOs is the key for the EOs to maintain its low level of entropy. It has been clearly shown that thermodynamic entropy can be considered as a special case of Shannon's information entropy (Jaynes, 1957) where the enlarged state space with high level of entropy indicates the missing information when viewed from a macro-level. This hypothesis treats information flow the same way as the energy (e.g., supply) flow.

Hypothesis 5:

Edge organizations are "evolutionary" in the sense that the "Focus" is maintained and/or achieved through evolving "fitness functions" of both individuals and organization, and the "Convergence" is realized by self-organizing mechanisms. Our proposed approach assumes a dynamical and evolutionary process of organization actions in which agents interact and self-organizing based on their own performance assessment. We hypothesize that the Focus & Convergence concept (Alberts, 2007) can be mapped to our view of Edge Organizations.

4. ESO: A ENTROPY AND SELF-ORGANIZING MODEL OF EDGE ORGANIZATIONS

Our exploration of features and agility of Edge Organizations is simulation based and we propose an *Entropy and Self-Organizing (ESO)* Model of Edge Organizations. Figure 3 illustrates the dependent, independent, and control variables of the model. In the following, we introduce the key concepts of ESO model and discuss the characteristics and implications of these concepts.

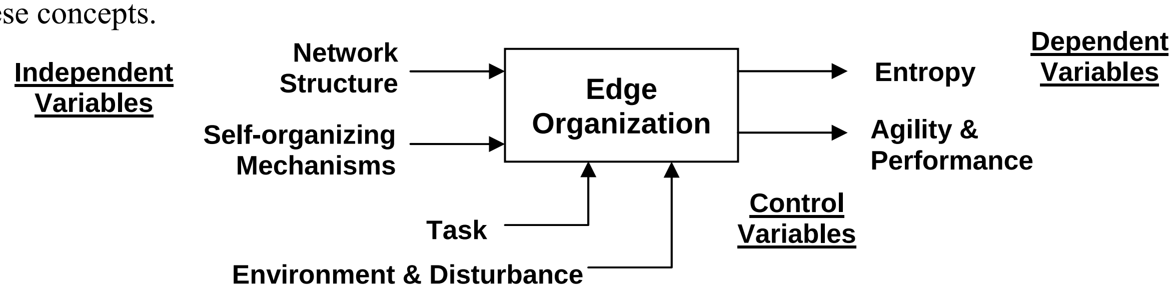


Figure 3: A Self-Organizing Model of Edge Organizations

4.1 EDGE ORGANIZATIONS AS SELF-ORGANIZING SYSTEMS

In our ESO model, an edge organization is defined as a self-organizing system, which is defined as follows.

Definition 1 (Self-Organizing System): Given a finite set of agents $Agt = \{a_1, a_2, ..., a_N\}$, their communication relations: $R_{comm} = \{rm_{a_1a_2}, rm_{a_1a_3}, ..., rm_{a_ia_j}, ..., rm_{a_{N-1}a_N}\}$, their control relations: $R_{control} = \{rn_{a_1a_2}, rn_{a_1a_3}, ..., rn_{a_ia_j}, ..., rn_{a_{N-1}a_N}\}$, their action rules: $U_{act} = \{ua_{a_1}, ua_{a_2}, ..., ua_{a_N}\}$, their interaction rules: $U_{interact} = \{ub_{a_1a_2}, ub_{a_1a_3}, ..., ub_{a_ia_j}, ..., ub_{a_{N-1}a_N}\}$, their partially shared knowledge: $K_{sh} = \{k_{a_1a_2a_5}, k_{a_1a_3}, ..., k_{a_ia_ja_ma_n}, ...\}$, a set of tasks: $T = \{ts_1, ts_2, ..., ts_L\}$, and the environment: Env, a self-organizing system S_{so} is defined as:

$$S_{so} = \{Agt, R_{comm}, R_{control}, U_{act}, U_{interact}, K_{sh}; T, Env\} \quad \blacksquare \tag{1}$$

In the above definition, communication relations define "*who can talk to whom*", while control relations specific "*who can order whom (to do something).*" Both relations are most likely to be dynamic and time dependent, although they can be set to be static. Action rules specify "*how agents should deal with the environment excluding other agents*", and interaction rules define "*how agents should deal with each other*". Again these rules can be either static or dynamic. Shared knowledge indicates "*which knowledge is shared among whom*". A piece of knowledge *k* can be a *goal* or *objective*, a *fact*, a *statement* of some agent that can be either true or false, or a commonly accepted *norm*. Based on the above definition, we can derive following characteristics of edge organizations.

- ***Homogeneity (homogeneous vs. heterogeneous):*** the degree to which agents share relations, rules and knowledge.
- ***Connectedness (loosely vs. tightly connected):*** the level or degree of connections among agents through communication and control relations.
- ***Centrality (centralized vs. decentralized):*** the degree, closeness, betweenness and cluster coefficient levels.
- ***Sophistication (simple vs. sophisticated):*** the level of complexity and size of rule sets and knowledge set.
- ***Sharedness (weak vs. strong sense of whole):*** the level and amount of shared knowledge of the whole system, e.g., shared goals, norms, processes, activities, rules, relations, and awareness of the environment.

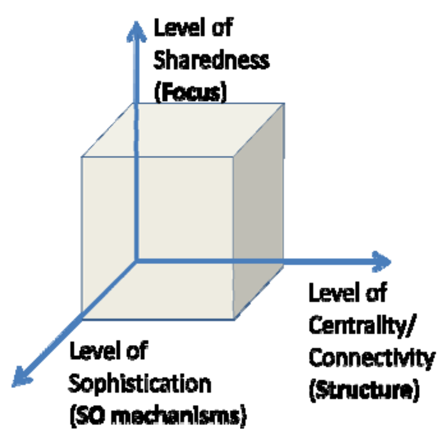


Figure 4: Space of Exploration

The above characterization provides us with a three dimensional space of research exploration, as shown in Figure 4. In this space, the edge organization concepts such as focus, self-organizing mechanisms, and networking structure corresponds to levels of sharedness, sophistication and centrality/connectedness, respectively

4.2 SIMULATION DESIGN

To explore the edge organization space illustrated in Figure 4, we developed a simulation design that is simple in the level of sophistication but rich enough in other dimensions for us to address the hypotheses described above. Figure 5 provides an overview of our simulation design.

- **Organization**
  - o Homogeneity: homogenous
  - o Connectedness: modestly connected
  - o Centrality: centralized & decentralized
  - o Sophistication: simple
  - o Sharedness: weak & medium
- **Field**
  - o Valuable areas
  - o traps
  - o Blocks & Openings
  - o Enemies (for 2-party)
- **Mission**
  - o Occupy valuable areas
  - o Avoid traps
  - o Annihilate enemies (for 2-party)
- **Agent**
  - o Actions: move, find new attractors & traps
  - o Interactions: identify others, issue and receive information
- **Enemy situations**
  - o Conventional:
    - – Predictable field situations (i.e., layout of the field)
  - o New:
    - – Highly unpredictable field situations (i.e., valuables, traps & blocks pop-up randomly e.g., terrorist situations)
- **Performance**
  - o Effectiveness: attractors occupancy
  - o Efficiency: distances traveled

Figure 5: Simulation Design

To evaluate the performance of different C2 organizations including edge organizations, we designed a virtual 2D battlefield based on the MASON software platform (http://cs.gmu.edu/~eclab/projects/mason/). The battlefield is a bounded square with featured areas in it. The featured areas include the *valuable areas* that attract agents to occupy, the blocks that the agents cannot move through, and the traps where the agents cannot move again once entered.

Definition 2 (Environment): In our simulation design, the environment *Env* is defined by a bounded battle field in which there are valuable areas: $V=\{v_1,v_2,...,v_Q\}$, disaster traps: $D=\{d_1,d_2,...,d_P\}$, and blocks: $B=\{b_1,b_2,...,b_R\}$. We have:

$$Env=\{V,D,B\}=\{v_1,v_2,...,v_Q,d_1,d_2,...,d_P,b_1,b_2,...,b_R\}\ \blacksquare \qquad (2)$$

The environment can be either static and predictable or dynamic and unpredictable. To capture the dynamical change of the environment, we define the environment at given time t_i, $Env(t_i)$, as a situation $S(t_i) = Env(t_i)$. We have:

Definition 3 (Situation): For a given environment, the situation *St* at time t_i is defined as

$$St(t_i) = \{s_1(t_i), s_2(t_i), ..., s_{Q+P+R}(t_i)\} = Env(t_i) \blacksquare \quad (3)$$

It can be seen that a situation item s_j can be a valuable area, a trap, or a block. An agent can be aware of one or more specific situation items. If the agent knows part/all the situation items correctly at a given time, then we say that the agent has the partial /full situation awareness at that time.

Two types of tasks are defined in the simulation. One is "ts_1 = *occupy valuable areas*" and the other is "ts_2 = *annihilate of enemy forces*". In a one-party simulation, ts_1 becomes the only task considered. In case of two-party simulation, a combat is finished when either one of the two parties fulfill both ts_1 and ts_2. Given the above concepts we can introduce the definition of agent.

Definition 4 (Agent): An agent a_i of party *j*, capable of performing actions $C_i = \{act_1, act_2, ...\}$ under action rules ua_i and interaction rules ub_i charged with tasks $Ts_i \subseteq \{ts_1, ts_2\}$, equipped with organization knowledge $Ko_i = \{ko_1, ko_2, ...\}$ and situation knowledge $Ks_i = \{ks_1, ks_2, ...\}$, and currently located in $loc_i = \{x_i, y_i\}$ at state $sta_i \in \{move, trapped, occupied\}$, we have:

$$a_i = \{j, Ts_i, C_i, Ko_i, Ks_i, u_{ai}, u_{bi}, loc_i, sta_i\} \blacksquare \quad (4)$$

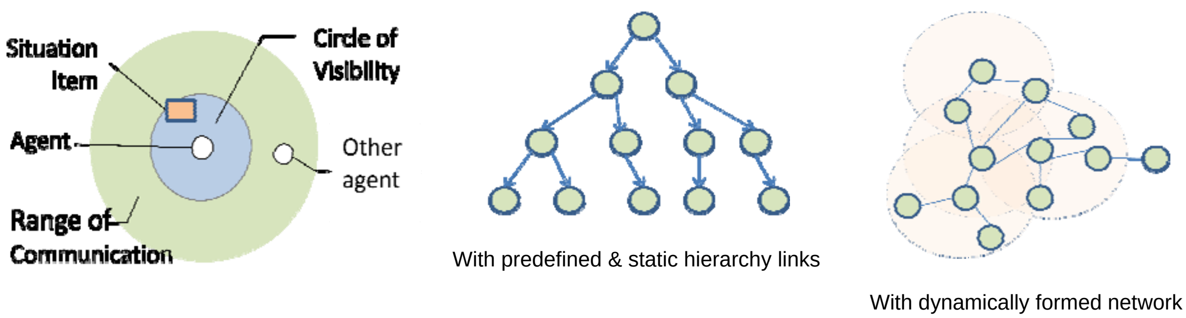
In our simulation design, an agent can perform some or all of five actions, i.e., $\{sense, move, communicate, assignTask, stay\}$. Action and interaction rules are listed in Table 2.

Table 2: Agent Action and Interaction Rules

Actions	Rules
Sense: Recognize situation items and agents	1) Put all situation items within the visibility range into the *recognized-situation-list*. 2) Remove situation items out of the recognized list when they are out of the range 3) Put all agents within the communication range into the *recognized-agent-list*. 4) Remove agents out of the recognized list when they are out of the range
Move: Change location (x,y) one step at a time	5) Move randomly in x or y direction if no valuable area, trap or block is recognized. 6) Move toward the closest valuable area if one or more valuable areas are recognized. 7) Move away from traps if recognized. 8) Avoid blocks and find passages toward valuable areas if needed.
Communicate: Pass *Ko* & *Ks* to others when potential exists	9) In *Hierarchy* setting, communicate only with those who are on a pre-defined hierarchical communication list. 10) In *Edge* setting, communicate with all those who are on *recognized-agent-list*.
Collaborate: Help other when requested	11) In *Hierarchy* setting, collaborate with only those with whom a pre-defined control link exist. 12) In *Edge* setting, collaborate with all those who are on *recognized-agent-list*.
Stay: No action for the next move	13) Stay with a valuable areas whenever the agent is in the area. 14) Stay with a trap whenever the agent is trapped.

As illustrated in Table 2 and Figure 6, an agent in our simulation model does the following in a simulation session. 1) Move in the field randomly in either x or y direction one step at a time; 2) Sense situation items and other agents and collect the sensed information; 3) Avoid traps, move around blocks, and move toward valuable areas and stay if reached, 4) Send and receive information to and from other agents about the situation.

The relations between agents are established differently in different organizational settings. In case of Hierarchical setting, both communication and control links are predefined and they remain static, while in Edge settings, communication relations are dynamically established depending on the spatial relations between agents, as shown in Figure 6(b) and 6(c), respectively. As shown in Figure 6(c) the control relations in Edge organization is not clearly defined. It is hypothesized that the agents with more links to the others and those with more information than others will likely to gain control from the "power" of having more links and more information rather than from the "authority" as in the case of hierarchy. An example scenario of simulated battle field is shown in Figure 7. The agents' goal is to occupy as many valuable areas as soon as possible.



(a) Agent in a Field (b) Hierarchical Organization (c) Edge Organization

Figure 6: Agent and Organizations of Different Settings

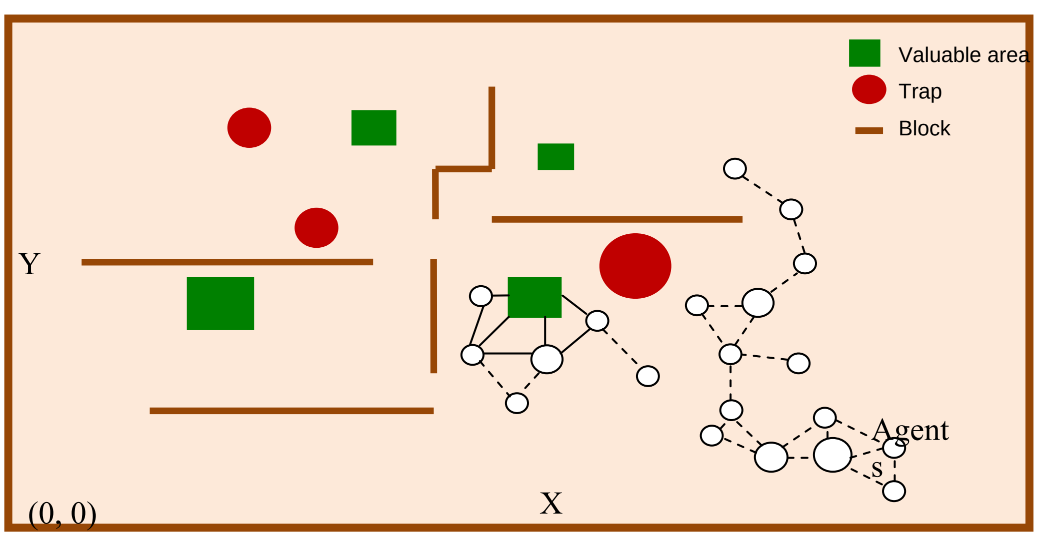


Figure 7: The Simulated Battle Field (1-Party Case)

4.3 ORGANIZATIONAL ENTROPY AND SITUATION AWARENESS

Developing sensible and effective measures to evaluate the state, performance, and agility of edge organizations has been a major task for research on combat and warfare in general and for the edge organization research in specific (Alberts, 2007). In our research we divide effectiveness measures into two categories. The first category, namely *organization entropy and situation awareness*, measures the *state* of an edge organization at a given time in a mission process and its *potential* to continue and complete military missions. The second category, namely *performance and agility* provides a result-oriented view of how effective an edge organization is when missions are ended either successfully or in failure.

Developing an adequate entropy measure is a challenge. Generally, organizational entropy should be a measure of disorder, or disorganization of organizations. In military organizations, the level of entropy can be ultimately determined by the inability to perform military actions that contribute positively to the mission *focus*. There can be various cases in which military organizational entropy increases. Examples include casualties, injuries, loss, or lack of supply, of equipments, and loss or degradation of communication. Carvalho-Rodrigues (1989) suggested attrition based combat entropy that measures the level of organizational disorder as a result of number of casualties occurred in both friend and enemy sides. Ilachinski (2004) proposed spatial entropy that measures the spatial distribution of solders in the battle field. Recent work by Sprague and Dobias (2008) suggested using more complex system measures such as fractal dimension, Hurst exponent, and self-similarity parameter to measure both spatial and temporal distributions of combat forces. Common to all these previously suggested measures is the object of evaluation: the physical states (i.e., casualties, spatial and/or temporal distribution) of combat forces. Unlike all these measures, in our research we look into the reason that leads to such physical states: the *inability of making proper decisions* by the agents engaged in military operations. Therefore, we define military organizational entropy by measuring an organization's inability to make proper decisions.

Definition 5 (Decision Difficulty): For a given agent a_i working on a task of type ts_j, if the average complexity of ts_j is Cx_j, then the decision difficulty of ts_j for a_i can be defined as follows:

$$Q_i = Cx_j \times (AmountOfInformationNeeded) \quad \blacksquare \tag{5}$$

We assume that for a given military organization, there are M information sources and N agents involved in the military operations. For agent a_i, the (*AmountOfInformationNeeded*) can come from any or all of the M information sources and/or N agents. If we further assume the probability for a_i to choose information source m is $p_i(m)$, and the probability for a_i to communicate with agent a_n is $p_i(n)$, then by following Shannon's (1951) entropy definition we have:

$$\begin{aligned} Q_i &= Cx_j \times (AmountOfInformationNeeded) \\ &= Cx_j \times \left[\sum_{m}^{M} p_i(m)\log(\frac{1}{p_i(m)}) + \sum_{n}^{N-1} p_i(n)\log(\frac{1}{p_i(n)}) \right] \end{aligned} \tag{6}$$

When agent a_i has total K different tasks, we have:

$$Q_i = \sum_{k}^{K} Cx_j \times \left[\sum_{m}^{M} p_i(m) \log(\frac{1}{p_i(m)}) + \sum_{n}^{N-1} p_i(n) \log(\frac{1}{p_i(n)}) \right] \quad (7)$$

Summarizing over all agents, we define organizational entropy (decision difficulty) as follows.

Definition 6 (Organizational Entropy): For an organization with K tasks, N agents, and M information resources, its organizational entropy measured as a summation of decision difficulties of all agents is defined as:

$$Q = \sum_{k}^{K} Cx_j \times \sum_{i}^{N} \left[\sum_{m}^{M} p_i(m) \log(\frac{1}{p_i(m)}) + \sum_{n}^{N-1} p_i(n) \log(\frac{1}{p_i(n)}) \right] \blacksquare \quad (8)$$

It can be seen that the second item of the above equation is the "*entropy of actionable information*" of military organizations. Based on this definition of organizational entropy, we can derive following implications about edge organizations.

- **The equilibrium state**: As shown in Eq. (8), the maximum entropy is reached when all $p_i(m)$ and $p_i(n)$ are equally distributed for all agents. This is the "no structure at all" or "gas" situation where everyone can talk to everyone else in the organization but has no idea about how to differentiate other agents. The corresponding organization is anarchy and has no focus, no norm, and no reference at all for an agent to acquire needed information in order to make proper decisions.

- **Information potential**: To reduce entropy level and move away or keep away from equilibrium, an organization must maintain information potential between agents and/or influx of information from external sources. This suggests that "everyone knows everyone else knows" is not necessary a desirable situation in the sense that little information will flow between agents, leading to an inaction situation. New discovery of the field situation by the agents and/or new influx of information from external sources can create new information potentials and promote more information flows, resulting in reduced organizational entropy. How to create and keep information potential can be an important issue for edge organization design and management.

- **Structural entropy vs. system entropy**: Eq.(8) can be used to describe organizational structural entropy that depends only on the topology of communication links or channels available without counting the distribution of information. In this case, it can be seen that a complete network of agents will likely create a high entropy situation since agents may not have information about who knows what. This non-discriminative networking based high entropy situation can be improved by introducing information potentials and letting agents explore and recognize the potentials. It is therefore important for an edge organization to maintain effective self-organizing mechanisms that allow agents efficiently discover information potentials so that the system entropy can be reduced.

The above implications of the organizational entropy measure of Eq.(8) has led us to developing measures that can evaluate the information potential of an organization at a given time. For the simulation scenario discussed above, we introduce the following information potential measure.

Definition 7 (Information Potential): Given a set of agents $Agt = \{a_1, a_2, ..., a_N\}$ and a set of situation items $St(t_i) = \{s_1(t_i), s_2(t_i), ..., s_L(t_i)\}$, the information potential with regard to situation item s_l is defined as:

$$PI_{s_l} = \frac{2}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} | a_i s_l - a_j s_l |; \quad a_i s_l = \begin{cases} 1, \text{ if } a_i \text{ is aware of } s_l \\ 0, \text{ if } a_i \text{ is not aware of } s_l \end{cases} \tag{9}$$

or

$$PI_{s_l} = \frac{4Ks_l(N - Ks_l)}{N^2}, \quad \text{where } Ks_l \text{ is the number of agents who are aware of } s_l. \tag{10}$$

Summarizing through all situation items, we define the organizational information potential as

$$PI = \frac{2}{L \cdot N^2} \sum_{l=1}^{L} \sum_{i=1}^{N} \sum_{j=1}^{N} | a_i s_l - a_j s_l |; \quad a_i s_l = \begin{cases} 1, \text{ if } a_i \text{ is aware of } s_l \\ 0, \text{ if } a_i \text{ is not aware of } s_l \end{cases} \tag{11}$$

or

$$PI = \frac{4\sum_{l=1}^{L} Ks_l(N - Ks_l)}{L \cdot N^2}, \quad \text{where } Ks_l \text{ is number of agents who is aware of } s_l. \blacksquare \tag{12}$$

From Eq.(9) we can see that if no agent knows situation item s_l, then the information potential for s_l will be 0. When s_l is first discovered by an agent, the information potential of this situation item will start to increase; after it reaches the maximum value 1.0 when half of the agents know the situation item, it will decrease until being zero again, when all the agents become aware of s_l. The increasing/decreasing rate of information potential depends on spatial distribution of agents and the communication speed between agents.

The concept of information potential described above can further be extended to evaluate organizational situation awareness. We introduce the following definition.

Definition 8 (Situation Awareness): Given a set of agents $Agt = \{a_1, a_2, ..., a_N\}$ and a set of situation items $St(t_i) = \{s_1(t_i), s_2(t_i), ..., s_L(t_i)\}$, the situation awareness for situation item s_l is defined as follows.

$$As_{s_l} = \frac{1}{N} \sum_{i=1}^{N} a_i s_l; \quad a_i s_l = \begin{cases} 1, \text{ if } a_i \text{ is aware of } s_l \\ 0, \text{ if } a_i \text{ is not aware of } s_l \end{cases} \tag{13}$$

Summarizing over all the situation items, we define organizational situation awareness as follows.

$$As = \frac{1}{L \cdot N} \sum_{l=1}^{L} \sum_{i=1}^{N} a_i s_l; \quad a_i s_l = \begin{cases} 1, \text{ if } a_i \text{ is aware of } s_l \\ 0, \text{ if } a_i \text{ is not aware of } s_l \end{cases} \blacksquare \tag{14}$$

The entropy, information potential and situation awareness measures described above are all changing dynamically during the execution or simulation process of mission operations. The time history of these measures will be important indicators of how well the information flow and decision making processes are facilitated by both organizational structure and policies or focuses and agent self-organizing mechanisms. We expect our simulation based case studies will lead us to better understandings of edge organizations with the help of these indicators.

4.4 ORGANIZATIONAL PERFORMANCE AND AGILITY

Given our simulation design discussed in Section 4.2, the performance measures are relatively straightforward. That is, the goal of our 1-party simulation is to have "as many agents occupying as many valuable areas as possible" and "do so as fast as possible". We introduce the following effectiveness and efficiency measures.

Definition 9 (Mission Effectiveness): Given a set of agents $Agt = \{a_1, a_2, ..., a_N\}$ carrying out occupying missions in the environment $Env = \{V, D, B\} = \{v_1, v_2, ..., v_Q, d_1, d_2, ..., d_P, b_1, b_2, ..., b_R\}$, the mission effectiveness is defined as

$$\begin{aligned} & Effe = \frac{\sum_{i=1}^{Q} occupied(v_i) - \sum_{i=1}^{P} trapped(d_i)}{Q}; \\ & where \\ & occupied(v_i) = \begin{cases} 1, \text{ if } v_i \text{ is occupied by at least 1 agent} \\ 0, \text{ if } v_i \text{ is not occupied} \end{cases} \\ & trapped(d_i) = \begin{cases} 1, \text{ if at least 1 agent is trapped by } d_i \\ 0, \text{ if no agent is trapped in } d_i \end{cases} \end{aligned} \tag{15}$$

■

Based on this performance measure, an organization should strive to occupy all valuable areas and avoid being trapped in any of the traps. Crowding in one or a few valuable areas is not rewarded well. For a given effectiveness measure, the efficiency of achieving the end performance can be measured by the "*time*" needed to complete the mission and the "energy" applied, measured by total distance traveled by the agents.

Agility, on an organizational level, refers to efficiency with which an organization can respond to change. Agility is not about how to respond to changes but it is about having the capabilities and processes to respond to its environment that will always change in unexpected ways. Following

Alberts (2007), in our research we define the concept of an organization's agility in terms of its *agile performance* and *fundamental agile capabilities*. More specifically, we have:

Definition 10 (Performance Agility): For a given set of agents $Agt = \{a_1, a_2, ..., a_N\}$ carrying out occupying missions in the environment $Env = \{V, D, B\} = \{v_1, v_2, ..., v_Q, d_1, d_2, ..., d_P, b_1, b_2, ..., b_R\}$ the performance agility of the organization is defined as

$$Agl_P = B \cdot Robustness + S \cdot Resilience; \quad (B\ and\ S\ are\ weights) \tag{16}$$

$$Robustness = 1 - \frac{\Delta Effe(\Delta Env)}{Effe(planned)} \tag{17}$$

$$Resilience = 1 - \frac{\Delta Effe(\Delta Agt)}{Effe(planned)} \blacksquare \tag{18}$$

As shown in the definition, performance agility measures how the organization performance varies depending on the exogenous changes ΔEnv (robustness) and endogenous changes ΔAgt (resilience). Less variation or less sensitivity to the changes means high level of performance agility.

Besides performance agility, we also attempt to measure the process agility, which we call fundamental agility because it indicates fundamental inherent reasons why performance agility can or cannot be achieved. We introduce the following definition,

Definition 11 (Fundamental Agility): For a given set of agents $Agt = \{a_1, a_2, ..., a_N\}$ carrying out occupying missions in the environment $Env = \{V, D, B\} = \{v_1, v_2, ..., v_Q, d_1, d_2, ..., d_P, b_1, b_2, ..., b_R\}$ the fundamental agility of the organization is defined as

$$Agl_F = A \cdot Responsiveness + B \cdot Flexibility + C \cdot Innovativeness + D \cdot Adaptiveness; \quad (A, B, C, D\ are\ weights) \tag{19}$$

$$Responsiveness = 1 - \frac{ResponseTime}{MaxEffectiveResponseTime} \tag{20}$$

$$Flexibility = \frac{NumberOfMethods}{NumberOfTasks} \tag{21}$$

$$Innovativeness = \frac{NumberOfInventedMethods}{TotalNumberOfMethods} \tag{22}$$

$$Adaptiveness = \frac{NumberOfChangedMethods}{TotalNumberOfMethods} \blacksquare \tag{23}$$

The word *methods* used in the above definitions refer to organizational processes and structural relations. While performance agility Agl_P is a dependent variable, fundamental agility Agl_F is an intermediate system variable and can be influenced by self-organizing mechanisms.

5. CONCLUDING REMARKS

The changes of military missions to date have led to the demand for more agile command and control organizations. On the other hand, the advancement of information technology has created a technological environment in which such organizations can be enabled. Although sharing information among peers and pushing decision powers to the edge will likely make conventional rigid C2 organizations more adaptable, our current understanding of, capability of managing edge organizations is very limited. In our research, motivated by a physical metaphor of edge organizations, we propose to treat edge organizations as self-organizing systems and attempt to deepen our knowledge of edge organizations by clarifying the interplays of network structures, self-organizing mechanisms, and organization performance and agility with entropy as an intermediate variable. We developed an ESO (entropy and self-organizing) model of edge organizations in which basic concepts, simulation design, and various entropy, performance and agility measures are proposed. Our proposed ESO model integrates the perspectives and insights from organization theory, dynamic and complex systems, and edge organization research. The analysis of the model and evaluation measures has generated useful insights about the characteristics of edge organizations.

Our ongoing research is focused on developing a multi-agent simulation framework based on the MASON platform. We are now in the process of designing simulation runs and create hypotheses testing plans. We have started to collaborate with ELICIT research group to make sure that the ESO simulation results will be comparable with ELICIT experiment data sets. It is expected that the insights gained from simulation studies and from comparisons with ELICIT will help us further improve the ESO model and develop better understanding of edge organizations.

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