Complex Adaptive Systems-based Toolkit for Dynamic Plan Assessment

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Abstract

The military battlespace can be seen as an amalgamation of a large number of simpler entities or military units organized in a specific hierarchy, each with its own understanding of the overall mission, knowledge of operational doctrine, and local perception of the threat environment. Though orders and guidance emanate down through the chain of command, it is the actions at the lower levels (*i.e.* the individual agents) where we see the combat occurring. It is through the chaotic and adaptive behavior of the individual agents or players that the emergence of global behavior is induced. Emphasis on emergent simulation behavior over predetermined behavior enables the simulation to focus on what is possible to occur rather than what is probable. The potential to explore a multitude of possible outcomes from similar initial conditions makes a complex adaptive systems approach to simulation well suited for effects-based operations evaluation and course of action assessment. The Complex Adaptive Systems-based Toolkit (CAST) for Dynamic Plan Assessment will support Air Force air campaign operations through the integration of combat agent behavior models, effects-based operations environment models, and a complex adaptive systems simulation engine. Specific challenges include modeling interactions between agents and environment; formulating an agent model with the potential for emergent group dynamics; and applying the models and simulation to a realistic urban operations scenario.

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1. Introduction

Complex adaptive systems research stems from artificial life theory (Langton, 1988) where complex and unpredictable behavior derives from a set of simple rules. Like artificial life, complex adaptive systems focus on behavior but with a particular interest in the emergence of complex behavior and group dynamics from basic individual rules and actions. Unlike traditional artificial intelligence-based simulations (Tsatsoulis, 1991), which tend to model high-level behaviors explicitly, complex adaptive systems restrict the model to low-level behaviors and rely on emergence of high-level behavior through multi-agent and agent-environment interactions. Furthermore, artificial intelligence requires an overall global perspective and extensive knowledge elicitation of the target domain to support the top-down synthesis of behaviors. Complex adaptive systems stress a localized view of the environment by employing a bottom-up approach to modeling behavior. Complex adaptive systems function by defining a simple set of rules for the simulation then allowing complex behavior to emerge from what was originally simple. This approach requires explicit representation of each element within the simulation. While the base entities may have a simple representation and basic rules for operation, the actions of one element influence all entities, thereby creating complex interactions between the set of entities.

Recent examples of artificial life and complex adaptive systems include application to financial markets such as the dynamic interdependent relationship between electric power and natural gas markets (Thomas *et al.*, 2004). Other examples include application to the stock market (Arthur, 1999) where individual traders can be seen as agents with their own local perspectives and behaviors, while the global view is of the stock market itself. A more encompassing perspective is the use of artificial life and complex adaptive systems techniques in the computational study of economies (Tesfatsion, 2002). In the realm of social science, (Epstein & Axtell, 1996) explore social structure and group behavior using a bottom-up agent-based simulation approach for sociological issues. New practices in management also recognize the utility of viewing business as a complex system (Santosus, 1998). (Regine & Lewin, 2001) explain how allowing bottom-up solutions to business and management situations can lead to greater efficiency as well as more creative and powerful solutions to problems that do not necessarily respond well to top-down directives. Culture itself has also been viewed as a complex adaptive system (Jenner, 2000), consisting of an evolving cultural framework that drives society's survival and adaptation rather than a static social construct for the arbitrary preservation of behavior or history.

2. Military Modeling and Simulation

Mathematical modeling of military conflict traditionally uses an attrition-based model such as Lanchester’s (1956) series of differential equations that relate a military force’s attrition to adversarial military strength. The equations encapsulate the observation that the rate of attrition is proportional to the strength of the opposing force, and forms the basis for most traditional warfare modeling and simulation. These types of models treat a military force as an aggregate whole rather than a complex system of individual components and function well when modeling traditional homogeneous military conflict (*e.g.* army versus army).

2.1 Modern Warfare and Complex Adaptive Systems

Ilachinski (1999) demonstrated the application of complex adaptive systems techniques to modeling warfare, specifically land combat simulation and analysis. The major thesis of his research is the evolution from traditional attrition-based mathematical models (Lanchester's equations) to a more individual entity-oriented (agent-based) framework. Modern military conflict no longer resembles homogeneous combat between relatively similar forces. Modern conflicts are asymmetric, where one adversary has significantly different assets and tactics than the other. Traditional models fail to capture the shift in fundamental tactics that emerge with a large difference in force size and composition. Furthermore, conflicts have moved from open battlefields to dense urban environments where additional considerations regarding collateral damage become more significant. Finally, the primacy of attrition's influence on military outcome has diminished as other factors including political, economic, and social ramifications have greater weight on military success. All of these factors reduce the effectiveness of traditional attrition-based modeling techniques. Ilachinski observed that complex adaptive systems address the deficiencies of traditional modeling by representing individuals rather than aggregating entities into a monolithic representation.

2.2 Effects-Based Operations

Effects-based operations describe an approach to a tactical situation where the focus of concern centers on specific effects to military objectives rather than a specific action (Smith, 2002). The effects-based approach relies on a system-wide understanding of the situation, environment, as well as the direct and indirect effects of any action as ramifications propagate throughout the system. To achieve reliable results, the system-wide understanding must include all elements within the situation as well as the interrelationships between all entities.

Because high-level behavior emerges from the interactions of the simulation elements rather than being explicitly encoded as agent behavior, complex adaptive systems theory is well suited for effects-based operations evaluation. Complex adaptive systems have the potential to explore a multitude of possible outcomes from the same (or similar) initial conditions. The nature of complex adaptive systems does not tend towards any single solution, but to a variety of possibilities, which is more inline with real combat situations. In contrast, traditional simulation techniques yield what is most probable to occur rather than what is *possible* to occur. For these reasons, complex adaptive systems approaches to military simulation address key elements of modern warfare concerns.

2.3 Culture

Organizational and cultural factors are increasingly more significant to military operations as demonstrated by recent missions in Afghanistan and Iraq (Cordesman, 2003a; Cordesman, 2003b). Complex Adaptive systems address the increasing need to model societal and cultural factors within the area of interest. The role of civilians and other non-combatants (and their associated behaviors) in the combat space adds a level of complication to the simulation environment by introducing additional groups and faction goals. Traditional simulation techniques that explicitly delineate the interactions between each faction would become exceedingly unwieldy as the number of factions involved increase. CAS is especially suited for these types of complex interactions by allowing the interactions to emerge from basic actions rather than stating them explicitly. Similarly, base cultural and societal norms can be encoded into the basic agents rather than enforcing high-level actions representative of the local culture. For example, low-level cultural features might include metrics for introversion, aggression, leadership, resolve, or dogma.

3. Environment Model

3.1 Dependency

A nodal dependency model represents the interdependencies between various centers of gravity[1] found in the simulation environment. Figure 3-1 illustrates a nodal dependency model example for city infrastructure. The illustration shows that a SAM Site requires at least one adversary agent in close proximity to the site and executing an operation action for the SAM Site to be functional. Communication towers need a civilian agent operating it and electricity to be functional. Electricity to the communication tower is only available if there is a power line connecting the communication tower to a power plant, and the power plant itself has an operator running it.

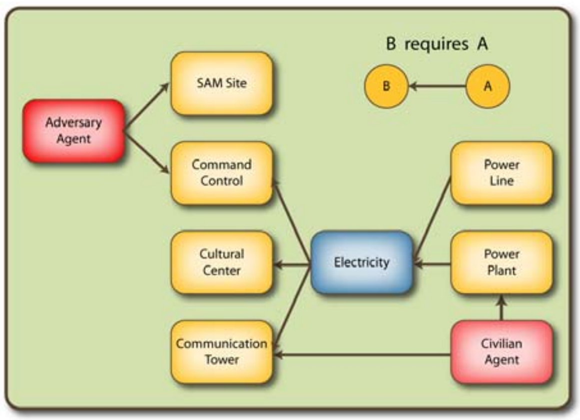

Figure 3-1: Nodal Dependency Model

The nodal dependency model for the simulation environment establishes relationships between entities; furthermore, multiple dependencies and a hierarchy of dependencies creates the initial means for alternatives and choice necessary for supporting effects-based operations analyses. The dependency model shows several options for affecting the communication tower, if any of the required components (operator, power line, power plant, or power plant operator) are not present, then the communication tower will not function and communication tower effects on the environment and surrounding agents are nullified.

3.2 Redundancy

In addition to establishing requirements for entities, the complex adaptive system environment may also exhibit alternatives via redundancy, where multiple means are available to meet the requirements of a component. Redundancy takes the form, 'A requires B or C,' where supplying B alone is sufficient to operate A, but if B is not available then C serves as an adequate alternative. As with straightforward dependency, redundancy provides a mechanism to support effects-based operations within the complex adaptive system by providing alternatives. Figure 3-2 illustrates the redundancy with respect to the communication tower example.

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[1] Centers of gravity include entities and systems of strategic value. The concept and terminology originates from Prussian military theorist Carl von Clausewitz.

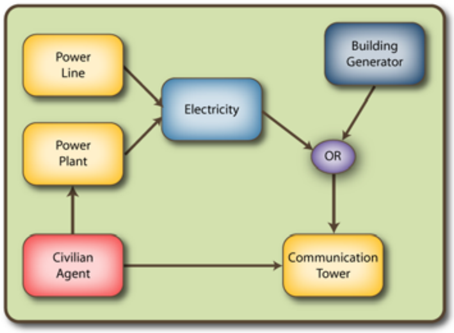


Figure 3-2: Redundancy Model

Together the dependency and redundancy models provide the foundation for effects-based operations. The component-by-component nodal model for the interrelationships between environment entities and agents also dovetails well with a complex adaptive systems approach where low-level characterizations, base behaviors, and localized definitions provide the basis for the emergence of high-level behaviors and global patterns.

4. Agent Model

Agents consist of a set of rules that determine the action taken by the agent and a set of behavior moderators that influence the execution of the rules. Figure 4-1 illustrates the agent model. Input parameters include perception of environment, effects acting on the agent, and a list of actions available to the agent at the current time and situation. Several behavior moderators influence the decision-making process; ultimately leading to a selected action that determines the effects the agent has on the environment and other agents. These effects, along with information on how others might perceive the agent and the actions available to be performed upon the agent, comprise the output of the agent model.

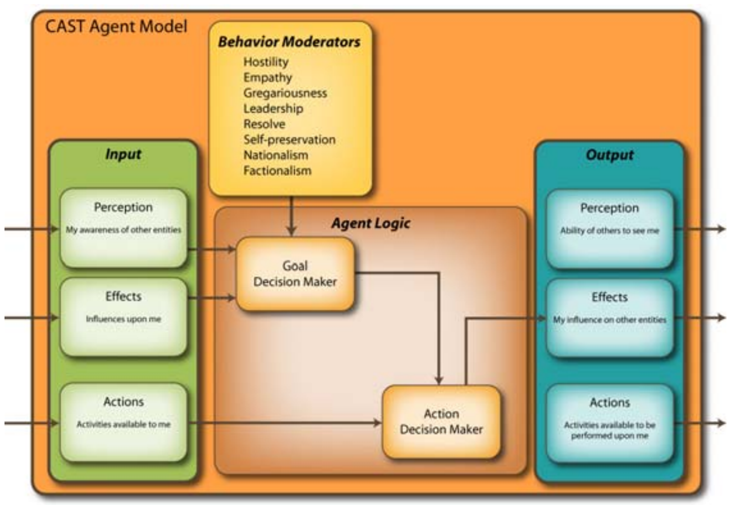


Figure 4-1: Agent Model

4.1 Input/Output Criteria

Perception is a complete list of all entities in the environment of which the agent is aware. Whether or not an agent perceives an entity is determined by comparing perception criteria of the entity with the abilities and state of the agent. For example, an entity might have the perception criteria of ‘line of sight.’ A line of sight calculation determines whether or not the agent can perceive the entity. If the agent can perceive the entity, then the system sends the entity’s information to the agent for further processing; otherwise the agent ignores the entity as if the entity was not present.

Effects consist of a separate list from perception since entities can affect agent even if the agent cannot perceive the entity. Effects describe influences the environment (*i.e.* other entities) imposes upon the agent that affect decision-making. For example, an agent with high leadership might engage in propaganda and nationalistic actions that affect other agents by increasing their individual resolve behavior moderator. With higher resolve, these agents become less likely to be deterred from their goals.

Actions use the same filter as the perception model since perception is a requirement for all actions. In other words, an agent cannot interact with an entity it cannot perceive. Furthermore, actions contain additional requirements regarding which agents perform the action. The agent verifies that it meets all requirements before enacting the action.

4.2 Agent Logic

The development of an agent logic system for decision-making and action selection emphasizes emergence of group dynamics and behaviors while adhering to the tenets of complex adaptive systems. To avoid direct encoding of complex behavior into individual agents, all possible actions are predefined and action selection avoids complex evaluation of the situation state. Selection of an action follows a two-step process. First an agent selects a goal to actively seek. Goals consist of simple humanistic desires such as survival, work ethic, and nationalism. Selection of a goal depends upon agent environment factors and behavior moderator values. Once a goal is selected, then the decision making process reviews the available actions for a compatible selection that contributes towards meeting the chosen goal. Multiple logic systems for goal and action selection are under investigation; however, providing the system does not engage in planning or coordination, the complex adaptive systems properties are maintained.

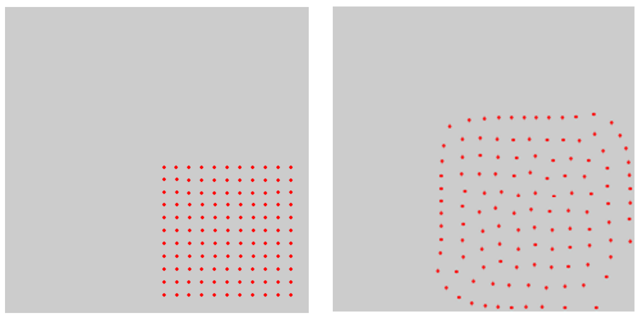
4.3 Behavior Moderators

The set of behavior moderators allows greater diversity in decision-making as well as deeper interaction and influences between the environment and agents. Behavior parameters influence the agent’s decision-making regarding actions in a given situation and attribute a measure of individualism for each agent. For example, an agent with high resolve might ignore the base rule “move away from danger,” in order to reach its goal while an agent with low resolve would be more easily deterred or suppressed.

Collectively the behavior parameters constitute a rudimentary culture model; for example, a highly social culture is modeled with agents that have a high gregariousness behavior moderator and are more apt to form tight groupings. Deeper cultural organization modeling hinges on identifying relevant behavior moderator parameters and appropriate parameter values for various cultures and organizations.

Behavior moderators support and enhance the notion of emergent behavior within the complex adaptive system. In addition to emergent group dynamics from simple base actions, behavior moderators influence the process of emergence and help create different emergent behaviors based on parameter value. For example, a behavior moderator, gregariousness, which regulates the affinity an agent has for being near other agents, has direct and indirect influences on how the group dynamics of the complex adaptive system evolve.

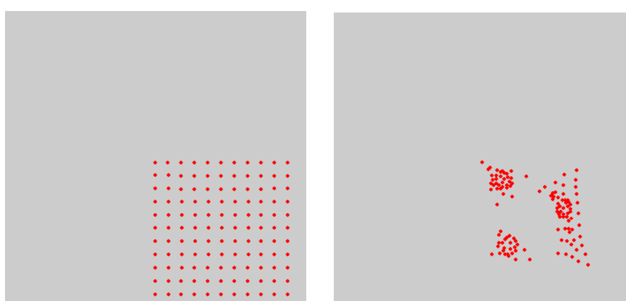
Figure 4-2 illustrates an agent configuration that evolves from a set of agents arranged in a grid (a) with low gregariousness behavior moderator values. As the simulation progresses (b) the agents move to spread out away from each other and cover a larger area. Because the agents have low gregariousness, their initial separation distance is smaller than their intolerance for proximity to other agents and encourages individuals to move away from other agents; collectively this leads to an expansion of the group configuration until a distance compatible with the agent's lack of gregariousness is reached.



a) initial configuration   b) group response

Figure 4-2: Low Gregariousness

Figure 4-3 shows the same simulation as Figure 4-2 except with highly gregarious agents. In this case, the agents have a higher tolerance of being near each other than their initial configuration. As a result, the agents move towards each other and form a dense mob. Again the system as a whole demonstrates emergent behavior, but the behavior expressed differs from the previous example. Behavior moderators themselves have direct and indirect effect on emergent properties within the system.



a) initial configuration   b) group response

Figure 4-3: Emergent Behavior with High Gregariousness

The role of behavior moderators becomes more significant within the complex adaptive system when combined with the effects and interactions agents have with the environment. Entities and other agents influence the agent through the behavior moderator parameters, thus affecting the behavior of individual agents and the system as a whole.

5. Results and Conclusions

The emergent qualities of complex adaptive systems are well suited to address the uncertain and evolving nature of modern warfare. Rather than explicitly coding military doctrine and behaviors into a simulation, the complex adaptive systems approach to military modeling seeks to have behaviors emerge from a simple set of base actions. The advantages of such an approach include ease of programming and unexpected, yet logical, results. Furthermore, complex adaptive systems are compatible with increasingly important military concepts such as effects-based operations.

We are in the process of exploring further the role complex adaptive systems can provide to modern effects-based military operations and military conflict simulation. Defining the base requirements, effects, and interrelationships of the simulation environment entities establishes the basis for effects-based operations support within the complex adaptive system. Furthermore, interaction between the environment and agent decision-making through behavior moderator parameters provides the link between an effects-based environment and the complex adaptive agent system. Together, the agents and environment form a system where military theory and situational courses of action can be explored.

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References

Arthur, W. (1999). Complexity and the Economy. *Science,*(April).

Cordesman, A. (2003a). *The Instant Lessons of the Iraq War.* Center for Strategic and International Studies.

Cordesman, A. (2003b). *The Lessons of Afghanistan: Warfighting, Intelligence, Force Transformation, Counterproliferation, and Arms Control.* Center for Strategic and International Studies.

Epstein, J. & Axtell, R. (1996). *Growing Artificial Societies: Social Science from the Bottom Up.* Cambridge, MA: MIT Press.

Ilachinski, A. (1999). Towards a Science of Experimental Complexity: An Artificial Life Approach to Modeling Warfare. In *Proceedings of 5th Experimental Chaos Conference.* Orlando, FL.

Jenner, R. (2000). *Cultural symbols, and group consciousness: culture as an adaptive complex system.* San Francisco State University.

Lanchester, F. W. (1956). Mathematics in Warfare. In J. R. Newman (Ed.), *The World of Mathematics* (pp. 214-246). New York: Simon and Schuster.

Langton, C. (1988). Artificial Life. In C. Langton (Ed.), *Artificial Life*. Reading, MA: Addison-Wesley.

Regine, B. & Lewin, R. (2001). *Weaving Complexity and Business: Engaging the Soul at Work.* New York: Textere.

Santosus, M. (1998). Simple, Yet Complex. *CIO Enterprise Magazine,* 15 April.

Smith, E. (2002). *Effects Based Operations: Applying Network Centric Warfare in Peace, Crisis, and War*. Washington, DC: DoD CCRP.

Tesfatsion, L. (2002). *Agent-based Computational Economics: Growing Economies from the Bottom Up.* Ames, Iowa: Iowa State University.

Thomas, W., North, M., Macal, C., & Peerenboom, J. (2004). From Physics to Finance: Complex Adaptive Systems Representation of Infrastructure Interdependencies.

Tsatsoulis, C. (1991). A Review of Artificial Intelligence in Simulation. *ACM SIGART Bulletin,* 2(1), 115-121.