RULE SETS FOR SENSE AND RESPOND LOGISTICS:

THE LOGIC OF DEMAND NETWORKS

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Submitted 30 March 2004 by
Alidade Incorporated and Industrial Science, LLC
under Contract No. GS-23F-8010H
for the Office of Secretary of Defense,
Office of Force Transformation

ABSTRACT

This paper summarizes research into a method of control for complex logistics networks. The use of rule sets as the motivating mechanism in the effective performance of adaptive logistics systems is discussed and a method for rule set derivation through environmental observations is introduced. Different types and uses of rule sets are defined and explored. A simulation model for experimenting with rudimentary rule sets is presented and a representative method for analysis using the model is discussed.

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I. INTRODUCTION

Sense and Respond – Transforming for the Information Age

The Office of Secretary of Defense, Force Transformation Office, has been developing a concept for adaptive logistics called the Sense and Respond Logistics Concept (SRLC). Sense and Respond Logistics applies the same logic that has transformed other Industrial Age industries into adaptive new, Information Age enterprises – the logic of networks and complex systems – to military logistics.

The Sense and Respond Logistics Concept relies on two fundamental assumptions:

- That complex networks perform better than chains in uncertain environments (in particular, military conflict at the tactical level)
- That form follows function – the structure, dynamics and evolution of complex networks are created by demand signals that course throughout the network, carrying information about the consumptive behavior of the network's collective, adaptive behavior.

Readers unfamiliar with complex systems research might suppose that the basic "sense and respond" behaviors are accomplished by distributed sensors providing information to a central control mechanism that *reactively* instructs specific network elements how to respond. Such reactive control is achievable only in very simple systems (or systems "made" simple by brute force effort or the heavy, constraining hand of over-control). True adaptive behavior in a complex system, however, cannot be reactive. Adaptive behavior, especially in a collective, comes from converting specific information from an uncertain environment into general rules that improve collective performance. The "steering wheel" type of control that is the hallmark of Industrial Age management has to be abandoned in favor of indirect control of distributed elements by using robust, generalized rules that can withstand dramatic shocks and surprises yet still adapt in longer time scales as the environment or competitive context also adapts. Mastering the seemingly subtle difference between reactive response and adaptive response is crucial to understanding Sense and Respond concepts. This paper will explore the central issues surrounding adaptive behavior and rule set development.

The Sense and Respond Logistics Concept

Since complex systems are very sensitive to context, the basic tenets of the Sense and Respond Logistics Concept are presented before adaptive behavior and rule set development are explored. Prototypical Industrial Age Warfare is characterized by limited communications, massed forces, centralized command, control and decision making, and information that is difficult to obtain and hard to share. Introducing IT to military force structures is serving to change some important facets of warfare. A new prototype is characterized by physical dispersion, distributed information, and decentralized control. These new characteristics increase ambiguity and uncertainty of operating of a future military force:

- ambiguity and uncertainty of purpose, because units are not compelled to act in tight formations or groups

- ambiguity and uncertainty of boundaries, because IT applications and networking can create connections and associations between elements of a force that heretofore might never have interacted

- ambiguity and uncertainty about the structure of an organization, as teams and elements task organize themselves to adjust to unfolding opportunity and risk

- ambiguity and uncertainty about what to measure and assess, as the purposeful collective behavior of a networked force can be more important than, say, the location and movements of individual elements.

The Sense and Respond Logistics Concept was developed to cope with these ambiguities. The concept relies on adaptation, flexibility, agility and responsiveness, all within a "learning," networked context (in contrast to a reactive or predictive, highly optimized model of the supply chain). Sense and Respond Logistics relies on clever commanders using and sharing local information to improve logistics support, rather than centrally collecting information and controlling processes, dictating local decisions from a remote perspective. Sense and Respond Logistics aims to reduce ambiguity of purpose by translating commander's intent into local rule sets; about boundaries by placing local coordination of modular units at a premium; about essential structure by clearly articulating roles and responsibilities rather than directing behavior; and about measurements by providing a deeper understanding of competitive dynamics.[1] Sense and Respond Logistics proposes to achieve these aims by enabling self-synchronization through local coordination with IT systems, by encouraging interaction, connection and recombination at the lowest levels possible so that innovative teams can emerge to meet local challenges, by closing feedback loops so that all levels and perspectives in the force can learn from each other, and by vigorous education and training in the most complex and challenging extremes of the operational spectrum.[2]

The Sense and Respond Logistics concept favors flexibility rather than focusing on a set of "optimal" processes, creating a level of complexity in logistics that matches the complexity in operations. Enabled by IT, Sense and Respond Logistics is an Information Age concept not just because IT is employed. It is an Information Age concept because it exploits the advantage from Information Age models of decentralization, adaptation and self-synchronization to solve challenging logistics problems. Sense and Respond Logistics transforms highly optimized supply chains into dynamically adaptive demand networks that more closely conform to unfolding battlefield conditions, while remaining intimately connected to commander's intent, thereby enabling more fluid operations and creating an ability to seize opportunities as they develop.

Organization of the Paper

Any military conflict has an extraordinarily large number of potential futures yet there is only one actual future. An ability to create robust rule sets either *a priori* from simulation or analysis or by observing the environment and discerning key relationships more quickly than an adversary is a key competency for Sense and Respond Logistics. Achieving this competency means achieving a capacity for "complex control." Section II explores the relationship between the complexity and control in complex systems and describes the fundamental scientific considerations in complex control. Section III describes specific mechanisms by which rule sets achieve complex control. Section IV discusses the type, use and behavior of rule sets in a complex system. Section V presents a simulation model of a complex logistics system and describes how rule sets can be derived from simulation. Section VI is a concluding summary.

II. OPTIMIZATION, COMPLEXITY, SCALE AND CONTROL

In the domain of practical management, optimization is closely allied with control – managers seek to optimize a system mainly to influence or control the things they manage. Indeed, when a system is deemed "optimized," modern managers assume events and processes are in a sweet spot of productivity, efficiency and profitability. An optimal system implies that "things are under control." If a system becomes less than optimal, experts are consulted who try to regain control by dissecting processes to locate sources of even greater effectiveness.[3] Optimization, however, can fail to provide control in most uncertain, dynamic environments. To explore this apparent paradox, this section presents three main points. First, that strict optimization is best applied to very stable systems, usually those that are highly engineered or are not subjected to uncertain environments (i.e., "simple" systems). Second, that at the tactical level, most military systems are not "simple," but very robust and dynamic, possessing a range of complex behaviors. Third, that the degree of optimization a system allows and the degree of complexity inherent in a system is related in a general property of complex control: the best control mechanism is one that matches the complexity of the controlled system. These three complementary ideas provide a new perspective for control of complex logistics processes.

Optimization v. Adaptability

The extent to which a system can be optimized does not solely depend on the instabilities and uncertainties within the system itself. The capacity for a system to be optimized also depends on the instabilities and uncertainties within other systems that the system is connected to and instabilities and uncertainties within the environment. Paradoxically, in very unstable or uncertain competitions and environments, too much efficiency can actually impair the ability of a system to function properly. To see how this might happen even in a very simple, linear system, consider the problem of "makespan" in production line fabrication. A piece of metal that proceeds through a milling process consisting of several machining steps is the object of a process that literally "spans the making" of the piece. If a certain amount of time is required on each machine, then the total milling time plus transfer and set up time is the total makespan. Transfer and setup time is more generically termed "slack time." A process with sufficient slack time can tolerate small failures, allowing time for operators to re-configure or employ work-arounds to put the process back on schedule.[4] As the slack time is shortened, however, the probability that the entire process fails can increase dramatically. This is shown in Figure 1, which graphs makespan (horizontal axis) against the chances that a process is completed without failure (vertical axis).

The analogy to supply chains is direct: if too much slack is removed from a supply chain, the entire chain becomes much less tolerant of change and logistics operations can fail catastrophically. Of course, supply chain operations are much more complex than the finely engineered, "simple" process of production line fabrication. Furthermore, logistics operations are not just inherently complex, but they incur additional complexity and uncertainty because they are inextricably connected to combat operations themselves. Information Age warfighting concepts suggest that fluid, self-synchronizing military forces will be the norm, at least at the tactical level. It has been proposed that the primary source of advantage in distributed, networked forces arises from networked effects that are distributed in many dimensions throughout a force and can be summoned for use in the manner of advantage chosen by clever commanders based on evolving conditions.[5] Supply chains with too much slack removed through optimization poorly serve such adaptive, distributed forces in complex environments. The makespan analogy applied to supply chains justifies the first main point, that strict optimization is best applied to very stable systems, usually those that are highly engineered or are not subjected to uncertain environments.

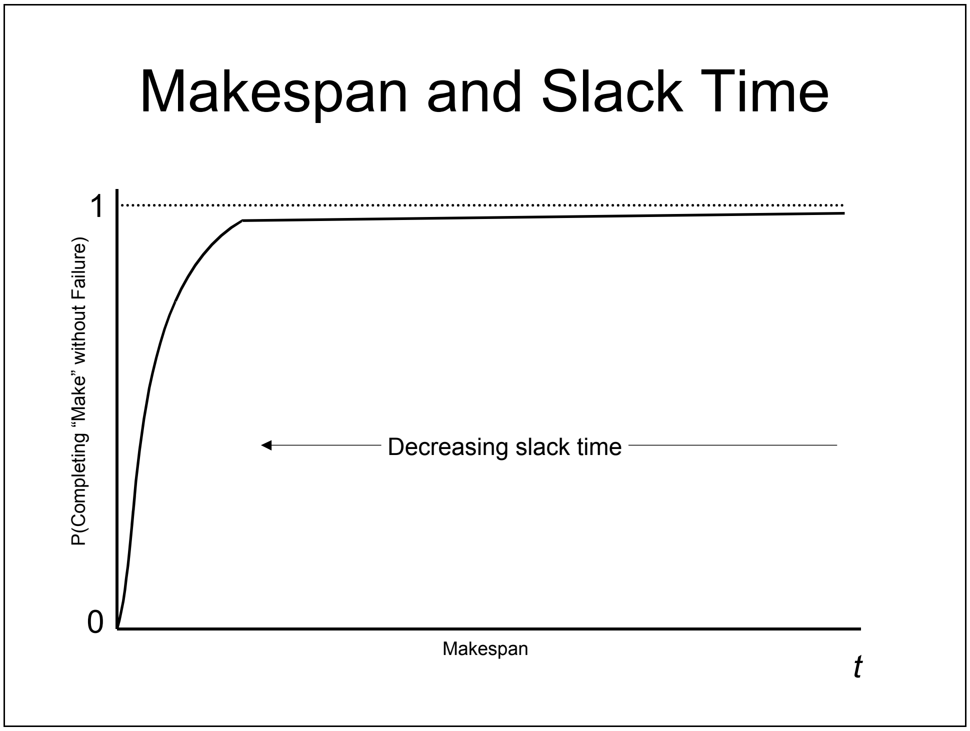

Figure 1

Complexity and Scale

The complementary concepts of complexity and scale can help bring the optimization-control relationship into tighter focus. If *complexity* is measured as the number of ways a system can be described, then it is helpful to think of the *scale* at which useful descriptions can be found.[6] To illustrate, consider a large amphibious landing. At the three-star general's level, the landing can be described in terms of ships, objectives, Marine Expeditionary Units (MEUs) assigned and the total number aircraft sorties available. From the perspective of an amphibious ship captain or MEU commanding officer there is much more detail, including transit lanes, synchronized waves, landing zones and flight schedules. In addition, there are some issues and decisions at the three-star scale that are not relevant, useful or perhaps not even observable at the commanding officers' scale. From the individual Marine's viewpoint, there is a host of detail that changes rapidly from one moment to the next, particularly while attempting to cross a hostile beach under fire or while egressing a transport helicopter in a contested landing zone. This fine scale detail, while important to the individual Marine, is nonetheless not as useful at the scale of a commanding officers or the three-star's staff.

This continuum from a coarse description at a high scale to a more detailed, yet still aggregated, description at medium scales, to a great deal of rapidly changing detail at the finest scales is a property of most complex systems. In the more complex parts of such systems, fine scale descriptions tend to be more informative to decision makers at the lowest scale. In less complex parts of a system, coarse descriptions are sufficient. Figure 2 is a graph of the relationship of complexity to scale for littoral operations such as this notional amphibious operation. It has a curve typical of systems with a great deal of complexity in one part, moderate complexity in another part and relative simplicity in yet another part.[7] The curve is "scale free": there is no single scale at which the all the important system behaviors are described. Systems exhibiting such a complexity-scale profile are called scale free systems. These systems require "multi-scale representation" to show behaviors and structures at the scale at which they are most informatively displayed.[8] Another way to think of this curve is as a description of the information collectively required by all decision makers in a complex military organization. Figure 2 graphically displays the essence of the second main point, that most military systems are very robust and dynamic, possessing a range of complex behaviors.

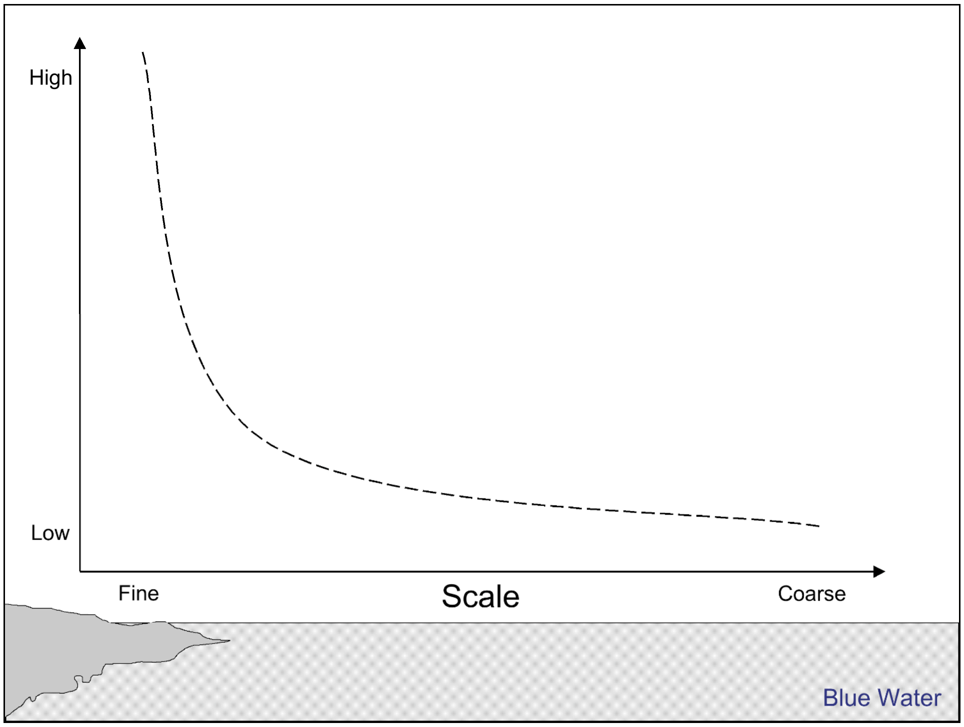

Figure 2

"No Free Lunch" Theorem For Control

In Mathematics and Computer Science, optimization is the analytical process of finding solutions to very hard problems in the shortest time possible. Researchers have recently derived the "No Free Lunch (NFL) Theorem" of optimization, which proves there are no "universally best" optimization routines. Algorithms perform well on one type of problem at the expense of poor performance on other types of problems because the success of an optimization routine depends on the extent to which the structure of a routine matches the structure of a problem.[9] In other words, the scale of the best routine is the same as the scale of the problem. Therefore, there exist no universally efficient problem-solving routines for scale free problems, only routines that work best on different parts of a problem. A collection of different routines that work best on different parts of a problem would exhibit the same scale free properties as the problem itself.

The same logic can be applied to control of scale free systems. If a system includes parts with different degrees of complexity, then local behaviors occur at scales and complexities substantially different from global behaviors. A globally optimized control process cannot, therefore, control all complex local behaviors. By treating the consumptive behavior of a force as a "problem" to be solved by logistics, one can propose a similar "No Free Lunch Theorem for Logistics": the best logistics system is one in which the complexity of the logistics process most closely matches the complexity of operations.[10]

If a logistics network exists merely to re-supply forces in peacetime garrison, then one might call the demand-supply interaction a "closed system," meaning that exogenous factors do not greatly impact an observer's ability to monitor the logistics system, decide how to control the system and then successfully control it. Combat operations (as well as many other non-combat operations) are "open systems," as enemies and adversaries often thwart even the best-designed plans.[11] Even for friendly observers, the control task can become increasingly complex merely by the addition of competition. In such cases, friend and foe are faced with the difficult challenge of controlling a complex system. Associating the degree of a system's complexity to ease by which it can be controlled by a regulator has a pedigree in Control Theory, where it is discussed as the Law of Requisite Variety.[12] The Law of Requisite Variety states that a controller must have at least as much complexity as the system it controls.[13] This, therefore, supports the third and final point of this section, that the best control mechanism is one that matches the complexity of the controlled system.

III. THE APPLICATION OF RULE SETS TO COMPLEX CONTROL

Introduction

The need for complex control of adaptive military systems has never been greater. Although rudimentary military networks have existed for many decades, preliminary concepts for advanced networked forces began to emerge in the early 1990s. These concepts mirrored a similar phase of technological innovation in other industries: the initial thrust was in developing systems to help people perform current tasks better. One drawback, however, is that there is an upper limit on improving existing processes with IT networks – the upper limit of performance for the process itself.

Soon after visions of networked warfare began to circulate in the defense community, concepts for smaller distributed forces began to emerge. The basic assumption behind these concepts is that distributing a military force creates more options for a commander, increases the surveillance burden of an adversary, and allows massed fires while forces remain dispersed. Without proper networking, however, distributed forces are at risk. There is, therefore, great advantage to both networking and distributing. Military applications have a unique characteristic that profoundly capitalizes on distributed, networked effects: advantage can emerge from a broad pool of inputs and manifest itself in a multitude of ways, each of which will not likely be evident to an opponent until advantage is ready to be applied.[14]

Methods of sense-making and control in complex systems will therefore continue to grow in importance as concepts for future distributed, networked forces mature. This section relates complex control theory to the use of rule sets and has three subsections. First, a general theory of complex control is developed and discussed. Second, the mechanisms by which systems create simple rule sets for responsive adaptation are examined. The section concludes with a discussion of the cycle of alternately gaining and losing control that systems inevitably experience when they interact with the real world.

Control in Complex Systems

One of the biggest challenges in controlling competitive complex systems arises from the fact that not only are behaviors occurring at many different scales (including time scales), but that many of the behaviors are the result of actions that one side itself cannot control: the actions of the adversary.[15] Controlling such a system requires an ability to discern patterns (signals) in the observed dynamics of the system (that include both signal and noise). Some types of signals are usually evident and known to both sides. These signals include information about the basic structure of the environment and the competition, as well as information about the competitors themselves. This information is not likely to change during the time scale of the competition. After the basic structure (signal) is determined, all other observations might appear random (noise). However, within this “apparent noise” are two other types of information: dynamic patterns yet to be discovered and true noise.[16] As more observations are made, the goal is to extract signal out of the apparent noise and combine it with the structural information already known to create an even clearer picture of the competitive landscape. This “learning through feedback” is central to success in controlling complex systems (and one of the hallmarks of the Sense and Respond concept).[17] To achieve a deeper and more formal definition of adaptive control in complex systems requires non-traditional ways of describing pattern, signal and noise. This subsection formally presents the underlying technical arguments for a deeper and more formal treatment of complex control and begins with some basic definitions:

- *Entropy* is variously defined as a measure of wasted effort, lost energy, uncertainty or randomness.[18] In the context of this paper, entropy is a measure of the amount of information extracted from a system: a decrease in a system’s entropy is associated with an increase in what is known about how the system works

- *Shannon Entropy (H)* can be defined as a measure of the uncertainty inherent in an observer’s receipt of a signal[19]

- *Algorithmic Information Content (K)* measures the extent to which a received signal can be compressed into a more compact description of the signal. It is sometimes defined as the shortest bit stream that can be used to describe another bit stream[20]

- *Total System Entropy ($S = H + K$)* is a measure of the amount of information gained by observing a system: a decrease in a system’s entropy is associated with an increase in what is known about the system by observation

- *Noise ($N = 1 - S$)* is randomness that contains no information about how a system works

Figures 3 and 4 show how these definitions are related. Consider a bit stream of finite length n that is observed over some time, t. As t progresses, more information is received by the observer about the bit stream. If there were a perfect transfer of bits to the observer (i.e., noiseless channel), at some t all n bits would be received and Shannon Entropy, H, would be zero. Figure 3 shows the case when the entire bit stream has been received but the bit stream is completely random. In this case, although the Shannon Entropy is zero, the Algorithmic Information Content, K, is at a maximum of 1 – there is no shorter way to describe a random bit stream than by using the entire bit stream. In other words, the Total System Entropy is preserved, indicating that there is no pattern for the observer to discern, even when the bit stream is observed with perfect clarity.

Figure 4 shows a more realistic set of observations. In this case, the Shannon Entropy is again reduced to zero but the Algorithmic Information Content is reduced as well – the observer discovers a more compact way of describing the bit stream. The Total System Entropy decreases, indicating that there is a pattern for the observer to discern and more is known about the system after observation than before observation.[21] The systems described in these two figures have unique features that must be modified before the ideas can be more directly applied to complex control. First, the preceding discussion assumed that the bit stream was of fixed length. In dynamic, competitive complex systems, the amount of information is never fixed. Indeed, deciding when sufficient information has been received (as contrasted with foreknowledge of the total amount of information present) can be one of the most difficult decisions in competition. Second, the bit stream is assumed to be received over a noiseless channel. Not only is noise a key feature in almost all competitive complex systems, but discerning a signal out of noise can be another of the most demanding tasks in such systems.

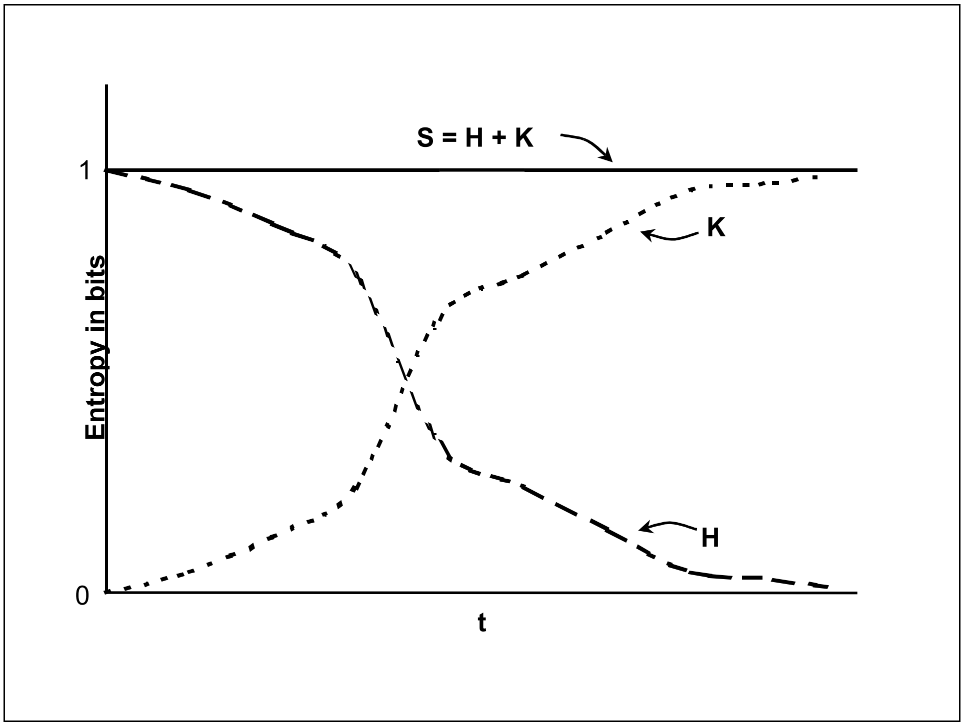

Figure 3

In control of complex systems, *H*, *K* and noise interplay in the following way. As an observer samples a system, the observer can piece information together into patterns as they seem to emerge. As a practical point, however, just how much of this originally assessed pattern is noise and how much is signal can never be known, because what appears as pattern early on might be rendered irrelevant as more definitive patterns subsequently emerge.[22] Control of complex systems can be achieved by continuously observing and comparing new observations to existing patterns. The more complex a system, the more difficult it will be to successfully complete this process of determining pattern, re-sampling the apparent noise that remains (both in new observations and noise that already resides in existing, emergent patterns) and then interacting with the system to influence future behavior.

Great difficulty, however, lies in fact that an observer must watch a system for an infinite time to completely determine which part of a system is structure and which is purely random noise.[23] Since no one has an infinite amount of time to watch a system (particularly not during dynamic lethal competition), the complex control problem cannot be solved completely (incidentally, this is also one reason why complex systems cannot be optimized). The best one can do is achieve learning through feedback more quickly than the system and the environment changes (or at least learn at a faster rate than an opponent learns).[24]

It is therefore even more important to interact with a competitive system at as many scales as possible. This ensures that one observes important behaviors on the scale at which they occur and increases the chances that actions on a particular scale might be obscure to a competitor who is not observing at that scale. Lastly, controlling one's own system is much easier than trying to control an enemy's system, because even if plans are interrupted, friendly operations are still driven by commander's intent. The insight instilled in each decision maker by commander's intent can be a crucial advantage in complex competition, since in the midst of confusion, a great deal of apparent noise makes sense when viewed through the lens of commander's intent. By contrast, trying to control by observations alone is one of the most difficult tasks in complex environments, and certainly more difficult than observation aided by experience, intuition and foresight informed by commander's intent.

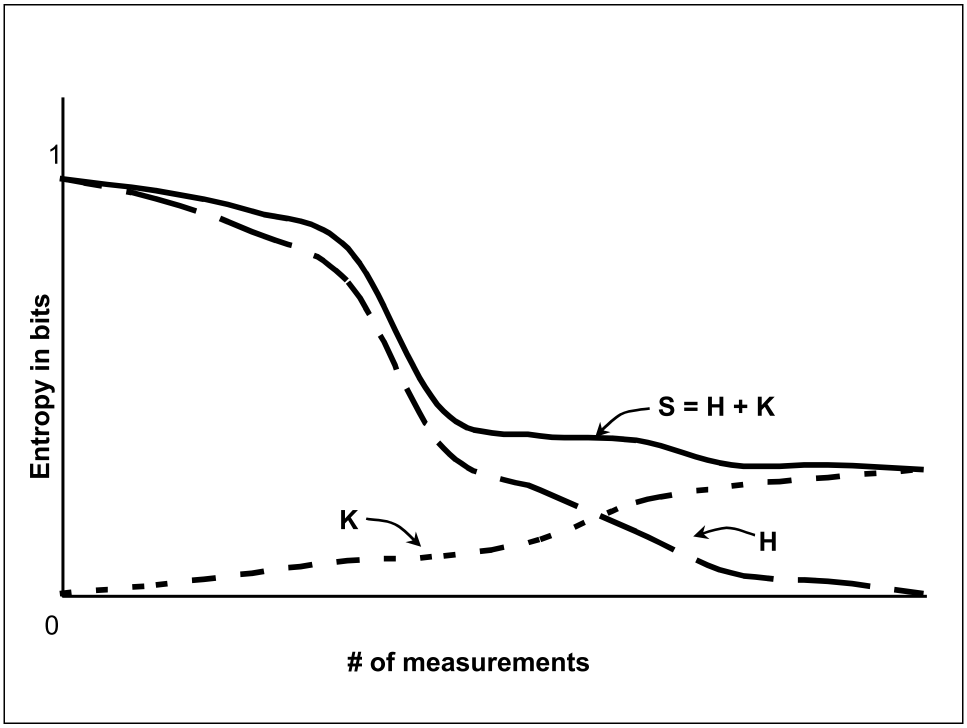

Figure 4

Obviously, discerning the structure of a system is easier if the observer is informed by *a priori* knowledge of the system (such is the case in the military, for example, by intelligence and threat assessments or by expectations that friendly forces will conform to commander's intent). Observation without such insight can substantially hamper efforts to discern pattern from noise. This is one reason why learning how to control an adversary's system by remote observation alone is so difficult.

Rule Sets: Internal Models for Adaptation

The preceding discussion might appear to be no more than technical arcana if not for the inclusion of the most important part of the Sense and Respond Logistics Concept, the humans who must translate observations about a competitive environment into operative language with which to make decisions and direct action – the language of rule sets.

Just what are these mechanisms for rule-making? The answer to this question lies in a closer examination of the relationship between a complex system and its competitive environment. No system of interest to the defense community exists in isolation – each system is contained in an environment, which except in the most trivial cases, includes all competitors as well. As stated earlier, a system that adapts to its environment does so by learning. Some questions naturally follow:

- What does it mean to learn?
- How does a system learn?
- How can it be known if a system is learning at a rate that contributes to successful adaptation?

The preceding subsection partially answered these questions by suggesting that control of complex systems can be achieved by continuously observing and comparing new observations to existing patterns. This, however, is more of a goal statement than identification of a useful method for learning in a complex environment. As a step toward a more useful method of learning, we must first examine the interplay between what are known as the *external complexity* and the *internal complexity* of an adaptive system.

External complexity is a measure of "the amount of input, information or energy obtained from the environment that the system is capable of handling or processing." This type of complexity can be thought of as "data complexity." Internal complexity is a measure of the representation of the input, information or energy by the system, or as some have termed it, "model complexity." It has been suggested that successful adaptation is achieved by increasing external complexity while decreasing internal complexity. In practical terms, successful adaptation is achieved by being able to observe and process a great deal of information and convert that information into simple rules. The rules can then be used to process an even greater amount of environmental and competitive information during subsequent observations.[25] This feedback loop is one manifestation of the well-known "learning curve," which is used to explain how systems perform increasingly better as they learn. Of course, a formal representation of these ideas can be accomplished using the taxonomy of *S*, *H*, *K* and *N*, above.

Still, this is a description of what is to be done and not a method for how to do it. Key to arriving at a method is to recognize that external complexity and internal complexity are operative at different time scales. External signals are observed individually, as apparent noise, until they can be associated with an internal pattern (either with an pattern derived by analysis *a priori* or by comparing them to signals already received). Either way, there is a time lag between the receipt of a signal and its conversion into an existing or emerging internal model of the external environment. The model is an aggregate of all the individual signals yet, somewhat counter-intuitively, it is simpler than all the signals themselves.[26]

Learning, then, can be thought of as the "transformation of correlations into associations … and these associations serve to predict and anticipate future events." [27] In other words, learning is converting observations from a complex world into simple rule sets that help a system cope with the world's complexity. This is sufficient to answer the first question, "What does it mean to learn?" and contributes to progress in answering in the second question, "How does a system learn?" but does not yet constitute a specific method.

Interestingly, what might seem to be the hardest question, "How can it be known if a system is learning at a rate that contributes to successful adaptation?" provides insight into the seemingly easier question of how systems learn. Again, examining the interplay between external complexity and internal complexity is instructive. If the external complexity of a system is less than the internal complexity, then the system is confounded by signals from the environment. It is not learning, but actually getting more and more uninformed by the environment and therefore less able to adapt. In other words, the system has a complicated plan for a simple world.

If the external complexity and the internal complexity of the system are roughly equal, then the system has constructed a virtual model of the external environment. By making the internal view of the world no simpler than the signals received from the world, the system can adjust its performance and strategies no more quickly than the rate at which the world itself unfolds. This argument supports one of the key concepts in this paper, that reactive response is not adaptive response.

The best adaptation occurs when the external complexity remains higher than internal complexity, so that internal rule sets are robust even when signals from the external environment change at a high rate. Short time scale signals (individual signals from the environment) do not invalidate longer time scale rule sets (patterns encoded into a model of the world) and successful adaptation occurs.

There are two important implications of this point, which are also borne out in research into learning rates in complex systems. The first implication is that larger, more general rules are better than specific rules in complex environments. Over-complicated, nested rule sets create a more virtual internal representation of the external environment and therefore provide for less adaptation. Although general rules are less efficient, they are more robust to dramatic changes in system input or uncertain environments. Put differently, the system must choose between good-enough rules for most cases or perfect rules for cases that are unlikely to occur.

The second implication is that the small set of general rules that create robust behaviors most quickly are not usually refinements of each other. When more than one rule explains a significant amount of a system's total behavior, these rules must all be general rules. By definition, a general rule cannot be derived from another general rule and both rules remain general. Otherwise, the rule that produced the derived general rule would redundantly describe the same external complexity but with a higher internal complexity than the derived rule, so the producing rule would cease to be general. Using Set Theory, one would say that the most adaptive rule sets contain rules that are not subsets of each other.[28]

A method for how a system learns and adapts can now stated directly. An adaptive system takes specific, detailed information from its competitive environment and creates general rules. By comparison, a successfully adaptive system does not take general information from its competitive environment and create specific rules, because in competitive systems this is a form of specialization that is typically followed by extinction. A successfully adaptive system does not take specific information from its competitive environment and create specific rules, since this means the system has created a reactive, virtual representation of the world that cannot admit adaptation. Finally, a successfully adaptive system does not take general information from its competitive environment and create general rules, because that would mean the system operates in a simple environment for which adaptation is not required. An adaptive system successfully adapts by taking the complex and making it simple. In doing so, an adaptive system is by definition inefficient, a fact that raises substantial cultural issues, since inefficiency is anathema to traditional managerial sensibilities.

Adaptation Over Longer Time-scales

Clearly, however, a system cannot continue to create useful general models indefinitely. Otherwise, there could be no winners in long-term competition – internal models would keep converging to the most robust ensemble of rules and relative advantage would diminish over time. The reason that this does not happen is that, as discussed above, any system of interest to the military is an "open" system, interacting with a competitor in an uncertain environment. The Second Law of Thermodynamics says that the information in this larger, open system is diverging into many states, a situation that should not allow for useful, general rules to be devised indefinitely. In addition, radical changes in information conditions at all scales due to, for example, innovation, surprise or blunder, can likewise decrease the effectiveness of rule sets. Energy expended to create order in one part of an open system must always dissipate back into the rest of the system. No rule set, therefore, is forever robust. The environment and competitors can – and usually do – invalidate the best rules that humans or machines can devise. The system must then begin learning anew. The character of this longer-term adaptation, a learning-relearning cycle, is also addressed in the complex control literature.[29]

Consider a system introduced to an environment with complete ignorance of the environment or competitors. Initially, this system would perceive all input as potentially relevant and external complexity would be low and internal complexity would be high. Without a good *a priori* model, the internal complexity would not converge to a general rule set quickly. Coarse scale exploration of the environment would be the most useful strategy because the system cannot yet process complex data. Even when starting with just general information about the environment or the competition, however, internal complexity can still decrease.[*] A longer time scale evolution from a state of low external complexity and high internal complexity to high external complexity and low internal complexity can result as the system learns through this initial coarse exploration. Even with complete ignorance as initial information conditions, an adaptive system can continue to derive and refine general rules that are robust and ensure survival, so long as the time scale at which the environment changes is longer than the timescale at which the system learns.

But learning rates are not linear. It is often the case that an adaptive system – even one starting from conditions of ignorance – can learn at a rate much faster than the environment and competition changes. If the environment or competition changes much more slowly than an adaptive system learns, adaptation is not valued and specialization results. Specialization results from a persistent state of low external complexity and high internal complexity. In other words, a stable environment means that very simple inputs are all that are required to create a successful model of the world. Since it need not be robust, this model can be increasingly refined. But since this simple model is not the product of complex inputs, the model cannot be robust. If future information conditions change substantially (which they inevitably will since the system is open), the model will rapidly become invalid. When this occurs, the system must return to a general exploration of the environment to start the adaptation process all over again. This cycle from exploration to exploitation and specialization back to exploration is typical of complex control problems. Again, the need for *a priori* rule sets is highlighted.

Such a cycle from exploring to exploiting back to exploring has been documented in natural observation and artificial simulation of ant foraging. A typical cycle starts with the ant collective possessing no knowledge of the location of a food source. As the ants leave the nest, they each begin a random search of the area around the nest. If one were to measure the "spatial entropy" of the collective (that is, the extent to which there is a coherent physical pattern), one would see that this value would be quite high. Since the ants are moving about randomly, then their spatial locations cannot have a coherent pattern. In addition, the Shannon-type of entropy that measures the amount of information the average ant has about food source location is at a maximum. When an ant finds food, then it follows a simple rule: take some of the food to the nest and leave a pheromone trail en route. Other ants can sense the pheromone trail, and as their random walk leads them across the trail, the pheromone scent triggers another simple rule set: follow the trail to the food, take some of the food to the nest, and leave additional

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[*] As an operational example, negative information in subsurface warfare is still information. Lack of information on a target – knowing where the target is not – is a kind of useful information that is profitably applied to military searches.

pheromone en route. Over time, the pheromone trail gets stronger. More ants find the food and return to the nest leaving more pheromone. The spatial entropy of the ant's collective behavior very quickly decreases as the familiar pattern emerges of ants shuttling from their nest to a food source. In addition, the amount of information about food source locations that the average ant "knows" begins to grow, so the Shannon-type of entropy about food source location decreases as well. When the collective has exploited all the food, however, ants cannot follow their rule set and pheromone starts to evaporate. The ants' coherent pattern begins to breakdown and both the spatial and Shannon types of entropy begin to increase. But the increase in spatial entropy also coincides with a new random search that will eventually locate additional sources of food, and the exploration-exploitation-exploration cycle begins all over again.

Ant foraging behaviors are both produced by and create a natural cycle of adaptation over long time scales. The remarkable part is that same rule sets that exploit the food source guarantee its depletion through non-linear positive feedback loops (increasingly stronger pheromone trails). Just as remarkable is the fact that the same rule sets that find the food to being with help re-set the system once the food is depleted. The next section will focus on the mechanisms of adaptation, the types and uses of robust rule sets.

IV. TYPES AND USES OF RULE SETS

Introduction

The last two sections defined complex control and discussed how adaptation is achieved by turning complex observations into simple rule sets. An earlier statement asserted that not all rule sets are equal – for example, that some are more complex than others, some are applied to different behaviors, etc. This section will explore the idea that there are distinct types and uses of rule sets. It begins with a general discussion of rule set types and then discusses the different types and uses themselves. The section includes rule set type definitions as a precursor to presentation in Section V of a method for creating rule sets by simulation.

What Are Rules?

Webster's New Universal Unabridged Dictionary defines the noun and verb "rule" variously as

> "[noun] (1). An established guide or regulation for action, conduct, arrangement, etc. (2). A complete set or code of regulations … (3). A fixed principle that determines conduct; habit; custom … (4). A criterion or standard. (5). Something that normally or usually happens or obtains; the customary or ordinary course of events … (6). Government; reign; control … (8). Way of acting; behavior. (9). … a decision or order … (10). A method or procedure for computing or solving a problem. … Synonyms – government, sway, control, direction, regulation, law, canon, precept, maxim, guide, order, method…
>
> [verb] (1). To have influence over … (2). To lessen or restrain. … (3). To have authority over; to govern; to direct … (4). to determine … (2). To stand at or maintain a certain level …" [30]

Clearly, "rule" is a word that as both a noun and a verb enjoys rich usage in the English language.[*] It appears also that the language of Sense and Respond Logistics would want to include all these meanings, yet there is a world of operational difference between, for example, a "regulation for action" and something invoked to "lessen and restrain." One sense of the word seems to suggest positive, active behavior while the other hints at negative, constraining activities. Even in the short research history of the Sense and Respond Logistics Concept, there have been experimental results that indicate a need for a language of rules every bit as rich as the English language usage. The following subsection will introduce different types and uses of rules that have already emerged

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[*] "Ruleset" as a compound word is not in the dictionary. As a coincidental point of triviata, "alidade" is derived from the Arabic word for "rule."

during the development of the concept. This list is meant to be inclusive and in many ways corresponds to the simple dictionary list above, a list that should serve as inspiration in the discovery of more types of Sense and Respond rules.

Types and Uses of Rules

This list of rule types was compiled from on-going Sense and Respond Logistics Concept research, including the initial white paper concept development effort, the Sense and Respond Focused Concept Group deliberations and the modeling effort described herein. Some rule types were selected because they were observed in an operational context from one of the research efforts. The following list therefore provides both a definition and discussion of each type and, where applicable, an example of the type's instantiation within an operational context.

Rules as Authorized Actions

Rules can be the fully prescribed actions that elements of a system are directed to take. Such rules tend to require explicit control of an element, which suggests that an element provided with only authorized actions will not take any unauthorized action. Rules as authorized actions should only be cast as very general rules in Sense and Respond applications since they are very likely to cause inaction if the conditions under which the rules were devised are no longer operative in the logistics operation. As an example of this type of rule within the context of the analytical model discussed in Section V, units in the simulation were directed to operate at a particular tempo during each of thirty 24-hour periods.

Rules as Conditional Responses

A different kind of rule is operative when conditional responses are invoked. Conditional statements, long the norm in computer programming, are of great use to the Sense and Respond Logistics Concept since many operational rules must be digitally instantiated in an automated logistics system or analytical model. As anyone who has written substantial computer code can attest, however, nested conditional statements can be extremely confusing to create and de-bug, and not infrequently contribute to pathological behavior. This is because the statements can be invoked in an extraordinarily large number of ways as the environment or competition unfolds, some of which cannot be foreseen by computer coders until the code interacts with actual data. As an example of this type of rule within the context of the analytical model discussed in Section V, units in the simulation have different behaviors under different tempo conditions that are triggered by information conditions both at the coarse scale (tempo of activity in the box to which a unit is assigned) and the fine scale (level of fuel in a vehicle‘s tank).

Rules as Forbidden Behaviors

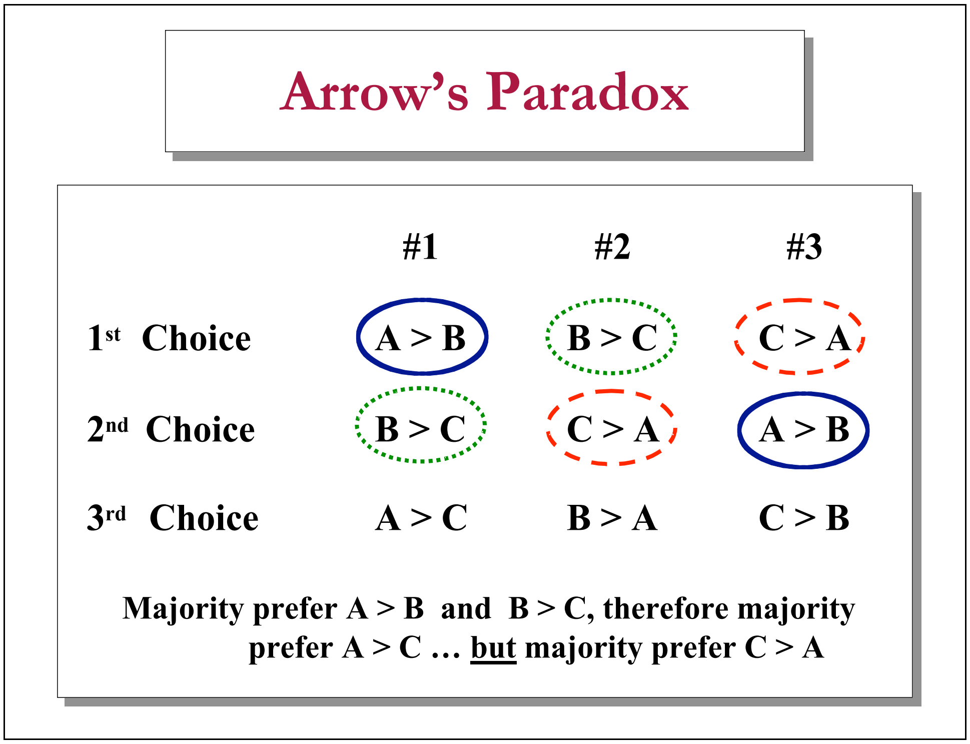
This type of rule is a complement to rules as authorized actions. In this case, however, the actions, conditions or behaviors are prevented from occurring based on a particular inhibiting rule. As with the more positive variant of this rule type, forbidden rules should be invoked mostly as very general rules since a complete determination of all the specific activities to forbid cannot be known in advance. Otherwise, rather than cause inaction, these rules may actually create unintended actions. As an example of this type of rule within the context of the analytical model discussed in Section V, units are prohibited from leaving the operating area to which they are assigned by preventing them from crossing the borders of these areas (not by prescribing what specific directions and speeds they are authorized to drive).

Global Rules v. Local Rules

Global rules are rules that apply to every element in a Sense and Respond Logistics scenario and are triggered by with global information (information available to all elements in a scenario). Local rules are rules that apply to some smaller subset of elements and are triggered by either global or local information (information only available to a subset of elements). The requirement for global rules to be triggered by global information only draws a distinction between true global rules and cases in which local rules are contained in every element in a scenario. There is a natural tension in any distributed, adaptive system between global rules and local rules, in that global rules tend to be coarse scaled and implicit and local rules tend to be detailed and explicit. For this reason, local rules tend to conflict more often with global rules than global rules conflict with local rules. An example of this type of rule within the context of the analytical model discussed in Section V occurs when tactical fueling vehicles invoke local rules based on observations within a two mile radius – a local decision based on local knowledge – and the M970 tanker trucks deploy to re-supply points once tactical fueling vehicles report their empty status to a central adjudicator – a global decision based on global knowledge.

Conflicting Rules

As more rules are added to a rule set, there is an increasingly higher potential that the rules will conflict with each other, particularly if the rules are nested or mutually dependent. The well-known Arrow's Paradox, shown in Figure 5, is an example of how conflicting conditions can invalidate a sound rule set. The figure shows the ranked preferences of three actors, Actor #1, Actor #2, and Actor #3. The first actor prefers Option A over Option B, Option B over Option C, and by transitivity must prefer Option A over Option C. Similarly, Actor #2 and Actor #3 have transitive preferences of the options A, B and C. As a collective, then, a majority (two out of three) rank Option A over Option B and Option B over Option C. Invoking transitivity, then, two out of three actors should also prefer Option A over Option C. Inspection of the ranking, however, shows that two out of three of the actors prefer Option C over Option A. The paradox shows that even with very few decision makers and a very small decision set, there can be many group choices that are conflicted. As the number of choices grows to a handful and the number of decision makers increases modestly, it becomes nearly impossible to satisfy the group or its members with a good, all-encompassing rule set. Not all conflicting rules sets are bad, however. There are times when conflict should be engineered into a simulation to control or dampen behaviors. An example of conflicting rules within the context of the analytical model discussed in Section V occurs when the tactical vehicles routinely have local rules in conflict with global rules. The global rule to proceed at high speed (high-tempo rule) is often in conflict with a rule that requires units to decrease speed at 50% fuel state. The high-tempo global rule is in conflict when local information (fuel levels) triggers a local conservation rule.



Arrow's Paradox

	#1	#2	#3
1st Choice	A > B	B > C	C > A
2nd Choice	B > C	C > A	A > B
3rd Choice	A > C	B > A	C > B

Majority prefer A > B and B > C, therefore majority prefer A > C … but majority prefer C > A

Figure 5

Rule Applicability

There are cases in which not all rules apply equally to all elements in a system. This is know as the "Red Lily Effect," after a scene in a French farce in which nobles discuss the illegality of vagrancy in Paris. Although this law technically applied to the nobles, it only really applied to the indigent of that city.[31] This effect occurs because rules will inevitably be crafted without enough understanding of the potential future states of a system. Under this type of rule, elements are sporadically rather than consistently invoking rules, and causality becomes harder to trace and the impact of particular variables become harder to assess. This effect was observed in the context of the analytical model discussed in Section V when there were a very larger number of tactical refueling vehicles. Since there were so many refueling vehicles, the conservation rules were not consistently invoked, so it was harder to discern if they were indeed good conservation rules.

Rule by Exception

There are cases in which rules should be invoked by exception, meaning that a rule set might be required to create very narrowly defined, specific behaviors. When such rules are invoked, it is usually to ensure a rarely occurring event is noticed and the anomaly that caused the event is addressed. In this case, the rule is usually invoked when all other authoritative, forbidden, or conditional rules are in force and conditions for the anomaly arise. These types of rules can be used when a system is performing relatively well, but manual intervention can create the conditions where a better performance can be achieved. Following each complete commodity distribution cycle in early Sense and Respond Logistics modeling cases, it was possible to quickly and coarsely check system performance and re-direct effort based on common sense, urgency or special information conditions. Usually the exception rules served to move a small quantity very quickly with a special vehicle (such as a helicopter). Rules by exception are also useful when there are very logistics structures within a more complex, adaptive structure. The exception rule can be invoked to prevent adaptation and force the system to send particular commodities to particular customers.

Dutch Boy Rules

A central premise of the Sense and Respond Logistics Concept is that it will operate under uncertainty. Therefore, since one cannot know all the right rules for adaptive behavior ahead of time (that is, *a priori*), determining "sufficient" rules becomes an indispensable skill in planning for and managing Sense and Respond Logistics. Section III made the case that adaptation is a process of developing simple rules from complex environmental or competitive information. It also asserted that good adaptive behavior emerges from a small number of simple, general rules. From the beginning of rudimentary attempts to model Sense and Respond, the analytical results bore out these assertions. In very many cases, simple rules devised by a committee of subject matter experts produced "sufficient" rules that quickly produced robust, adaptive behavior. Focus for system improvement then shifted from improving traditional metrics such as average stock levels to looking for "floor statistics," indications that distribution of a particular commodity was accomplished very poorly, albeit in only a very few cases. For example, average stock level indicated there was good performance over a million runs from a particular rendition of the exploratory mode, yet a small number of runs exhibited pathological behavior. These poor-performing cases were more closely examined, and special rules were created that imperceptibly improved average performance but absolutely corrected the poor performance. These were called "Dutch Boy" rules, after the fictional character who prevented a flood by putting his finger in a hole in a dyke. By making a tiny correction, the Dutch Boy prevented a huge, global catastrophe. Similarly, Dutch Boy rules are used to improve reliability of the rule sets themselves rather than overall performance levels. Although the overall performance levels were significantly improved, pathological behavior of a particular set of rules was prevented and the system as a whole was much more robust.

Over-constrained Rule Sets

The two fundamental assumptions of Sense and Respond Logistics – that complex networks perform better than chains and that complex form follows adaptive function – are valid so long as the logistics challenges are complex and the environment remains uncertain. It is possible to invalidate the assumptions of Sense and Respond Logistics and obviate the need for adaptive logistics by over-constraining the logistics system with overly restrictive rule sets. This can occur when only a relatively small subset of all possible configurations of the logistics system satisfies the rule set. To clarify, these are not necessarily conflicting or Red-Lilly rules, as discussed above, but a set of rules that is internally consistent yet not robust – requiring more precise information about the environment or less uncertain information conditions than less constraining rules for good performance.

Rule Sets and Force Structure

Sense and Respond Logistics assumptions can also be invalidated when force structure supersedes the need for rules. This is perhaps a good definition of the difference between an Industrial Age process and an Information Age process: an Industrial Age process depends more on hardware (force structure) than software (rule sets) to accomplish a task. For example, the Soviet Red Army was famous for insisting on a 3:1 force advantage before they would go on the offensive. This level of overkill dogmatically ensured that the details of tactical combat were less important and that uncertain information conditions had less impact on battle outcome. One advantage of a Sense and Respond command and control philosophy, however, is that extra force structure can be applied directly to combat effect rather than to risk mitigation. An example of the interplay of rules and force structure within the context of the analytical model discussed in Section V would be seen if there were so many additional SIXCONs and tanker trucks introduced into the scenario that the rule sets become increasingly less important to logistics system performance.

A Priori Rules

Sections II and III suggested that one strategy to improve adaptation is to create a general internal model of complex competition prior to interaction with the environment or a competitor. Development of such *a priori* rules is an important competence that fulfills the same need in Sense and Respond processes as current methods of operational and tactical planning do for Industrial Age systems. Experience is one method of developing *a priori* rule sets, but particularly in military contexts, the cost of experience can be too much to bear. An alternative to hard-won experience is computer simulation. A method for creating *a priori* rules with simulation is presented and discussed in the following section.

It is worth noting, however, that complex systems can adapt without a set of *a priori* rules.[32] As discussed in Section III, the resulting adaptation does not converge to stable conditions as quickly as when an *a priori* rule set is present.

V. DEVELOPING *A PRIORI* RULE SETS WITH SIMULATION

One of the challenges of complex control, particularly in situations involving lethal conflict, is that experience is costly. Training, experimentation and simulation relieve an organization of some of the burden of expensive experience (although, of course, there is never any substitute for the real environment and a real competition for creating the best rule sets). But *a priori* development of even an approximate set of rule sets can certainly enhance adaptation and speed the development of more robust rule sets in real life. One way to create *a priori* rule sets in Sense and Respond Logistics is with simulation. Alidade Incorporated and Industrial Science, LLC, were engaged to produce such a simulation.

Simulating Sense and Respond

The initial Sense and Respond Research was followed up by a "Focused Concept Group" that was charged with bringing the Sense and Respond Logistics Concept to a new level of specificity. To accomplish this objective, Alidade Incorporated was engaged to explore the two components of Sense and Respond Logistics – network structures and dynamic responses to demand signals.

The research examined network structures to formalize initial claims about the type and structure most appropriate for adaptive supply under uncertain conditions (including, but not limited to, combat). Research into network structures is inherently associated with researching how a system responds to demand signals – most real networks are formed to satisfy real-world demands subject to real-world constraints. By examining how demand signals might be satisfied by self-synchronized behavior in adaptive networks, the research provided initial insights into the demand-related negotiations, rule sets and constraints that give rise to the most appropriate types of structures.

The Focused Concept Group used "toy" models with very simple rule sets and small networks to explore rudimentary Sense and Respond dynamics. These models did not comport exactly with the initial descriptions of the desired characteristics of Sense and Respond Demand Networks for the primary reason that the types of network structures that enable Sense and Respond operations are quite complicated and difficult to model. Indeed, no model exists which captures all the characteristics of Sense and Respond Logistics. To begin exploratory research within the funding and time constraints faced by the Focused Concept Group, however, the simple toy models proved useful. For example, the simplified rules and networks in the toy models helped explore and explain the critical Sense and Respond mechanisms of growth and preferential attachment. The toy models showed how networks could evolve even with significant random connection logic and no central direction yet provide relatively stable behaviors that adaptively responded to perceived demand signals.

As useful as the toy models were, they had significant limitations. Some of these limitations were:

- Very time-intensive for coding, set-up and analysis
- Dramatic increase in complexity for even the smallest scenarios
- Long run-times for even the smallest scenarios
- Inability to handle large networks (> 100 nodes, > 200 links)
- Inability to quickly devise, implement and test new rule sets
- Poor instrumentation
- No run-time or data visualization capability
- No method to capture and analyze network statistics
- Limited ability to re-use code
- Specialized computer language skills were required
- Substantial training required
- Code obscure and difficult to modify

To overcome these limitations, a more useful and relevant model was planned for this phase of Sense and Respond Logistics research. A more sophisticated model was therefore designed with features that include:

- Easy and quick to code, set-up and analyze
- Moderate increase in complexity even for large scenarios
- Short run-times even for large scenarios
- Ability to handle large networks (> 100 nodes, > 200 links)
- Ability to quickly devise, implement and test new rule sets
- Good instrumentation
- Run-time or data visualization capability
- A method to capture and analyze network statistics
- Good ability to re-use code
- Specialized computer language skills not required once the model has been distributed for use
- Minimal training required
- Clear computer code that is easy to modify

Alidade Incorporated and Industrial Science, LLC, were engaged to produce such a model. The model was called an "experimental model," because its main purpose was to experiment with and refine rule sets for Sense and Respond Logistics. The next two sections describe the model specifications and the expected functional usage, respectively.

Model Architecture

There are three basic types of modeling architectures available to programmers. The first is the traditional "process-oriented" coding technique in which flow charts are used to design sequential processes and routines that execute a simulation’s main functions. Iteration and “go to” commands that invoke particular lines of code are the only deviation from sequential processing. These models are not inherently flexible and code is difficult to re-use.

The second type is Object Oriented (O-O) programming. This technique focuses on the creation of software “objects” that invoke each other to execute a simulation’s main functions. O-O programming is very useful for managing very large, complicated computer models. Most simulations used by DoD today were developed using Object-Oriented techniques.

The third type of architecture is called “agent-based modeling” because simple pieces of computer code called “agents” populate a simulated environment and interact with each other based on individually interpreted rules and information. This architecture is useful for studying the intricate dynamics of man-made and natural complex systems such as economies, societies, cultural norms, traffic jams, ecosystems, immune systems and evolution. The experimental model uses this third type of architecture. Agents in the simulation represent real-world objects, such as battalions, companies, platoons or squads, and have behavioral rules that cause them to act (move, consume, communicate, etc.) in accordance with locally or globally processed information.

The software was written using the Java programming language, a popular language that is “portable,” since it can be written and run on many different operating systems and does not require the operating system a model is written on be the same as the operating system a model is run on. This ensures that the simulation is freely distributable within the DoD logistics modeling community and, because of the sizable market of Java-skilled programming talent, modification need not be exclusive to the model builders. Although the model is sophisticated enough to explore complex networks, it is simple enough to be run on the personal computers and laptops available to typical defense community action officers and analysts. In other words, no expensive or exotic computer hardware is required for this model.

The underlying toolkit for the model is the RePast (REcursive Porous Agent Simulation Toolkit) simulation engine, developed by the University of Chicago's Social Science Research Computing Group. RePast is a software framework for creating agent-based simulations using the Java language. It provides a library of classes for creating, running, displaying and collecting data from an agent-based simulation. RePast can take screen captures (snapshots) and create demo runs (movies) of running simulations. Borrowing significantly from its predecessor, the Swarm simulation toolkit, models created with RePast can be considered "swarm-like." RePast includes such features as run-time model manipulation with Graphic User Interfaces (GUIs).

RePast treats a simulation as a “state” machine whose state is determined by the collective states of all its components. These components can be divided up into either “infrastructure” or “representation” components. “Infrastructure” components are the various mechanisms that run the simulation, produce displays, collect data, etc.

“Representation” components are software components that the modeler constructs, such as logistics vehicles and road networks. The state of the infrastructure is then the state of the display, the state of the data collection objects, etc. The state of the representation is the state of what is being modeled: the current values of all agents' variables, the current value of the space or spaces in which they operate, etc.

In RePast, any changes to the states of the infrastructure components and the representation components occur through a schedule object. RePast allows a user to build a simulation as a state machine in which all the changes to the state machine occur through a schedule. This provides clarity both for the modeler as well as the software designer seeking to extend the toolkit.

The simulation uses the OpenMap™ for geographic maps, a Java-based toolkit for building applications requiring geographic information. OpenMap is a set of components that understand geographic coordinates. These components show map data, as well as handle user input events to manipulate that data. With OpenMap components, the model can access data from legacy applications in a distributed modeling framework. The technology base underlying OpenMap was developed in a DARPA collaborative mapping research project. OpenMap is used today by in a number of DARPA and military sponsored programs including ALP (Advanced Logistics Program) , Ultra*Log, AMP (Analysis of Mobility Platform), CoABS (Control of Agent Based Systems) , GAMAT (Global Air Mobility Advanced Technology), JLACTD (Joint Logistics Advanced Concepts Technology Demonstration) and SensIT.

Agent-based models are typically built to allow users to rapidly and efficiently reconfigure the model, allowing ready exploration of large parameter spaces, diverse scenarios and important excursions. This is the case for the experimental model. Users are able to vary the parameters of the model for each run (or even during each run) typically without significant software changes. A batch mode allows the creation of “parameter spaces” – vast regions of variable interaction with many, many combinations of input parameters. In these parameter spaces, global and local minima and global and local maxima can be observed as well as the “ruggedness” (non-linearity) of multi-dimensional “landscapes” (response surfaces). In addition, the user is able to modify negotiation rules, parameters, numbers, locations and behaviors of agents, as well as other aspects of rudimentary Sense and Respond logistics.

Computers are digital machines, however, and some rule sets and behaviors must be translated into a digital language from natural (human) language before they can be observed in the model. Because of this, major changes to rules and behaviors will normally require software composition rather than just data entry. When this was required, every effort was made to make the model easily modified throughout the range of data elements implied by the rule set or behavior. This ensures the model has enough flexibility to explore complex logistics questions yet is still easy enough for someone with only basic computer skills to understand, modify, run and analyze.

Model Context

The simulation can represent either a simulated region of the world (to support, for example, an exercise or a specific analytical project) or a specific region of the world with two-dimensional (earth surface) topographic features. Other dimensions or features such as altitude, depth, trafficability, sea state or road networks can be represented by data elements, software code or other modeling techniques. The model is capability of representing a joint military force conducting complex operations. The first logistics operations and forces to be modeled – Class III logistics for a company level Marine Corps force – were determined in conjunction with other members of the Sense and Respond Logistics development team. The level of resolution (that is, the size of smallest unit represented), however, can vary as determined by the specific logistics questions that subsequent vignettes are developed to answer. Agent-based models are particularly useful for projects in which different levels of resolution are required for different applications of the same model.

A key required feature of the model is the creation of adaptive networks that transport commodities based on the demand signals of a force. These networks represent tactical level operations, the demand behaviors that arise from these operations and the supply efforts that satisfy the demand. In addition, the experimental model is capable of representing traditional logistics operations so that differences (if any) between traditional logistics and Sense and Respond Logistics can be measured. The units in the simulation are capable of forming dynamic networks and sub-networks of demand and supply that change based on operational considerations. The particular demand-supply transactions result from some level of negotiation between demander and supplier. A key feature of Sense and Respond Logistics is that this negotiation, as well as the actual transmission of the demand signal and receipt of supply, need not be direct. Indeed, indirect interactions are a primary mechanism that differentiates Sense and Respond Logistics from other logistics concepts.

Model Metrics

The model is capable of displaying metric values in a "scorecard" window during model run (in real time) as well as writing to a file for detailed data analysis. Since the final set of metrics for Sense and Respond Logistics has not yet been determined, any list of specific metrics will be incomplete. At a minimum, however, for multiple classes of supply, the model is capable of tracking:

- Supply levels at each node
- Flow rates at important junctions
- Cumulative supplies delivered at each node
- Cumulative supplies delivered throughout entire networks
- The total amount of handling required ("logistics churn")
- Time required to meet specific levels of supply
- Statistics by pre-defined groups of nodes (e.g., by company or battalion)

With post-processing, the model is also capable of tracking the following network statistics:

- Link/node ratio
- Path Lengths
- Degree Distribution
- Clustering Co-efficient
- Clustering Distribution
- Neutrality

Other metrics and statistics can be determined as contexts and scenarios are more fully explicated in future studies.

Model Usage

Agent-based models, while extremely flexible and easy to operate, are nonetheless not usually finely detailed. The main reason for this is that they are typically created to explore the gross behaviors of a complex system rather than the subtleties of a finely engineered system or mature process. The experimental model is no different. Since Sense and Respond Logistics is a new concept, requiring substantial simulation and analysis before a final, stable system can be fielded, it is important to explore the gross behaviors of the system first. Once the major behaviors, most important negotiations and most influential rule sets are discovered, then more detailed simulations can be created to refine these initial solutions. The main purpose of the model, then, is to understand the basic behaviors and mechanisms of Sense and Repond Logistics. To do this, other functions, described in the following paragraphs, will be required.

No new concept or system should be adopted simply because it is new – it must clearly outperform the existing concept or system. Indeed, most innovation experts suggest that an order of magnitude improvement is required for shifting to a new system. Otherwise, the cost of switching to the new concept or to develop a new system may not make the innovation a good return on investment. Obviously, there are difficulties in modeling future systems, but there are even bigger challenges comparing a model of an old system with a new system. Not least of these is the well-known problem of "model-specific" results, wherein level-of-resolution issues, software code idiosyncrasies and computational choices can affect the result of a model. In order to compare the existing logistics system with a future system, therefore, the experimental model can model traditional logistics as well as Sense and Respond Logistics. This will ensure the purest comparison of the new and the old.

At the same time that the Alidade-Industrial Science team developed the experimental model, Synergy, Inc., was developing a prototype Sense and Respond Logistics management system. The Synergy system used rule sets and intelligent agents (similar, but not identical to, the agents in an agent based model). The primary usage of the experimental model is to explore Sense and Respond behavior and inform the development of the rule sets and agent parameters used by the management system.

A final function of the model is basic research. Since little is known about the Sense and Respond Logistics Concept other than the original scientific and technical work created by Alidade and the Focused Concept Group, each new rendition of Sense and Respond Logistics contributes significantly to the Sense and Respond knowledge base. Again, using the experimental model for exploration is much more economical than using the prototype logistics management system. A significant aspect of the reports generated by the experimental model will be about the concept of Sense and Respond in general. It is therefore hoped that the experimental model will also help in furthering the Sense and Respond concept to other military topics, such as combat or intelligence operations.

Although not explicitly required by this contract, the experimental model may eventually prove useful as a rudimentary planning tool for Sense and Respond Logistics. With an eye to this possibility, the Alidade-Industrial Science team has taken care to ensure no decision in platform selection, software applications, data input or other considerations will preclude the experimental model from being used in this way. It should also be stated, of course, that no addition work was incurred under this contract for ensuring the future compatibility of the experimental model with the Synergy prototype Sense and Respond Logistics management system.

Use of the Model to Develop Rule sets

The experimental model is an Agent Based Model of a notional, adaptive logistics system. As such, the agents in the Alidade simulation represent the physical entities in a military operation that consume commodities. They have characteristics that represent physical attributes, such as speed, burn rate, fuel tank capacity, etc. They also have characteristics that represent informational attributes, such as rule sets, simple informational messages that can be passed between agents or data elements that can be read by other agents. Synergy's logistics management system is a network-based information and control system that uses intelligent agents to operate an adaptive logistics system. Agents in this system are pieces of software that monitor the state of a physical entity, communicate that state to other agents and enact or conform to rule sets that govern logistics behavior.

One way in which the uses of both software products differ is in number of times each is designed to run for a particular context. Since the Synergy system is a logistics management system, it is designed for one continuous run for the duration of an operation to manage logistics operations.[*] The Alidade experimental model is designed to run as many times as practical to uncover the dominant rules and important levers in a particular logistics operation. The Synergy system is focused on accurately passing information and executing rules; the Alidade model is focused on testing as many possible outcomes of potential rule sets as possible.

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[*] Although, as a prototype system multiple runs of the same scenario might be conducted for testing, experimentation, etc.

This highlights an important point of interaction and collaboration between the two systems. Experts or doctrinal publications can provide the rule sets to drive the Synergy system, but since each operational context is different, how these rule sets play out under uncertainty can vary, sometimes to a great degree. The management system cannot "game out" a large sample of the ramifications of or responses to these variations, but the experimental model can. Therefore, prior to execution of rule sets in the management system, the rule sets can be tested in the experimental model for robustness, pathological behavior, or sensitivity to information conditions or to the survivability of the physical elements they govern. When fully mature, the experimental model should allow for testing of the rule sets for a particular context within a matter of hours, making it a good candidate for an operational planning tool. In addition, the large sample of outcomes and behaviors produced by the experimental model should also be a useful source of new rule sets that are not contained within an expert's experience base or in doctrinal publications.

As a practical matter, however, collaboration between the management system and the experimental model will not likely be automated (at least in the early stages of the development of each system). While care was taken in the inception of both products to ensure that they were compatible – for example, each uses the Java™ language, OpenMap™ geographical datasets and other open source content – there are structural differences in each system that make automated interaction unwieldy. The first difference is that the management system is a more generic application than the experimental model. For example, the screens in the management system are meant to be used for all decision and monitoring points in the logistics system with relatively minor changes. In the experimental model, by contrast, each new application means that a new representation of a physical entity must be created, complete with physical characteristics, and caused to function in an operationally meaningful way, such as drive toward an objective, fight with an enemy, etc.

Another difference is in how rule sets are instantiated. In the logistics management system, an expert system is used to input the rules to the system and to make them operative, requiring only textual entries in an input screen. In the experimental model, each new rule set will likely require program code changes or the addition of new entities. In the early implementation of the experimental model, these changes may be substantial, requiring a few days of coding substantially different, new contexts. As the model matures, re-use will allow coders to take existing structures and modify them more easily, requiring, perhaps, a few hours of re-coding to change contexts. Some very mature agent based models require only a few minutes to reconfigure, but this is achieved after the model is quite mature, having almost all of the agent classes built for re-use and significant effort expended on input screens and menus. Since the most important intersection of the logistics management system and the experimental model is with rule sets, Alidade coordinated with Synergy software engineers to mutually determine the input and output methods that achieve the best interaction between the two products given the time available for this phase of the project. The final version of the experimental model contains the appropriate screens or mechanisms that support these methods.

An Example of Rule set Exploration

The following paragraphs describe a notional rule set exploration using the Sense and Respond Experimental Model. The exploration consists of five steps: Context Definition, Experiment Design, Model Runs, Output Analysis and Iteration.

Context Definition

The specific context developed for the first rendition of the Sense and Respond Logistics Experimental Model is Class III logistics for a company level Marine Corps force. This force consisted of an M1A1 tank company with 3 platoons of 4 tanks. These tanks consumed 60 gph of fuel at high speed (45mph), 30 gph at cruising speed (30mph) and 0 gph while idling (0mph). Each tank has a 505-gallon tank. In addition to the tanks, there was a light armored vehicle (LAV) company with 18 LAVs that consumed 12 gph while at high speed (60mph), 6 gph while cruising (30mph) and 2 gph at idle (0mph). Each LAV has a 71-gallon tank. Also in this force was an infantry company with 24 HMMWVs. These vehicles consumed 8 gph at high speed (55mph), 4 gph at cruising speeds (30mph) and 1 gph while idling (0mph). Each HMMWV has a 25-gallon tank.

Supporting this force was a Marine Corps Combat Support Service Element (CSSE). The CSSE consisted of 20 M970s 5000 gallon tanker trucks that themselves consumed 1.5 gph at 25mph from a 150-gallon tank and 84 5-ton trucks (with 900 gallon SIXCON fueling trailers). The 5-ton trucks consumed 4 gph at 25mph from an 82-gallon tank. The tanks, LAVs, HMMWVs and 5-ton/SIXCONs were equally distributed in three adjacent 50mi X 50 mi areas. Each area had one of three different rates of activity each day: High Tempo (vehicles moved at high speed), Medium Tempo (vehicles moved at cruising speed) and Low Tempo (vehicles were at idle). The 5-ton/SIXCONs were allowed to supply each other in addition to the tactical vehicles.

The tactical vehicles had some simple rule sets initially derived from doctrine. This rule set stated that if the vehicle were in a high tempo area, then the vehicle would travel at high speed until 50% of their fuel was consumed, then shift to cruising speed until 25% remained, at which point it then idled. If the vehicle were in a medium tempo area, the vehicle would cruise until 25% remained, and then idle. If the vehicle were in a low tempo area, it would stop and idle.

The 5-Ton/SIXCONs circulated throughout each region at a constant speed. These vehicles also had their own rule set. Foremost, they were to keep the 5-ton truck tank full, requiring a 10-minute stop to do so. When they encountering another vehicle, if it was another 5-ton/SIXCON, they would conspire to equalize their tank levels if the difference between the tank levels exceeded 450 gallons (requiring both to stop for 10 minutes). If the vehicle were a tactical vehicle with a fuel tank level less than 75% capacity, they would refuel the tactical vehicle (requiring a 10 minute stop for both). When the SIXCONs were empty, they were to report their state and return to the edge of the operating area where an M970 would meet them for a 1-hour refueling stop. There were two Combat Service Support Areas (CSSAs) supplying the M970s with fuel.

Experiment Design

The next step in rule set exploration is to design an experiment using the experimental model. Since a computer simulation is a digital machine, each potential logistics rule set, as well as the behavior of elements to be simulated, must be converted to a digital representation. This is accomplished with various modeling techniques, including data tables, relationship diagrams, mathematical equations, etc. For an exploration to be successful, however, the digital representations must cover a broad range of input values. The selection of the range of the values is just as important as the representations themselves. If too narrow a range is selected, then only a small part of the solution space will be searched. If too broad a range is selected, then unrealistic inputs may contaminate the output. Moreover, if the interval between values for a particular range of input is too large some important combinations of input values might not be examined. Finally, if the interval between values for a particular range of input is too small, then the solution space can get far too large to be practically evaluated with anything but the most powerful computers.

This last point bears a deeper discussion. If one were to look at 7 different input values at 10 levels of resolution, then the total number of points in the solution space would be 10^7 = 10,000,000 different data points. Since the experimental model necessarily has randomness built in to its processes, then each data point must be explored with a statistically significant number of runs, each with a different random seed. If the number of required runs for each point is 100, 1000, or 100,000 (depending on degrees of freedom and the character of stochasticity), then the total number of runs, which is equal to the number of data points multiplied by the number of runs per data point, can start to grow by many orders of magnitude. In the following analysis, four different input values – the level of fuel that triggers equalization between SIXCONs, number of SIXCONs, SIXCON speed and number of M-970s – were chosen to explore the rule sets listed in the previous section. If each of these were examined at each percentile of their allowable value, then the simulation must be run at least 10^4 = 10,000 times. Each point was iterated 100 times, so the total number of runs for the experiment would be 1,000,000. This particular rendition of the experimental model required about 3.5 minutes per run (which represented a 30 day logistics cycle) on a standard desktop computer, so the total time for the experiment would be more than 3.5 million minutes, or more than 6 years on a standard desktop computer.

There are techniques to prevent having to search the solution space in such a brute force manner. One of the most useful techniques is the method of Orthogonal Latin Hypercubes, which, for 7 variables or less, chooses 17 different vectors representing orthogonal samples of the solution space. In essence, this method “screens” the solution space of over 17^4 = 8,352,100, which would take a typical desktop almost 48 years to exhaustively explore, in less than 100 hours. Faster machines or small clusters of desktop computers can be cheaply obtained and easily configured to reduce this to only a few hours or even a few minutes. Columns 2-5 of Table 1 list the Latin Hypercube input vectors for the notional exploration.

Parameter	Trigger Level	SIXCONs	SIXCON Speed	M-970s	Results Avg. Fuel (Percent) Lowest Observed (Percent) Avg. Churn (Gals) Xfer'd to Tactical (Gals) SIXCON Xfer (Gals)
Range	(0.1-1.0)	5-100	5-50 mph	3-100	
Run #1	4	100	42	39	62 0 408,658 216,795 191,863
Run #2	2	29	44	58	60 0 369,228 197,241 171,987
Run #3	2	47	8	27	75 0 742,657 343,947 398,710
Run #4	3	64	19	100	74 0 706,581 338,759 367,823
Run #5	8	94	25	15	73 0 661,388 333,887 327,501
Run #6	10	35	22	82	74 0 670,208 337,746 332,462
Run #7	7	23	50	33	51 0 237,752 143,878 93,874
Run #8	6	88	39	94	66 0 472,483 252,012 220,471
Run #9	6	53	28	52	73 0 645,486 328,526 316,961

Table 1

Parameter	Trigger Level	SIXCONs	SIXCON Speed	M-970s	Results Avg. Fuel (Percent) Lowest Observed (Percent) Avg. Churn (Gals) Xfer'd to Tactical (Gals) SIXCON Xfer (Gals)
Range	(0.1-1.0)	5-100	5-50 mph	3-100	
Run #10	7	5	13	64	75 0 734,547 351,083 383,463
Run #11	9	76	11	45	75 0 723,267 347,559 375,709
Run #12	9	58	47	76	56 0 296,443 169,458 126,986
Run #13	8	41	36	3	69 0 539,924 290,060 249,864
Run #14	3	11	30	88	72 0 628,812 320,069 308,743
Run #15	1	70	33	21	71 0 597,324 310,829 286,495
Run #16	4	82	5	70	73 0 684,405 317,753 366,652
Run #17	5	17	16	9	75 0 718,191 342,020 376,171

Table 1 (cont.)

Model Runs

Once the experiment is designed, the model is run the requisite number of iterations for analysis. The experimental model can display dynamic graphics and output directly to the screen so that analysts can verify proper model behavior during a run. This, however, will substantially slow the elapsed time to build the entire output data set, so once the model is deemed to be running appropriately, the analyst should turn off all graphics and have the output write directly to text files or Excel™ spreadsheets, which also facilitates the next step in the exploration, analysis of the output.

Output Analysis

The output of the exploration designed by the Orthogonal Latin Hypercube method is listed in Column 6 of Table 1. The table represents a set of 17 different values for four input variables (selected by the method so that they are a representative sample of all combinations of all variables for the entire value range of all variables) and a set of five output values for each set of input variables. The five output metrics are the average fuel level in the tactical vehicles (as a percent), the lowest observed fuel level (as a percent), the average "churn" in gallons (that is, the average number of gallons of fuel transferred, considering the same gallon pumped twice, for example, as two gallons of churn), the number of gallons transferred to tactical vehicles and the number of gallons transferred between SIXCONs.

Another way to think about Table 1 is as a set of logistics processes. For example, Run #3 shows that with a trigger level of 0.2, 47 SIXCONs traveling at 8 mph being refueled by 27 M-970s combine to produce an average fuel level of 75%. Similarly, Run #14 shows that with a trigger level of 0.3, 11 SIXCONs traveling at 30 mph being refueled by 88 M-970s combine to produce an average fuel level of 72%. An analytical process must then be used to determine exactly how the changes in the four input variables accounted for the 3% difference in average fuel level. Was the 0.1 change in trigger level as important as the addition of 61 M-970s? Are 61 more M-970s overkill? Perhaps more SIXCONs would improve average fuel percentage instead? Do some of the variable changes have no impact at all? These and other questions can be explored with a technique called multiple regression analysis.[33]

Multiple regression treats the Orthogonal Latin Hypercube entries in Table 1 as independent variables, treats the output values as dependent variables and produces five equations that would derive the set of dependent variables from the set of independent variables.[34] The coefficients in these equations indicate the extent to which changes in outputs are due to changes in particular inputs. The usual way to use this knowledge about inputs and outputs in multiple regression analysis is to look for variables that have the most impact on outcomes. These variables are usually of most interest to consumers of analysis like managers, scientists, etc., since they are the important control levers in a process. When using a model to derive rule sets, however, it is more important to find the variables that have little or moderate impact on outcomes, because these are the inputs for which the rule sets are most robust. If multiple regression shows that outcomes produced under a set of *a priori* rules are not significantly impacted over the entire range of a particular variable, then these rules are more robust with respect to these variables than a rule set that is more sensitive to changes in this same input.

A multiple regression was performed on the data in Table 1. The regression produced five equations, one for each of the output metrics. The regression statistics showed that for four of the five metrics, only one variable had a consistent, significant impact on outcomes, SIXCON speed. This knowledge can now be used to refine the rule set. For example, adding to the existing rule set a global rule that keeps SIXCON speed in a more narrow range of 8-16 mph would keep average fuel levels between 74-75 percent, regardless of how the force structure might change, what the trigger levels are or how many M-970s are available.

The one metric for which this would not work, however, is problematic. Inspection of Table 1 shows that in every case at least one vehicle runs out of fuel sometime in the 30-day cycle. Although multiple regression shows that no input variable significantly impacts this output and the rule sets quite robustly produce this outcome, it is in practical terms a very negative outcome, one toward which no logistics system should want to adapt. In this case, the regression analysis has unveiled a structural problem with the rule sets that warrants changes in the original rule set, perhaps, for example, to the threshold level at which tactical vehicles shift from high speed to cruising speed in high tempo operations. Once a suitable fix has been postulated, then another experiment (of 17 iterations of 100 runs) should be run, this time, say, with speed in a more narrow range. Multiple regression should again be accomplished and the process repeated until a sufficiently robust rule set is identified.

In addition to classic statistical analyses, the model output can also be used to perform network analysis. At the end of each model run, an adjacency matrix that identifies which vehicles transferred fuel to other vehicles is created in the Excel™ spreadsheets. These spreadsheets can be imported into any one of many network analysis packages. For the following analysis, the UCINET software package was used. At the most basic level of analysis, the software produces a visualization of the network. Figure 6 shows the fuel transfer network from the eastern-most operating area during a specific 30-day cycle. Although it does not have the specificity of statistics, visual inspection can suggest which units had the most transfer activity and provide a general picture of the system dynamics. A three-dimensional, rotating representation provided by UCINET, such as the one in Figure 7, can provide a more compelling visualization, but two- and three-dimensional pictures cannot capture high-dimensional complexities in networks.

UCINET has network statistic routines that can provide more precise information on this fuel transfer network. For example, the Characteristic Path Length, a measure of the average shortest chains in the fueling network, can be computed.* In this network, the Characteristic Path Length is 1.74, indicating that, on average, each fuel transfer chain was 1.74 links long. This shows the indirect nature of some sense and respond negotiations.

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* To account for natural skewness in networked data, this "average" is actual the middle value (median) of the ranked average shortest chains from each node to every other node.

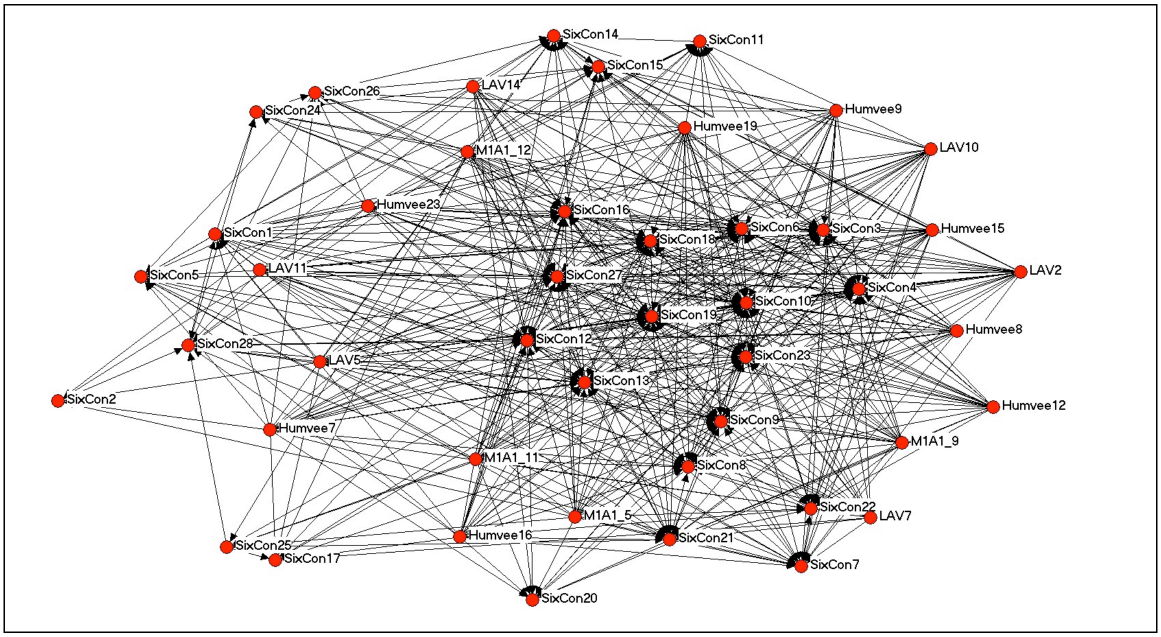

Figure 6.

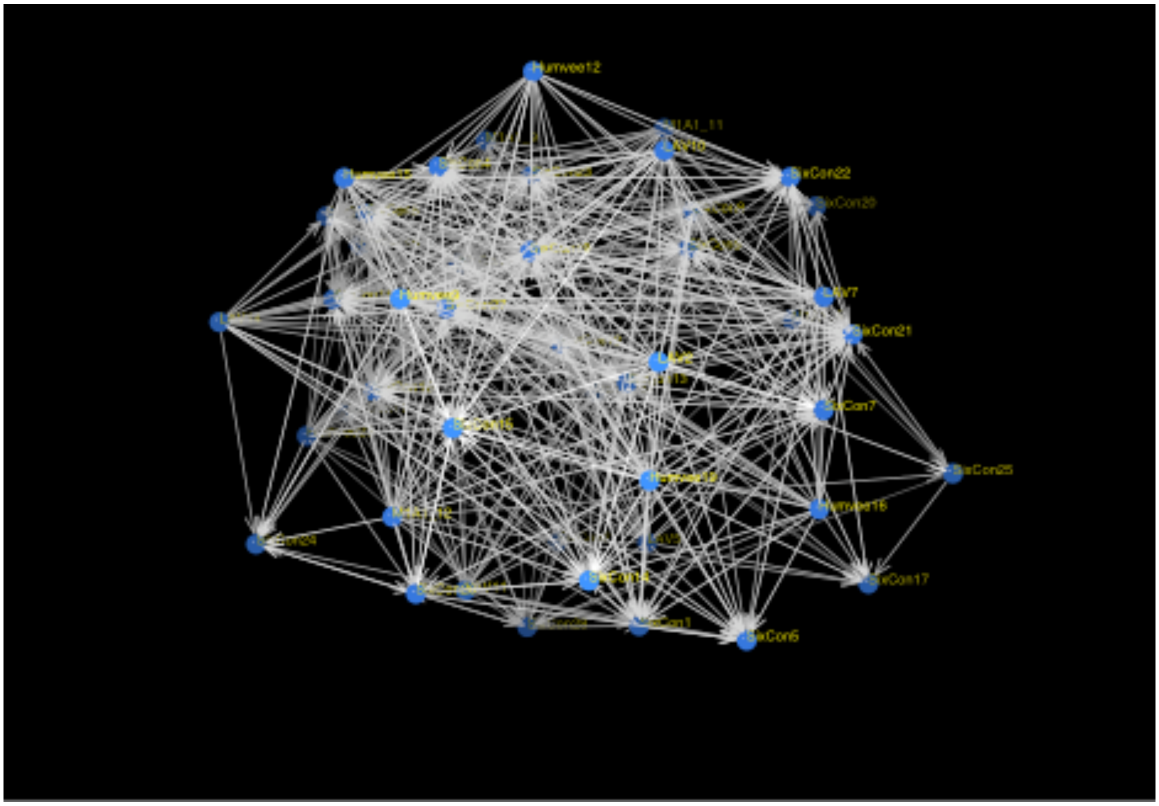

Figure 7.

An additional statistic is the link to node ratio, which can be directly computed from the UCINET output. In this fueling network, the ratio is 11.5 links per node, which is quite high compared to other types of adaptive networks. This is likely because the simulation covered 30 days of activity and recurring connections are counted. Since earlier sense and respond research suggested this ratio should be about 2:1, further analysis could parse the 30 day scenario into smaller segments of where the ratio is about 2:1 and see if adaptive behavior is present. Closely related to the link-node ratio is neutrality, a metric that describes the amount of additional structure an adaptive network should have. One measure of neutrality is the number of links divided by one less than the number of nodes, again about 11.5. Once more, the data could be parsed to examine this statistic.

A network's clustering coefficient describes the extent to which there is local cohesion between nodes. The clustering coefficient is 0.25, which indicates there is a good connectivity at the local level in this network. It is also useful to chart how this coefficient is distributed among all vehicles in the area. Figure 8 shows the distribution of clustering coefficients as a skew distribution of clustering, which suggests adaptive behavior.

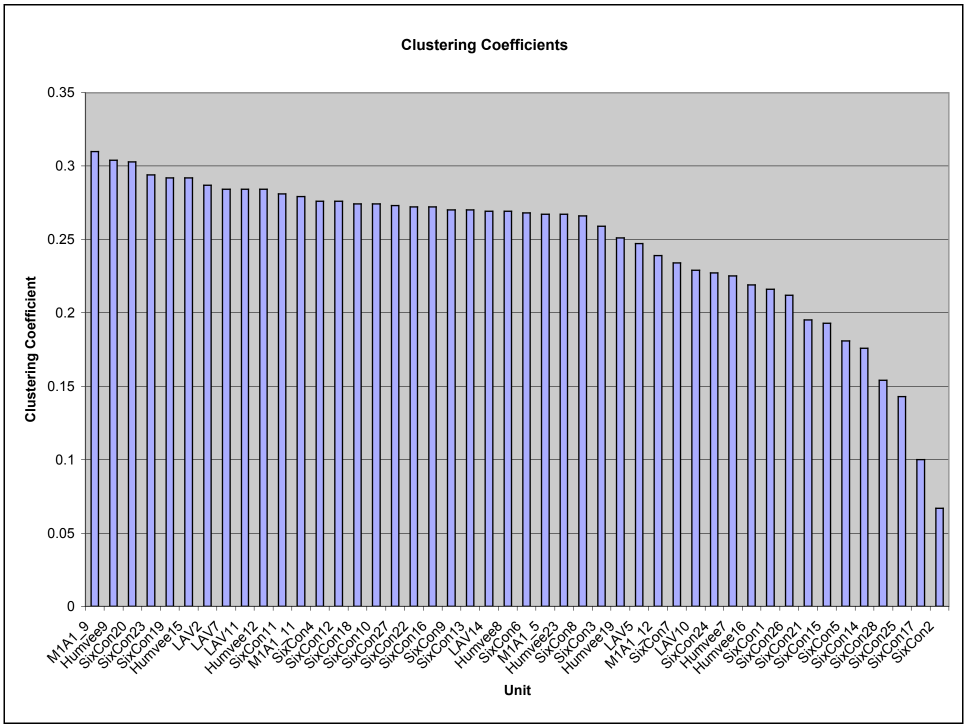

Figure 8

Finally, Figures 9 and 10 display the degree distribution (out-degree for fueling vehicles and in-degree for fueled vehicles), which shows what vehicles fueled (or were fueled by) how many other vehicles. Note the bimodal distribution in Figure 10, which indicates a the network dissortatively mixes fueling vehicles and fueled vehicles, which should be expected (SIXCONs can fuel each other but tactical vehicles cannot, nor can they fuel SIXCONs).

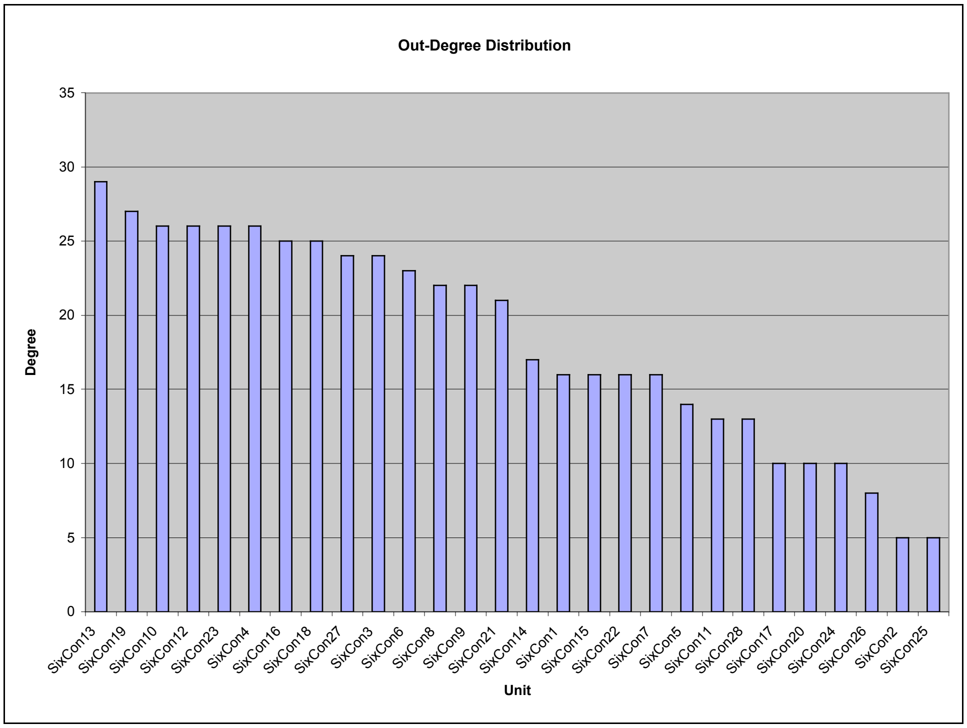

Figure 9

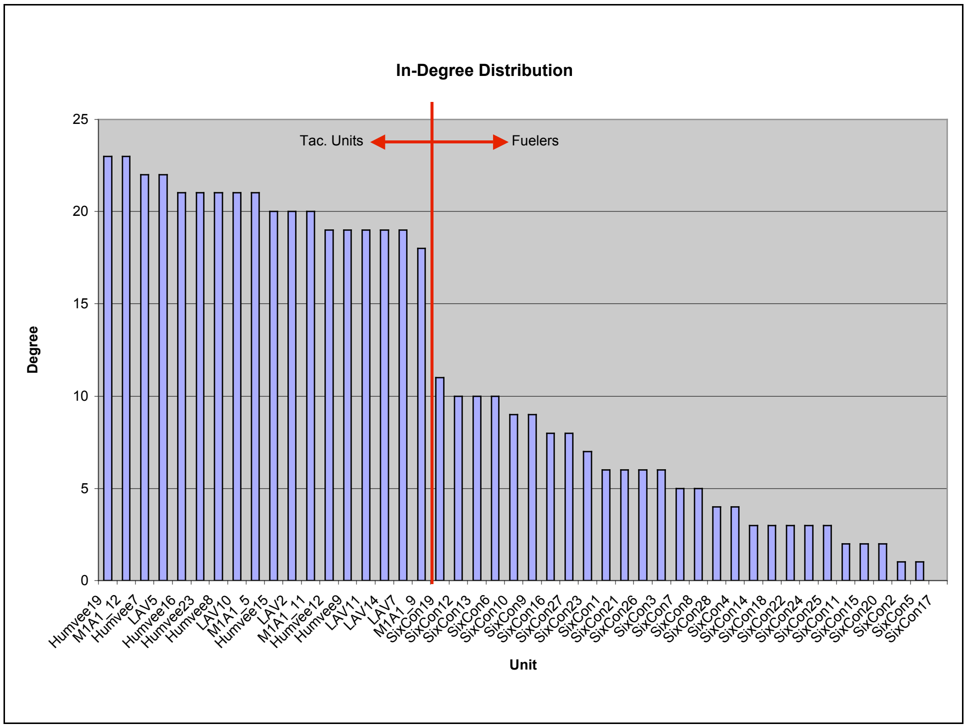

Figure 10

Iteration

The experimental model is designed to be iterated for as many iterations as are required to develop acceptable rule sets. As discussed earlier, early experiments may take many days. As the dominant rules begin to emerge, however, it is expected that the time required for subsequent experiments should decrease. An ideal rule set derivation would start with an initial, time intensive excursion but settle into a cycle of minor changes and short, iterated experiments.

Another reason to iterate the model would be to explore the rate at which the rules converge. One way to measure this would be to track the network statistics over smaller increments than 30 days to determine the point at which, for example, initially incoherent behavior transitions to coherent, adaptive logistics. This would answer the earlier question about whether a system was adapting quickly enough for its environment as well as provide useful simulated data on logistics systems learning curves.

VI. CONCLUDING COMMENTS

Summary

This paper has summarized research into a method of control for complex logistics networks. After an introduction to the Sense and Respond Logistics Concept, the relationship between the complexity and control in complex systems and the fundamental scientific considerations in complex control were discussed. The specific mechanisms by which rule sets achieve complex control, and a method for how a system learns and adapts was stated directly – an adaptive system takes specific, detailed information from its competitive environment and creates general rules. This sentence describes concretely the difference between adaptive behavior and reactive behavior: true adaptive behavior in a complex system cannot be reactive. Adaptive behavior, especially in a collective, comes from converting specific information from an uncertain environment into general rules that improve collective performance. In doing so, the system is under indirect control of distributed elements by using robust, generalized rules that can withstand dramatic shocks and surprises yet still adapt in longer time scales as the environment or competitive context also adapts. The paper also discussed the type, use and behavior of rule sets in a complex system. Different types and uses of rule sets were defined and explored, and examples were provided.

Note on the Experimental Model

The paper also presented a simulation model of a complex logistics system and describes how rule sets can be derived from simulation. The use of rule sets as the motivating mechanism in the effective performance of adaptive logistics systems was discussed and a method for rule set derivation through environmental observations was introduced. A sample use of the model to derive rule sets was provided.

The experimental model has been issued on a CD and is available through the Office of Secretary of Defense, Force Transformation. The CD includes all the files and routines required to run the model in an MS Window™ operating environment, including downloaded routines and libraries. Sample data is included in the executable files on the CD.

Accompanying the CD is a 12-page manual with step-by-step instructions for downloading the latest version of routines and libraries, as well as instructions for loading and executing RE-Past. Instructions on how to use UCINET for network analysis is also contained in the manual.

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[1] The inspiration for and most of the language used to describe Sense and Respond Logistics comes from Stephen H. Haeckel, *Adaptive Enterprise: Creating and Leading Sense and Respond Organizations*, (Harvard Business School Press, Boston, MA, 1999).

[2] Jeffrey Cares and Linda Lewandowski, unpublished, undated DoD white paper, "Sense and Respond Logistics: turning Supply Chains into Demand Networks."

[3] The link between management, control and optimization is evidenced by the curricula content at most Masters in Business Administration (MBA) programs. See, for example, Harvard (www.hbs.edu/mba), MIT (http://sloanserver.mit.edu/courses) or Stanford (www.gsb.stanford.edu/mba). All websites accessed 30 March 2004.

[4] For mathematical detail on and discussion of makespan, just-in-time manufacturing and the Toyota production system see http://www.toyotaproductionsystem.net, accessed 30 March 2004.

[5] Jeffrey R. Cares, Raymond J. Christian, Robert C. Manke, *Fundamentals of Distributed, Networked Military Forces and the Engineering of Distributed Systems,* NUWC-NPT Technical Report 11,366, 9 May 2002, NUWC Division Newport, 1.

[6] For a full mathematical treatment of complexity and scale in complex systems see Section 8.3 of Yaneer Bar-Yam, *Dynamics of Complex Systems,* (Addison-Wesley, Reading, MA, 1997).

[7] For a complete discussion of the impact of complexity and scale on littoral operations, see Yaneer Bar-Yam, "Multiscale Analysis of Littoral Warfare," CNO Strategic Studies Technical Paper, 2002.

[8] The concept of multi-scale representation has direct application to military command and control problems. For a short definition of this concept, see http://www.necsi.org/guide/concepts/multiscale.html, accessed 30 March 2004.

[9] David H. Wolpert and William G. Macready, "No Free Lunches For Search," Santa Fe Institute Working Paper 95-02-010, http://www.santafe.edu/sfi/publications/wpabstract/199502010, accessed 30 March 2004.

[10] Cares and Lewandowski, Sense and Respond Logistics: Turning Supply Chains into Demand Networks.

[11] The case for treating military systems as open systems is made by the Deputy Director, J8 (Wargaming, Simulation & Analysis), The Joint Staff, Vincent P. Roske, Jr., in "Opening Up Military Analysis: Exploring Beyond The Boundaries," *Phalanx,* (Online) June 2002, Volume 35, Number 2, http://www.mors.org/publications/phalanx/jun02/lead.htm, accessed 30 March 2004.

[12] W.Ross Ashby, *Introduction to Cybernetics, Part II, Variety,* (Chapman & Hall, Ltd., New York, 1957).

[13] http://artsci-ccwin.concordia.ca/edtech/ETEC606/principles/law.html, accessed 30 March 2004 has a discussion of the Law of Requisite Variety and some useful links.

[14] Jeffrey R. Cares, Raymond J. Christian, and Robert C. Manke, *Fundamentals of Distributed, Networked Military Forces and the Engineering of Distributed Systems,* NUWC-NPT Technical Report 11,366, 9 May 2002, NUWC Division Newport, 1.

[15] This thesis is explored in Robert Axelrod, *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration,* (Princeton University Press, Princeton, NJ, 1997).

[16] True noise is the equivalent in military lexicon to classic Clausewitzian "fog and friction." See Barry D. Watts, *Clausewitzian Friction and Future War*, McNair Paper Number 52, October 1996 at http://www.ndu.edu/inss/macnair/mcnair52/m52cont.html, accessed 30 March 2004. Chapter 7, "The Inaccessibility of Critical Information," is particularly pertinent to control in complex systems.

[17] See Seth Lloyd, "Learning How to Control Complex Systems," *SFI Bulletin,* Spring 1995, at http://www.santafe.edu/sfi/publications/Bulletins/bulletin-spr95/10control.html, accessed 30 March 2004. Haeckel, Ch. 5, directly connects Lloyd's theory of control to sense and respond system.

[18] http://www.math.psu.edu/gunesch/entropy.html, accessed 30 March 2004, is a web portal containing a host of links to scientific web pages discussing the various uses of entropy.

[19] Claude E. Shannon, "A Mathematical Theory of Communication," *The Bell System Technical Journal,* Vol. 27, pp.379-423, 623-656, July, October 1948, is still the best reference for this concept.

[20] See Chaitin, *The Limits of Mathematics: A Course on Information Theory and the Limits of Formal Reasoning.*

[21] Both these cases are mathematically derived in W.H. Zurek, "Algorithmic Information Content, Church-Turing Thesis, Physical Entropy, and Maxwell's Demon," Zurek, ed., *Complexity, Entropy and the Physics of Information,* (Addison-Wesley Publishing Company, New York, 1991).

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[22] This occurrence has a mathematical equivalent in Gödel's Incompleteness Theorem. See Chaitin, *The Limits of Mathematics: A Course on Information Theory and the Limits of Formal Reasoning.*

[23] For a formal proof of this statement and a complete treatment of the concepts of randomness, sense-making and Information Theory, see Gregory J. Chaitin, *The Limits of Mathematics: A Course on Information Theory and the Limits of Formal Reasoning,* (Springer-Verlag, New York, 1998), *The Unknowable (Springer Series in Discrete Mathematics and Theoretical Computer Science,)* (Springer-Verlag, New York, 1999) and *Exploring Randomness (Discrete Mathematics and Theoretical Computer Science),* (Springer-Verlag, New York, 2001). For an application of these principles to distributed systems, see Jon Barwise and Jerry Seligman, *Information Flow: The Logic of Distributed Systems,* (Cambridge University Press, New York, 1997). For a discussion of how these concepts are applied to observation, cognition and decision, see Tor Nørretranders, *The User Illusion,* (Penguin Books, New York, 1998). Further exploration of the information content of physical systems is found in Wojciech Zurek, ed., *Complexity, Entropy and the Physics of Information,* (Addison-Wesley Publishing Company, New York, 1991).

[24] Seth Lloyd, "Learning How to Control Complex Systems".

[25] Juergen Jost, "External and Internal Complexity of Complex Adaptive Systems," Santa Fe Institute Working Paper 2003-12-070, http://www.santafe.edu/sfi/publications/wplist/2003, accessed 30 March 2004. Similar themes are explored in Feldman and Crutchfield, "Structural Information in Two-Dimensional Patterns: Entropy Convergence and Excess Entropy," Santa Fe Institute Working Paper 02-12-065, http://www.santafe.edu/sfi/publications/wplist/2002, accessed 30 March 2004; Fatihcan Atay and Juergen Jost, "On the Emergence of Complex Systems on the Basis of the Coordination of Complex Behaviors and their Elements," unpublished working paper, dtd. November 5, 2003; and Carlos Gershenson and Francis Heylighen, "How Can We Think the Complex," unpublished, undated.

[26] Jost, "External and Internal Complexity of Complex Adaptive Systems," 3-4.

[27] Jost, "External and Internal Complexity of Complex Adaptive Systems," 5.

[28] Ricard V. sole, et al., "Self-Organized Instability in Complex Ecosystems," *Phil. Trans. Royal Soc. Series B, Special Issue: The Biosphere as a Complex Adaptive System,* 2002.

[29] The following discussion is adapted from Manoj Gambhir, Stephen Guerin, Daniel Kunkle and Richard Harris, "Measures of Work in Artificial Life," and Stephen Guerin and Daniel Kunkle, "Emergence of Constraint in Self-Organizing Systems," white papers, http://www.refish.com, accessed 30 March 2004..

[30] Webster's New Universal Unabridged Dictionary, (Dorset and Baber, New York, 1983).

[31] Sidney Axinn, *A Moral Military,* (Philadelphia: Temple University Press, 1989), 168-169.

[32] Marcelino Quito, Jr., et al., "Memory and *a priori* Best Strategy in Complex Adaptive Systems," *Complexity,* Vol 9, No. 3., 41-45.

[33] A good tutorial on the value and proper use of multiple regression techniques can be found at http://www2.chass.ncsu.edu/garson/pa765/regress.htm#cases, accessed 30 March 2004.

[34] One of the underlying assumptions in multiple regression is linearity, which may not be an appropriate assumption for some types of adaptive systems. The statistical tools that perform multiple regression usually indicate if linearity is appropriate. More sophisticated tools can then be used to test for other types of independent-dependent variable relationships. Nonetheless, multiple regression is typically the best technique with which to start.