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Course of Action Analysis within an Effects-Based Operational Context

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Abstract

This article summarizes information related to the automated course of action (COA) development effort. The information contained in this document puts the COA effort into an operational perspective that addresses command and control theory, as well as touching on the military planning concept known as effects-based operations. The sections relating to the COA effort detail the rationale behind the functional models developed and identify technologies that could support the process functions. The functional models include a section related to adversarial modeling, which adds a dynamic to the COA process that is missing in current combat simulations. The information contained in this article lays the foundation for building a unique analytic capability.

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1.0 Introduction

Effects-based operations (EBO) is one of three operational process concepts used to transform a commander's intent into military actions. Military actions in this context include economic, psychological, informational, diplomatic, and combat activities. The automated course of action (COA) effort fits into the construct of EBO as a supporting technology. EBO provides a context for defining the fitness function requirements of the COA process. In this case, those requirements drive us toward complex adaptive systems analysis. The construct to be described is based on a state model that moves the systems in conflict from some initial state to a desired terminal state. The COA process is the process for identifying actions or effects that transition the systems through a set of intermediate states to the terminal state.

The other operational concepts include objectives-based operations and target-based operations. The literature explores the concept of effects-based operations at the operational level in an air combat context. What we learn from these articles is that effects-based operations can be identified in allied actions in support of the invasion of the European mainland. In particular, analyses can be found assessing the impact of the air operations intended to mitigate the support and/or re-supply of German forces by rail during and subsequent to the invasion. A very interesting thesis by Major Beagle explores the successes and failures of effects-based operational concepts in four major operations.

What is not discussed in the literature is the application of EBO at the strategic and tactical levels or its employment in land and sea operations. We will address those aspects and describe some of the rationale for developing the functionality of the COA process that will be described in subsequent sections.

1.1 Operational Concept Descriptions

Target-based operations (TBO) involve the identification and selection of adversarial assets and applying sufficient force to destroy those assets. Implicit in that statement is that the function associated with the target is destroyed and that reconstitution times are long compared to the strategic mission. Target-based operations have a long historical basis and are the most common of the operational concepts. The most comprehensive application for TBO is found in the domain of attrition-based warfare. Luttwak defines attrition-based warfare as "…warfare waged by industrial methods. The enemy is treated as a mere array of targets, and success is to be obtained by the cumulative effect of superior firepower and material strength, eventually to destroy the full inventory of enemy targets." TBO might be characterized as the most quantitative of the concepts from a perspective of our ability to assess success or failure of a combat action. With limited assets, TBO, while seemingly devoid of planning complexity, will incur some of the analytic burden associated with effects-based operations.

Objectives-based operations are a conceptualization of mission intent from which courses of action can be defined and from which measures of effectiveness may be derived. An interesting aspect of objectives-based approaches is the natural association with state space analysis. In determining an objective, we are naturally defining a terminal state of the adversary and ourselves. Objectives-based operations seem to be most applicable to the strategic and operational levels of military planning. The fractal nature of objectives-based operations does permit the methodology to be applied down to the tactical level. At the strategic and operational level, the methodology appears to assume a more qualitative characteristic, while at finer levels of aggregation, it takes on more quantitative aspects. At the lowest levels of aggregation, there appears to be an overlap of objectives-based and target-based approaches.

Effects-based operations on the other hand appear to fit the operational and tactical regimes, and provide a natural foundation for establishing and defining combat measures of effectiveness. A situation in which objectives-based and effects-based operations complement each other exists at the strategic level. Like objectives-based approaches, effects-based planning supports the notion of state space analysis in the planning cycle. What we find is that effects-based approaches naturally focus on the transitions between states rather than the static states of the systems supporting the conflict. It is for this reason that the objectives-based and effects-based approaches seem to support each other.

The literature seems to demonstrate a focus of EBO on air operations in high-intensity conflict situations. We hope to show by the end of this article that it equally supports land and sea operations in a broad spectrum of conflict. Asymmetric warfare planning appears to be the most demanding of operational planning environments and a natural fit for the employment of effects-based operational planning. In the sections that follow, a detailed examination of effects-based operations will be attempted and potential technologies will be proposed for addressing the core requirements of this operational concept.

1.2 Trends Impacting EBO

We need to examine some of the trends contributing to the new environment that military planners must contend with. The most significant change is the vision of military operations in the 21st century. JV2020 and net-centric warfare define the foundations and concepts of modern warfare. We see a vision in which massed effects replace massed force, in which rapid response and increased tempo are required to achieve the force multiplication ratio needed to compensate for smaller force sizes. We see a direction being pursued that requires greater reliance on sensors and the data they generate. With that trend comes a greater need for data fusion in our operational systems, and greater dependency of these systems for our forces' survival.

We see a diminishing capability to forward-deploy our forces, requiring us to deploy our forces from bases within our borders to areas of conflict. This presents a unique difficulty in providing the deployed force with sufficient material to operate and survive in the deployed theater. This is resulting in new systems with lighter armor, and new weapon systems with smaller rounds. These factors aid in the reduction of the logistics load but add significantly to the information gathering and processing requirements. Precision can compensate for the size and volumes of the rounds fired, but it makes bomb damage assessment (BDA) more difficult.

The types of conflict faced are also changing. We are likely to face far more humanitarian aid situations, policing operations, and situations such as those we are now facing in the Middle East. If we take population trends into consideration and surmise that future adversaries will not attack our strengths, we will be faced with the inference of combat in urban terrains. Urban environments in combat would have a complex mix of combatants and non-combatants. The concern for minimizing collateral damage requires the use of precision weapons and has resulted in the emergence and deployment of non-lethal and low-collateral-damage weapons. This is likely to be one of the most significant drivers for change in the operational planning methodology.

In the past, we have been able to use overriding force and a short “lever” to achieve military success. We now have less force and must begin to employ a longer lever to achieve these successes. Finding the right lever is a fundamental capability associated with effects-based operations.

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2.0 Analytic Environment

In this section, we endeavor to define the functional models associated with effects-based operations from a planning perspective. The model is based foundationally on state space theoretics, which provide a useful integration of objectives and effects-based operations.

The concept behind Figure 1 is the idea that we are trying to move a system from some initial state S_0 through a series of intermediate states to a final goal state S_n. The redundancy of states at state "S_i" is intended to demonstrate an uncertainty in achieving the desired intermediate state. This uncertainty has two basic components. The first contributor to the uncertainty of state "S_i" is due to the uncertainty in state S_{i-1}. Intelligence may not be able to uniquely identify all conditions defining that state. This also applies to characterizing state "S_i". Deception, sensor performance uncertainties, and the loss of intelligence gathering assets contribute to this uncertainty. The second contributor is due to the fundamental dynamics of the combat systems. The mathematics of combat exhibit the chaotic foundations of combat. The result is that small uncertainties in state characterizations can quickly result in significant deviations from planned state trajectories.

State transitions are triggered events; e.g., transition from "S_{i-1}" to "S_i" is brought about through triggering event T_{i-1}. The triggering events can be the effects being orchestrated in the operational planning phases. The goal might be to render an adversary incapable of supporting a force

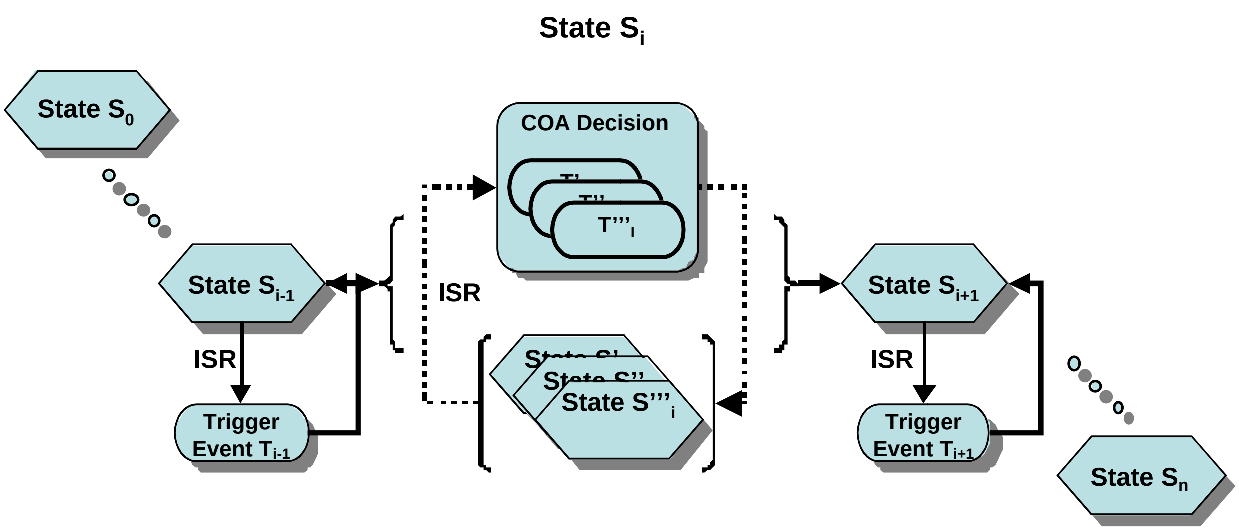

Figure 1. State space model from a command perspective.

that is to come under attack. The effect sought would be to force the adversary into employing slower routes of re-supply. Achieving this effect may be accomplished by disabling their rail system or suppressing their ability to use air re-supply assets. The core analysis associated with effects-based operations lies in the COA decision process identified in Figure 1.

2.1 Command and Control

The manner in which effects-based considerations contribute to the planning process is a function of the command and control paradigm being employed. In Figure 1, we see evidence of a command system that may be representative of future command systems. If we replace the state "S_i" functionality with a simple state and triggering event, as in the neighboring states, we have a command by plan concept. Command by plan can be characterized as developing a combat course of action with a few contingencies that may be executed should conditions warrant them. Once the plan is initiated, there is very little control of the system; it must run its course. In this model of command, effects-based considerations will be employed during the initial planning phase of an operation. Advantages of EBO are limited to the operational levels of planning. Actions may be initiated at state S_j that will produce effects at state S_k, the implication being the level of effort required to produce the effect is significantly less if applied at S_i than waiting until S_k.

The literature contains a great deal of discussion about the JV2020 vision and the implications to command theory. The discussions are, however, very qualitative and do not identify the characteristics or mechanics of "command by influence." This is the command concept that can take advantage of the promises alluded to in JV2020. Interesting studies are being conducted here and in Australia that explore the ideas associated with nonlinear and chaotic control systems. I think they may provide a foundation for exploration into command by influence. Figure 1 will provide a reference basis for the discussion that follows.

Glass (1997) presents a control system that is very similar to the model in Figure 1. In this situation, a system is defined that obeys the following relationship:

$$x_{n+1} = f(x_n, p_n) \tag{1}$$

In this representation, the perturbations p_n are equivalent to the triggering events in Figure 1. The idea is to identify the starting state x_s and the terminal set T, which consists of one or more terminal states, and to define sets of perturbations that can be applied to the system at each system state to drive the system to a terminal state.

$$\begin{aligned} S_1 &= \{ f(x,p) : p \in P \} \\ S_n &= \{ f(x,p) : x \in S_{n-1}, p \in P \} \end{aligned} \tag{2}$$

In an unperturbed system, the nominal values of the perturbations can be applied at each point. The unique feature of this control strategy is that there is significantly greater control of the system during operations. It is this control during operations that permits effects-based considerations to be incorporated into the tactical level of combat planning.

A second control approach for chaotic systems involves efforts by Paskota (1997), who breaks the problem into two distinct parts, the targeting component and the feedback correction component. This process might involve the planning of operations prior to an action, with adjustments to ensure that the operation follows the trajectory defined in the target or planning process. Based on a dynamic model of the form given in Equation 3, we can define an optimal control that transitions the system from an initial state to a desired terminal state.

$$
\begin{aligned}
x_{n+1} &= f(x_n) + u_n \\
u^* &= \left\{u_0^*, u_1^*, \cdots, u_{n-1}^*\right\}
\end{aligned}
\tag{3}
$$

u* is the optimal control vector, which results in a state trajectory as defined in the next expression.

$$
x^r = \left\{x_1^r, x_2^r, \cdots, x_n^r\right\} \tag{4}
$$

The interesting aspect of this hybrid model is the feedback correction component. This feature permits a level of control during the execution of an operation and is a natural point for integrating effects-based considerations into the problem. The feedback correction is accomplished as follows:

$$
u_k = u_k^* + K_k(x_k - x_k^r) \tag{5}
$$

In one model, sets of predefined points in the state trajectory were selected for assessment and correction. In Figure 1, we might say that a selected point was state S_i, at which point detailed intelligence was collected and compared to the expected state of the system. Deviations from the expected state resulted in slight changes in the tactics in order to steer the system back onto the trajectory defined in the target or pre-planning process. This is a starting point for studies of command by influence and provides an effective integration point for effects-based considerations.

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3.0 Automated COA

In this section, we explore the foundations of an automated course of action algorithm that can be used as an aid by command authorities tasked with developing operational plans. The description begins with a bit of rationale for the approach and then explores the functional models in some level of detail.

3.1 Background Considerations

The development of an automated course of action algorithm necessitated a look into a building-block approach to assembling the COAs. Two approaches were possible. The first involved the identification of sets of combat kernels that could be assembled into a plan. The second approach involved using statistical representations for all of the combat functions, and the distribution parameters of the assembled components would be defined automatically. Both approaches could take advantage of evolutionary computational technologies. The assembly of sets of combat kernels could be accomplished by using genetic programming technologies, while the use of statistical representation of the functions could use evolutionary strategies as the fundamental analytic assembly technology.

While exploring the different approaches, it was decided that both had a role in the process at different levels of organizational planning. At the tactical level, defining all combat functions and combat elements by statistical distributions permitted the use of evolutionary strategies as the prime optimization technology. This permits significant flexibility and speed in defining the tactical operations necessary to transition the systems from state to state. At the operational level, the kernel approach made more senses, since this would be the principle interface to the mission commanders.

3.2 Functional Models

The approach proposed defined a set of functional models for COA development at an operational and at a tactical level. The construct is based on the state space representation of the systems, and tactical level actions provided the transition mechanisms at the operational level.

Figure 2 captures the essential elements of the COA process. The “core function” in the figure is a representation of the tactical level COA process. At the tactical level, the process involves identifying sequences of operations that will transition the system from the initial state to some desired terminal state. The mechanics of the process is similar to a genetic algorithm in which solutions are proposed and assessed against some fitness function, and modifications are made in order to determine a better solution.

The functional model incorporates adversarial modeling, tactical modeling, and the processes of converting a commander's intent into operational objectives and the

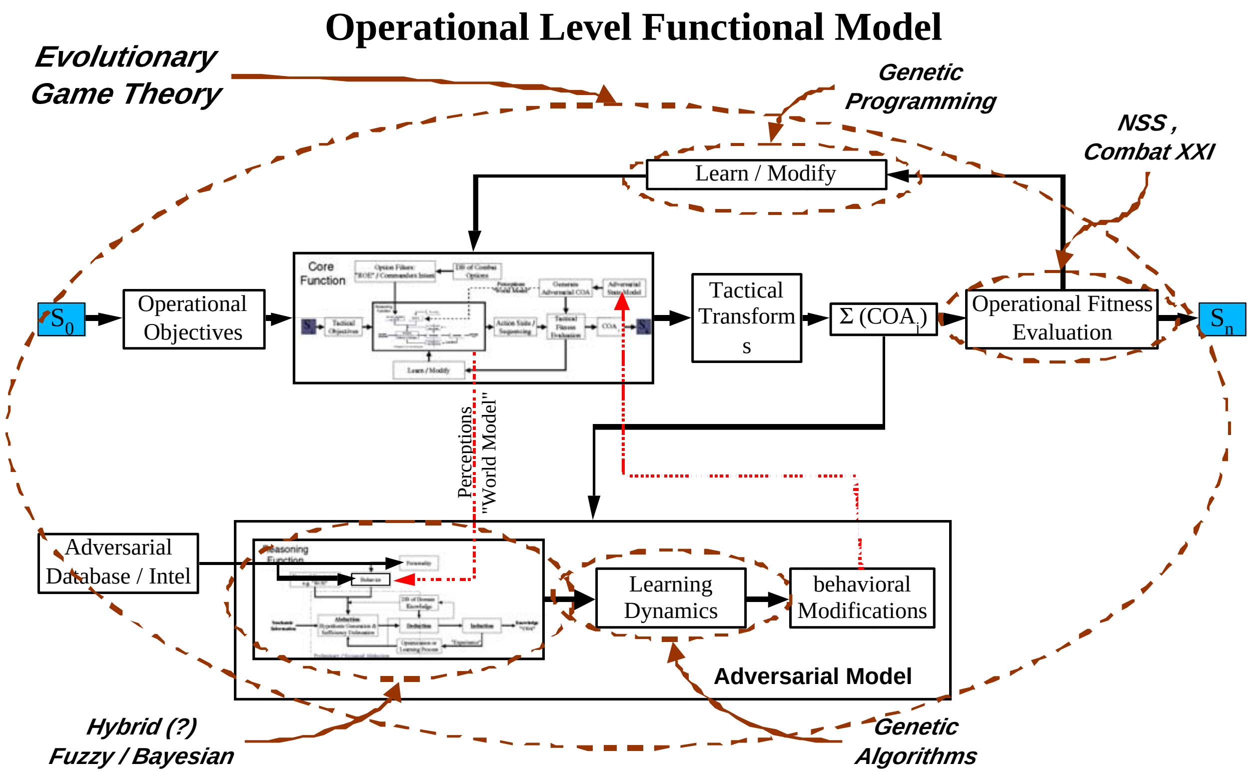

Figure 2. **Operational level functional model of the COA process.**

tactical operators into assemblages of combat kernels for use in operational-level simulations. The fitness functions at this level are based on existing combat simulations such as Naval Simulation System (NSS), the Joint Conflict and Tactical Simulation (JCATS), or any of the many other algorithms. The feedback loop is the mechanism for finding the optimal solution and finds its basis in evolutionary computational technologies and/or control theory.

The orange ellipses in Figure 2 provide first order estimates for the technologies that might be employed to realize the function circled. Many of the functions are believed to be tractable by the newer generation analytic technologies, such as fuzzy logic, Bayesian networks, genetic programming, etc. An interesting aspect of the total problem is the semblance of these combat functional models to evolutionary game theory.

The important aspects of the model from an effects-based perspective are the "adversarial model" and the "operational fitness evaluation" sub-functions. Within these functions, detailed system analyses are possible that can support effects-based operations. Detailed knowledge of the systems being attacked and the interactions of the different systems are critically important to being able to predict the response of an adversary.

Figure 3 provides a detailed look at the tactical level COA process. The basic functional structure is very similar to the operational level with the exception of a greater level of constraint structuring in order to capture aspects of "rules of engagement" and available combat options. The mathematical objectives at this level are to define tactical operations that will result in the system state transition at the operational level. The other major difference is the use of statistical representations in the fitness functions.

3.3 Statistical Fitness Functions

The MORS Military OR Analyst Handbook provides a number of models for use in statistically based combat simulations. The handbook defines statistical models for terrain that demonstrate a range of applicability from gravel and boulders to mountain ranges of massive scale. The model is represented by the following set of equations.

$$f_k(x,y{:}s) = a(S)\cdot h_k \cdot \exp(-[\frac{1}{(s\rho_k)} Z^{0.5}]^{\sigma_k}) \quad (6)$$

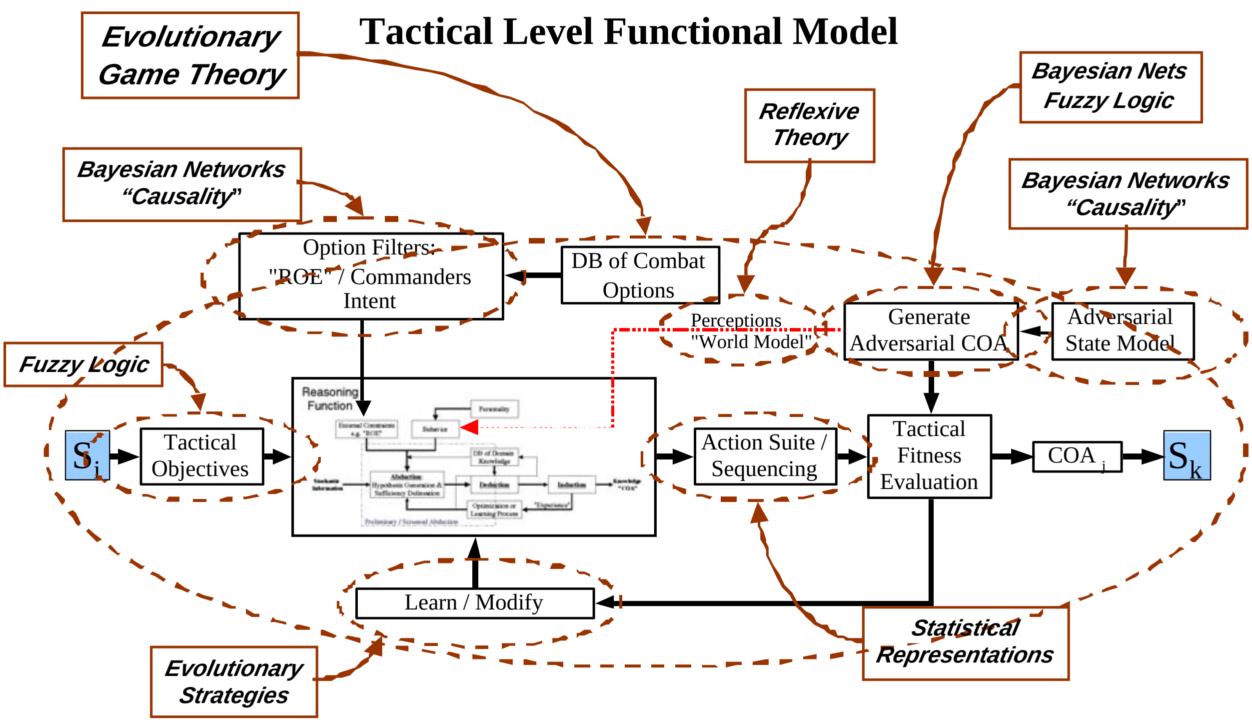

Figure 3. Tactical level functional model of the COA process.

$$Z = [\frac{(x-\varepsilon_k)^2}{\mu_k} + \frac{(y-\eta_k)^2}{\nu_k} + \alpha]$$

$$\alpha = 2\lambda_k \frac{(x-\varepsilon_k)}{\mu_k}\frac{(y-\eta_k)}{\nu_k} \quad (7)$$

$$a(s) = s = \frac{s_0}{(1-U)}$$

U is defined as a random number in the interval [0,1]. s_0 represents the minimum feature size of interest in the analyses that will use this representation. The remaining parameters (Greek symbols) represent statistical parameters defining each hill or mountain. The subscript is over the n features in the model. They are characteristic of a normal distribution. The exception is σ_k which is a parameter that represents the "flatness" of the hill crest, and λ_k which defines the orientation of the hill (value ranges from -1 to 1). With this representation for the terrain other parameters can be estimated based on the model, e.g., line-of-site metrics, mobility, etc.

Finally, the weapon systems that are to be played in this simulated terrain can also take advantage of statistical characterizations. This step is very natural since many of the performance characteristics are already defined in statistical terms; they fit into this construct without difficulty. Systems, including the biological component, can be defined with sets of data in the forms depicted in the next figures. The choice of distribution can represent a broad range of characteristics that can be used in the evolutionary models of the COA algorithms.

These fitness representations are useful because of the evolutionary strategies used as an optimization algorithm. One approach is to define the statistically defined parameters that will result in a successful encounter with an adversary. The algorithm,

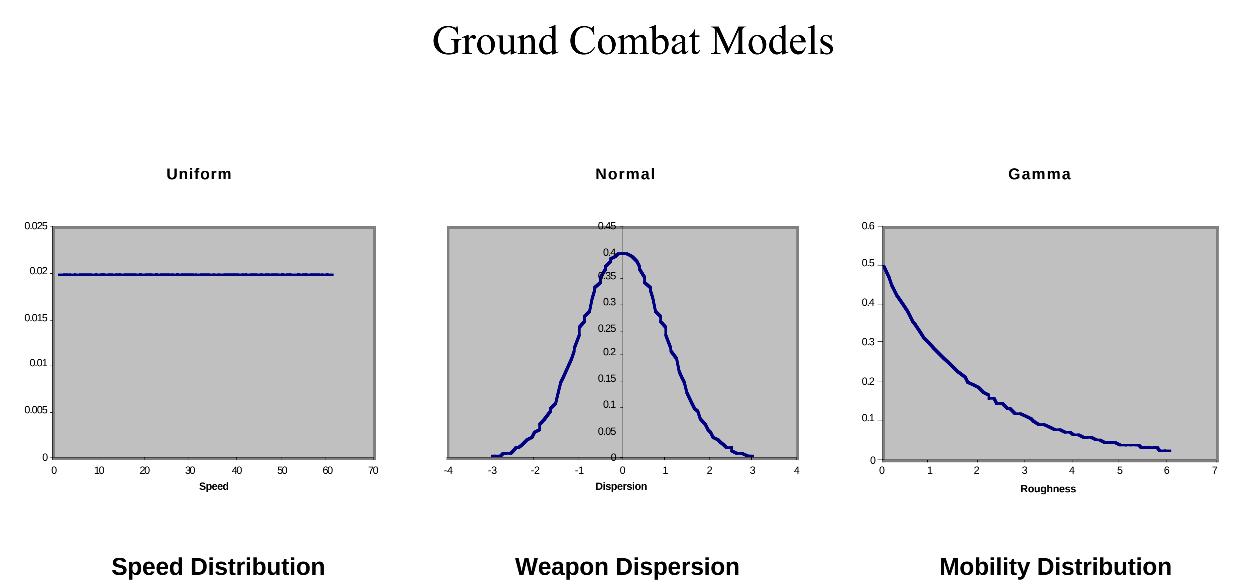

Figure 4. Statistical representations of weapon system characteristics.

which has been defined by Fogel (1995), is a model of evolution, but unlike genetic algorithms, which operate in integer space, this algorithm is defined to operate in real-number space. The evolutionary strategies methodology, which is a real variable equivalent to the discrete GA, will evolve the values for the parameters, as well as which system or tactic to employ and the timing of that application. Like the GA solution to a problem, a set of possible solutions (chromosomes) is generated and the set tested to determine the ranking of these solutions. A new generation is created based on the rankings determined for the parent set. A series of operators is applied to this descendant solution set, which becomes the basis for the next step in the fitness analysis.

The chromosomes in an evolutionary strategy differ from a GA chromosome in that it carries a “strategy” parameter along with the level for a variable. The form of this population of chromosomes is defined below.

$$\begin{aligned} \overline{P} &= (c_1, c_2, \cdots, c_n) \\ c_i &= (op, sp) \\ \overline{OP} &= (o_1, o_2, \cdots, o_m) \\ \overline{SP} &= (s_1, s_2, \cdots, s_m) \end{aligned} \tag{8}$$

c_i is a single chromosome representing a possible solution to the posed problem. The variable op is the level assumed for a variable, and sp is the strategy parameter. The search over the response surface is facilitated through the use of a series of operators, including mutation and crossover. The mutation operator behaves in a manner defined by the next expressions.

$$\begin{aligned} op_{mut} &= op + N_0(sp) \\ op_{mut} &= (o_1 + N_0(s_1), o_2 + N_0(s_2), \cdots, \\ &\quad o_m + N_0(s_m)) \end{aligned} \tag{9}$$

In this last expression, N_0 represents a draw from a zero mean normal distribution. The strategy parameters, s, can be viewed as the variance of the normal distributions. The process for mutating the strategy parameter is demonstrated in the next expression.

$$sp_{mut} = (s_1 \cdot A_1, s_2 \cdot A_2, \cdots, s_m \cdot A_m), \tag{10}$$

in which A_i is randomly chosen from α or $1/\alpha$ depending on the random variable E, which is drawn from a uniform distribution ~U[0,1].

$$\begin{aligned} A_i &= \alpha \quad if\ E < 0.5 \\ A_i &= \frac{1}{\alpha} \quad if\ E \geq 0.5 \end{aligned} \tag{11}$$

The literature recommends that α be set to 1.3 for 100 or fewer parameters in a problem, and set to a smaller value for greater numbers of parameters in a problem.

3.4 Adversarial models

Adversarial models are an important component in next generation warfare. Adversarial models provide a basis for assessing the impact of actions being taken against them, and they provide an analytical foundation for identifying optimal tactics for achieving combat objectives. As part of the course of action development effort, a series of very simple evolutionary game theory models were run in a effort to gain a quantifiable metric for the importance of dynamic adversarial models in the development of operational plans.

Evolutionary game theory is a variation of game theory in which games are repeated so the players can learn and adjust their behaviors in an effort to achieve a Nash equilibrium or an evolutionary stable strategy (ESS). Nash equilibrium and ESS are strategies selected or evolved by the players in which they can do no better with another strategy when playing against a player with an unknown strategy. The game model was designed to be a competitive game in which there are winners and losers. The game is based on the selection of 1 of 10 numbers that are used in the game. The ultimate strategy is to select a number that will maximize the offensive payoff and minimize the defender's payoff.

The baseline situation in Figure 3 involves both the offense and the defense learning in an isolated environment. Delayed learning refers to a situation in which the defender was prohibited from learning until 200 iterations into the simulation. The final two offensive and defensive plots show the effects on strategy selection in which the payoff was statistically determined and there was a cohort group for the principle player to share experience with. A cohort group, in this case composed of four information sharers, consists of players that can share knowledge of the game. The contour maps

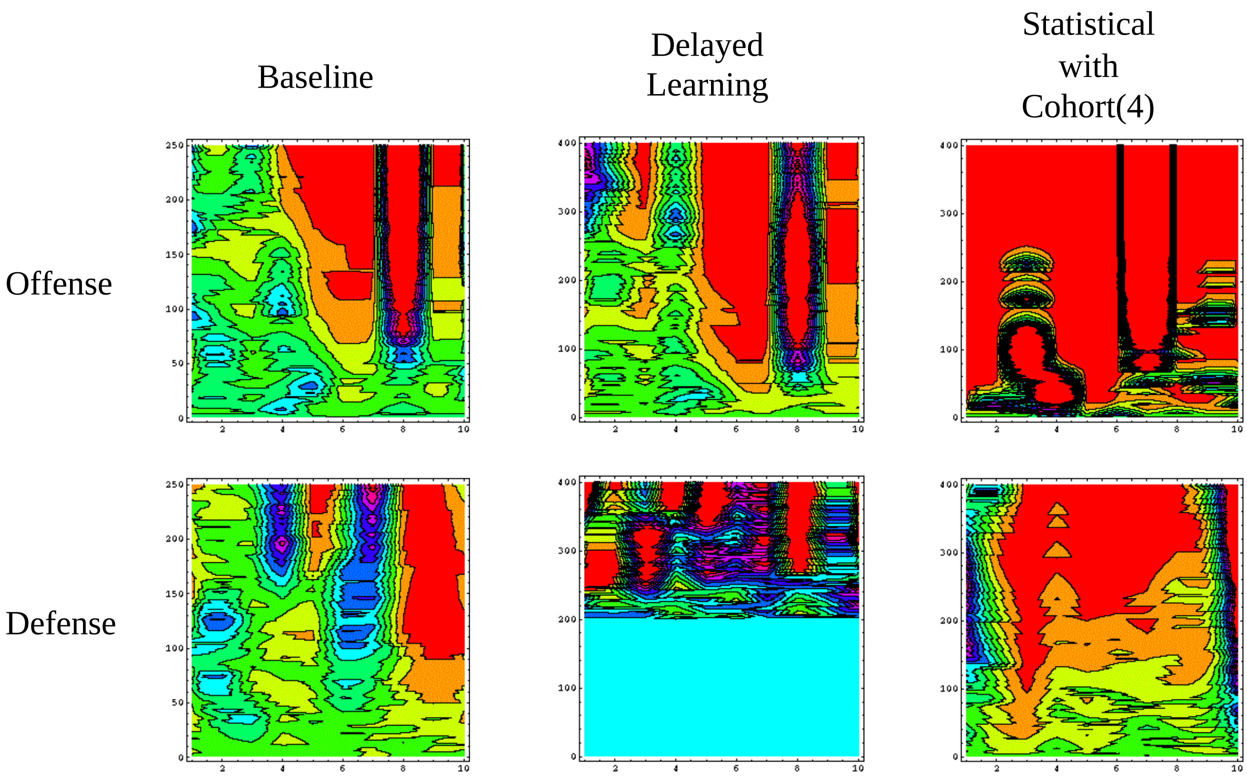

Figure 5. Evolution of strategies under varying scenarios.

reflect the probability of the agent selecting one of the 10 strategies available, red indicating the highest (and regrettably the lowest) probability values. The key observation is the change in ultimate strategy when both sides are allowed to learn. In the delayed learning case, the offense is rapidly evolving to strategy 8 until defensive learning is allowed, and we begin to see a shift toward strategy 1 and 4 with a decrease in strategy 8.

3.5 Cognition-Based Decision Making

The need to consider adversarial models in combat mission analysis is evidenced by the simple game theory analyses and by the fact that in some aspects of effects-based operations the metric may reflect an adversarial "state of mind." In order to begin to address the second requirement, we need to be able to capture the mind-set of the adversary. Mind-set also plays into the evolution of an adversary's choice of tactics. Some work in human cognition has led to a representation of cognition that is based on C. S. Peirce's philosophies.

This model is a basic Peircean model of cognition with two minor modifications. The model captures the three principle components of cognition: abduction, deduction, and induction. The output of this model is knowledge or courses of action (COA). This is a result of the model becoming an integral part of a combat simulation system to augment command decision-making. As we have indicated, abduction provides the mechanism for generating potential theories or hypotheses to solve a problem. A refinement of the abduction process is to include a second-level cognitive analogical process. Analogics involves the search for solutions through a process of analogy; e.g., early atomic models resembled planetary models;

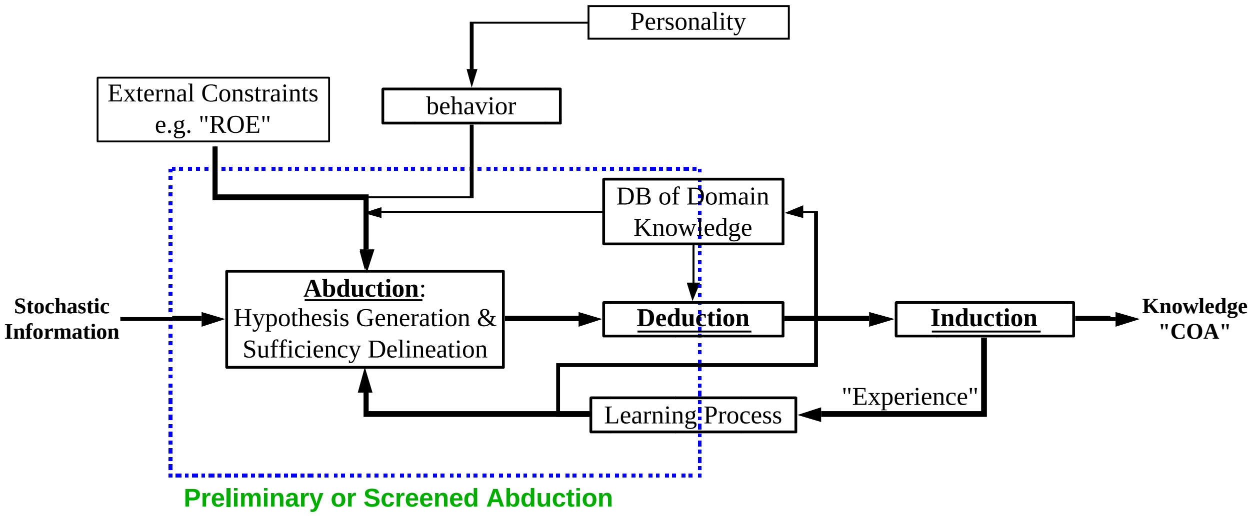

Figure 6. Hybrid cognition model based on Peirce's model of scientific inquiry and Nozawa's cognitive interrpretation.

therefore, atomic forces were postulated to obey a similar inverse square law. In this model, analogics is an internal function associated with the abduction function; it is a specialized form of abduction.

The deductive process is potentially the most understood part of the cognition model. Deduction is the process everyone schooled in mathematics understands. It is a process of demonstrating the connections between premises and conclusions. It can be considered the application of a specific rule to a single case. Significant levels of effort have been expended in this area. Pattern recognition is a heavily researched form of deduction.

The final component of the model is the induction process. Induction draws a general conclusion or hypothesis from a sampling of cases. There are a number of interesting research efforts in this area, as well as work into the foundations of induction and its relationship to the scientific method. D. Mayo's work in this area is an excellent example. Unique to Peirce's model of cognition is the update or correction mechanism, which is represented by the lower feedback loop in Figure 6. Induction provides a mechanism for validating a hypothesis to a problem, as well as providing the foundation for learning by the system.

It is the abductive process coupled to the deductive and inductive processes that provides a mechanism for solving problems that have not been pre-experienced. The solution has opened the door to a large number of possibilities and technology questions that could ultimately impact information technologies and the decision sciences.

The main divergence from a pure Peircean model involves the inclusion of behavior and personality into the process. This inclusion begins to integrate cognition dynamics into the total cognition modeling process and allows for the inclusion of the soft factors that influence decision making. These features are based on the theories of Lefebvre and Apter. The mechanism can be viewed crudely as a sliding, filtering mechanism to the abduction process. A despot may consider the use of children as low-tech mine detectors while a western civilized leadership would not consider that as a potential solution to detecting mines.

Implementation of an adversarial model within the COA construct can be accomplished through the application of a number of technologies. One approach is to develop a database of fuzzy logic rules that capture the behavior of the commander, e.g., rules of the form:

IF choke-point AND elevated_site THEN locate_squad_weapon

The variables "choke_point" and "elevated_site" are fuzzy conditions that, if satisfied to a critical level, will result in the consequent condition being set up. Fuzzy logic provides a mechanism for capturing the behavior of an adversary or differences in an adversary and folding them into a dynamic combat scenario. The flexibility of fuzzy rule bases involves the unlimited expansion capability, the ability to respond to conflicting rules, and the order independence of the rule sets.

A second technology that could be used is based on Bayesian networks. In this case, the network would be used to capture enemy doctrine, such as ambush tactics, and evidence concerning the suitability of a location as an ambush site would be entered into the network. The resultant tactical option distribution would provide the basis for placement of weapons or choice of tactics, again using simple draws from a uniform distribution.

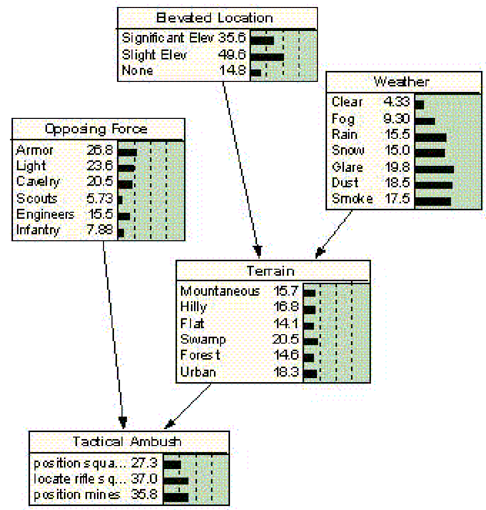

Figure 7. Simple demonstration Bayesian network.

While the example in Figure 7 was developed using random data, we can see from this example that by adding pieces of evidentiary data we will modify the distribution associated with the variable "Tactical Ambush." The final distribution based on the evidence can provide the discrete distribution of likely tactical situations faced by the friendly force. Performing random draws from the resultant information adds robustness to the analytical results generated in the analysis.

4.0 Mathematics of EBO

Up until now, we have established the environment in which effects-based operations need to be considered. The key aspect is in the "fitness" evaluations during the course of action development phase. The fundamental requirement for doing effects-based planning is the ability to capture and represent adversarial systems in the planning process. The difficulty becomes determining what may constitute a complete representation of those systems. A second difficulty is the fact that these systems are nonlinear and complex. Mathematical models would take the form given below.

$$\begin{aligned} \dot{x}_1 &= f_1(x_1, x_2, \cdots, x_n) \\ &\vdots \\ \dot{x}_n &= f_n(x_1, x_2, \cdots, x_n) \end{aligned} \tag{12}$$

The various independent variables include economic parameters, transportation capabilities, production levels, money supplies, factors associated with the political system, social and societal metrics, the state of mind of the leadership, etc. Along with these considerations is a comparable set of military factors associated with the military system, the deployment of forces and reserves, estimates of the enemy courses of action, capabilities including morale, training, and fighting ability, status of the weapons, weapons stores, etc. The key to effects-based planning is the ability to predict the response of an adversary given a set of actions.

The models alluded to in Equation 6 are a macro representation of the systems. These macro models are representative of sets of descriptions rewritten in the form of sets of first-order differential equations. The factor being studied is the observed behavior of a composite of discrete entities associated with the economic system, or the production and transportation systems, or the military systems. The systems describe complex adaptive systems in which we are assessing the macro aspects of these systems, not the low-level entity behaviors.

There are advantages to working with these macro descriptions. In particular, we have the ability to use the nonlinearities to our advantage. Earlier we indicated that we need to find a new lever in combat planning and analysis. It is the nonlinear sciences that can provide a mechanism for identifying those levers. Chaotic systems provide two interesting features that can play a significant role in effects-based planning. One feature involves the attractors, which are characteristics of the set of system equations. Attractors are points in phase space that a system will either avoid or gravitate towards. Identification of these attractors then permits the analyst to find an optimal trajectory that will result in the system transitioning to a terminal state that may be near the attractor. Having discovered the optimal trajectory, it becomes a "simple" process of assessing the current system state with respect to the chosen trajectory and devising small adjustments to maintain the track along the desired trajectory.

The other characteristic of chaotic systems is that phase space trajectories can diverge significantly with small changes in initial conditions. Two trajectories in phase space that differ by a small amount δ will diverge based on the following rule.

$$\|\delta(t)\| \approx \|\delta(0)\| \cdot \exp(\lambda \cdot t) \tag{13}$$

The parameter λ in the expression is the Liapunov exponent and is a characteristic of the set of system equations. This feature permits us to create effects with minimal application of force. With the trends toward small-yield, high-precision weapons and long logistics tails, the massing of effects becomes the rule instead of the massing of force. In this case, we would identify an indirect effect that would, over a period of time, create the desired effect. For example, knowing that an adversary's power system is operating at near capacity would permit the attack of a small switching station, which will force a chained overload in the distributions circuits, which would trip circuits until the power being used by a shipping lock might fail or a communications center might fail. Instead of destroying the lock or the communications center, we have achieved the same result with the application of a small force that gets magnified over time. A key is understanding the system infrastructure and the fact that it is being run at maximum capacity.

A second advantage of this characteristic of chaotic systems involves bomb damage assessment (BDA) or bomb damage indicator (BDI) analysis. With the employment of highly accurate, small-yield weapons, we are faced with a complex BDA problem. Normal visual assessments are not likely to be very conclusive. What we must do is identify indirect metrics that are indicative of the effect sought. The indirect indicator, like the indirect effect, will grow with time based on the same laws defined in Equation 7. The indicator of the intended effect will grow to a level consistent with the technology being used to assess the effect.

4.1 Complex Adaptive Systems (CAS)

In the previous section, we presented a set of systems equations that represents the dynamics of the adversarial systems. These expressions are the heuristics, or representations, of certain emergent or macro behavior of a complex adaptive system. The complex systems are basically the interactions of numerous simple interacting sub-systems or entities. For example, in an economic system the entities consist of production, consumer, transportation, banking, and trade entities. Each has a behavior that is characteristic of that entity and that interacts with other like entities and with dissimilar entities in the system. A complex adaptive system is a complex system in which the entities comprising that system can adjust their behavior as a result of externalities acting on the system. This is the model of a system that must be considered in effects-based operations. Combat must be viewed as a complex adaptive system consisting of many interacting autonomous and semi-autonomous entities that evolve over the course of an action. An essential characteristic of the study of complex adaptive systems is the fact that a reductionist approach to gaining an understanding is inadequate. The reductionist approach involves looking at the system in finer and finer detail in order to understand the behavior. In CAS, a collectivist approach must be taken. In this construct, in order to understand the system, it must be considered in total, as an open system that is driven by the nonlinear feedback between macro states and the behavior of the underlying entities.

Ilachinski defines eight characteristics of complex adaptive systems: 1) their behavior stems from a large collection of interacting components; 2) complex systems are typically organized hierarchically; 3) macro behavior is self-organized with decentralized control; 4) the macro behavior is emergent; 5) long-term behavior is typically non-equilibrium; 6) aspects of CAS are niches that need to be filled rather than are defined; 7) behavior cannot be described by reductionist methods; and 8) structure and dynamics are the characteristics of these systems as opposed to some equilibrium state.

In order to predict the behavior or the response of an adversary or one of his many systems, we need to look at these systems from the perspective of complex adaptive systems theory. It is via this mechanism that we are able to estimate the effects our actions are having on that adversary. If we rely on a representation at kick-off, we fail to capture the adaptation that will naturally occur. We may decide to eliminate a communications switching station in order to mitigate the effectiveness of their control systems. The adversary may switch to cell phones retaining a high degree of capability. Using the differential expressions, we are likely to miss the change in communication behavior due to the actions taken, and improperly assess his communications capability.

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5.0 Practical Aspects of EBO

In this section, we explore some practical aspects of effects-based operations. The topics are few and do not cover all aspects that need to be covered but provide a starting point for instantiating this concept.

5.1 Tactical Level Considerations

As mentioned earlier, much of the literature explores effects-based operations from an operational perspective. This constraint needs to be relaxed in complex systems. We outlined a paradigm of command and control that is based on chaotic system control principles and identified an influence mechanism that could easily be viewed as a tactical level adjustment mechanism. This tactical level trajectory adjustment mechanism could employ effects-based concepts. The fundamental change that needs to occur in order for this to happen is that targets must be viewed as functions and the tactical actions being designed as actions to deny that function to an adversary. Taking this approach expands the options that are available to a commander. When employing non-lethal or low-collateral-damage weapon systems, you must view the target as a function. The down side of this approach is the fact that bomb damage assessment or bomb damage indicators become significantly more difficult to evaluate.

5.2 Precision Strike/ Engagement

A phenomenon being seen in weapons development is the move towards greater precision in strike capability. As our adversaries move into urban environments and begin focusing on asymmetric warfare, the need for precision continues to increase. This added precision provides combat tools for use in effects-based operations. With high precision, we can perform surgical strikes that mitigate the potential for unintended secondary effects. Unintended secondary effects may involve collateral damage in an urban environment that results in a populous that is averse to our presence, resulting in a significant will to resist or an active participation by civilians in the support of actions being taken by our enemy. A second benefit of this move toward highly accurate systems coupled to effects-based operations is the ability to reduce the weapons loads required to achieve mission success.

5.3 Bomb Damage Assessment and Indicators BDA/BDI

Comments earlier indicated that BDA will be far more difficult in EBO operations because of the indirect nature of the effects being sought and by the probability of smaller yield, highly accurate weapons being employed. An approach for conducting BDA or, more appropriately, bomb damage indicator analyses, BDI, is through statistical approaches. As part of the EBO planning process, damage indicators must be identified in conjunction with the effect being sought. This provides the intelligence gathering components of a force with guidance in the search for data that can indirectly determine the success or failure of the effects campaign being executed.

A statistical approach that may work in this class of BDI is one based on acceptance sampling. Acceptance sampling is a statistical process to assess the quality or capability of an underlying process to meet its functional requirements, usually a production process. In a production process, we have product coming off of a production line; the sample testing involves pulling units and making measurements against criteria established as part of the process design. Measurements determine the acceptability of the lot associated with the sample tests being conducted. Within this sampling regime, two types of testing can be found, variables testing and attributes testing. In attributes testing, a set of measurements is taken against a predefined metric. If a sufficient number of these measurements deviates from the accepted value, the lot is rejected. Variables testing is a bit more sophisticated. In this case, measurements are taken and a sample mean and standard deviation are estimated. The sample means are compared to an expected population mean, and statistical tests determine whether the sample belongs to the population mean. If they are from separate distributions, the lots are rejected.

Significant levels of theory and experience have gone into the development of this kind of testing methodology. The question is, the applicability to of these techniques to the problem of BDA. The first issue involves the transformation between physical product and the information product associated with BDI. If we view the acceptance sampling effort as a method for assessing the control or quality of the underlying process, we do have a similarity in mission. We are trying to assess the status of some function or process that we have decided to affect in our effects-based operational plans.

Another issue in applying this methodology is the identification of the variables that must be measured. Unlike the simple task in a production process, sophisticated systems analysis techniques and multi-spectral data fusion algorithms will have to be employed to information that will be collected for use in these sampling plans. The systems analysis requirements are associated with the fact that we will likely have to use secondary or indirect effects to assess the status of the primary function that we are trying to affect. The multi-spectral aspects are required to put sufficient confidence on the results to ensure we have achieved the desired results. Establishing high levels of confidence may be the most difficult part of the problem. A Hog driver told me "…unless I see a smoking hole in the ground, I would not fly anywhere near an ADA site that is a functional kill."

The "product" becomes an interesting problem for this approach. One approach might be to assume that product is a communications block for a specified time interval associated with the function being affected. We can then identify additional blocks of information to be collected and used in the "measurement" process. The model being suggested involves blocks of temporal information becoming the products associated with the process we are attempting to affect. The approach seems possible but requires the collection of information for a period of time, which may not be conducive to real-time retargeting. There may be modifications to the process, in which predefined numbers of "defects" would automatically lead us to conclude that we have not achieved the level of effect desired and retargeting must be conducted.

6.0 Conclusions

In this article, we have tried to put EBO into a process or system context in order to identify where and how effects-based planning would occur in combat mission planning and analysis. We have also tried to show how the changes occurring in military doctrine will impact command and control theory and the course of action development process. The final point that we need to understand is that the tool needed to perform the detailed systems analysis that will be required to enable EBO in military planning is complex adaptive systems analysis. The level of analysis and intelligence collection during the intelligence preparation of the battlefield (IPB) will be significant in order to minimize the uncertainty in initial system conditions and will continue during operations to support the concepts of command by influence and the tactical adjustments needed. The COA process that was developed as the core effort of this LDRD project provides the functional basis needed to develop an automated capability for use in next-generation combat planning tools and decision aids.

The two appendices that follow are briefings prepared in association with this research effort. The first briefing contains information that is systemic to the automated COA process and was briefed at the Naval Post Graduate School as well as the American Institute of Aeronautics and Astronautics (AIAA) Command and Control working group. Portions of this briefing were presented to SPAWAR in an effort to identify areas of common interest. A result of the SPAWAR interactions resulted in a small demonstration effort that focused on a technology that supports the COA process as envisioned in this work. The focus involved using Taguchi techniques in a sensitivity study to demonstrate the advantages of this technology as an alternative controller. The utility of Taguchi or design of experiment techniques as an alternative fitness evaluation mechanism and as a demonstration of a crude form of statistical induction was demonstrated in this short study. The briefing of these results is captured in appendix B.

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Appendix A. DoD Briefing of the COA Functional Model

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Slide 1

Systems Analysis & Simulation

DoD Related Analysis Issues

August, 2001
Michael Senglaub, Ph.D.

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Slide 2

Automated COA Development

- Efforts
  - Foundation efforts
  - Collaborative efforts
  - Development
- COA Status
  - Functional Models
  - Evolutionary Game Theory Construct
  - Cognition
    - LDRD
    - JFCOM “Predicting Intentions”

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Slide 1

DoD Related Briefing Topics

- Automated COA Development
  - State Space Representations
  - Chaotic Control Theoretics
  - Functional models
    - Operational Level
    - Tactical Level
  - Evolutionary Game Theory
  - Cognition / Reasoning
    - Peircean Logic and Theory of “Sign”
- Analytic Technology “Toolbox”

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Slide 4

Analytics with a DoD Emphasis

- Analytic Technology “Toolbox”
  - Taguchi Analyses (Sensitivity Methodology)
  - Bayesian Representations (BN)
  - Fuzzy Logic
  - Genetic Algorithms / Programming
  - Evolutionary Strategies (ES)
  - Neural Nets

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Slide 5

Automated COA Introduction

- The MDMP is being rendered more complex
  - Dramatic increases in data / information
    - While demanding:
      - ✓ Increases in tempo
      - ✓ Increases precision / strike
      - ✓ Increases in maneuver capability
  - Greater sensitivities to the non-linearities of combat
    - Requires greater functional area coupling
  - Shifts from "attrition" based to "effects" based targeting
    - Requires detailed "understanding" of an adversary's system

Greater demand for analysis and less time to do it

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Automated COA Objectives

- Objectives:
  - Identify a functional solution to automating the COA process
  - Identify and verify the applicability of specific evolutionary technologies to solving aspects of the COA process
  - Develop an approach that avoids static adversarial strategies
  - Develop an approach that can recognize, and identify solutions to novel problems with varying degrees of uncertainty

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Automated COA Considerations

- State Representations
  - Initial state (All forces)
  - Terminal state of the adversary
  - Operational efforts proceed through many states
  - Tactical represents the transformation between states
  - Non-linear / Chaotic Control (C^2)
    - “Command by Influence”
- Modern Analytic Technologies
  - Modify combat representations
  - Identify combat “kernels”
- Multi-Player, Non-Static adversary
  - Coalitions are becoming the “norm”
  - Predict the behavior / response of an adversary

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State Representation & Analysis

Linear State Equation

$$\dot{z} = Az + B \Rightarrow x_i \approx z_i + {}^{b_i}\!/_{a_i} \Rightarrow \dot{x} = Ax$$

Non Linear State Equation

$$\dot{x} = f(x)$$

Jacobian

$$J = \left. \begin{pmatrix} \partial f_1/\partial x_1 & \partial f_1/\partial x_2 & \cdots \\ \partial f_2/\partial x_1 & \partial f_2/\partial x_2 & \\ \vdots & & \ddots \end{pmatrix} \right|_{x = x_0}$$

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Control of Non-Linear Systems

Targeting Set Control (P-chains)

Ref. "Creating and Targeting Periodic Orbits", Glass et.al.

$$x_{n+1} = f(x_n, p_n)$$

$$i.c. \rightarrow x_s$$

$$S_1 = \{ f(x_s : p \in P \}$$

$$S_n = \{ f(x,p) : x \in S_{n-1} \;\&\; p \in P \}$$

- **Identify the initial state and a set of terminal states**
- **Find a set of perturbations "p_n" that will transform the system into the terminal set.**

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Control of Non-Linear Systems (2)

Hybrid Non-Linear Control

Ref. "combined Controls for Noisy Chaotic Sysstems", Paskota et.al.

$$x_1(k+1) = f_1(x(k)) + u(k)$$

$$x_i(k+1) = f_i(x(k)), i = 2,3,\ldots n$$

Target Control

$$u^* = \left\{ u^*(0), u^*(1), u^*(2), \ldots u^*(N-1) \right\}$$

$$\Rightarrow x^r = \left\{ x^r(0), x^r(1), x^r(2), \ldots x^r(N), \right\}$$

Feedback Control

$$u(k) = u^*(k) + K_k(x(k) - x^r(k))$$

"Command by Influence" ???

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Solution Proposal

- Operational level plans consist of state trajectories comprised of an integrated set of tactics
- The promise of the information age is the ability to gather and process massive amounts of information
  - Enabling new models of command
  - Implicit understanding of an adversary
  - Dynamic understanding of adversarial systems
    - Infrastructure and economic as well as combat
- Decoupling of temporal feedback
  - Permits a different analytical construct
    - Greater functional coupling at a tactical transformation level

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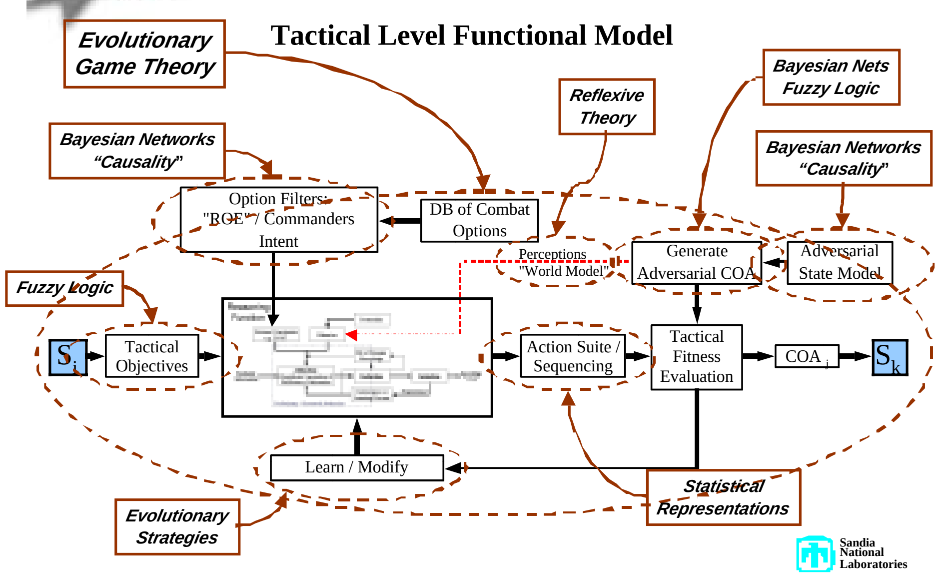
COA - Tactical Level

Tactical Level Functional Model



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COA - Tactical Level

- Tactical level operations
  - Transitions system state
  - Reflect ROE and Commanders Intent
  - Can be defined statistically
    - Provide opportunity for using "evolutionary strategies" (ES) in the optimization process
  - Permit feedback with adversary
    - Non-static models of an adversary
  - Provide a mechanism for chaotic control
    - Identification of measurable "peg" points in state transitions

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Statistical Representations

Terrain Model

$$f_k(x,y:s)=a(s)h_k\cdot\exp\left(-\left(\frac{1}{(s\rho_k)}[Z]^{1/2}\right)^{\sigma_k}\right)$$

$$Z=\left[\frac{(x-\epsilon_k)}{\mu_k}\right]^2+2\lambda_k\frac{((x-\epsilon_k)(y-\eta_k))}{(\mu_k\nu_k)}+\left[\frac{(y-\eta_k)}{\nu_k}\right]^2$$

$$a(s)=s-\frac{s_0}{(1-U)}$$

Ref. Military OR Analyst's Handbook

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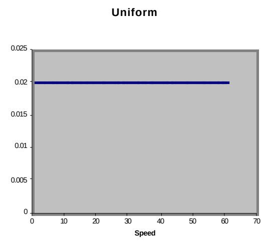
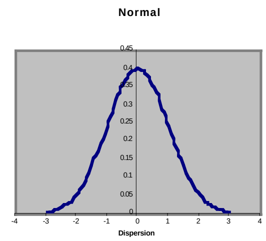
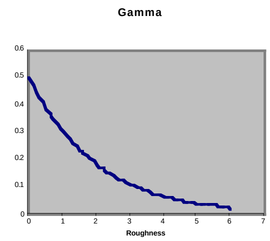
Statistical Representations

Ground Combat Models







Speed Distribution **Weapon Dispersion** **Mobility Distribution**

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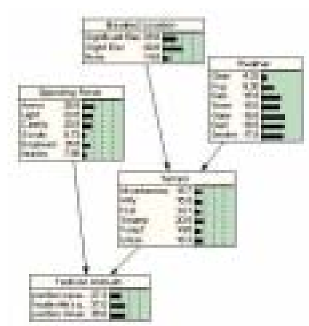
Tactical Decision Methodologies

Fuzzy Logic

IF infantry AND slight_elevation THEN locate_rifle_team

Fuzzy Variables:
Opposing_force
Terrain
Tactical_ambush
Fuzzy Levels:
Infantry
Slight_elevation
Locate_rifle_team

Bayesian Networks



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COA - Operational Level

- Greater emphasis on information for use in command decision making
  - Implications are a fitness functions that are readily interpretable.
    - NSS, WARSIM, JCATS, etc.
- Complex integration of adversarial behavior
  - How does he/she respond to friendly actions?
  - What drives those responses?
    - Culture, politics, psychology, physiology

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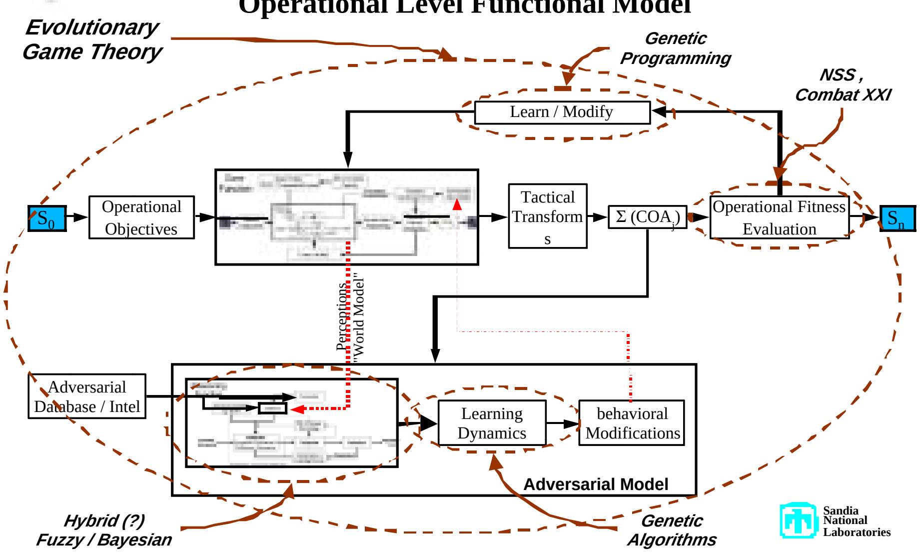
COA - Operational Level

Operational Level Functional Model



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Cognition / Reasoning

- Objectives:
  - Identify Cognition Models
    - Support Decision Making
    - Capture Adversarial Intent
    - Reasoning on problems previously unseen
  - Explore the Role of Formal Logics
    - Knowledge validation & consistency checks
  - Explore Knowledge Capture
    - Move away from Dyadic logics
  - Integration of Sociology & Psychology
    - Cultural Influences on Decision Making
    - Psychological Influences
  - Explore the Dynamics of Cognition

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Human Cognition

- Reasoning Model (Peirce)
  - Model of scientific inquiry
    - Technical systems engineering model defined in MIL-STD499A
  - Abduction (Analogic), Deduction, Induction
  - Peirce's "semeiotic"
    - Grammar
      - ✓ The study of what must be true for signs
    - Critical Logic
      - ✓ The study of the conditions of the proper use of signs
    - Formal Rhetoric
      - ✓ The study of the formal conditions under which signs can be communicated, developed, understood, and accepted

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Peirce’s Cognition Model

- Deduction
  - The argument which shows a necessary connection between premises and the conclusion
    - Logical deduction has its basis in mathematical reasoning
- Induction
  - Draws a rule from the results of sample cases
    - Three types: crude, quantitative, and qualitative
      - Crude: Denying an event because it seldom happens.
      - Quantitative: Arguments based on a random sample
      - Qualitative: Involves the verification or confirmation of a hypothesis
- Abduction
  - The formulation of hypotheses, the process by which we arrive at plausible explanations of unique events
  - Analogic
    - The formulation of hypotheses through analogy
      - E.g. planetary systems and atoms

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Peirce’s Description of Reasoning

Reasoning consists of the formulation of a hypothesis through abduction, from which a series of experiments are postulated using deductive techniques. The results are evidence in the inductive stage to verify or confirm the hypothesis.

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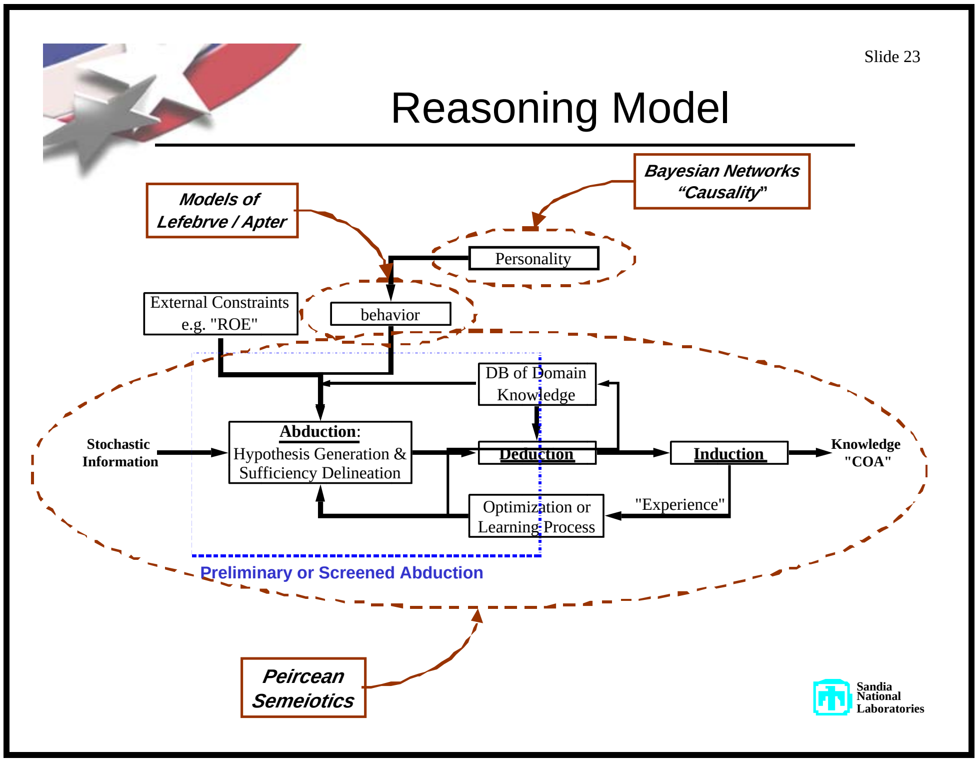

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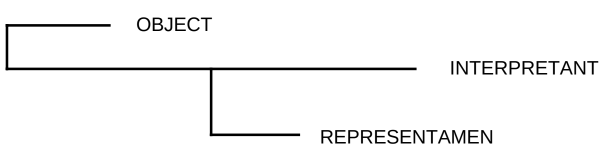
Semeiotic

- Peircean "Sign"
  - "A sign or representamen, is something which stands to somebody (the interpretant) for something (the object) in some respect of capacity."



TRIADIC SIGN

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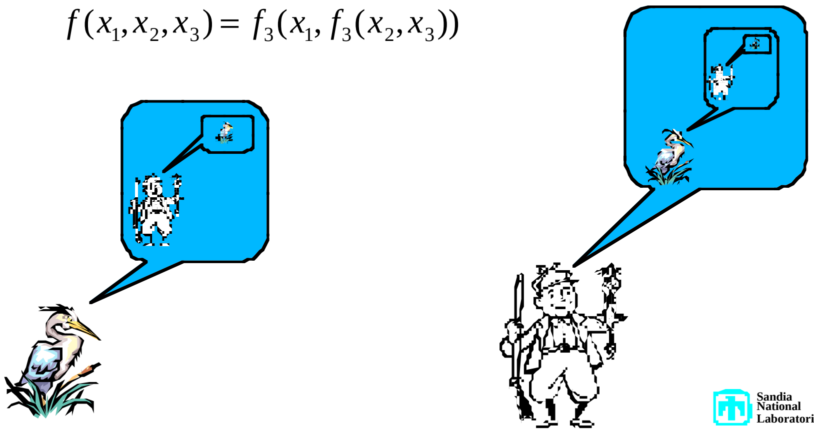
Reflexive Models (Lefebvre)

$$f(x_1,x_2,x_3) = x_1 + (1-x_1)(1-x_2)x_3$$
$$f_3(x,y) = 1 - y + x \cdot y$$
$$f(x_1,x_2,x_3) = f_3(x_1, f_3(x_2,x_3))$$



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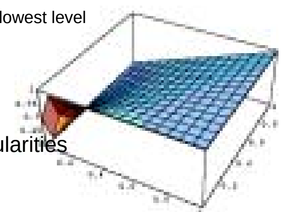
Reasoning Dynamics

- Chaos and human behavior
  - Feelings, Thoughts, Wishes (Lefebvre)
    - ✓ Feelings most important, then thoughts with wishes the lowest level of importance
    - ✓ Wishes subsumed results in the “realist model”
    - (0,1) define the poles of the variables
      - ✓ E.g. ("feel fear", "do not fell fear")
  - Indecision occurs in regions removed from the singularities
    - Reason ends up in a loop
      - ✓ Need something to force a change in (F,T,W) state
      - ✓ Explore a coupling of Bayesian Nets to this cognitive dynamic
- Provide foundations for building high fidelity adversarial decision models



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Evolutionary Game Theory (EGT)

- Evolutionary Game Theory
  - Game theoretic for repeated games
    - Allows players to modify their strategies
    - Dynamic vs. static games (Nash equilibrium)
  - Learning or replicator dynamics
    - Initial model based on Brian Arthur's work
  - Initial exploration of statistical Games
  - Initial exploration of cohort effects on learning
  - Ultimately replace with a Peircean model of reasoning and learning

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EGT - Analytic Experimentation

- Game Construct
  - “matching pennies”
    - 10 strategies
  - Generic payoff functions
    - Strictly positive, Win/Loss, Maximized difference
  - Fitness evaluation is a integrated simulation
  - Assess the magnitude of learning feedback
  - Assess the initial strengths of the strategies

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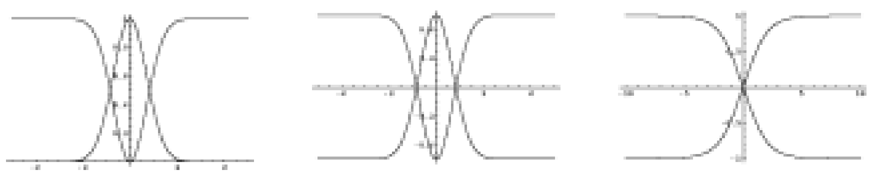
EGT - Payoff Functions

Strictly Positive **Win / Loss** **Maximized Difference**



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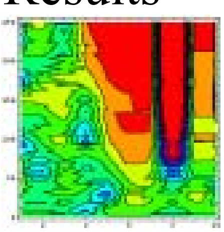
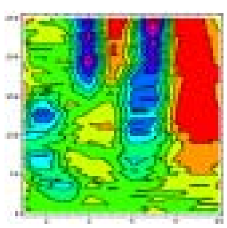
Evolutionary Game Theory - Results

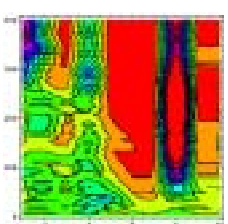
Baseline

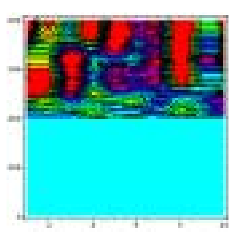




Offence Defence

Delayed Learning





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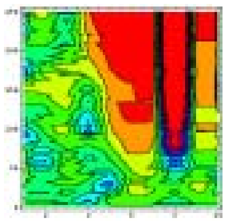
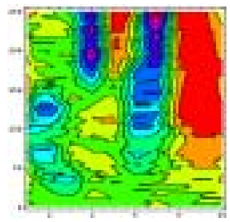
Evolutionary Game Theory - Results

Baseline

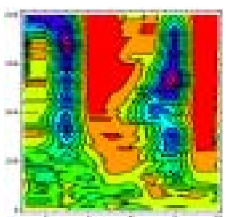


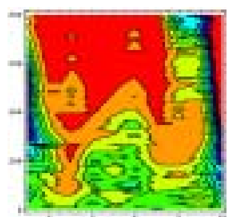


Offence

Defence

Statistical Payoff





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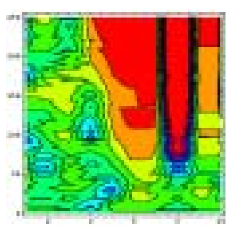
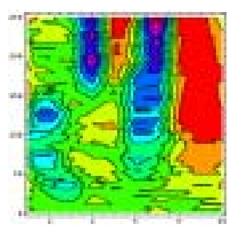
Evolutionary Game Theory - Advanced

Baseline

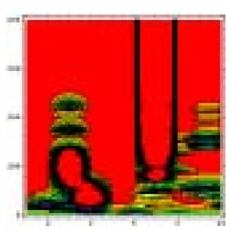


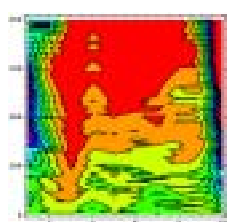


Offence

Defence

Statistical with Cohort(4)





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Analytics with a DoD Emphasis

- Analytic Technology "Toolbox"
  - Taguchi Analyses (Sensitivity Methodology)
  - Bayesian Representations
  - Fuzzy Logic
  - Genetic Algorithms / Programming
  - Evolutionary Strategies
  - Neural Nets

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Taguchi Techniques

- Design of Experiment Technique
  - Efficient use of resources
    - Experimental design based on Orthogonal Matrices
  - Preserves certain statistical metrics
    - Variance, Confidence Intervals, etc.
  - Exploits Inherent Non-linearities
- Application Areas
  - Production
  - Sensitivity analysis

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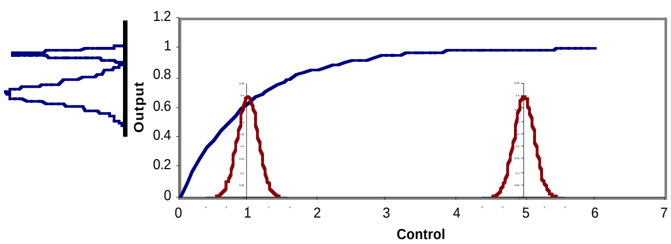
Robust Design



Setting chosen for control variables differentially impacts system response

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Control & Noise Variable Analysis

Factor Analysis

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

Noise Analysis

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

Etc.

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

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Setup for a Taguchi Analysis

- Scenario or Application Analysis
- Variable Analysis
  - Identify control factors & noise factors
    - ✓ Control factors are parameters that can be controlled by a designer, operator, or analyst.
    - ✓ Noise factors reflect natural variability, and may be difficult to control in a given context.
- Determine the MOE / MOP
    - ✓ Not limited to a single metric.
- Determine the Degrees of Freedom
    - ✓ Determines the minimum number of experiments and impact Orthogonal matrix selection.
- Setup Experiments & Execute
- Analyze the Results Accumulated

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Confounding or Non-linear Effects

Orthogonal Matrix for L_9

Exp. #	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Analysis Structure

$$\bar{R} = \frac{1}{9}\sum R_k$$

$$\bar{R}_{A_1} = \frac{1}{3}\sum_{1}^{3} R_k$$

$$\bar{R}_{B_2} = \frac{1}{3}\sum (R_2 + R_5 + R_8)$$

$$etc.$$

Linear Graph for L_9

A ——**C,D**—— **B**

Determines where interactions will show up in the results

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Bayesian Networks

- Bayesian Statistics
- Normative Expert System
- Directed Acyclic Graphs (DAG)
- Characteristics
- Potential Applications

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Slide 40

Bayesian Statistics

$$P(A|B) \cdot P(B) = P(A,B)$$
$$P(B|A) \cdot P(A) = P(A,B)$$

$$P(B|A) = \frac{(P(A|B) \cdot P(B))}{(P(A))}$$

Characterizes Bayesian rule, the posterior distribution is a function of the prior distribution, P(B), modified by the condition that A would result should B occur.

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Normative Expert Systems

- Alternative to rule based systems
  - Model the domain
    - Not the expert
  - Support the expert
    - Do not replace the expert
  - Based on probability calculus and decision theory
    - Not on an uncertainty calculus tailored to rules

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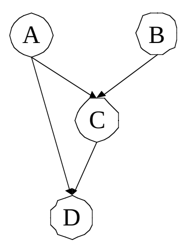
Causal or DAGs

$f(x_j) =$



Defines the causal dependencies of the variables associated with the model

$$P(U) = \prod_i P(A_i | pa(A_i))$$

$$P(A,B,C,D) = P(D|A,C) \cdot P(C|A,B) \cdot P(A) \cdot P(B)$$

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Characteristics

- Compact representations
- Bayesian updates
  - Expert priors
- Marginalization
- Decision modeling
- d-separation
- Tools for learning causality
- Research areas
  - Belief propagation
  - Tree clusters and junction trees

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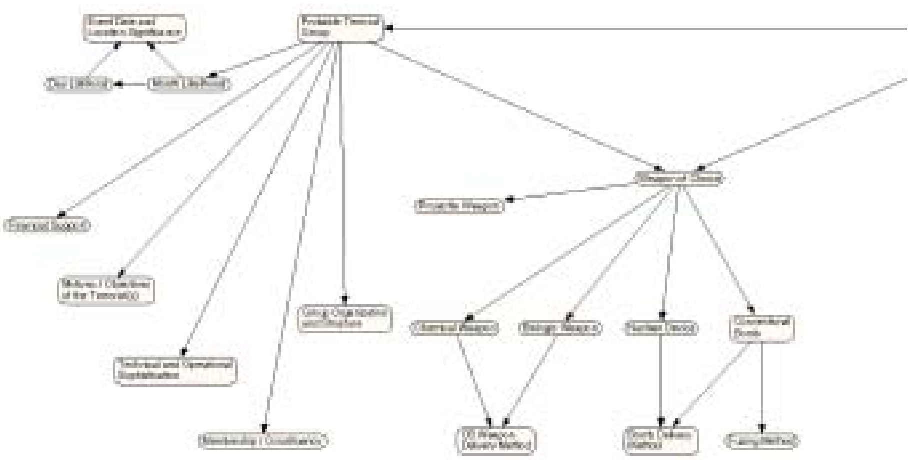
Terrorism Example



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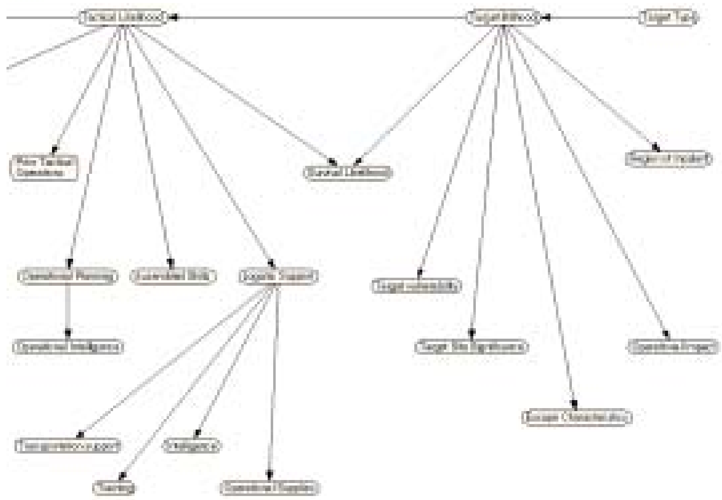
Terrorism Example



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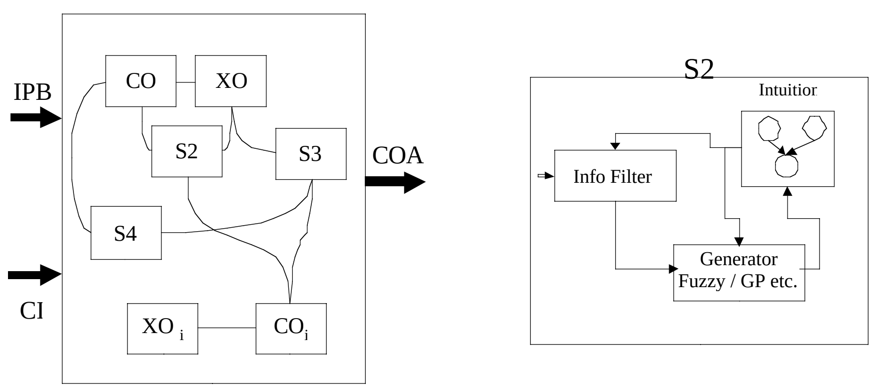
Application



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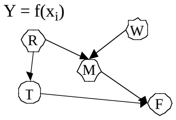
Application (Cont.)

Identify Variable:
Risk aversion (R)
Weather (W)
Terrain (T)
Morale (M)
Force Ratios (F)
X={x1,x2,...}

→

Define Dependencies:
Y = f(x_i)



↓

Populate / Train BBN:
Expert Opinion
Combat Simulations
R(1), W(4), T(2), M(3), F(2)
R(1), W(3), T(4), M(1), F(2)
...

→ Deploy

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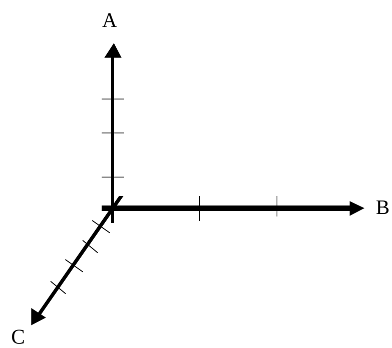
Joint Probability Distribution

P(A, B, C)
with
A ~ { A1, A2, A3 }
B ~ { B1, B2 }
C ~ { C1, C2, C3, C4 }



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Hierarchical Reasoning

- Distant, Approaching Object
  - Shapes: Point or fuzzy oval, dust cloud
  - Features: Multiple overlapping fuzzy shapes
  - Detail: two cars racing across the desert
- Efficient decision making
  - Minimum amount of information
  - Risk defined confidence level

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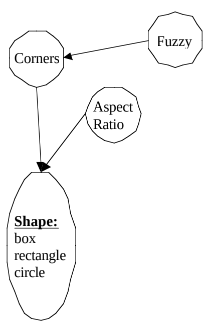
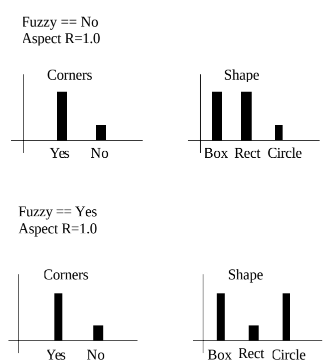
Bayesian Reasoning





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Evolutionary Strategies

- Similar to Genetic Algorithms
  - Operates on real variables (vs. integer representations)
  - Employs level variable and strategy variable
  - Employs mutation and cross-over operators (like GAs)

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Evolutionary Strategies

Model (Chromosomes)

$$P=(c_1,c_2,\ldots,c_{n-1},c_n)$$
$$c_i=(op,sp)$$
$$OP=(o_1,o_2,\ldots,o_{m-1},o_m)$$
$$SP=(s_1,s_2,\ldots,s_{m-1},s_m)$$

Mutation Operators (Variable Level)

$$OP_{mut}=op+N_0(sp)$$

$$OP_{mut}=(o_1+N_0(s_1),o_2+N_0(s_2),\ldots,o_m+N_0(s_m))$$

Mutation Operators (Strategies)

$$SP_{mut}=(s_1\cdot A_1,s_2\cdot A_2,\ldots,s_m\cdot A_m)$$
$$A_i=\alpha \quad \text{if } E<0.5$$
$$A_i=1/\alpha \quad \text{if } E\geq 0.5$$

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Appendix B. SPAWAR Briefing of a Taguchi Sensitivity Study

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NSS Taguchi Sensitivity Analysis

- DRUG INTERDICTION IN THE CARIBBEAN
  - Oct 16th 2001

- Dr Michael Senglaub, PhD
  - (Sandia National Labs)

Mr Patrick A. Sandoz
(ROLANDS & ASSOCIATES Corporation)

Study Objectives

- Explore a Parallel Controller Concept
  - Concept Description
    - Taguchi Analysis
  - Demonstration Implementation
- Demonstration of Capabilities
  - Scenario Description
  - Variable Analysis & MOE's
  - Taguchi Setup
  - Results Analysis
- Identify Areas of Common Interest
  - Computational Technologies
  - Mission Areas Support

Slide 2

Taguchi Controller Concept

Taguchi analysis is a form of "design of experiment" technique, using orthogonal arrays as the basis for experimental setup.

- **Benefits**
  - **Enables experimental / analytic efficiency**
    - **Typical L_8 matrix(used in this study) requires 8 experiments**
    - **Full factorial experiment series requires 128 experiments**
  - **Orthogonal matrix enhances statistical analyses**
    - **Error variance estimated by "bottom" half of the factors**
      - **Post experiment analysis identifies dominant factors. Minimally important factor errors can be used to estimate error variance.**
      - **Estimate is a biased estimate but can be used in standard statistical tests and to estimate the confidence intervals of the factors.**
  - **With some care can aid in the identification of non-linear effects**
    - **Confounding effects can be easily determined from interaction tables**
- **Down Side**
  - **Current application very hands on; factor analysis, tables of arrays, manual generation of custom arrays**

Slide 3

Taguchi "Control" & "Noise" Analysis

Factor Analysis

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

Noise Analysis

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

Etc.

Exp. #	Factor A	Factor B	Factor C	Factor D	Etc.
1	1	1	1	1	
…					…
k	4	2	3	1	
…					…
n	6	4	5	2	

Slide 4

Setup for a Taguchi Analysis

- **Scenario or Application Analysis**
- **Variable Analysis**
  - **Identify control factors & noise factors**
    - **Control factors are parameters that can be controlled by a designer, operator, or analyst.**
    - **Noise factors reflect natural variability, and may be difficult to control in a given context.**
- **Determine the MOE / MOP**
    - **Not limited to a single metric.**
- **Determine the Degrees of Freedom**
    - **Determines the minimum number of experiments and impact Orthogonal matrix selection.**
- **Setup Experiments & Execute**
- **Analyze the Results Accumulated**

Slide 5

Confounding or Non-linear Effects

Orthogonal Matrix for L_9

Exp. #	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Analysis Structure

$$\bar{R} = \frac{1}{9}\sum R_k$$

$$\bar{R}_{A_1} = \frac{1}{3}\sum_{1}^{3} R_k$$

$$\bar{R}_{B_2} = \frac{1}{3}\sum (R_2 + R_5 + R_8)$$

$$etc.$$

Linear Graph for L_9

Determines where interactions will show up in the results

Slide 6

Scenario Description

- Use NSS to model Caribbean drug runner interdiction by air assets
- Build and run a multi-case study with Study Variables that account for:
  - Drug runner tactics
  - Search force composition
  - Search effort allocation
  - Search sensors capabilities
- Use Taguchi techniques during experiment design and output analysis

Slide 7

Scenario Basics

- Area of Operations
  - Eastern Caribbean Sea
  - Atlantic, vicinity of the Bahamas
  - Atlantic, vicinity of the Antilles
- Sea Based Drug Traffic
  - Originating off the Colombian and Venezuelan coasts
  - Consisting only of surface traffic in the “Transit Phase”
  - Covering a two week period
  - Destined for Puerto Rico and Southern Florida
- Interdicting Forces
  - Resource-constrained air search assets
  - Objectives are Detection, Classification, Tracking – no Engagement

Slide 8

Scenario Basics(2)

- Drug Runner Routes
  - Starting points
    - Random locations off the Colombian and Venezuelan coasts
    - Random start times – 0 + 2.0 hours to 0 + 170.0 hours
  - Route types
    - Aggressive (3 routes)
    - Conservative (2 routes)
  - Destinations
    - Puerto Rico (2 Aggressive, 1 Conservative routes)
    - South Florida (1 Aggressive, 1 Conservative route)
  - Average transit times
    - Shortest 18 hours (25 ft "Go-Fast" boat, shortest route)
    - Longest 7 days (Coastal Freighter, longest route)

Slide 9

Scenario Basics(3)

- Drug Runner Route Types
  - Direct Puerto Rico (Aggressive)
    - Across the Caribbean to Puerto Rico
  - Antilles Short (Conservative)
    - Easterly along the South American Coast, then Antilles to Puerto Rico
  - Antilles Long (Conservative)
    - Easterly along the Coast, through the Antilles, then Bahamas to Florida
  - Haiti East (Aggressive)
    - Across the Caribbean to southern Haiti coast, then easterly to Puerto Rico
  - Haiti North (Aggressive)
    - North across the Caribbean, thru the straits between Cuba and Hati
    - Bahamas to Florida

Slide 10

Scenario Basics(4)

- Search Areas
  - Launch Locations
    - Puerto Rico: P-3s, E-2Cs, 1 C-12M squadron
    - Florida: 1 C-12M squadron
    - N/A for Acoustic Sensor patterns
  - Search area types
    - Open Ocean (3 areas)
      - Outer Bahamas, open ocean north of Puerto Rico, east-central Caribbean
    - Cluttered Ocean (4 areas)
      - Inner Bahamas, Antilles, Haiti-Jamaica coastal, Puerto Rico-Dominican Republic coastal

Slide 11

Scenario Logistics

- Locations of Effort
  - R&A Offices in Monterey, California
    - Preparatory data and information gathering
    - Scenario/script definition and development
    - Study Variable definition and variable Level determination
    - Study implementation in NSS (Version 3.1 AE)
      - Dell "Latitude" running Windows 2000
    - Completion of runs generating MOE output spreadsheets
  - SANDIA National Laboratories
    - Study direction and coordination
    - Study Variable and Level refinement
    - Orthogonal Taguchi experiment case matrix development
    - Analysis of output using Taguchi techniques

Slide 12

Scenario Logistics(2)

- Data Sources
  - NSS Unclassified Baseline Database
    - Sensor capabilities and platform definitions
  - Internet Searches
    - Navy (SOUTHCOM) and Coast Guard sites
    - GAO – www.druglibrary.com
    - U.S. Customs Service – congressional testimonies and other documents
  - Operational Experience
    - R&A, SPAWAR, NPS
  - SANDIA National Laboratories
    - Acoustic Sensor top-level parameters

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Slide 13

Scenario Logistics(3)

- NSS Implementation
  - Force Structure and Scenario Development
    - Database Administrator and Input Modes
    - NSS data development and input
    - Tactical instructions and responses
    - MOE definitions and selections
  - Multiple Runs of each Experiment Case
    - Study Management Mode
    - Varying random number seeds
    - Variations to the baseline (Excursions)
    - Output files containing specified MOE data
    - Generate spreadsheet output for analysis
    - Capture case playbacks for demonstration

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Slide 14

Variable Analysis & MOE's

- Variables and "Factor Levels"
  - Search Force Composition
    - Baseline – 1 P-3 mission, 1 E-2C mission, and 2 C-12M missions per day
    - Baseline + UAV – Add 1 UAV mission per day to Baseline
    - Baseline + Ocean Sensor – Add 4 24 hour acoustic sensor patterns to Baseline
    - Baseline + UAV + Ocean Sensor – All three types of sensor systems included
  - Search Resource Allocation (Search Area Selection)
    - Open Area – Prefer (by 2:1) easy to cover open ocean areas
    - Cluttered Area – Prefer (by 2:1) harder to cover inter-island and coastal areas
  - Drug Runner Tactics (Route Selection)
    - Aggressive – Prefer (by 2:1) shorter, faster, more direct open ocean routes
    - Conservative – Prefer (by 2:1) longer routes with more protection and cover
  - Search Sensor Capabilities
    - Very Good – Much better than average, no degradation of any sensor
    - Very Poor – Much worse than average, possibly due to bad weather

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Slide 15

Measures of Effectiveness

- Three MOEs selected
  - Number of drug runner detections
  - Average time until first detection
  - Total tracking time
- MOEs compiled for each drug runner boat type
  - 25 foot "Go-Fast" speed boats (8 per run)
  - 45 foot "Go-Fast" speed boats (8 per run)
  - Fishing trawlers (8 per run)
  - Small coastal freighters (6 per run)
- Total of 12 MOE's compiled for each Experiment

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Slide 16

Taguchi Analysis Setup

Baseline L_8 Orthogonal matrix

$L_8\ (2^7)$					Factor			
	Experiment	1	2	3	4	5	6	7
	1	1	1	1	1	1	1	1
	2	1	1	1	2	2	2	2
	3	1	2	2	1	1	2	2
Levels	4	1	2	2	2	2	1	1
	5	2	1	2	1	2	1	2
	6	2	1	2	2	1	2	1
	7	2	2	1	1	2	2	1
	8	2	2	1	2	1	1	2

Modified L_8 Orthogonal matrix

Mod $L_8\ (4^1,2^4)$					Factor			
	Experiment	1	2	3	4	5	6	7
	1			1	1	1	1	1
	2			1	2	2	2	2
	3			2	1	1	2	2
Levels	4			2	2	2	1	1
	5			3	1	2	1	2
	6			3	2	1	2	1
	7			4	1	2	2	1
	8			4	2	1	1	2

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Taguchi Analysis Setup(2)

Variable Levels and Column Assignments

Factor	Level	Column Assignment
OPFOR Tactics	1 = Aggressive	5
	2 = Conservative	
Resource Allocation	1 = Open Ocean Area	4
(Op Area)	2 = Cluttered Ocean Area	
Force Mix	1 = Baseline (BL)	3
(Hardware)	2 = BL + UAV	
	3 = BL + Ocean sensor	
	4 = BL+UAV+Ocean sensor	
Pr(Identification)	Pr + 1.4std	6
	Pr - 1.4std	

Note: Variables and Factors are used interchangeably

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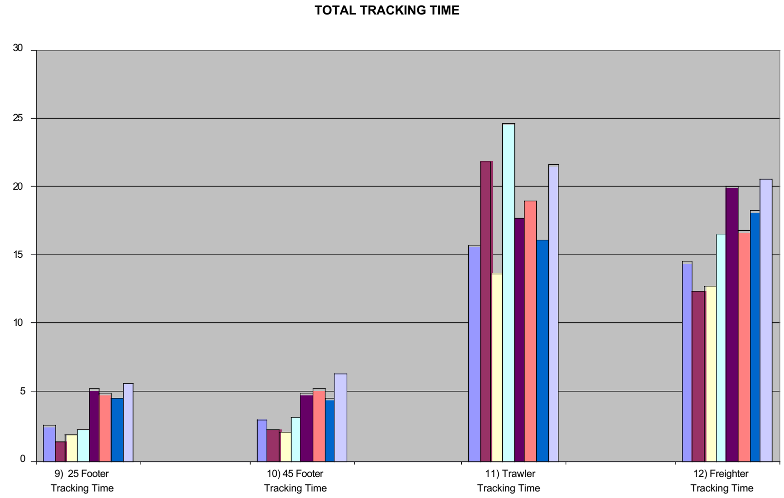
Total Track Time



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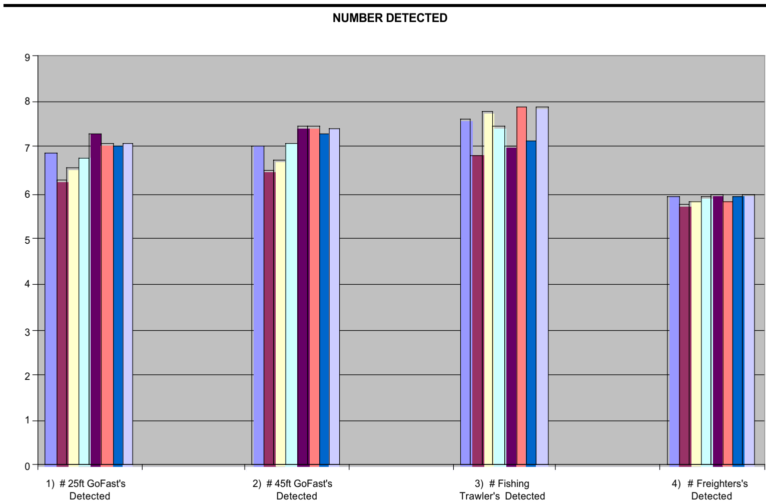
Number Detected



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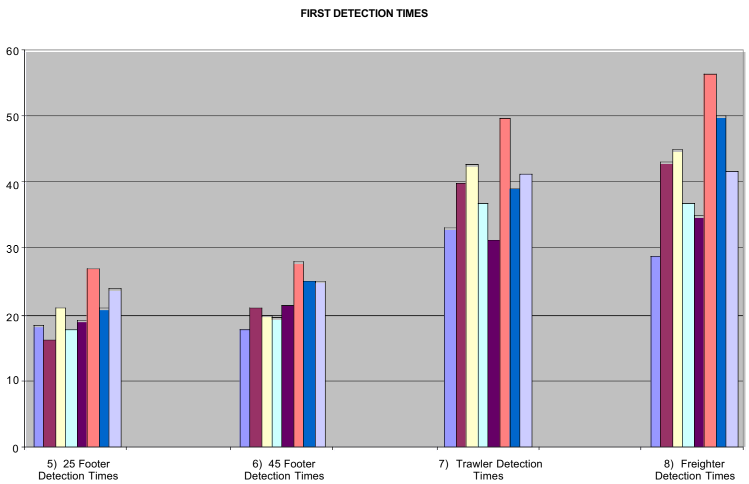
First Detection Times



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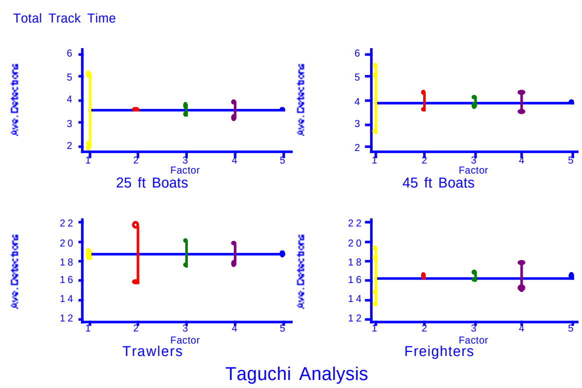
Results Interpretation

- Factors in the plots
  - Factor 1: Force Mix with 4 levels
  - Factor 2: Resource Allocation in the Operational Area
  - Factor 3: Opposition Force (OPFOR) tactics
  - Factor 4: Probability of Detection/Identification
  - Factor 5: Held open to explore non-linear effects between factor 1 and factors 2,3 &4
    - The modified Orthogonal matrix confounds the non-linear effects
- Graphs of results
  - Mean behavior over the factor levels
  - Effect of a factor on average, given the ranges of the other factors
  - Each slide is a single MOE on four target types

Slide 22

Scenario Results



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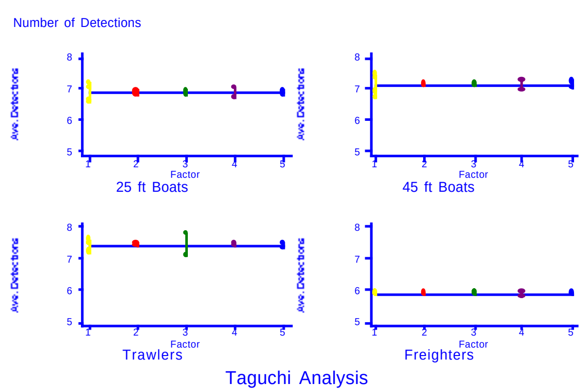
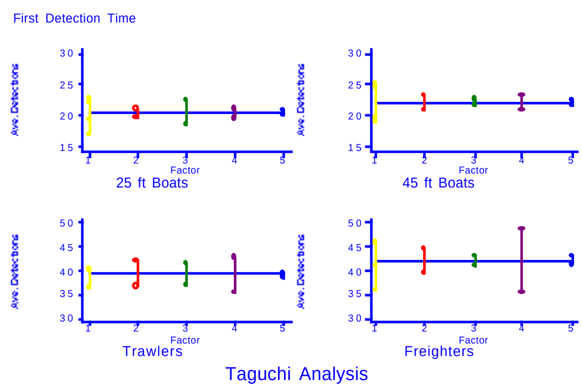
Scenario Results



Slide 24

Scenario Results



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Observations

- **MOE can significantly impact decision making**
  - **Almost no sensitivity to factors for "Number of Detections" MOE, the other MOE's demonstrate clear dependencies of the study factors**
- **"Target" Impacts dominant sensitivity**
  - **" Force Mix" is the most important factor when looking for "go-fast" boats and freighters but minimal impact on trawlers**
- **"Force Mix" factor explored new sensor concept**
  - **Provides support for new acquisitions in complex integrated environments**
- **Provides requirements evaluation for new concepts**
  - **Pr of detection demonstrates the importance of component capabilities in 'system of system' context**

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Areas of Common Interest

- Effective and efficient complimentary team skills
  - SPAWAR, R&A Corp., SNL
    - Command of operational imperatives
    - Analysis and algorithm expertise
    - Computational development expertise
- Desire to expand and extend analytic capabilities
  - Greater domain of application
  - Integration of decision aids
  - Increased capability through the application of advanced computational technologies
- Use as a research tool
  - Explore Command & Control theoretics
  - Explore information operations in a dynamic environment
  - Understand operational and system limitations in asymmetric warfare

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Proposed Activities

- Decision Support Systems and Technologies
  - Web Based Interface Options
    - Development of a Taguchi controller / decision aid
    - Bayesian decision aid for use with JFACC
    - Setup Agents
  - Develop "cognition based" decision algorithms
  - Integration of dynamic adversarial models
  - Optimization Decision Aid
    - Identification of areas for optimization
    - Technologies for optimization
- 21st Century Warfare
  - Implications to NSS of RDO and EBO
  - OOTW
    - Terrorism (Vulnerability analysis)
    - Asymmetric warfare

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Proposed Activities(2)

- Follow-on Taguchi type studies
  - Inclusion of logistics components
  - Homeland security studies
  - Requirements development for sensor systems
  - Scenario expansion
    - Adversarial Air
    - Departure and arrival phase interdiction
    - Surfaced based search assets
- Scalability studies of NSS on MP machines
- Benchmarking “Information Operations” Models
- Collaborate with NPS research activities.

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