A METHODOLOGY FOR TECHNOLOGY EVALUATION AND CAPABILITY TRADEOFF FOR COMPLEX SYSTEM ARCHITECTURES

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Abstract

Evaluating the benefit of technologies for complex system architectures that consist of many heterogeneous interoperating assets continues to be a challenge. While modeling and simulation tools provide a means to quantitatively analyze capabilities at the "system-of-systems" level, it is difficult to execute large-scale discrete event simulations such as military campaign codes without resorting to human-in-the-loop analysis. The proposed methodology for technology evaluation incorporates several best-in-class practices and identifies a technique that uses surrogate models and intelligent agents to reduce the burden on human analysts while alleviating the confounding effects of technologies and tactics.

1 Introduction

"Systems-of-systems" are often dominated not by the attributes of individual systems, but rather, the complex interactions of multiple systems that combine to provide a capability. Unfortunately, technology development is usually system or subsystem-centric and the quantitative impact of technology infusion, technology refresh, and spiral development is difficult to measure at the system-of-systems level. A structured methodology that enables technology evaluation with respect to top-level capabilities is needed to address this issue.

To quantify the benefit of technologies in the presence of variable capability and evolving threats, a hierarchical, object-oriented modeling and simulation (M&S) environment is proposed.

Even with a physics-based M&S environment, the impact of technologies is difficult to quantify due to the confounding effect of tactics on the performance of individual systems: *tactics should be optimized to take advantage of the benefit of new technologies*.

A major thrust of this research is the development of a technique that uses surrogate models to provide intelligent forecasting ability to asset-level cognitive processes. Using surrogate models, the behavior of intelligent agents can be "tuned" to exploit technology infusion in a manner that allows quantitative technology assessment to occur on a fair playing field.

2 Technology Evaluation

The 1991 Persian Gulf War was a 42 day conflict dominated by the use of advanced technologies such as stealth aircraft, precision guided munitions, and integrated intelligence, surveillance and reconnaissance. The success of the U.S. military in this conflict can trace its origins to the late 1970's when Secretary of Defense Harold Brown and Under Secretary of Defense for Research and Engineering William Perry devised the "offset strategy" which sought to offset Soviet numerical superiority through the development of advanced technology in critical areas [1]. As a result of this strategic planning, the United States has leveraged its advanced technology in several military conflicts with great success.

Continued technological superiority relies on the identification of a technology portfolio that will provide maximum effectiveness against future threats; however, in the technology-dominated marketplace, identifying such a portfolio can be a daunting proposition. A review of existing methods reveals that there is no rapid, parametric, capability-focused methodology for technology evaluation for large-scale systems-of-systems.

The least elegant (but arguably the most effective) method for evaluating technologies is physical experimentation. Seen heavily in the software and electronics industry, new products will incorporate candidate technologies in a pilot program. If accepted by the marketplace, their use becomes widespread, typified by the ubiquitous camera phone, which began life in Japan as the J-Phone in 2000.

The United States Air Force (USAF) and other organizations use a panel of expert scientists, engineers, and senior leaders called the Scientific Advisory Board (SAB) to formulate a long-term plan for technology utilization. Originally instituted in 1944 and led by Theodore von Karman, the original purpose of the SAB was to examine advances in basic science and analyze how these discoveries may affect the employment of airpower. More recent studies have relied less on outside input from scientific leaders and have been very tightly focused on specific vehicles, qualitative information, brainstorming, and anecdotal evidence [2].

The Technology Development Approach (TDA), developed by Dr. Donald Dix, is a *qualitative* method for identifying expected technology impacts at the system-of-systems level. The TDA examines several technology efforts and objectives and proposes point-estimates for the Key Performance Parameters (KPP's) for each technology. These technologies are then rolled up into the subarea goals for the proposed system, and extrapolated to expected improvements in Measures of Effectiveness (MoE's). The TDA is constructed using expert opinion, brainstorming, and qualitative analysis [3].

In contrast to primarily qualitative methods, some quantitative techniques exist. Technology Identification, Evaluation, and Selection (TIES), developed by Kirby and Mavris, is a "comprehensive and structured method to allow for the design of complex systems which result in high quality and competitive cost to meet future, aggressive customer requirements" [4]. This technique uses physics-based modeling to quantitatively assess the impact of technologies by representing the KPP's as "k-factors". While TIES can be seen as a quantitative extension of the TDA approach, traditional applications of the method have been primarily focused on the evaluation of Measures of Performance (MoP's) for a system and have to date not addressed the issue technology evaluation for large-scale heterogeneous systems [5].

The AFRL is actively engaged in a research effort to "integrate new methodologies and tools with existing 'industry-standard' tools to effectively test the effects of new technologies on air vehicle capability" [6]. An AFRL program, Quantitative Technology Assessment (QTA), which may be viewed as an extension of TIES to the capability level, is enabled through constructive simulation[1] and parametric modeling [7]. This technique, well suited for system-of-system studies and evaluation of technologies with respect to capability-level MoE's, serves as a model of a superior process for technology evaluation.

The key attributes of the aforementioned methodologies are qualitatively ranked relative to each other and are illustrated in the radargram in Figure 1. In the figure, the largest area is analogous to the "best" technique for quantitative technology evaluation for systems-of-systems. The red shaded area indicates that QTA is the current best-in-class method for technology evaluation for large scale complex systems; however, the proposed approach (blue line) will identify several modifications are needed to address potential issues with the QTA process.

[1] Constructive simulation involves simulated people operating in a simulated world.

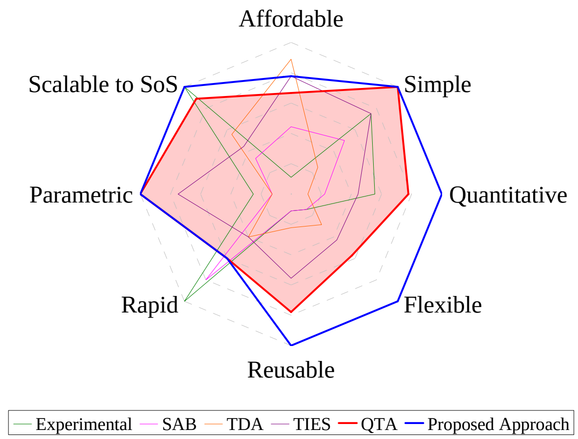

Fig. 1. Overview of Technology Evaluation Approaches.

First, a rapid simulation process is needed to explore a large design space. Secondly, in a simulation, system effectiveness is a function of both the technologies present and the tactics employed. The confounding effect between these two must be managed. Finally, the simulation cannot be slowed by the demands of having human decision makers in the loop. The proposed methodology must address each of these concerns.

3 Shifting to a Capability-Based Focus

Throughout the Cold War, military acquisition was threat-based: systems were procured to counter specific threats posed by a known enemy, the Soviet Union. While this strategy was effective, the current military situation is drastically different from that of the past forty years. The Air Force is in the midst of a transformational process to address this issue [8]. In the 2002 Air Force Posture Statement, Air Force Chief of Staff General John P. Jumper said, "Our goal is to make warfighting effects and the capabilities we need to achieve them, the driving factor for everything we do. This enables (us to develop the capabilities needed) to answer a broad range of challenges posed by potential adversaries, while also developing the (assets needed) for the future" [9]. To understand the motivation for this statement, it is necessary to define a capability:

"the ability to achieve an effect to a standard under specified conditions through multiple combinations of means and ways to perform a set of tasks" [10].

Key to this definition is the notion of *effects*. "Effects are associated with a desired outcome or result" [10]. Capabilities describe what must be done to achieve desired effects, avoid overlaps and redundancies with other means, and identify relationships between systems. The most critical aspect of capability-based planning is that **capabilities are not solution specific**. There may be a near-infinite number of ways to achieve a desired effect, all with different risk, cost, and degree of difficulty for implementation.

Assessing the degree to which capabilities are provided requires the use of scenarios or vignettes to provide context for technology analysis. A suite of scenarios can be used to span the range of potential conflicts in terms of geography, political constraints, force mix, and enemy capability.

The desire to perform capability-centric analysis *drives the need for a modeling and simulation environment* that can incorporate physics-based models of technologies and systems while simulating their performance in a relevant environment using appropriate scenarios. Techniques which use purely *qualitative* methods are inappropriate for capability-based analysis because it is difficult to quantify the impact of a technology at the capability-level due to the complex interactions between systems that are not always intuitive to subject-matter experts.

4 Elements of the Methodology

The realization of a simulation-based, capability-focused methodology for technology evaluation requires that several technical challenges be overcome. Some of these technical challenges can be addressed through application of best practices from a variety of disciplines:

- Large-scale systems-of-systems are comprised of many elements that may need to be modeled. A **functional decomposition, brainstorming tools** and the **Systems Modeling Language (SysML)** can be used to scope the problem.

- A **Morphological Matrix** or **Matrix of Alternatives** is a useful technique to reduce the scale of the problem to a manageable set of "threads" to be analyzed with physics-based models.
- The desire to use physics-based models of systems and technologies is counterbalanced by the need for rapid simulation. **Neural Network surrogate models** can enable rapid trades while retaining the appropriate degree of fidelity and capturing the non-linear behaviors which are typical of discrete event simulations.
- Creating accurate neural networks relies on the use of effective sampling techniques. **Central Composite** designs, supplemented by a space-filling **Latin Hypercube** are most appropriate for this class of problems. Coupling the two explores the extremes of the design space and richly samples the interior, as demonstrated by Mavris, et. al [11].
- **Monte Carlo Simulations** are an effective way to account for noise and uncertainty in the simulation process. They can also be used to perform domain-spanning exploratory studies when coupled with surrogate models that reduce execution time.
- Since little research has been conducted on optimization techniques for this class of problems, the "no-free-lunch-theorem," proven by Wolpert and Macready in 1995, dictates that a **Random Search** is best suited when optimization is required because a random search is universally "good" across the space of existing problem sets [12].
- The focus of the methodology should be on a technology portfolio that is **robust across scenarios**, not an optimal solution to a single point scenario that may never occur [13].

These elements can be synthesized into the initial formulations of a structured methodology; however, the previous statements are *assertions*: "something declared or stated positively, often with no support or attempt at proof" [14]. A matrix of alternatives, shown in Figure 2, depicts some of the potential options available and the choices made (highlighted) for each technical challenge. While the synthesis of the proposed methodology in this matrix of alternatives is primarily the result of qualitative judgments based on observations from a literature search, highlighting different entries

Proposed Solutions to Technical Challenges (Assertions)	Determine Elements of Architecture	Provided by Customer	Functional Decomposition	Literature Search	Brainstorming Tools	Other
	Reduce Scale of Problem	Committee Approach	SysML	Matrix of Alternatives	Other	
	Speed Up Processes	None	Linear Approximations	Qualitative Mapping	Surrogate Models	Other
	Type of Surrogate Models	Polynomial Response Surface	Neural Networks	Radial Basis Functions	Kriging	Other
	Sample from Design Space	Random	Full Factorial	Central Composite	Latin Hypercube	Other
	Account for Uncertainty	Monte Carlo	Quasi-Monte Carlo	Petri Nets	Markov Chains	Other
	Optimization Algorithm	Gradient-Based	Genetic Algorithm	Simulated Annealing	Random Search	Random Walk
		Mixed Integer Programming	Coordinate Pattern Search	Grid Search	Other	
	Methodology Focus	Optimization	Robustness	Other		

Fig. 2. Matrix of Alternatives for Method Synthesis: Assertions Made Based on Observations and Literature Search.

would result in the synthesis of a methodology that differs only slightly from that proposed herein. In the case of the aforementioned assertions, the identification of a best-in-class technique may be problem specific and does not significantly impact the overall objective of the methodology.

On the other hand, some technical challenges cannot be overcome by assertions and further exposition is necessary through experimental means. For example, although a capability-focused analysis requires a simulation-based approach, a major technical challenge arises in the desire to use scenarios and simulations to evaluate technology effectiveness: the assumptions of the scenario and the tactics employed usually have a much greater influence on the MoE's than individual technologies.

There are three ways to account for tactics in a simulation:

1. Holds tactics constant.
2. Allow tactical variables to be controlled by the user and varied in the simulation.
3. Optimize the tactics to best exploit technologies.

Since tactics are usually developed after technologies have been implemented, holding tactics constant will result in suboptimal solutions and unfairly penalize some technologies [15]. Secondly, allowing the user to control all tactical variables will result in so many degrees of freedom that the modeling and simulation effort will likely be bogged down by the "curse of dimensionality." The best of the three proposed alternatives is to optimize tactics to maximize the benefits provided by each candidate technology or suite of technologies. From this decision a new question arises: is it possible to "account for the myriad of tactical decisions possible without resorting to a man-in-the-loop style analysis?" [15]

In the military community, simulations are usually executed on a grand scale over periods of months and are essentially computerized "sand-table" games used to evaluate force level effectiveness. Driven by experienced generals, decisions are guided primarily by a human-in-the-loop assessment of the state of the scenario and an experience-guided (gut-feeling) decision on how to proceed. It is proposed that this decision-making process be approximated using machine learning, agent-based modeling, and surrogate models.

Machine learning is an overarching discipline concerned with the development of algorithms that enable computers to emulate intelligent behavior, primarily through the identification of patterns.

The field of agent-based modeling and simulation (ABM/S) relies on creating relatively simple "agents" and defining the interactions between agents in such a way to generate realistic system level behavior with relatively unsophisticated subsystem elements. Through the appropriate establishment of rules, objectives, and rewards for a group of agents, some decisions can be made automatically without human interaction. "The major strength of ABM/S comes from the fact that it is a simple, versatile, and flexible method that is well suited for studies of complex non-linear systems" [16].

While a surrogate model is literally "a replacement model," the term refers to highly accurate approximations of physics-based phenomenon using a parametric equation. A popular approach is the use of Response Surface Equations (RSE's), a polynomial equation based on a Taylor series expansion that aims to address the variability of a response around a baseline value that encapsulates a majority of the behavior of a more complicated physical model. The coefficients of the model are usually determined using a least-squares regression. A valid surrogate model has an error term that is normally distributed with a mean of zero and a standard deviation of 1. While polynomial surrogate models have been demonstrated for a wide range of engineering problems, discontinuous behaviors cannot be readily modeled with polynomial surrogates. An alternative technique, artificial neural networks, are used to address this issue. Based on connectionist theories about the structure of the human brain, a typical arrangement for a feedforward neural network has three layers, the input layer, the hidden layer and the output layer. This structure is shown below in Figure 3.

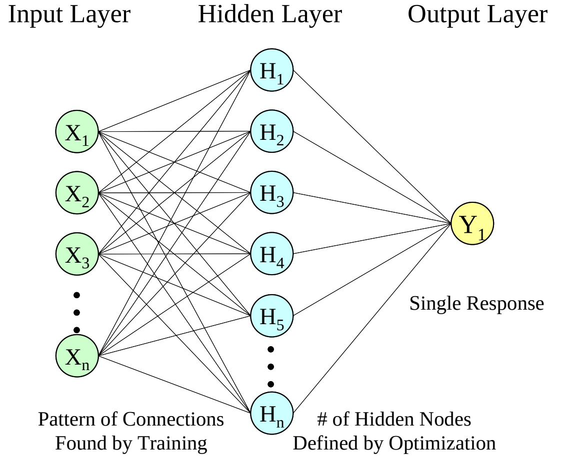

Fig. 3. Structure of a feedforward neural network.

This surrogate modeling technique calculates the value of the k^{th} response, R_k, using the formula:

$$R_k = c_k + d_k \left[e_k + \sum_{j=1}^{N_H} \left(f_{jk} \left(\frac{1}{1 + e^{-\left(a_j + \sum_{i=1}^{N} (b_{ij} X_i)\right)}} \right) \right) \right]$$

Where the coefficients *a, b, c, d,* and *e* are determined for each of the *i* design variables, X_i, and *j* hidden nodes through an iterative minimization of the error between the actual and predicted response. A sigmoid function of the form:

$$S(z) = \frac{1}{1 + e^{-z}}$$

is used to scale the coefficients between the input layer and the hidden layer while a linear relationship calculates the link between the hidden layer and the response. The sigmoid function allows the neural network model to approximate highly discontinuous or nonlinear functions with a high degree of accuracy.

Both polynomial and neural network surrogate modeling techniques will be leveraged in the proposed approach where appropriate.

5 Creating an Intelligent Battle Manager

Experience is "active participation in events or activities, leading to the accumulation of knowledge or skill" [14]. While man-in-the-loop battle management is traditionally performed by an experienced general, the central tenets of machine learning support a hypothesis that an intelligent battle manager or "Meta-General" can be provided with enough "experience" to make realistic human-like decisions. Such an approach was famously depicted in the climax of the 1983 film *WarGames* [17] (Figure 4).

Fig. 4. The War Operations Plan Response (WOPR) Computer Testing Scenarios at "NORAD" in the 1983 film *WarGames* [17].

While one paradigm for machine learning has the computer test multiple approaches and learn in real-time, this approach is not appropriate for technology evaluation since the learning rate would be confounded with technology effectiveness. For example, if a "smart" battle manager with a substandard technology may be more effective at the campaign level than a less intelligent battle manager with a "good" technology. To avoid this effect, technologies must be compared using a Meta-General with uniform intelligence. To address this issue, one approach would be to use the simulation in two modes: training and analysis.

In the training mode, an algorithm would generate a large number of engagements at random. Strategy and supporting tactics would also be created stochastically and the outcome of the choices made against the threats provided would be assessed against relevant MoE's across a range of technology options. The trained battle manager would be used in analysis mode to recognize patterns from its "prior experience" and recommend the strategy that was most effective based on an assessment of the battlefield and a comparison to the experience base. While this action is essentially a multi-dimensional table lookup, such operations are computationally expensive. A popular approach in computer science is the use of neural networks for pattern matching [18]. It is hypothesized that a neural network model could be used to capture the essence of this table in an equation that can be rapidly evaluated with a random search to interpolate between "known" situations.

To test this hypothesis, a simple engagement scenario was created in Microsoft Excel® for a strike aircraft. Friendly input parameters include the use of stealthy (F-22) or non-stealthy aircraft (F-15), the type of bomb carried, the type of missile carried, and the ratio of ground to air weapons loaded onto the strike aircraft. Parameters defining the threat include the density of Time Critical Targets (TCT's), Surface-to-Air Missiles (SAM's), and enemy fighters. The range to the target is also a parameter used in the simulation.

Four measures of effectiveness were calculated by a conditional probability-based simulation and approximated by neural network surrogate models: the number of aircraft lost, the percentage of TCT's killed, the percentage of SAM's killed, and the percentage of fighters killed. The neural network models can be exercised using the JMP® software package graphical interface called the prediction profiler (Figure 5).

The prediction profiler is an interactive environment that serves as a "calculator" for the neural network but also allows multiple trends to be viewed simultaneously. In Figure 5, the four responses are depicted on the y-axis while the requisite input variables are shown on the x-axis. Each of the trendlines can be interpreted as a partial derivative of each MoE with respect to the scenario/design parameter on the x-axis. The overall range of the y-axis for each MoE can be interpreted as a total derivative, that is, how the MoE's change as all scenario/design parameters are varied over their entire ranges. For example, while *Fighters Killed* and *Aircraft Lost* range from [0,1], the maximum attainable value for *TCT's Killed* is approximately 85% while for *SAM's Killed* this value is only about 60%.

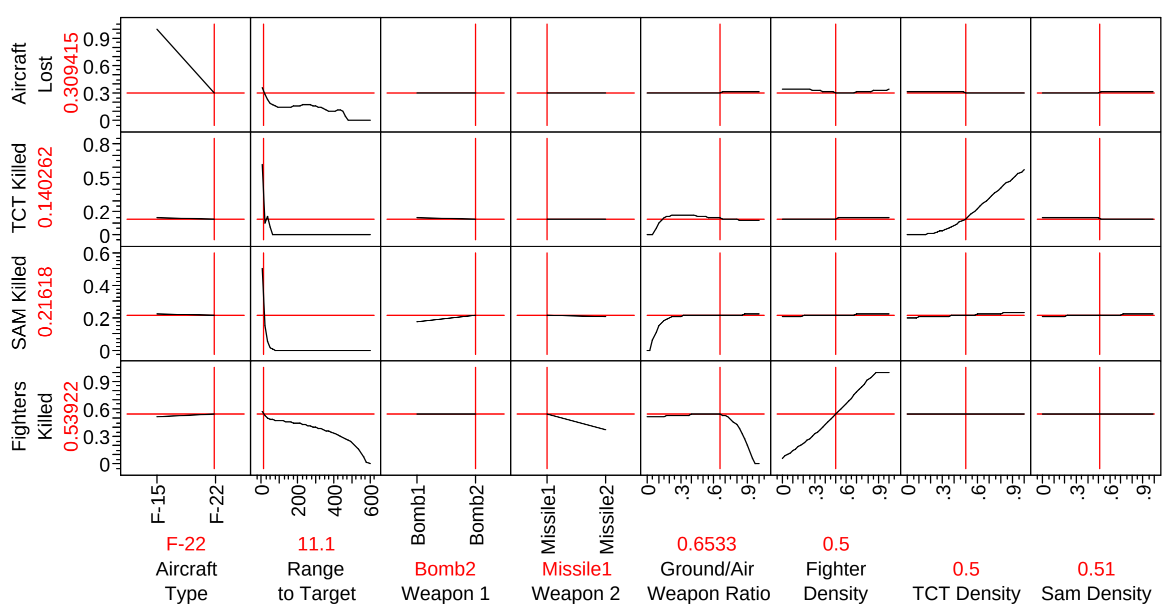

Fig. 5. Prediction Profiler Demonstrating the Use of Neural Network Surrogate Models for Battle Management.

Increasing the total derivative requires that the relationships (trendlines) be changed or that the ranges on the scenario/design parameters be increased.

The prediction profiler can be used to draw conclusions about the scenario based on the relationship between MoEs and the scenario/design parameters. For example, the upper left box shows the trend for aircraft type: stealthy airframes tend to fare better overall than non-stealthy airframes. Also, TCT's and SAM's can only be killed at very small ranges due to the limited range of bombs. Aircraft are lost at all ranges, but predominantly at shorter range. Finally, the ground to air weapon ratio has a strong influence on targets killed: when no ground weapons are carried, the number of ground targets killed goes to zero.

It is also important to note that while the trends indicated by the partial derivatives are generally valid across the design space for *polynomial* surrogate models, changing the values of the input variables can result in drastically different partial derivatives across the discontinuous regions captured by the neural network surrogate models. The specific examples above have been experimentally determined to be valid for both the physical model and the surrogate across the design space.

After a verification and validation process has been conducted, these surrogate models serve as a record of what is effective in certain situations. During the simulation, the Meta-General gathers information about the world around itself through external sensors. For example, if certain airborne sensors are used, the number and type of hostile ground targets can be determined. From these external sensors, the Meta-General can determine the fighter density, TCT density, and SAM density. Then, knowing the range to a desired target, a random search can be used to query the surrogate models to determine what type of aircraft and weapons should be used as well as a preferred ground/air weapon ratio for the hostile region. The battle manager will be driven to make the best possible decisions taking into account asset availability and predetermined rules of engagement. As the simulation progresses, both the status of friendly aircraft availability and the density of the enemy will change, which can drive the intelligent battle manager to make different decisions. This simple example is used to demonstrate the viability of the neural network surrogate modeling approach to intelligent battle management. Future efforts will involve more degrees of freedom and constraints and a more realistic scenario dominated by complex interactions between systems.

6 Enabling Intelligence at the Asset Level

As military organizations move toward more network centric operations, the capabilities provided by computers and communications offer the possibility of consolidating complete battlespace control under a single commander. This approach is inconsistent with Air Force doctrine which states: "Centralized control and decentralized execution of air and space power are critical to effective employment of air and space power" [19]. Therefore, the Meta-General approach detailed in the previous section should be confined to strategy determination and campaign planning, avoiding micromanagement of tactics.

However, as previously mentioned, improper selection of tactics will lead to suboptimal technology choices. A means must exist to allow individual agents at the system level to determine their tactics to best exploit the benefits provided by a new technology. To address this issue, an approach that uses intelligent agents at the asset level is proposed.

While the simulation is governed by the laws of physics, agent behavior within these constraints is defined by cognition models: rule sets that define what an agent should *do* under various operating conditions. Through the identification of a canonical set of actions, goals, and constraints, a computerized agent can be tuned with "artificial intelligence" to imitate what a human would do under similar circumstances. Different behaviors can be triggered by changing the agent's goals or altering its perception of the world.

One such perception is the agent's beliefs about its own abilities, defined by the properties of a vehicle such as top speed, turn rate, takeoff field length required, fuel weight, and excess power to name a few. If an agent has a means to calculate each of these performance parameters in real-time, it can forecast potential responses to enemy actions. For example, if an agent knows that its top speed is very high, the likelihood of the "escape" operation is significantly increased. If one of the agent's goals is its own survivability, it would prefer to escape rather than engage if it was possible to predict that the escape operation would be successful.

Unfortunately, the evaluation of these parameters can be a computationally expensive procedure that sometimes involves iteration or the solution of systems of equations. For a single agent, this is a trivial computational burden; however, for complex system architectures dominated by large numbers of heterogeneous, interacting agents with different operating conditions, the computational effort to evaluate these parameters for all agents at each time step is extreme. Realistic and detailed asset-level intelligence cannot be enabled without a means to speed up this computation process. Surrogate models are proposed as a means to provide intelligence to individual agents without causing an unrealistic computational burden.

A proof-of-concept example of this technique is given for an air superiority fighter. A critical parameter in air-to-air combat is the *specific excess power*, which is related to the ability of an aircraft to instantaneously change potential energy into kinetic energy (and vice versa). Different physical characteristics of an aircraft may contribute to its specific excess power in terms of top speed, turn performance, climb performance, horizontal acceleration, and the like. Technologies impact the physical characteristics and hence contribute to the production of excess power. A "performance vector of attributes" (PVA) that summarizes the ability of an aircraft to perform various maneuvers can therefore be written as:

$$PVA = \alpha(\Delta Speed) + \beta(\Delta Turn) + \delta(\Delta Accel)...$$

Where $\Delta Speed$, $\Delta Turn$, and $\Delta Accel$ represent the amount of excess power in each type of maneuver and α, β, and δ are scale factors on the importance of each maneuver for the mission being performed. For example, in a high-speed penetration mission, speed may be more important than turn performance whereas the opposite may be true for a high-altitude dogfight. For a given mission, the numerical value of the PVA can be used as the trigger for the cognition model to decide whether to fight or to flee: if the PVA is sufficiently high, the aircraft is predicted to win an engagement against a notional adversary.

In Figure 6, three dimensional contours for excess power are shown across the flight

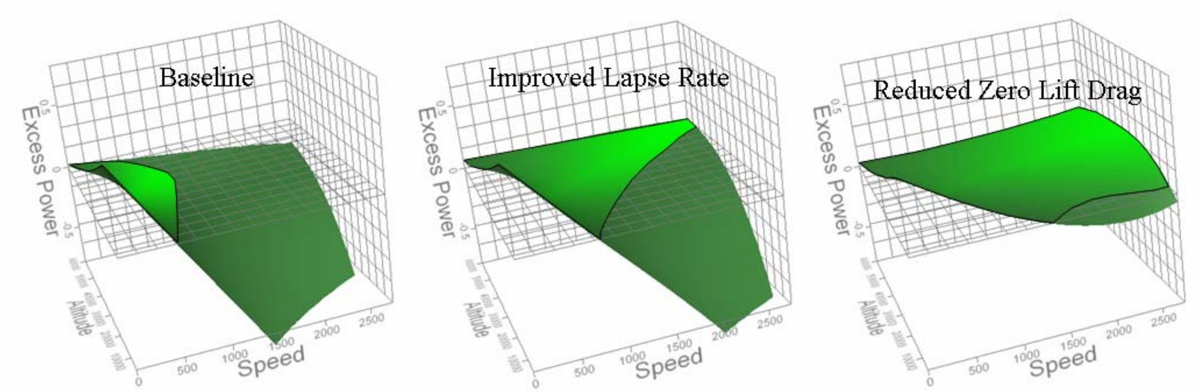

Fig. 6. Illustration of How Excess Power Changes Across the Flight Envelope as Technologies are Infused on the Discipline-Level Metrics (Improvement Shown in Bright Green).

envelope (altitude vs. speed). Shaded regions indicate portions of the flight envelope where specific excess power is greater than zero. A PVA that takes excess power into account would therefore favor engagement in cases with larger shaded areas. In addition to the baseline case, two examples are shown, one for improved lapse rate indicating a better propulsion system and another for reduced zero lift drag which could represent better aerodynamic design or internal weapon bays.

An intelligent agent would use the surrogate model to calculate its PVA before deciding whether or not to engage an adversary. Many of the inputs to the surrogate model are attributes of the agent at a given instant in time that can be determined through sensors of the external environment (including the speed and altitude). Other inputs to the surrogate model are given as “k-factors” which are scaling parameters on other discipline-level metrics to represent the infusion of technology.

As new technologies are given to the agent in the form of these k-factors, it can utilize the surrogate model to rapidly recalculate potential maneuvers, which will enable or disable certain cognitive paths depending on user defined thresholds that represent the allowable risk on a given mission. The formulation of cognition models and PVA’s for different missions is an area of ongoing research.

7 Conclusions and Future Work

A shift in military acquisition to a capability-based focus requires that resources be allocated with respect to the effects achieved. Identifying a suite of technologies to provide capabilities against future threats requires the use of a modeling and simulation environment to quantitatively calculate the *effectiveness* of proposed solutions. Although some elements of a structured methodology can be determined through a literature search of best-in-class techniques (see Figure 2), a critical issue that arises in simulation-based technology evaluation is the confounding issue of technologies and tactics.

A proposed solution at the campaign level is the use of machine learning algorithms and an intelligent super-agent or Meta-General to simulate human cognition processes and identify appropriate strategies. As a proof-of-concept, this technique was validated for a simple probability-based mathematical example. The doctrine of decentralized execution negates micro-management of tactics by the Meta-General and requires an alternate approach at the system level. A proposed approach uses surrogate models to provide an intelligent forecasting ability to individual agents. This technique was validated using an energy-based formulation for excess power calculation.

While each of these techniques was demonstrated in turn using a mathematical experiment representative of those seen in a real problem, future research will synthesize these elements into the holistic process and demonstrate the ability of the proposed methodology to evaluate the effectiveness of technologies at the “system-of-systems” level without the confounding impact of tactics. An example problem of significance to the military acquisition community will be selected and an appropriate experimental environment for modeling and simulation will be constructed.

Of interest is the ability of the proposed methodology to function outside the realm of mathematical curiosity and on a challenging problem of interest dominated by complex interactions, multiple heterogeneous systems, and unpredictable emergent behavior resulting from the synthesis of systems within a campaign-level modeling and simulation environment.

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