

BALANCING INFORMATION ANALYSIS AND DECISION VALUE: A MODEL TO EXPLOIT THE DECISION PROCESS

Paul Hyden

Naval Research Laboratory
4555 Overlook Ave, S.W.
Washington, DC 20375, USA

Stephen Russell

Naval Research Laboratory
4555 Overlook Ave, S.W.
Washington, DC 20375, USA

ABSTRACT

In a time of competing and constrained resources the value of intelligence analysis to decision value is an elusive factor to quantify. This issue is confounded by ever-increasing initiatives to increase information sources and automate the decision workflow. In order to effectively evaluate possible changes to information analysis and related decision workflows, it is critically important to characterize key features of the decision process. This paper presents a theoretical Commander's decision problem: "Should I attack and where?" In the context of this problem a model, based on a simplified time dilation optimization methodology, is developed to examine the effects of intelligence analysis strategies on the decision workflow and process. The model is evaluated using several initial assumption cases and the implications of are discussed.

1 INTRODUCTION

There are many challenges to the decision process that intelligence analysis is intended to support. Many of these obstacles boil down to time/speed, quality/clarity, and availability/utility. As a result not only do decisions result in trade-offs there are implicit tradeoffs within a decision making process. Decision-making and the processes necessary to support it may be viewed from many different perspectives depending on the scope of the decision. These perspectives include strategic level goals and objectives down to the individual decisions and judgments made by analysts that support mission activities and commanders' intent. While individual decisions made by analysts form the basis and support for higher order objectives and choices, analysts base their judgments and individual decisions on available information.

The internal process-related tradeoff is one of acceptable intelligence analysis and rigor against decision timeliness and outcome value. In this context, intelligence analysis can be viewed as a critical and scarce resource, one of which has been well documented (MacDonald and Oettinger 2002; Pappas and Simon 2002). To the extent that intelligence analysis is required and considered a valued resource, it follows that quantifying and optimizing the decision process can provide direct and tangible benefits to decision making. Moreover as organizations seek to deploy tools that facilitate and automate decision making processes, it will become increasingly important to understand the key features of the intelligence analysis characteristics and decision-making environment/workflow

To this end, in this paper a theoretical Commander's Problem example problem is put forward, around which a model is developed that allows the evaluation of various intelligence analysis strategies. The analytical strategies provide an initial perspective on modeling analysis-effort-value relationships that can be used to characterized features of an optimal decision process within the context of the generalized Commander's Problem. The paper is organized as follows. Section 2 provides background on information and intelligence analysis within the context of decision making. Section 3 discusses the relationship

of rigor to intelligence analysis and decision value. The Commander's Problem, the model, and its evaluation are presented in Section 4, followed by conclusion in Section 5.

2 BACKGROUND

A historical review of warfare, particularly those engagements involving counterinsurgency reveals a noteworthy constant – none has been effectively carried out without a methodology for gathering and disseminating timely and accurate intelligence data (Clark 2006). The ability to capture large amounts of data and the plenitude of modern intelligence information sources provides a rich cache of technical intelligence e.g. signals and sensors (SIGINT and MASINT), imagery (IMINT), as well as human and open source intelligence (HUMINT and OSINT). The vastness of this information presents significant challenges to its management and exploitation for decision-making processes. While there are many techniques for managing information collected and derived from these sources, the exploitation of intelligence assets for decision-making remains an ongoing challenge complicated by the ever-increasing amounts of data collected. Consistent with Herbert Simon's classic (1969) intelligence-design-choice model of the human decision phases, intelligence (observation of reality and collection of data) and analysis is at the forefront of this challenge.

2.1 Information and Intelligence Analysis

Modern military intelligence analysis is a complex process that involves sorting through huge amounts of multi-format data (e.g. written and oral reports, geospatial imagery/video, tables of numeric data, and video and audio) from a wide variety of sources, combining seemingly unrelated events to construct an accurate depiction of, and make predictions about, temporally-dynamic situations. Intelligence analysis, as a form of abductive reasoning (Schum 1987), is a special case of information analysis. However unlike common information analysis, intelligence analysis is fomented by the additional problems of secrecy and adversarial intent. Performed in the support of goals that often extend beyond those of the analyst and occurring in a context where the consequence of insufficient analysis are substantial, intelligence analysis is conducted to influence decisions where other agents are directly operating to affect or manipulate the same decisions. The essence of intelligence analysis is to transform data into information, something of value, which can be actionable in the context of decision-making, potentially at a variety of levels (e.g. tactical, operational, and strategic).

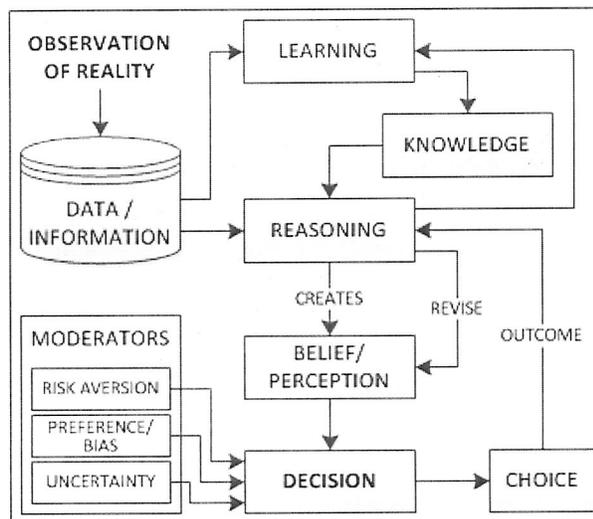


Figure 1. Conceptual individual decision-making process

2.2 Intelligence Analysis and Decision-making

At a functional level, intelligence analysts evaluate hypothesis within a given domain seeking evidence to confirm or reject those hypotheses. In a document (Clawson 2008) titled "What Does (Should) An Analyst Do? A Brief Introduction for New Analysts" produced by the Naval Surface Warfare Center, analysts plan, execute and explain. Planning in this context is taken as determining the question(s) to be answered, and to define the scope of the study. In other words, define the problem. Execution is about the research

and evaluation itself. Explaining not only includes conveying the results, but also ensuring that the execution has sufficient rigor to explain the outcome. The direct parallel made by this operational description of what intelligence analysts do and decision-making processes is apparent. In decision-making one observes reality and defines the problem (plan), gathers support for or against an alternative (execute), and then makes a defensible (explained) choice based on the execution.

Figure 1 illustrates an individual's internal decision process. Reality is observed, and this is collected as data, which is then applied to learning or directly to a reasoning activity. The reasoning activity gets inputs as either knowledge or raw data/information and uses this to create or revise an individual's belief, which is directly applied to judgments and decisions. The decision may be moderated external factors (not comprehensively illustrated in Figure 1) such as individual propensity for risk, preferences, and uncertainty. The outcome of the decision (choice) is evaluated through the reasoning activity and manifested in further observations of reality. The process in Figure 1 represents lower level functions that occur in the execution of a broader intelligence cycle.

Intelligence analysis is conducted as part of a cycle that generally follows the activities necessary for decision-making (Funk and Sorensen 2005). This cycle, which consists of six significant steps (planning and direction, collection, processing and exploitation, production, dissemination, and utilization) that occur sequentially, translate the need for intelligence about a particular aspect of the battlespace, mission, or threat into a knowledge-based product that is provided to decision-makers. This cycle incorporates intelligence development, implicitly consistent with conceptual models of human judgment and decision-making. Figure 2 illustrates the intelligence cycle, intelligence development, Hogarth's (1987) judgment model and Simon's (1969) decision model. Figure 2 horizontally aligns the components of the conceptual models with the corresponding elements and activities in the intelligence development process and cycle.

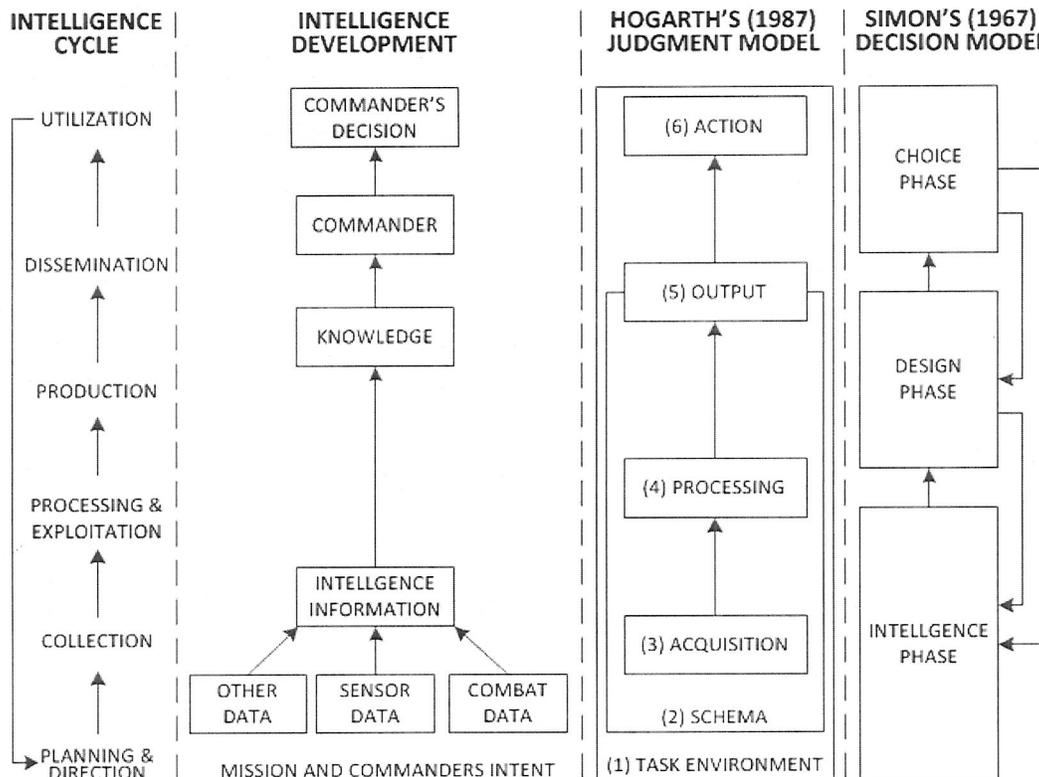


Figure 2. Intelligence cycle/development and conceptual models of human judgment/decision-making

While there are several other models of the intelligence cycle and decision-making, including TPED (tasking, processing, exploitation, dissemination), TPPU (task, post, process, use), TCPED (task, collect, process, exploit, disseminate), and the ubiquitous OODA (observe, orient, decide, act) loop, these models describe activities similar to those shown in Figure 2. The intelligence decision-analysis process is intrinsically recursive and cyclic with feedback loops. If everything is ideal, the loops inform each other: feedback from tactical loops will guide decisions at higher loops and vice versa.

It is noteworthy that the broader portion of Figure 2 (all but the topmost parts, across all 4 columns) deals with the acquisition, collection and processing of data. Not to minimize its importance, choice is a relatively small portion of the process. As the Department of Defense expands its capability to collect ever-increasing amounts of data from such systems as real-time/near real-time (RT/NRT) full motion video (FMV) systems e.g. Predator, Constant Hawk, and JSTARS, the larger portion of the decision-making value chain is challenged by the sheer data volume. The impediments posed by the volume of data are compounded by workflows within the decision process and the architectures of the systems employed to facilitate those workflows.

3 RIGOR AS A CHALLENGE TO BALANCING ANALYSIS-DECISION VALUE

Faced with significant production pressures (Johnson 2005) and expanding data availability (Patterson, Roth et al. 2001), resulting data overload deluging the professional analyst, it is increasingly easy for analysts to be trapped by shallow, low-rigor analysis (e.g., analysts typically use basic and unproductive search strategies according to Dominguez et. al, 2005). Given similar pressures, it is also increasingly difficult for decision makers to recognize when an analysis is not of sufficient rigor for a given decision. This uncertainty impacts the analysis process and it is also an elusive metric.

When is enough, enough in intelligence analysis? The fact that many analysis processes are time limited suggest that enough is enough when time runs out. However rigor can take on additional dimensions particularly when large amounts of data are involved: were the right tools applied? Was sufficient data explored? Was the right methodology used? Conventional perspectives for measuring analytical rigor focus on identifying gaps between what was actually done versus a prescribed or "standard" method, with rigor variously defined as the "scrupulous adherence to established standards" (Crippen, Daniel et al. 2005) the "application of precise and exacting standards" (Military Operations Research Society 2006) and the "unspoken standard by which all research is measured" (Davies and Dodd 2002). These definitions of rigor generally speak to the process.

Within the structure of a "rigorous" process there is an implicit dependence on the techniques and tools utilized within that process, implying "appropriateness." From a practical standpoint some data collection or analysis tools/techniques are viewed as "more" rigorous than others. If techniques are tools in analysts' toolbox, then this is like saying that "a saw is better than a hammer because it is sharper." Consider this issue in the context of intelligence analysis, which has been described as the process of "making inferences from available data" and determining "the best explanation for uncertain, contradictory, and/or incomplete data" (Trent, Patterson et al. 2007). The problem becomes the use of the appropriate tool(s), applied to the appropriate methodology, with appropriate depth or scope. This selective balance of tools, methods, and judgment, which may vary from analyst to analyst in highly collaborative, dynamic environments frames the problem of rigor in an analysis process and underscores the inherent uncertainty from both the analysts and decision-makers viewpoint.

Some work has been conducted on analysis rigor, notably that of Zelik, Patterson, et al. The summary of their efforts showed that providing process insight to participants initiated changes in perceptions of rigor. It was also found that professional analysts tended to use similar cues in making judgments of rigor; however, the ways in which those cues were transformed into composite assessments of rigor were more varied. A surprising finding was that when study participant were guided to focus on when a product was ready to forward to a decision maker, this led to the development of a revised definition of rigor,

reframing it as a multi-attribute, emergent measure of sufficiency rather than a measure of process deviation (Zelik, Patterson et al. 2007).

As the changing technological and social landscape of intelligence analysis exacerbates the already difficult task of detecting when analysis is of sufficient rigor, it becomes increasingly uncertain for both the analyst and decision maker to define a congruent optimal level of rigor. While it may be feasible to determine nominal measures of rigor or define rigor as a management objective, a better understanding of rigor is necessary before these constructs can be effectively applied to decision-related analysis workflows and decision support systems.

Fundamentally, the challenge to achieving equilibrium between analysis effort/speed and decision value is striking an appropriate, if not optimal, balance between the decision process and the outcome value. Given the decision process is comprised of a workflow that includes data consumption, processing, and communication/execution, it maybe possible to tune the process such that the workflows involved are designed to exploit the particular structure of the decision opportunity.

4 DECISION-DRIVEN OPPORTUNITIES: MODELING THE DECISION-MAKING PROCESS

This section presents a model of a decision life cycle and the potential to optimize information analysis in order to maximize decision-making execution. Identifying, describing, and modeling commonly repeated decision-making processes provide awareness and focus of the challenges inherent in the process. In particular the focus is on those features of the decision process that offer opportunities for optimization.

In order to evaluate possible changes to current decision workflows, it is important to model the key features of the decision process. In controlled environments, the efficacy of the decision-making process can be evaluated over numerous trials and in a variety of scenarios. While the modeling process necessarily simplifies some aspects of the real world decision process, key themes of decision process challenges are preserved and analyzed. A spectrum of approaches from analytical models through discrete-event simulation and process modeling approaches through to role-playing simulations can be useful to understand the decision-making environment and workflow.

The interesting feature of a decision process is that time is explicitly introduced in the process. In general, decisions are continuous processes. Upon inception, the default decision is generally the status quo, and the time allowed before an absolute deadline allows us to continuously update that decision. Of course, decisions can be made before a deadline, and often the value of a decision is enhanced if provided early. Along the way, the choice of what data is analyzed is a key driver in the ability to make a timely and effective decision.

Automation opportunities that address the decision process itself are less well studied in the intelligence domain, compared to other domains, e.g. commercial manufacturing and finance. In the latter domains, delays in making a decision (time to market) can significantly influence costs and profits. The following section illustrates a time dilation model motivated by a manufacturing scenario (Hyden and Schruben 2000) applied to intelligence analysis and decision making.

4.1 A Commander's Problem: Should I attack and where?

Although simplified of important details, it is instructive to consider the lifecycle of a decision process selecting between a relatively small number of alternatives. For the purpose of illustrating a stylized decision process, we describe a greatly simplified decision problem. This scenario allows an examination of key features of the intelligence decision-making process and highlights some of the opportunities and challenges for improvement.

Suppose a commander on the ground has identified two hostile targets. Given to resource constraints, the commander can only attack one target. In order to choose the target that has the greatest level of tactical value, the commander have decided to enlist the help of intelligence analysts. A full study of each

target would take two days, although the analysis on each target decomposes naturally into two single day blocks of analysis. Due to the difficulty of managing the analysis, the effort assigned to study the targets cannot be delegated with any finer detail than a single day unit of analysis. Resource constraints at the intelligence analysis office limit the commander to using only one analyst per day. Further, tactical requirements will force the commander to choose a target in two days.

Somewhat surprisingly, this simple scenario offers a rich array of analytical content to model the challenges in analyzing decision making. The scenario has been winnowed enough to be described by the following simple structure: The commander's problem is to allocate two days of analysis-time between four units of analysis-needs required for his alternatives. The ultimate decision of where to attack is at least partially determined by the choice of where/how to allocate intelligence analysis effort. As shown in **Error! Reference source not found.**, a choice of A_1 implies that an analyst will be assigned to study the first analysis block of target A; A_2 implies an assignment to the second analysis block of Target A and the ++

It is assumed that both targets have a minimal level of tactical importance. Based on previous data or perhaps the intuition of the analyst, it is also assumed that any segment of the study reveals one additional marginal unit of tactical value with probability p , where $0 < p < 1$. It is further assumed that the partitioning of analysis and targets insures that this probability is independent for each block of analysis. Allow $A_1=1$ if the analysis of Block 1 for target A reveals an additional threat, and 0 otherwise. Putting this together, yields $P(A_1=1)=p$ and $P(A_1=0)=1-p$ and each of A_1 , A_2 , B_1 , and B_2 are Bernoulli random variables with parameter p . Hence, a priori, the probability distribution on the number of marginal units of tactical value for each target is binomial with parameters p and $n=2$. So, stated explicitly, the probability that Target A has k units of marginal tactical value is $p^k(1-p)^{(2-k)}$ for $k=0,1,2$; and it is assumed that Target B has the same distribution.

4.2 Modeling the Commander's Decision Problem

Given the above description, the task is to choose the target with the greatest tactical value given the information provided from the commander's intelligence analysis. The third choice, a common default of many decision scenarios, is to do nothing. Initially the correct decision is to choose a target when it has the most tactical value, and to do nothing in the case where the targets have the same value. Later, this assumption will be varied to examine the sensitivity of the measures to aforementioned assumptions. To serve that decision, it is necessary to decide what data to analyze. To evaluate the quality of the decision, a value of 1 will be assigned whenever a correct decision is made.

The decision process that has the highest expected value will be presumed to be the best decision process, which in this weighting, corresponds to maximizing the probability of a correct decision. Here the term 'decision process' is used to describe the procedure by which the decision is output. Since the output of this decision process is a function of stochastic input, it is necessary to evaluate the process using tools from probability. The method of evaluating the decision process is also critical and can drive the choice for the optimal strategy.

Outcome	Correct Decision
Target A has greater tactical value	Choose target A
Target B has greater tactical value	Choose target B
Target A and target B have equal tactical value	Do nothing

Table 1: Correct Decisions for a Commander's Problem

Since both the labeling of the targets and the units of analysis on each target are arbitrary, it is safe to assume without loss of generality, that the first unit of analysis is always spent on A_1 . Initially the commander has two basic choices. Either the analyst could be tasked spend two days studying target A (A_1, A_2) or alternatively, tasked to spend one day of analysis on each target (A_1, B_1). Careful study of the scenario reveals some significant details in the commander's choice that can be used to enrich the

model decision analysis. Consider, while the commander has two days to determine the attack, it is reasonable to allow for an early decision by the commander on the target choice. That is, the commander may decide the target after 0, 1, or 2 days. This is a significant enrichment for many decision making scenarios, as it is reasonable to assume that a target-analysis is more valuable the earlier it gets to the commander, recognizing that the outcome of a quick decision may result in a lower quality outcome.

Another subtle choice is available in the allocation of the analyst. Having revealed the results of A_1 , the second day of analysis can be chosen as a function of the results obtained at any time during day one. To the practical point of optimizing the decision process, it is straightforward to automate this choice. In this way, the allocation of our analytical resources can be dynamically adjusted to fit the needs of a specific decision process, even in this simple scenario.

Taking these enrichments together, this simplified commander's problem reveals six natural, fully automatic, discrete strategies for analyzing the targets as shown in Table 2.

Strategy	Comments
None. No target is analyzed.	No information is provided to the commander, but the attack can be launched immediately.
One day only. A_1	Only target A is examined, and target A is only examined for 1 day. However, the attack can be launched after 1 day.
Deep. (A_1, A_2)	Target A is examined fully for 2 days. Target B is unexamined. The attack is launched after two days.
Broad. (A_1, B_1)	Both targets are examined, but only for one day each.
Variable Hybrid 1 (Greedy). A_1 then A_2 if A_1 exposes risk, otherwise B_1	Completely study target A if preliminary analysis reveals a threat. Otherwise, study target B.
Variable Hybrid 2 (Scanning). A_1 then B_1 if A_1 exposes risk, otherwise A_2	Study both targets if preliminary analysis reveals a threat. Otherwise, completely study target A.

Table 2: Strategies for a Commander's Problem

Taking the strategies shown in Table 2, a plot can be made of the expected value for each strategy as a function of the probability that any day of analysis discovers a threat, shown in the figure as p . Some intuitive results become clear in the plot shown in Figure 3. As expected, more analysis generally increases the expected value of the decision process. An example is provided later illustrating whether this information actually changes our decision. In this case, the uniformly superior strategy is to simply allocate the same amount of analysis to each target. The special place where $p=0.5$ also highlights that the policies converge when the possibility of finding a threat is merely a coin flip. The choice of where to analyze is not important in that single instance.

	Weight of correctly choosing target A	Weight of correctly choosing target B	Weight of correctly choosing to do nothing
Case 1	1	1	1
Case 2	1	1	0
Case 3	.25	.25	1

Table 3: Weights of Correct Decisions in Evaluating Decision Process

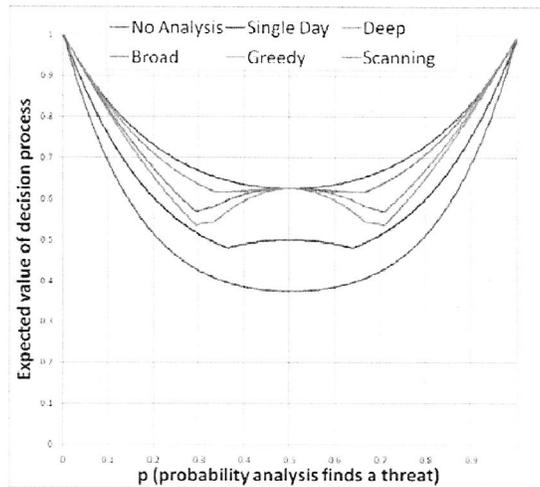


Figure 3. Expected Value of Decision Process as a Function of p (Case 1)

This example becomes more interesting when our initial decision output assumptions are adjusted. For example, suppose the evaluation of a correct decision is changed so that zero weight is given to 'Do nothing' as the correct choice. With this weighting, it is necessary to make a choice between the two alternatives, because simply choosing to 'Do nothing' does not enhance the value of the decision process. Figure 4 shows what is the best decision process in that case and several interesting changes happen. First, the shape of the response curves change significantly compared to the first case (Figure 3). When p is very large or very small, the targets are more likely to be tied in importance. Since the value of being correct in these instances was removed, the value of the decision process drops to 0 as p gets close to 1 or 0. This is probably closer to the commander's true decision. This is because the targets really do have equal weight; there isn't any need to discern between the targets based on tactical value. The commander can choose between the targets based on any other number of objectives, which themselves could be the subject of further analysis. For example, the best path for the commander may be simply to attack one of the targets without further analysis.

Another interesting phenomenon is that the value of dynamic policies emerges in this case, where the 'Do nothing' choice is correct. The structurally similar 'greedy' and 'scanning' strategies each are optimal over a range of values of p . However, if examined carefully, it is apparent that one strategy is again superior over all values of p : the 'deep' strategy. The optimal strategy in our first case (Figure 3), the 'broad' strategy, is now inferior to all other strategies that use 2 days of analysis. In fact, the value is even worse for the 'broad' strategy because now the '1 day' strategy performs just as well and provides the answer in one less day. By choosing the 'shared' strategy in this case the information value provided by the second day of analysis has been lost. In the special case where $p=0.5$, there is no increased value to spending a second day of analysis, no matter where that day is spent.

As a final case example (Figure 5), the weight of correct decisions on choosing a target is decreased to 0.25 while the value of correctly "Doing nothing" is returned to 1. In this case, being correct about delaying an attack is valued much more than choosing a target, perhaps because the commander's resources are particularly constrained. In this case, there is almost no value in analyzing the target at all.

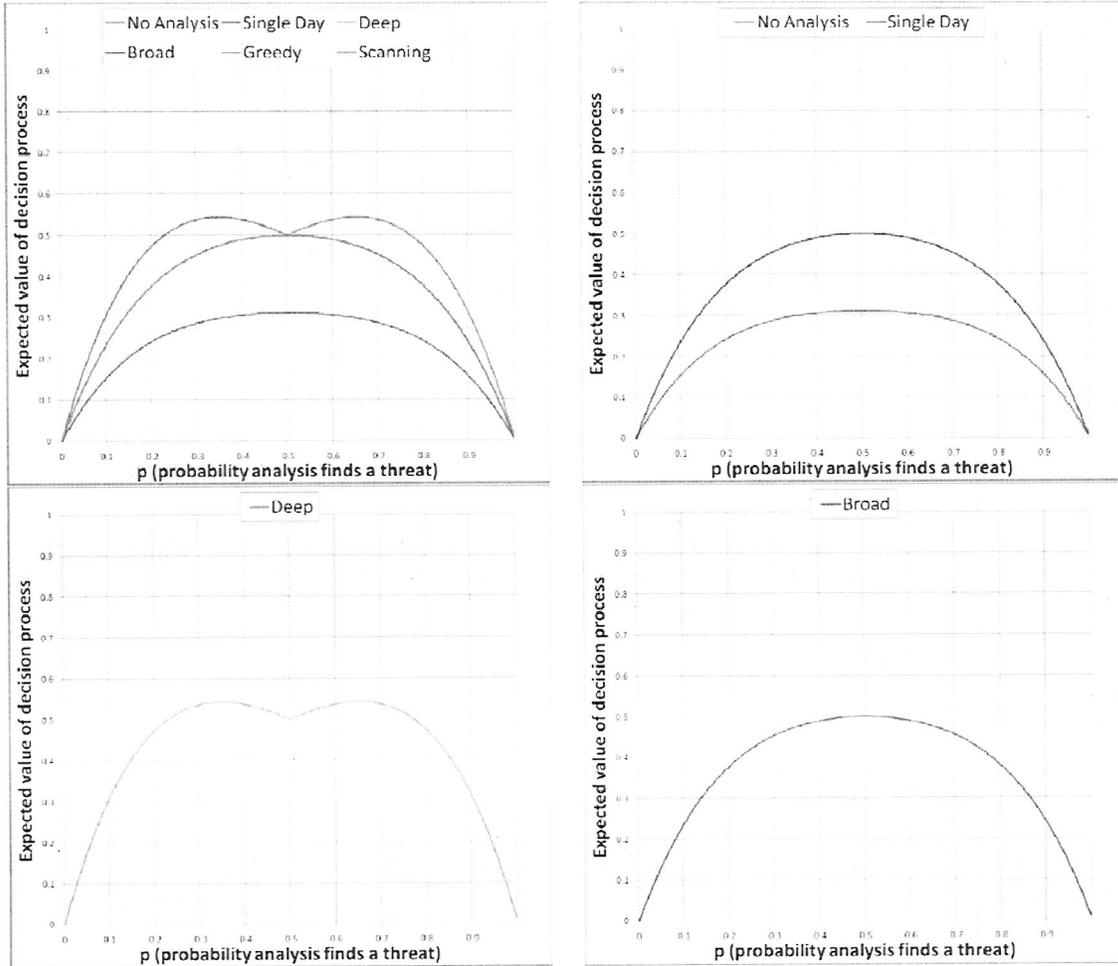


Figure 4. Expected Value of Decision Process (Case 2)

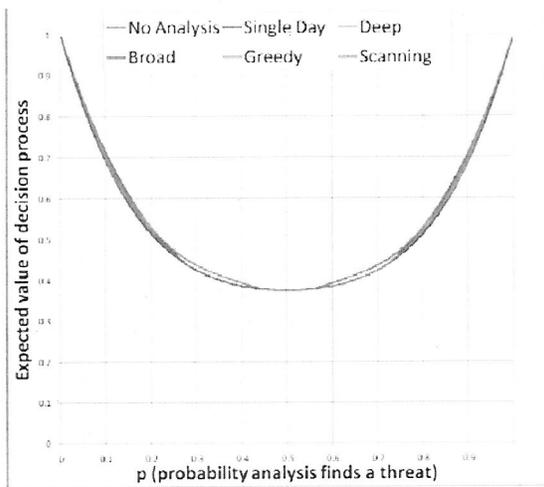


Figure 5. Expected Value of Decision Process (Case 3)

5 CONCLUSION

This research shows that the underlying measures associated with evaluating a decision process can drive optimal strategies for data collection and evaluation. To the extent that intelligence analysis is required and a valued resource, the implications of affecting speed and effort in the analysis task can provide overall gains in decision making. Further, as organizations seek to increasingly automate both analysis and decision making functions and workflows the importance of optimizing analysis in the context of adequate rigor and output value will demand methods that provide quantifiable methods to tuning the overall process.

These points are illustrated through a Commander's Problem example and the development of a model where the effects of different intelligence analysis strategies on the theoretical Commander's decision process could be assessed. Presupposed in the Commander's Problem example is that the intelligence analyst has the ability to measure the value of targets and that those measures align with the specific needs of the commander. While the developed model begins with simplified assumptions initially, the simplicity gave the ability to focus on the key elements of the decision, and incrementally add those elements that provided the greatest value to the analysis. In this way, it was possible to systematically work both ends of the problem, starting from a simple controlled process and adding the complexities of a real situation.

The complexities of real world decision problems are varied, complex and not necessarily limited to the cases applied within the developed model. For example, in cases where time is severely constrained, it may be necessary for analysts to commit their limited time to rigorously justifying the decision. However, this research illustrates that these choices fundamentally affect the optimal design of a decision process. Different approaches provide new opportunities to exploit the particular structure of the decision process and optimize data analysis in order to drive decisions as quickly as possible based on the correct metrics. Future work is planned to develop a simulation based on this model that will exercise the model under additional assumptions and more complicated scenarios.

6 REFERENCES

- Clark, D. (2006). *Vital Role of Intelligence in Counterinsurgency Operations*. Carlisle, PA, U.S. Army War College, Carlisle Barracks.
- Clawson, D. A. (2008). *What Does (Should) An Analyst Do? A Brief Introduction for New Analysts*. Dahlgren, VA, Naval Surface Warfare Center, Dahlgren Division (Code W21).
- Crippen, D. L., C. C. Daniel, et al. (2005). *Return to Flight Task Group*. Washington, DC, U.S. Government Printing Office.
- Davies, D. and J. Dodd (2002). "Qualitative research and the question of rigor." *Qualitative Health Research* **12**: 279-289.
- Funk, R. and R. Sorensen (2005). *State Machine Modeling of TPED and TPPU*. NDIA 8th Systems Engineering Conference, San Diego, CA, USA, Defence Research and Development Canada.
- Hogarth, R. (1987). *Judgement and Choice*. Chichester/New York/Brisbane/Toronto, John Wiley and Sons.
- Hyden, P. and L. Schruben (2000). *Improved decision processes through simultaneous simulation and time dilation*. Proceedings of the 32nd Conference on Winter Simulation, Orlando, FL, USA, Winter Simulation Conference. Society for Computer Simulation International.
- Johnson, R. (2005). *Analytic culture in the US Intelligence Community: An ethnographic study*. Washington D.C., USA, Government Printing Office.
- MacDonald, M. M. and A. G. Oettinger (2002). "Information Overload: Managing Intelligence Technologies." *Harvard International Review* **24**(3): 44-48.

- Military Operations Research Society. (2006). "MORS special meeting terms of reference. Paper presented at Bringing Analytical Rigor to Joint Warfighting Experimentation." 2010, from <http://www.mors.org/meetings/bar/tor.htm>.
- Pappas, A. A. and J. Simon (2002). "Daunting Challenges, Hard Decisions: The Intelligence Community: 2001 – 2015." Studies in Intelligence **46**(1).
- Patterson, E. S., E. M. Roth, et al. (2001). "Predicting vulnerabilities in computer-supported inferential analysis under data overload." Cognition, Technology, and Work **3**: 224–237.
- Schum, D. A. (1987). Evidence and inference for the intelligence analyst. Lanham, MD, USA, University Press of America.
- Simon, H. A. (1969). The New Science of Management Decision. New York, NY, USA, Harper & Row.
- Trent, S. A., E. S. Patterson, et al. (2007). "Challenges for cognition in intelligence analysis." Journal of Cognitive Engineering and Decision Making **1**(75-97).
- Zelik, D., E. S. Patterson, et al. (2007). When Is Analysis Sufficient? A Study Of How Professional Intelligence Analysts Judge Rigor. Columbus, Ohio, USA, Cognitive Systems Engineering Laboratory, Department of Industrial and Systems Engineering, The Ohio State University.