Application of Human Decision Field Theory to Estimation of Air-to-Ground Combat Identification Latencies

Glenn O. Allgood, PhD, PE
Jack C. Schryver, PhD
Lauren G. Hatchell (Louisiana State University)
Oak Ridge National Laboratory
P.O. Box 2008
Oak Ridge, TN 37841-6085
865-574-5673; 865-574-4710
allgoodgo@ornl.gov; schryverjc@ornl.gov

Dwight P. Miller, PhD
Sandia National Laboratories
Albuquerque, NM
505-845-9803
dpmille@sandia.gov

ABSTRACT: *This paper describes the development and use of a "Speed of Service" Fixed Wing to Ground simulation model incorporating decision field theory to provide a bounded variable analysis of latency in the FCS system. Latency is described in terms of Time-to-ID based on a CID notional model – CID need, transponder internal delays and duty cycle, digital transmission time, CID message extraction time, data link (shooter–target–shooter–ground station), time to ground platform display, and human decision-making. Simulation runs demonstrate effects of target density, confidence, and network delay on total latency and number of decision cycles. The results of the model will be applied to technology requirements and specifications.*

1. Introduction

In November 2001, DARPA (PM Objective Force) established a Future Combat Systems (FCS) Integrated Support Team (FIST) to support their analytic efforts in developing the basic constructs of the FCS System. The Team was composed of Department of Energy Laboratories (INEEL, ORNL, SNL), MITRE, IDA, and other organizations. One functional team within FIST, the Combat Identification Team, has a mission to support DARPA/PM with analytic studies in the area of Combat Identification (CID). Specifically, its mission is to conduct technology analysis and trade studies, develop specifications from functional requirements, develop CID notional architecture(s), and conduct FCS System of Systems studies and analyses to assess impact and affordability of any proposed CID solution on the FCS.

The FIST CID team participated in the CID Working Group chaired by PMTIMS. The Phase I effort of the WG culminated in the development and recommendation of the FCS CID Increment 1 Notional Architecture. The notional architecture consists of millimeter wave for vehicle-to-vehicle, laser RF for vehicle-to-dismount and back, radio-based combat identification (RBCI) for rotary aircraft and UAVs–to-ground, and radar tag technology for fixed-wing-to-ground CID (Figure 1). The notional architecture represents a strict mapping of technology solutions onto FCS platform requirements (ground-to-ground, ground-to-air, air-to-ground). What is missing is supporting analysis to determine if this is a workable solution and, if it is, what impacts it will have on the FCS C4ISR architecture (network). This paper describes an initial modeling and simulation effort by the FIST CID team to address one of the major aspects of the system operational issues – what are the time requirements for CID air-to-ground data/information flow across the network? In this model, this event is called the
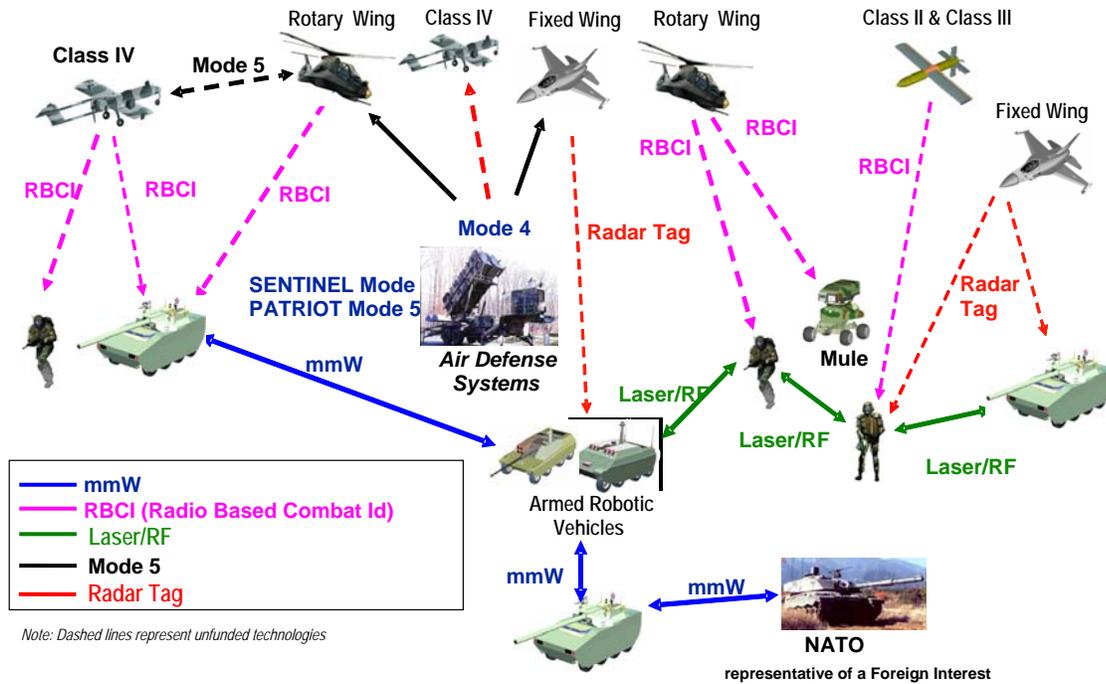
Figure 1. FCS Combat Identification Increment 1 Notional Architecture showing technology solutions and links to operational platforms.

Speed of Service (SoS). The parameters of interest include latency (or time lags), network configuration, interrogator/transponder relationships, and the human-decision process. The human-decision process is modeled using decision field theory [12], which provides both latency and outcome predictions on binary decisions made under time pressure and uncertainty. The following provides details on the model and results from an initial simulation for an NLOS engagement.

2. Speed of Service/Human Decision-Making Model

Figure 2 shows the general structure of the Speed of Service/Human Decision-Making (SoS/HDM) model. There are four major network nodes with associated links. The nodes/links are (1) interrogator to transponder and back, (2) interrogator to source node, (3) source node to C2 node, and (4) C2 node to shooter node. Each node/link pair has a descriptor detailing the parameters associated with the model. These parameters are either directly used in the calculations or are aggregated into the probability distribution function representing that particular element of the network. A close examination of one of the nodes will show the level of detail available in the model. Using the Command and Control node as the example one can see the three processing steps contained

within the node. The first step deals with message extraction and display and is characterized by message extraction, processing by tactical decision aids, and reformat and display. The next step is the 'commander's decision' process which is modeled by the incorporation of decision field theory. One important aspect of this node is the bi-directional flow of information. If the commander's confidence in the data is low, or the data are not within some time window of the current event, the commander can retask to increase confidence in the decision. This allows the commander to use situational awareness (SA) to increase confidence in CID assessment. The final step at the C2 node is 'message format for retransmit' on network. Although simple in construct, the model can be easily reconfigured to provide a different representation of the FCS network.

This general CID network model was chosen because it could be used to represent several echelons of CID function without major changes to the program. These representations can include NLOS, BLOS, and LOS and are easily simulated by appropriate selection of network nodes and links and setting of appropriate parameters. Although originally developed to calculate overall latencies in fixed wing to ground CID, the model can be applied to ground-to-ground and ground-to-air simulations.
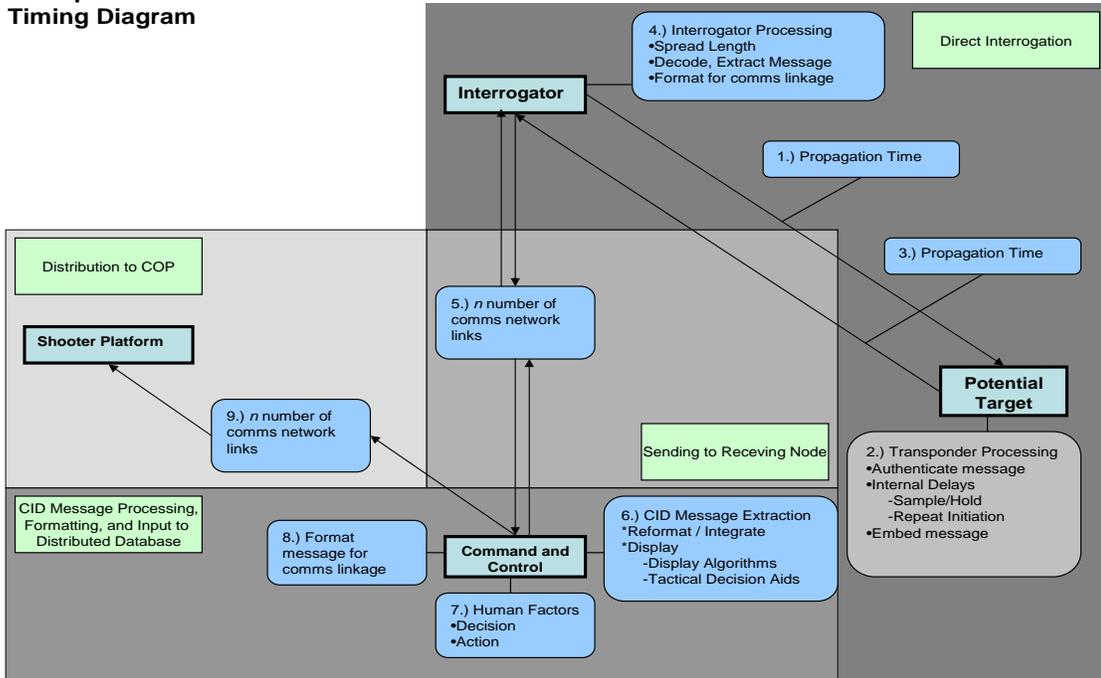
Figure 2. CID SoS Model depicting network links and descriptors along with node parameters.

3. Queuing and Renewal Theory in the SoS/HDM Model

Section 2 described the general structure of the SoS/HDM Model. There is a flow of events occurring where information/data packets are passed from interrogator to transponder, back to interrogator, and then pushed into the network for further analysis and decisions at higher echelons or nodes. This flow can be thought of as a queuing process where each node receives information or data and works on it to extract the information of importance. Upon extraction, analysis is performed with the outcome being a control decision. This information/data is then reformatted, packaged and transferred through the network to the next node for higher levels of abstraction and processing. The key parameter of interest in this model is the time between initiation of the CID process and the end of a cycle. Figure 3 shows the process flow diagram associated with the model. A CID cycle is either terminated due to a retask of information, Battle Damage Assessment function invoked, or identification pushed onto a stack/list for future assessments.

In the current model, each packet's (information/data) time to next node and node processing times are independently distributed, i.e. its probability distribution function for transmission between nodes and the time for processing at each node (N_j) are independent of previous events.
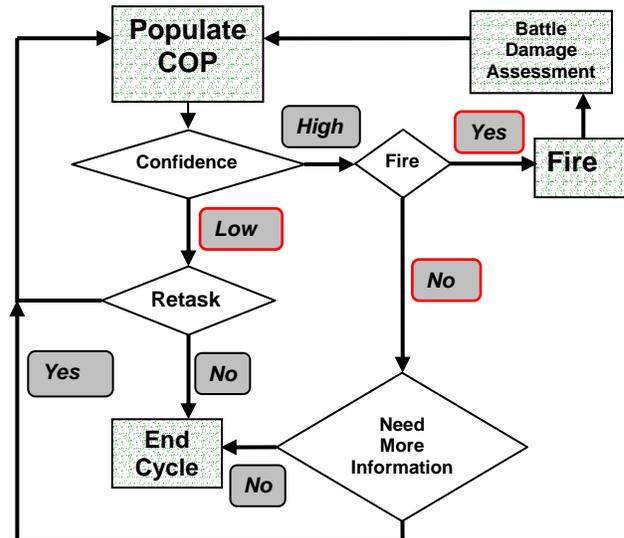

Figure 3. CID process flow diagram representing human decision factors (enemy identified with intent to engage) and ending states for CID cycle. Ending states are (1) request for BDA function, (2) retask, and (3) identified entity pushed to stack or list of future targets.

With the above argument as a basis, the SoS/HDM model is developed as a queuing/renewal model. Referring back to Figures 2 and 3, information/data flow from one point (node) to another and at arrival, request a form of processing or attention. The taxonomy of this model is

designated as *GI/GI/1*. Here GI in the first position is any general distribution of inter-arrival times which are independent; GI in the second position represents a general distribution of service times; 1 in the third position represents the number of parallel servers. The specific details of queuing models can be found in [1] and [2]. In addition, times between events (time across network until arrival at a node and node processing times) are considered independently and identically distributed with arbitrary probability distribution functions. This is the definition of a renewal process [3]. A variety of network configurations and probability distributions associated with network configuration and service along with processing times can be managed from this general model to allow different scenarios to be run.

4. Human Decision-Making

We now briefly review existing models in human-automation interaction and their applicability to battlefield decision-making. An important approach to qualitative aspects of decision-making in the battlespace is the naturalistic decision-making framework within which the well-known recognition-primed decision model was developed (e.g., [4]). This model rests on the often-documented observation that well-trained experts rely mostly on pattern recognition processes to prime decision-making in real time. Cohen, et. al [5] expanded on that framework by describing a set of critical thinking or metacognitive strategies to augment recognition processes in uncertain environments.

Another class of high-resolution models seeks to explain cognitive processes involved in decision-making, and typically describe the content of decisions as well as the processes themselves. These models are typically highly parameterized, and considerable effort may be necessary to populate the models. For example, the Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE) is a pilot model of situation assessment [6]. COGNET is a modeling framework for human operators in real-time multi-tasking computer environments [7]. Finally, a system of computational agents called TAIPE, or Tactical Assistants for Interaction Planning and Execution, was implemented to aid human operators to manage multiple tasks [8].

Computational models have the advantage of providing numerical predictions of decision-making. Therefore, they can be tested using actual data from laboratory or field situations, and improved or modified to better account for data. Parasuraman [9] surveyed a number of computational models of decision-making. Computational models tend to be process-based, and can provide quantitative predictions requiring only a moderate

effort in parameterization. For a recent introduction to decision theory in a psychological context, refer to [10]; a comprehensive overview of decision-making with military applications is in [11]. The study of decision-making in uncertain environments has a long history in the psychological literature. Early researchers sought prescriptive models to instruct decision-makers regarding optimum techniques to arrive at good decisions. The basic idea was to maximize the expected value of a decision, if the decision were to be repeated in similar contexts on numerous occasions. Here we focus on computational models that grew out of an expected value maximization approach to decision-making.

We began the current modeling effort with a few general observations about the commander's decision process for CID: (1) high costs associated with errant decisions; (2) uncertainty about targets and related information; (3) limited time for deliberation; (4) presence of electronic decision aids; (5) availability of additional contextual information; and (6) delayed feedback of effects of firing on targets. We concluded that the naturalistic decision-making framework was not well-suited for decision-making under uncertainty or prediction of decision-making latency.

Busemeyer and Townsend [12] developed decision field theory (DFT) in order to understand the motivational and cognitive mechanisms that guide decision-making under uncertainty. Built on a foundation of random, subjective-expected utility (SEU) theory, DFT lends itself particularly well to situations involving deliberation under uncertainty, where the human decision-maker's task requires accepting or rejecting a binary choice presented by an automated aid, such as in automated target recognition or battlefield-damage assessment.

The main emphasis in DFT is on the deliberation process itself, instead of the specific content of deliberation. According to Busemeyer and Townsend, deliberation involves information seeking, weighing of consequences, and conflict resolution, and "is manifested by indecisiveness, vacillation, inconsistency, lengthy deliberation, and distress."

SEU theory summarizes a binary choice under uncertainty in a 2 X 2 matrix (Figure 4). The basic mathematical model of choice can be represented as a weighted sum of benefits and costs. Suppose a battlefield commander faces a decision to act on information provided by a CID decision-aiding system. A device has identified an object as friendly. There is an implicit binary choice here; the commander must accept or reject the friendly designation. Ground truth dictates that the object is actually friendly or a masked enemy.

Weights are assigned to the amount of attention allocated to the possibility that an object is friendly (W_{S1}) or an enemy target (W_{S2}). The preference state (strength of

	S1: Friendly	S2: Enemy
A1: Accept Friendly CID message	**+2**	**-8**
A2: Fail to accept Friendly CID message	**-10**	**+4**

Figure 4. 2 X 2 Cost matrix from SEU theory shows example gains (black) and penalties (red) associated with row choices (A1, A2) as a function of column ground truth (S1:Friendly, S2:Enemy).

each decision alternative) is calculated as a linear combination of weights and costs, and expressed in subjective units that are not directly observable. Suppose we arbitrarily assign $W_{S1} = 0.4$ and $W_{S2} = 0.6$. The preference for A1 is $(0.4)*(2) + (0.6)*(-8) = -4.0$, and the preference for A2 is $(0.4)*(-10) + (0.6)*(4) = -1.6$. In this example rejection of the friendly tag is regarded as less negative than accepting the friendly designation. However, different values for weights and costs could result in qualitatively different predictions.

Different scenarios may have large effects on the values of utilities in the cost matrix. For example, we expect that the miss penalty $u(1,2)$ will be subjectively greater in a LOS engagement as compared to an NLOS engagement.

In mathematical terms the strength of the preference for A1 or A2 is:

$$V_i = W_{S1}*u(i,1) + W_{S2}*u(i,2) \qquad [1]$$

where $u(i,j)$ is the utility of Ai given that Sj actually occurs. The weight is sometimes considered a probability of occurrence, or alternatively the amount of attention given an outcome during the decision process. In the former case: $W_{S1} + W_{S2} = 1$. The model selects the direction of the outcome with the greater preference value (V_i):

$$d = V_1 - V_2 \qquad [2]$$

The first action A1 is chosen when d>0; the alternative action is chosen when d<0. Recently, Sheridan and Parasuraman [13] applied expected value analysis to decide whether to automate a function or allocate it to a human operator.

The basic SEU model can account for preference direction but it is deterministic. Real decision processes are characterized by switching attention among possible events during a sequence of discrete 'trials'. On one trial the decision-maker may focus primarily on S1, and another trial the attention may switch back to S2. Attention is therefore better described as a random sequence of transitions among states, and preferences may change from trial to trial as we might expect in real decision-making under uncertainty. We express the preference state as:

$$P = V_1 - V_2 = d + \varepsilon \qquad [3]$$

and ε is the trial-to-trial fluctuation of preference state. Random SEU theory can account for both direction and strength of decisions.

According to random SEU theory, a single preference 'sample' is taken on each trial. The sample reflects the static allocation of attention toward events for that particular trial. DFT is a sequential SEU model in that it views deliberation as a sequence of samples that are accumulated leading up to a single decision or choice. The sequence of samples reflects the switching of attention from one event to another as the decision-maker weighs the consequences of various choices. The accumulation of evidence is mathematically represented as a diffusion process [14], where results of a current sample are added to the previous preference state. Each sample is a random variable, and the current preference state takes a random walk due to momentary fluctuations in attention and preference. Preferences are updated as follows:

$$P(n) = P(n-1) + [V_1 - V_2] \qquad [4]$$

Since each sample is a random variable, the preference state takes a random walk, reflecting search for information, and momentary fluctuations in attention and preference. However, the fluctuation of the decision process must terminate in finite time. An inhibitory decision threshold is used to force a decision after the magnitude of the current preference state reaches a critical value (θ) in either direction. A small inhibitory threshold mimics the effect of time pressure by forcing a decision immediately following a weak accumulation of evidence in one direction. A large inhibitory threshold relaxes the process, allowing deliberation to continue until a sustained momentum is achieved in a particular direction. This formulation allows DFT to predict decision latency as well as choice.

The DFT model uses several parameters when updating preference during deliberation. These parameters reflect cognitive characteristics of individual commanders or biases introduced by prevailing conditions in the decision environment. Humans often either underutilize or overly rely on automated aids [15]. Recently, it has been suggested that humans adopt a 'perfect automation' schema that when contradicted by apparent errors, result in an overemphasis on the failure and strong negative bias toward the automated aid [15]. Similarly, in another recent study, when a diagnostic aid committed an error on an 'easy' problem, trust in the aid was subsequently undermined [16]. At least one study has examined partnering of college students and automated aids in a static laboratory CID-type task [17]. It was found that participants tended to overutilize the BCIS-type system, and that increasing the reliability of the automated aid did not affect performance or increase utilization. Decision-maker bias with respect to automated aids is represented in the model by an additional parameter (z) that initializes the deliberation process at an anchor point rather than a neutral position. Decision-making often does not begin with a neutral disposition toward either alternative. Typically deliberation begins with a preference in a certain direction due to either prior knowledge, past experience, or a generalized (dis-)trust in automation. Allowing for initial bias toward automation provides the model enough flexibility to account for preference reversals resulting from interactions between time pressure and preference strength. A decision-making error in the form of a preference reversal can occur when inappropriate bias with respect to automation exists in a high time pressure context.

The amount of trust in automated aids is also embedded in attentional weight parameters assigned to the binary cost matrix. For example, an enduring distrust in positive Blue force (friendly) identification from a BCIS-type system is likely to be expressed in greater weight given to consideration of the enemy (S2) outcome, combined with reduced weight for the friendly (S1) outcome.

Decision-making is also affected by serial position in the sequence of preference samples. Primacy prevails when information has greater influence if it occurs early within a deliberation sequence. Conversely, information attended to later carries more weight whenever a recency effect is operational. A grow-decay rate parameter (s) is used to simulate serial position effects. If $0<s<1$, recency effects are produced; if $s<0$, primacy effects dominate. If $s=0$, serial position effects are absent.

The decision-making literature often refers to a psychological phenomenon called the approach-avoidance conflict. According to this hypothesis, consequences of an action become more salient as the possibility of taking an action increases. The attractiveness of a reward or the aversiveness of a punishment become more intense as one approaches the point of commitment to an action/decision. The approach-avoidance conflict is modeled in DFT by multiplying a goal gradient parameter (c) with the current preference state to generate a new preference state during deliberation. The parameter c combines approach and avoidance gradients, which are both functions of distance from the inhibitory threshold. In an avoidance-avoidance conflict, c is positive, causing the preference state to vacillate, thereby slowing the termination of deliberation. For approach-approach conflicts, c is negative, and preference state races toward a decision boundary.

We can now construct the entire updating rule for DFT model. The preference state is a sequence of samples beginning at value $P(0) = z$. The update rule is:

$$P(n) = [1 - (s+c)]*P(n-1) + [\delta + \varepsilon(n)] \tag{5}$$

where δ is the direction of preference, s is the growth-decay rate for serial position effects, c is the goal gradient for approach-avoidance, and ε is a random deviation with a mean equal to zero and variance equal to σ^2. The sequence of samples terminates deliberation when $P(i) > \theta$, the inhibitory decision threshold.

In summary, additional parameters include an initial preference state to represent automation bias, a growth-decay rate to account for serial position effects, a goal gradient to mimic approach-avoidance behavior, and random fluctuation to mimic the nondeterministic nature of deliberation under uncertainty. Deliberation terminates when a freely-varying inhibitory decision threshold is crossed from the inside to simulate effects of time pressure. The ability of the decision-making model to capture these well-known phenomena from several decades of laboratory research on human decision-making constitutes a significant first-order level of conceptual validation of DFT.

The age of the timestamp from the CID system affects parameter settings by decreasing confidence: preference strength is decreased, and there is a shift from primacy to recency as a function of increasing age.

A critical limitation of the original formulation of DFT is that it applies only to static decision-making, and cannot be used for decision environments that change during the deliberation process. Nor does it allow for active information seeking regarding specific details of a tactical situation to reduce uncertainty. The SoS/HDM framework provides a mechanism for dynamic decision-making through retasking when a final decision is not reached

during a single decision cycle. In essence, a third decision category representing 'retasking' was added to the binary choice to 'shoot' or 'not shoot'. However, DFT provides for only two possible outcomes that are reached by crossing a threshold preference strength on either the negative or positive side. Although more recent formulations of DFT permit multiple outcomes [18], we extended the original model to capture the 'special' category of indecision leading to retasking. A new parameter representing the indecision threshold was added to the model. The indecision threshold ($\lambda < \theta$) generates a tighter band around the null preference point that is contained within the band determined by the inhibitory decision threshold. If the preference strength crosses this new threshold from the outside and remains at that level, thus exhibiting a weak preference for either alternative, then the current decision cycle exits in a state of indecision. An indecisive outcome initiates a round of retasking which incurs additional delays from the network. Entering the decision-making module again after retasking has the effect of strengthening the initial preference state. This action increases the chance of reaching a decision on the next decision cycle. Multiple retasking is possible until a definite choice is reached by crossing the choice threshold.

The model currently implements a simple notion of the effect of retasking on decision-making; i.e., retasking increases confidence due to better situation awareness. But increased situation awareness does not always decrease uncertainty with respect to trust in automation. Cohen [19] presented a quantitative model of a commander's knowledge of situation-specific automation performance. Instead of developing an enduring bias toward automation, the decision-maker in uncertain environments learns through experience to formulate a context-sensitive attitude toward automation. The differentiated concept of trust states that people learn the situations for which automation can be trusted, and those situations that do not engender trust. Cohen uses a decision tree model to encode the implicit situation-specific knowledge the decision-maker builds regarding trust in automation. The root of the tree represents the amount of trust present in the most general case, and increasing depth in the tree reveals trust associated with more specific situations. Each link shows the subjective weight given to automation performance in the situation shown in the downstream node. Implementation of a decision tree model of the commander's knowledge of automation would allow for a more appropriate level of trust in a particular CID system to be reflected in a dynamic decision-making model.

5. SoS/HDM Application Program

The SoS/HDM model has been encoded using MATLAB^{TM}. The program has a data hierarchy that coincides with the interrogator/transponder pair, command and control, and network configuration. The program has two major processing nodes, *direct interrogation* and *network*. For 'direct interrogation' the program provides further definition in terms of interrogator and transponder processing and distance (fixed calculation based on range to target). The interrogator and transponder processing is further broken down into elements such as decode/encode, authenticate message, internal delays, and embed message, as examples. Each allows a probability distribution function to be defined. The ''network' is broken down into two major elements – one C2 node and a number of data links. Currently, the number of data links has only a probability distribution function (PDF) associated with them. The C2 node, on the other hand, allows input to describe human factors (decision and action) and C2 processing (extraction, formatting, and display).

The application currently has algorithms that produce closed- and open- form PDFs. The closed-form solution is produced by convolving input functions and plotting the result. The open-form solution is derived from a simulation that yields an array of data points, which is plotted using a histogram function.

Although originally developed for an NLOS fixed wing to ground scenario, the program can be used to model many other scenarios by varying the number of comms network links and setting unused steps to 0. The program also supports a scenario in which a retask decision is made at the C2 level. A retask scenario is defined by the following model: direct interrogation, data link(s) to C2, C2 processing and retask decision, data link(s) to interrogator, direct interrogation, data link(s) to C2, C2 processing and confirmation/rejection, data link(s) to COP. The user has the option to use the same parameters for the retask as the original processing or enter different parameters. The default parameters used in the human decision-making module, especially the cost matrix parameters, were estimated based on responses to a written survey given to three military subject matter experts. For the runs described here, each new retask shifts the initial bias closer to the shoot decision boundary and increases the preference strength of the shoot choice.

6. Methods and Preliminary Results

The scenario modeled in this paper is shown in Figure 5. It has a forward element (dismounted soldier) gathering data (ISR) in the battlespace for an NLOS engagement.
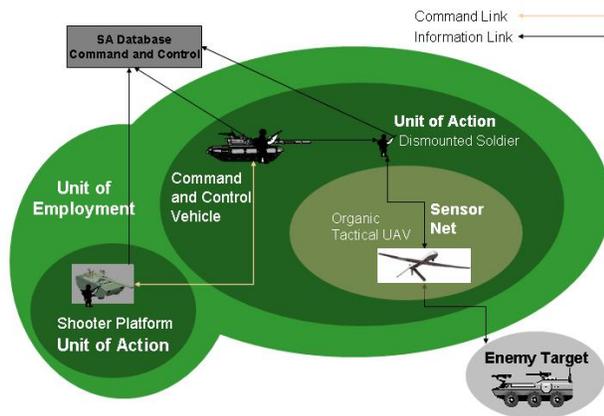
Figure 5. SoS model scenario. Forward element uses OUAV in ISR and then relays information to UoA command on red element. UoA Commander uses SA to make decision and calls for fire on red target.

The asset available to the element is an organic UAV with a non-cooperative technology as part of its mission package. Details provided by the technology only show that it is not Blue. Upon receipt of this information the forward element encodes information in appropriate format and relays across the network to UoA commander. The UoA commander then proceeds to use SA to provide higher-level details to determine disposition and provide CID. At this time, the CID cycle is complete, based on Figure 2. There is still a need, though, to use the network to call for fires on the Red vehicle. There is also the possibility of a retask to gather further information or data. Retask could take place due to a need to gather further information or to reduce and/or eliminate any uncertainties in the information or data. This could be a result of non-synchronous data in the distributed data base.

The specific parameters assigned to the data hierarchy are shown in Table 1. The number of network links to C2 and the shooter was held constant at 10 links. Results for each module are based upon 500 independent simulation runs. A factorial design was implemented in the simulation runs with two independent variables: target density in the current region and human confidence in CID system. Three levels of density were simulated: friendly (low), neutral (medium), and enemy (high). The effect of increased density was to elevate the initial bias to shoot, and preference strength to shoot. Trust or confidence in CID was low, medium or high. When the parameter values are set to low confidence, the model is biased toward recency and avoidance of negative consequences by making it harder to reach the decision threshold. High confidence is characterized by a balance between primacy/recency, and approach/avoidance.

Mathematically, the medium confidence condition is set halfway between low and high confidence.

Table 1. Assigned Latencies*

Transponder	0.5
Interrogator	1.5 (0.2)
Network links to C2	2.5
C2 input processing	1 (0.5)
C2 output processing	2
Network link to shooter	2.5

*Std. dev. shown in parentheses

Results of the first simulation experiment are shown in Table 2. Total CID latency equals all the system delays across the network enumerated in Table 1 plus human decision time. The number of decision cycles is the original decision cycle plus the number of required retaskings. The mean total latency ranged from 75 sec. to 290 sec., and the number of decision cycles varied from 1-4. Statistical significance tests have not yet been performed, but standard errors are shown in parentheses. The effects of density and confidence are essentially the same for Total CID latency and number of decision cycles. CID latency and the number of decision cycles apparently decreased as a function of increasing target density from friendly, neutral, to enemy regions. Latency and the number of decision cycles also apparently decreased with increasing confidence in the CID system.

Table 2. Mean Latencies (Sec.) Generated from Variable Density and Confidence

Density in region	Confidence	No. of Decision Cycles	Total CID Latency
Friendly	Low	3.69 (0.02)*	290.3 (0.74)
	Medium	3.46 (0.02)	289.3 (0.67)
	High	2.27 (0.02)	219.2 (0.63)
Neutral	Low	2.62 (0.02)	218.7 (0.59)
	Medium	2.14 (0.02)	148.7 (0.53)
	High	2.14 (0.02)	148.2 (0.51)
Enemy	Low	1.69 (0.02)	146.9 (0.48)
	Medium	1.44 (0.02)	76.8 (0.33)
	High	1.24 (0.02)	75.4 (0.33)

* standard error shown in parentheses

A second simulation experiment using the same scenario was conducted to estimate the effects of the number of network links. Adding network links not only increases the number of steps across the network, but has a direct effect on deliberation as reflected in the model. Recency bias increases while the strength of preference to shoot decreases as a function of the age of the timestamp of the CID presented in the COP. Results in Table 3 suggest that both total latency and number of decision cycles

Table 3. Mean Latencies (Sec.) Generated from Enemy Region under Medium Confidence with Variable Number of Network Links

Number of Links	No. of Decision Cycles	Total CID Latency
1	1.16 (0.02)*	47.0 (0.25)
5	1.28 (0.02)	59.8 (0.28)
10	1.47 (0.02)	76.1 (0.34)
15	1.64 (0.02)	193.2 (0.55)

* standard error shown in parenthesis

increase as a function of age. The range of total latency is from 47 to 193 seconds, whereas the number of decision cycles is contained within a narrow range (1-2) for this condition.

7. Conclusion

The SoS model has been verified in its operation based on the constructs of a realistic fixed wing to ground scenario. This verification includes a node-to-node check and overall system performance. The latency calculations seem to be reasonable based on the input parameters but need to be vetted against parameters from real-world operations. The effects of target density, confidence and network delay on total CID latency of number of decision cycles are also psychologically plausible. The model does provide a venue to perform bounded variable assessments that would allow calculation of total latency budget and the identification of points in the network where the opportunity exists to reduce overall time-to-ID.

We are currently integrating the SoS model into an FCS CID System of System application that will be used to assess how well a candidate technology supports the functional needs of FCS CID. The model is used in conjunction with a technology data base to calculate latency and network impact in an Air-to-Ground Risk Assessment that is being conducted by the FIST CID Team.

Latency predictions are likely to be sensitive to the exact values of some of the decision-making model parameters used in the implementation, indicating a need to collect or procure data for purposes of parameter estimation.

Further model validation and refinement of decision-making model parameters could be performed by conducting real-time, interactive, human-in-the-loop simulation experiments with CID systems as in [20].
However, much insight can also be gained from a study of the relative effects of approximate ranges of parameter values on latency, and sensitivity studies of decision-making parameters on latency. As an example of the latter, it would be important for system designers to know whether the extent of the CID latency budget depended critically on individual cognitive characteristics of commanders in the field.

Acknowledgment

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Author Biographies

GLENN O. ALLGOOD, PhD, PE, is a Senior Research Engineer at Oak Ridge National Laboratory, and is the Principal Investigator for the Future Combat Systems Integrated Support Team for Combat Identification. He has degrees in mathematics, electrical engineering, operations research and engineering science and mechanics. He received his joint PhD in Operations Research and Engineering Science and Mechanics from the University of Tennessee, Knoxville, TN. He has published over 80 papers in the fields of human factors, cognitive science, advanced computational methods, large scale systems integration, economics, wireless technologies, biomedical engineering, and advanced prognostics and health assessment.

JACK C. SCHRYVER, PhD is a Research Staff Member at Oak Ridge National Laboratory, and is co-lead investigator for the Future Combat Systems Integrated Support Team for Human Dimensions. He received a PhD in cognitive psychology at the University of California, Irvine, and a B.A. in psychology from the University of California, Los Angeles. He is responsible for development of the human decision making model for the CID Speed of Service model.

LAUREN HATCHELL is currently an undergraduate student pursuing degrees in electrical and computer engineering at Louisiana State University. She is a participant in the Higher Education Research Experience (HERE) program at Oak Ridge National Laboratory working under the supervision of Dr. Glenn Allgood. She is responsible for the coding of the CID Speed of Service application.

DWIGHT P. MILLER is co-lead investigator for the FIST Human Dimensions task, and a Distinguished Member of the Technical Staff at Sandia National Laboratories in Albuquerque, New Mexico. He has over 20 years of experience in the fields of human factors, ergonomics, cognitive engineering, and environmental psychology. He received his PhD in experimental psychology from The Ohio State University in Columbus, and a BSEE from Lafayette College.