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# Replication of human operators' situation assessment and decision making for simulated area reconnaissance in wargames

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**Abstract**

This paper describes a replication model of human operators' situation assessment and decision making in a simulated area reconnaissance wargame. A variety of factors that affect human operators' threat assessment and decision making were identified and categorized based on interviews with Subject Matter Experts and a review of defense doctrine on area reconnaissance. By combining these factors with the capabilities of existing synthetic environments, a schema consisting of a set of Bayesian networks and associated joint probability distributions for human operators' situation assessment and decision making was developed. To verify and validate the proposed schema, a software system was designed and implemented, and then used for analyzing the consistency between the replicator's decisions and human players' decisions. Results showed that the proposed approach replicated human operators' situation assessment and movement-based decision making in the wargame with high consistency.

**Keywords**

situation assessment, decision making, area reconnaissance, wargames, Bayesian networks

## 1 Introduction

Herein, a *wargame* refers to a simulated conflict or campaign carried out to test military concepts and operations, and *wargame replication* refers to the process of repeating the execution of a specific wargame multiple times to enable statistically valid analysis in an environment that can be sensitive to the impact of random factors.[1]

To enhance the quality and effectiveness of existing wargame replication in synthetic environments, this project explored the modeling and replication of human operators' situation assessment and decision making for simulated area reconnaissance (recce) in wargames. Although both movement and engagement decisions were built into the model, only the situation assessment and resulting movements are evaluated here as a simple example of decision making in the presence of threats without delving into the specific rules of engagement. The evaluation was accomplished by comparing simulated decisions to actual player decisions.

The decision of when and where to move takes into account a variety of battlefield considerations, including current and available cover, other ground features (e.g., observability), health status (including armor considerations relative to opposing weaponry), and ranges of detection and engagement. A benefit of comparing movements is that they are easily observed and relatively straightforward to assess intuitively in the presence of threats, whereas the dynamics of combat can rely heavily on many complex judgments and also the attitudes of the players involved (e.g., strategy

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of ammunition use, aggression, impact of actions on overarching mission goals, coordinated fire, etc.) such that the links between observable system variables and the players' decision making factors are less clear.

This article is organized as follows. Section 2 reviews existing methods, techniques, and models for situation assessment and decision making in command and control (C2). The aim of this section is to provide some background on different approaches to the topic. Section 3 summarizes the test scenario that the wargame and replications are based upon. Section 4 depicts the results of ground combat analysis for area reconnaissance. Based on the analysis, Section 5 presents a schema with Bayesian networks which is used for the replication of human operators' situation assessment and decision making in wargames. Section 6 describes the software design and implementation for the replication model, while Section 7 reports on the validation experiments and results, with a discussion in Section 8. The last section, Section 9, concludes this article with an overview of the study's salient features.

## 2 Modeling of situation assessment and decision making

Situation or threat assessment and decision making are key components in military C2,[2–6] and a multitude of approaches exist to enable their modeling and simulation. A large portion of the examples below incorporate some form of Bayesian network or a closely related design, as was chosen in this project. Indeed, Bayesian inference is a powerful approach for decision making under uncertainty. It is widely used in military modeling and simulation, and for good reason. It provides a means to combine prior information about decision making factors with new knowledge in a well-defined, statistical way, while making available methods to handle uncertainties in sensory inputs, errors, incomplete information, and ranges of values, to name a few. Bayesian networks and its many extensions and variations together provide an overarching framework to define the probabilistic relationships that exist between variables in the model. In addition, they provide a means to combine and then sum their contributions to an overall decision term.

### *2.1 Modeling situation and threat assessment in C2*

Models of situation and threat assessment in C2 are composed of two components: (1) generic situation and threat assessment models; and (2) adversarial intent models. Various techniques apply to representing each, including Bayesian networks, fuzzy computing, Markov processes, neural networks, and others.

Situation and threat assessment models have been developed previously in a military context. Endsley proposed a generic theory of situation awareness[7] and measurement.[8] Cao et al.[9] used a Bayesian belief network model to assess the impact of a sea-based command, control, communications, computers, intelligence, surveillance and reconnaissance (C4ISR) system on an amphibious operation. Lampinen et al.[10] modeled threat assessment for joint C2 with Bayesian networks, and their results demonstrated improved situational awareness and decision support. Again using Bayesian networks, Ma and Fu[11] developed a situation assessment model for battlefield forces to ameliorate troop balance. By combining Bayesian networks with a cognitive framework, Wang and Wang[12] proposed an approach to recognize target types based on sensor data, and the results demonstrated the effectiveness of the support provided to decision making in C2. Bladon et al.[13] applied Bayesian networks to develop situational awareness tools for use in decision aids in C2 to help operators improve performance. To achieve situational awareness that supports C2 decision making in time and mission stressed settings, Hick's[14] team combined game theory and modified Bayesian inference to aid multi-source data fusion. With the integration of Bayesian networks, utility and influence diagrams, Brynielsson and Arnborg[15] explored high-level agent interactions to improve threat prediction and situation analysis in C2 processes. Jones et al.[16] studied situational awareness for an army infantry platoon using fuzzy cognitive mapping techniques, and the results showed the consistency between the approach and army planning procedures.

Adversarial intent is an important component in threat assessment and a challenge research area. Using Bayesian networks, Gilmour et al.[17] proposed a model of adversarial intent to describe the influence of an adversary's beliefs on behavior and the possible relationships between an adversary's goals and the actions chosen to realize those goals. To predict an enemy's tactical intention, Johansson and Falkman[18,19] explored a Bayesian approach based on protection values, target type, weapon type, distance, and direction. Bell et al.[20] developed a preliminary software architecture that implemented models of adversarial intent with (1) intelligent mobile agents to collect information, (2) information fusion technologies to generate evidence, (3) an intent inference engine to model interests, preferences, and context, and (4) Bayesian networks to model the possible decision making behavior of an adversary. Santos' group[21–23] developed a cognitive architecture for adversary intent inference with goals, rationale, and action. To support knowledge acquisition for adversary course of action prediction, Brown et al.[24] reported a method with the Intelligence Preparation of the Battlespace (IPB) process via interaction with Subject Matter Experts (SMEs) and military planners. Other studies on adversarial intent with uncertainty inference include Nguyen[25] and Pioch et al.[26]

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## 2.2 Modeling decision making in C2

Problem solving and decision making are concepts that describe the processes of memory retrieval, reasoning to satisfy some goal, belief about the state of the world, and choice from a number of alternative solutions or actions to form an option or a course of action.[27,28]

A variety of decision making models have been proposed, for example, the Satisficing model,[29] the Garbage Can model,[30] the Strategy Selection model,[31,32] the Cognitive/Disjunctive model,[33] the Lexicographic model,[34] the Elimination By Aspects (EBA) model,[35] the Recognition Primed Decision (RPD) model,[36,37] the Additive Difference model,[34] utility theory, expected utility theory, multiattribute utility, game theory, probability, Bayes' theorem, Markov chains, utilitarianism,[38,39] the Decision Architecture model[40] and the Elicitation process.[41]

The RPD model is a popular choice among decision making models. It focuses on how people make quick, effective decisions when faced with complex situations. Warwick's team proposed a computational RPD model.[42,43] Patterson et al.[44] explored the dynamics of the RPD model using dynamic information flow and logic operators.

Cognitive analysis and task analysis are other kinds of approaches used for decision making. Warwick and Archer described three task network approaches to model decision making: (1) the Improved Performance Research Integration Tool (IMPRINT) with goal-oriented task networks; (2) task networks to represent information flow in planning, rehearsal, execution and assessment phases to predict effectiveness of decisions; and (3) the Minerva 2 long-term memory model[45,46] to characterize the RPD model.[45,47] COGNET (COGnition as a NEtwork of Tasks), reported by Zachary et al.,[48] is a cognitive architecture consisting of perception, cognitive processes and motor action that employs task networks to represent procedural knowledge. It has been used to model decision making in the anti-air warfare domain. Revello et al.[49] studied automated strategy generation with powerful search techniques like evolutionary computation in the strategies space. Sieck and Klein[50] analyzed and compared the roles of Decision Analysis and Cognitive Task Analysis in decision making.

A multitude of decision making models rely on Bayesian inference. Moffat's team developed a group of models for decision making in a conflict simulation involving air, land and maritime assets, making use of Bayesian inference along with other relevant techniques.[51,52] Perrin et al.[53] exploited Bayesian programming to make decisions for robot navigation. To enhance the effectiveness of C2 decision making, the integration of game theory, influence diagrams and Bayesian inference was studied by Brynielsson,[54] and in an approach proposed by Enderwick and McNaught,[55] Bayesian techniques supported decision making in an asymmetric urban wargame scenario with situation data that included the following as state variables: time, weapon features, environmental attributes and enemy data.

Markov decision processes, microworlds, neural networks and fuzzy logic are also used to model decision making. Middlebrooks' team developed a simulation system[56–58] that applied Partially Observable Markov Decision Processes (POMDP)[59,60] to optimize decision making under uncertainty for military C2 systems. Gonzalez et al.[61] explored the modeling of dynamic decision making with the microworld concept and cognitive demand analysis. Lastly, with influence factors of manpower strength, supplies (food and ammunition), infantry support, air support, and casualty rates, Gill and Sohal[62] explored a neural network approach to model battlefield perception and decision making.

## 2.3 Model selection

The main techniques used for situation assessment and decision making were reviewed in the scoping phase of the project and are briefly summarized in this section. Each technique has its advantages and limitations. For example, the RPD model is very useful for experienced practitioners working with relatively familiar situations, especially under high time pressure, but it is unlikely to be used by novices with limited domain experience. The cognitive task analysis method, based on a detailed understanding and formal representation of the areas of expertise, can lead to higher human-like performance, but the fairly time-consuming method cannot handle complicated and dynamic feedback in a real-time environment. Neural networks can learn from data to enhance their performance, but a large diversity of training is required for real-world operation, and it would be difficult to allocate much time for neural network training in a real-time simulation environment. Rule-based systems are a classical and sound technique for human behavior modeling, but their deterministic feature and the difficulty to acquire domain experts' knowledge limit their applications in some areas. Decision trees are simple to use and easy to understand, but determining the best split of each node and selecting optimal combining weights to prune algorithms contained in the decision trees are complicated tasks that require much expertise and experience. Compared to other methods, Bayesian networks, due to their sound mathematical foundation, consistent and theoretically solid mechanism for processing uncertain information, and intuitive causal relationships, have been widely used for prediction analysis and decision making, although there are some limitations, such as the acyclic property and lacking of explicit

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interpretation. Battlefield simulations are fraught with scenario-based uncertainties, for example, sensor data, human behavior, and enemy information. It is the robust capability to handle uncertainty that led to the selection of Bayesian networks as a starting point for the replication procedure.

Notable deficiencies to the approach relate to computational intensity in larger networks or exploratory ones, difficulties incorporating new terms (learning) and unforeseen events (completeness), the quality of prior information and its potential to distort or invalidate computed results, and the fact that such networks may have to be tuned in a largely ad hoc manner to match observed behaviors or to generate desired ones. Nonetheless, by virtue of their simplicity and wide-ranging applicability, Bayesian networks have more than proven their utility.

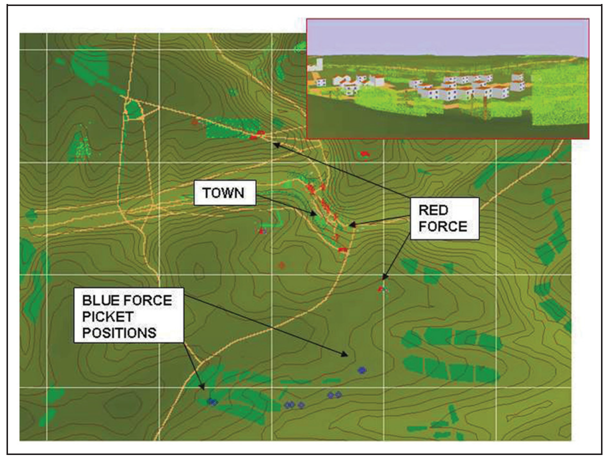


**Figure 1.** Blue and Red force dispositions. The grid spacing is 1000 m.

## 3 Wargame scenario – Recce Picket

A Recce Picket Scenario was used as a test bed to prototype the development of a decision making architecture that would serve for wargame replication. The original wargame was part of an operational research study to determine the effectiveness of various options for recce vehicle outfitting. The excursion to define a decision making schema for the wargame grew out of a desire to improve replication by incorporating more complex decision making options than were possible at the time with the system used. This excursion did not contribute to the original study.

In this scenario, Red forces had been seen in and around a town. Blue force reconnaissance elements had set up a picket around the town to allow follow-on forces to effectively deal with the threat. A ''picket'' refers to a soldier or small group of soldiers maintaining a watch, in this case, a watch for the enemy. The Blue force consisted of nine observer vehicles, one of which played a dual command/observation role. The scenario was cast in an irregular warfare setting amidst mixed urban and open terrain (Figure 1). The terrain allowed for chance contact to occur. Engagements were possible between Blue force armored vehicles and Red force vehicles or dismounted soldiers. Ranges of engagement measured approximately 500 to 2000 meters. The scenario was played four times by human interactors operating simulated equipment in a simulated environment. Movements, engagements and actions were recorded in a database for all entities in the wargame. The time limit for the game was set to fifteen minutes, and players stopped the game clock at will to input their entities' actions, resulting in a real-time delay of a few seconds. This time limit was determined during practice games as a reasonable cut-off for capturing all of the relevant action.

Red positioning and sensor capabilities were such that it would be difficult if not impossible for Blue to evade detection by Red for more than a few minutes, thus engineering a situation where conflict and interaction were unavoidable. In a sense, the situation can be described as a ''doomed recce'' scenario, thereby engaging much of the decision making space captured in the schema.

Four SMEs with recent operational experience in the domain of interest participated in the design and conduct of the reference wargame (i.e., featuring human decision making), and also reviewed all project materials and results. In addition, an SME from the sponsor organization participated in the game design and reviewed the final results.

Blue players executed actions with full manual control of vehicle positioning, movement and the ability to engage the enemy based on the goals of the operation, terrain, detections and established military tactics, techniques and procedures (TTPs) as well as rules of engagement. Limited automation was possible as well – players could plan out a path of movement by setting control nodes on the screen for a vehicle to follow at a selected speed. In general, these movements were kept short and simple. Overall, the observer and command vehicles were controlled in a way consistent with expectations about how they would be controlled in reality. There was little or no difference between the actual representations of observer vehicles and the command vehicle in the simulation environment – they were simply played differently to reflect their different roles. A senior military officer with recent and relevant operational experience reviewed the wargame

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action on a display screen to ensure consistency with expectations of a true battlefield scenario.

## 4 Ground combat analysis

In order to generate the information requirements needed to develop a replicator for human operators' situation assessment and decision making, ground combat analysis was conducted early in this project with an iterative cycle of knowledge capture and systematic organization.[63]

Knowledge capture and analysis was achieved over a series of SME interviews that extracted a systematic description of the relevant tasks, relationships, and knowledge requirements needed to build a cognitive task analysis. The SME had served for over 9 years as a commissioned officer with the Canadian Armed Forces, having completed operational tours in both Somalia and Bosnia. The individual also served on the Joint Staff at National Defence Headquarters with the National Joint Training Section. The results of cognitive task analysis were also validated by other SMEs mentioned in Section 3.

As one of the project goals was to maintain consistency between military doctrine and simulation validity (in respect of classification limits), a review of military standards relevant to game conduct – in particular Ground Manoeuvre Reconnaissance[64] – was also carried out in conjunction with the interviews.

There are a number of traditional reconnaissance tasks to consider. Examples are route reconnaissance, area reconnaissance, and point reconnaissance.[64] This project focused on area reconnaissance delineating a minimum of three phases: (1) the move to the area; (2) the over watch or provision of local security; and (3) the conduct of the area reconnaissance itself. To appropriately decompose the mission scenario to a level of task detail pertinent to the reconnaissance scenario, individual variables were selected and described in terms of their impact on war-game replication in computer simulation.

The following list of assessment factors derived from the National Defence Land Force Ground Manoeuvre Reconnaissance[64] provided an initial framework during the SME interviews. These factors represent the full spectrum of information that should be considered during a reconnaissance objective.[63]

a) Aim:
   i. derived from mission analysis;
   ii. confirmed desired rate of advance;
   iii. confirmed number of desired routes if not assigned/detailed;
   iv. by-pass and picketing policies;
   v. commander critical information requirements, and priority intelligence requirements;
   vi. implied Areas of Interest (AoIs) not assigned from higher.
b) Adversary:
   i. known or suspected positions;
   ii. assessment of recent tactics employed;
   iii. all recent threat reports and activities within the area to be traversed;
   iv. assessed adversary size;
   v. capabilities:
      1) mobility
      2) direct and indirect fire assets
      3) chemical, biological, radiological, and nuclear assets
      4) air/aviation assets
      5) electronic warfare assets;
   vi. known or assessed locations of adversary sympathizers.
c) Ground:
   i. canalizing ground (i.e., heavily restrictive to vehicle maneuvering);
   ii. routes parallel to main route(s) and all laterals to the main route(s);
   iii. dominating ground;
   iv. hydrographic features;
   v. built-up areas;
   vi. woods, contours, and depressions that may impede vehicle movement;
   vii. possible alternate routes;
   viii. other ground factors: for example, bridges, culverts, terrain, obstacles, etc.
d) Own troops:
   i. follow-on forces equipped;
   ii. lateral liaison with flanking formations (if any);
   iii. support and resources available;
   iv. disposition of own force.
e) Weather, time and space:
   i. day or night;
   ii. effects of weather;
   iii. any timings of rates imposed by higher authorities.
f) Mine or blast threat:
   i. mines;
   ii. improvised explosive devices (IEDs);
   iii. booby traps.
g) Available overlays and products:
   i. geomatic products;
   ii. aerial photos;
   iii. satellite imagery;
   iv. population data.

Most of the factors are important for situation assessment and decision making in area reconnaissance. However, owing to the complexity of real area reconnaissance in

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battlefields, the majority of existing synthetic environments only represent a microworld of the real battle space proficiently.

A few synthetic environments were reviewed for suitability to represent the features needed for robust situation assessment and decision making. They included the Joint Conflict and Tactical Simulation (JCATS), One Semi Automated Forces (OneSAF), Close Action Environment (CAEn), Virtual Battlespace 2 (VBS2), Scenario Toolkit and Generation Environment (STAGE), Unity 3D, and AnyLogic. It seems to be a great challenge in synthetic environments to gather or generate the information needed for threat assessment and decision making, especially when data acquisitions and evaluations must occur over limited time spans dictated by a combination of the operational rhythm, the number of replications desired, and the computer power applied to replications. Near real-time replication or better is a preferred outcome, as it opens up the possibility that the implementation can enter into wargames involving mixed human and synthetic interactors. Such decision making factors include many of those listed in the previous sections, in addition to detailed data related to aims or adversarial intent, human behavior, obstructions, advanced weather, etc. Fortunately, a somewhat minimally sufficient subset of the required data was obtainable from most synthetic environments. This included entity types, the position and speed of vehicles and other entities, weapon types and parameters, sensor types and parameters, routes, ranges, etc. In general, however, gathering all of the required data proved to be a non-trivial exercise, and in a practical simulation experiment involving multiple, interacting simulations the complexity of the task is bound to increase.

## 5 Schema for situation assessment and decision making in wargames

The schema in the project refers to the Bayesian networks and associated joint probability distributions used for replicating human operators' situation assessment and decision making processes in the area reconnaissance wargame.

### 5.1 Factors affecting stay/move decision making

A variety of factors affect situation assessment and decision making, but as mentioned only a handful can be simulated. For the stay/move decision making schema, key factors were identified through consultation with the SME that were both readily available through simulation data streams and highly relevant to the task at hand. They are as follows (listed alphabetically):

- enemy intent;
- exposure (self) and visibility (target);
- health (self/target);
- location (self/target);
- probability of kill;
- protection ability;
- routes available;
- sensor range (self/target);
- terrain;
- threat level;
- vehicle type (self/target);
- weapon type (self/target).

For most factors in the list above, a small number of "state levels" were implemented to represent a practical range of state identifiers that could be realized during game play, typically (but not always) ordered by some notion of "high" to "low" or "good" to "bad." For example, the three levels defined for the Health factor included "Good,""Medium," and "Bad." Fuzzy functions were used for computing the probabilistic values of the levels. For instance, if the current health were 70%, the degree of "Good" may be 0.8, "Medium" 0.2, and "Bad" 0.0 with the fuzzy functions' computing, and if the current health were 40%, the degree of "Good" may change to 0.0, "Medium" to 0.8, and "Bad" to 0.2. However for some factors, such as "Enemy intent," the relevant data could not be acquired from most of the available synthetic environments. In this case, the system maintained a default, mid-range value for use in the model and to support future extensions. Section 5.3 will discuss fuzzy functions in detail.

### 5.2 Development of Bayesian networks

At any given decision point during the wargame, the purpose of the Bayesian network developed in the schema was to decide on the next action of a participating unit based on the current situation in the dynamic simulation of area reconnaissance, taking into account all of the factors identified above. Four simplified, alternative decision outcomes related to movement and observation or enemy engagement were identified:

- stay-observe;
- stay-engage;
- move-advance;
- move-withdraw.

So, for instance, engaging while on the move was not considered to be a valid option, nor was observing while on the move. As an example, based on the self-sensor range (i.e., the sensor range of the blue side force) and enemy contact, three cases were considered for Bayesian network development:

- enemy outside self-sensor range;

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- enemy inside self-sensor range and before contact;
- enemy inside self-sensor range and after contact.

If an enemy is outside self-sensor range, the decision is certainly ''move-advance'' because there is no threat found. Alternatively, if the enemy position is detected to be inside self-sensor range, then depending on the enemy contact there are two Bayesian networks identified: one pertaining to decision making ''before contact'' and the other for decision making ''after contact.'' Once a decision is made, it can be passed off to a simulation-specific layer of code for implementation.

Before contact with the enemy, the visibility from the current location, the concealment at the current location, and the concealment in routes leading from the current location are considered to predict observation success. This schema drives the unit to a position with maximum enemy visibility and minimum self-exposure.

After contact with the enemy, self-protection and perception of the enemy's ''resolve'' (defined below) both contribute to the final decision, as shown in Figure 2. On the Self Protection side, Enemy Weapon Range, Enemy Weapon (type), and Self Vehicle (type) are rated as accurately as possible and the Self Guard capability is evaluated. This value is used together with Self Location and Self Health to compute the overall Self Protection ability. Enemy Resolve combines intent with qualities of position and resilience. To assess Enemy Resolve, a sub-network is constructed based on Enemy Intention and Enemy Protection. The Enemy Protection evaluation mirrors that of Self Protection, and is based on Enemy Exposure, Enemy Vehicle (type), and Enemy Health, together with Self Visibility, Self Weapon Range, and Self Weapon (type). The considerations in the Bayesian network are by no means exhaustive. However, the schema does capture the main components of logic for a single blue vehicle operating more-or-less independently on the simulated battlefield. Note that the threat from enemy weapons depends on the coupling of weapon attributes to Self Guard attributes and the coupling was chosen to impact decision making under Self Protection (i.e., an enemy weapon that is out of range or ineffective against the self-vehicle type equates to strong Self Guard). In essence, the full threat in consideration of self-protection, enemy intent, and enemy position/resilience is not taken into account until the top stay/move decision node is evaluated and all factors have been rolled in.

## 5.3 State probability distributions

A Bayesian network is formed from a Directed Acyclic Graph by associating probabilities with each state that a node in the graph may take on at a given time. The state of each leaf node in the Directed Acyclic Graph is derived from scenario execution results or scenario settings, while the state of each intermediate node or the root node is computed by the Bayesian inference engine via joint probability distributions in the system.

To keep the schema generic and flexible, the nodes in the Directed Acyclic Graph do not depend on any particular synthetic environment. A downside to this approach was that, in many cases, the scenario results data created by the CAEn simulation execution did not directly contain the values of states required by the Directed Acyclic Graph. Such values had to be interpreted from the best available data. Where necessary, algorithms were developed to derive the state values of leaf nodes in the networks. In particular, fuzzy functions were created to manage probability computations on the observed data. For example, given a distance to the enemy of $x$ and distance thresholds $d1$ and $d2$ with $d1 < d2$, the following equations were used to compute the probability that self-exposure is ''High,''''Medium,'' or ''Low'' respectively:

$$SelfExposure_H = \begin{cases} 1 & if\ x < d1 \\ 1 - 2 * (x - d1)/(d2 - d1) & if\ d1 \le x < (d1 + d2)/2 \\ 0 & if\ x \ge (d1 + d2)/2 \end{cases}$$

$$SelfExposure_M = \begin{cases} 0 & \text{if } x < d1 \text{ or } x \ge d2 \\ 2 * (x - d1)/(d2 - d1) & \text{if } d1 \le x < (d1 + d2)/2 \\ 1 - (2 * x - d1 - d2)/(d2 - d1) & \text{if } (d1 + d2)/2 \le \mathrm{x} < d2 \end{cases}$$

$$SelfExposure_L = \begin{cases} 0 & \text{if } x < (d1 + d2)/2 \\ (2 * x - d1 - d2)/(d2 - d1) & \text{if } (d1 + d2)/2 \le x < d2 \\ 1 & \text{if } x \ge d2 \end{cases}$$

where $x$ is the current detection distance of self or adversary and $d1$, $d2$ are detection distance thresholds for the sensors. The values of $d1$ and $d2$ may be in the range of hundreds or thousands of meters, depending on the scenario.

These functions automatically normalize the sum of values to unity at each level. The thresholds for *SelfExposure* were determined by typical sensor ranges in consideration of the scenario. For instance, 500 and 2000 meters were proposed and validated by the SMEs as a reasonable starting point to begin testing.

## 5.4 Joint probability distributions

For each intermediate node and the root node in Figure 2, a joint probability distribution was developed to determine the dependency on lower level nodes. In this project, the joint probability distributions were captured through interviews with the SME. Table 1 shows a sample joint probability distribution.

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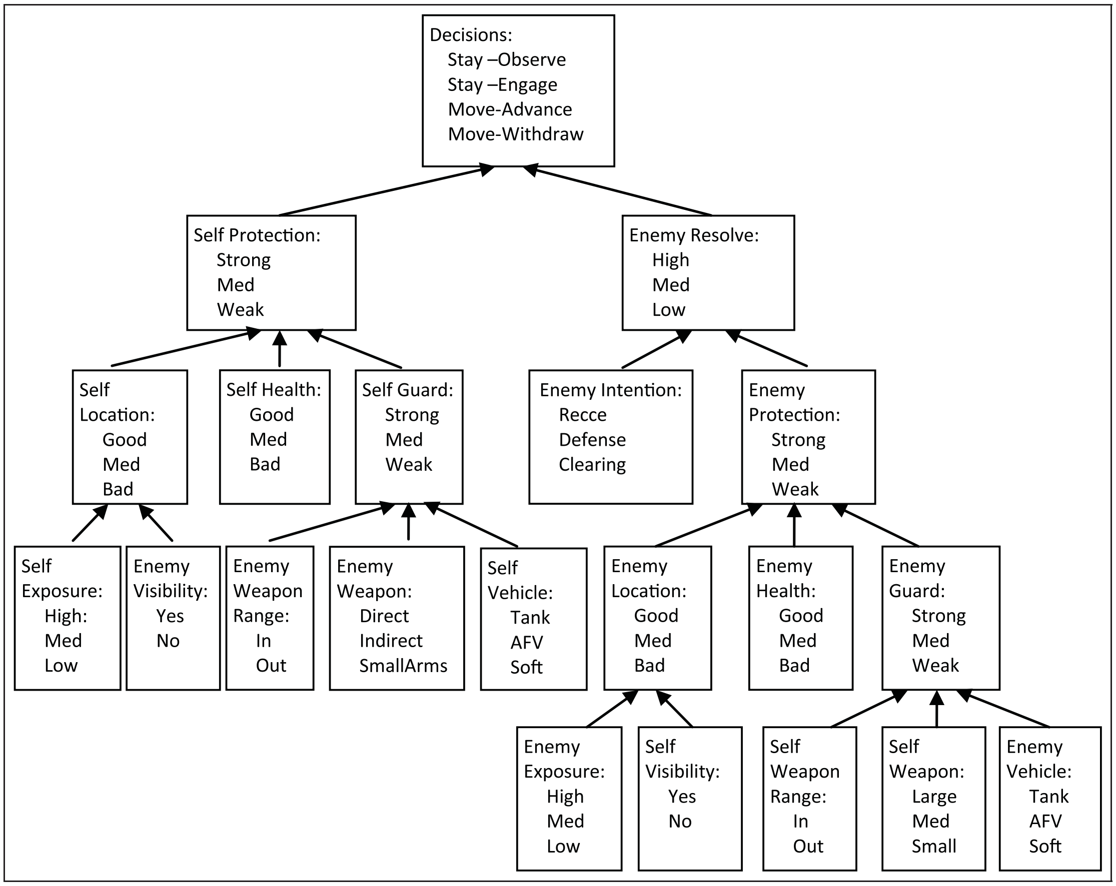


**Figure 2.** Directed Acyclic Graph for situation assessment and decision making after contact.

**Table 1.** Example of joint probability distributions.

| Self-exposure | Enemy visibility | Self-location | | |
|---|---|---|---|---|
| | | Good | Med | Bad |
| High | Yes | 0.3 | 0.4 | 0.3 |
| High | No | 0.0 | 0.1 | 0.9 |
| Med | Yes | 0.6 | 0.3 | 0.1 |
| Med | No | 0.2 | 0.3 | 0.5 |
| Low | Yes | 0.99 | 0.01 | 0.0 |
| Low | No | 0.3 | 0.4 | 0.3 |

## 6 Software design and implementation

The Dynamic Replicator of Decision Making (DRDM) tool is the software system that implements the replicator in the project to simulate human operators' situation assessment and decision making in area reconnaissance wargames, and includes C++ and Java code, Transmission Control Protocol/Internet Protocol (TCP/IP) sockets, and MS-Access Database (DB) components, as shown in Figure 3.

In Figure 3, *CAEn Scenario Data* represents a database that contains all wargame observables, that is, data and results for each run executed in the CAEn environment, including location, health, weapons, weapons fire, Detection-Recognition-Identification (DRI) status, sensors, casualties, etc. The results of human player commands and actions were all stored in the wargame database. Their intentions and reasoning, however, were not stored – these could only be deduced at a later time through SME interviews to form the essence of the decision making schema and resultant Bayesian networks.

The *DRDM Sense Interface* in the figure converts the *CAEn Scenario Data* into the proper format required by the *DRDM Engine* – the Bayesian inference engine in the system.

The *Situation Assessment and Decision Making Knowledge Base* (*SA-DM KB*) is an eXensible Markup Language (XML) file library that represents all the Bayesian networks used for the dynamic situation assessment and decision making.

The *Human Decision Identifier* recognizes the decision of a human player in the *CAEn Scenario Data* for a given time point. *CAEn Scenario Data* actually contains no explicit human decisions for movement or staying. This system recognizes whether or not the current human

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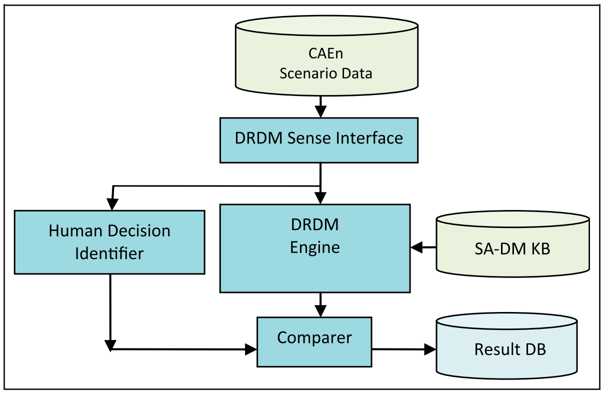


**Figure 3.** Implementation of Dynamic Replicator of Decision Making (DRDM).

decision, at any given time, is ''move'' or ''stay'' by computing the speed of each unit at the given time. *CAEn Scenario Data* provides the positions of each unit at each time point, from which the system can compute the speed of the unit, and then use the speed to identify the human decision as move or stay.

The *DRDM Engine* module is responsible for generating the current decision based on up-to-date situation data for any given unit at any given time index. The velocity computation for an entity is an important factor to determine its stay or move state value. A reference displacement over a fixed interval of time, say 0.01 meters in five seconds, was used to distinguish between stay and move states in the battlefield setting.

To compare the DRDM move/stay decisions to those of the players, the *Comparer* module was developed, with results saved in the *Result DB*.

## 7 Validation experiments and results

The *Recce Picket Scenario*, composed of four games developed by Defence Research & Development Canada (DRDC), Centre for Operational Research and Analysis (CORA), was used for verification and validation of the DRDM system, which simulated a picket operation within a mixture of urban and open terrain.

An MS-Access database management system was used to store and organize the scenario data from CAEn execution, in which there were 13 tables holding various parameters and execution results taken from the interactor game data streams. Fields included ammunition types, casualties, DRI information, initial strength, call signs, repetitions, scenarios, movement, sensor types, unit types, and weapon types.

In total, 734 decision points were identified in the four games with 175, 210, 214, and 135 decision points in each game, respectively. For each decision point in each game, the DRDM system completed the following tasks on a per vehicle basis: retrieved the *CAEn Scenario Data* observations; called the Bayesian inference engine to generate the decision of the replicator based on the observations; identified the human decision at the same time point by measuring wargame observables; and finally compared the consistency between the replicator's decision and the human decision at the given time point.

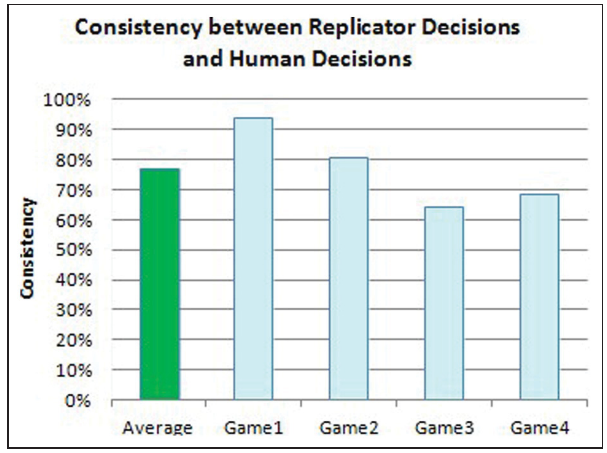


**Figure 4.** Consistency between replicator and human player decision making.

Figure 4 shows the test results of the replicator. The scenario data used corresponds to data acquired in all four games for a blue team composed of nine members (vehicles), including a command vehicle. The leftmost bar in Figure 4 shows the average consistency of the four games, and the other bars represent the consistency measured in the individual games.

The results show that the average consistency between the replicator's decisions and the human players' decisions computes to about 77%. The biggest discrepancy in behavior was observed to occur with the command vehicle. Each vehicle was provided with the same independent decision network, which oversimplifies the decision space in that case. In a sense, the results single out the command vehicle as noncompliant, to a certain degree, with the decision-making schema and they also provide a quantitative measure of that noncompliance. Indeed, the command vehicle is the most likely candidate to behave differently from the others, as it must focus on coordination while maintaining an effective and holistic overview of the evolving situation. Approaches that incorporate C2 structures are required to assign vehicles different roles in the scenario.

## 8 Discussion

Based on analysis of the test results, two main distinguishing factors stood out: (1) differences between scout vehicles and the command vehicle in the same game; and (2)

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differences across the four games. For the first difference, the main focus of current tests was the performance of autonomous, more-or-less independent vehicles, rather than the performance of a C2 process. Therefore, the tests for the commander vehicles were not separated out from the scout vehicles. An obvious next step would be to provide and test a customized Bayesian network for the command vehicle and updated networks for the scout vehicles that incorporate the relevant C2 structures.

As for the differences in results between games, several possibilities present themselves. For one, the outcomes in player games tend to vary considerably. This is why multiple games are played and then replicated – to acquire statistics that one can draw conclusions from with confidence. Some scenarios may evolve into situations where C2 factors are more prominent than in other runs, a feature that was not captured. Furthermore, variability in the game action inevitably leads to variability in the decisions that need to be made, and players do not always make the same decisions when presented with the same or nearly same the situations. In effect, not all decision factors are being modeled (e.g., C2, human variation, etc.) and only some of the finer decision making nuances that come into play are captured by the model. Thus, a certain amount of deviation has to be expected. Recording the decisions and decision factors step by step as the games are being played and incorporating them by design into an upgraded version of the Bayesian networks would help to alleviate these shortcomings. That said, such a task is complicated by the desire not to interrupt the flow of game play or interfere with its progression in any way.

This work demonstrated the strength of Bayesian networks to model uncertainties in area reconnaissance. However, it is the numerous uncertainties that make the modeling complicated. Further tests, including the parameter and structure tuning of the Bayesian networks, may be conducted to improve the effectiveness of the model.

## 9 Conclusions and future directions

This paper describes a replicator system of human operators' situation assessment and decision making in wargames. Based on SME interviews and doctrine review for ground combat analysis, a number of factors that affect human operators' situation assessment and decision making were identified and categorized, including factors related to goals, adversaries, ground, own troops, weather, time and space, mine or blast threat, and available overlays and products. With the capability analysis of existing synthetic environments, a sub-set of the assessment factors was identified and used to develop a group of Bayesian networks for the replication of human operators' situation assessment and decision making for area reconnaissance in wargames. To verify and validate the proposed approach, a software system was developed, and a group of consistency tests were conducted with CAEn scenario data. The results showed that for move/stay decisions, the overall consistency between the replicator decisions and human players' decisions was about 77%. Furthermore, during the project the decision making Bayesian network was linked to a simulation environment (VBS2) where the entities played out a portion of the wargame autonomously.

We conclude that the proposed approach shows promise for the replication of human operators' situation assessment and decision making in wargames.

The main contributions of this paper consist of (1) proposing an approach to dynamically replicate human situation assessment and decision making for simulated wargames, (2) identifying a set of factors that may be extracted from existing synthetic environments for threat assessment and decision making for simulated wargames, (3) developing a group of causal relationships among the factors for engagement and movement in threat assessment and decision making in simulated wargames, and (4) demonstrating the feasibility of Bayesian networks for situation assessment and decision making for simulated wargames.

A variety of interesting issues were raised in the project development process for future consideration, including how to measure the decision making performance, how to tune the decision making schema to enhance consistency with games played, how to gauge the impact of C2 and how to incorporate it, and how to best integrate the replicator system with synthetic environments in a general way to support dynamic wargame replications on multiple systems.

As a next step, future work needs to focus on refining the stay/move decision – C2 incorporated – followed by full replication of the scenario in a suitable replication environment. With a better understanding of the threat dynamics as understood through the stay-move decision, the engagement (combat) decision making factors can be somewhat isolated and then explored using the same technique. Difficulties implementing the lower level actions in the target environment used in the study and also difficulties gathering the necessary information from it were inhibiting factors that proved to be more challenging to overcome than initially expected.

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