A CANADIAN APPROACH TOWARDS NETWORK ENABLED CAPABILITIES – I: SIMULATION VALIDATION & ILLUSTRATIVE EXAMPLES

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ABSTRACT
This paper presents an approach to understanding networked enabled operations using agent-based simulations. We describe the newly created agent-based software ABSNEC, highlighting some of its salient features: the ability to represent human factors towards the analysis of battle outcomes in network operations; and the ability to represent realistic force structures with tiered C2 architectures. We provide affirmative results of three validation techniques to date on the model. Finally, we demonstrate the utilization of ABSNEC to acquire meaningful insights for analysis through two examples: a study on the interrelationship between fratricide, human factors and situation awareness; and generation of alternative combat strategies for a military engagement.

Keywords: agent-based model, network enabled capabilities/operations, human factors, military operations research, model validation

1. INTRODUCTION

Network Enabled Operations (NEO) and Network Enabled Capabilities (NEC) are increasingly being recognized as critical enablers of military capability in the 21st Century and essential for military transformation. However, we are still unable to define their full potential. Although NEO/NEC concepts have enormous potential to transform and improve defence capabilities, there are risks associated with these issues. NEO/NEC depends heavily on technology but may be vulnerable to asymmetric attack. There are also concerns about the ability of the Canadian Forces to interoperate and integrate with allies who have greater or lesser sophistication with respect to NEO/NEC. To turn potential into reality, we have to assess, explore and understand the impact of NEO/NEC.

In a network centric system, humans are often required to extract, interpret and validate (machine) information from raw data at one or more points along the path from source to users. However, information is not the same as raw data. Often, raw data must be understood and interpreted by humans to produce information. It is well known that networks are the most efficient means devised to date for distributing en-masse large volumes of data. However, any networked system can, and also will, distribute erroneous data just as efficiently as valid data. Regardless of whether it is incorrect human interpretation, simple typographical errors, or faults and limitations in sensors, defective data can be quickly distributed across any war-fighting system. In summary, humans can produce large-scale damage effects quickly in a networked environment. Numerous case studies of this problem exist. These include for example the USS Vincennes incident, the Kosovo tractor bombing incident, and the more recent bombing of Canadian troops in Afghanistan. It is essential to stress that in each of these networked operations, multiple human errors, compounded by sensor limitations contributed to tragedy.

Time has always been of critical importance in military networked operations and combat. In a typical discussion of Command and Control, it is taken as axiomatic that the information presented to the commander must be timely as well as accurate and complete. Little or nothing is said about how timely is timely enough; nor is any yardstick given by which to measure timeliness. We propose to develop a measure of performance based on the timeliness and quality of information under the influence of human error (the human-in-the-loop effect). This NEO/NEC performance metric has the potential to establish a baseline for comparing future networked operations. Such a metric could redefine the rules of engagement in networked operations or combat and may provide a decision tool enabling CF and NATO allies to recognize and exploit opportunities to integrate sensors, weapons, and platforms in optimal NEO/NEC architectures to achieve greater value from future capital investments. Finally, it may be able to improve force effectiveness, decrease combat casualties due to enemy actions, and to decrease confusion-related friendly fires.

Our research involves using analytical modeling and agent-based simulation to quantify and assess the impact of timeliness and quality of information towards NEO/NEC. Currently, there exist a number of battlefield-specific ABM platforms, such as Map Aware Non-uniform Automata (MANA) (McIntosh et al 2007), ISAAC/EINSTein (Ilachinski 2000), WISDOM II (Yang et al 2006) and BactoWars (Millikan et al

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1996). A set of commonly used ABMs were recently reviewed by Railsback et al (2006). Our recent contribution, ABSNEC, models after the well-known MANA, developed by the New Zealand Defence Technology Agency. MANA has been widely used in the international defence science community and is acknowledged to be one of the leading agent-based distillation combat models. ABSNEC has a high degree of similarity to MANA, but its design is much better suited to the implementation of the new capabilities required by the Canadian research projects.

Among ABM models, ABSNEC is designed to effectively model networking and human factors. According to a recent survey for the NATO MSG-088 report on Data Farming in Support of NATO (to be published), ABSNEC remains to be the only system that is designed for networked operations studies that can efficiently track multiple intangible human factors parameters. It balances powerful features against the need for transparency, simplicity and execution speed. It adheres to the design philosophy pioneered in the Project Albert series of workshops in that it uses relatively simple representations of physical systems (distillation modeling), with an emphasis on the behavior and interaction of the entities within the model (agents). A list of some particularly important features of ABSNEC is as follows:

1. Detailed network characteristic modeling capability, such as latency and bandwidth, built into the model;
2. Ability to create custom algorithms that define network agents that control routing and capacity assignment;
3. Ability to represent human factors such as stress, fear, and other human factors towards the analysis of battle outcomes in network operations;
4. Ability to define custom agent state triggers with a simple graphical user interface; and
5. Ability to represent realistic force structures with tiered C2 architectures.

The above features are explained in detail in the ABSNEC users' manual. This paper will address the validation to date conducted on the model and will explore two illustrative case studies highlighting the unique features of ABSNEC.

2. MODEL VALIDATION

A simulation model is an abstract representation of a physical system and intended to enhance our ability to understand, predict, or control the behaviour of the system. As such, the simplification and assumptions will introduce inaccuracies to the simulation model. An important task is to determine how accurate a simulation model is with respect to the real system. The main difficulty remains to be there is no a universal approach for the validation. Balci (1998) presents 75 validation, verification, and testing techniques that are largely used in validating the models of engineering and business processes. The ABSNEC validation approach to date involves using 3 different techniques – face validation, model-to-model comparison and simple statistical analysis/test.

2.1. Face Validity

Face validity is asking the subject matter experts (SME) whether the model behaves reasonably and makes subjective judgments on whether a model is sufficiently accurate (Balci, 1998).

We consider the Ben Hasty scenario (Horne 2011) originated by the U.S. Naval Postgraduate School, for which 50 Red agents oppose 125 Blue agents. An additional 25 Blue agents are on their way to give Blue a 3:1 size ratio with Red prior to attacking. Blue could attack now (with only 125 agents) and take Red by surprise. However, the question addressed in the scenario was:

What would happen if Blue delayed the attack and waited for reinforcements?

Subject matter experts (SMEs) were consulted to describe tactics that Red could use to improve their outcome in a battle with Blue. The SMEs identified three tactics for Red: fortified defence, obstacle placement, and use of a spoiling force. In the fortified defence, Red clusters tightly together and waits for Blue to attack. In the obstacle placement tactic, Red uses obstacles to force Blue to attack through narrow choke points. And, for the final tactic, Red uses a spoiling force to immediately engage Blue. The spoiling force continues to attack Blue as they retreat towards the remainder of the Red agents that are waiting in a fortified defensive position. ABSNEC is used here as the agent-based platform to sample a large possibility of Red tactics and to data farm possible outlier results where Red is able to defeat Blue. What is of key importance in the face-validation process is whether any outlier results can reproduce the SME's recommendations.

In the scenario considered here, a Blue force of 150 soldiers is assembled and sets out to reach a goal within Red territory. The smaller Red force (50 soldiers) tries to defend this home location. All soldiers (both Blue and Red) have a sensor range of 1km and a weapon range of 1km. The sensor has a 100% probability of detection and the weapon has a 40% probability of kill.

Agents in ABSNEC move based on affinity forces to various targets. These affinities can be integer values from -10 (strong repulsion) to +10 (strong attraction), and can be uniquely defined for different states of the agent. In the Ben Hasty scenario, each Blue agent has two states: *Advance* and *Attack*. In the *Advance* state, Blue agents move towards their waypoint goal in Red's territory with a waypoint affinity of +10. When a Blue agent detects a Red agent, it enters the *Attack* state where it maintains the waypoint affinity of +10, and adds to it an enemy affinity of -5. Each Red agent also

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Table 1 - NOLH sampling points for Red agents

	Advance			Defend		
	Wp	Fr	En	Wp	Fr	En
1	-4	10	6	-5	9	-3
2	-9	-5	8	-10	-4	1
3	-8	-1	-9	3	6	-5
4	-6	3	-4	1	-8	10
5	5	9	-1	-4	-10	-8
6	10	-4	-3	-9	5	6
7	3	-6	10	8	-1	-4
8	1	8	5	6	3	9
9	0	0	0	0	0	0
10	4	-10	-6	5	-9	3
11	9	5	-8	10	4	-1
12	8	1	9	-3	-6	5
13	6	-3	4	-1	8	-10
14	-5	-9	1	4	10	8
15	-10	4	3	9	-5	-6
16	-3	6	-10	-8	1	4
17	-1	-8	-5	-6	-3	-9

has two states: *Advance* and *Defend*. If Red agents wait in their starting location in the *Advance* state, and have an enemy affinity of +5 when an enemy is detected in the *Defend* state, then *all* Red agents will be killed, taking out an approximately equal portion of Blue agents before being wiped out. The goal of the scenario is to “farm” the space of possible Red affinities for these two states and look for an emergent behaviour that is beneficial to Red. Three possible target affinities (Enemies, Friends, and a Waypoint at Red home/Blue goal) can be varied for two different states (*Advance* and *Defend*) creating a 6-dimensional space to be explored. A Nearly Orthogonal Latin Hypercube (NOLH) sampling technique (Cioppa and Lucas, 2002) was used to limit the possible combinations of affinity choices and reduce the number of computations.

The sample points in the NOLH are listed in Table 1. It should be remarked that the space-filling and nearly orthogonal properties of the chosen sampling points have been independently verified. The mean number of kills for Blue versus the mean number of kills for Red is plotted in Figure 1 with the corresponding sample numbers. Ellipses show the

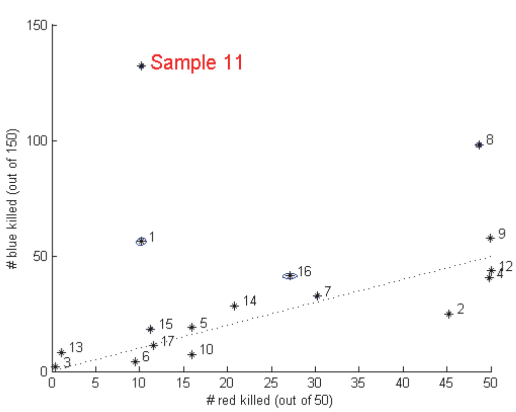

Figure 1 - Results for NOLH sample points

corresponding standard error of the mean about each point. The dotted line represents a one-to-one kill ratio. Points above this line correspond to tactics where Red is more efficient than Blue at killing. Samples in the top left corner of the figure are ideal for Red, i.e. large amount of Blue killed with low amount of Red killed.

Sample 11 is an outlier in upper left quadrant, and it is a beneficial solution for Red. The screen plot/animation results for Sample 11 (see Figure 2) reveals that the Red agents cluster together, back into the Red home location, and fight Blue. If Blue continues to push through, Red has a negative affinity to the Blue agents and will run away.

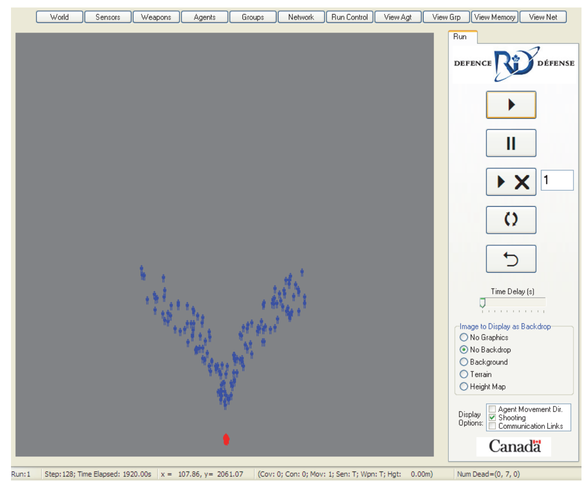

Figure 2 - ABSNEC screenshot for sample 11 of the Ben Hasty scenario

The behaviour of Red in Sample 11 exemplifies the fortified defence tactic identified by SME as a way to improve Red’s battlefield outcome. The strong agreement between the ABSNEC simulation output and SME recommendation therefore brings us one step closer to accepting ABSNEC as a credible simulation solution.

2.2. Model-to-Model Comparison

Using model-to-model comparison (Balci, 1998), also known as docking or back-to-back testing, we compare various results of ABSNEC to results of MANA on the Ben Hasty scenario. Real world phenomenon can be represented by different conceptual models, and different research groups or individuals can implement conceptual models differently using a variety of programming languages or different simulation toolkits. These computational models may also be run on different platforms. The intent of this validation test is to investigate whether different simulations using similar input data produce similar results, trends and agent behaviours. One should be cautioned not to expect the simulation results to be identical, since agent-based simulation is built on simple probability and cellular automata principles. The essence of the model comparison exercise is to examine, upon applying data farming techniques on Ben Hasty

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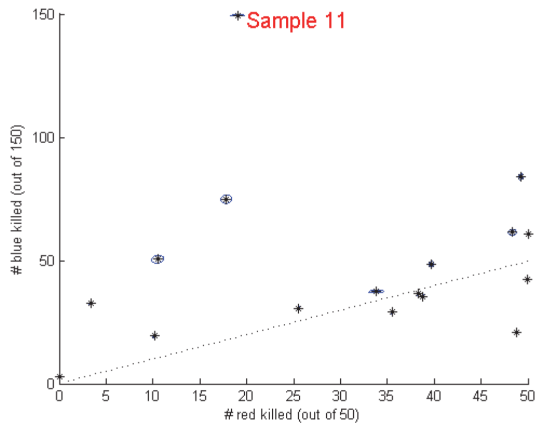

Figure 3 - Ben Hasty scenario results using MANA

scenario using ABSNEC and MANA, whether or not the simulations produce a similar trend and kill pattern. Most importantly, can the different platforms identify similar outliers for Red? Figure 3 highlights the Ben Hasty results at the same NOLH sample points using MANA.

Comparing Figure 3 with ABSNEC output Figure 1, it is gratifying to notice that they both exhibit similar trends for the number of Red and Blue killed. Of particular interest is that the two platforms simultaneously identify the same sample outlier - SAMPLE 11, albeit the differences in Blue and Red killed.

2.3. Comparison with Lanchester Equations

Finally, we compare the output data of ABSNEC with the output data of the classical Lanchester equation (Lanchester, 1956). The Lanchester model has been the fundamental model for developing theories of combat and for calculating attrition of forces in military engagements. The governing differential equations are subject to fairly stringent assumptions (Przemieniecki, 2000). For example, both forces are homogeneous and are continually engaged in combat; each unit or individual weapon is within the maximum weapon range of all the opposing units; and the effective firing rates are independent of the opposing force level. As a result, there is no shortage of criticism on the Lanchester assumptions and on the accuracy of the predicted force strength for any real military engagement (Helmbold, 1994). Nonetheless, the Iwo Jima Battle provides a case where the Lanchester model does provide an excellent agreement between the Lanchester predicted results and the actual American troop strength (Engel, 1954). The success is attributed to the fact that the governing parameters in the Iwo Jima scenario are fairly consistent with the assumptions in the Lanchester equations. In view of this, in this final validation test, we will introduce identical Lanchester assumptions in ABSNEC simulation. The generalized Lanchester equations incorporating C4ISR efficiency (Ng, 2006) are given as follows:

$$\frac{du}{dt} = \frac{-\beta vu}{a - f(a-u)} \qquad (1)$$

$$\frac{dv}{dt} = \frac{-\lambda uv}{b - e(b-v)} \qquad (2)$$

where u, v are the number of surviving units in each force at a time after the battle begins; λ, β are the corresponding kill probabilities; a, b are the initial values of u and v, respectively; e, f are the C4ISR efficiency of each force. For $e = f = 1$, these equations reduce to the direct fire scenario. For $e = f = 0$, these equations reduce to the area fire scenario.

To track force strength between the Lanchester and ABSNEC output, we need to understand how the two models represent area fire. In the Lanchester model, area fire represents the case where target information is not updated, and targeting weapons cannot tell if they are firing on live or dead target, i.e. C4ISR efficiency of zero. In ABSNEC, weapons are not related to the C4ISR efficiency of the force. Therefore, to simulate area fire Lanchester equations in ABSNEC, agents in each force do not die when hit by an enemy weapon, but lose the ability to fire back. Essentially, each force is given an initial picture of the enemy forces positions, but is unable to update that initial picture to show when an enemy is killed. To simulate different levels of C4ISR efficiency, agents in the simulation will die when hit by a weapon with a probability equal to the C4ISR efficiency. Therefore, agents that are hit with probability λ, β and die with e, f and are no longer targeted. This is the desired effect of C4ISR efficiency.

To summarize, in the direct fire scenario, an agent hit by the opponent weapon will be killed, whereas in the area fire scenario, the same agent represented is considered dead and its weapon is removed, but remains alive as a target for the enemy force. In the 25% C4ISR efficiency case ($e = f = 0.25$), if an agent is hit by opponent weapon there is a 25% chance that the agent will die, and a 75% chance that the agent will change to a weaponless state and remain a target. Table 2 summarizes the comparison of ABSNEC and Lanchester model results for a scenario with 50 Blue agents against 20 Red agents that was run 1000 times. The force size for both Red and Blue was averaged over all runs for each simulation time step, and the difference

Table 2 - ABSNEC/Lanchester comparison results

	Average Absolute Difference (Blue)	Average Absolute Difference (Red)	Average difference at final time (Blue / Red)
Direct fire	0.171	0.121	0.213 / 0.000
50% C4ISR efficiency	0.290	0.306	0.479 / 0.007
Area fire	0.156	0.021	0.171 / 0.006

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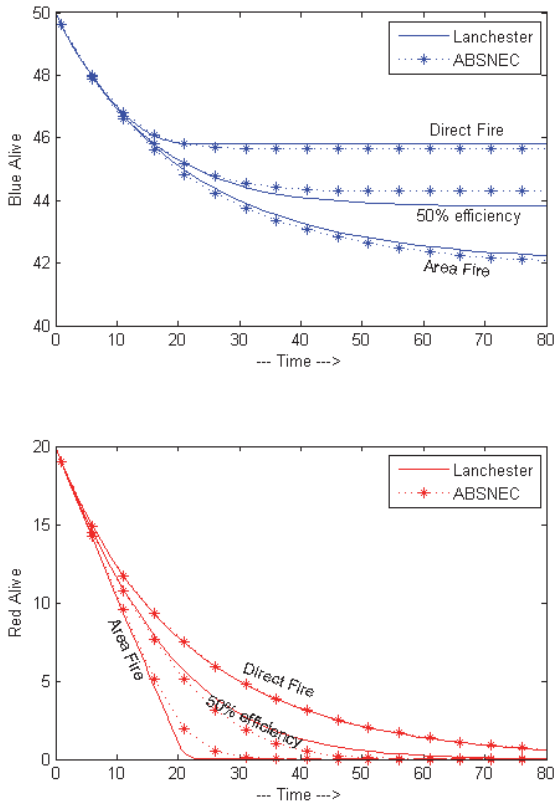

Figure 4 - Comparison of Lanchester's equations with ABSNEC

between this average and the solution to the Lanchester equation was used to calculate the average absolute difference for each side. Also shown, is the end state (steady state) difference in number of agents for each side. The differences between the two models are very small (much less than a single agent). Figure 4 is provided as a visual comparison of these results.

In summary, the affirmative results of the three validation techniques: face validation (using validation by SMEs), model-to-model comparison (ABSNEC versus MANA) and simple statistical analysis/test against the well known Lanchester equations provide clear evidence on the validation of ABSNEC to date. Furthermore, it instills an underlying confidence in the fidelity of ABSNEC in generating meaningful insights to complement complex military decision-making.

3. EXAMPLES

3.1. Example 1: Fratricide versus Situation Awareness

The objective of this example is to study networked operations with humans in the loop. The unique feature of ABSNEC – the ability to track intangible parameters such as morale, fatigue and combat stress – can be fully exploited to learn about why and how friendly fire happens and hopefully to prevent similar incidents in the future. Friendly fire casualties can have direct impact on troop morale, mission success, and public perception. A number of things can lead to friendly fire. One of the most common is miscommunication, which can result in unclear orders or lack of knowledge about troop movements. When allied troops are added to the mixture, maintaining lines of communication can be even more difficult, especially if language barriers and differing rules of engagement are being surmounted. Poor weather conditions and combat stress can also lead to a friendly fire incident in which a soldier mistakenly believes that he or she is shooting at the enemy. When a leader issues unclear or ambiguous orders, this can also be problematic when combined with conditions which prevent soldiers from using their own judgment. Incidents of friendly fire abound, however, it is extremely difficult to collect/gather relevant statistics for analysis.

Our fictitious scenario is based on the incident reported by the United States Department of the Army (2007) with modifications. An aerial gunship (e.g. the AH-64 Apache) has mistakenly identified a neutral target as an enemy. The gunship crew waits for additional information to confirm (or refute) the target, but the surrounding infrastructure concealing the target, the physical location of surveillance assets, and the structure and reliability of the available communication network can delay this confirmation/refutation. The gunship crew believes that this target is a threat, and they are in prime position to strike, so while they wait for additional information, the gunner's finger is on the trigger and the crew's stress level begins to rise rapidly. Beyond some threshold, the gunship crew will no longer feel justified in waiting for a target confirmation and choose to kill the target. The commander in charge is capable of ordering the gunship to stand down, but will not make that decision until a sufficient level of situational awareness is obtained. The commander receives discrete pieces of the situational awareness map from its two surveillance assets: a UAV (air surveillance asset) and a Humvee (ground surveillance asset). The commander also requires very up-to-the-minute information with a certain degree of synchronicity between the two sources. Beyond a lower threshold level of situational awareness, the commander will send an intermediate command to the gunship. The intermediate command will ease the stress of the gunship crew, but will only provide a temporary solution. Without further intervention, the gunship crew's stress level will still rise beyond the threshold level, causing them to kill the target. Once the commander has a complete situational awareness map, a "stand down" order is sent to the gunship, and if it is received prior to the gunship crew reaching their threshold stress level, then the neutral target will be saved. A visual description of the scenario is summarized in Figure 5.

In general, value of information is comprised of two main attributes: timeliness and quality of information. Timeliness is the degree to which mission performance depends on timely and perhaps perishable information (Perry 2005). Quality of information refers

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to the completeness and accuracy of information. That is,

$$\begin{aligned} \begin{matrix} Value\ of \\ Information \end{matrix} &= \begin{matrix} Joint\ Probability\ Function\ of \\ Timeliness\ \&\ Quality\ of \\ Information \end{matrix} \\ &= f(Timeliness, Quality) \end{aligned}$$

For this scenario, this concept simplifies to the following expression:

Let T = event where timely information is received prior to threshold stress level is reached,
Q = event where information is received prior to threshold stress level is reached is both complete and accurate

$$P(useful\ information) = P(T \cap Q) \qquad (3)$$

In our context, fratricide will occur whenever no useful information is received prior to gunship crew's stress threshold value is reached.

$$\begin{aligned} P(fratricide) &= 1 - P(useful\ information) \\ &= 1 - P(T \cap Q) \qquad (4) \end{aligned}$$

Since useful information refers to the degree of successfully correcting the situation awareness map, lowering the stress level of gunship crew and stopping the attack, the remainder of this example will demonstrate using ABSNEC to compute the probability of successfully correcting the SA map such that the stress threshold level will not be reached.

In this fictitious scenario, it is assumed that the gunship agent's stress level starts to rise at an arbitrary 2 units per second. Also, at the start of the scenario, the UAV and Humvee are in the area and begin sending their SA to the Commander. The Commander then makes decisions based on the percentage of the total picture received from both surveillance assets. The sensor at the gunship sees a single target (that it has mistakenly identified as an enemy); however, the UAV and Humvee each see five separate targets and will attempt to send a single packet through the network for each target. When these packets arrive at the Commander, they populate the Commander's SA map, but are obsolete after they reach a certain age. The UAV and Humvee continue to send each of these five packets at regular intervals, but some of the packets might be lost in transfer.

Once the Commander's SA map has received 6 of the total 10 packets concerning the misidentified neutral target, the *Hold* command will be sent to the gunship. (It is to be recalled that of the 10 packets, 5 are from the UAV, and 5 are from the Humvee). When the *Hold* command is received, the gunship's stress level will only increase at 1 unit per second. Out of the commander's SA map of 10 packets, whenever 8 of them on the neutral target have been received, the *Stand Down* command is sent and the gunship's stress level will stop increasing. If the *Stand Down* order is received before the gunship reaches its threshold level of stress, then the gunship will not fire its weapon, and the neutral target will be saved.

In this simple example, the SA map will be enriched more quickly if fewer packets are being dropped in the communication link. That is, useful content of the SA map is inversely proportional to probability of packets being dropped in link. To a first order approximation then, stress versus the enrichment of the SA map is analogous to the behavior of stress versus the probability of dropped packets.

The described scenario was run using ABSNEC for different probabilities of packets being dropped in the communication links between the surveillance assets and the commander. For each probability of a dropped packet, the scenario was run for 1000 replications and the average success of the mission was recorded. Figure 6 shows the probability that the neutral target was killed (i.e. fratricide) against the probability that a

Figure 5 - "Fratricide and Intangible Parameters" scenario layout

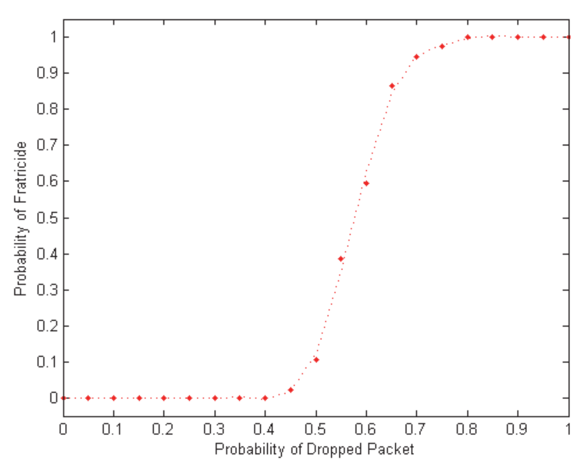

Figure 6 - Probability of fratricide when packets are dropped in the network

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packet was lost.

Letting x = probability of dropped packets, Figure 6 reveals the following

$$P_{fratricide}(x) \begin{cases} = 0 & if\ x \leq 0.4, \\ > 0 & if\ x > 0.4. \end{cases} \quad (5)$$

The chance of fratricide can thus be lessened if one can use technology to reduce the packet drop rate between communication links, a recommendation that hardly comes as a surprise for this example.

A salient feature of ABSNEC is that it can track up to 6 intangible parameters. Using this feature, a more realistic scenario can be explored in which the gunship crew experiences both stress and an immense fear of being shot at by the wrongfully identified enemy. A simple screenshot from ABSNEC in Figure 7 illustrates how two human factors (stress and fear) can be used to trigger an alternate state for the agent when they reach a specified level.

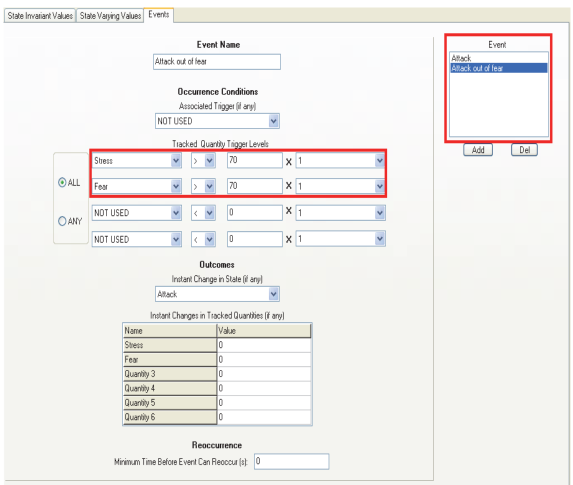

Figure 7 - Screenshot from agent events tab; used to trigger agents to a new state.

Previously, the gunship would fire on the target if its stress levels rose above a set threshold (arbitrarily defined at 120). In the revised scenario, a secondary condition was set where the gunship would now fire if both stress and fear levels rose beyond a lower threshold of 70. Both of these events trigger the gunship into the *Attack* state, where it proceeds to kill the target.

For illustrative purposes, fear levels rise at 1 unit per second. When the *Hold* order is received from the commander, the gunship agent's fear then rises at 2 units per second. When either *i)* fear and stress both rise beyond 70, or *ii)* fear is less than 70 and stress is above 120, then the gunship will enter the *Attack* state and kill the target. An example of fear and stress levels is shown in Figure 8. At 21 seconds, the *Hold* order is received and both stress and fear rates change. At 47 seconds, fear rises beyond 70, and at 56 seconds stress

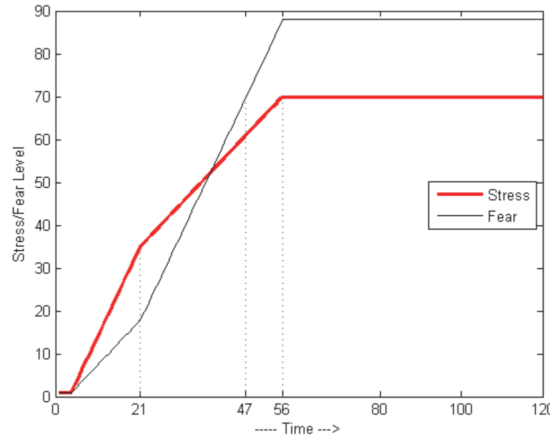

Figure 8 - Sample stress and fear levels

hits 70, which triggers the *Attack* state and ends the simulation.

Figure 9 shows the summary of results for the revised scenario. To achieve the same mission success as the previous case, the probability of a dropped packet in the communication links must be lowered due to the creation of the additional fear trigger. In other words, for the same probability of dropped packet, there is now a higher probability of fratricide. (It was verified from the simulation output data that both event triggers were activated throughout the simulation, i.e. sometimes stress levels triggered an attack with low fear levels, and sometimes elevated fear levels caused the gunship to attack at lower stress levels.)

Even though the example is fictitious, it provides us a means to understand the relationship between fratricide, stress, fear and situational awareness. Similarly, our approach can easily be adapted to study other aspects of networked operations with humans in the loop. Last, but not the least, our approach provides us a means to quantify the effect of training on combat outcomes. It has been acknowledged that training might reduce fear among military operators. Reduced fear would result in a less steep (more flattened) fear curve in Figure 8, which in turn would shift of the

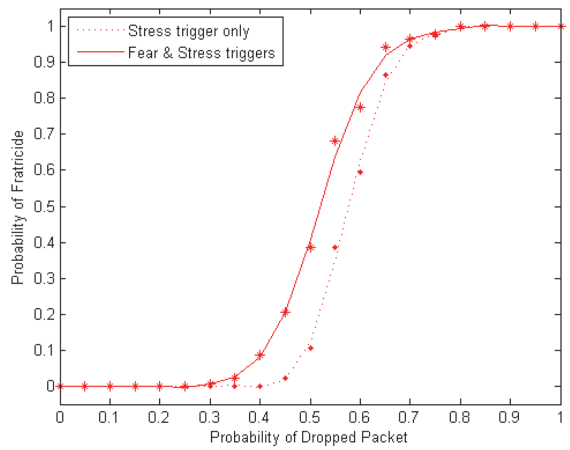

Figure 9 - Effect of additional triggers causing the gunship to fire

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Probability of Fratricide curve (Figure 9) to the right, reducing the chance of fratricide.

3.2. Example 2: Ben Hasty revisited

The aim of this example is to demonstrate that by combining data farming techniques and the distinctive feature of ABSNEC, i.e. the ability to represent realistic force structures with tiered C2 architectures, we can generate valuable, and perhaps unpredictable, combat strategies. Moreover, the simplicity of ABSNEC provides a viable method of performing quick turnaround studies to NEO/NEC scenarios.

The Ben Hasty scenario as was presented in the Validation Section, ended with the demonstration that the Red tactic identified using ABSNEC was one of the recommendations by the SMEs. In this example, ABSNEC was used to repeat the data farming process for Blue and search for beneficial tactics that would help Blue defeat the improved Red tactics demonstrated in Sample 11. To do this, Red affinities found in Sample 11 were held constant while the Blue parameter space of affinities, intermediate waypoints, and issued commands are explored. The initial setup of the scenario is shown in Figure 10. The Blue force is divided into two teams: Blue1 and Blue2. Each team starts in the Advance state and moves towards its team's intermediate waypoint. When a Blue agent reaches its intermediate waypoint, it changes to the Flank state and continues to move towards the final goal. If a Red agent is detected, the Blue agent that detected it changes into the Attack state. Each Blue team maintains a situation awareness (SA) map. This SA map is sent to the Blue Leader at a constant rate with a fixed delay of 150 seconds (arbitrarily chosen). The Blue Leader combines the two SA maps and uses the ratio of total friends to total enemies to make command decisions. These command decisions are then sent to both of the Blue teams with a fixed communication delay of 150 seconds.

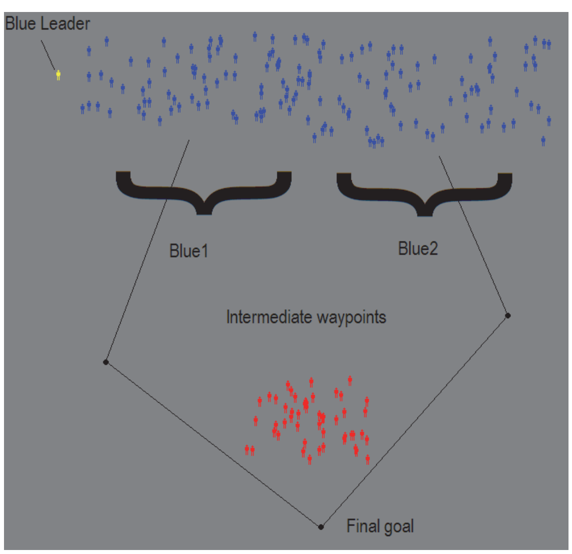

Figure 10 - ABSNEC screenshot (with labels) for example 2

Sixteen agent affinities, four positional variables, and four command variables, were used in the data farming procedure to find a suitable strategy for Blue to counterattack Red. These 24 variables are listed below, along with their associated ranges. As stated earlier, agent affinities can be integer values from -10 (strong repulsive) to +10 (strong attractive). Waypoint affinities have been restricted to only attractive forces to ensure agents do not simply run away from their final goal.

Blue States and Affinities

Advance

- Next waypoint…………………….........[1, 10]
- Others in own group ……...……......... [-10, 10]
- Friendly group …………….................. [-10, 10]
- Target assigned by commander.......... [-10, 10]

Flank (entered when intermediate waypoint is reached)

- Next waypoint.………….………….. [0, 10]
- Others in own group …………………… [-10, 10]
- Friendly group ……………………….. [-10, 10]
- Target assigned by commander .... [-10, 10]
- Enemy sensed by own sensors……….. [-10, 10]
- Enemy positions sent via network…….. [-10, 10]

Attack (entered when enemy detected with organic sensor)

- Waypoint …………………………….. [-10, 10]
- Others in own group..………………… [-10, 10]
- Friendly group ……………………….. [-10, 10]
- Target assigned by commander .... [-10, 10]
- Enemy sensed by own sensors ………..[-10, 10]
- Enemy positions sent via network ..….. [-10, 10]

- Intermediate waypoint location for Group1 ……
  ($0 < x_1 < 10,000$, $0 < y_1 < 15,000$)
- Intermediate waypoint location for Group2 ……
  ($0 < x_2 < 10,000$, $0 < y_2 < 15,000$)
- If friend/enemy < *A*, Then *CommandA*
- If friend/enemy > *B*, Then *CommandB*

The last two listed items are of particular interest. Using these logic statements, command decisions (*CommandA* and *CommandB*) can be made based on friend to enemy ratios *A* and *B*. For our example, the commands are chosen from one of the three states of the Blue agents, i.e. *Advance*, *Flank*, or *Attack* for values of *A* and *B* of 1, 2 or 3.

The 24 possible factors are used to create a NOLH sampling pattern and the runs were performed in ABSNEC. The resulting number of kills for each run is shown in Figure 11. Similar to Figure 1, the one-to-one kill ratio is plotted in Figure 11 as a dotted line. Points above this line correspond to scenarios where more Blue were killed than Red. Note, there are no points where Blue was able to kill a large number of Red and receive less casualties than Red, i.e. points below the dotted line. In summary, no advantageous tactic was found for Blue when Red adopts the tactic of Sample 11 (from Section 2).

Now, assume the 150 Blue agents are given, in addition, a Beyond Line of Sight (BLOS) weapon (e.g.

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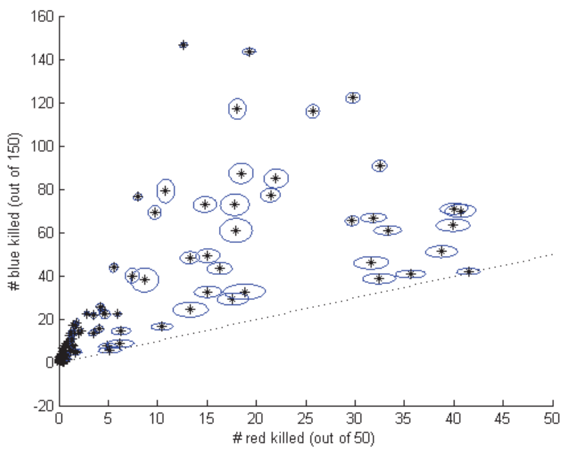

Figure 11 – Data farming results for Blue tactics against Red.

artillery). Data farming was performed using these sample points. The resulting kill ratios for each sample point are shown in Figure 12.

The points in Figure 12 are the average of 100 iterations at each of the sample points in the NOLH. There is a single outlier that exists below the dotted one-to-one kill ratio line and to the right of the graph. In other words, Sample 9 provides an advantageous tactic for Blue, where Blue is able to inflict more kills than casualties received. A screenshot for a single iteration of Sample 9 is shown in Figure 13 and the agent affinities, waypoint locations, and command rules are shown below.

In Sample 9, the agents start out at the top of the screen, spread out (due to their negative affinity towards friends), and move towards their intermediate waypoints (*Wp1* and *Wp2*). There is also repulsion between the two groups, *Blue1* and *Blue2*. This repulsion between groups causes the two groups to split up and surrounding Red.

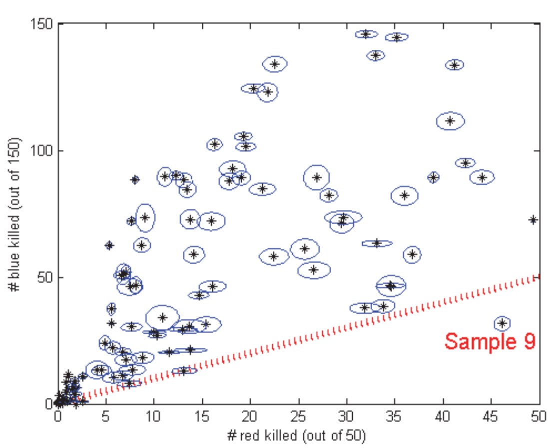

Figure 12 – Data farming results for Blue with a BLOS weapon added to Blue's side.

Blue States and Affinities

Advance

Waypoint ….………………………….... 10
Others in own group ……...………..... -10
Friendly group ……………................. -9

Flank (entered when intermediate waypoint is reached)

Waypoint ……………………..………. 10
Others in own group ………..……….... -1
Friendly group ……………………….. 5
Enemy sensed by own sensors ...……. 7
Enemy positions sent via network ..…. 5

Attack (entered when enemy detected with organic sensor)

Waypoint ……………………………. -5
Others in own group ………………... -6
Friendly group ………………………. -6
Enemy sensed by own sensors ……… 10
Enemy positions sent via network ...…. 5

Blue Leader Command Choices

- Intermediate waypoint location for Group1 …… (2739, 9156)
- Intermediate waypoint location for Group2 …… (2583, 11617)
- If friend/enemy < 3, Then *Flank*
- If friend/enemy > 3, Then *Attack*

Next, *Blue1* reaches its intermediate waypoint, *Wp1*, switches to the Flank state, and moves towards the final goal (where Red is located). *Blue2* continues to move towards *Wp2* by winding around Red's location. As members of *Blue2* reach *Wp2*, members in *Blue1* that have not reached *Wp1* move up over the north end of Red's location in order to maintain a separate distance from *Blue2*. Now, Red is completely surrounded and remains in one place, and as Blue agents reach their intermediate waypoints they move towards Red and come within sensor range. Then they send sensed Red locations to the Group Leader, who then sends it to the BLOS weapon. The BLOS weapon

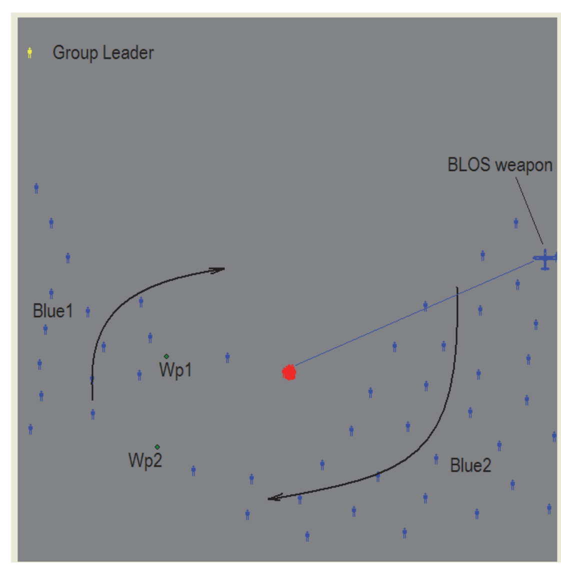

Figure 13 – ABSNEC screenshot from Sample 9

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fires on the location of the Red agents it sees on its SA map which is 30 seconds old by the time it commences firing. Red and Blue agents have the same sensor and small arms weapons range. As a result, some Blue agents are killed as they get too close to the clustered Red agents, but because they approach the Red agents in small numbers and are spread out, the Blue casualties are kept small. In summary, an alternative Blue strategy has been developed to counter an effective Red strategy by exploring the parameter space using ABSNEC.

By combining data farming techniques and the distinctive feature of ABSNEC to represent realistic force structures with tiered C2 architectures, we have demonstrated the capacity to generate valuable, and perhaps unpredictable, combat strategies. Moreover, the simplicity of ABSNEC provides a viable method of performing quick turnaround studies to NEO/NEC scenarios.

CONCLUSION

We have introduced and highlighted some of the distinctive characteristics of the Canadian agent-based model known as ABSNEC (Agent-Based System for Networked Enabled Capabilities).

Next, the paper presents affirmative results of three validation techniques applied to date on the model: face validation (using validation by SMEs), model-to-model comparison (ABSNEC versus MANA) and simple statistical analysis/test against the well known Lanchester equations. The validation results instill an underlying confidence in the fidelity of the model in generating meaningful insights to complement complex military decision-making.

In the first illustrative example, we utilize ABSNEC to investigate the interrelationship between fratricide, combat stress, fear and situation awareness. The example opens the door to other 'human in the loop' operational studies. The second example combines ABSNEC's ability to represent realistic force structures with tiered C2 architectures and data farming techniques to generate unpredictable insights on combat strategies. In summary, the examples furnish compelling evidence to establish ABSNEC as a valuable analytical tool with which to better understand NEO/NEC concepts under the influence of the human error (human in the loop effect).

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