A Crystal Box Process Used to Validate Dynamic Decision Networks: How Agent-Based Simulations Help Dynamic Decision Networks

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ABSTRACT

The Crystal Box Process provides a forum to collaborate ideas while examining the validity of models of interest. In this paper the model of interest is a Dynamic Decision Network (DDN). DDNs are new decision tools that can help decision makers make optimal and timely decisions given information overload. DDNs have been proven to be a good approximation to Dynamic Programming, the gold standard in decision making optimization, but only for simple decisions. Exploration with agent-based simulation (ABS) can scope and validate the DDNs approximation for complex decision problems. This paper explains the Crystal Box Process, and how it is implemented through the use of ABS to examine some DDN models developed for military decision makers.

Keywords: Dynamic Decision Networks, Agent-Based Simulation (ABS), Crystal Box, Data Farming, Design of Experiments.

1. THE CRYSTAL BOX PROCESS [1]

The Crystal Box Process provides a forum to share ideas, successes, and failures among colleagues. In this paper, this process is applied to Dynamic Decision Network (DDN) models in order to validate their accuracy. The motivation behind creating the Crystal Box Process was to eliminate the stove pipe or black box mentality to solving problems, by promoting collaboration where ideas are shared.

[1] The *Crystal Box Process* seemed an appropriate name after attending a DoD presentation entitled the *Glass Box*. The *Glass Box* gained origin from "Battelle PNWD," originally funded by the Advanced Research and Development Agency's (ARDA) Novel Intelligence from Massive Data (NIMD) program.

2. CRYSTAL BOX OBJECTIVES

It is our goal in this paper to show how the significant factors in the DDNs can be determined. The Crystal Box Process openly invites/permits others to model scenarios in another venue in order to validate, correct, or narrow the focus of the DDNs for future work. Specifically, the current problem statement is as follows: How will Agent-Based Simulations (ABS), specifically, Map Aware Non-uniform Automata (MANA), validate the DDN's effectiveness? The scope of this problem is to create a simulation vignette in MANA that models a simple warfighting scenario, which replicates the same scenario previously modeled as a DDN. Using a Nearly Orthogonal Latin Hypercube design of experiment, the intent is to datafarm over various parameters and then to perform a regression analysis in an attempt to validate the parameters in the DDN. Exploratory analysis combined with a regression analysis, scoped by specific measures of effectiveness (MOE), provides a comparison between the results from datafarming and the DDN output. This comparison identifies significant factors in the DDN models.

3. AGENT BASED SIMULATIONS

Agent-based Simulation (ABS) is a low-resolution simulation that compliments and augments previously established more computationally intensive physics-based simulation models. The role of ABS is not to replace high-resolution models but to support them. Over the past few years, ABS has increasingly proven useful to the Department of Defense (DoD) in primarily two areas. The first is to use ABS in an exploratory analysis in order to gain insights and to narrow the focus of seemingly endless possibilities of factors, parameters, and variables; this expedites building high-resolution physics-based simulations [1] which in the end saves time and money on the front end of a simulation project. The second area is to use ABS to offset timely resource intensive key battlefield objectives that otherwise require excessive recourses in physics-based models.

ABS offers quick scenario generation, fast run times, and rapid data turnaround times, thereby allowing the analyst to consider many alternatives in a short amount of time. These ABS characteristics enable us to concentrate on possible insight, surprise, and outliers that may arise in the analysis. In addition, ABS compliments and augments physics-based models permitting analysts to examine the problem over a greater range of plausible possibilities, while helping to fix the aforementioned quantities [2].

4. MAP AWARE NON-UNIFORM AUTOMATA

We chose Map Aware Non-Uniform Automata (MANA) as the agent-based simulation-modeling tool for this research. MANA's individual agent and squad situation awareness (SA) aptitude, coupled with its networked communication parameters support use of this tool to model scenarios also modeled by the DDNs.

Using Lindquist's explanation [3] of each word in the acronym MANA, we have:

- Map Aware — Agents are aware of and respond to, not only their local surroundings and terrain, but also a collective registry of recorded battlefield activities.

- Non-Uniform — Not all agents move and behave in the same way (much like soldiers, sailors, or airmen).

- Automata — Agents can react independently to events, using their own "personalities." Personalities, in general, are propensities that guide an agent's actions to move.

Analysts use MANA for two reasons. The first is because the behavior of the entities within a combat model (both friend and foe) adds possibilities to the analysis of the possible outcomes. The second is because analysts have limited time to determine particular force mixes and each side's combat effectiveness necessary for programming into higher resolution models [2].

5. DYNAMIC DECISION NETWORKS

DDNs solve a specific class of decision problems that are complex and repetitive in nature by merging concepts of Bayesian networks [4] and influence diagrams [5]. For a full explanation of DDNs refer to Kobylski [6]. DDNs can be very efficient for complex decision problems and thus a good alternative for decision makers where there is a lot of information and time is of the essence. They are an ideal aid for a decision maker faced with multiple uncertain variables, conflicting objectives, and many opportunities to collect information. The DDNs provide insights not only into what decisions to make, but also when to make them.

For simple decision problems, DDNs were shown by Kobylski to be a very good approximation to dynamic programming (DP) [7], the "gold standard" in decision making optimization. Unfortunately, DP is highly intractable and inefficient for even the simplest of decision problems and thus is not a realistic decision tool for use in military decision making.

6. SCENARIO

The scenario used in this paper involves the use of portable sensors[2] and is illustrated in the MANA Scenario Screenshot shown in Figure 1. In this scenario, a platoon leader is tasked with keeping a route clear during a dignitary visit. Two to three days ahead of the visit, the platoon leader clears the area and posts single sensors to monitor high threat locations. At some point prior to, or during the visit, an alarm goes off, or the sensor goes dead, and the platoon leader must decide if it is necessary to send troops to investigate and re-clear the locations.

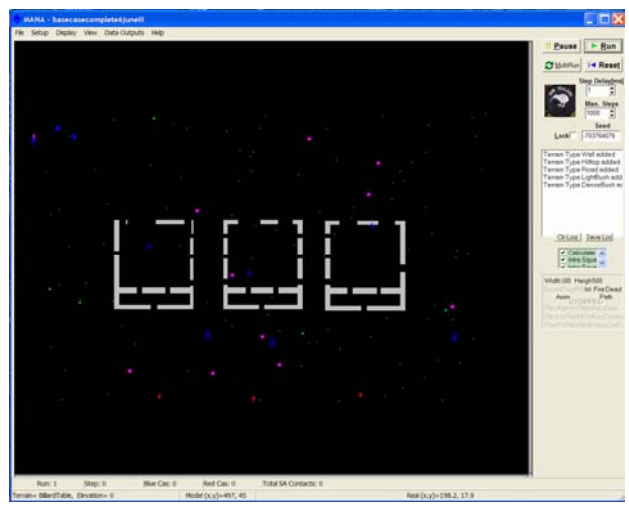

Figure 1. MANA Scenario Screenshot

For the simulation of this scenario, the dignitary who is accompanied by troop escorts travels along a route extending from the upper left hand corner of Figure 1 to the upper right hand corner of Figure 1. In the middle of the screen there are three buildings. Insurgents enter the building in order to gain a clear line of site and kill the dignitary traveling along the route. In each building there exist sensors with alarms to identify threatening insurgents to the platoon leader.

7. ANALYSIS

Proper selection of the MOEs focuses the analysis. The need to accomplish the mission in the given scenario

[2] The sensor scenario was developed by Brian Souhan, United States Military Academy.

assists in the selection of MOEs. The mission is to keep the buildings clear while keeping the dignitary alive. Hence, the MOEs which quantify the mission accomplishment for this analysis are: survival rate of dignitary to reach the endpoint (final waypoint) and the percentage of Red insurgents killed in buildings (ability for Blue to re-clear a building).

Using a Nearly Orthogonal Latin Hypercube (NOLH) DOE, we examined 18 uncorrelated factors which resulted in 129 design points. Figure 2 outlines the 18 uncorrelated factors examined. We ran 30 replications of the simulation for each design point for a total of 3870 simulation runs.

Factors used for Data Farming (Terms found in MANA)	***Explanation of Factors (Terms found in DDN)***
Fuel Tank Capacity for Sensor I	Initial Battery Life of Sensor, (AKA Dead Sensor)
Fuel Tank Capacity for Sensor II	Initial Battery Life of Sensor, (AKA Dead Sensor)
Fuel Tank Capacity for Sensor III	Initial Battery Life of Sensor, (AKA Dead Sensor)
Latency for Ghost Sensor Agents Communication	Possible Decision to Delay Sending Troops to re-set a Dead Sensor
Movement Speed for Dignitary	Simulates LOS from Reds Location / Location of threat / Type of Threat
Non Default Movement Speed for Reaction Teams	Simulates Size of Area: How Large an Area is that a Team Needs to Reclear
pk for Red Insurgent I	Simulates Clear LOS vs. Obstructed LOS, i.e. clear LOS has pk = 1, Obstructed LOS has pk less than 1
pk for Red Insurgent II	Simulates Clear LOS vs. Obstructed LOS, i.e. clear LOS has pk = 1, Obstructed LOS has pk less than 1
pk for Red Insurgent III	Simulates Clear LOS vs. Obstructed LOS, i.e. clear LOS has pk = 1, Obstructed LOS has pk less than 1
Sensor Capabilities for Red Insurgents I, II, III	Simulates LOS and Distance Between Threat and Dignitary
Home, Way Point 1, Way Point Final for Blue Route of March	Simulates Distance Reaction Teams Needed to Travel to Re-Clear Threat
Concealment for Sensors I, II, and, III	Simulates Insurgents Ability to Disarm Each Sensor
Number of Agents for Rain and Wind	Increase Probabilities in Rain and Wind Setting off the Sensor Alarm
Number of Agents for Electrical Storm	Increase/Decrease Probabilities in Electrical Storm Setting off the Sensor Alarm
Number of Agents False Alarm Tripper	Simulates the Probability of a the Sensor Alarm having a False Positive
Number of Agents for Sensors I, II, and III	Number of Sensors Placed in Each Building
Range Transmission for Sensor I, II, and III	Signal Strength of Each Sensor
Reliability Transmission for Sensor I, II, and III	Simulates Obstructions within Signal Path: i.e. Extra Buildings, Radio Interference, Jamming

Figure 2. Eighteen Uncorrelated Factors

Throughout the analysis, we discovered some insight and surprise that both complemented the initial DDN model as well as suggested possible contradictions or improvements needed to the original DDN model.

Exploratory analysis showed that decisions resulting in reaction teams spending more time re-clearing locations increased the survival rate of the dignitary. To our surprise, we found that sensor alarms triggered due to inclement weather, even while the building was clear of insurgents, caused troops to re-clear buildings and this ultimately led to the increased survival rate of the dignitary. The significance of the inclement weather factors contradicted the original DDN model. According to the DDN, an increase in wind and rain, given a vacant building, did not yield a decision to re-clear the building with reaction teams.

In the simulation, the triggered alarms due to weather caused the platoon leader to send reaction teams to re-clear the building. Hence, decisions yielding the reaction teams to spend more time re-clearing buildings increased the survival rate of the dignitary. We observed in the simulation that this occurred because the reaction teams were already present in the building to immediately intersect the arrival of any insurgents. Otherwise, the re-clearing teams had to travel over a greater distance after reacting to the insurgents triggering the building's sensors, and eventually arriving after the insurgents successful fires upon the dignitary.

The lesson learned is that the reaction teams must know ahead of time that there is a need to patrol a building prior to the insurgent's arrival. Militarily, this means that an increased patrolling of specified threat locations increases the survival rate of the dignitary. The bottom line is that the teams need to be more proactive rather than reactive.

We claim that modeling a single sensor inside a high threat area is possibly not as sensible as other solutions. Rather, setting multiple alarms outside the location may facilitate identifying the insurgents' arrival path, and predict the specific location where the insurgents will enter in the near future. Our recommendation to the DDN modeler was to set up multiple alarms outside the buildings, so that when triggered, they ultimately predict the insurgents' route to a specific building. This recommendation to improve the DDN model would not have surfaced without analyzing the given surprise pertaining to the weather factors.

Exploratory analyses also showed that a shift from a clear line-of-sight (LOS) to an obstructed LOS between a Red insurgent and the Blue dignitary increases the survival rate of the dignitary. This is a simulation discovery complimenting the DDN model. It suggests that a decreased LOS from the insurgent to the dignitary reduced the threat level to the dignitary. This observation was measured by a significant split on this factor occurring in a regression analysis tree. Similarly, the decision value emphasizing the need to re-clear the building in the DDN model decreased as the LOS decreased. We claim that the value of the DDN model's decision to re-clear a location is justified given its current parameter values.

A regression analysis identified the most significant factors to include in the DDN model. Identifying these significant factors provided the DDN modeler feedback regarding which factors should not be eliminated (or possibly added) when narrowing the scope of the DDN model. The most significant factors measured by the survival rate of the dignitary in reaching the endpoint are: (increase) the LOS and distance between threat and

dignitary, and (increase) the number of Blue sensors in locations. The most significant factors indicated by the percentage of Red insurgents killed in buildings are: (increase) the number of Blue sensors in buildings and (increase) the amount of fuel (battery life) of sensors.

We also developed the following model to quantify each MOE in the form of:

$$\hat{y} = \widehat{\beta}_o + \sum_{i=1}^{k} \widehat{\beta}_i x_i \qquad (1)$$

where

$\hat{y} = \text{MOE}$

$\widehat{\beta}_0 = \text{intercept}$

$\widehat{\beta}_1 = \text{parameter estimate}$

$x_i =$ parameter (or factor)

Recall that the MOEs for our scenario are the survival rate of the dignitary in reaching the endpoint and the percentage of Red insurgents killed in buildings. As shown in Figures 3 and 5, the coefficient of variance (R^2) for the model describing each MOE is not high. The most significant factors as measured by a *t*-test are also listed in Figures 3 and 5. Notice these are the same significant factors identified in the regression analysis described earlier. These factors are listed under the heading Parameter Estimates in Figures 3 and 5. Referring to Figure 2, we see that the sensor capabilities for Red insurgents simulates the LOS and distance between the threat and the dignitary, the number of agents for all sensors simulates the number of sensors placed in each building, and the fuel tank capacity for sensor 2 simulates the initial battery life of each sensor.

Helping validate each model, we see that the Q-Q plots (Figures 4 and 6) are also reasonably good.

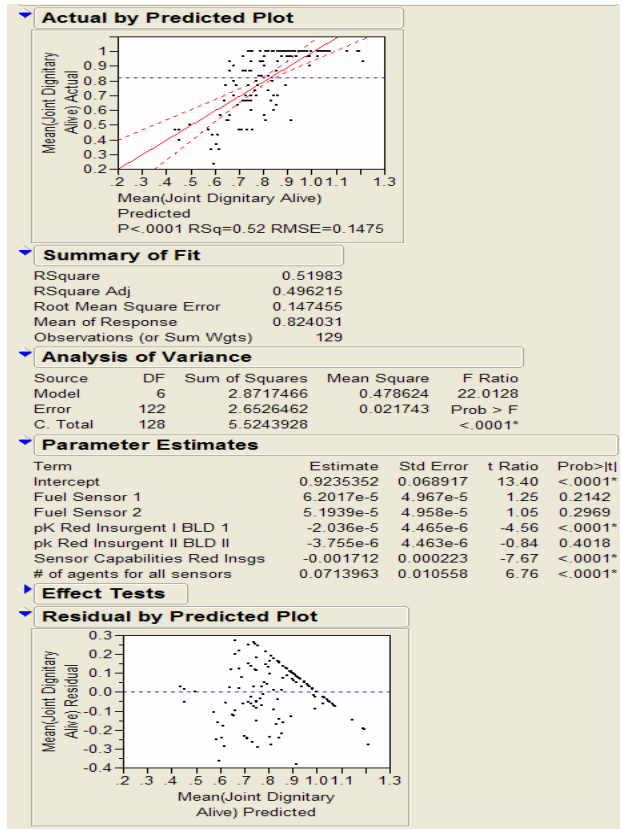

Figure 3. Model: $\hat{y}$ = Survival Rate of Dignitary to Reach his Endpoint

The residual plot in Figure 3 has a slight pattern to it. Further tests were needed to identify the goodness of fit for this model. The Q-Q plot in Figure 4 suggests a well fitted model since the error plotted appears to have a normal distribution.

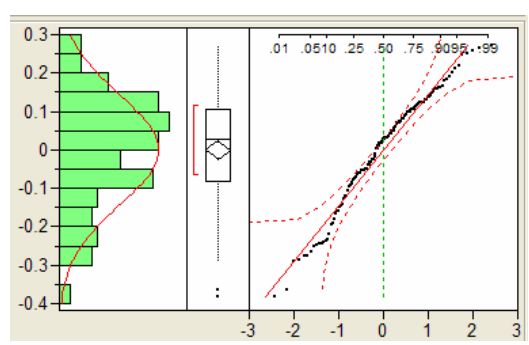

Figure 4. Q-Q Plot: $\hat{y}$ = Survival Rate of Dignitary to Reach his Endpoint

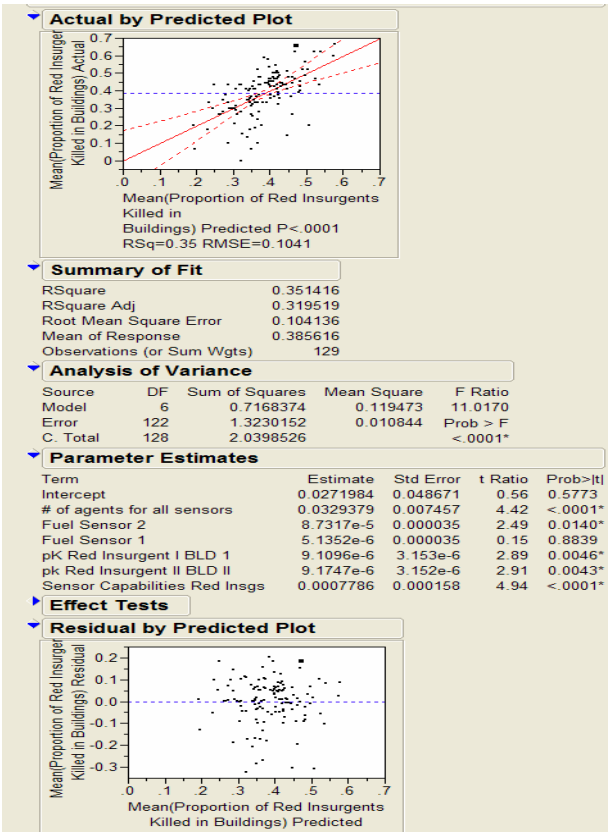

Figure 5. Model: $\hat{y}$ = Proportion of Red Insurgents Killed in Buildings

The lack of a pattern shown in the residual plot in Figure 5 suggests a well fitted model and provides a plausible argument that the error has a normal distribution. We observe a fairly good normal distribution in Figure 6, reinforcing this assumption, and establishing that our model has good parameter estimates.

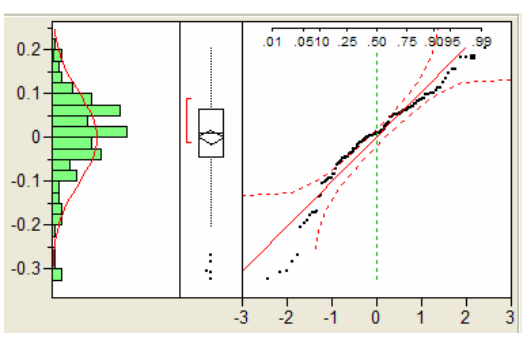

Figure 6. Q-Q Plot: $\hat{y}$ = Proportion of Red Insurgents Killed in Buildings

8. CONCLUSIONS

The most significant factors identified by the survival rate of the dignitary to reach his endpoint are: (increase) the LOS and distance between threat and dignitary, and (increase) the number of Blue sensors in locations. The most significant factors indicated by the Red insurgents killed in buildings are: (increase) the number of Blue sensors in buildings, and (increase) the amount of fuel (battery life) of sensors.

The above mentioned four factors found in the regression analysis and these same repeated factors found in the fitted model prove to be very significant to the DDN model. Should the DDN modeler choose to narrow the scope of the model, he/she should not eliminate these four factors from the model.

The Crystal Box Process allows all findings to be shared with the DDN modeler and provides the DDN modeler the ability to better the network model. Similar results show promise with respect to the modeler's notion to use certain probabilities in each model, and in turn verify the DDN to a certain extent. Contradictions between model results provide the DDN modeler plausible insight to change, eliminate, or verify his/her work while ultimately improving the DDN model. Identifying the most significant factors enables the DDN modeler to narrow the focus of the DDN and ultimately help decision makers in the future.

9. REFERENCES

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