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Integrated Systems Understanding using Bayesian Networks: Measuring the Effectiveness of a Weapon System

Alta de Waal
CSIR
adewaal@csir.co.za

Abstract: Complex systems can be described as systems-of-systems as it comprise of a hierarchy of systems. The links between sub-systems are often obscure and non-linear and this results in a lack of whole systems view and appropriate understanding of the system. At the core of the research question is the investigation of Bayesian networks as a method to integrate sub-system behaviour in order to evaluate final system performance. The research case study is the measurement of effectiveness of the Frigate Self Guided weapon system. The results indicate that the method integrates and quantifies links between sub-systems to an extent where questions posed by the end-user can be answered in a quantitative manner.

1 Introduction

The purpose of the study is to investigate the use of a Bayesian network (BN) as an integrative method to model complex systems. The model should be able to make links between sub-systems explicit and measure the effectiveness of the system based on input variables. The Frigate Self Guided (FSG) system was used as a case study as it is a good example of a complex system comprising of various interdependent sub-systems.

The outcome of the study is a BN that represents the complex causal chain between variables in sub-systems. The BN produces quantified results that provide answers on critical effectiveness queries posed by the end-user. These results lead to better understanding of the limitations and strong points of the system. It also verifies the impact of processes, procedures, drills and rules of engagement on the system, especially for stressing conditions[1].

The FSG system is the weapon system on the newly acquired corvettes (Figure 1) of the South African (SA) Navy. The main purpose of the corvettes is to maintain a positive presence in the South African exclusive economic zone (EEZ). The FSG serves as the self-defence mechanism for the ship. A key issue in understanding the limitations and strong points of the FSG is how to define, measure and quantify *being effective* in the context of the intended application of the weapon system and the natural environment in which it must operate[1]. The effectiveness of the FSG weapon system is not equivalent to a simple combination of sub-system performances, but rather the synergy of sub-systems to give a required effect. The modelling approach followed was to[1]:

- develop a BN model utilising the causal dependencies along the engagement timeline of the weapon system. Identify the sensitive performance drivers such as the influence of natural environment on system performance.
- evaluate the weapon system behaviour and performance, and gradually introduce more realistic system influencers with natural operating influences.
- verify and validate the model with the system and subsystem subject matter experts, and compare the effectiveness of the different system configurations within a defined scenario.

Figure 1: Corvette F124

The key aspects of the sub-systems of the FSG system namely the sensors, the combat management system and the seeker missile were integrated in a BN model and visualised with a graphical interface. The following observations could be made:

- Very late detection of targets will definitely compress the engagement timeline, eventually becoming unacceptable.
- Severe degradation of respective sub-system and weapon system performances due to natural environment conditions compresses the engagement timeline further. The compressed timeline causes the target engagement to fail eventually.
- Firing policies will alleviate the pressure on the engagement timeline for stressing conditions like multiple targets, and pop-up targets.

South Africa has limited capacity at present to respond to new areas of technology in terms of acquisition and implementation decisions. Typically, knowledge and understanding of a new system are limited to a few resources that are actively involved on a research project. Even then, the knowledge about that system is sometimes disparate. The reason for this is because complex systems are “systems of systems” and experts on sub-systems do not necessarily understand the complex links between sub-systems. This results in a lack of a whole systems view and appropriated understanding of the system. We believe that a modelling technique such as BNs provide structure and guidance for understanding the complex synergy between sub-systems. However, it is not a static “system picture” but an interactive *what-if* tool: The BN produces posterior probability distributions on system variables given an observed event or hypothetical scenario. This makes it much more usable as it facilitates analysis, evaluation and interpretation and ultimately complex decision making. In a resource constraint country such as South Africa, integration of knowledge of new technologies is vital in order to address and promote innovation.

2 Bayesian Networks

A language is needed to represent complex systems such as the FSG system. There are many perspectives on representing complex systems such as mathematics, knowledge engineering and artificial intelligence. BNs are a combined representation from a mathematical and knowledge engineering point of view: From a mathematical point of view, BNs gives a concise specification of any full joint probability distribution[2]. From a knowledge engineering point of view, a BN is a type of graphical model. The basic attribute of this type of graphical model is causality[3]. To summarise, a BN represents cause-and-effect relationships in a system explicitly and captures the uncertain knowledge about these relationships.

A BN consists of nodes (variables), arcs (the causal relationships between variables), and conditional probability tables (CPT) (describing the strength of the causal condition between two or more variables)[3]. The nodes and arcs make up the qualitative part of the BN, while the probability tables are the quantitative part of the BN.

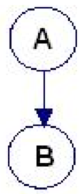

Figure 2: A Bayesian network consisting of two nodes

With regard to the quantitative part of the BN, probabilities are assigned to the states of the nodes. Every node is defined by the states (or values) that it takes on. States can be anything from sequential intervals to descriptions such as *yes* and *no*. The states of a node must be mutually exclusive and exhaustive. The absence of arcs between nodes implies conditional independence[4] and this compactness is an example of a local (sparse) structured system[2]. This simplifies the computational effort associated with the BN from an exponential to a linear growth in complexity[2]. Since the BN makes use of conditional probabilities, the Bayes' rule for calculation of conditional probabilities may be used. Mathematically, Bayes' rule states[3]:

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}} \qquad (1)$$

or, in symbols

$$p(X = x \mid e) = \frac{p(e \mid X = x)\, p(X = x)}{P(e)} \qquad (2)$$

where $p(X = x \mid e)$ denotes the probability that the random variable X has value x given evidence e. The denominator on the right hand side of the equation is a normalising constant.

Once the BN is constructed, it is used to estimate the values of query nodes, given the values of observed nodes[5]. This process is called inference and a BN can perform two inference tasks. One is to do top-down reasoning where 'root' nodes are observed and we predict the effects[5] (option (a) in Figure 3). The other way is to do bottom-up reasoning where 'leave' nodes are observed and we infer the causes[5] (option (b) in Figure 3). The second task is the more interesting one as it reasoning in the 'opposite' direction of the constructed arcs in the network.

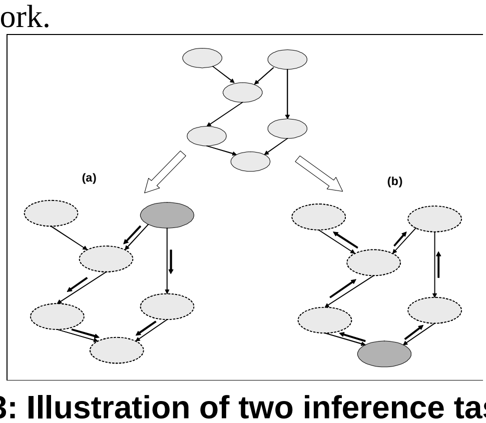

Figure 3: Illustration of two inference tasks in a BN

3 The FSG System Model

3.1 A timeline approach

The approach in modelling the FSG system is to establish a probabilistic model that utilises the causal dependencies along the engagement timeline[1]. The engagement timeline represents all the events that take place during a target engagement. Figure 4 illustrates a simplified engagement timeline. Although the timeline could be interrupted at any point, it follows a typical sequence of events. The first event is the 'first plot' of a target by the search radar and the last event (of a successful timeline) is 'target intercept'. The measuring unit for the timeline is seconds it can be translated to range (km) from ship if the target velocity is known. The timeline measures effectiveness of the FSG system as it aims to answer the question 'did the intercept happen in-time (or far enough from the ship) not to endanger the ship?'[1].

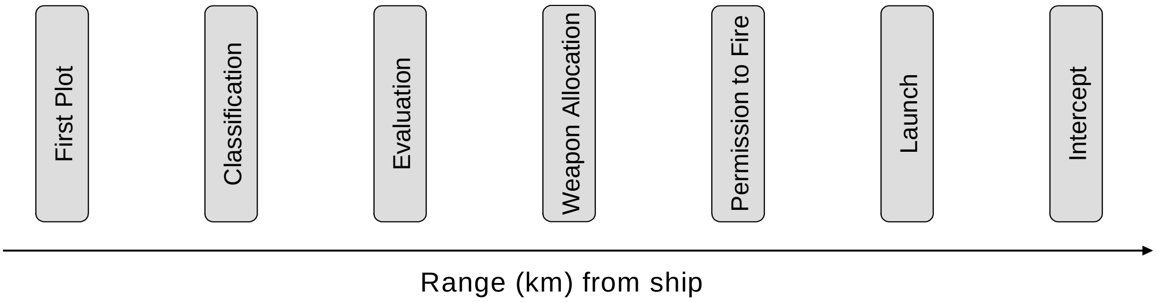

Figure 4: Typical Engagement Timeline

The variation in duration of events depending on operating scenarios influences the length of the timeline. Each timeline event is associated with a sub-system of the FSG system. For example, the event 'first plot' is associated with the search radar system. The duration of the first plot is influenced by other variables from the Search Radar, other sub-systems and external influences.

3.2 The Causal Structure

The first step in developing the model is the construction of the graphical structure comprising of nodes and arcs[4]. The graphical structure represents the engagement timeline together with the variables influencing the duration of the events. The first step was to determine the critical events in an engagement timeline model together with the logical and correct sequence of the events as it builds up to 'target intercept'[1].

As the FSG is a new system and not yet operational, no *integrated* understanding of the engagement process does exist. A workgroup consisting of experts on sub-systems of the FSG and other similar weapon systems was put together in order to develop the causal structure of events and influences. This workgroup is an independent expertise group on the FSG system in South Africa. The graphical structure of the BN was constructed in a facilitated workshop. We based the criteria for inclusion of variables on the lesson learned from Borsuk *et al.*[1], namely that it must be either (1) controllable, (2) predictable, or (3) observable. This is a simplification strategy that prevents researchers from pushing their 'pet processes' to be included in the model without adding value to the model[4]. Variables that adhere to the above-mentioned criteria and influence the engagement timeline were included in the model.

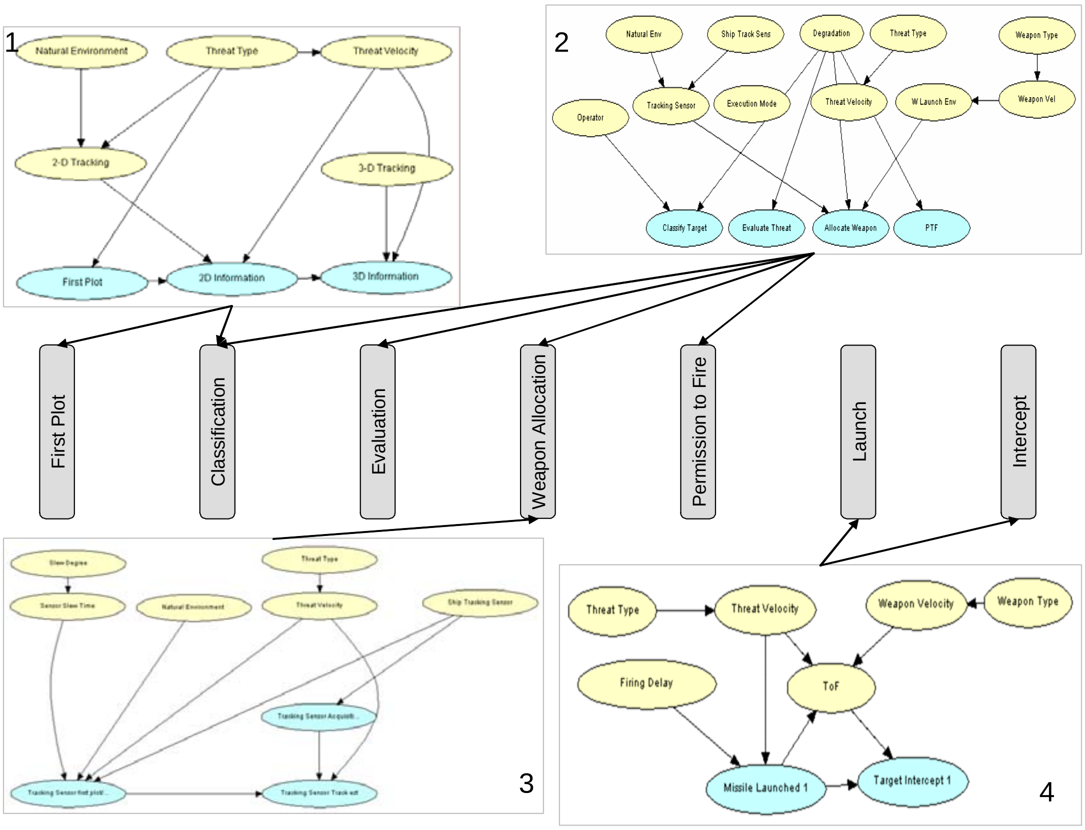

Figure 5: Full FSG System model

Figure 5 is a graphical representation of a simplified version of the full BN model describing the FSG system. The square nodes represent the timeline events and the surrounding blocks contain the networks representing models of sub-systems. The four sub-systems identified in the FSG system are 1) the Search Radar system, 2) Combat Management Suite (CMS) system, 3) the Tracking Sensor system and 4) the Missile system. The numbering corresponds with the numbering of the graphical structures in Figure 5.

3.3 Quantification of the BN model

Once the graphical structure of the model is established, the next step is to define the strength of the causal relationships. As was mentioned before, no integrated expertise on the FSG system does exist. However, mathematical and physical models on some of the sub-systems do exist. In other cases, the only form of knowledge available on sub-systems is that of expert judgment. Two approaches were followed in order to utilise the (limited) existing knowledge on the FSG system: Where models did exist, the Monte Carlo algorithm[2] was used to generate data. Figure 6 is an example of Monte Carlo simulation results that were used to populate a conditional probability[6].

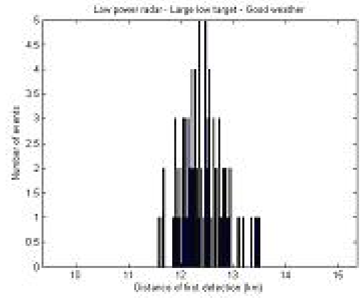

Figure 6: Histogram of data generated for a conditional probability

It must be noted that there are some difficulties when using existing models for BN quantification purposes. Firstly, the discrepancy between assumptions made on both the sub-system model and the BN model levels could be too large to accommodate. Secondly, the sub-system model output may not map directly onto the requirements of the BN and the practical implication of data requirements may not be cost effective[6].

The other quantification approach that was followed, was the elicitation of expert judgment. This was done in cases where models for sub-systems did not exist, or where it was too difficult to use sub-models because of reasons mentioned above.

Elicitation of probabilities from experts is a major challenge. It is a time consuming task and experts are often reluctant to provide numbers as they feel unable to do so with a high level of accuracy[7.]

Van der Gaag *et al.*[7] designed a method for eliciting probabilities that combines the ideas of transcribing probabilities as fragments of text and of using scale with both numerical and verbal anchors for marking assessment. We adapted their approach it in the following way: Experts were asked the following two questions:

- Given a specific configuration of scenario variables, what do you expect the average time of a timeline event to be?
- What is the uncertainty associated with the expected average time of a timeline event?

The answers to the questions are the mean and standard deviation that forms the parameters of a Gaussian distribution. To assume a Gaussian distribution could be seen as a gross assumption, but we felt that given the lack of a whole systems view and appropriate understanding of the FSG at that time, it was the best estimate at the time. As understanding on the system improves and more validated models become available, these probabilities will be updated and refined while the graphical structure of the model stays unchanged.

3.4 The Integrated Model

The graphical structure and associated conditional probability tables were integrated in a commercially available software package Hugin®[8]. Inference is the task of calculating the posterior probability distribution for a set of *query* variables, given an observed event[2]. The explicit outcomes of inference are marginal probabilities on all *query* variables in the BN. For the FSG model the query variables are the timeline events. The results are presented as normalised histograms. This provides a more complete representation of the uncertainty associated with the queries than statistical summaries[1]. The histograms were translated from time to range from ship using a constant threat velocity assumption. In terms of evaluating results, range from the ship is a more relevant parameter than time.

4. Results

The following hypothesis is analysed with the BN model as an example of a typical hypothesis posed by the user.

> *The environment degrades the performance of the FSG system in terms of success criteria to intercept the target outside the 2km zone from the ship.*

In order to test the hypothesis, the performance of the FSG model was analysed for two environmental conditions: a clear, sunny day and stormy conditions. The x-axis of each graph in Figure 7 range from 30 km (left) to 0 km (right) from the ship. The upper row histograms represent the clear, sunny day scenario and the lower row histograms represent the stormy conditions. The histograms represent the uncertainty calculated from the observed events.

The dotted line on the right hand side of the graphs represents the 2 km zone from the ship. Any histogram (or at least the highest point of the histogram) beyond this line represents events occurring inside the 2 km zone of the ship.

The 'Permission to Fire', 'Launch' and 'Intercept' events of the lower graph occurs inside the 2 km zone which indicates that severe degradation of the respective sub-system performances due to natural environment conditions compresses the engagement timeline. The compressed timeline causes the target engagement to fail eventually.

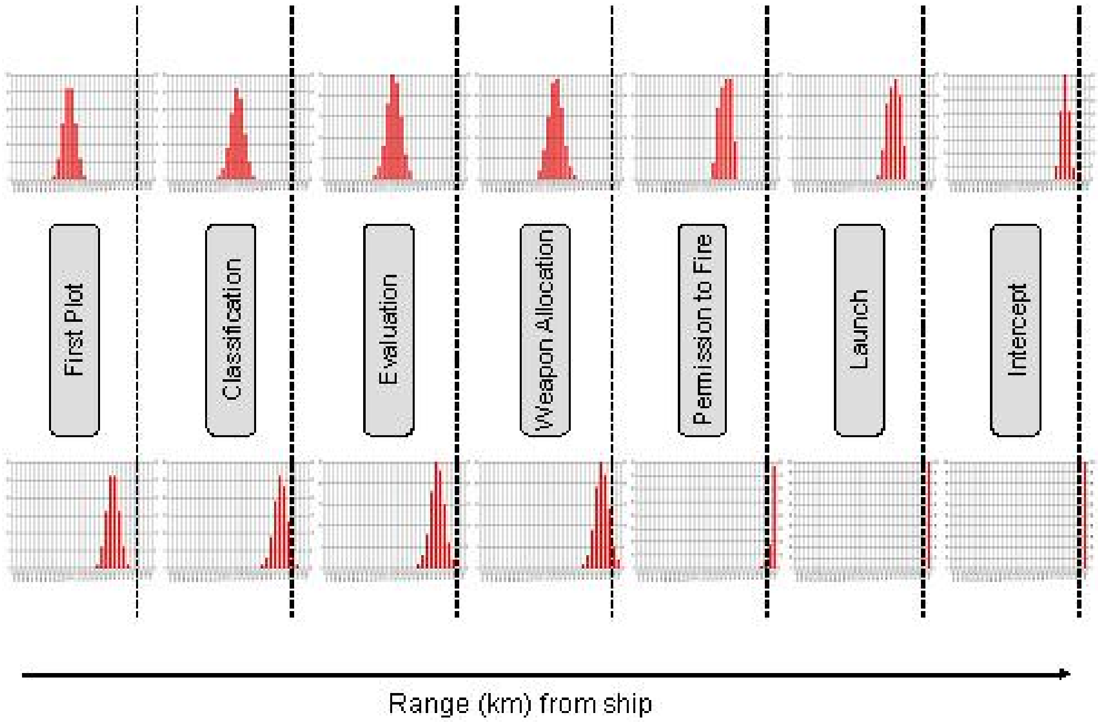

Figure 7: Results for a clear, sunny day (upper row graphs) and stormy conditions (lower row graphs)

Other analyses by the BN model indicated that very late detection of targets will definitely compress the engagement timeline, eventually becoming unacceptable. Firing policies that must be carefully developed and implemented by the user will alleviate the pressure on the engagement timeline for stressing conditions like pop-up targets.

The key issue in understanding the limitations and strong points of the system is how to define, measure and quantify *being effective*. The results summarise the effectiveness of the

FSG system. It can be used to adapt and improve processes, procedures, drills and rules of engagement to comply with the ability of the system. For example, it was shown in the results that carefully planned firing policies could alleviate pressure on the engagement timeline for stressed conditions. The effectiveness of different system configurations were compared which provides insight for trade-off decision that needs to be made.

5. Conclusions

A large percentage of the required knowledge about the weapon system is not documented but exists in the form of mental models of people with first hand experience of the weapon system. The structured modelling approach facilitates the process of turning tacit knowledge into explicit knowledge. Borsuk *et al.*[4] states that the purpose of such a modelling process is to develop a model that more realistically represents the knowledge about the system rather than the system itself.

Through active participation team members develop a shared understanding of the system. Synergy between expert groups develops during the workshops as experts start to understand the 'bigger cause-and-effect picture' of the weapon system. This improves the overall knowledge and understanding of the weapon system. The model can also be seen as a framework that serves as a focusing mechanism for research efforts on the system.

The behavioural model, as the output of the study is a useful and concise documentation of the system. It can serve as a record of why certain options were selected and others not. This facilitates explaining and selling the solution to stakeholders as well as to those that will be impacted directly. However, it is not a document, but a dynamic and interactive *what-if* tool. This makes it a much more usable discussion tool than a static document.

The instantaneous *what-if* analysis results produced by the BN model are of huge benefit to users of the model. This implies that the model can be used as a discussion tool, training tool and ultimately, a decision-support tool.

The BN modelling approach has shortcomings. Firstly, a BN is a diagonal acyclic graph[3] which implicates that arcs represent one-way causal influences between nodes. It cannot explicitly represent system feedbacks. Dynamic BNs is an option to accommodate temporal links in the model, but it need to adhere to graphical model assumptions[5] which may not be flexible enough to handle the dynamic aspects of a complex system[4].

Another shortcoming and focus of future work is the lack of understanding of aggregation of uncertainty. A BN makes two assumptions regarding uncertainty. The first assumption is implicated through the graphical structure and the second assumption is implicated through the parameters (probabilities). Proper uncertainty analysis is needed to understand the aggregation of uncertainty to the final result. Closely related to this issue is the issue of sensitivity analysis in order to identify sensitive variables to the system effectiveness. This will provide more insight and understanding in the complex interaction of the system.

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