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Test and evaluation for enhanced security: A quantitative method to incorporate expert knowledge into test planning decisions

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Abstract

Complex systems are comprised of technical, social, political and environmental factors as well as the programmatic factors of cost, schedule and risk. Testing these systems for enhanced security requires expert knowledge in many different fields. It is important to test these systems to ensure effectiveness, but testing is limited to due cost, schedule, safety, feasibility and a myriad of other reasons. Without an effective decision framework for Test and Evaluation (T&E) planning that can take into consideration technical as well as programmatic factors and leverage expert knowledge, security in complex systems may not be assessed effectively. This paper covers the identification of the current T&E planning problem and an approach to include the full variety of factors and leverage expert knowledge in T&E planning through the use of Bayesian Networks (BN).

Keywords: test and evaluation, Bayesian networks, qualification, decision aids

Introduction

T&E of enhanced security in complex systems must consider a wide variety of factors beyond basic performance, cost, schedule and risk[1]. Even if effective T&E can be identified, it may be restricted due to cost, schedule, safety, feasibility and a myriad of other reasons[2]. It is important to plan T&E early in the development of the system – at a time when experts may not be available to provide input[3]. It is also important to perform the T&E within the budget originally estimated at the beginning of the program[4]. How can expert knowledge be leveraged to support these early planning decisions? How can the plan be reassessed later in the program as new requirements develop or situations change? Can the relationship between the driving factors in the decision be understood well enough at a later date in order to modify a decision? Can the risk of such decisions be truly understood? These are all questions that have dominated the T&E field for years. This paper proposes a method to assess the full scope of driving factors, their relationships and leverage expert knowledge to provide a decision aid that supports T&E planning throughout the program development cycle.

Objective

This research examines the viability of using Bayesian Network (BN) models to support T&E planning in an environment where technical, environmental, social and political constraints are coupled with the traditional cost, risk and schedule constraints. This initial research narrows the problem to focus on one aspect of T&E – specifically vibration testing with an emphasis on six degrees of freedom (6DOF) vibration testing[4]. Technology has advanced to the state where 6DOF vibration shakers and control systems capable of high frequency tests are possible, but the problem using these systems is far more complex than traditional single degree of freedom (SDOF) tests[5]. This challenges programs as they strive to plan T&E. BN models may provide the framework to aid planning of T&E with complex constraints. This paper discusses the application of BN models to 6DOF vibration testing, but this approach and the results of this research could be applied to other T&E problems, especially in complex systems where relationships between constraints need to be understood in order to test for enhanced security.

Background

A BN model is a probabilistic graphical model that represents the factors in a decision by a probability and their relationship to the other factors. The instantiation of a particular factor will impact a related factor according to their joint probability distribution. The output of a BN model is a probability reflecting the likelihood or risk of some possibility[6]. The graphical model supports the use of this decision aid by providing a visual tool that is readily understood. The BN is represented as a directed acyclic graph[7] where each node in the graph has a probability and the nodes are connected by arrows that describe their causal relationship[8]. The arrows communicate the state of the parent node(s) and represent the operation of calculating the joint probability value of the dependent node[9]. BNs are based on the Bayesian theorem which is the inference of the posterior probability (also called belief) of a hypothesis according to some evidence[7]. Belief is expressed as a probability[10].

A simple example of a BN model is shown in Figure 1. This view of the model shows the probability distribution of each factor and the impact of their relationships while still being a graphical model. The output of the model (Losses) is a probability reflecting the risk of loss.

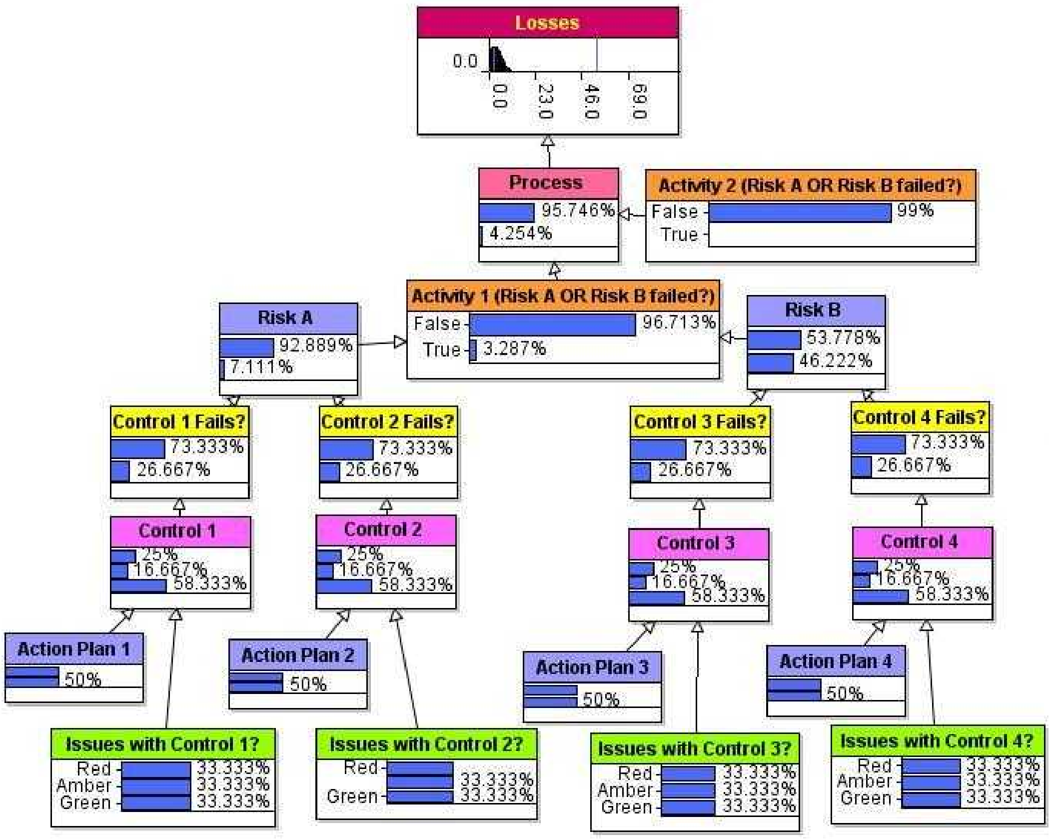

Figure 1: Simple example of a Bayesian network depicting risk control with probability distributions shown[11]

There are two basic types of probabilities that can be assigned to factors in a BN model: physical and Bayesian. Data, such as from experiments, generate physical (or frequency) probabilities. These probabilities are associated with random systems and the events tend to occur at a persistent rate or frequency in a long run of trials[12]. There is no physical probability until you perform an experiment and obtain data. In the Bayesian view, a probability is assigned to a hypothesis (as in the instance when a system has not yet been developed), whereas under the physical view, a hypothesis is typically tested without being assigned a probability[13]. Bayesian probabilities can be developed from expert judgement – a key benefit with T&E activities as there are many experts with years of experience and knowledge that can be captured and utilized.

Benefits of BN Models

There are many benefits to using BN models as they have characteristics that may enable the planning of T&E to include complex technical, social, political and environmental factors. A major advantage is that the BN models can be calibrated and validated with expert data and historical data to derive confidence in results[14]. This research resulted in 15 factors delineating the strengths of BNs valuable to addressing complex problems[4]. Eight of the strengths are shown in Table 1.

Table 1. Bayesian Network Model Strengths

Strength	Description
There are available software packages for generating BN models[8]	The software removes the calculation load and allows one focus on factors, relationships and their behavior. The ability to display the information in a format that is readily understood by engineers is a valuable communication tool. Many packages also include validation routines such as sensitivity analyses
BN models support expert evaluation whether the model is a useful approximation of reality[14]	The causal relationships make it possible for domain knowledge experts to assess the model. For instance, an expert can readily assess in improbable relationship between two factors.
BN models support explanation, exploration and prediction[15]	Explanation (bottom-up reasoning) provides a diagnostic capability. Exploration (top-down reasoning) supports understanding of the system. Prediction changes values of factors at any location and provides details of the type and amount of change[10].
BN models can be updated quickly to support adaptive decision making[7]	As programs progress and changes are made, the model can be run with the changes to assess the impact. Impact data includes what and how much.
BNs have a transparent nature – relationships between factors are made explicit[10]	Transparency facilities understanding how the model is built and eases review by domain experts who are not BN experts[15].
BNs reduce subjectiveness	Allows quantification of qualitative data from SMEs[17].
BNs have a modular structure[10]	A modular structure allows parts of the network to be readily extracted and combined with other structures. It also allows integration with different sub-models (i.e. social, economic, ecological)
BN models give a quantitative output[17]	The uncertainties are propagated through the model to the final output.

BN Models – Use of expert opinion and other subjective input

In some cases, data is rare or not available at all. How can one make decisions in the absence of data? One method is to model expert judgments. It is common throughout science, engineering and medicine for experts to make judgments on such matters so it is natural to express these directly in the BN model[18]. Many experts provide input to T&E planning for complex systems. Because the systems are so complex, there is no single expert for all aspects and a BN model provides the ability to combine inputs from all the experts.

When building BN from expert input, the probabilities will be Bayesian[16]. Bayesian probability is also called 'belief', evidential, subjectivist or personal probability. It can be assigned to any statement, not just a random process, as a way to represent its subjective likelihood or the degree to which the statement is supported by the available evidence. There are opposing schools of thought between the groups supporting the two types of probabilities. However, statisticians of the Bayesian school typically accept the physical probabilities as important but consider the calculation of Bayesian probabilities as valid and necessary[12].

Understanding the subjective expert data and how it is used in the BN model is important. Bayes' theorem provides an expression for the conditional probability of **A** given **B**, which is equal to

$$\Pr(A|B) = \Pr(B|A)\Pr(A) \,/\, \Pr(B)$$

where Pr(B|A) is the probability of B given A, Pr(A) is the probability of A and Pr(B) is the probability of B. BN models use Bayesian learning, or updating, by iterating through this equation. The initial probabilities (initial state of the model) is called the prior. The equation is calculated with some likelihood (observation or evidence) and the resulting probability is the posterior. In the next iteration of the equation, the posterior becomes the prior and so on.

$$\Pr(A|B) = (\Pr(B|A)\Pr(A) \,/\, \Pr(B)) * \Pr(A) \text{ where}$$

$$\Pr(A|B) = posterier, \Pr(B|A)\Pr(A)/\Pr(B) = likelihood, \Pr(A) = prior$$

To execute this equation, there must be some initial probability. Physical probabilities do not exist before there is data. However, Bayesian probabilities can take information from experts or other sources and a belief probability can be assigned. Through the process of updating as evidence is gained and the model updated, that initial belief probability may be confirmed or it may be changed.

This explanation deserves a final note of caution. Even though Bayesian learning can update a prior probability based on expert opinion, the desire is to ensure the expert data is as accurate as possible (thus the solicitation of an expert) [9]. The subjectiveness of the expert must be considered. Numerous factors can limit a person's judgment (regardless of their expertise) including heuristics, biases, values, attitudes and motivations. There are techniques for eliciting expert judgment to minimize the subjectiveness[10,17]. In addition, expert input can be combined with data. One theory is the best approach is to use expert input for the initial estimate of probabilities (prior probabilities), which are then updated with observed data. This combined approach is recommended as purely data driven BN models tend to be too complex and lose accuracy[19].

BN model application philosophy

How would a BN Model be used in planning T&E activities? The application of the BN model to aid in T&E planning comes into play after the model has been validated. The validation of the model provides information about the limitations of the model. These limitations should be taken into consideration when using the model.

At the beginning of the program information about the proposed program will be gathered and the BN Model exercised. The steps below outline how the model might be used.

1. Gather information and set assumptions: For all the factors in the model, gather the information known about the program. Note that there may not be information about every factor. In those cases, there are three options: a) make assumptions and document so the model can be revisited should the assumption prove wrong b) let the model choose the default value for that factor – document this as an assumption as well. This too should be revisited should the value prove to be something different. Or c) Intentionally exercise different options of the factor in the trial scenarios performed by the model for planning. Based on the desired outcome, be sure to communicate back to the program what the required state of the factor should be. Also document this as an assumption so it can be tracked.
2. Create scenarios: With the gathered data, assumptions, and list of factors desired to be examined, open the model and create multiple scenarios. For each scenario, document the value of each factor (most BN model software will let this information be saved as an instance of the model).

- *Default scenario*: Create a default scenario where all factors are left at the default with the exception of the factors for which information was obtained.
- *Default/assumption scenario*: Create a scenario similar to the default scenario with the addition of the assumptions
- *Trial scenarios*: Create scenarios as needed similar to the default/assumption scenario except adding different values for the factors desired to be examined. The values for each factor can be entered via a table – for all scenarios at once. Most BN model software allows this method of entry for ease and timeliness. Some allow values to be uploaded via various file formats such as .csv.

3. <u>Run model</u>: Run each scenario through the model. For each result that appears promising (for instance, a resulting probability of 75 percent or greater), run a sensitivity analysis on the factors to determine the key contributors. If no results are satisfactory, run a sensitivity analysis on the default and the default/assumption scenarios to determine key factors.
4. <u>Analyze results</u>: Examine the key factors. If the results are acceptable and the key factor values seem reasonable and logical, the process is complete and you have the qualification prediction. If the results are not desirable and/or the factor values are such that they can be changed or do not seem reasonable, assess which factors should change
5. <u>What-if scenarios</u>: Add additional scenarios to the model to include the proposed factors changes based on the sensitivity analysis. Run the model with the new scenarios. Analyze the results. Repeat as necessary.
6. <u>Make recommendations</u>: Based on the results from the model, make the proposed recommendation. The recommendation will be T&E option 'X' with a certain probability range (the range ensures the uncertainty is included). Included with the recommendation is the information on assumptions for various factors as well as the key drivers. Note that it is possible to have an output from the model that the T&E activity is not recommended – along with the resulting low probabilities for all test options and an explanation of the key factors driving that assessment.
7. <u>Document results</u>: Save an instance of the model with all trials. This could be useful later in the program if the decision needs to be revisited. Document the recommendation with

the probabilities, key factors and assumptions. Store all in a location where it can be retrieved.

Table 2. BN models: Overview of function in practice

Step	Activity	Notes
Build the model	Use the body of existing T&E data, expert information and new research to identify factors, relationships and probabilities related to the security system	The existing body of T&E data is large and is important to build a good model
Validate the model	Use historical data, peer review and new test data to validate the model	Initial validation is needed before using the model, but it should continue to be validated as it is updated throughout its life.
Use the model	Gather information about the proposed program – relative to the factors in the model	Information is not required for every factor – available information is used and the model calculates probabilities for all other factors based on the historical/ expert data used to build/validate the model
	Run a simulation to determine predicted T&E approach and probabilities	Create one or more scenarios as needed.
	Review the results – of the proposed approach as well as calculated results for factors that were not pre-defined in this simulation	The end result of the probability for a T&E plan may be acceptable but one factor may have a result that gives it a value unlikely for this particular program (i.e. one knows the political approval will not be granted). The T&E plan has a final answer but it is the combination of the factors that make it powerful (and possibly incorrect if ignored).
	If the probability output for the T&E plan is acceptable and the probabilities for the non-defined factors seem reasonable, document this as the plan	Capture the probabilities and the states of factors – identify program risks around factors as needed to ensure areas with larger uncertainty are tracked

Step	Activity	Notes
	If probability output is not acceptable (too risky), perform sensitivity analyses to determine key drivers. Can any of these be addressed as part of the T&E plan? If so, re-run simulation with changes. Continue process until the probability of the T&E plan is acceptable	Document the requirements for factors that are changed with the revised simulation. They will become part of the qualification plan.
Continue to update the model	Keep the model and plan current. As the program progresses, ensure the factors used in the model have not changed. If they do, reassess the model and make changes to the plan as needed.	Even if a factor does not change, but instead becomes more uncertain (say a new program risk is opened on a factor), the model can be reevaluated with the updated probability for that factor to assess any potential impacts

The BN model prediction: To use or not to use?

The output of the BN model is a prediction (of the best T&E method, for instance) along with the key factors driving that prediction. The output is not the decision; it is information to make a decision. The argument for BN models is the increased fidelity of information to aid in decisions[20]. Table 3 below shows the information provided from the BN model. Information is provided to accept the prediction, to know how to change the prediction if desired and to know when to reevaluate the decision.

Table 3. Decision aids resulting from BN model

BN model output	Decision aid
Qualification option prediction	Best qualification option based on a probability
Uncertainty of all the factors relevant to the decision	The probability is provided in a range so the impact of the uncertainty can be understood (i.e. 56% ± 4%)
Key drivers behind the prediction	Factors that may be considered for change if the prediction is undesirable or if the percentage is not as high as desired. This gives the decision maker the power to know *how* to change the decision if the recommendation is not desired for some reason.
Documentation of the assumptions that went into the decision	This gives the decision maker the power to accept the assumptions and ensure the factors meet the assumptions

	or the ability to know when the decision may need to be reevaluated (because an assumption proved not to be true)

Conclusion

BN models have unique strengths that facilitate the use of expert knowledge and the assessment of the driving factors in the full decision space in a quantitative manner. These strengths provide an opportunity to plan T&E activities for complex systems such as enhanced security systems. Current research focuses the application of a BN model on 6DOF vibration testing for qualification. A later expansion of this research could be to extend the methodology to other T&E disciplines and ultimately to the entire T&E planning effort.

About the authors

Davinia Rizzo is a principal systems engineer at Sandia National Laboratories. She has been a systems engineer for the last 20+ years working primarily in the defense industry for companies such as Lockheed Martin, Bell Helicopter, and Raytheon. Davinia holds a BS in mathematics, MBA in engineering management and a MS in systems engineering. She is currently pursuing her Ph.D. in systems engineering at Stevens Institute of Technology. Her research topic is a predictive analysis framework for six degrees of freedom vibration qualification.

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