Use of Bayesian Networks for Qualification Planning: Early Results of Factor Analysis

Davinia B. Rizzo\textsuperscript{a*}, Mark R. Blackburn\textsuperscript{b}

\textsuperscript{a}Sandia National Laboratories, P.O. Box 5800 M/S 0472, Albuquerque 87123, USA
\textsuperscript{b}Stevens Institute of Technology, 1 Castle Point on Hudson, Hoboken, 07030, USA

Abstract

This paper discusses the factor analysis that provides the basis for development and use of Bayesian Network (BN) models to support qualification planning in order to predict the suitability of Six Degrees of Freedom (6DOF) vibration testing for qualification. Qualification includes environmental testing such as temperature, vibration and shock to support a stochastic argument about the suitability of a design. Qualification is becoming more complex because it involves significant human expert judgment and relies on new technologies that have often never been fully utilized to support design assessment. Technology has advanced to the state where 6DOF vibration tests are possible, but these tests are far more complex than traditional single degree of freedom tests. This challenges systems engineers as they strive to plan qualification in an environment where technical and environmental constraints are coupled with the traditional costs, risk and schedule constraints. BN models may provide a framework to aid Systems Engineers in planning qualification efforts with complex constraints. Previous work identified a method for building a BN model for the predictive framework. This paper discusses validation efforts of models derived from the factor analysis and summarizes some recommendations on the factor analyses from industry subject matter experts.

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* Corresponding author. Tel.: +1-505-844-2339; fax: +1-505-212-0381.
E-mail address: dbrizzo@sandia.gov
1. Introduction

This paper discusses the early results of the factor analysis generated when developing a Bayesian Network (BN) model to aid qualification planning. Qualification is defined in the Systems Engineering Book of Knowledge as “evidence that the design will survive in its intended environment with margin. The process includes testing and analyzing hardware and software configuration items to prove that the design will survive the anticipated accumulation of acceptance test environments, plus its expected handling, storage, and operational environments plus a specified qualification margin. Qualification testing usually includes temperature, vibration, shock, humidity, software stress testing, and other selected environments”\(^1\).

Developing a qualification plan is a complex Systems Engineering problem. The traditional programmatic factors of cost, schedule and risk are combined with an increasing array of technical factors to create a multi-dimensional problem space. The problem space has become so complex it cannot be easily visualized and suggests the need for an improved decision framework.

While cost, schedule, and risk are factors affecting qualification planning, the technical factors can be the key driver. To date, research in systems engineering qualification planning focused on addressing the cost, schedule, risk and quality aspects of the problem\(^2\). This research proposes to add technical factors to the decision space. This research focuses on a subset of qualification requirements in order to be manageable, though the proposed concept could be expanded to all aspects of qualification. For the initial stages of research, the problem is narrowed to a subset of qualification planning: vibration – with an emphasis on including multi-axis or six degrees of freedom (6DOF) vibration testing in the traditional single degree of freedom (SDOF) solution space. The method for the research involves utilizing a BN model to develop the framework that takes advantage of the decades of knowledge of vibration tests as well as the causal technical factors in the current problem space. The remainder of this paper discusses the process and the factors selected for the BN model.

2. Background

2.1. Need for a Qualification Decision Aid

Today program plans are developed in the initial stages of the program lifecycle and require systems engineers and program managers to commit to estimates for the remaining stages of the program. These commitments are formulated early in the program bid process based on decisions made before the full technical staff is available. The plans are further adjusted as estimates are scrubbed for cost reductions through accepting a reasonable amount of risk. Cost, schedule, risk and technical factor trade-offs are a necessity\(^3\). The resulting problem is that it is difficult to plan qualification. The risk of making a poor decision may not be realized until the end of a program when the qualification evidence is not sufficient to support the requirements. At this point, returning to re-test, re-analyze and/or re-design is exponentially more expensive\(^4\). Rework at a late stage in the program often exceeds 20 percent of the initial development cost\(^5\).

The qualification planning problem is difficult to address without a useful decision aid to consider the multi-faceted problem space or a method to update the qualification plan as issues arise. Plans are bad, started too late or too constrained to adjust during the course of the program.

There is a gap in the literature for qualification planning that incorporates technical factors along with cost, risk, schedule and quality. In the literature, qualification-planning (or verification and validation) research has resulted in various decision models or frameworks that do not consider technical factors\(^2\). A predictive framework and method for making qualification decisions, based on quantitative and qualitative data for technical factors, is needed to address this problem.

2.2. Vibration Qualification Problem Space

Vibration tests are common activities in many qualification plans. The tests have become increasingly complex with advances in technology affecting the test article, sensors, vibration machines and their controllers\(^6\). Advances in vibration machines and controllers have led to simulations of the environment (tests) in multiple degrees of freedom.
simultaneously. There is no longer a generic prescription for vibration qualification because of the widely available technology. It has been shown that 6DOF tests identify unique failure modes and expose the test article to greater fatigue damage resulting in a more comprehensive qualification test, yet require much more information to develop test specifications. Furthermore, careful planning of the tests is required as the selection and definition of the test control strategy can affect the results. This implies the need for well-informed decisions when planning vibration qualification tests.

Based on the literature review, there is clearly great value in effectively assessing and predicting a successful qualification test. This research will focus on vibration qualification tests – including 6DOF tests that have the capability to identify unique failure modes but are very difficult to define and execute properly. A successful vibration qualification test is predicted by numerous technical factors, both quantitative and qualitative. Quantitative vibration factors may include test frequency, test article configuration/material, test control scheme, shaker configuration, test fixture, test article modes, operational environmental data available, test specification, test article response data, test failure data, funding, project cost and schedule data. Qualitative factors may comprise subjective subject matter expert (SME) opinion concerning test effectiveness, limitations, and advantages. A principal challenge of this proposed research is identifying the 6DOF factors that influence a successful qualification test and how they are causally related. The ancillary challenge is the determination of how these factors can be used to better predict 6DOF qualification tests. The development of a predictive analysis framework based on the results of the two challenges is the most important facet of this research. This paper discusses the results of the research addressing the first challenge.

2.3. BN Models as a Tool to Address Vibration Qualification Planning

In this research, careful examination of the need for a qualification planning decision aid characterized the problem space and the types of information to be considered. The qualification planning problem is one where there are a large number of factors with some sort of relationship between them that must be understood to make good decisions. BNs capture and work with that type of information. A BN is a directed acyclic graph - a graphical model that encodes the joint probability distribution (either physical or Bayesian) for a large set of factors. Each factor is entered as a node. Each node contains the possible states of the factor and their discrete probability values. The nodes are connected by arrows that describe the causal or correlative relationship between the nodes. The arrows convey the state of the parent node(s) and denote the operation of calculating the joint probability value of the dependent node. The direction of the arrow depicts the direction of the causal relationship. 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. Belief is expressed as a probability.

BN models provide a method to address the complexity of qualification planning – particularly for determination of the suitability of 6DOF vibration testing for qualification. The graphical model structure allows different types of factors and knowledge from various sources to be integrated within a single framework. BNs also promote independent assessment of each factor as well as the relationship between the factors making it possible to compute the predictive distribution on the outcomes of possible actions. The BN structure is ideal for combining prior knowledge, which often comes in causal form, and observed data. BNs can be used, even in the case of missing data, to learn the causal relationships and gain an understanding of the various problem domains and to predict future events.

In BNs, expert or Subject Matter Expert (SME) domain knowledge can be coded as prior distributions where prior means that the probability distributions are defined before and independently of processing any possible sample data. This allows for combining SME knowledge with statistical data in a very practical way. BNs are an excellent tool for capturing and explicitly communicating uncertainty. The models can identify not only the relationships between factors, but the strength of those relationships. BNs allow reasoning with uncertain states, with limited information, and under changing conditions. The models are graphical and easy to understand – aiding in communication. Ultimately, BN models are an effective tool to capture and reason about vibration qualification planning data to inform decisions.
3. Factor Analysis

3.1. Building a BN Model

Developing a BN model involves understanding the problem space, identifying factors and relationships and then quantifying the factors. The structure of the BN model includes the structure of the model, the discretization of the factors, and parameterization. Discretization is converting continuous data into discrete data. This allows the data to be used as a probability. If done improperly, discretization can destroy useful information. Care should be taken to ensure the resulting discrete states are a valid interpretation of the state space of the factor. Parameterization is the conversion of expert solicited data to discrete values.

In general, good practice should be followed in developing the model. This involves clearly defining the model purpose and assumptions underlying the model. Data as well as information elicited from experts should be used to develop the BN model. For the model structure (the number of nodes (factors) and arrows), care should be taken so that the model is neither too simple nor too complex as it explains the system. All factors must affect (or be affected by) the final output and be either manageable, predictable or observable. Factors whose impact is insignificant should be excluded. If necessary, split the model into modular subnetworks. Transparent reporting of the whole modelling process, including its design, factors, implementation and evaluation should be planned into the process.

This paper covers the initial development phase of the model structure: the identification of the factors and relationships. This paper also covers early validation of the structure. At this point discretization and parameterization for the factors are not assigned. The product of this stage that can be reviewed is a graphical diagram of the factors and their relationships.

Early validation of the model structure at this stage is important to prevent model inconsistencies, inaccuracies and subjectiveness. Specifically, if the factors and their relationships in the model are incorrect, then the results will be incorrect. Additionally, the structure should be carefully designed to maximize transparency and ensure the design is easy to follow. Too many factors reduce the accuracy of the model. Finally, careful design of the methods to gather information from SMEs should be considered. There are techniques for eliciting expert judgment to minimize subjectiveness.

3.2. Identification and Selection of Factors

The identification of factors was based on the following criteria:

- Previously identified as driving factors in literature (cost, schedule, risk, etc.) OR a technical factor
- Reflective of current technology but adaptable
- Affect or are affected by the output (causal – not symptomatic)
- Unbiased

The process for identifying the factors based on the above criteria was an iterative process that included literature searches, review of historical test data/reports, SME interviews and screening experiments. Figure 1 shows one of the test configurations from the screening tests. Factors were first identified from literature and historical test data and assessed based on the criteria. Initial relationships were defined from available data and an initial BN graphical model created to aid SME review. SME interviews provided feedback on the factor selection and relationships. Finally a 2K fractional factorial Design of Experiments (DoE) screening test was also performed to reinforce factor selection.

The factors selected are shown in Table 1. The factors are grouped into three main categories relating to the success (risk of rework/retest) of the qualification activity. The factor categories are: 1) capability to perform the test, 2) the ability to obtain meaningful qualification data from the test, and 3) the ability to meet programmatic constraints impacting the test activity.
3.3. Relationships between Factors

A relationship between factors is defined as a change in one factor causing a change in another factor relative to the risk of a successful 6DOF test. While some relationships can be gleaned from screening experiments and historical data, the significance of the relationships is not always apparent in the data. Initially all possible relationships were defined, but not all are meaningful. This indicated the need to understand the strength of the relationship. Assessment of relationship strength requires SME input. Not all SMEs are well versed with evaluating

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**Table 1. 6DOF Vibration Qualification Factors.**

<table>
<thead>
<tr>
<th>Category</th>
<th>Factor</th>
<th>Characteristic</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capability to Perform Test</td>
<td>Ability to Measure Response</td>
<td>Manageable, or Predictable</td>
<td>2,26,9,8</td>
</tr>
<tr>
<td></td>
<td>Environment/CONOPs</td>
<td>Observable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Cross Spectral Density Terms</td>
<td>Manageable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Destructive VS Non-Destructive</td>
<td>Manageable</td>
<td>2,34,32,33,35</td>
</tr>
<tr>
<td></td>
<td>Size, Weight</td>
<td>Observable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Test Item Variability</td>
<td>Predictable</td>
<td>2,28,24</td>
</tr>
<tr>
<td></td>
<td>Hazards</td>
<td>Observable or Manageable</td>
<td>2,9,35</td>
</tr>
<tr>
<td></td>
<td>Resonant Mode</td>
<td>Observable</td>
<td>2,26,28,29,30</td>
</tr>
<tr>
<td></td>
<td>Boundary Conditions</td>
<td>Manageable or Observable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Difficulty to Control (shaker control)</td>
<td>Predictable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td>Ability to Provide Valuable Data From Test</td>
<td>Difficulty of setup</td>
<td>Predictable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Margin Testing Required</td>
<td>Manageable</td>
<td>2,35</td>
</tr>
<tr>
<td></td>
<td>Test Item Materials/Construction</td>
<td>Observable</td>
<td>9,6,8,7,27,28,29,30,31,40,24</td>
</tr>
<tr>
<td></td>
<td>Test Item Failure Mechanism</td>
<td>Predictable</td>
<td>5,24,35</td>
</tr>
<tr>
<td></td>
<td>Test Item Linearity</td>
<td>Observable or Predictable</td>
<td>2,8,24</td>
</tr>
<tr>
<td></td>
<td>Test Data requires Special Analysis</td>
<td>Predictable</td>
<td>2,9,8,24</td>
</tr>
<tr>
<td>Ability to Meet Program Management Constraints</td>
<td>Cost</td>
<td>Predictable</td>
<td>6,36,37,38,39,40</td>
</tr>
<tr>
<td></td>
<td>Schedule</td>
<td>Predictable</td>
<td>2,3,4,5,32,41,37,38,40,34,35</td>
</tr>
<tr>
<td></td>
<td>Access to 6DOF shaker</td>
<td>Observable</td>
<td>2,26</td>
</tr>
</tbody>
</table>
the BN graphical model or creating influence diagrams. It is important to gather input from the SMEs – specifically the right type of information, gathered in a consistent manner with unbiased results.

The goals of the process to gather relationship information for the BN model structure are:
- Unbiased assessment of relationships
- Strength of relationships
- Indication of unidirectional and bidirectional relationships
- Enough information to make the determination if the relationship is a driver and needs to be included in the model

As mentioned in the previous section, the initial relationships were identified from historical test data and literature. As the factors were refined, an unbiased method to gain input and concurrence from SMEs was needed. Interactions with SMEs were planned in advance. Questions/guidance for input from SMEs were identified and based on general guidance for question wording for surveys. The method to glean relationship data from the SMEs, or to define the initial structure of the model nodes, was based on structural knowledge assessment. Structural knowledge assessment is used to represent the structural properties of domain-specific knowledge. The structural knowledge assessment for this research utilizes the Pathfinder algorithm, which derives a network from proximities for pairs of factors. Proximities can be obtained from similarities, correlations, distances, conditional probabilities or other measure of relationship.

The tool used to implement the structural knowledge assessment was the Intelink JPathfinder Graphical User Interface. This java-based program allows the researcher to input the factors and each SME to perform pairwise comparisons of each factor to the other and save the results in a unique file. The SMEs evaluated two factors at a time, rating on a scale of 1-10 whether the factors impacted each other. The scale ranged from 1 (no impact) to 10 (very strong impact). For instance, if the Environment/CONOPS factor was a very rough environment which would require a large amount of displacement on a shaker, it could have a very strong relationship with the Shaker Control factor. Whereas the Test Data requires Special Analysis factor has no impact on the Shaker Control factor. The process was repeated for every combination of factors. The entries from the SMEs were saved in a unique file for each SME. The JPathfinder tool imports all SME files and performs an analysis of the inputs to generate a network structure of the factors showing relationships. Correlation data is shown to indicate the degree of agreement among the input from the various SMEs. Figure 2 shows the output of the JPathfinder tool with the input from the SMEs.

![Fig. 2. Structural network of vibration qualification factors](image-url)
The output from the JPathfinder tool reflects the relationships graphically. A table also provides the strength and correlation of the relationships. The resulting network is not final - further refinement of the model is needed based on the information. Relationships that are weak or have poor correlation should be reviewed for exclusion from the model. The accuracy of the model can be reduced by including unnecessary relationships. The strength of the relationships is examined. The data is put into Excel to allow graphical comparison of the strength of the relationships for various factor. The comparison is shown for all factor relationship groupings to identify the key factors driving 6DOF vibration qualification decisions as shown in Figure 3. These relationships were compared to historical test data for a quick validation. The decisions to remove relationships or factors from the BN model structure is based on engineering judgement when reviewing the Pathfinder and historical data. Assumptions were documented as the model structure was defined. At this point the BN model structure is generated in the BN tool and a graphic generated for validation efforts.

The SME input to the factor selection and relationship definition is a source of uncertainty. However, in this case the data (a pre-defined set of factors/relationships) is not available. How can one make decisions in the absence of data? One method is to model expert/SME 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. The advantage is that a BN model can be developed with the SME data and tests/analyses used to validate the model. During the validation efforts described in Section 4, analyses will be performed to reduce uncertainties due to SME input.

3.4. Validation of Factor Selection

The output of this phase of the research is a graphical diagram from the BN model as shown in Figure 4. Note that the factors are shown in green. The output node is shown in red. The blue and tan nodes group common factors and serve to simplify the model graphically. These groupings are also shown in Figure 3 as they reflect groups of factors that can impact each other. The validation activity for this phase is to obtain feedback from experts. The diagram is readily understood by most and errors such as incorrect relationships or missing factors can be identified. This peer review is called face validity. A bias can be introduced if the same experts provide the data to develop the model and perform this validation step. While it is appropriate to have the experts review the graphical model, it is best to have some experts not involved with developing the model review it as well. Before moving to the next phase, the corrections identified by the experts are incorporated.

In this research, SMEs from the industry 6DOF working group at the ESTECH 2016 conference were engaged to provide validation input. These were different SMEs than provided input to the model structure development. In order to evaluate the model structure, the SMEs were asked two questions:
1) Face validity evaluation - Does the model structure contain all and only the factors and relationships relative to the model output?

2) Convergent validity evaluation – does the number of factors and arrows (relationships) and structure of the model look similar to the structure in other Systems Engineering BN decision models?

The majority of the discussion from the SMEs focused on the factors and their definitions. No new relationships were identified but clarification to the definitions of several factors were discussed to aid in later quantification efforts. All SMEs agreed there is no similarity to other Systems Engineering BN models as they do not contain technical factors. However, as far as size of BN models for decision aids in general, the number of factors are reasonable (not too many). A few SMEs expressed concern there were too many factors for the model to ultimately be validated and useful.

4. Future Work

The next step in the BN model development is quantification of the factors. This includes the discretization and parameterization of each factor. For many of these factors, the available data for the quantification is sparse so the selection of the method to identify the values is important. Once quantification is complete, multiple validation efforts will be performed to verify the input. Efforts include a factor analysis to identify sensitivities, logic errors, comparison to historical test data to verify probability distribution and SME assessment. This helps to reduce uncertainties due to SME input. Once validation efforts are complete, a case study will be performed to demonstrate performance of the model – both in ease of use, applicability of output and accuracy of output.

5. Conclusions

Qualification includes environmental testing such as temperature, vibration, and shock to support a stochastic argument about the suitability of a design. Systems are becoming more complex and, as test technologies are expanded, the options and complexity for qualification tests have increased. Without an effective decision framework for qualification planning that can take into consideration technical as well as programmatic factors, some new technologies in qualification testing are not being fully utilized. This challenges systems engineers as they
strive to plan qualification in an environment where technical, environmental, and political constraints are coupled with the traditional cost, risk and schedule constraints.

BN models have characteristics that may enable the expansion of qualification planning to include complex technical factors in order to plan qualification efforts in an environment with complex constraints. The research described in this paper shows the process to identify factors and relationships for a BN model to aid in qualification planning. Key observations include the need for unbiased input from SMEs even though BNs are designed to rely largely on SMEs. Also, assumptions must still be made in the process as there are too many relationships to address all in the model. Instead, key drivers need to be identified. Finally, future work involving the quantification of the factors may prove to be the most difficult portion of the research. This research hopes to demonstrate the use of BN models to aid in vibration qualification decisions. A later expansion of this research could be to extend the methodology to other qualification disciplines and ultimately to the entire qualification planning effort.

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1 Certain commercial software products are identified in this paper. These products were used only for demonstration purposes. This use does not imply approval or endorsement by Sandia National Laboratory or Stevens Institute of Technology, nor does it imply these products are necessarily the best available for the purpose. Other product names, company names, or names of platforms referenced herein may be trademarks or registered trademarks of their respective companies, and they are used for identification purposes only.