A Predictive Analysis Framework for Six Degrees of Freedom Vibration Qualification

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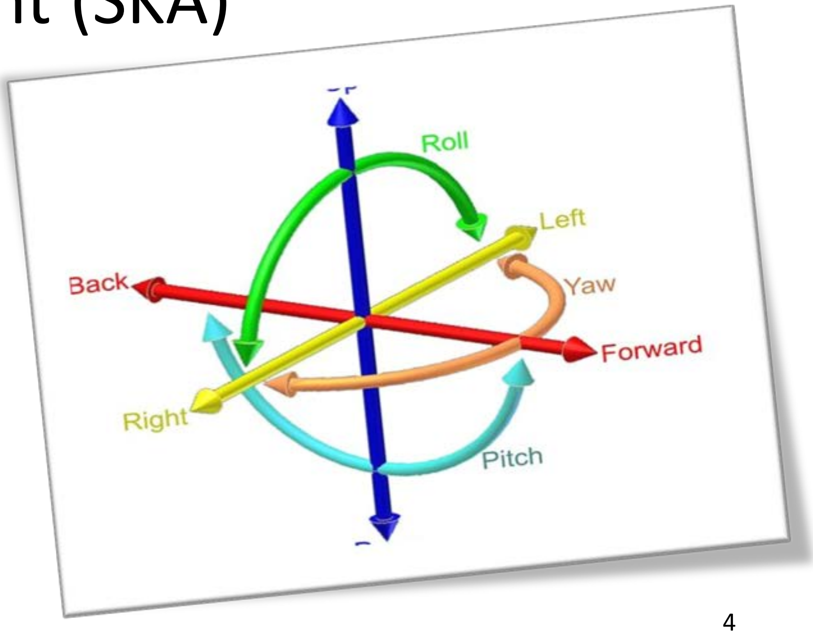
Outline

- Definitions
- Problem Statement
- Results
  - Building the BN Model
  - Validation
- Conclusion/Recommendations

Definitions

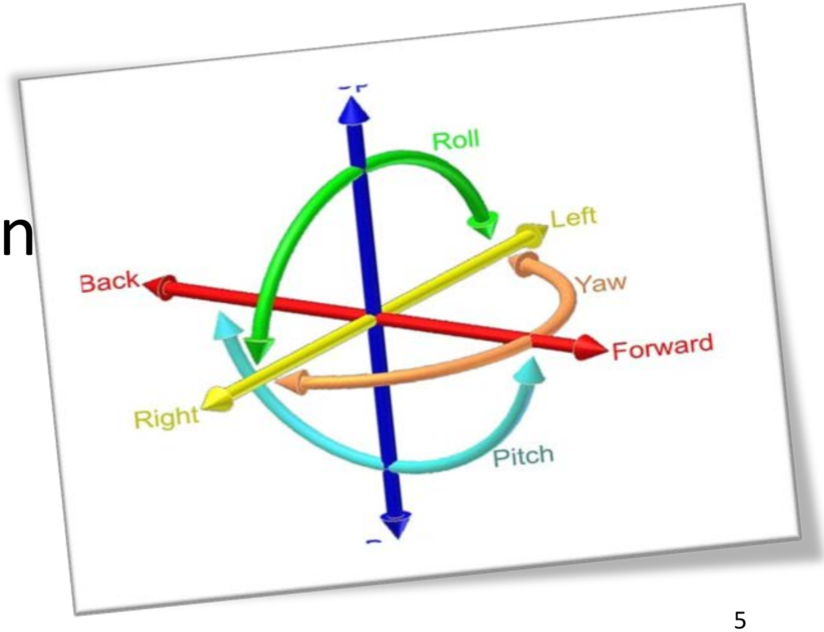
Definitions

- Qualification
- Six Degrees of Freedom (6DOF)/ Single Degree of Freedom
- Bayesian Network Model
- Structural Knowledge Assessment (SKA)



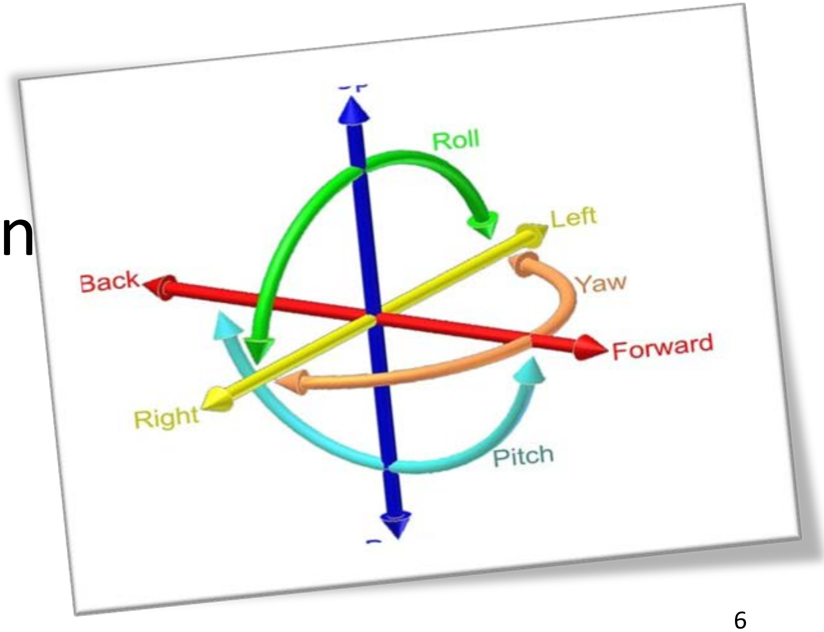
Definitions

- Qualification
  - Functionality over environments with margin
  - Qualification planned early in the program and executed at the end
    - Significant driver of cost and schedule
- Six Degrees of Freedom (6DOF)/ Single Degree of Freedom
- Bayesian Network Model
- Structural Knowledge Assessmen



Definitions

- Qualification
- Six Degrees of Freedom (6DOF)/ Single Degree of Freedom (SDOF)
  - — Vibration testing on shakers
  - — 6DOF has benefits over SDOF but is very complex
    - o Not always possible
- Bayesian Network Model
- Structural Knowledge Assessmen



Definitions

- Qualification
- Six Degrees of Freedom (6DOF)/ Single Degree of Freedom
- Bayesian Network Model (BN Model)
  - Acyclical directed graph
  - Built on Bayes theorem
  - Excellent for reasoning when empirical data not available
- Structural Knowledge Assessment (SKA)

Definitions

- Qualification
- Six Degrees of Freedom (6DOF)/ Single Degree of Freedom
- Bayesian Network Model
- Structural Knowledge Assessment (SKA)
  - Tool used in education, medical and cognitive sciences
  - Human knowledge is structural (facts and relationships)
  - Captures the structure of knowledge
    - Typically used for comparison to measure learning

Problem Statement

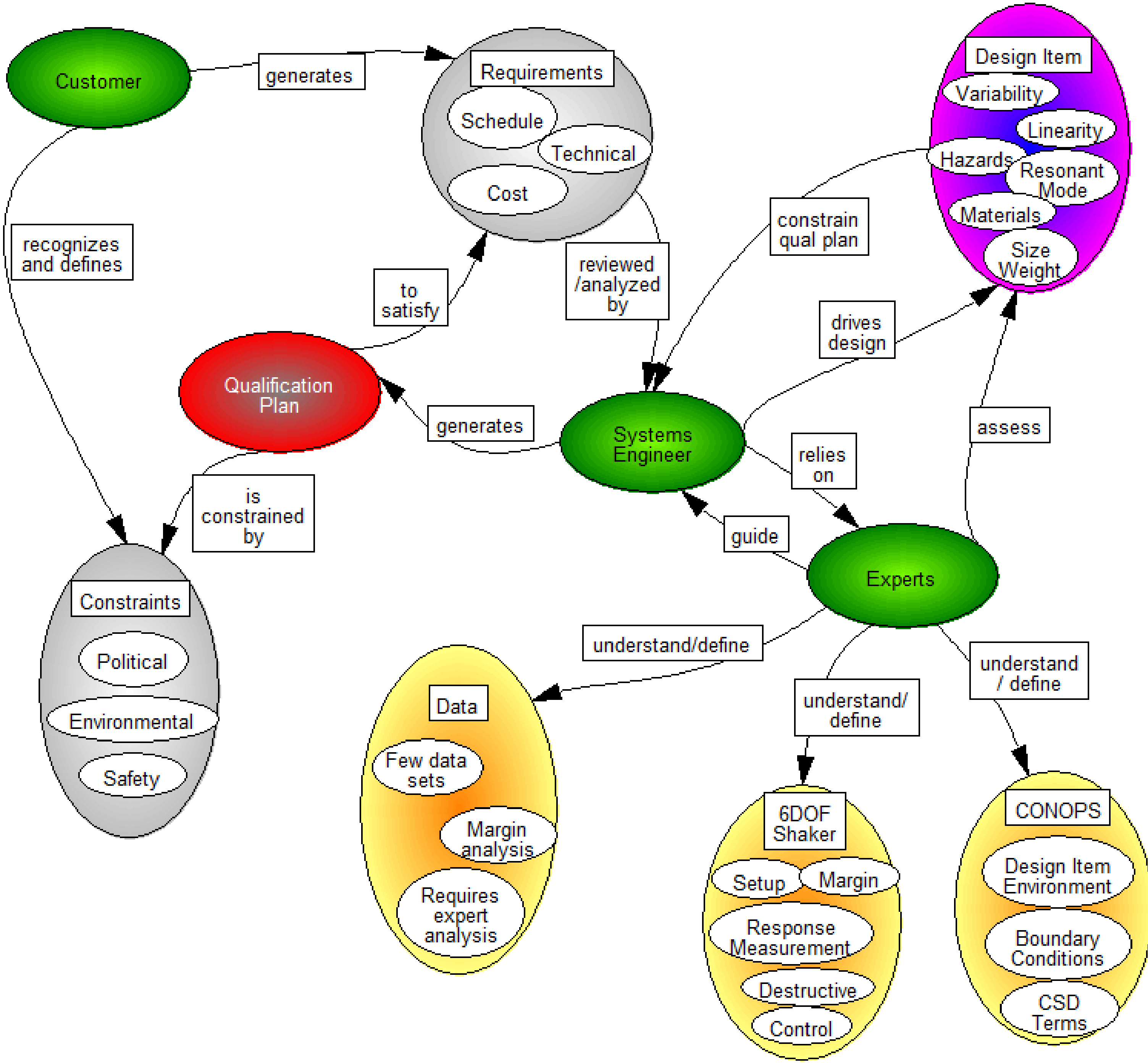
Problem Statement

Imagine:

- You: Systems Engineer
- Customer defined requirements
- Real world constraints
- Solve a technically complex problem
  - You aren't an expert in the particular field
- You rely on experts
  - What if experts aren't available?
  - What if data isn't available?

Not hard to imagine!

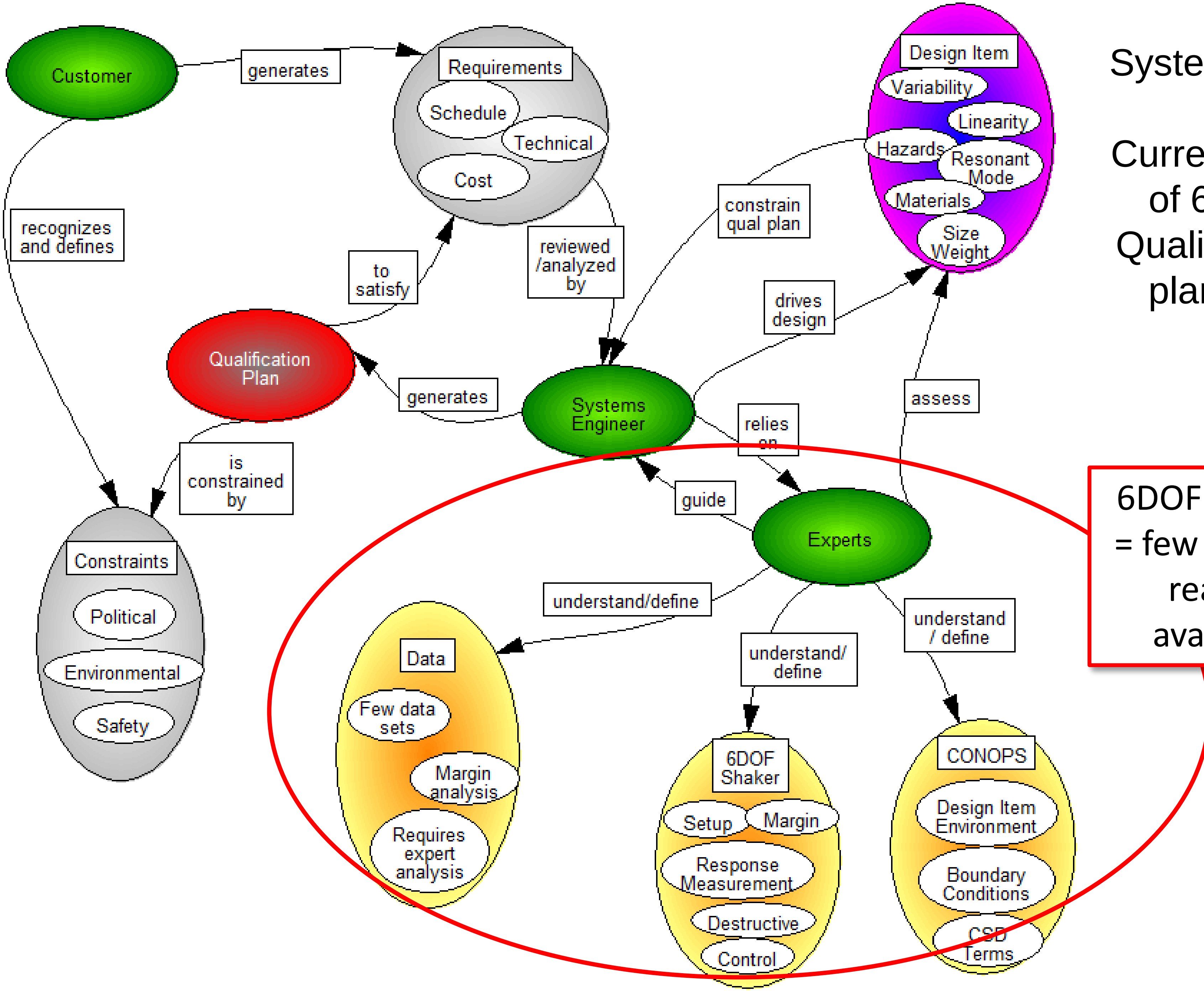
Systemigram – Current state of 6DOF Qualification planning



6DOF vibration - many benefits but very complex

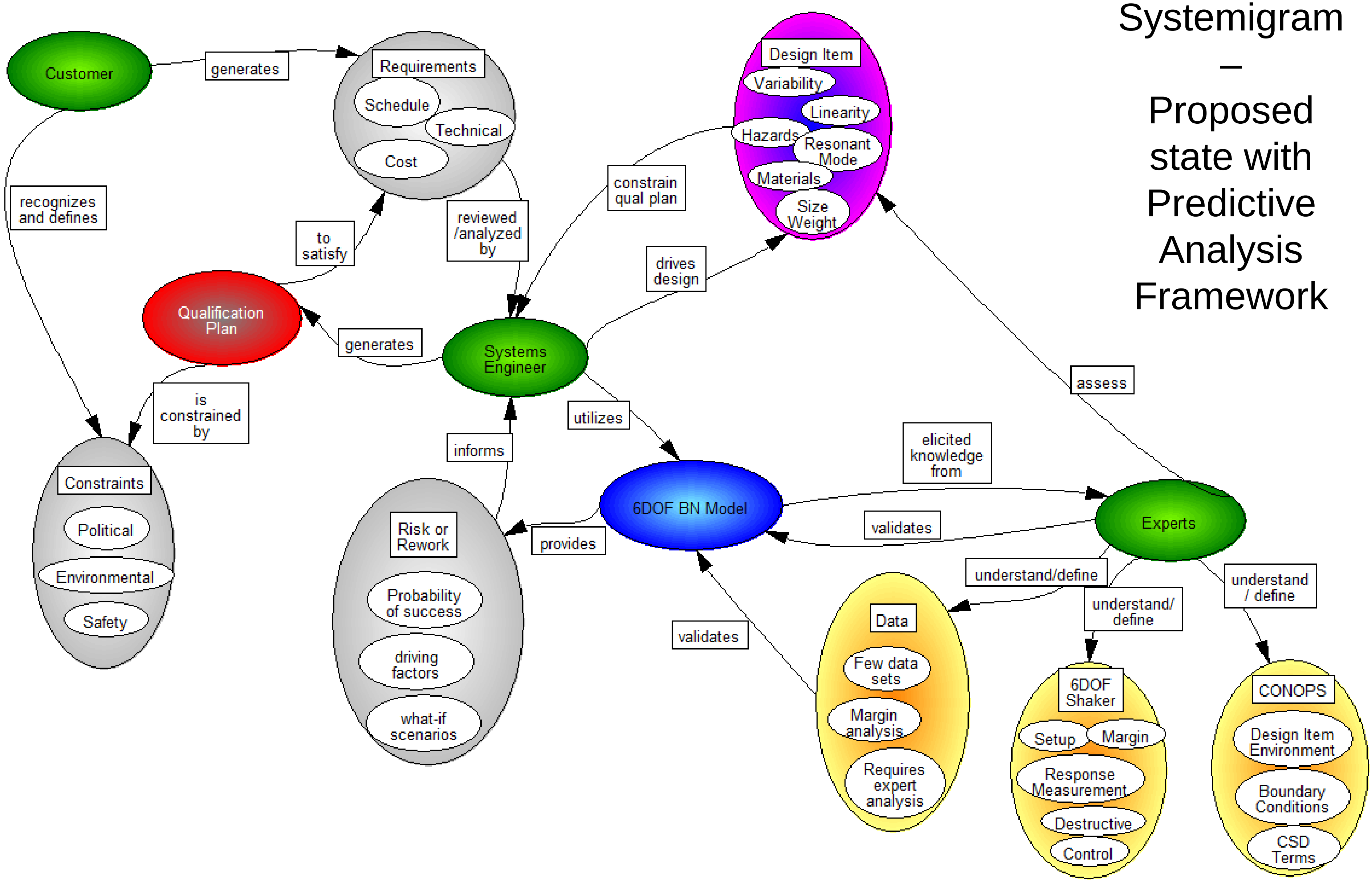
Causal technical factors must be considered (expert required)

Systemigram – Current state of 6DOF Qualification planning



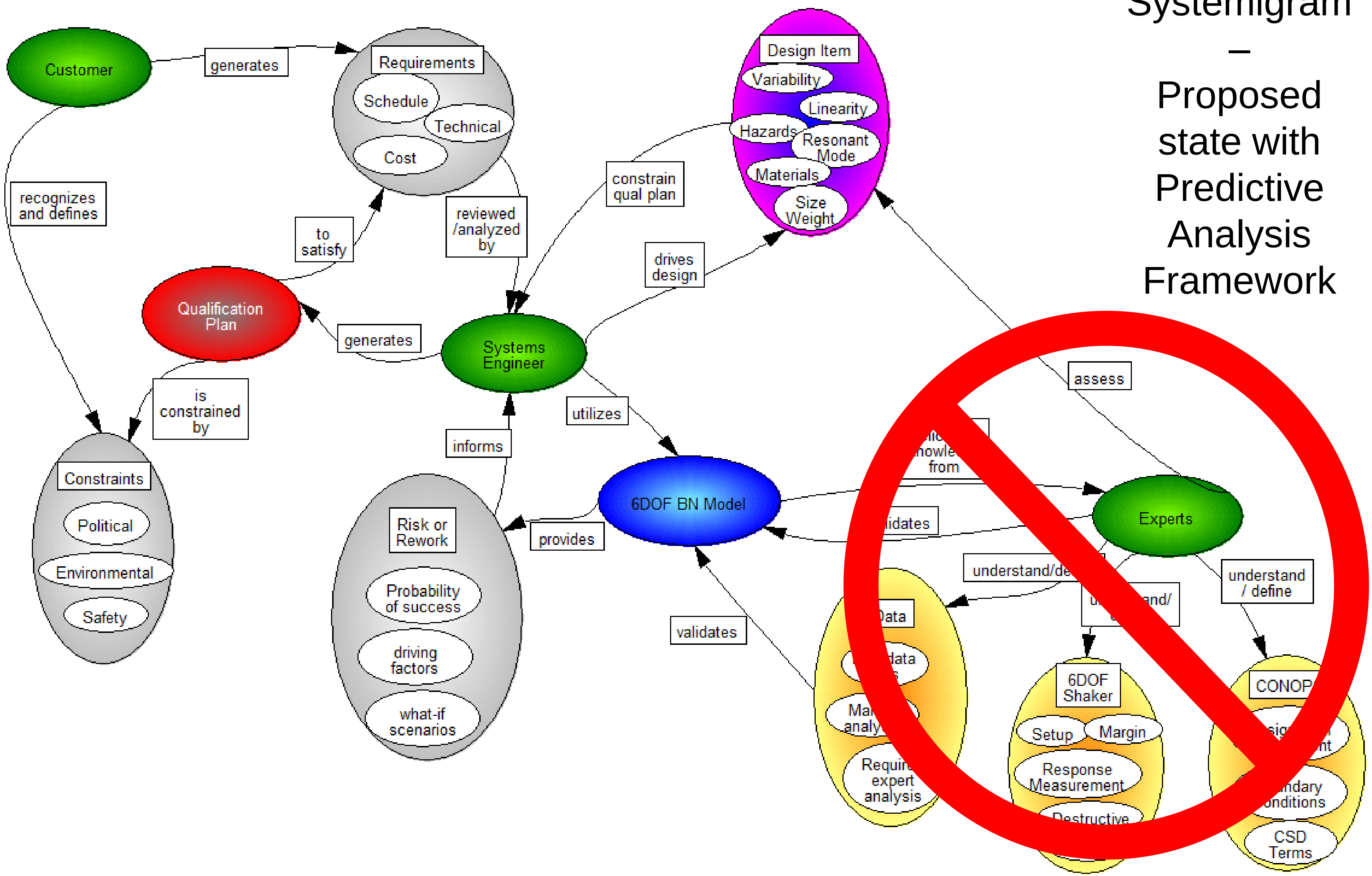
6DOF experts = few and not readily available

Systemigram – Proposed state with Predictive Analysis Framework



SYSTEMS ENGINEERING RESEARCH CENTER

Systemigram – Proposed state with Predictive Analysis Framework



Problem Statement

- What?
  - —Incorporate technical factors into decision space
  - —Extremely limited data / reliance on experts
- Why? (GAPS)
  - —Systems engineers are required to make decisions about complex subjects[1]
  - —Experts and/or data may not be available
  - —Existing qualification decision models focus on cost, schedule, risk and quality only[2]
- How?
  - —Use a Bayesian Network model
  - —Capture the technical factors and expert knowledge
  - —Understand the risk of using 6DOF tests for qualification

Results – Building the BN Model

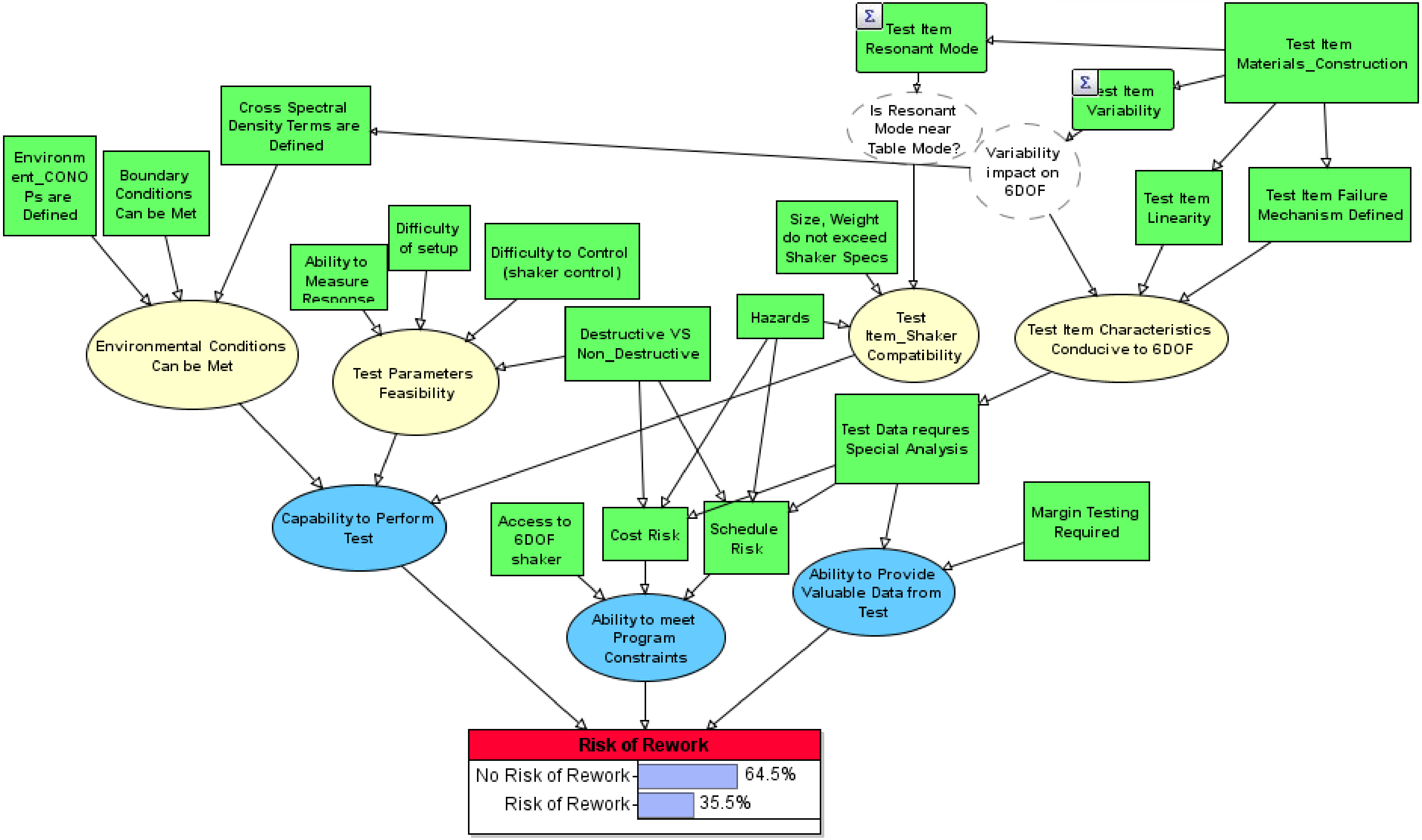
Building the BN Model

- Build BN Model - Critical Effort

1. Identify Causal Factors
   - Literature review, screening experiment
2. Identify Relationships
   - Based on expert input
   - Novel approach – Structural Knowledge Assessment[3]
3. Identify Factor Probability Distributions
   - Based on expert input
   - Modified Sheffield Elicitation Framework (SHELF)[4]

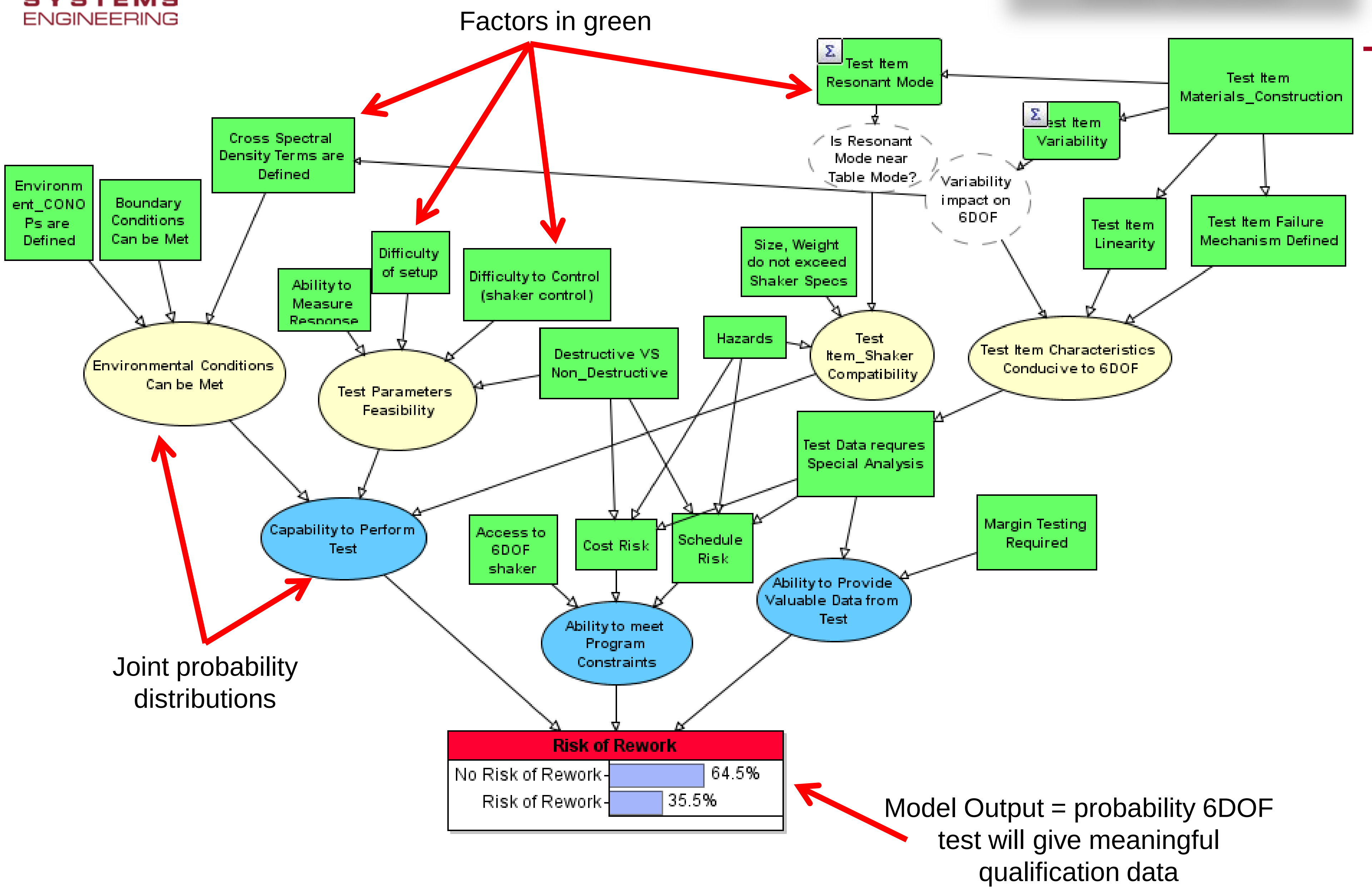
Expert elicitation drives modal accuracy when data is limited

Model Structure

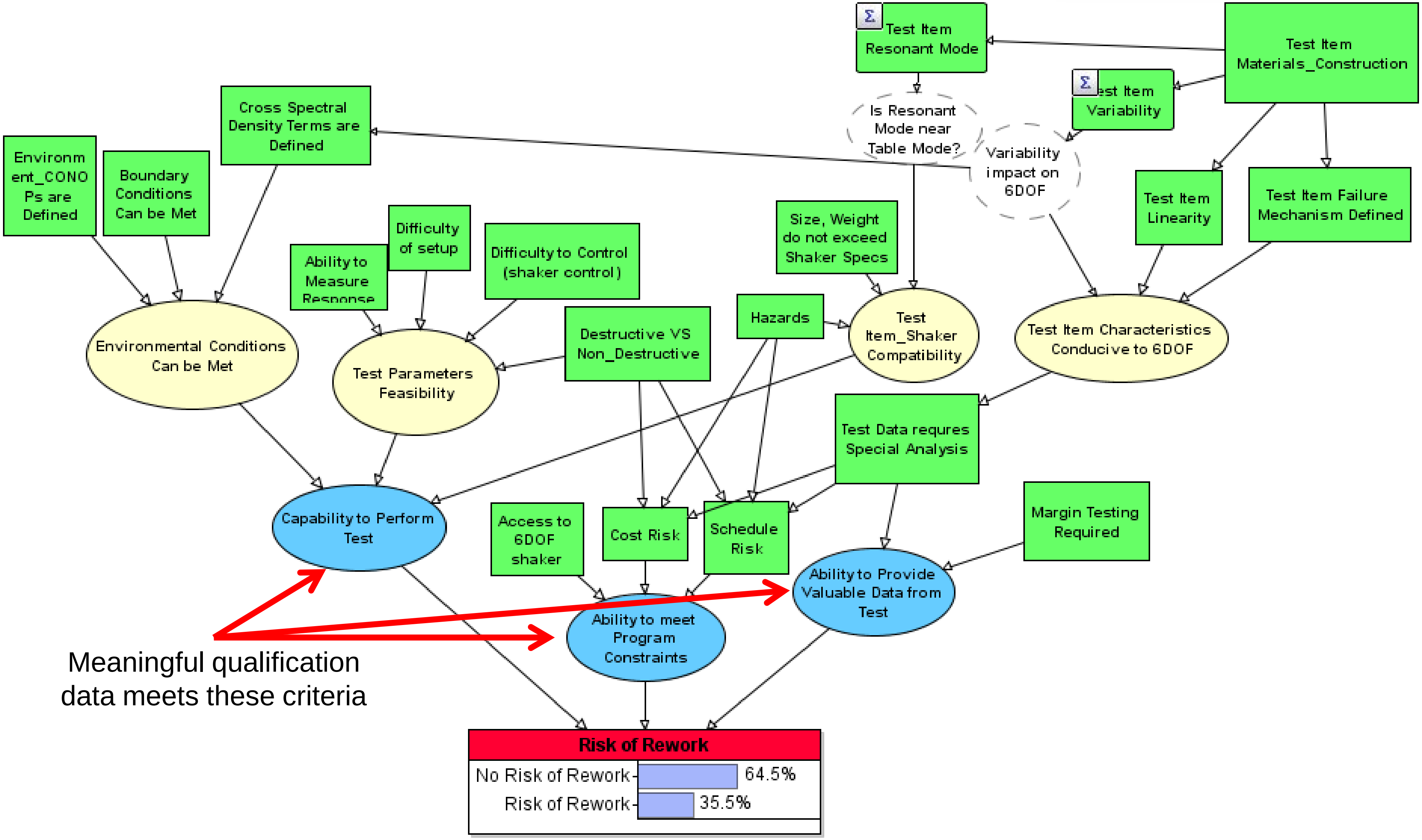


SYSTEMS ENGINEERING

Model Structure



Model Structure



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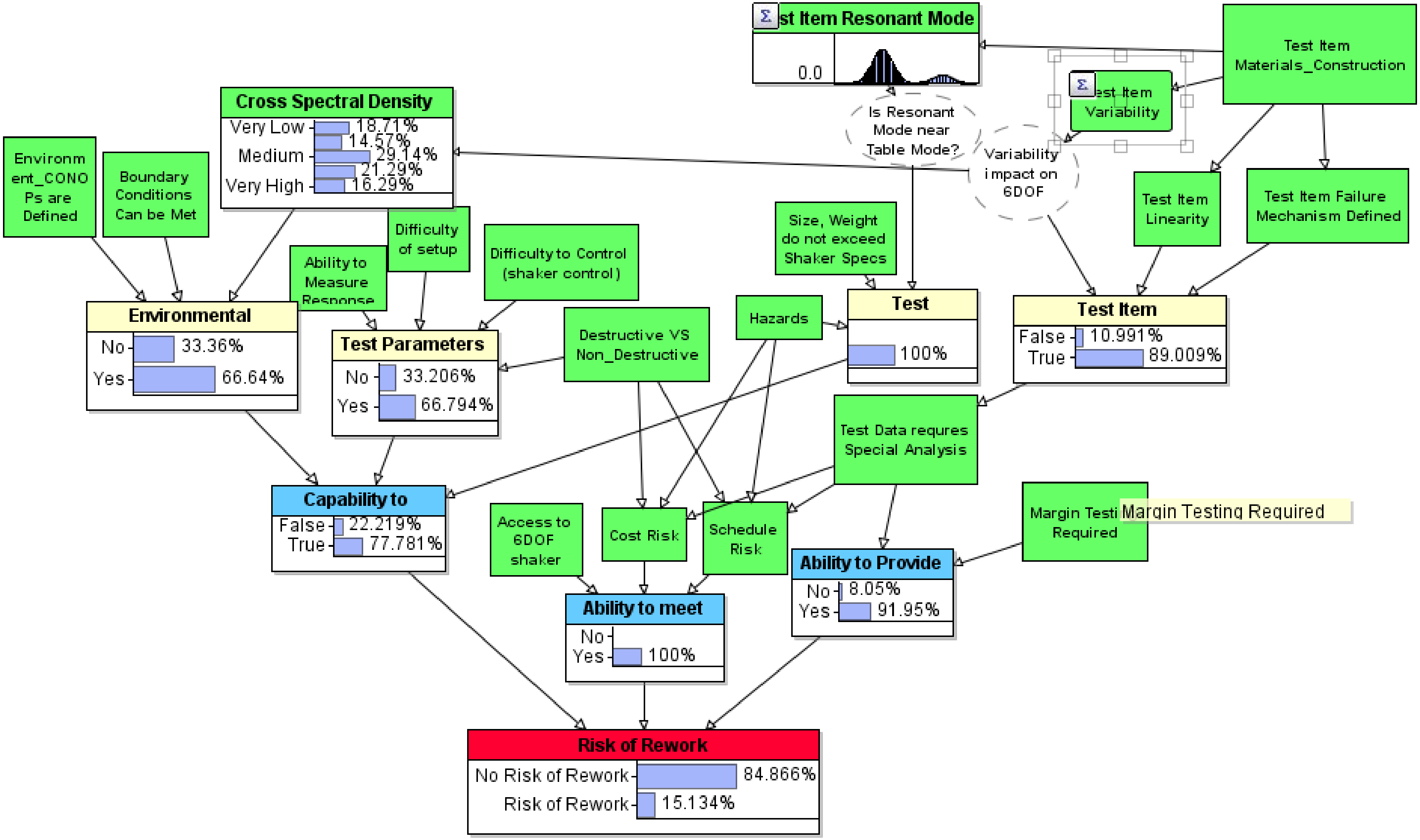
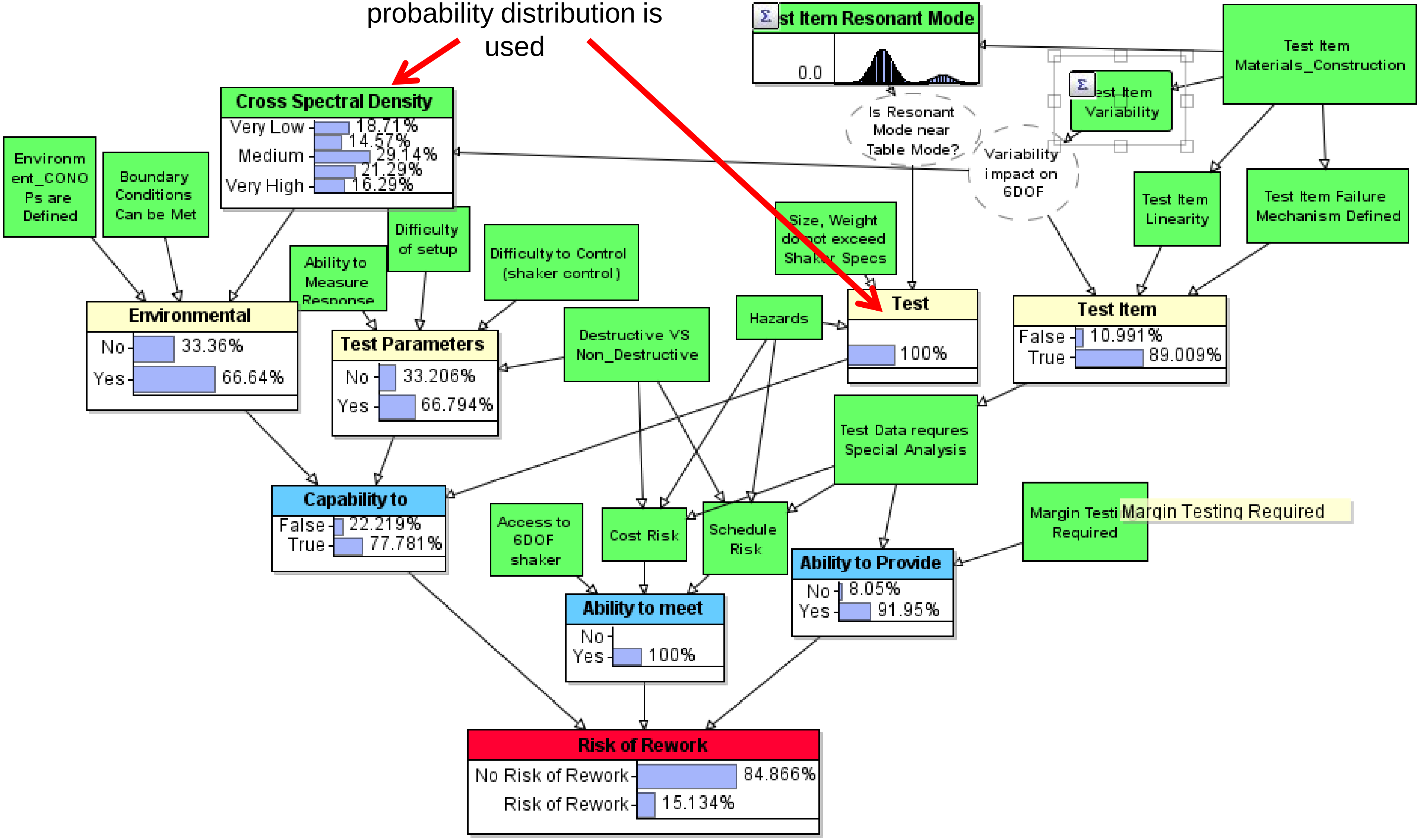


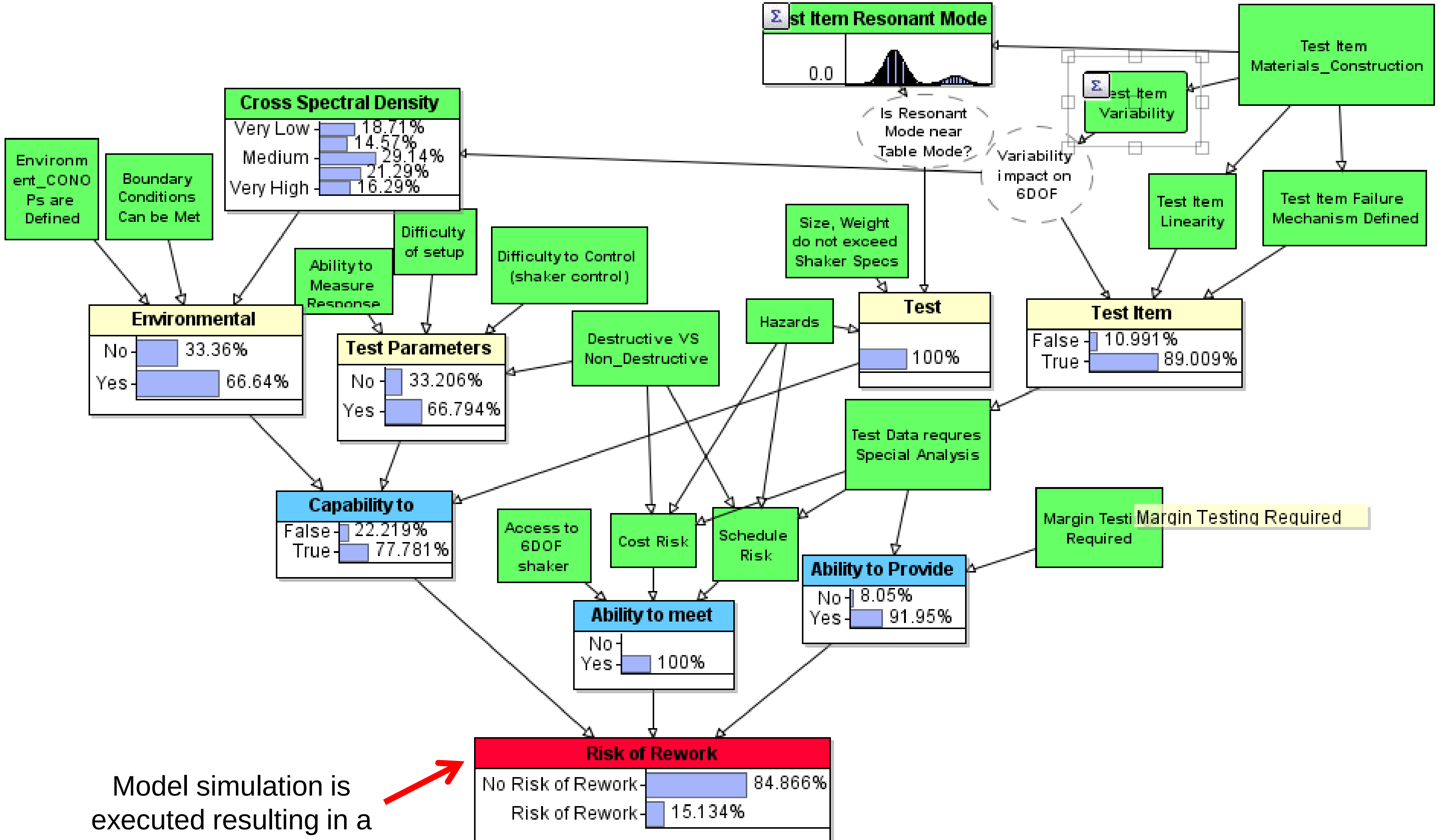
Model Use

Observations entered for each factor. Otherwise, probability distribution is used



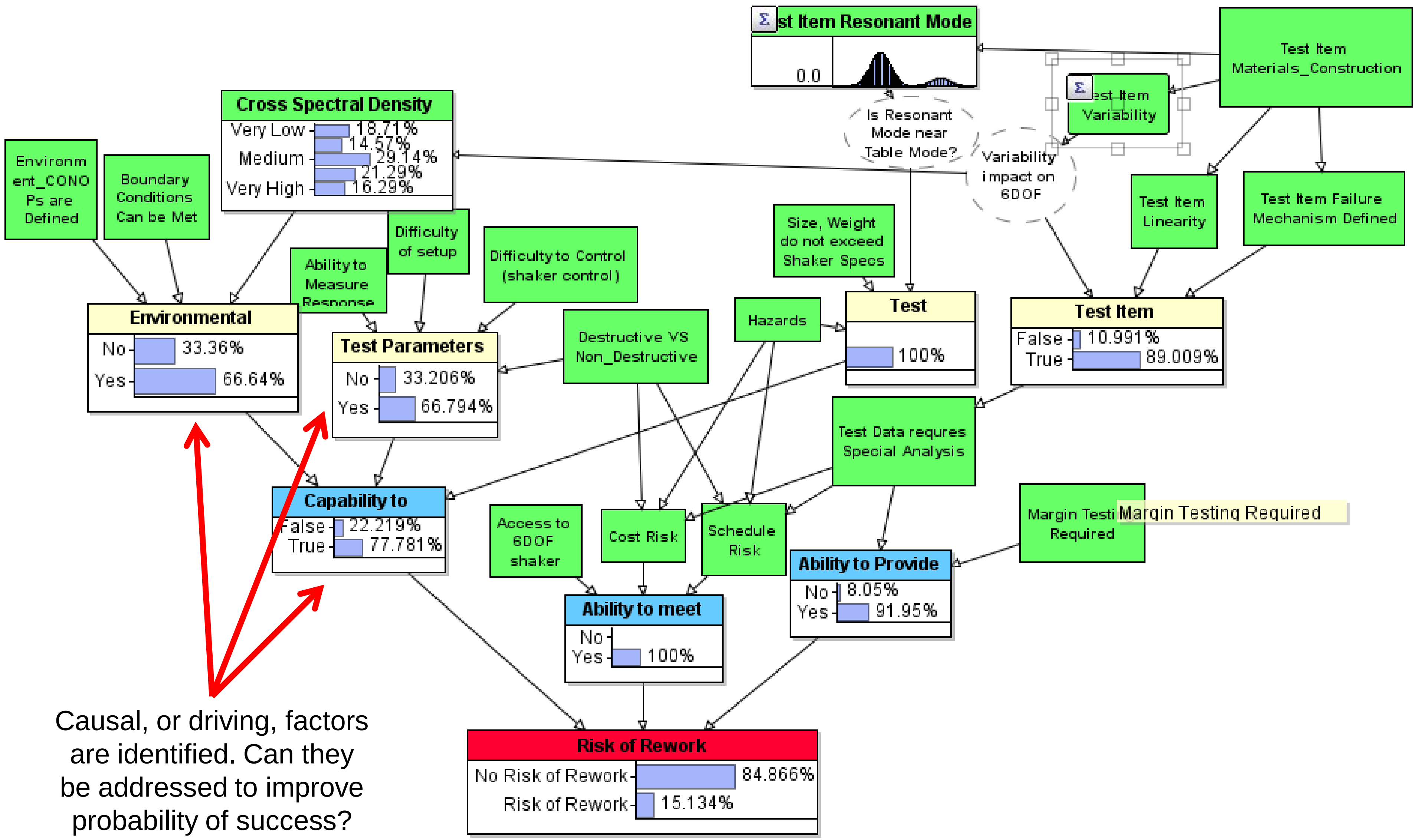
Model Use

SYSTEMS



Model simulation is executed resulting in a probability of success or rework

Model Use

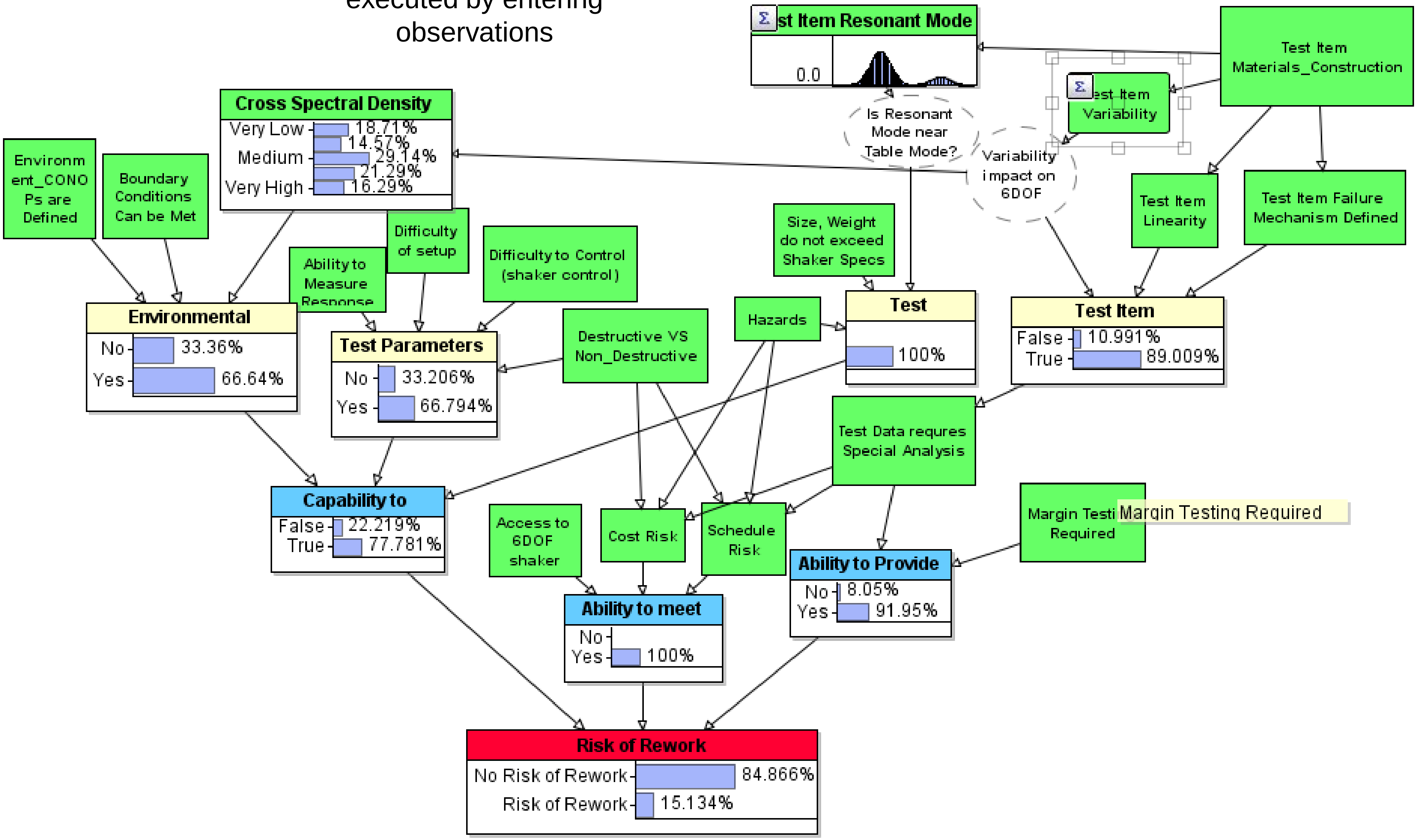


Causal, or driving, factors are identified. Can they be addressed to improve probability of success?

Model Use

SYSTEMS

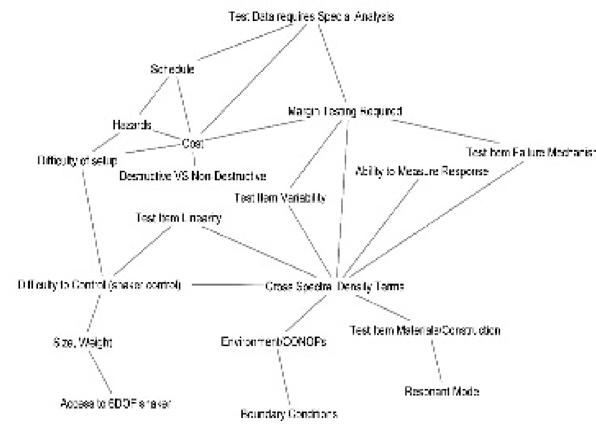
What-if scenarios executed by entering observations



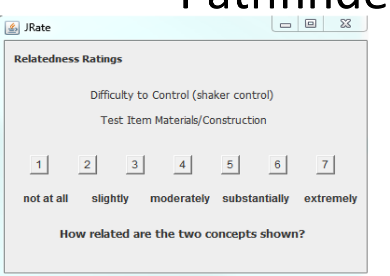
Model Use

Structural Knowledge Assessment

- All possible relationships between factors is a large list



- Need:
  - — Unbiased assessment of relationships
  - — Strength of relationships
  - — Determine whether the relationship is a driver
- SKA was modified to derive BN model relationships
  - — Used in education, medical and cognitive science fields
  - — Represents the structural properties of domain-specific knowledge
  - — Factors presented in pairs to expert who rates based on the strength of the relationship
  - — Pathfinder algorithm: derives a network from proximities for pairs of factors



Structural Knowledge Assessment (SKA) used to elicit relationships from experts

Sheffield Elicitation Framework

- Prior elicitation: discretization and parameterization
  - Elicit priors from experts in an unbiased manner
  - Quantitative and qualitative data
  - Probability of an event AND
  - Probability of the probability (uncertainty)
- SHELF method - objectively elicit priors from experts and incorporate data in the process
  - Multi-step process
  - Provides 'evidence dossiers'
  - Requires working meetings with the experts
- Roulette and Quartiles methods
  - Clear definition of factors defined in advance
  - Assign probability distributions
  - I modified to support qualitative data

SHELF used to elicit probability distributions from experts

Results - Validation

Validation

Iterative Validation Approach

1. Verification of the model – Tolerance, deterministic, structured walk-thru, built-in tools with BN software
2. Validation of factors – screening experiment, peer review with industry working group
3. Validation of relationships and probability distributions – multiple expert peer review with SKA and SHELF, convergent and concurrent validity with other BN models
4. Validation of model performance – prediction metric 98.3%
5. Validation of model performance with historical test data - historical prediction metric 83.3%
6. Validation test cases – two test cases, 8 teams total, examine the effectiveness of the model to aid decision AND assess *learning* through the use of the model - validation case study metric 100%

- Demonstrated the model is effective as a decision aid in planning 6DOF qualification
- Demonstrated the model is effective in teaching key technical concepts

Conclusions

Conclusions

- **Effective decision aid** that could significantly **reduce the cost of rework** in vibration qualification efforts.
- Expand into other areas of Systems Engineering – Method to **capture expert knowledge** in a **predictive framework** to **guide system decisions** when the experts are not available.
  - Technical factors included
- **Ideas/Methods** to **help develop** BN Models – **Expert elicitation**
  - Use of the Structural Knowledge Assessment to elicit SME input on relationships between factors in an unbiased manner.
  - Customized SHELF framework for expert elicitation of quantitative and qualitative factor probabilities
- Method to **accelerate learning** relative to the causal information in the model

Recommendations

- Use BN Models for critical systems engineering problems requiring assessment of technical factors
- Use BN Models for high risk programs where changes are expected
- Use BN Models to capture expert knowledge
- Use BN Models to accelerate learning
- Use BN Models to work with socio-technical systems
- Make sure the definitions and assumptions for the model are understood

Questions?

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Questions?

Thank you!

References

1. INCOSE. Systems Engineering Handbook. Kreuger, M., Walden, D., Hamelin, D. (Editors). International Council on Systems Engineering, San Diego, V.3.2.2., 2011.

2. Rizzo, D., Blackburn, M. Use of Bayesian networks for qualification planning: a predictive analysis framework for a technically complex systems engineering problem. Procedia Computer Science, 61, 2015, 133-140.

3. Stevenson, J., Shah, S., Bish, J. Use of Structural Assessment of Knowledge for Outcome Assessment in the Neuroscience Classroom. The Journal of Undergraduate Neuroscience Education 15 (1) 2016, A38-A43.

4. Oakley J. E. and O'Hagan, A. SHELF: the Sheffield Elicitation Framework (version 3.0). School of Mathematics and Statistics, University of Sheffield, UK , 2016.

Bayesian Network Models

Converting Expert Judgement to a Probability

Physical or Bayesian Probabilities

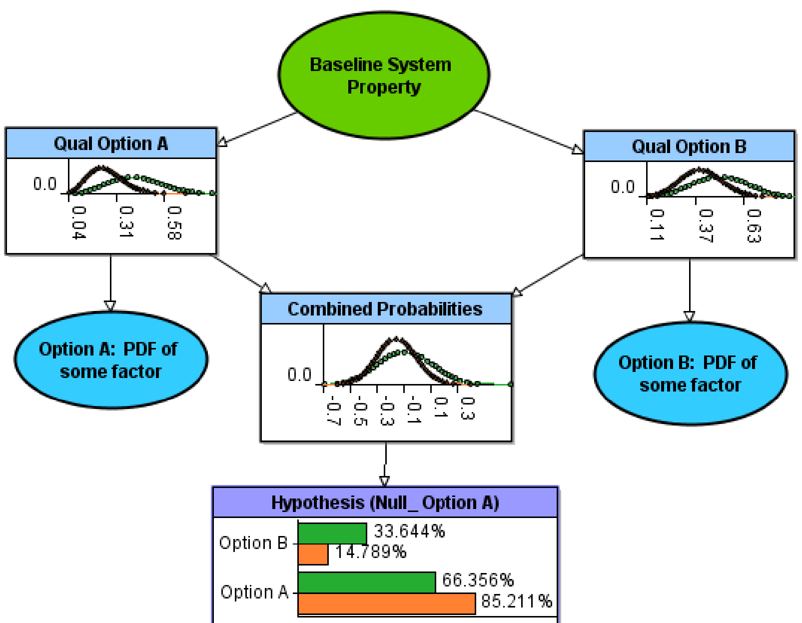
- Physical – test, get data, assign probability
- Bayesian – probability is assigned to a hypothesis
  - Experts give best hypothesis
  - Probability is updated as more info is obtained
  - Can have a probability before a test is run or data available

$$\underbrace{\Pr(A|B)}_{\text{Posterior}} = \underbrace{\frac{\Pr(B|A)}{\Pr(B)}}_{\text{Likelihood}} * \underbrace{\Pr(A)}_{\text{Prior}}$$

The research 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.

Bayesian Networks (BNs) are designed for that purpose.

- A BN is a directed acyclic graph
- Each factor is entered as a node with a probability
- Nodes are connected by arrows that describe their 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.



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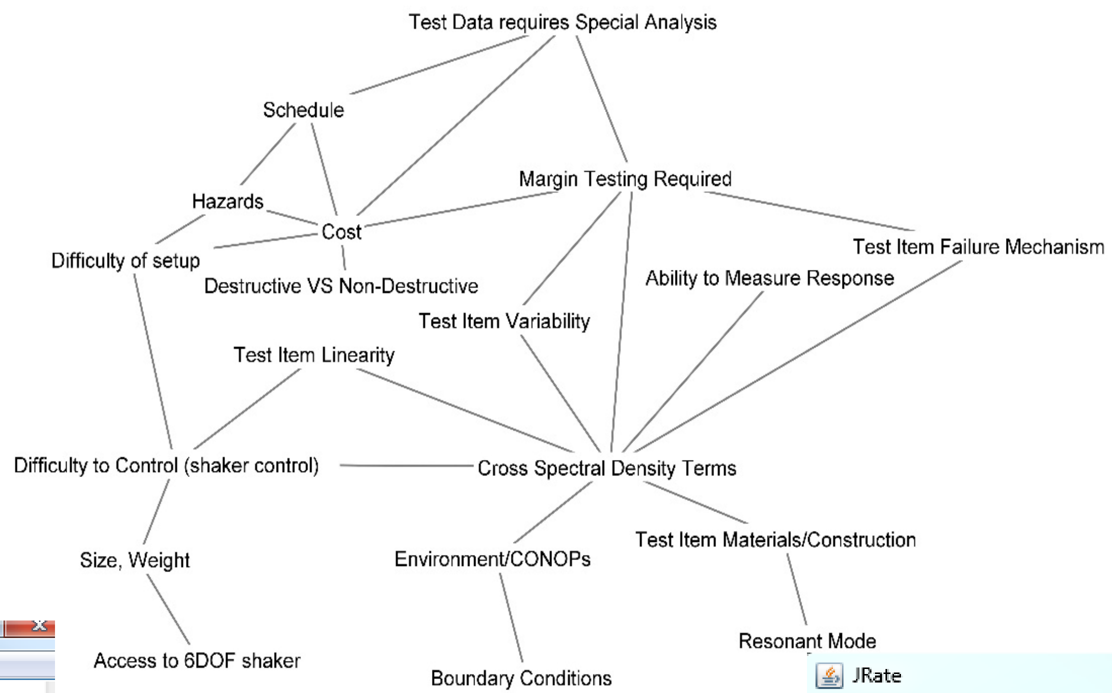
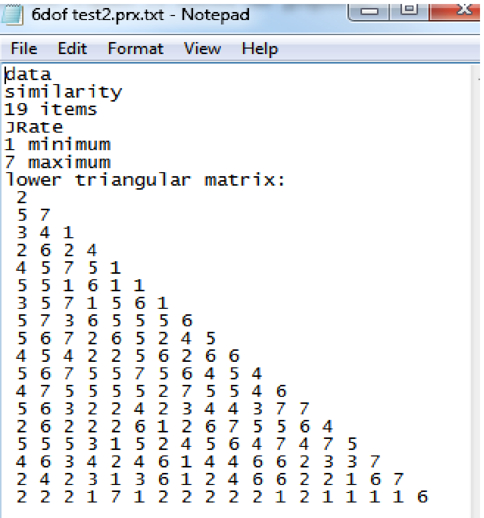
BN Models

- Bayesian Network Model chosen for predictive analysis framework
  - Capture technical factors
  - Handles and contains information about incomplete data
  - Assess and manage uncertainties
  - Handles disparate data types
    - Quantitative, qualitative, expert knowledge
  - Documents assumptions – can defend or revisit
  - Can perform what-if scenarios
  - Provides quantitative output

Building the BN Model - SKA




6dof test2.prx.txt - Notepad

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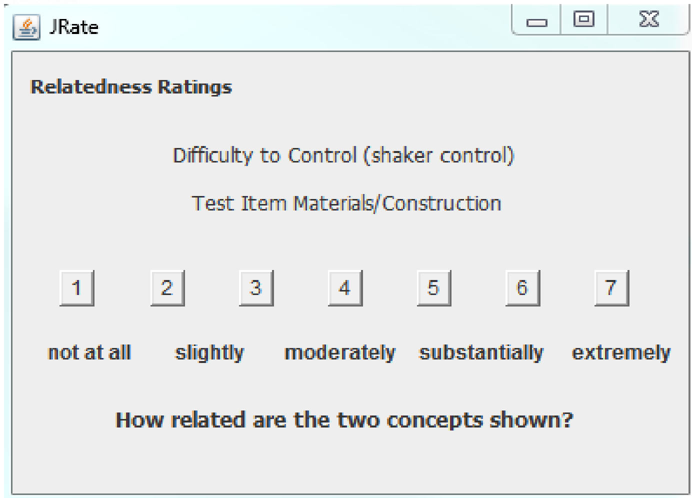
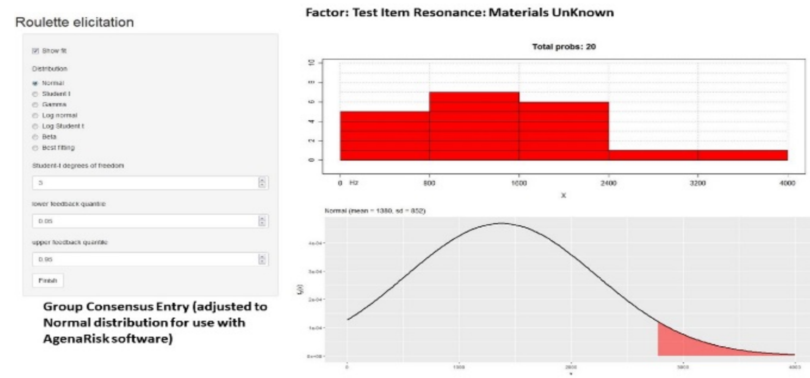


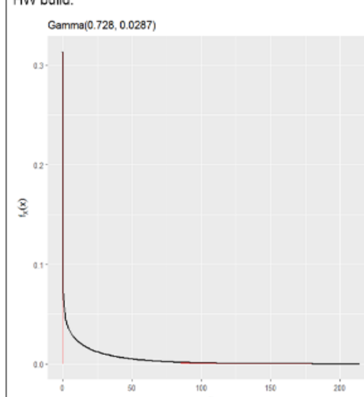
Sheffield Elicitation Framework

- **Prior elicitation: discretization and parameterization**
  - Probability of an event AND
  - Probability of the probability (uncertainty)
  - Ask for intervals instead of fixed value
  - Multiple experts, real time feedback



Group Consensus Entry (adjusted to Normal distribution for use with AgenaRisk software)

- **SHELF method - objectively elicit priors from experts and incorporate data in the process**
  - Multi-step process that includes software implemented in R
  - Provides 'evidence dossiers' prior to the elicitation to help experts understand the available data
  - Includes feedback loops to verify input and converse with other experts
  - Requires working meetings with the experts, who arrive pre-briefed with the process and the data

Group plausible range	0 Hz to 500 Hz
Group elicitation	**Method:** Quartile **Judgements:** Median 15 Hz, Q1 5 Hz, Q3 35 Hz
Fitting and feedback	Updated fitting distribution after discussion of failures in HW build: 
Chosen distribution	Gamma (0.728, 0.0287)

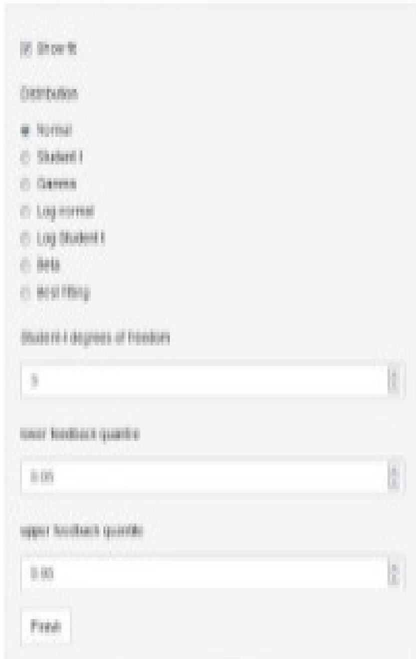
- **Roulette and Quartiles methods**
  - Clear definition of factors defined in advance
  - Individual factors and multivariate factors (joint pdf)
  - Assign probability distributions
  - I modified to support qualitative data

SHELF

Microsoft Word Document

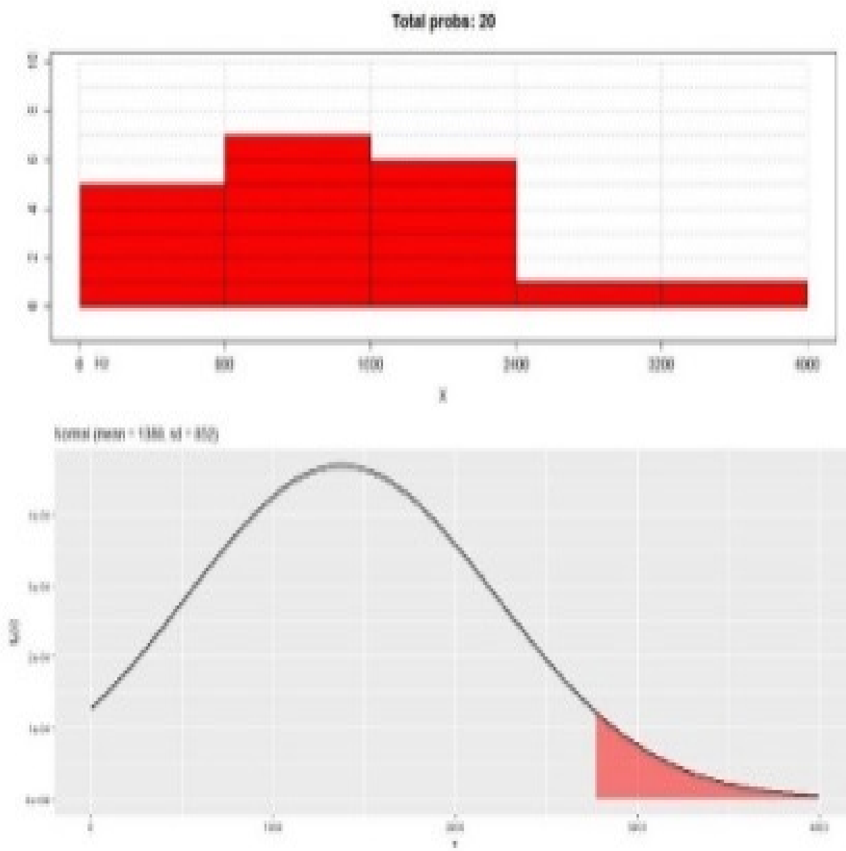
Microsoft Word Document

Roulette elicitation



Group Consensus Entry (adjusted to Normal distribution for use with AgenaRisk software)

Factor: Test Item Resonance: Materials UnKnown



Case Study

Team A – mechanical test team from the test organization. Have extensive experience with 6DOF testing.

Team B – mechanical test team from a weapons program. Used to performing mechanical vibration tests. Have limited experience with 6DOF testing.

Test Scenario 1 – generic dynamic object (bolted cylinder)

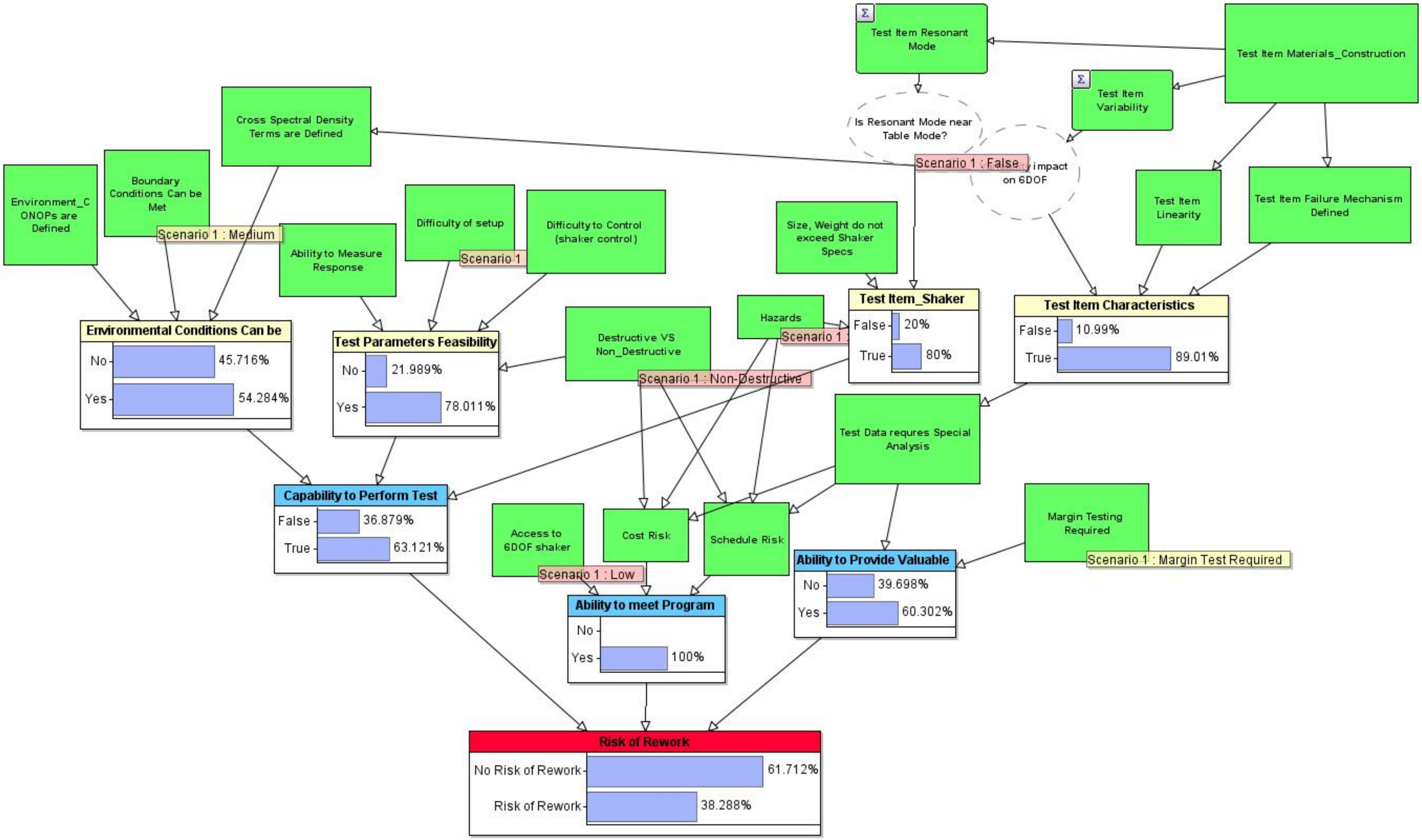
a)Performed with Vee model – Team A

b)Performed with BN Model – Team B

Test Scenario 2 – electromechanical component

a) Performed with Vee model – address failure – Team B

b) Performed with BN model – address failure – Team A



Second Test Case Initial Model Simulation

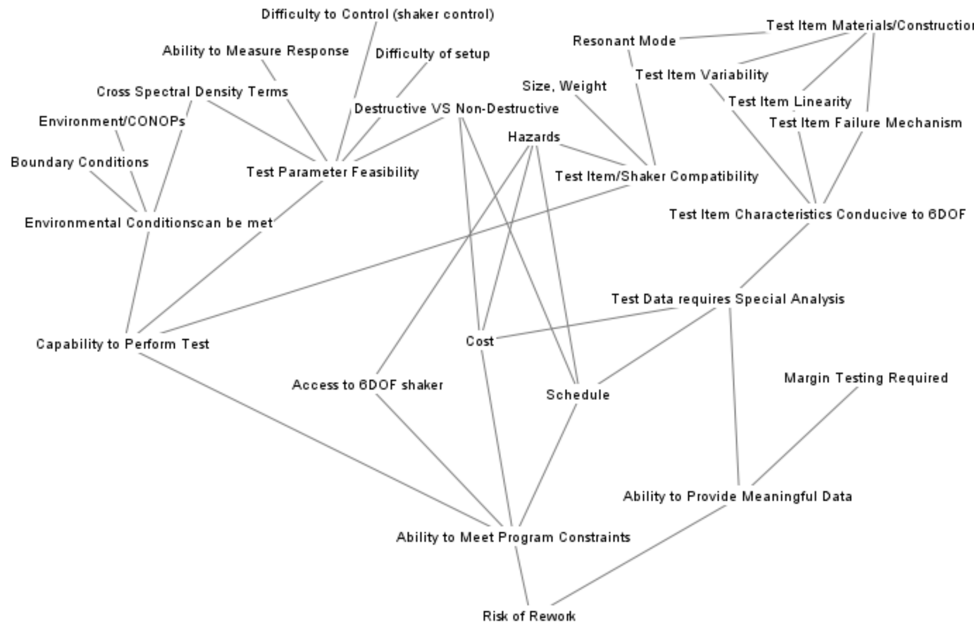
Second Case Study

Correlations – initial SKA	6DOF Baseline Truth	Team C	Team D	Team E	Team F	Team G	Team H
6DOF Baseline Truth	1	0.255	0.149	0.138	0.182	0.214	0.283
Team C	0.255	1	0.436	0.533	0.436	0.508	0.473
Team D	0.149	0.436	1	0.311	0.738	0.437	0.587
Team E	0.138	0.533	0.311	1	0.341	0.422	0.378
Team F	0.182	0.436	0.738	0.341	1	0.532	0.553
Team G	0.214	0.508	0.437	0.422	0.532	1	0.447
Team H	0.283	0.473	0.587	0.378	0.553	0.447	1

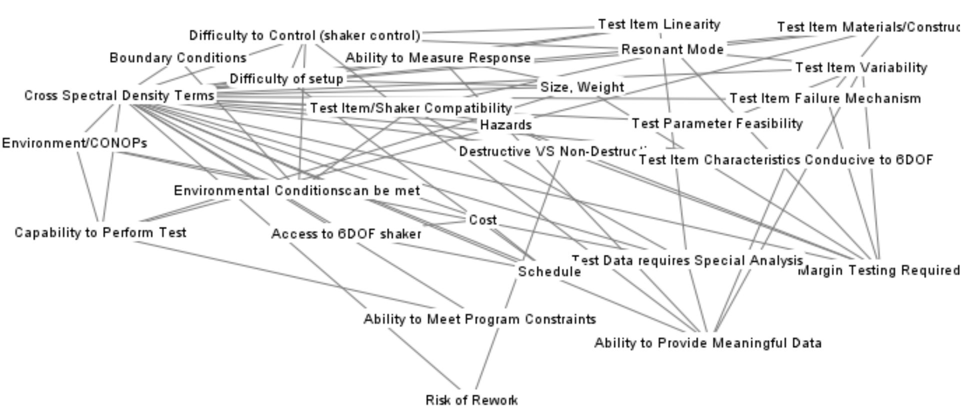
Correlation of Initial SKA Results and 6DOF Baseline Truth SKA

Correlation of Final SKA Results and 6DOF Baseline Truth SKA

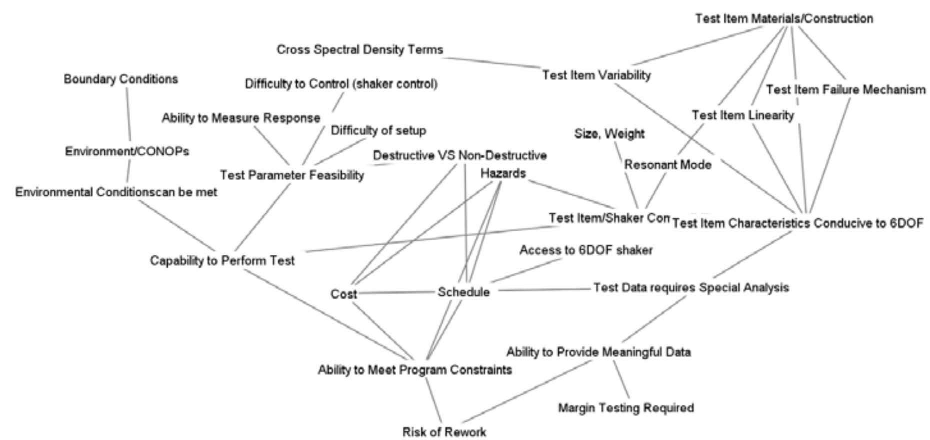
Correlations – Post Learning	6DOF Baseline Truth	Team C	Team D	Team E	Team F	Team G	Team H
6DOF Baseline Truth	1	0.931	0.821	0.956	0.905	0.962	0.862
Team C	0.931	1	0.804	0.896	0.883	0.902	0.802
Team D	0.821	0.804	1	0.81	0.75	0.83	0.706
Team E	0.956	0.896	0.81	1	0.877	0.924	0.822
Team F	0.905	0.883	0.75	0.877	1	0.885	0.778
Team G	0.962	0.902	0.83	0.924	0.885	1	0.828



'Truth' SKA for Final 6DOF BN Model

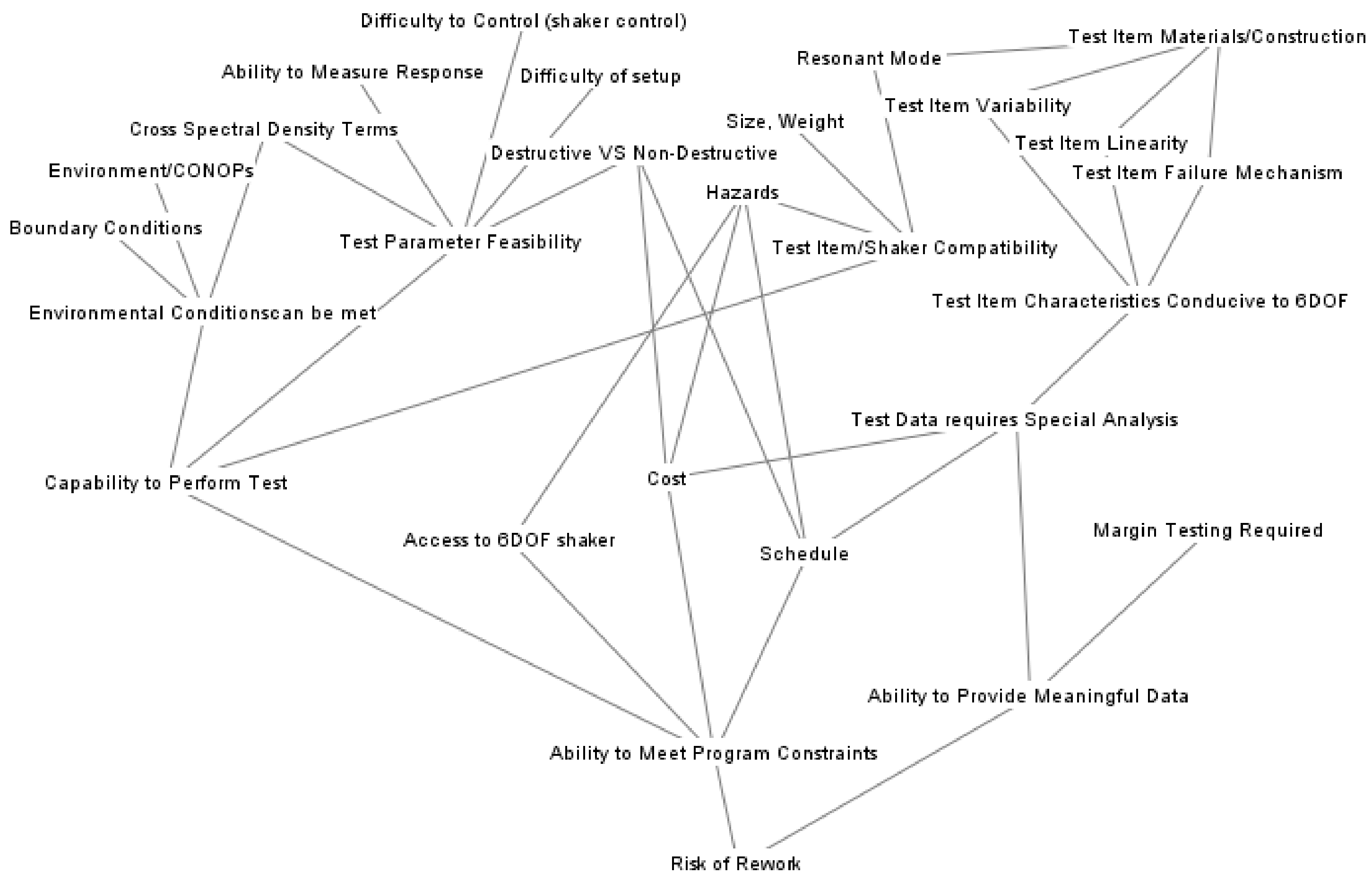


Example Initial SKA for a Validation Team (Team E)



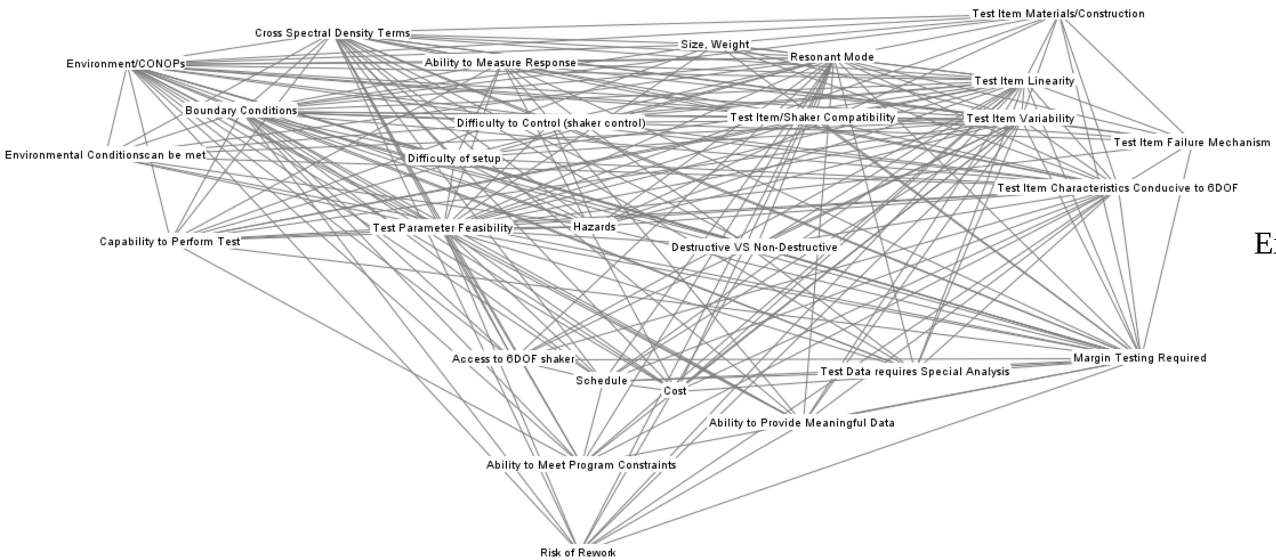
Example Final SKA for a Validation Team (Team D)

Case Study SKA



'Truth' SKA for Final 6DOF BN Model

Case Study SKA



Example Initial SKA for a Validation Team (Team F)

ESULTS AND 6DOF BASELINE TRUTH SKA

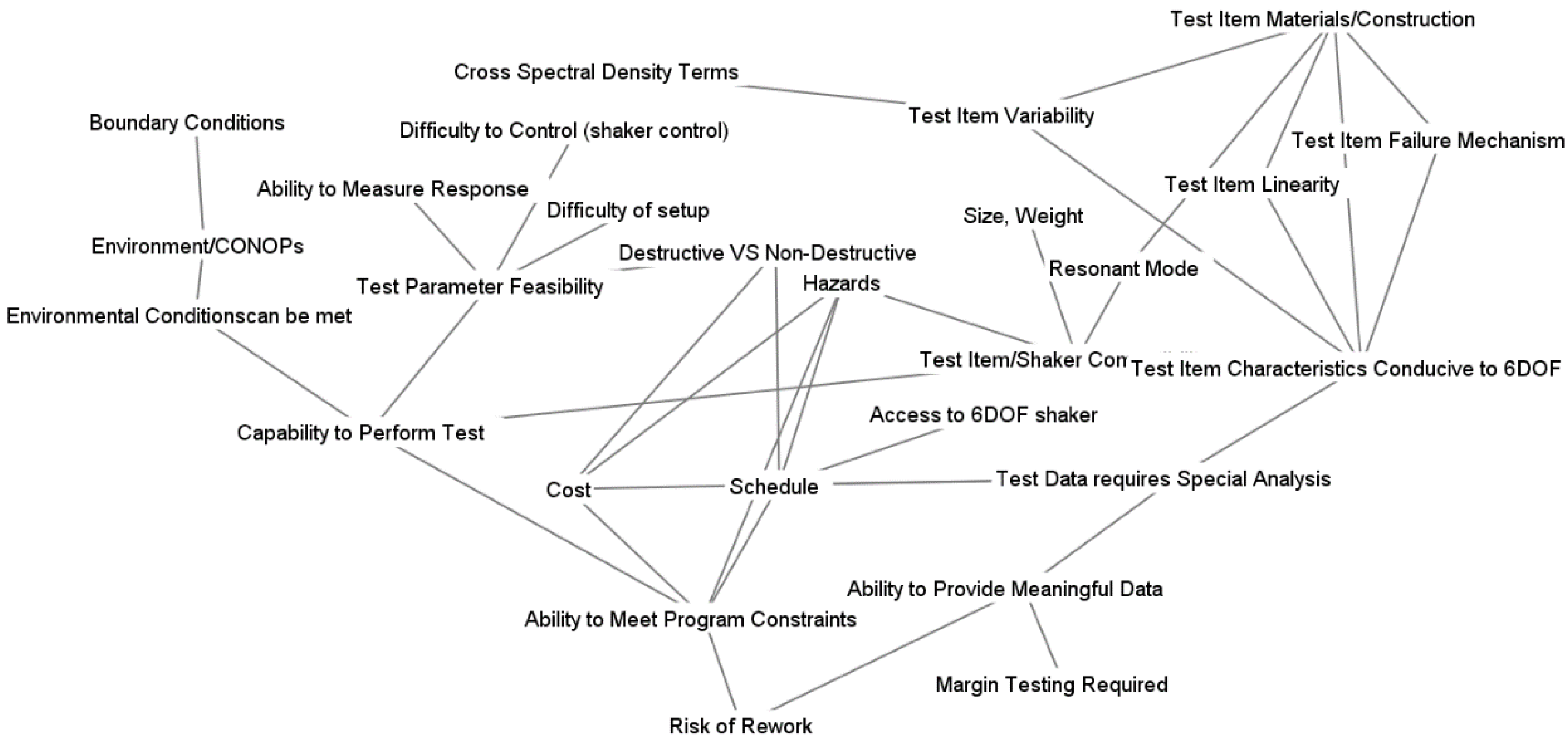
Correlations – initial SKA	6DOF Baseline Truth	Team C	Team D	Team E	Team F	Team G	Team H
6DOF Baseline Truth	1	0.255	0.149	0.138	0.182	0.214	0.283
Team C	0.255	1	0.436	0.533	0.436	0.508	0.473
Team D	0.149	0.436	1	0.311	0.738	0.437	0.587
Team E	0.138	0.533	0.311	1	0.341	0.422	0.378
Team F	0.182	0.436	0.738	0.341	1	0.532	0.553
Team G	0.214	0.508	0.437	0.422	0.532	1	0.447
Team H	0.283	0.473	0.587	0.378	0.553	0.447	1

TABLE 1. INITIAL SKA RESULTS AND 6DOF BASELINE TRUTH COMPARISON STATISTICS

Net1	Net2	#Links in Net1	#Links in Net2	#Common links	C-E[C] *	Similarity **	S-E[S] ***
6DOF Baseline Truth	6DOF Baseline Truth	27	37	37	37	33.1	1
	Team C	27	37	61	11	4.6	0.126
	Team D	27	37	235	18	-6.8	0.071
	Team E	27	37	67	10	2.9	0.106
	Team F	27	37	219	24	0.9	0.103
	Team G	27	37	103	14	3.1	0.111
	Team H	27	37	217	24	1.1	0.104

* number of common links minus the number that can be expected by chance
** number of common links/Links in Net1 + Links in Net2 minus common links
*** similarity minus similarity that can be expected by chance

Case Study SKA (Post Model Use)



Final SKA for a Validation Team (Team D)

Case Study SKA (Post Model Use)

TABLE 1. CORRELATION OF FINAL SKA RESULTS AND 6DOF BASELINE TRUTH SKA

Correlations – Post Learning	**6DOF Baseline Truth**	**Team C**	**Team D**	**Team E**	**Team F**	**Team G**	**Team H**
6DOF Baseline Truth	1	0.931	0.821	0.956	0.905	0.962	0.862
Team C	0.931	1	0.804	0.896	0.883	0.902	0.802
Team D	0.821	0.804	1	0.81	0.75	0.83	0.706
Team E	0.956	0.896	0.81	1	0.877	0.924	0.822
Team F	0.905	0.883	0.75	0.877	1	0.885	0.778
Team G	0.962	0.902	0.83	0.924	0.885	1	0.828
Team H	0.862	0.802	0.706	0.822	0.778	0.828	1

Case Study SKA (Post Model Use)

TABLE 1. FINAL SKA RESULTS AND 6DOF BASELINE TRUTH COMPARISON STATISTICS

Net1	Net2	#Links in Net1	#Links in Net2	#Common links	C-E[C] *	Similarity **	S-E[S] ***
6DOF Baseline Truth	6DOF Baseline Truth	27	37	37	37	33.1	1
	Team C	27	37	30	30	26.8	0.811
	Team D	27	37	37	32	28.1	0.762
	Team E	27	37	33	32	28.5	0.842
	Team F	27	37	34	33	29.4	0.868
	Team G	27	37	27	27	24.2	0.73
	Team H	27	37	48	37	31.9	0.771

* number of common links minus the number that can be expected by chance
** number of common links/Links in Net1 + Links in Net2 minus common links
*** similarity minus similarity that can be expected by chance

Future Work

1. How to evaluate a BN model based on expert input with limited data (less than 100 pieces of data).
2. Examine meaningful metrics for BN models built with expert input – not data. Specifically where the model is used to inform decisions rather than provide an exact prediction.
3. Continue examining best methods to elicit priors from experts in a non-biased manner – understanding that experts may not want to learn about BN models in order to participate.
4. Examine best use of BN models in systems engineering. It takes a considerable amount of work and cost to develop a BN model when data is poor. Where does it make sense to generate a BN model?
5. Examine the best ways to update BN models. What does the process look like?
6. Examine the efficiencies gained from using BN models to reassess a preplanned qualification effort after a failure or requirements changes.
7. Examine the user interface with the BN model – from a non-BN model user perspective, i.e. systems engineers using the tool. How can systems engineers use, or create, a BN model without first becoming a BN expert?
8. Examine the use of BN models to accelerate learning. Does this only help learn the technical knowledge captured in the model? Could this be used to teach system engineering in general? It teaches cause and effect like experience – but is it as effective as actual experience (retention?).
9. Examine combining game theory and BN models to transfer expert knowledge to non-experts.
10. Is the learning gained from using the BN model temporary (short-term memorization) or more permanent?