# Analysis Quality Index - What confidence do you have in your risk analysis?

Leila Salhi[1], Jacek Stecki[2], Chris Stecki[3]

[1,2,3] PHM Technology Pty Ltd, Melbourne, Victoria, 3104, Australia

*lsalhi@phmtechnology.com*
*jstecki@phmtechnology.com*
*cstecki@phmtechnology.com*

## ABSTRACT

OEMs and operators of complex mission/safety critical systems are faced with the requirement to mitigate design and performance risks and their economic consequences. A key issue for any engineering organization is the integrity of the analysis that is used to support significant commercial decisions. Analysis outputs used to establish or validate performance criteria should have an appropriately high level of confidence associated with them when entering into significant financial contracts. While risk assessment methods and techniques for analysis are well defined and understood and are captured in various international military and commercial standards, the issue of analysis quality has traditionally been neglected and is not adequately covered in most commercially available engineering analysis tools. The quality of data inputs determines the quality of analysis outputs. A key factor is the source of the parameters used in an analysis. For example input data may be sourced from operational data, or may be based on the engineering judgement of an individual or a third party organization. This paper outlines an approach to analysis quality assessment in a model based engineering environment, focusing on the sources of data and ancillary information to generate an Analysis Quality Index (AQI) for the analysis. The AQI is generated as a dashboard reporting function for the engineering model that is used to provide a confidence rating on the analysis outputs. Analysis Quality Index capability was incorporated into Maintenance Aware Design environment (MADe) software, an integrated tool-set that combines engineering risk analysis capabilities to support systems engineering, design and through-life support.

## 1. INTRODUCTION

Risk management has become a hot topic over the last decade, its ever increasing application to engineering systems is not always driven by purely technical considerations (Ross, K., & Main, B.W. (2001)). Factors like compulsory compliance with standards (MIL, ISO) and regulation (e.g. FAA), risk of litigation and thus possible audits of the risk assessment process, reliability dependent insurance costs, changes in system management approaches (Product Life Management (PLM), Life Cycle Management (LCM)), changes in sustainment of technical systems (Performance-based Contracts (PBC)), risks to environmental safety etc. cause increased awareness that failures of engineering assets can have penalties.

Operation of an engineering system inevitably leads to system degradation or failure of various degrees, which generate financial, operational (ceased function of the system) and physical risks to assets, human operators or the environment.

To deal with these issues a range of methodologies have been proposed and accepted, especially in the military sector, there are over 150 methodologies dealing with risk management in engineering systems.

The process of risk management is a two-step process:

- Formalized risk identification using various methodologies of risk analysis - Failure Mode and Effects Analysis (FMEA), Failure Mode, Effects and Criticality Analysis (FMECA), Reliability Block Diagram (RBD), Fault Tree Analysis (FTA), etc. see International Standards Organization (ISO) (2004).
- Risk elimination by changes in system design, maintenance, operation etc.

Of course we must remember that risks are assessed and dealt with during the design process, albeit not necessarily using formalized methods.

The objective of risk identification is to determine how the system may fail, and how such failure affects system safety, performance, availability, etc. Analysis provides metrics of risks (e.g. criticality, reliability) which are the basis for corrective actions (e.g. design changes or changes in maintenance procedures). The formalized risk identification, depending on how and when it is applied, has varying impact on risk reduction. Ideally, it should be concurrent with design of the system so risks identified during design process can be eliminated and/or minimized by modification to design. This approach is optimal in terms of cost, time and degree of risk reduction.

However in practice, formalized risk identification (FMEA, RBD, FTA) is not conducted concurrently with design or is carried out too late to accommodate design changes. In these circumstances, risk analysis has only limited impact on the system design and is often conducted at completion of the design process to generate contractual deliverables or achieve compliance.

The 'concurrent with design' approach is also not possible when dealing with legacy systems. In the case of such a system, we may only use workaround solutions to mitigate risk (better maintenance, sensing) as design changes are often not feasible or possible. Methods like Reliability Centered Maintenance (RCM), Maintenance Effectiveness Review (MER) and Back-fit RCM are used to determine maintenance practices which can reduce operational risk. These methods often lead to outcomes such as Condition Based Maintenance (CBM) and Prognostics and Health Management (PHM).

With a growing importance of risk management methodologies, the quality of the methods is becoming important. Low quality of risk assessment may increase rather than decrease the cost of designing and operating of technical systems.

According to a Google search, the topic of quality of risk assessment is very prevalent - 60,000k results for "risk analysis engineering" and 81,200k results for "quality of risk analysis" engineering – it is currently seen as an important attribute of risk management. Table 1 presents the most widely used methods of risk assessment:

## 2. THE PROBLEM – CURRENT APPROACHES THAT IMPACT THE QUALITY OF RISK ANALYSIS

The current industry approaches to support risk analysis are primarily database or spreadsheet based software. The use of such software to conduct the required analysis generates a number of significant issues in terms of the cost of conducting analysis, quality of the analysis, system level analysis and scheduling (Bednarz & Marriott (1988), Kara-Zaitri C., Keller A., Barody I. & Fleming, P. (1991), Ormsby A., Hunt J. & Lee M. (1991). The main factors impacting the quality of analysis are the quality and quantity of data used.

- Limited knowledge capture / reuse

Spreadsheets are an obstacle to knowledge transfer which impacts the quantity of data available for risk analysis. The fact that spreadsheets can normally only be updated by the people that created them, is also critical to ensure maximum coverage of the risk analysis. Spreadsheets are not easily configuration managed based on operational data or as changes in the platform are made. Furthermore, the results of a performed analysis cannot be automatically transferred and used to support related analysis methods.

Table 1. List of the most widely used methods of risk assessment according to Google search results (June 2014)

| Method of risk assessment | Quantity |
|---|---|
| FMEA | 3,270k |
| Reliability Diagram | 20,600k |
| Fault Tree | 30,000k |
| Fault Analysis | 45,200k |
| Failure Analysis | 113,000k |
| Performance Based Contract | 70,200k |
| Engineering Risk Audit | 34,400k |
| Condition Based Maintenance | 16,700k |

- Inconsistency of terminology

The quality in the analysis is significantly impacted by the lack of industry wide taxonomies to define functions and failure concepts, which brings issues of ambiguity and inconsistency of terminology. Risk analyses are also artefact driven (based on attributes of the platform) and performed on a specific state of the system. A snapshot of the system is thus captured by the analysts in spreadsheets and the designer is rarely involved in all iterations of the analyses - this can lead to poor data quality that is used in the risk analysis.

- Retrospective analysis

Usually analysis is done retrospectively (rather than concurrently) at the end of the design process using spreadsheets/database FMEA/FMECA mainly to document the outcomes for compliance or contractual requirements. Evans J. (1992) in his editorial wrote "..The idea that all the experts and number-crunchers should come in after a design was virtually complete, and second-guess the designers was stupid to begin with..".

- Disparate models

Industry practice usually relies on the usage of disparate models of a platform and its Bill of Materials (BOMs) that reside within the functional stovepipes of an organization. This is an obstacle for comparing and controlling the data. Inconsistencies in models such as holes in the BOMs or in the structure of the system may cause coverage losses that are not obvious using spreadsheets.

- Bottom-up – inductive approach.

Current methods to conduct risk analysis are inductive (based on brainstorming) and use a bottom-up approach. It is therefore difficult to visualize and aggregate all the data in order to analyze a system in whole. Each piece of the system data is stored by each stakeholder in spreadsheets. This implies a suggestive process to support the risk analysis process as the assumptions underlying analysis, data sources and knowledge of thought processes of the team members are generally not recorded. As a result, the quality and coverage are affected: a bottom-up approach may result in comments being missed (coverage) and missing the source of the data (brainstorming).

- Subjective analysis audit

Various FMEA guides/books stress the importance of FMEA quality see Carlson. C. S. (2012) and McKinney B. (1991). However, the FMEA quality audit is rather subjective as it relies on subject matter expertise and often is limited to checking that the standard procedure was correctly followed. This does not provide accurate and objective assessment of the quality of analysis. A major problem is repeatability of FMECA when carried by a different team of analysts (Bell D., Cox L., Jackson S. & Schaefer, P. (1992)).

- Platform reliability based on design parameters

In current engineering practices, designers do not necessarily understand how the operators will use the system and this is a critical issue for the reliability of the platform as (Reliability, Availability and Maintainability) RAM / (Integrated Logistics Support) ILS should be based on operationally determined RAM parameters rather than the design parameters. Design parameters are normally sourced from third party references that do not account for concept of operations, environment, etc. Thus it is important to document the source of the information, and list associated assumptions or else quality issues will occur.

- Isolated system analysis

Historically individual technical risk assessments associated with the deferral of maintenance or acceptance of technical defects are conducted in isolation using spreadsheets and therefore do not take into account the potential dependencies across the platform. This could lead to either safety issues or equipment breakdown and thus additional efforts to mitigate risk. Integrating isolated analysis on the higher system level by merging different spreadsheets is almost impossible due to potential taxonomy and hierarchy issues. This impacts the quality of the aggregated analysis performed at the system level.

## 3. MAINTENANCE AWARE DESIGN ENVIRONMENT (MADE)

MADe (Rudov-Clark S., Stecki J. & Stecki C. (2011)) is a model-based engineering software tool for conducting risk assessment (FMECA, RAM, RCM, FTA) – where each element in the model is associated with a number of key attributes such as its functional description, the specific physics of failure information (cause, mechanism, fault, symptoms) – as shown on Figure 1- and their relevant criticality based on the system performance requirements.

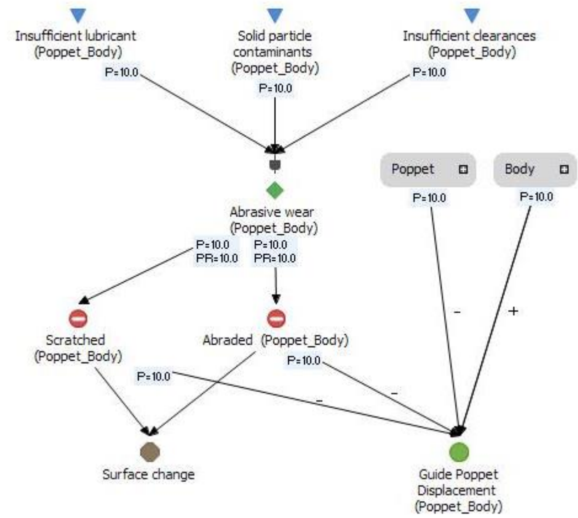



Figure 1. MADe Failure diagram - mapping of failure concepts

MADe utilizes simulation to propagate and trace the dependencies and impacts of any fault injected into the system as shown on Figure 2. This data is used to generate a functional risk assessment based on the associated physics of failure. Simulation is an important feature of the tool, as with highly complex systems it is difficult to identify how the impacts of a failure will propagate – without this knowledge it is impossible to accurately determine the criticality of a specific failure mode.

MADe automates the dependency mapping of a system using the functional path propagations that are generated in the model. The system model is easily updated, modified and MADe enables to conduct 'what-if' analysis for an actual or proposed design and its constituent systems, components and parts.

As it is simulation based, the software is fundamentally and significantly different from spreadsheet/databased tools because the model and therefore the analysis is extensible, objective and repeatable. As a Model Based Engineering (MBE) tool, MADe offers a number of advantages over available spreadsheet/database FMEA/RAM toolsets.

- Knowledge capture, reuse and transfer

All knowledge about the system and its components is captured in models which can be saved and reused for any other project. These user developed models are stored in a re-usable directory called a Library.

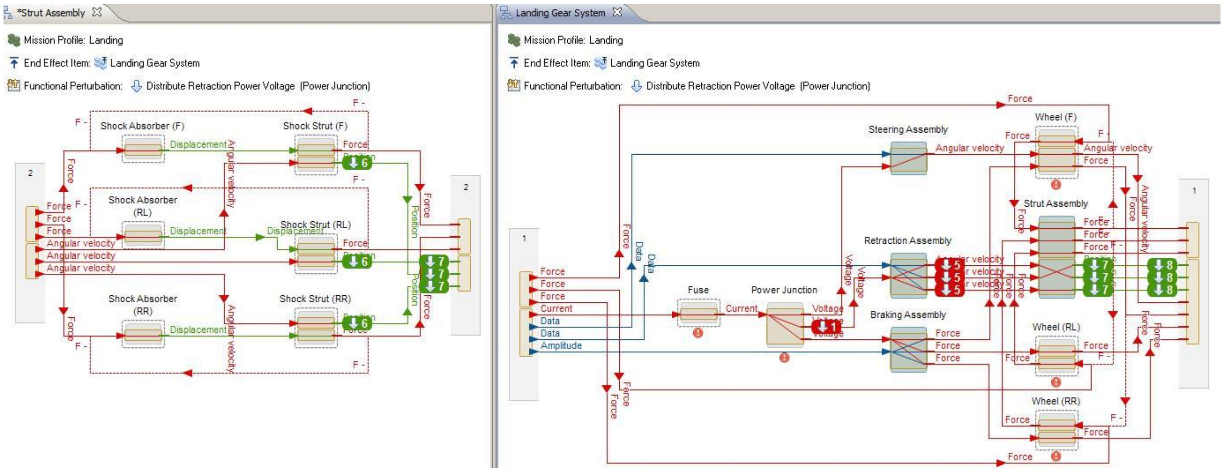


Figure 2. MADe functional diagram of landing gear - showing failure propagation

Models of components/systems can be loaded from the Library and re-used to represent a new system (dependencies will be automatically established). The key benefit is the improved quality of analysis, as knowledge is captured and re-usable for future projects.

- Standardized taxonomy

MADe uses standardized taxonomy of functions/failure concepts to ensure that there is consistency of terminology (and therefore understanding) within the organization and currency of data at each stage of the platform life-cycle (Rudov-Clark, S.D. & Stecki, J. (2009).

Audit and validation are based on the input of references for the sources of data. A standardized taxonomy brings objectivity in the performed analysis.

- Concurrent engineering

Model-based Engineering (MBE) enables concurrent engineering features such as functional simulation which means that the development of a system model can be associated with the functional requirements of a system rather than a specific design. This enables the ability to generate the model - and conduct modelling analyses - at the conceptual stage of the design process to evaluate the impact of changes to the design and mitigate risk at an early stage in the platform life-cycle.

- Integrated capabilities

MADe uses a single model (a *Single Source Of Truth (SSOT))* as basis for other analysis tasks. A model of the system is used for reliability analysis (both functional and hardware), sensor selection (sensors coverage), Reliability Centered Maintenance (RCM) etc. This eliminates the need to export data or results of analysis as the same model is used for all the analysis.

- Configuration management of the analysis

Because MADe generates each analysis based on the common system model, the impacts of any changes made by other functional groups within the organization are automatically reflected in the model (and thus future analyses). This considerably improves the quality of analyses as data come from a *SSOT* model.

- Integrated system analysis

The toolset uses automated dependency mapping which eliminates the manual determination of the impacts of failures across the system. This enables risk analysis to be based on objective and verifiable data. MADe automatically establishes these connections and updates them when the system model is modified. This is a major benefit for increasingly complex and integrated systems. The level of details and dependency mapping enable risk identification at the platform level down to the component level leading to enhanced traceability of data.

- Dependencies mapping

A functional model represents a flow of energy, material or signal in the system. Based on *(SSOT*) model of the system, functional relationships and failures/effects dependencies in a system for both functional and physical failures are defined using standardized taxonomies.

- What if..” and “As is..” analysis

“What if...” analyses are often focused on the rearrangement of connections between models and/or inclusion of different components. This capability is normally too time consuming to be achieved using a database approach, but can be expedited using a MBE approach (e.g. copy-paste and library re-use) leading to otherwise unachievable options.

MADe has the ability to update the parameters in the model based on operational data in order to conduct analysis of the system based on an 'as-is' performance state rather than 'expected' (design) state. This has a significant impact on the supportability posture for equipment.

- Objective analysis audit

An objective approach to conduct risk analysis is beneficial for audit purposes and quality checking. A good example of efficient risk analysis verification is FMECA. Using an AQI, the analyst can easily check the completeness of the analysis based on the quality and quantity of the data inputs. When it comes to project management, an AQI can provide a means to evaluating the confidence level of a system globally or a particular risk analysis in order to validate a project.

- Effective integration with the organization IT architecture (specifically PLM).

Current challenges in PLM consist in using a single point of truth for the RAM / ILS analysis that can be shared by the design / supportability engineering communities. As a simulation based model, MADe offers the ability to configuration manage the associated ILS analysis and outputs for a system and automatically regenerate the artefacts that result from any modification to the design or changes to the maintenance regime.

## 4. ANALYSIS QUALITY ASSESSMENT

For any analysis or simulation based analysis, poor quality inputs or improperly defined scenarios create meaningless results. How then to assess the quality of risk analysis?

Analysis Quality Index (AQI) is the process of determining that an analysis provides a correct outcome or solution. An AQI may be applied to numerous different analyses or algorithms (e.g. FMEA, Criticality, Reliability) to evaluate and document the accuracy of the results. An AQI process is implemented in MADe to increase data quality and enable objective audit of risk analysis. The main function of an AQI is to enable the modeler to capture the assumptions used during the process of creating the model. A work flow assessing an AQI is shown in Figure 3. In MADe the process starts with setting up annotation policy Figure 4.

The findings from an AQI can be used to document an analysis or query the effectiveness of another analysis. An example of this is performing an AQI on a FMEA to determine the confidence of a particular subsystem, which when integrated to the system level can identify high-risk areas in a project.

When carrying out engineering functions, assumptions may not be listed, or listed after the fact leading to poorly documented work.

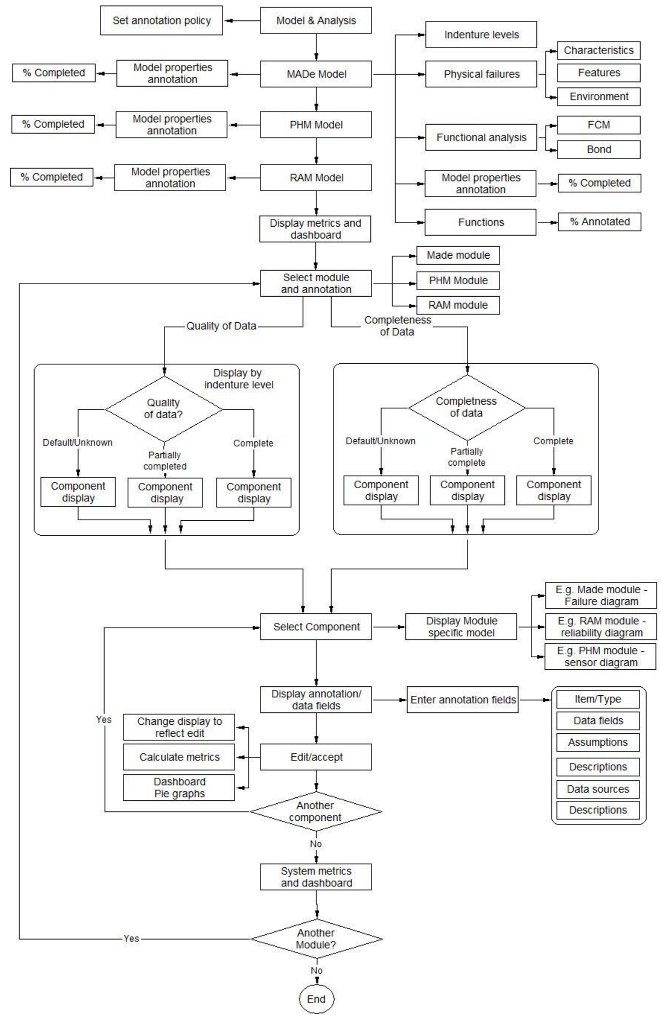



Figure 3. AQI workflow implemented in MADe

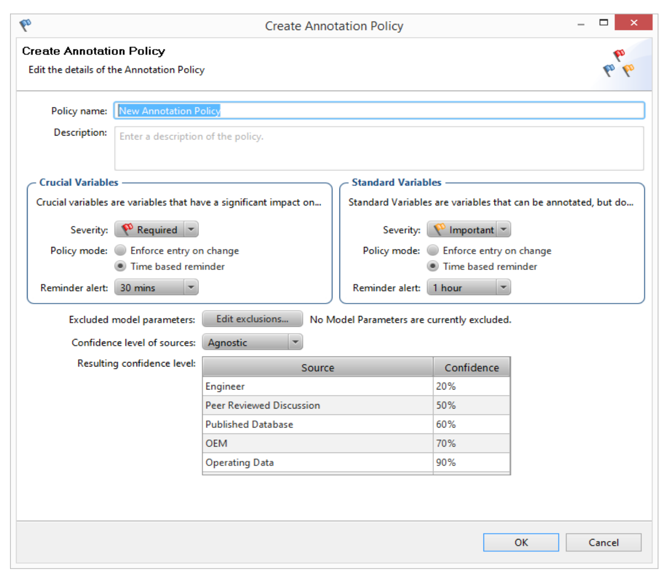



Figure 4. Annotation policy setting

The quality of the assumptions, data and parameters used in a model directly affects the integrity of any analysis output. The solution for this issue in MADe a user enters assumptions for each piece of data, Figure 5.

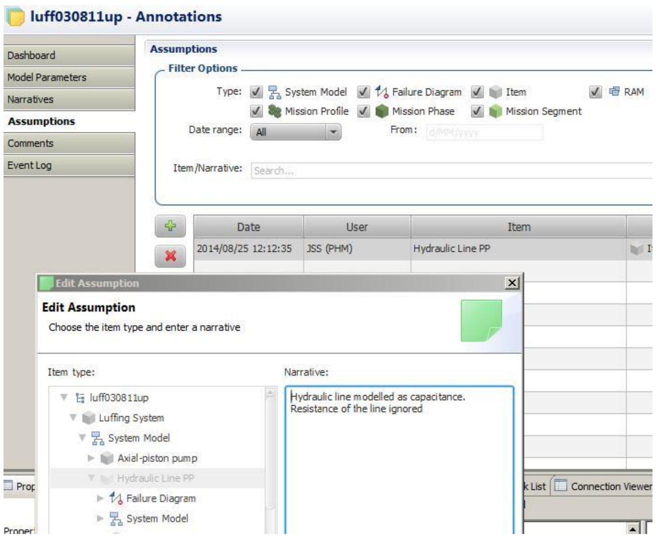



Figure 5. Editing/entering assumptions

However, it is difficult to keep track of the data sources and assumptions that support any parameter used in a model, particularly if multiple stakeholders (including departments, groups, teams and external suppliers) are involved in system development. Therefore a structured approach to documentation and assessment of data quality is essential.

Considering the evolutionary nature of a model, it becomes necessary to capture this information concurrently as the user is modelling. Using this facility will allow more accurate models based on listing of the relevant assumptions, detailed entries including narratives and more consistent processes by capturing considerations. Shown in Figure 6, each parameter edited or changed in the model can be tracked and assessed using an annotation feature that requires each stakeholder to document his data.

To summarize the data quality assessment of a model-based risk analysis such as FMEA/FMECA, requires evaluation of two key metrics:

- Completeness of Data (Data Coverage)
- Data Quality

Once those two metrics are assessed, they can be aggregated to determine the overall confidence level of a particular risk analysis or completeness of a model. An AQI becomes increasingly important as the analysis or models become more complex, thus requiring greater control and management of a larger set of data. The quality assessment concept is especially beneficial for model-based risk analysis.

### 4.1. Data Coverage

The AQI is a metric that may be used to determine the completeness of data used in the analysis. Missing data regarding the system can result in poor coverage of the risk analysis, especially in a complex analysis where there are numerous inputs required. If any of these inputs are missing then the completeness of the analysis is weakened. Completeness can be considered as the ratio the amount of data entered / the amount of data required. Therefore if all data for a process/analysis is entered then the completeness would be 100%, providing a high confidence with the process/analysis. A higher completeness will improve confidence during an audit and prove better traceability of the analysis. Although it is important to note that while an analysis/process is complete, it may not be high quality.

### 4.2. Data Quality

Data quality involves documenting the source, confidence level and assumptions underlying each piece of data that is used as an input parameter for the analysis.

This process aims at documenting critical questions regarding a model or a particular analysis:

- Where does a particular parameter or data set come from?

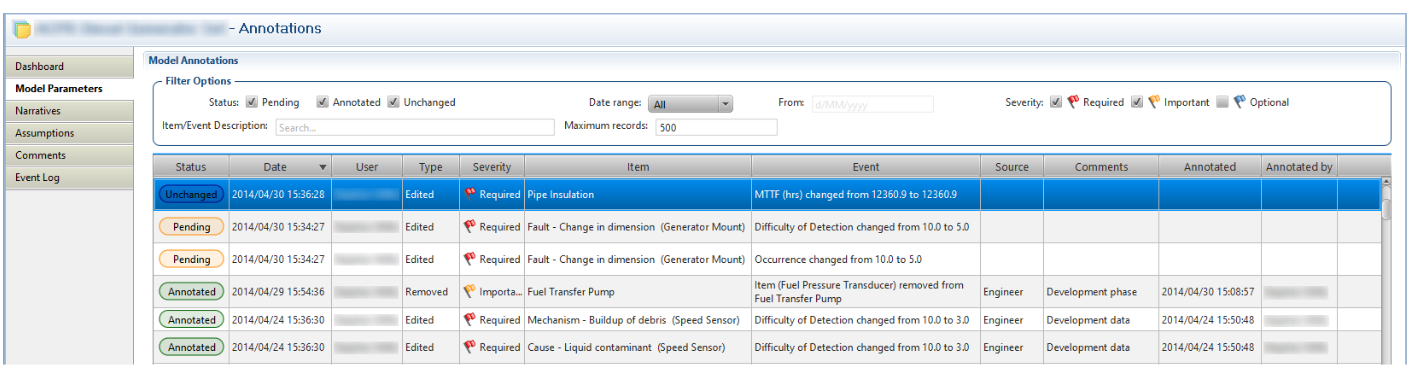



Figure 6. Annotation summary

- Who sourced this data?
- Why was it set to this particular value?
- Which confidence to assign to a particular data?

The quality of data can range from conceptual (brainstorming) to collected data (operation) and is important in defining the quality of the data used in the analysis. Previous articles on the quality of analysis (Evans J. (1992).) explain that in order to avoid poor data quality, "it is essential for everyone with a real-word problem to insist on an adequate, numbered, list of assumptions, where the assumptions are in reasonably plain language". To rank quality, different categories can be assigned which correspond to different sources (e.g. engineer, database, etc.). By defining a data source type, a confidence level can be assigned to each type which may be aggregated to provide an overall level of confidence. As the quality of the data sources increases so does the quality of the analysis. The categories and weightings of sources can be adjusted for specific environments or applications. It is also important to track the source where data is obtained from, note the source of the information, time/date of data entry and allow annotation of a particular entry. This information is automatically updated as data is being annotated in the model to provide the percentage of annotated data, data quality, as well as an overall confidence level in the model as shown in Figure 7 and Figure 8.

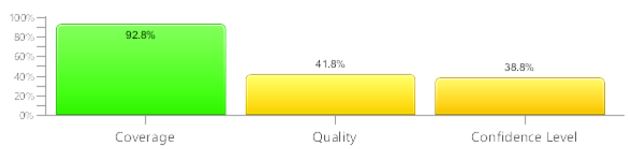



Figure 7. Coverage, quality and confidence level

## 5. CONCLUSION

This paper has outlined a unique approach to assess the quality of risk analysis in a model based engineering environment. In current industry approaches, the extensive usage of spreadsheet/database based tools to conduct risk analysis generates a number of significant issues in terms of cost of conducting analysis, quality and objectivity of the analysis, as well as system level analysis. To solve those issues, it is essential to conduct data quality assessment focusing on the quality and quantity of data used as parameters in the analysis. A good example of assessing the quality of analysis is to apply data quality assessment to model-based risk analysis. The quality assessment process implemented in the MADe software provides objective auditability of all relevant information regarding a particular analysis or a whole system. The confidence level in analysis outputs and thus the quality of analysis are optimized by:

- Documenting and reviewing all parameters used in the model / analysis.
- Mitigating posting cycle issues as expert knowledge to a project file is retained.
- Ensuring that all relevant supporting assumptions are captured.

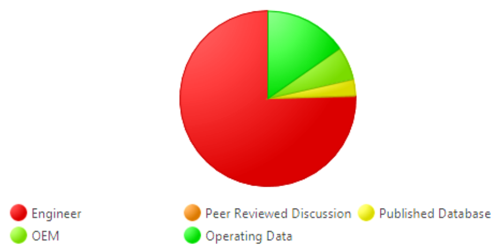



Figure 8. Pie chart showing origin of data

## 6. FUTURE WORK

While this paper has focused on presenting the application of data quality assessment to a model-based risk analysis (AQI) there are other possible applications of data quality assessment.

- Model Quality Index (MQI)

This is the process of assessing the manner and degree to which data used in a model is an accurate representation of the real world and of establishing the level of confidence of this assessment. This index would be useful in model or simulation environments to determine the validity and correctness of a model compared to the system it is based upon. The findings from an MQI could be useful in learning how to create a more accurate or correct model of a system.

- Process Quality Index (PQI)

This is the process of assessing the confidence and adherence to a particular workflow or process. This could be applied to an engineering process and used to assist learning of a new process or even the audit of an existing process within a company. Findings from a PQI could be applied back into the process to optimize it for its function within a company.

## REFERENCES

International Standards Organization (ISO) (2004). ISO 31000:2009: Risk Management - Principles and Guidelines. Genève, Switzerland: International Standards Organization

Bednarz, S. and Marriott, D. (1988). Efficient Analysis for FMEA. *Proceedings of the 1988 IEEE Annual Reliability and Maintainability Symposium* (416-421), January 26-28, Los Angeles, CA, USA.

Bell D., Cox L., Jackson S. & Schaefer, P. (1992). Using Causal Reasoning for Automated Failure Modes and

Effects Analysis (FMEA). *Proceedings of the I992 Reliability and Maintainability Symposium* (343 – 353), January 21-23, Las Vegas, NV, USA.

Carlson. C. S. (2012). *Effective FMEAs.* Hoboken: John Wily & Sons, Inc.

Evans J. (1992). Editorial - CBIA. *IEEE Transactions on Reliability*, vol. 41, 1. March 1992.

Evans J. (1992). Editorial - The Demise of R&M. *IEEE Transactions on Reliability*, vol. 41, 1, . March 1992.

Gilchrist, W. (1993). Modelling failure modes and effects analysis. *International Journal of Quality and Reliability Management*, 10(5), 16-23.

Hunt J.E., Pugh D.R. & Price C.P. (1995). *Failure Mode Effects Analysis: A Practical Application of Functional Modeling.* Applied Artificial intelligence, 9( 1), 33-44.

Kara-Zaitri C., Keller A., Barody I. & Fleming, P. (1991), An Improved FMEA Methodology. *Proceedings of the 1991 IEEE Annual Reliability and Maintainability Symposium* (248-252), January 29-31, Orlando, FL, USA.

McKinney B. (1991). FMECA, The Right Way. *Proceedings of the 1991 IEEE Annual Reliability and Maintainability Symposium* (253-259), January 29-31, Orlando, FL, USA.

Ormsby A., Hunt J. & Lee M. (1991), Towards an Automated FMEA Assistant. In Rzevski G. & Adey R. (Eds), *Applications of Artificial Intelligence in Engineering VI* (739-752), Southampton, Boston: Computational Mechanics Publications.

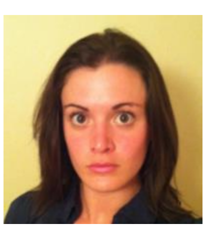
Ross, K. & Main, B.W. (2001). Risk Assessment and Product Liability. *Product Liability Committee, 34-38.*

Rudov-Clark, S.D & Stecki, J. (2009). The language of FMEA: on the effective use and reuse of FMEA data. *Sixth DSTO International Conference on Health & Usage Monitoring*, March 9-12, Melbourne, Australia.

Rudov-Clark S., Stecki J. & Stecki C. (2011). Application of advanced failure analysis results for reliability and availability estimations. *AERO '11 Proceedings of the 2011 IEEE Aerospace Conference* (pp 5), March 5-12, Big Sky, USA.

Wirth, R., Berthold, B., Kramer, A. & Peter, G. (1996). Knowledge-based Support Analysis for the Analysis of Failure Modes and Effects. *Engineering Applications of Artificial Intelligence*, 9(3), 219-229.

## BIOGRAPHIES



**Leila Salhi** is a junior engineer at PHM Technology. She studied physics engineering and micro-technology in a French engineering school and completed an associate's degree of management of high-tech innovation. She worked on a research project involving an Australian mining company during her internship at one of Royal Melbourne Institute of Technology University's research centers.

**Dr. Jacek Stecki** is the Chief Technology Officer of PHM Technology. He has over 40 years research and industrial experience working in Poland, Australia, USA and Italy, Norway, UK, Switzerland and Denmark. Research projects in fields of fluid power, risk management, machine condition monitoring and modelling and simulation. Director of the Centre for Machine Condition Monitoring, Monash University, Australia (1980-1998). Consultant in Australia, USA, Norway, Switzerland and Brazil with major industrial and mining companies in areas of fluid power, subsea engineering and machine condition monitoring.. He has also written over 120 technical and scientific papers on the subjects of maintenance aware design, fluid power, simulation, risk and reliability assessment (MADe software), model based diagnostics, tribological systems (contamination/wear).

**Chris Stecki** Chris Stecki is the CEO and Co-Founder of PHM Technology, the developer of the Maintenance Aware Design environment (MADe). MADe is currently used by Defence organisations and their suppliers in Australia, Europe and the US. Chris is a frequent presenter at industry and technical conferences around the world on engineering system design and supportability (particularly System Health Management). He has co-authored a number of technical papers relating to aspects of the engineering design process, and the advanced engineering and IT techniques used in the on-going development of the MADe software.