Risk Quantification for New Product Design and Development in a Concurrent Engineering Environment

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ABSTRACT
The challenges of product design and development in concurrent engineering are analysed. Bayesian Belief Networks are applied to map the relationships between risk events in a product’s life-cycle. This approach enables the concurrency between risk items to be captured and the cumulative effects of dependencies between risk events to be determined. The inheritance of risks between different phases is modeled and quantified, which is impossible by traditional project management techniques. The combination of these factors has resulted in a user-interactive, unique dynamic risk management software package, which has been commercialised and deployed successfully by a major international manufacturer.

Keywords: Product Development, Concurrent Engineering

1 INTRODUCTION
Risk management in concurrent engineering (CE) projects is an iterative and continuous process that occurs throughout the lifecycle of projects. Although faster product design, development and delivery are the intended outcomes of CE, one of the undesirable by-products is an increase in risks as a consequence of uncertainties between interdependent processes. Multi-disciplinary tasks, characterized by knowledge sharing and reuse as well as design co-ordination, are conducted concurrently in many product development projects in order to reduce the time needed to market new products or services and to optimize design activities [1]. The complexity and associated risks in planning and managing such projects are increased by the need to integrate the functions of both technical and non-technical (such as marketing and customer support) teams that may be distributed across geographical regions. According to Tseng et al [2], every aspect of engineering design and/or manufacturing capability has not been linked with customers and suppliers proactively throughout the product development process as well as lack of collaboration across boundaries. Thus, to expand from designing products to designing the complete product development process is rewarding but challenging as well, introducing several risks to CE projects.

The effectiveness of frameworks that aim for risk management in CE projects is determined by the degree of data sharing and reuse, as well as the available support for decision making processes within the projects [3,4]. Knowledge within such frameworks, encapsulated in the form of standardized operating procedures, can be used to generate scenarios that simulate the consequences of different risk management decisions. These results are useful in supporting decision making processes and augmenting critical dependencies between project risks, which are in turn used as feedback to risk analysis processes, hence creating the iterative nature of risk management processes.

This paper presents an Intelligent Risk Mapping and Assessment System (IRMAS™) that is developed to capture, assess, organize, store, share and update project related knowledge to support risk management in multi-site, multi-partner CE projects. It describes the utilisation of decision trees to map the relationships between risk item events in several phases of a product’s life cycle, modeled in IRMAS™, by applying Bayesian Belief Networks. This approach enables the concurrency between risk items to be captured and the cumulative effects of dependencies between risk item events to be determined. The inheritance of risks between different phases is also modeled and quantified. Additionally, validation of the model is discussed by using financial measurements gathered from industry.

The core of the research is a reasoning methodology used for Knowledge Elicitation which will not only support the decision-making process of the user, but also aid the knowledge retrieving, storing, sharing and updating process of manufacturing organisations. A total of 589 risk factors were identified for different project types, and information on 4372 factors and 136 lessons learnt were collected from previously completed projects. The system has been validated in industry and deployed by a major international manufacturing company.

This research also provides a systematic engineering approach to risk management of concurrent product and process development based on Risk Management Standards [5] and the Project Management Institute’s Guide to the Project Management Body of Knowledge [6].

2 THE INTELLIGENT RISK MAPPING AND ASSESSMENT SYSTEM (IRMAS™)
A review of current commercially available off-the-shelf risk management tools used for multi-site engineering projects by Zhou et al. [9] identified that these tools generally lack a systematic “risk roadmap” required to identify, capture, and visualize the causal relationship of risk factors and their accumulated and inherited impacts in CE product development projects. It was also found that commercial risk management tools available are unable to readily leverage off lessons learnt from previous projects. As a result, the effectiveness of knowledge sharing, re-use and management within the tools is limited to existing pre-defined knowledge [10]. Although new knowledge based on lessons learnt may be inserted into knowledge repositories, the process is usually manual and time-consuming.

IRMAS™ is designed as an agent-based project risk mapping and assessment tool in a web-based project collaborative workbench, aiming to support a ‘Design WITH’ approach. Figure 1 shows the conceptual structure of the system workbench and is briefly explained below.
2.1 Contextual Establishment Agent
The contextual component of IRMAS™ sets the scene for the organizational, project and regulatory requirements. The users identify possible sources of risks through a series of questions to estimate the inherent risks by assigning a weighting to the existing infrastructure of the organisation. These questions are retrieved from the Expert Interview Facility (EIF); a database where all questions related to each product development phase is stored and displayed to the users via the Virtual Workbench. The Virtual Workbench promotes interactions with multi-site project participants and facilitates communication. The workbench also allows the presentation of computed results in the form of a Risk Registry, after each phase of the project is covered by the user.

The Context establishment agent is built as a Java module and interacts with all other agents as described in the following sections.

2.2 Risk Identification Agent
The risk identification process focuses on product, process and project specific risks through EIF. The risk identification needs to be sufficiently generic enabling applicability for numerous projects, yet with the flexibility to capture critical details for future reference as a “lessons learnt” document. Risks are categorised as Schedule, Technical, External, Location, Organisational, Communication, Resource and Financial risks. Six overlapping phases of the product’s life cycle, i.e. conceptual design, preliminary design, detailed design, manufacturing, certification and customer service are covered based on interdependent processes of CE. Then, risk factors are defined within each risk category, narrowing down the scope of risk events. Interaction relationships are then expressed between risk factors through causal diagrams. This also facilitates the design of questionnaires, ensuring that the general risk information gathered is sufficient for the purpose and not repetitive in nature.

2.3 Risk Analysis Agent
After identifying product, process and project related risks, users proceed to initiate the computation of the significance of each risk by using the risk analysis agent. Both qualitative and quantitative techniques are used for calculating the magnitude of risks. The analysis is carried out for both the likelihood and impact (consequence) of all the identified risks.

The impact analysis is carried out using the Analytical Hierarchy Process (AHP) concept [11]. A comparative risk ranking technique is used by asking a comparative question about each risk event compared to another risk event. The information gathered through expert judgements is used to compile pair-wise comparisons to feed the AHP.

The physical form of the Bayesian Belief Network (BBN) [12] is the same as the causal diagrams developed as mentioned in section 2.2, with the addition of entities for user input in a backward chain mechanism. Some risk events are inputs to risk factors while others are outputs from a specific phase. Entities that inherit risks from previous phases are also added. These relationships are defined in BBN and their prior probabilities are determined through knowledge elicitation techniques as described in section 2.5.

The Delphi technique was utilised to collect 4372 items of information, including 1682 items relating to comparative ranking and 2690 to prior probabilities. This method used a written mode of communication for capturing the pertinent knowledge, while the expert interviews used verbal communication to transfer industrial expertise to IRMAS™.

The input data into the BBN as prior probabilities in the form of conditional probabilities were determined by domain experts. Considering that this is a subjective assessment of BBN properties, the conditional probabilities were found to vary depending on a domain expert’s experience and personal convictions. Hence, median values were defined for data sets to define a conditional probability for each pair of related activities in
the BBN. The conditional probability values gathered from experts was converted into prior probabilities at each node, as a combination of one or more pairs of activity relationships depending on a node.

**Dynamic calculations – incorporation of user input**

The causal diagrams form the basis for the development of the BBN with the addition of inherited activities which are only represented as a link in the description of the activity (Figure 2). Further, the act of reading probability occurrence of an activity itself can be represented as an activity in the BBN. This was found to be a necessary step in the construction of a BBN, to isolate user input physically from the activity and facilitate queries to and from the database repository. Thus, the physical nature of the BBN is expanded quite significantly in comparison to the causal network.

The user inputs consisted of values ranging from 1 (low) to 5 (high), and marked “L”. The corresponding values assigned to the user inputs were derived from expert interviews based on the occurrence likelihood of these risks (Table 1).

<table>
<thead>
<tr>
<th>Risk Event ID</th>
<th>User Input</th>
<th>BBN Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>P6-1.1L</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>P6-2.1L</td>
<td>3</td>
<td>0.88</td>
</tr>
<tr>
<td>P6-2.2L</td>
<td>1</td>
<td>0.74</td>
</tr>
<tr>
<td>P6-2.3L</td>
<td>1</td>
<td>0.65</td>
</tr>
<tr>
<td>P6-2.4L</td>
<td>1</td>
<td>0.51</td>
</tr>
<tr>
<td>P6-2.5L</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>P6-2.6L</td>
<td>1</td>
<td>0.10</td>
</tr>
<tr>
<td>P6-3.1L</td>
<td>2</td>
<td>0.35</td>
</tr>
<tr>
<td>P6-3.2L</td>
<td>1</td>
<td>0.46</td>
</tr>
<tr>
<td>P6-3.3L</td>
<td>1</td>
<td>0.10</td>
</tr>
<tr>
<td>P6-4.1L</td>
<td>2</td>
<td>0.74</td>
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<tr>
<td>P6-5.1L</td>
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</tr>
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<td>P6-6.1L</td>
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</tr>
<tr>
<td>P6-7.1L</td>
<td>1</td>
<td>0.81</td>
</tr>
<tr>
<td>P6-8.1L</td>
<td>1</td>
<td>0.60</td>
</tr>
</tbody>
</table>

Table 1: A sample user input and output from BBN for Phase 6 – The product life cycle.

The risk event occurring provides a starting point for the analysis of the true risk likelihood value for the project. This is stored in the database repository. The analysis agent queries the database for both the likelihood of occurrence of each risk event indicated by the user which is stored as a raw input and values for inherited risk events from previous phases. These are written into an instance of JavaBayes input file for the Product’s Life Cycle Phase network construct already containing prior probabilities. The JavaBayes solver then provides calculated posterior probabilities on querying. The complex agent then returns posterior probabilities to the database for further analysis of risk magnitudes. From the output column in Table 1 it is clearly evident that the user input is substantially modified after taking into account the knowledge from the domain experts in the form of conditional probabilities. The BBN agent in the intelligent risk mapping and assessment system has been validated against decisions from experienced project managers, and it provides a basis for risk analysis by project personnel who have limited exposure to the problem domain.

**Applying BBN to risk likelihood analysis**

The requirement for the BBN based decision support module arose in IRMAS™, as previously explained, from the need to determine the true likelihood of a risk item from user input into the questionnaire and to adjust the likelihood based on other connected risk events and prior probabilities of these events. Table 1 presents output from the Bayesian Belief Network constructed for Phase 6 of a CE design project of an industrial partner.

**2.4 Risk Mitigation Agent**

Based on the significance of risks computed by the risk analysis agent, users invoke the risk mitigation agent to select significant risk items to be added into a risk register for mitigation. The risk mitigation strategies are provided following the calculated risk magnitudes. The priority of a risk is not simply the magnitude of the risks but also the relevance of the risk likelihood and impact.

**2.5 Knowledge Management Agent**

A key feature of IRMAS™ is the reuse of expert knowledge and lessons learnt from previous projects that are stored for later elicitation in the system’s knowledge repository. In addition, the repository stores case studies, best practices, customer and supplier profiles, analysis results, risk factors, event drivers, and alternative mitigation strategies. Upon project completion, user-refined mitigation strategies as captured by the risk mitigation complex agent are reviewed and indexed in the repository. This knowledge management feature allows future projects to leverage off success factors and avoid past pitfalls.

Figure 2: A small portion of a causal diagram of **Phase 6** for IRMAS™.
A total of 589 risk factors were gathered to cover design and build, derivative design and build to print projects. Also, 136 lessons learnt and 35 Best Practices had already been stored in the knowledge repository.

3 VALIDATION

In this research, initially a first tier approximation method was used in order to ascertain any anomalies in the BBN component due to the complexity of the maps employed. Finally, the risk likelihood and consequence were combined and verified using financial measurements. The full validation of IRMAS™ is also carried out in two large scale new product development projects. It has already been decided to be deployed by a large international aerospace company and successfully commercialized.

3.1 First Tier Approximation Method

An approximation technique is used to pinpoint anomalies between the BBN maps and the causal diagrams. This is achieved by querying the cumulative probability for a node excluding the user input for that node. Then the BBN output for each node is checked so that it is not significantly different from the range between the cumulative probability and the user input for a specific node. The BBN maps of any risk item events identified as significantly different from this range were cross referenced with the original causal diagrams in order to determine any discrepancies. The responses of the users to occurrence of likelihood of risks in two aerospace projects are used to validate the accuracy of BBN output for all product development phases. The validation is successfully carried out by achieving on the average, 80 percent accuracy levels of risk likelihood approximations as shown in Figure 3.

3.2 Financial Measurements

The magnitude of the risk likelihood and its consequence was validated against financial measurements, specifically costing data for both of the case studies. This was achieved by ensuring that the output from IRMAS™ was proportional to the costing data. Any risk items identified outside this criterion were re-assessed for their prior probabilities and the knowledge elicitation process re-visited using the Delphi technique from experts. The financial measurements, similar to the initial validation outlined in section 3.1, show a good correlation between the IRMAS™ output and the costing data.

4 CONCLUSION

This paper describes how IRMAS™ is designed as an agent-based CE project risk management tool. The agents developed work collaboratively to identify and assess project risks. The wealth of knowledge in the knowledge repository is also reflective of the incorporation of explicit knowledge. Bayesian Belief Networks are applied to map the relationships between risk events in a product’s life-cycle. This approach enables the concurrency between risk items to be captured and the cumulative effects of dependencies between risk events to be successfully determined.

5 ACKNOWLEDGEMENTS

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6 REFERENCES


Figure 3: The percentage of accuracy achieved in BBN outputs for all phases of product development.