Expert Systems with Applications 36 (2009) 9879–9890

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Assessing new product development project risk by Bayesian network with a systematic probability generation methodology

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ARTICLE INFO

Keywords:
New product development
Bayesian network
Probability generation

ABSTRACT

New product development (NPD) is a crucial process to keep a company being competitive. However, because of its inherent features, NPD is a process with high risk as well as high uncertainty. To ensure a smooth operation of NPD, the risk involved in the process need to be assessed and the uncertainty should also be addressed properly. Facing these two tasks, in this paper, the critical risk factors in NPD are first analyzed. Since Bayesian network is specialized in dealing with uncertainties, those risk factors are then modeled into a Bayesian network to facilitate the assessing of the risk involved in an NPD process. To generate the probabilities of different kinds of nodes in a Bayesian network, a systematic probability generation approach is proposed with emphasis on generating the conditional probabilities of the nodes with multi-parents. A case study is also given in the paper to test and validate the critical risk factors as well as the probability generation approach.

1. Introduction

In response to a competitive business environment, new product development (NPD) has been playing an essential role in the success of many companies (McCarthy, Tsinopoulos, Allen, & Rose-Anderssen, 2006). NPD, by nature, is a relatively risky activity (Kahraman, Buyukozkan, & Ates, 2007; Kayis, Arndt, & Zhou, 2006; Ozer, 2001) as market competition and product technology advancement are often intense (Di Benedetto, 1999; Mullins & Sutherland, 1998; Srinivasan, Haunschild, & Grewal, 2007). Because of NPD's inherent features, NPD decisions inevitably encounter a considerable amount of uncertainties which may result in negative consequences of the targeted performance (Kahraman et al., 2007; Kayis et al., 2006). Managing risks of NPD projects is therefore becoming important as it is a means to evaluate and mitigate risks of NPD projects (Cooper, 2003; Kayis, Arndt, & Zhou, 2007; Smith, 1999). However, several researchers have found that risk handling in NPD projects in many organizations is often done by using informal and unsystematic methods and based largely on management perceptions (Calantone, Di Benedetto, & Schmidt, 1999; Cooper, 2006; Gidel, Gautier, & Duchamp, 2005; Griffin, 1997). There is an increasing need to develop a systematic and effective method to assess the NPD project technical risks at the early design stage which helps designers to make decisions among alternative designs from project risk point of view.

On the other hand, Bayesian network (BN) is a probabilistic graphical model that represents a set of variables and their probabilistic dependencies. Generally speaking, BN can represent the complex relationship among the elements in a reasoning process. It is a computational model of human reasoning, and of how people integrate information from multiple sources to create coherent stories or interpretations (Cooper, 2000; Eleye-Datubo, Wall, & Wang, 2008; Ren, Wang, & Jenkinson, 2007). BN can imitate human's reasoning process in a quantitative and relative accurate way, and more importantly, it can update the knowledge when new evidence becomes available. This is considered as its prominent merit because it is helpful in a dynamic environment, such as the NPD environment, where new evidence is available from time to time. However, most of the current BN research in NPD project only focuses on the construction of the structure of BN and on the inference of BN, not on the determination of probabilities in BN, which is a necessity before the inference in BN can be performed. Monti and Carenini mentioned a probability generation approach in BN (Monti & Carenini, 2000), but such an approach is only restricted to generating the conditional probability of a node with a single parent. It is thus not applicable for most BN problems with multi-parents, such as NPD.

Based on what has been mentioned above, this paper, with the development of a systemic probability generation methodology, attempts to propose a BN based assessment method, fitting to

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doi:10.1016/j.eswa.2009.02.019

multi-parent situation, to evaluate the NPD project risks. Two areas have been investigated and described in this paper. The critical risk factors in NPD project execution and their interrelationship will be firstly investigated and presented. The second is to develop a BN network for these factors with a systematic probability generation approach, with emphasis on generating the conditional probabilities of the nodes with multi-parents, to facilitate the assessment of NPD project risks. An industrial case is used to demonstrate the effectiveness of this proposed methodology.

2. Literature review

This section consists of two main parts. The definition of NPD project risk factors and existing studies in NPD project risk factors are discussed in the first part. Then, the current risk analysis methods are elaborated on in the second part.

2.1. NPD project risk factors

Risk is an inherent part of business and public life (Tchankova, 2002). It is the opportunities and dangers associated with uncertainty caused by incomplete data and information, or with uncontrollable outcomes. Risk management is the process of understanding potential risks and making positive plans to mitigate, eliminate or take advantage of them (CIMA, 2002; Shaw, Burgess, & Mattos, 2005). It can be realized by a three-step process that includes understanding all the uncertainties, attributing measures to uncertainties and optimization (Focardi & Jonas, 1998). NPD project is a stochastic problem which could be considered as multiple levels of tasks (Anderson & Hoglejar, 2005; Gidel et al., 2005). The NPD project risk is defined as an uncertain event or condition which could result in a negative effect on NPD technical project's objectives. The accomplishment of NPD milestones could be influenced if the associated risks are not managed properly. Furthermore, evaluation of potential project risks prior to the implementation of NPD projects should be made so that projects with higher probability of failure can be determined and as a result companies can handle it before making substantial investment in NPD projects. NPD project execution risk has not been highly focused on in literatures. Although some studies have been done in the area, their essence does not pinpoint at risk factors of NPD project execution. Risk-based NPD evaluation remains vague in many areas (Keizer, Vos, & Halman, 2005; Shaw et al., 2005). In consideration of the theoretical interpretation of risk factors, existing studies in NPD risks can be categorized into three main streams.

The first stream focuses on NPD project management, such as Ayag and Ozdemir (2007), Dey and Ogunlana (2004), Lee, Tsai, and Jih (2006) and Nadkarni and Shenoy (2001). For instance, Nadkarni and Shenoy (2001) proposed a casual map for product development decisions, in which three major industry factors are developed, namely market dynamic, product life cycle and market share distribution. However, the decision context lacks theoretical explanations and is not specially focused on the NPD project risk. Although Dey and Ogunlana (2004) identified some risk related factors for an innovative project, the scope of the study was distinctively devoted to the build-operate-transfer construction project only. To sum up, the first stream of NPD study is not directly related to risk factors of NPD projects. Though the second set of literature addresses the risk related factors in NPD projects, they focus more on a general discussion of risk factors of NPD process (Kahraman et al., 2007; Leithhead, 2000; Mobey & Parker, 2002; Mullins & Sutherland, 1998). Risks factors in terms of technology, human and organization, have been highlighted in the study of Mobey and Parker (2002), but it paid little attention to the interpretation of factors and their sub-categories. Furthermore, business operation risk rather than NPD project execution risk was concentrated on. Similar situation has also been found in the study of Kahraman et al. (2007), risks factors in terms of finance, technique, management and personnel were pointed out but not extensively discussed. The third stream research focuses more on risk management in NPD project (Calantone et al., 1999; Chen, Lee, & Tong, 2007). However, they were not devoted to risk factors of NPD project execution. Calantone et al. (1999) and Chen et al. (2007) emphasized the importance of risk management in NPD activities and proposed a hierarchy for NPD project selection. Nevertheless, their models only coped with the generalized operational considerations in NPD projects than specifically in NPD project risks. In general, the theoretical interpretation of the NPD project execution risk has not yet been supported and an in-depth investigation in the area deems necessary.

2.2. NPD project risk analysis

Many decision methods and techniques have already been employed for risk analysis, such as: behavioral model, failure mode and effects analysis (FMEA), technique for order preference by similarity to ideal solution (TOPSIS), analytical hierarchy process (AHP), analytical network process (ANP), Bayesian network (BN) etc. However, all these tools mentioned, to some extent, have some underlying weaknesses when applied in a complex situation, such as the NPD environment.

Behavior models (Leithhead, 2000; Mobey & Parker, 2002; Mullins & Sutherland, 1998) can neither accommodate complex decision making nor analyze uncertainties quantitatively. As for the application of FMEA (Carbone & Tippett, 2004), since FMEA is in essence a scoring method, it can only indicate the average of performance in a single score and cannot present the true diverse nature of an assessment. On the other hand, a human's judgment, e.g., the human's knowledge on the distribution of different risk states, cannot be modeled by just a precise number by pre-aggregating various types of information. Therefore, FMEA can only be used as a tool for an initial assessment or a rough assessment categorization tool. Kahraman et al. (2007) proposed a fuzzy TOPSIS to analyze the decision-making process in NPD based on the technique of TOPSIS developed by Hwang and Yoon (1981). In such a method, the analysis model of NPD decision making is constructed in a strict hierarchy. However, the practical decision analysis of NPD is a complex problem and thus the analysis cannot always be modeled in a strict hierarchy.

AHP has also been applied in NPD risk analysis (Chen, Lee, & Tong, 2006, 2007; Lam & Chin, 2005; Roger, Calantone, Anthony, & Jeffrey, 1999; Saaty, 1980). On one hand, AHP is a rather straightforward approach which is very easy to understand and implement. On the other hand, the successful application of AHP is based on the assumption that the problem can be constructed in a strict hierarchy in which the elements in the same level are independent of each other. This independency assumption, however, is often difficult to be met in practical applications, especially when there are many aspects to be considered and the relationship among those aspects are very complicated.

To solve the independency problem of AHP, analytic network process (ANP) was then proposed by Saaty (1996). ANP is a more general form of AHP to handle more complicated interrelationships, including dependences, interactions, feedbacks etc., among the elements both in the same level and in different levels. With such a feature, ANP has already been successfully applied in many fields including NPD analysis (Ayag & Ozdemir, 2007; Cheng & Li, 2005; Meade & Presley, 2002; Meade & Sarkis, 1999). Despite the above applications, there are also limitations concerning ANP. For example, ANP can only express relationships among different elements through relative weights generated from pair-comparisons

and the convergence of a so-called super-matrix. It cannot quantify or explicitly demonstrate influences among those elements. In addition, it is inconvenient for ANP to update results due to changes of information and decision factors in a dynamic environment like NPD, in which such changes may occur from time to time. Furthermore, analysis in NPD is usually carried out in an uncertain environment, but it is difficult for ANP to deal with such uncertainties (Jharkharia & Shankar, 2007; Yuksel & Dagdeviren, 2007).

Another potential method for the risk analysis of NPD is Bayesian network (BN). A BN model is a directed acyclic graph (DAG) with nodes labeled by random variables. It connects the variables with arcs, and this kind of connection expresses the conditional dependence by conditional probability tables between the nodes (Pearl, 1988). Different from the decision tools mentioned earlier in this section, BN is a tool for reasoning with probability. It can deal with problems which can be modeled in a network structure. In addition, BN can represent experts' knowledge in domains where such knowledge is probabilistic. More importantly, with the existing algorithms and software, it can conveniently update prior judgments when new evidence becomes available. Because of the above merits, BN has been applied in the analysis of new product development (Cooper, 2000; Nadkarni & Shenoy, 2001). However, in those applications, the emphases were mostly put on how to decide the structure of Bayesian networks, how to perform inference in Bayesian networks and how to analyze inference results. Little attention has been paid on how to generate conditional probabilities in Bayesian networks, which is a precondition for BN analysis.

For generation of conditional probabilities in Bayesian networks, the most classic approach is the noisy OR model (Pearl, 1988) and its generalizations (Diez, 1993; Cozman, 2004). However, such methods can only handle the cases where the states of nodes are binary and the parents of nodes are assumed to be independent. Lemmer and Gossink (2004) and Das (2004) proposed the definition of 'compatible' in order to release the assumptions of independence and the restriction to the binary that could reduce the burden of computation if there is a large amount of nodes. However, in the NPD environment, the definition of 'compatible' is not practical since every combination of parent nodes is possible in NPD environment. In addition, Das's approach is based on experts' direct estimation on the conditional probabilities which may inevitably involve subjectivity and biases, leading to unreliability and inconsistencies (Das, 2004). Monti and Carenini (2000) proposed another way to generate conditional probabilities using pair-wise comparisons. The idea of this approach can be traced back to Schocken's work (1993). In pair-wise comparison, experts only need to encounter two states instead of all the states of a node at a time when they give their judgments on the states' probabilities. In this way, the biases of judgments could be reduced significantly and the consistency of judgments could be easily maintained. However, Monti and Carenini (2000) only generated the conditional probabilities of a node with a single parent, while in Bayesian networks a node can have multiple parents.

Nevertheless, NPD risk management has attracted much attention in literature (Cooper, 2003; Kayis et al., 2006, 2007). However, the identification of risk factors in NPD projects has not been studied in detail (Keizer et al., 2005; Ledwith, 2000). Although BN has some advantages over other decision support tools to assess the risk of a NPD project, it need be improved to overcome certain limitations, particularly in generation of conditional probabilities. Having realized the above situations, the authors have made efforts to investigate critical risk factors in NPD project evolution, and develop a systematic methodology for generating conditional probabilities for nodes with multiple parents in Bayesian networks in order to facilitate more accurate NPD project risk assessment in a quantitative reasoning process. The results are reported in the following sections.

3. Constructing a NPD project risk network

Generally speaking, a BN is composed of two parts, namely, a qualitative part and a quantitative part. The qualitative part of a BN is a DAG, in which nodes with several states represent the variables of interest with uncertainty, expressed in probability, and the directed arcs pointing from a parent node to a child node represents the casual and conditional dependency relationship between those two nodes. The nodes without parents are called root nodes of the network. As for the quantitative part, it mainly refers to the relationship among a node and its parents. The relationship can be expressed by the probability of the states of such a node on the conditions of different combinations of its parents' states, and such conditional probabilities can be formed as a conditional probability table (CPT) of such a node. After specifying the structure as well as the conditional probabilities, a Bayesian network can be constructed. When new evidence becomes available that determines the prior probabilities of the states of root nodes, the inference is performed to calculate all the marginal probabilities of each state of all the nodes in the network according to the new evidence. Such an ability of updating the knowledge in light of new evidence is one of the most competitive abilities of Bayesian networks.

The authors have built an NPD project risk network to conduct a BN based analysis on NPD projects. The objective of this network is to assess NPD project risk in terms of a company's technical considerations and to facilitate the evaluation of NPD projects. The NPD project risk is firstly defined and elaborated. Then, its sub-factors and interrelationships among the sub-factors are addressed. The developed NPD project risk network is presented and described below.

3.1. NPD project risk (NPD_Risk)

The risk of a NPD project is defined here as the probability that the NPD project cannot be executed within the expected duration. Market fitness, technical competencies, financial issues and operational uncertainties are categorized as the critical aspects for the NPD project selection (Calantone et al., 1999; Gidel et al., 2005). Among these uncertainty aspects, company risk factors for NPD project execution in terms of technical consideration is highlighted in this study since technological impact usually brings most challenges in NPD decisions in a rapidly changing market (Ayag & Ozdemir, 2007; Calantone et al., 1999; Ledwith, 2000; Mullins & Sutherland, 1998). Project technical fitness was preliminary discussed in terms of product design (delights features), manufacturability, product quality and supplier stability (Calantone et al., 1999). In fact, NPD execution process can be categorized into three major steps, namely concept development and prototype development, manufacturing start-up and technical service (Ledwith, 2000). Uncertainties may be found throughout various stages of NPD. For instance, the likelihood of developing and acquiring an advancing technology, which belongs to risk in research and development, may affect product functions and performance. As well, the possibility to produce a new product is connected to the ability to incorporate the new technology into mass production. Higher production capability will certainly reduce NPD project risk. Furthermore, if a company has better understanding in the new product and process technologies, product reliability and service lifetime are more likely to be promised. In addition, it is important to have a reliable supply of material and outsourced components, which is essential to maintain stable cost, quality and delivery of supplies, especially if the technological uncertainty in NPD project

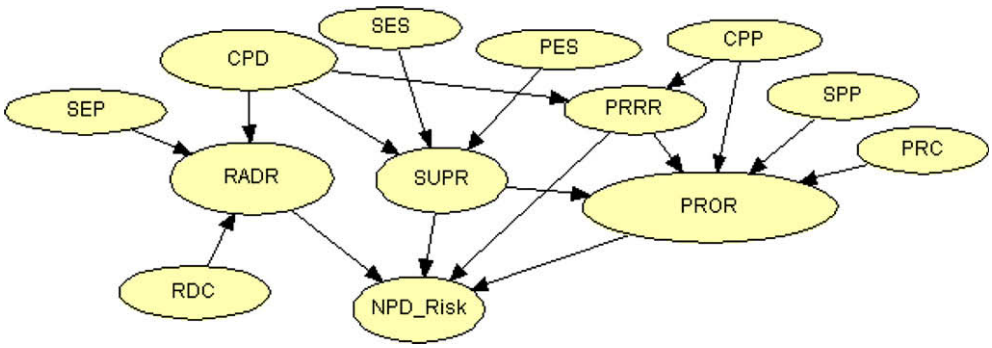

Fig. 1. NPD project risk network.

is intense (Gidel et al., 2005; Petricka & Echols, 2004; Ragatz, Handfield, & Scannell, 1997). In other words, a risky supply will lead to high NPD project risk. Accordingly, NPD project risk can be divided into four categories of sub-factors, namely, research and development risk (RADR), production risk (PROR), supply risk (SUPR) and product reliability risk (PRRR), which are further elaborated below and considered as the non-root nodes of the network. Those elements are represented by nodes while the interrelationships are represented by arcs, as shown in Fig. 1 where the abbreviations of nodes are defined in the following discussions and Table 1.

3.2. Research and development risk (RADR)

Research and development (R&D) risk is the likelihood that product specifications cannot be fulfilled within the expected schedule. It concentrates on a company's R&D concerns in NPD regarding R&D capability (RDC), product similarity (SEP) and product complexity (CPD). While difficulties in integrating an advanced technology into product functionality may happen, the likelihood of the company's R&D capability to overcome this is one of the major concerns of product development stage (Mullins & Sutherland, 1998). Also, employing common building blocks in the design stage is likely to ease the development of a new product (Ayers, 2005), since the experience gained in the past may be relevant to the comparable new product. It will result in the higher similarity of the new product as compared with the existing products. In addition, the complexity of product design should also be focused to evaluate how much effort should be put in achieving the R&D project (El-Haik & Yang, 1999). For instance, a number of DFX (design for manufacture, design for assembly, design for quality, etc.) principles and rules can be integrated in the product design stage to reduce the complexity of product design in the industries (Chen et al., 2007).

3.3. Supply risk (SUPR)

Supply risk is the likelihood that the supplier is not able to deliver quality raw materials/components within the expected schedule. The likelihood of a stable supply of materials is determined by different criteria. An existing and reliable suppliers' list is the first criterion, and risk can be shared by a list of reliable suppliers as they could bear the responsibility of the quality and availability of some critical components (Petricka & Echols, 2004), i.e., management of supplier performance (PES) is one of the critical factors. Secondly, if the similarity of new products and existing supplies (SES) is high, the company should already have track records of the required supplies (Zimmerman, 2007), and so a stable supply of material is easier to be achieved as a result to enhance new product feasibility (Petricka & Echols, 2004). Thirdly, the complexity of the new product (CPD) determines the company effort

Table 1
Description of root nodes of the NPD project risk network.

Root nodes	Description
CPD – Complexity of the product design	It is the measure of the extent to which the complexity of the product design is evaluated from the technical viewpoint on the nature and maturity of product technologies incurred in functional mechanisms and product features. More components and smaller size will generally cause higher complexity risk
SEP – Similarity of the existing product	It is the measure of the extent to which the new product design and the existing products in the company have common or similar product structure, functional mechanism, assembly methods, material/ component used, etc. It is the case in general that higher similarity brings lower R&D risk, and innovative product may have higher R&D risk
RDC – R&D capability	It is the measure of the extent to evaluate the company's potential to articulate successful R&D activities. It can be determined by the level of experience, knowledge and competence of the R&D engineers in the company and their track record in solving product design problems
SES – Similarity of the existing supply	It is the measure of the extent that evaluates the similarity and commonality of the raw material and outsourced components of the new product and the ones of existing products in the company. It is understood that higher similarity and commonality will have lower supply risk in both quality and delivery aspects
PES – Supplier performance	It is the measure of the extent that evaluates the reliability and quality of the suppliers. If the raw material and outsourced components can be supplied by the existing suppliers with good/acceptable performance, the supply risk is surely lower
CPP – Complexity of the production process	It is the measure of the extent that evaluates the complexity of the production process from the technical viewpoint on the nature and maturity of technologies incurred in production processes. The precision requirements, ease of assembly, requirements of specialized equipment/tooling, degree of automation, etc. will generally affect the complexity risk
SPP – Similarity of the production process	It is the measure of the extent that evaluates the similarity and commonality of the production process, equipment and tooling, operations procedure, etc. of the new product and the ones of existing products in the company. It is understood that higher similarity and commonality will have lower production risk in both quality and productivity aspects
PRC – Production capability	It is the measure of the extent that evaluates the company's potential to articulate successful production activities. It can be determined by machines/equipment precision, production process capability, competence of the production operators and engineers, effectiveness of quality assurance system, efficiency of maintenance, etc. in the company

required in NPD, for instance the NPD resources allocation (Bashir & Thomson, 1999) in human resources and supply of materials etc. Due to the higher complexity or advancement of new products, companies may encounter higher difficulties in searching for the suitable components. While those components should be able to fit the complex product purpose and align with the functionality of other components, extra efforts should be put in order to obtain a stable materials supply, such as collaborative NPD by the inclusion of manufacturing, suppliers and customers (Tan & Tracey, 2007).

3.4. Product reliability risk (PRRR)

Product reliability risk is the likelihood that a stable production process and an expected product performance in its service lifetime can not be fulfilled. The complexity of product design and production process, CPD and CPP, contributes to the achievement of reliable production and product performance. A simpler and reliable product design, e.g., by employing modular design (Nepal, Monplaisir, & Singh, 2007), multiphase development approach (Zimmerman, 2007), etc., will enhance the reliability and maintainability of a new product. By employing quality function deployment (QFD) approach (Braglia, Fantoni, & Frosolini, 2007), product reliability can be achieved by translating customers' requisites into functional requirements in the product design phase (Doganaksoy, Hahn, & Meeker, 2006). As well, a better management of production process will also enhance the reliability of a product. This view can be realized by the adoption of process capability analysis chart (PCAC), which is recognized as an essential element to product reliability assurance, throughout the manufacturing processes (Shu, 2004).

3.5. Production risk (PROR)

Production risk is the likelihood that the production requirements cannot be met within the expected schedule. It is affected by production process similarity (SPP), production process complexity (CPP), supply risk (SUPR) and production reliability (PRRR) and production capability (PRC). If a production history for producing similar components exists, the production risk can be reduced because the critical production process parameters are familiar (Zimmerman, 2007). Furthermore, the success of production may also be affected by the existing production capacity and the complexity of the new production process (El-Haik & Yang, 1999). As well, the fulfillment of production cannot take place if a reliable supply of materials components is absent. The collaboration between the company and suppliers is crucial to support NPD production process in time, quality and costs by sharing the workload to suppliers (Quesada, Syamil, & Doll, 2006). Also, a reliable production process is critical to achieve a stable production outputs in terms of production quantity and product quality (Nyberg, 2005), as it prevents the loss of idle, alternations and repairs. In addition, the production capability, which is able to articulate stable and reliable operational activities, is also critical to the fulfillment of the production expectation.

Next, the description of root nodes is addressed in Table 1. After constructing the structure of the network, i.e., the qualitative part of BN has been specified, the next step is to determine the quantitative part, i.e., the probabilities, in BN.

4. The proposed systematic approach in determining the probabilities of Bayesian network

As discussed in Section 2, few efforts have been focused on the generation of probabilities in BN. Although Monti and Carenini (2000) proposed to generate conditional probabilities by pair-wise comparisons to reduce the biases and ensure the consistency of experts' judgment, they only raised the idea in generating the conditional probabilities for nodes with a single parent, not for nodes with multiple parents. In this section, we propose a methodology to systematically handle three kinds of nodes in a Bayesian network, namely, nodes without any parent, nodes with a single parent and nodes with multi-parents. For nodes without any parent, our task is to estimate their prior probabilities, while for nodes with single or multi-parents, their states' probabilities conditional on their parents' states (or state combinations) should be approximated. Particular effort has been concentrated on the probability generation for nodes with multi-parents. The methodology is elaborated below.

4.1. Generation of prior probabilities

Suppose there are n states $S_1, S_2, \ldots, S_n$ of a node N which has no parent, and the probability of each state S_i, i.e., $P(S_i)$ need to be specified.

Traditionally, $P(S_i)$ is specified directly by experts, using their knowledge and experiences. When the number of states is small, such a method may be feasible. With the increase of states of a node, estimating probabilities directly to all states at one time may inevitably involve biases and inaccuracies.

An alternative way is to perform pair-wise comparisons between states for generating their probabilities. Since there are only two instead of n states considered at one time in a pair-wise comparison, it should be much easier to provide judgments by pair-wise comparisons than the direct estimation of probabilities. In the new approach, the prior probability of each state of a node can be determined by the following pair-wise comparison matrix:

	S_1	S_2	$\cdots$	S_n	ω
S_1	a_{11}	a_{12}	$\cdots$	a_{1n}	ω_1
S_2	a_{21}	a_{22}	$\cdots$	a_{2n}	ω_2
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_n	a_{n1}	a_{n2}	$\cdots$	a_{nn}	ω_n
$\lambda_{\max}$=		CI=		CR=	

In the above matrix, $a_{ij}(i = 1, 2, \ldots, n; j = 1, 2, \ldots, n)$ can be specified by questions like "comparing the state S_i with S_j, which one is more likely to occur and how much more likely?" and the value of a_{ij} represents the multiple of the likelihood of the presence of S_i over that of S_j. Note that from the meaning of a_{ij}, we can find that $a_{ji} = 1/a_{ij}$ and $a_{ii} = 1$, so there are $n(n-1)$ different comparisons in the above pair-wise comparison matrix. However, it is sufficient to provide $(n-1)$ inter-related comparisons rather than all the $n(n-1)$ different comparisons, although it is useful to have more comparisons for checking consistency.

Similar to Saaty's AHP, the relative priorities of S_i can be generated from the maximum eigenvector $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ of the matrix $(a_{ij})_{n\times n}$ and the consistency of the pair-comparison matrix can be checked by the consistency ratio CR = CI/RI, where CI is the consistency index, which is defined by $(\lambda_{\max} - n)/(n-1)$ ($\lambda_{\max}$ is the maximum eigenvalue corresponding to ω), and RI is a random index related to n as shown in Table 2. A pair-wise comparison matrix with CR less than 0.10 is considered acceptable.

Table 2
Random consistency index.

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Since the sum of all the elements in ω is 1 and its ith element ω_i represents the relative importance of the state S_i among all the states, it is natural to interpret ω_i as the prior probability of state S_i. In other words, we have

$$P(S_i) = \omega_i$$

4.2. Generation of conditional probabilities for a single-parent node

Suppose in a Bayesian network as depicted in Fig. 2, node N has a single-parent node M, and there are respectively n and m states at the node N and node M, which can be represented by S_{N1}, $S_{N2},\ldots,S_{Nn}$ and S_{M1}, $S_{M2},\ldots,S_{Mm}$ respectively. Our task is to estimate the probability of each state of the node N conditional on each state of the node M, i.e., $P(S_{Ni}|S_{Mj})$ ($i = 1, 2,\ldots,n$, $j = 1, 2,\ldots,m$).

Similar to the estimation of prior probability, there are two ways to generate $P(S_{Ni}|S_{Mj})$. For the reason mentioned in part 4.1, the pair-wise comparison method is used here. When the node M is in the state of S_{Mj}, the corresponding comparison matrix is given by

M is in the state of S_{Mj}	S_{N1}	S_{N2}	$\cdots$	S_{Nn}	ω_N
S_{N1}	a_{11}	a_{12}	$\cdots$	a_{1n}	ω_{1j}
S_{N2}	a_{21}	a_{22}	$\cdots$	a_{2n}	ω_{2j}
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_{Nn}	a_{n1}	a_{n2}	$\cdots$	a_{nn}	ω_{nj}
$\lambda_{\max}$=		CI=		CR=	

In the above matrix, a_{pq} ($p = 1, 2,\ldots,n$; $q = 1, 2,\ldots,n$) can be specified by questions like "if the node M is in the state of S_{Mj}, comparing the node N's state S_{Ni} with S_{Nj}, which one is more likely to occur and how much more likely?". After we get ω_{ij} ($i = 1,\ldots,n$), we can set

$$P(N = S_{Ni}|M = S_{Mj}) = \omega_{ij}$$

Since the node M has m states, m matrices should be constructed before we can get all ω_{ij} ($i = 1, 2,\ldots,n$; $j = 1, 2,\ldots,m$), which is the element of the conditional probability table for the node N with the single parent M. Such conditional probability table is shown as follows:

		State of node M			
		S_{M1}	S_{M2}	$\cdots$	S_{Mm}
State of node N	S_{N1}	ω_{11}	ω_{12}	$\cdots$	ω_{1m}
	S_{N2}	ω_{21}	ω_{22}	$\cdots$	ω_{2m}
	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
	S_{Nn}	ω_{n1}	ω_{n2}	$\cdots$	ω_{nm}

4.3. Generation of conditional probabilities for multi-parent nodes

If a node N with n states $S_{N1}, S_{N2},\ldots,S_{Nn}$ in a Bayesian network as depicted in Fig. 3 has k parents, namely, M_1, $M_2,\ldots,M_k$, and the node M_j has the states of $S_{M_j1}, S_{M_j2},\ldots,S_{M_jm_j}$ ($j = 1,\ldots,k$), it will be very difficult for experts to directly estimate the probability of each state of N conditional on the combination of the states of its parents, which is defined by $P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k})$; $i = 1,2,\ldots,n$; $p_j = 1,2,\ldots,m_j$; $j = 1,\ldots,k$. There are so many state combinations of the parents that it is very difficult to figure out the relationship between each combination and each state of N.

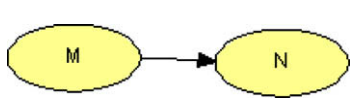

Fig. 2. Bayesian network with a single-parent node.

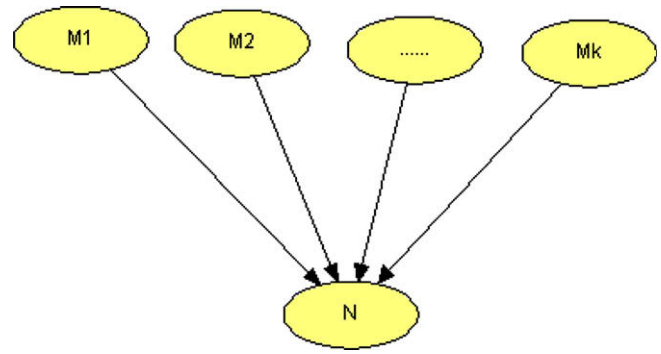

Fig. 3. Bayesian network with multi-parent nodes.

In Section 4.2, we generated the conditional probability of the node with a single parent. So, a natural question arises as to how we can generate the node's probability conditional on each of its parent first and combine those conditional probabilities to get the node's probability conditional on all its parents? This is investigated as follows.

As advocated by Kim and Pearl (1983), when a node A in a Bayesian network has two parents B and C, its probability conditional on B and C can be approximated by $P(A|B, C) = \alpha P(A|B)P(A|C)$, where α is a normalization factor which is used to ensure $\sum_{a\in A}P(a|B,C) = 1$. The above result can be generalized as follows:

$$P(A|X_1,X_2,\ldots,X_n) = \alpha P(A|X_1)P(A|X_2)\ldots P(A|X_n) \qquad (*)$$

In $(*)$, α is a normalized factor to ensure $\sum_{a\in A}P(a|X_1,X_2,\ldots,X_n) = 1$.

From Eq. $(*)$, we can see that, the probability conditional on multi-parents can be given by the product of the probabilities conditional on each single parent. Then, in our method, to calculate $P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k})$; $i = 1,2,\ldots,n$; $p_j = 1,2,\ldots,m_j$; $j = 1,\ldots,k$, we can first calculate $P\left(N = S_{Ni}|M_j = S_{M_jp_j}\right)$ using the method described in Section 4.2 and then get $P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k})$ from $P(N = S_{Ni}|M_j = S_{M_jp_j})$ using Eq. $(*)$ as follows:

$P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k}) = \alpha\prod_{j=1}^{k}P(N = S_{Ni}|M_j = S_{M_jp_j})$, where α is a normalized factor to ensure that $\sum_{i=1}^{n}P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k})$.

Since the estimation of $P\left(N = S_{Ni}|M_j = S_{M_jp_j}\right)$ is much easier than the direct estimation of $P(N = S_{Ni}|M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2},\ldots,M_k = S_{M_kp_k})$, the method proposed in this section will be more reliable.

After the structure of the Bayesian network is determined in Section 3 and the prior and conditional probabilities are specified in Sections 4.1–4.3, the whole Bayesian network has been constructed and the next step is to specify the input and the output formation of the Bayesian network.

4.4. The input and output formation

Once the Bayesian network has been constructed, the input of the network provides new evidence, i.e., the prior probabilities of the states of root nodes, with the prior probabilities of the states

for a certain node added up to 1. On the other hand, the output of the Bayesian network is the marginal probabilities of the states of each node. And these probabilities can be updated in light of new evidence. In our case, the most important output is the marginal probabilities of each risk state of different alternatives. Based on the results, an alternative with lower risk is preferred.

5. Case study

5.1. Case description

The BN based NPD project risk analysis methodology was validated with a case study in a multinational flashlight manufacturer which demonstrated the applicability and potential of this developed analysis methodology. The company is an ODM (original design manufacture) manufacturer of high-end flashlight products. Identifying customer needs is the first part of its concept development phase of the product development process. The resulting customer needs are used to guide the product designers for developing product requirements, generating product concepts, and selecting a product concept for further development. Every year the company has to assess more than one hundred product concepts and finally develops around twenty new products. A rational and systematic analysis and selection of appropriate product concepts are essential to minimize the NPD failure, in other words to increase the chance of success of the company.

The developed BN based NPD risk analysis methodology was validated in the task of assessing two alternative product design concepts of a new 2AAA penlight during the early product design stage. The two design alternatives, push button switch design and rotary switch design, are more or less able to meet the customer needs, at least the basic performance and functional requirements, and the targeted price range. They may, however, differ in the material used, product structure, manufacturing processes, optional functional and aesthetic features, expected quality, reliability performance, etc. The required information and knowledge were collected from the industrial experts. In this validation, the rationality, flexibility and transparency of the decision analysis process for an industrial product design were examined.

The validation process consists of two steps. The first step is to determine the conditional probabilities of non-root nodes in BN for NPD project risk analysis. Such probabilities reflect the company's strategies, operations and emphasis on the product design analysis, which may vary from company to company, but remain the same in the same company. The second step is to assess the specific alternatives through the specification of the prior probabilities of root nodes in BN. Such probabilities reflect the characters of a specific alternative, and thus they may be different from alternative to alternative, even if those alternatives belong to the same company. Both the steps will be carried out with a pair-wise comparison based approach and the values of pair-wise comparisons are determined by the experts of the collaborating company. After the above probabilities are determined, the inference can be performed to see which alternative is of lower risk and the alternative with the lowest risk should be selected.

Since NPD process is in a dynamic environment, it is very natural that the process may be under some changes. After the alternative has been selected in the above process, the risk of such an alternative may increase because of the changes of the environment. Under such circumstances, certain measures, which can be used to reduce the risk, should be taken. Since different measures may cause different effects, there is a need to select the most proper one. And the process of such selection is also demonstrated in the case study. The risk assessment of this case study is based on the Bayesian network of NPD project risk assessment established in Fig. 1, For each node of the BN, there are three states, namely, High (H), Medium (M) and Low (L).

5.2. Generation of conditional probabilities for NPD project risk assessment network

In determining the conditional probabilities of analysis criteria, pair-wise comparisons are used. Experts are interviewed and pair-wise comparison judgments are applied to pairs of homogeneous criteria. The Product Development Director of the company, who is qualified and experienced in both strategic and technical areas, provided the expert opinion to determine the conditional probabilities. Since there is no single-parent node, the efforts will be focused on the generation of conditional probabilities of multi-parent nodes.

Take the node 'PRRR', product reliability risk, as an example. As demonstrated in the Bayesian network, the node 'PRRR' has 2 parent nodes, namely, 'CPD', the complexity of product design, and 'CPP', the complexity of production process. According to the method in Section 4.3, we should get $P(\text{PRRR}|\text{CPD})$ and $P(\text{PRRR}|\text{CPP})$ first.

When the state of 'CPD' is 'H', as stated in Section 4, the expert should fill out the following matrix by answering the question like "neglecting the influence of the other parent on 'PRRR', when 'CPD' is in the state of 'H', which state of 'PRRR' is more likely to occur, and how much more likely?" For instance, in the following table, given that 'CPD' is at high (H) level of risk, the probability of 'PRRR' being at medium (M) level is 1/2 of the probability of 'PRRR' at high (H) level, and the probability of 'PRRR' at low (L) level is 1/3 of the probability of 'PRRR' at high (H) level. This is reasonable since higher complexity of the product design may lead to higher chance of suffering from performance problems in the product life and thus lead to higher level of uncertainties in product reliability.

The final pair-wise comparison matrix is generated as shown in Table 3.

From the above matrix and the discussion in Section 4.3, we can get the following result:

$$P(\text{PRRR} = \text{H}|\text{CPD} = \text{H}) = \omega_{\text{H}} = 0.5396$$
$$P(\text{PRRR} = \text{M}|\text{CPD} = \text{H}) = \omega_{\text{M}} = 0.2970$$
$$P(\text{PRRR} = \text{L}|\text{CPD} = \text{H}) = \omega_{\text{L}} = 0.1634$$

Similarly, we can get the probability of states of node 'PRRR' on the condition that the state of 'CPD' is M and L, and the results can be summarized in Table 4.

In the same way, the probabilities of the states of node 'PRRR' on the condition of different states of the node 'CPP' are listed in Table 5.

Table 3
The evaluation of the probabilities of PRRR conditional on CPD(H).

CPD = H	H	M	L	ω
H	1	2[b]	3[b]	$\omega_{\text{H}} = 0.5396$
M	1/2[a]	1	2[b]	$\omega_{\text{M}} = 0.2970$
L	1/3[a]	1/2[a]	1	$\omega_{\text{L}} = 0.1634$
CR = 0.0079		CI = 0.0046		$\lambda_{\max} = 3.009$

[a] Expert's judgments.
[b] Reciprocal of the expert's judgments.

Table 4
The probabilities of PRR conditional on CPD's different states.

PRRR	CPD = H	CPD = M	CPD = L
H	0.5396	0.1947	0.0333
M	0.2970	0.4895	0.2502
L	0.1634	0.3158	0.7165

Table 5
The probabilities of PRRR conditional on CPP's different states.

PRRR	CPP = H	CPP = M	CPP = L
H	0.4895	0.1947	0.0302
M	0.3158	0.4895	0.2263
L	0.1947	0.3158	0.7435

After the probabilities of all the states of the node 'PRRR' conditional on each state of its parent nodes have been generated, the probabilities conditional on the state combinations of both its parent nodes can be estimated in the way mentioned in Section 4.3.

For example, when both the state of 'CPD' and the state of 'CPP' are H, we will have

$$P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=\alpha P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPP}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=\alpha P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPP}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=\alpha P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPP}=\mathrm{H})$$

with $\alpha=\frac{1}{K}$ where

$$K=P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPP}=\mathrm{H})+P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPP}=\mathrm{H})+P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPD}=\mathrm{H})P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPP}=\mathrm{H})$$

From the above equations, we can get the following results:

$$P(\mathrm{PRRR}=\mathrm{H}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=0.6777$$
$$P(\mathrm{PRRR}=\mathrm{M}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=0.2407$$
$$P(\mathrm{PRRR}=\mathrm{L}|\mathrm{CPD}=\mathrm{H},\mathrm{CPP}=\mathrm{H})=0.0816$$

In a similar way, the probabilities of the state of the node 'PRRR' conditional on the other state combinations of its parent nodes (i.e., the conditional probability table of the node 'PRRR') can also be generated and the results are shown in Table 6.

The conditional probability table of the other nodes with parent nodes in the Bayesian network can be specified similarly.

5.3. Generation of prior probabilities of different alternatives

5.3.1. The alternatives

Having determined the Bayesian network of NPD project risk analysis, as described in Section 5.2, the developed BN-analysis methodology was used to assess two alternative product design concepts of a 2AAA penlight, as shown in Figs. 4 and 5. The new 2AAA flashlight is operated by two AAA size batteries with a major product requirement of a "lock-feeling" two-way on–off switch.

There are two product concepts generated, one is with a PBS (push button switch), Fig. 4, while another is with a rotary switch, Fig. 5. Both designs can meet the customer requirement that a solid "lock-feeling" with a "click" sound to indicate a clear on–off function. The PBS design is comparatively more complicated in terms of more parts involved and higher precision of parts required for the switching mechanism. However, such PBS design has been adopted in other larger models, AA sized version, in the company. The major concern for this new AAA PBS design is the higher precision requirement in the production of the miniature parts and the reliability of the switch assembly. The rotary switch is a novel design that requires less parts, simpler assembly procedure, and lower precision requirements. However, the manufacturability and reliability of the rotary switch design are not yet proved in mass production, so more uncertainties and risks are associated.

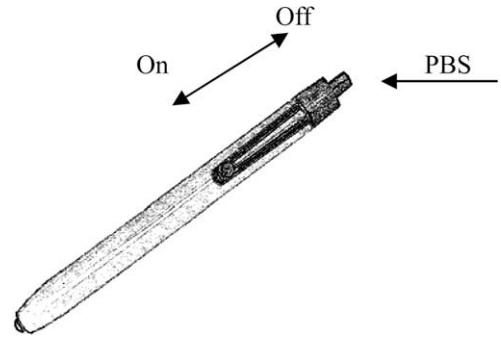

Fig. 4. Penlight design with push button switch (PBS).

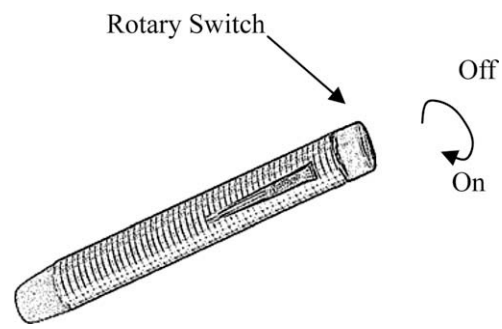

Fig. 5. Penlight design with rotary switch.

As indicated from a preliminary market survey, both switch designs are more or less of the same level of acceptance from user point of views on functions and appearance. The selection between these two product concepts is thus not an easy decision-making problem in which we have to simultaneously evaluate several inter-related criteria in order to minimize the NPD risks.

According to the developed NPD project risk analysis model, as shown in Fig. 1, and the developed BN based analysis methodologies, described in Section 4, data and expert judgments for the two design alternatives on each criterion were collected from the design teams of the company. Comparatively, more uncertainties are noticed in the evaluation of the rotary switch than the PBS as the company does not have the experience with the novel rotary switch design as much as the PBS.

5.3.2. Prior probabilities of two switch designs

According to the current situation of the company and the features of alternative 1, PBS, for the node 'SEP', Similarity of Existing

Table 6
Probabilities of PRRR conditional on different state combinations of CPD and CPP.

CPD	H			M			L		
CPP	H	M	L	H	M	L	H	M	L
H	0.6777	0.3478	0.0795	0. 3060	0.1004	0. 0167	0.0694	0.0182	0. 0017
M	0.2407	0.4814	0.3279	0.4965	0.6352	0.3152	0.3365	0.3448	0.0959
L	0.0816	0.1708	0.5926	0.1975	0.2644	0. 6681	0.5941	0.6370	0.9024

Table 7
The evaluation of probabilities of SEP for alternative 1.

SEP	H	M	L	ω
H	1	5[b]	8[b]	$\omega_H = 0.7334$
M	1/5[a]	1	4[b]	$\omega_M = 0.1991$
L	1/8[a]	1/4[a]	1	$\omega_L = 0.0675$
CR = 0.0812		CI = 0.0470		$\lambda_{max} = 3.0940$

[a] Expert's judgments.
[b] Reciprocal of the expert's judgments.

Table 8
The prior probabilities of different node for alternative 1.

Alternative 1	SEP	CPD	RDC	SES	PES	SPP	CPP	PRC
H	0.7334	0.7120	0.2052	0.7120	0.3914	0.6519	0.6519	0.2697
M	0.1991	0.2498	0.5251	0.2498	0.4893	0.2862	0.2862	0.5251
L	0.0675	0.0382	0.2697	0.0382	0.1193	0.0619	0.0619	0.2052

Table 9
The prior probabilities of different nodes for alternative 2.

Alternative 2	SEP	CPD	RDC	SES	PES	SPP	CPP	PRC
H	0.0428	0.1778	0.2500	0.1685	0.2500	0.0428	0.1685	0.2697
M	0.4358	0.3985	0.5000	0.4766	0.5000	0.4358	0.4766	0.5251
L	0.5214	0.4237	0.2500	0.3549	0.2500	0.5214	0.3549	0.2052

Products, by answering the question "considering the similarity of the existing products with alternative 1, which state is more likely to occur, and how much more likely", the experts give the following pair-wise comparison matrix. For instance, in Table 7, the probability of "SEP" at Medium (M) level is 1/5 of the probability of SEP at High (H) level, and the probability of SEP at Low (L) level is 1/8 of the probability of SEP at High (H) level. This is because such a PBS design has been adopted in other larger models, AA sized version, by the company.

As stated in Section 4.1, the priorities of each state, which are the elements in the principle eigenvector of the matrix, can be seen as their prior probabilities as long as the consistency is verified to be acceptable. In the above table, since CI = 0.0812, which is less than 0.1, the prior probability of the states of the node "SEP" is

$$P(\mathrm{SEP} = \mathrm{H}) = \omega_H = 0.7334$$
$$P(\mathrm{SEP} = \mathrm{M}) = \omega_M = 0.1991$$
$$P(\mathrm{SEP} = \mathrm{L}) = \omega_L = 0.0675$$

The prior probabilities of the other root nodes concerning alternative 1, PBS, can be generated in a similar way, and they are summarized in Table 8.

Similarly, the correspondent table for alternative 2, rotary switch is given in Table 9.

5.4. Assessment on alternatives

Under the initial knowledge acquired from the experts about alternative 1 and alternative 2, the result of the risk analysis of those alternatives can be performed by the inference in the Bayesian network. The inference is performed by the software named Andersen, Olesen, Jensen, and Jensen (1989) and the result is shown in Figs. 6 and 7.

From the result, we can see that under the initial conditions, the state probability of the risk for alternative 1 and alternative 2 are shown in Table 10.

If we assign the utility of the states as: Utility(H) = 0, Utility(M) = 0.5, Utility(L) = 1, we can get Utility(alternative1) = 0.4515 and Utility(alternative2) = 0.2693. Therefore, alternative 1 should be selected.

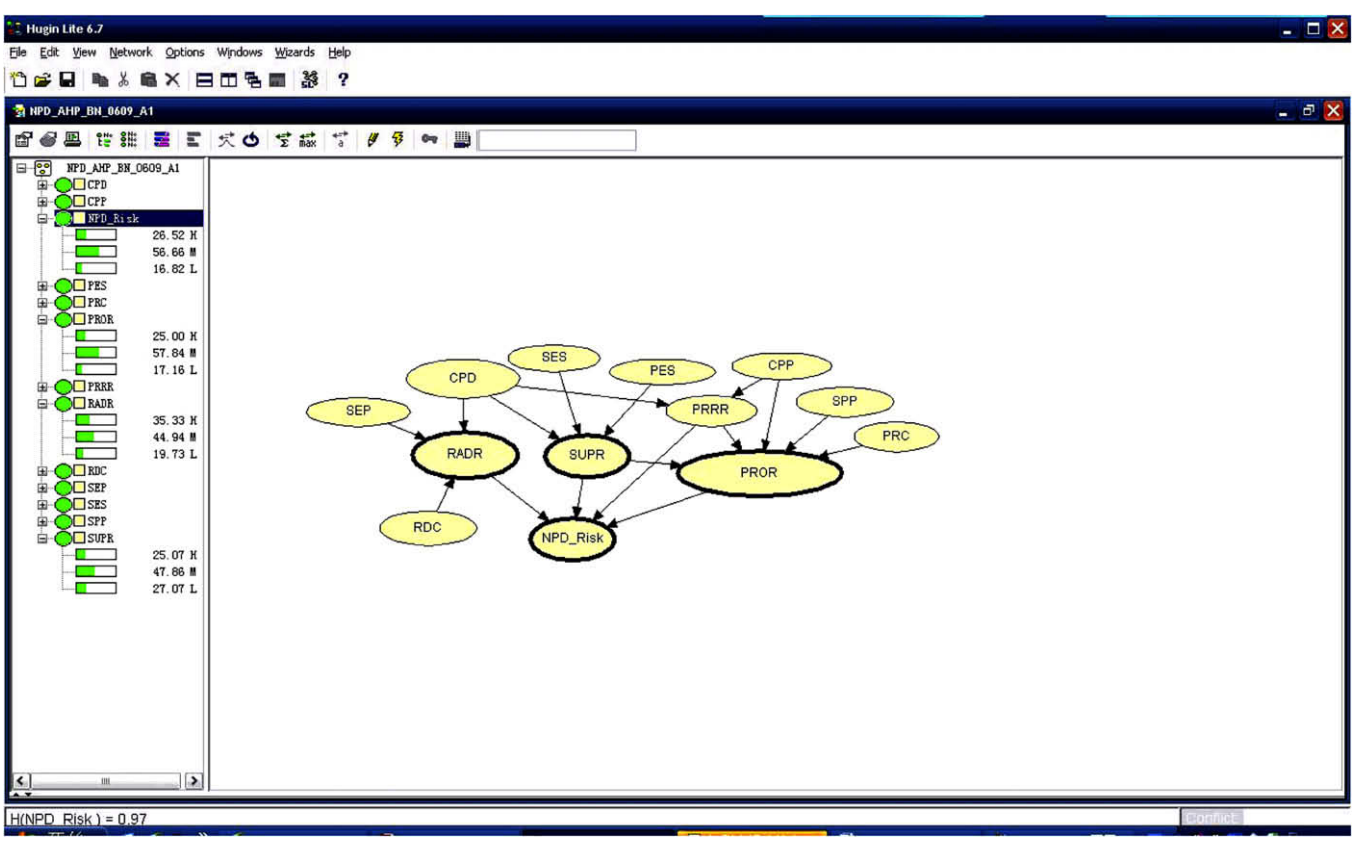

Fig. 6. Evaluation result of alternative 1.

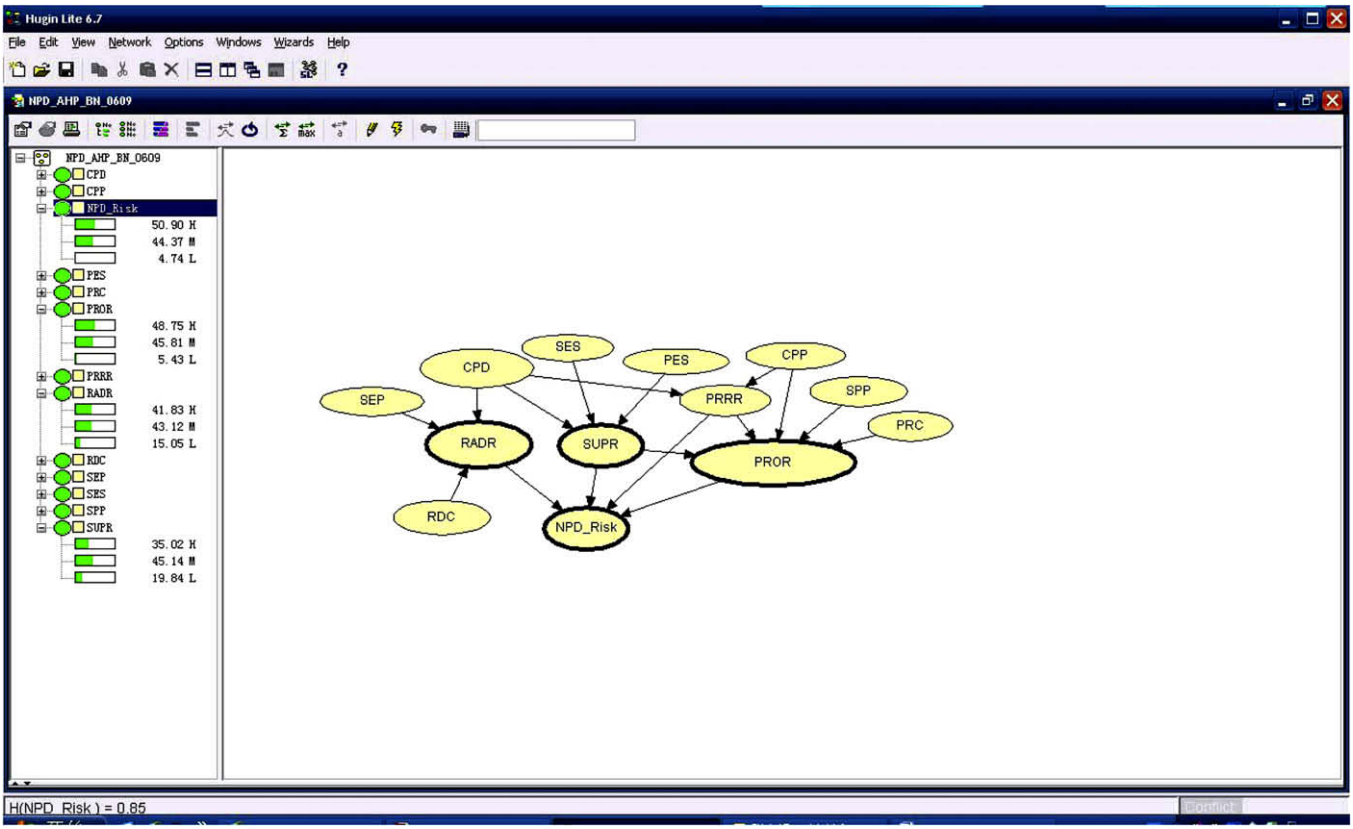

Fig. 7. Evaluation result of alternative 2.

5.5. Further improvement process

The environment of the NPD is always dynamic and uncertain, new evidences will come out from time to time. One of the most important features of Bayesian network is its ability to update knowledge in light of new evidence. After we compare two alternative product concepts as discussed in the previous sections, we would further improve the concepts with the BN methodology to either improve the rejected alternative 2 in certain weak areas so that it may reverse the selection decision, or further improve the selected alternative 1 in its weaker areas so as to achieve a better final solution.

In our case, for the selected alternative 1, as shown in Table 8, RDC, PES and PRC are the potential areas for further improvement because of a higher potential risk. Having discussed in the development team together with experts, there are two ideas for improvement.

5.5.1. Idea 1

The production engineering department will work together with the supplier to develop a special purpose machine to automate the production of two leaf springs which are the critical parts of PBS to ensure the quality of the suppliers' operation. As the supplier lacks sufficient in-house technical resources, this joint activity will help strengthen the supplier performance and thus increase the PES. The prior probabilities of the root nodes concerning this idea of improvement for alternative 1 are summarized in Table 11.

5.5.2. Idea 2

The subassembly of PBS can be subcontracted to a supplier who had experience in producing similar parts before. This outsourcing approach can thus increase the production capability (PRC) and R&D capability (RDC). However, the supplier performance becomes lower as more uncertainties related to the new supplier are expected. The prior probabilities of the root nodes concerning the idea 2 of alternative 1 improvement are summarized in Table 12.

As for the description of the two ideas of improvement for alternative 1, they are mutually exclusive. Hence, there is a need to make a comparison and decision between them. The question would be easily answered with the aid of the ability of inference

Table 10
The risk analysis result for alternative 1 and alternative 2.

NPD Risk	Alternative 1	Alternative 2
H	0.2652	0.5090
M	0.5666	0.4437
L	0.1682	0.0474

Table 11
The prior probabilities of nodes in improved alternative 1 (idea 1).

Alternative 1	SEP	CPD	RDC	SES	PES	SPP	CPP	PRC
H	0.7334	0.7120	0.2052	0.7120	0.50	0.6519	0.6519	0.2697
M	0.1991	0.2498	0.5251	0.2498	0.40	0.2862	0.2862	0.5251
L	0.0675	0.0382	0.2697	0.0382	0.10	0.0619	0.0619	0.2052

Table 12
The prior probabilities of nodes in improved alternative 1 (idea 2).

Alternative 1	SEP	CPD	RDC	SES	PES	SPP	CPP	PRC
H	0.7334	0.7120	0.35	0.7120	0.15	0.6519	0.6519	0.35
M	0.1991	0.2498	0.50	0.2498	0.45	0.2862	0.2862	0.50
L	0.0675	0.0382	0.15	0.0382	0.40	0.0619	0.0619	0.15

Table 13
The risk analysis result for idea 1 and idea 2.

Risk state	Idea 1	Idea 2
H	0.2563	0.3070
M	0.5675	0.5418
L	0.1762	0.1512

in the developed Bayesian network of NPD project risks. We can update our knowledge about the probability distribution of different state of the risk under two ideas (Table 13).

Under the above assumption of the utility of each state, the utilities of idea 1 and idea 2 are 0.4600 and 0.4221 respectively and thus idea 1 will be selected. After taking the measures of idea 1, the two alternative product design concepts will be re-evaluated with the BN analysis model. Following the same procedure, an optimized design can be obtained after several iterations.

6. Conclusion

A network relationship of critical risk factors in NPD project execution which is yet theoretically thorough is developed in this paper. The network is designed to facilitate the evaluation of NPD projects by determining the project execution risk. Four major nodes are identified, namely research and development risk, supply risk, production risk and product reliability. This network is further incorporated into a modified Bayesian network approach in order to facilitate a quantitative and more accurate risk-based NPD project assessment. By introducing the modified Bayesian network approach, the conditional probabilities of the nodes with multi-parents in Bayesian networks are generated.

When constructing a Bayesian network, the approach investigated in this paper for generating conditional probabilities can be used to help the elicitation of experts' judgments. This is achieved by the introduction of pair-wise comparisons to estimate the prior probabilities of root nodes and the conditional probabilities of single-parent nodes and by the generation of conditional probabilities of multi-parent nodes through the generation of conditional probabilities of each parent instead of estimating those conditional probabilities directly.

A two-stage risk analysis example is discussed in the case study example. In stage 1, a lower risk alternative is selected. In stage 2 appropriate risk reduction measures are taken into account. Both the analyses are fulfilled through the inference of Bayesian networks.

The proposed method in this paper has two major shortcomings. The first one is that it suffers from the problem of the so called "curse of dimension": If the number of the states of a node in Bayesian network becomes large or the structure of the Bayesian network becomes complex in which a node have many parents, the number of conditional probability tables will increase tremendously and a huge effort is required to fill in all the tables. The second shortcoming relates to the variety of input formation. As mentioned in Section 4.4, the input of the method proposed in this paper is the prior probabilities of the states of nodes and the sum of those probabilities must be exactly one. It implies that the experts should have complete knowledge about their judgments. Those requirements will limit the method since information provided by experts may be of various features (e.g., qualitative, quantitative, interval, fuzzy, etc.). Furthermore, in the context of NPD, it is understandable for experts to be ignorant in their judgments and such ignorance cannot be modeled in our method. For our future work, possible methods to overcome the above shortcomings would be sought. A framework which can accommodate various forms of input and can offer a flexible way for the experts to express their judgments is anticipated.

Acknowledgement

The work described in this paper is supported by a grant from City University of Hong Kong under SRG Projects Nos. 7001971 and 7002311.

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