# Chapter 14
# Project Risk Modelling and Assessment in New Product Development

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**Abstract** New Product Development (NPD) is a crucial process to maintain the competitiveness of a company in an ever changing market. In the process of developing new products of a high level of innovation, there are various types of risks, which should be properly identified, systematically analyzed, modeled, evaluated and effectively controlled. In this paper, the Bayesian Network (BN) method will be investigated to assess risks involved in NPD processes. A systematic method is examined to generate probabilities in BNs. Both the probability generation method and the BN model are demonstrated by a case study about the design of electronic products for a multinational flashlight manufacturing company.

**Keywords** Probability generation · Bayesian network · New product development · Risk evaluation

## 14.1 Introduction

As market competition and product technology advancement become increasingly intense (Di Benedetto 1999; Nadkarni and Shenoy 2001), the process of New Product Development (NPD) has become more important for the success of companies than ever before (McCarthy et al. 2006). However, due to the constant changes in market environments, the originalities in NPD process as well as the uncertainties involved in NPD, NPD operates with relatively high risks (Kahraman et al. 2007). Therefore, evaluating NPD risks becomes very important for a company to decide which project should be selected for further investment in face of several alternatives. However, it is found that risk evaluation in NPD projects in many

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organizations is often done by informal and non-systematic methods and based largely on management perceptions (Calantone et al. 1999; Cooper 2006). There is an increasing need to develop analytic methods to evaluate NPD project risks for helping designers to make decisions among design alternatives from project risk point of view.

A number of decision methods and tools have been developed for risk evaluation in NPD processes, such as Behavioral model (Monti and Carenini 2000), Failure Mode and Effects Analysis (FMEA) (Carbone and Tippett 2004), Analytical Hierarchy Process (AHP) (Chen et al. 2007), Analytical Network Process (ANP) (Ayag and Ozdemir 2007), etc. However, these tools, to some extent, suffer from certain underlying weaknesses when applied in complex NPD environments.

Another potential method for risk analysis in NPD is Bayesian Network (BN) (Pearl 1988; Cooper 2000), which can represent the dependant relationships among the factors of NPD in a network structure and quantitatively model uncertainties involved in risk evaluation in NPD. In most of the current research, however, the emphases were put on how to determine the structure of BN, how to perform inference in BN and how to analyze inference results. Little attention has been paid on how to generate conditional probabilities in BN, which is a precondition for BN inference.

For generation of conditional probabilities in BN, the most classic approach is the noisy OR model (Saaty 1980) and its generalizations (Diez 1993; Cozman 2004). However, such methods can only handle cases where the states of nodes are binary and the parents of nodes are assumed to be independent of each other. Monti & Carenin proposed another way to generate conditional probabilities using pair-wise comparisons (Mullins and Sutherland 1998). However, it only generates the conditional probabilities of a node with a single parent, while in BN a node can have multiple parents.

This paper is aimed to develop a systemic probability generation method and also attempts to propose a BN based evaluation method to evaluate NPD project risks.

## 14.2 The Proposed Approach to Generate the Probabilities in Bayesian Network

### *14.2.1 Generation of Probabilities of the Nodes without Parent*

The probabilities of the node without parents are the prior probabilities of the node's states. Therefore, if node $N$ has $n$ states $S_1, S_2, \ldots, S_n$, the probability of each state $S_i$, i.e., $P(S_i)$ needs to be specified.

Traditionally, $P(S_i)$ is specified directly by experts. However, if a node has many states, direct estimation of probabilities of all states at a time may inevitably involve bias and inaccuracy. Therefore, an alternative way is to perform pair-wise comparisons between states to generate the probabilities. Since there are only two instead of $n$ states to be considered at a time, the bias and inaccuracy of judgments can be

**Table 14.1** Pair-wise comparison matrix to generate prior probabilities

| | $S_1$ | $S_2$ | …… | $S_n$ | $\omega$ |
|---|---|---|---|---|---|
| $S_1$ | $a_{11}$ | $a_{12}$ | …… | $a_{1\mathrm{n}}$ | $\omega_1$ |
| $S_2$ | $a_{21}$ | $a_{22}$ | …… | $a_{2\mathrm{n}}$ | $\omega_2$ |
| …… | …… | …… | …… | …… | …… |
| $S_n$ | $a_{\mathrm{n}1}$ | $a_{\mathrm{n}2}$ | …… | $a_{\mathrm{nn}}$ | $\omega_n$ |
| $\lambda_{\max} =$ | | CI = | | CR = | |

reduced. Specifically, the prior probability of each state at a node can be determined by the following pair-wise comparison matrix (Table 14.1):

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

Similar to AHP, the relative priorities of $S_{\mathrm{i}}$ can be generated from the maximum eigenvector $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^{\mathrm{T}}$ of matrix $\left(a_{ij}\right)_{n\times n}$ and the consistency of the judgment can be checked by the consistency ratio CR (Saaty 1980).

Since $\sum_{i=1}^{n} \omega_i = 1$ and $\omega_i$ represents the relative importance of the state $S_i$ among all the states, it is natural to interpret $\omega_i$ as the prior probability of the state $S_i$. In other words, we have

$$P\,(S_i) = \omega_i$$

### 14.2.2 *Generation of Probabilities for Nodes with a Single Parent*

The probabilities of a node with a single parent are the probabilities of its states conditional on its parent's states (Table 14.2). If a node $N$ has a single parent node $M$ and there are $n$ and $m$ states for the node $N$ and the node $M$ respectively, which can be represented by $S_{N1}, S_{N2}, \ldots, S_{Nn}$ and $S_{M1}, S_{M2}, \ldots, S_{Mm}$ respectively, the probability of each state of the node $N$ conditional on each state of the node $M$, i.e., $P\left(S_{Ni}|S_{Mj}\right)$ $(i = 1, 2, \ldots n, j = 1, 2, \ldots m)$ should be estimated.

Similar to the above estimation, the pair-wise comparison method is used here to estimate $P\left(S_{Ni}|S_{Mj}\right)$. When the node $M$ is in the state of $S_{\mathrm{Mj}}$, the corresponding comparison matrix is given by:

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

**Table 14.2** Pair-wise comparison matrix to generate conditional probabilities of nodes with a single parent

| *M is in the state of* $S_{Mj}$ | $S_{N1}$ | $S_{N2}$ | ... | $S_{Nn}$ | $\omega_N$ |
|---|---|---|---|---|---|
| $S_{N1}$ | $a_{11}$ | $a_{12}$ | ... | $a_{1n}$ | $\omega_{1j}$ |
| $S_{N2}$ | $a_{21}$ | $a_{22}$ | ... | $a_{2n}$ | $\omega_{2j}$ |
| ... | ... | ... | ... | ... | ... |
| $S_{Nn}$ | $a_{n1}$ | $a_{n2}$ | ... | $a_{nn}$ | $\omega_{nj}$ |
| $\lambda_{max} =$ | | CI = | | CR = | |

$\omega_{ij}$ $(i = 1, \ldots, n)$, we can set:

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

Since the node $M$ has $m$ states, $m$ matrices should be constructed to get all $\omega_{ij}$ for $i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$.

### 14.2.3 Generation of Conditional Probabilities for Multi-Parent Nodes

If a node $N$ with $n$ states $S_{N1}, S_{N2}, \ldots, S_{Nn}$ in a BN 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 its parents' states, which is defined by

$$P\left(N = S_{Ni} | M_1 = S_{M_1p_1}, M_2 = S_{M_2p_2}, \ldots, M_k = S_{M_kp_k}\right);$$
$$i = 1, 2, \ldots, n;\ p_j = 1, 2, \ldots, m_j;\ j = 1, \ldots, k$$

In the above section, conditional probability of a node with a single parent is generated. So, a natural question arises as to how to 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 different combinations of its parents' states? This is investigated as follows.

In Kim and Pearl (1983), when a node A in a BN 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 $\alpha$ 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:

$$P(A|X_1, X_2 \ldots, X_n) = \alpha P(A|X_1) P(A|X_2) \ldots P(A|X_n) \tag{14.1}$$

In Eq. (14.1), $\alpha$ is a normalized factor to ensure $\sum_{a \in A} P(a|X_1, X_2, \ldots, X_n) = 1$.

From Eq. (14.1), 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 model,

$$P\left(N = S_{Ni} | M_1 = S_{M_1 p_1}, M_2 = S_{M_2 p_2}, \ldots, M_k = S_{M_k p_k}\right);$$

can be calculated as follows:

$$\begin{aligned} &P\left(N = S_{Ni} | M_1 = S_{M_1 p_1}, M_2 = S_{M_2 p_2}, \ldots, M_k = S_{M_k p_k}\right) \\ &= \alpha \prod_{j=1}^{k} P\left(N = S_{Ni} | M_j = S_{M_j p_j}\right) \quad \left(i = 1, 2, \ldots, n;\; p_j = 1, 2, \ldots, m_j;\right. \\ &\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad j = 1, ..., k) \end{aligned}$$

where $\alpha$ is a normalized factor to ensure that

$$\sum_{i=1}^{n} P\left(N = S_{Ni} | M_1 = S_{M_1 p_1}, M_2 = S_{M_2 p_2}, \ldots, M_k = S_{M_k p_k}\right) = 1$$

and $P\left(N = S_{Ni} | M_j = S_{M_j p_j}\right)$ can be generated from the method proposed in the above section.

Since the estimation of $P\left(N = S_{Ni} | M_j = S_{M_j p_j}\right)$ is much easier than the direct estimation of $P\left(N = S_{Ni} | M_1 = S_{M_1 p_1}, M_2 = S_{M_2 p_2}, \ldots, M_k = S_{M_k p_k}\right)$, the method proposed in this section is more reliable.

## 14.3 Application of the Method in Risk Evaluation of NPD

### *14.3.1 Case Description*

The developed approach to determine the probabilities of BN was validated in the context of NPD project risk evaluation for assessing two alternative product design concepts of a new 2AAA penlight in a multinational flashlight manufacturing company. The two design alternatives, Push Button Switch (PBS) design and Rotary Switch (RS) design, are more or less able to meet the customer needs. They may, however, differ in 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 Product Development Director of the company.

The validation process consists of three steps: to build a BN, to specify conditional probabilities and to determine prior probabilities. Conditional probabilities in BN reflect general relations among risk factors during the company's NPD process, which remain the same for different alternatives, while prior probabilities in

BN reflect the specific features of different alternatives, which may be different for different alternatives. After the probabilities are determined, inference can be performed to find which alternative is of low risk and alternatives with lower risk are preferred.

### *14.3.2 Bayesian Network Construction*

Based on the relationships among different risk factors in NPD and the experience of the expert, the BN to assess NPD project risk in terms of the company's technical considerations is built as follows:

The meanings of abbreviations of the nodes in Fig. 14.1 are summarized in the following table and each node in the BN has three states: High (H), Medium (M) and Low (L) (Table 14.3).

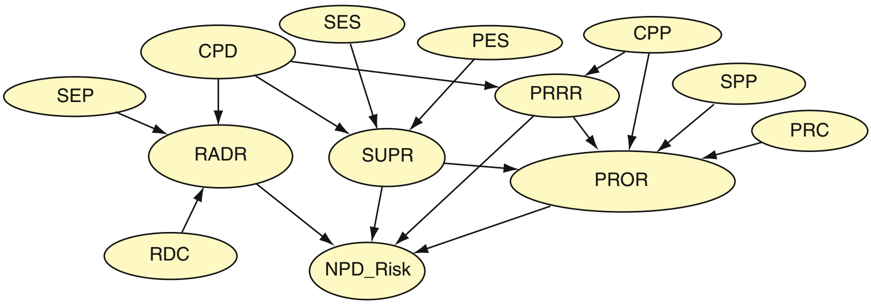


**Fig. 14.1** BN for risk evaluation of NPD project

**Table 14.3** Explanation of the Abbreviations in Fig. 14.1

| Abbr. | Meaning |
|---|---|
| SEP | Similarity of the existing product |
| CPD | Complexity of the product design |
| RDC | R&D capability |
| RADR | Research and development risk |
| SES | Similarity of the existing supply |
| PES | Supplier performance |
| SUPR | Supply risk |
| PRRR | Product reliability risk |
| CPP | Complexity of the production process |
| SPP | Similarity of the production process |
| PRC | Production capability |
| PROR | Production risk |

### *14.3.3 Generation of Conditional Probabilities in BN*

The node 'PRRR' will be selected as an example when generating conditional probabilities in BN. 'PRRR' has two parent nodes, namely, 'CPD' and 'CPP'. According to the method proposed, $P\ (PRRR|CPD)$ and $P\ (PRRR|CPP)$ should be calculated first (Tables 14.4 through 14.7).

When generating $P\ (PRRR|CPD)$ on the condition that CPD is in the state of 'H', the following matrix is obtained from the experts' opinions:

The number in the above matrix can be specified by answering the questions like: "Without considering 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 matrix, we can see that given that 'CPD' is at high

**Table 14.4** Evaluation of the probabilities of PRRR conditional on CPD is in the state of H

| CPD = H | H | M | L | $\omega$ |
|---|---|---|---|---|
| H | 1 | 2* | 3* | $\omega_H = 0.5396$ |
| M | 1/2# | 1 | 2* | $\omega_M = 0.2970$ |
| L | 1/3# | 1/2# | 1 | $\omega_L = 0.1634$ |
| CR = 0.0079 | | CI = 0.0046 | | $\lambda_{max} = 3.009$ |

#Expert's judgments, * reciprocal of the expert's judgments.

**Table 14.5** Probabilities of PRRR 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 14.6** 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 |

**Table 14.7** Probabilities of PRRR conditional on different state combinations of CPD and CPP

| CPD | H | | |
|---|---|---|---|
| CPP | H | M | L |
| H | 0.6777 | 0.3478 | 0.0795 |
| M | 0.2407 | 0.4814 | 0.3279 |
| L | 0.0816 | 0. 1708 | 0. 5926 |
| CPD | M | | |
| CPP | H | M | L |
| H | 0. 3060 | 0. 1004 | 0. 0167 |
| M | 0.4965 | 0.6352 | 0.3152 |
| L | 0. 1975 | 0. 2644 | 0. 6681 |
| CPD | L | | |
| CPP | H | M | L |
| H | 0. 0694 | 0. 0182 | 0. 0017 |
| M | 0.3365 | 0.3448 | 0.0959 |
| L | 0. 5941 | 0. 6370 | 0. 9024 |

(H) level, the probability of ‘PRRR’ being at the medium (M) level is 1/2 times the probability of ‘PRRR’ at the high (H) level, and the probability of ‘PRRR’ at the low (L) level is 1/3 times the probability of ‘PRRR’ at the high (H) level. This is reasonable since higher complexity in the product design may lead to the higher chance of suffering from performance problems in the product life and thus may lead to a higher level of risks in product reliability.

According to the discussion in the above section, we can get:

$$\begin{aligned} P\left(PRR = H|CPD = H\right) &= \omega_H = 0.5396 \\ P\left(PRR = M|CPD = H\right) &= \omega_M = 0.2970 \\ P\left(PRR = L|CPD = H\right) &= \omega_L = 0.1634 \end{aligned}$$

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 are summarized as follows:

In the same way, the probabilities of the states of the node ‘PRRR’ on the condition of different states of the node ‘CPP’ are listed in the following table:

After the probabilities of all the states of the node ‘PRRR’ conditional on each state of its parent node have been generated, the probabilities conditional on the state combinations of both its parent nodes can be estimated.

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

$$\begin{aligned} P\left(PRRR = H|CPD = H, CPP = H\right) &= \alpha P\left(PRRR = H|CPD = H\right) \\ &\qquad P\left(PRRR = H|CPP = H\right) \\ P\left(PRRR = M|CPD = H, CPP = H\right) &= \alpha P\left(PRRR = M|CPD = H\right) \\ &\qquad P\left(PRRR = M|CPP = H\right) \\ P\left(PRRR = L|CPD = H, CPP = H\right) &= \alpha P\left(PRRR = L|CPD = H\right) \\ &\qquad P\left(PRRR = L|CPP = H\right) \end{aligned}$$

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

$$\begin{aligned} K = \; & P\left(PRRR = H|CPD = H\right) P\left(PRRR = H|CPP = H\right) \\ & + P\left(PRRR = M|CPD = H\right) P\left(PRRR = M|CPP = H\right) \\ & + P\left(PRRR = L|CPD = H\right) P\left(PRRR = L|CPP = H\right) \end{aligned}$$

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

$$\begin{aligned} P\left(PRRR = H|CPD = H, CPP = H\right) &= 0.6777 \\ P\left(PRRR = M|CPD = H, CPP = H\right) &= 0.2407 \\ P\left(PRRR = L|CPD = H, CPP = H\right) &= 0.0816 \end{aligned}$$

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 as follows.

The Conditional Probability Table of the other nodes with parents in the BN can be specified in a similar way.

### 14.3.4 Generation of Prior Probabilities in BN

The prior probabilities can be generated through the pair-wise comparison matrix based on the features of two alternatives. For example, for alternative 1, which is the penlight design with PBS, the prior probability of the node SEP can be specified by the expert in the following matrix:

From the matrix, we can get:

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

Similarly, the prior probabilities of other nodes of alternative 1 and the prior probabilities of nodes of alternative 2 can be generated as follows (Tables 14.8 through 14.11):

**Table 14.8** The evaluation of probabilities of SEP for alternative 1

| SEP | H | M | L | $\omega$ |
|---|---|---|---|---|
| H | 1 | 5* | 8* | $\omega_H = 0.7334$ |
| M | 1/5# | 1 | 4* | $\omega_M = 0.1991$ |
| L | 1/8# | 1/4# | 1 | $\omega_L = 0.0675$ |
| CR = 0.0812 | | CI = 0.0470 | | $\lambda_{\max} = 3.0940$ |

#Expert's judgments, * reciprocal of the expert's judgments.

**Table 14.9** The prior probabilities of different node for alternative 1

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

**Table 14.10** The prior probabilities of different node for alternative 2

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

**Table 14.11** The risk analysis result for alternative 1 and alternative 2

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

### *14.3.5 Result*

After all the probabilities are specified, the BN inference can be performed to generate the risk levels of the two alternatives. The inference is performed by the software named Hugin® and the result is shown as follows:

If we assign the utility of the states as: $U(H) = 0, U(M) = 0.5, U(L) = 1$, we can get the utility of alternative 1 and 2 are 0.4515 and 0.2693 respectively. Therefore, alternative 1 should be selected.

## 14.4 Conclusion

A probability generation method in BN is proposed in this paper, which can reduce the bias in expert judgments when conditional and prior probabilities are estimated in BN. The method is applied in a real case study for risk evaluation in NPD.

The proposed method has two major shortcomings: it suffers from the problem of "curse of dimension" when BN is very complex and when there are many states at a node in BN; and it can only accommodate inputs represented by prior probabilities of nodes, which will limit the application scope of the methods since information provided by experts may have various inherent features (e.g., qualitative, quantitative, interval, fuzzy, etc.). For our future work, possible methods to overcome the above shortcomings will be sought. A framework which can accommodate various forms of input and can offer a flexible way for experts to express their judgments will be investigated

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