An Evidential-Reasoning-Interval-Based Method for New Product Design Assessment

Kwai-Sang Chin, Jian-Bo Yang, Min Guo, and James Ping-Kit Lam

Abstract—**A key issue in successful new product development is how to determine the best product design among a lot of feasible alternatives. In this paper, the authors present a novel rigorous assessment methodology to improve the decision-making analysis in the complex multiple-attribute environment of new product design (NPD) assessment in early product design stage, where several performance measures, like product functions and features, manufacturability and cost, quality and reliability, maintainability and serviceability, etc., must be accounted for, but no concrete and reliable data are available, in which conventional approaches cannot be applied with confidence. The developed evidential reasoning (ER) interval methodology is able to deal with uncertain and incomplete data and information in forms of both qualitative and quantitative nature, data expressed in interval and range, judgment with probability functions, judgment in a comparative basis, unknown embedded, etc. An NPD assessment model, incorporated with the ER-based methodology, is then developed and a software system is built accordingly for validation. An industrial case study of electrical appliances is used to illustrate the application of the developed ER methodology and the product design assessment system.**

Index Terms—**Evidential reasoning (ER), multiple-attribute decision analysis (MADA), new product development, product design assessment.**

I. Introduction

THERE is an increasing emphasis raised by both researchers and practitioners to enhance product design assurance in early design stages. They advocate to build in all the product attributes of performance, quality, reliability, safety, maintainability, serviceability, manufacturability, etc., during the product design process. Hence, the product design process becomes an increasingly complex decision-making problem in which one must simultaneously cater, in a rational way, for many interrelated criteria of both quantitative and qualitative nature. It is also noted that the design decision analysis has to be conducted on the basis of both precise numbers and subjective judgments that are imprecise and vague (fuzzy) in nature. Such uncertainties can be incurred due to a lack of evidence and understanding or human's inability of providing accurate judgments at early design stage of novel new products. This reveals that a better decision-making methodology is needed to facilitate product design assessment in situations where several performance measures like product functions and features, manufacturability and cost, quality and reliability, maintainability and serviceability, etc., must be accounted for, but conventional approaches cannot be applied with confidence.

The authors have looked into this problem and developed a novel rigorous assessment methodology that can be used to facilitate the assessment of new product design (NPD) alternatives in the early design stage. It allows the use of a combination of precise, imprecise, and vague information from domain-specific knowledge with acceptable confidence level. The developed methodology is able to deal with uncertain data and information in forms of both qualitative and quantitative nature, data expressed in interval and range, judgment with probability functions, judgment in a comparative basis, unknown embedded, etc. With the support of an electrical appliance manufacturer, the developed assessement methodologies have been validated with real-life data. Outcomes of the research are expected to significantly improve the decision analysis in such a vague and complex multiple-attribute environment, and they also enhance the effectiveness of product design assessment in early product design stage. This paper presents the developed methodologies as well as the validation case in the following sections.

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K.-S. Chin and J. P.-K. Lam are with the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong (e-mail: mekschin@cityu.edu.hk; me.lam@cityu.edu.hk).

J.-B. Yang is with the Manchester Business School, The University of Manchester, Manchester M15 6PB, U.K. (e-mail: jian-bo.yang@manchester.ac.uk).

M. Guo is with the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong, and also with the Institute of Systems Engineering, Huazhong University of Science and Technology, Wuhan 430074, China (e-mail: guomin_like@sina.com.cn).

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II. Evidential Reasoning (ER) Approach for Multiple-Attribute Decision Analysis (MADA)

A. Basic ER Models for MADA

Basically, the NPD problem is a MADA problem. For decades, many MADA methods have been developed, such as the well-known analytical hierarchy process (AHP) [31]–[33] and multiple-attribute utility theory [7], [23], [24], as well as their extensions, such as the interval-valued assessments approach, especially in weight evaluation process [2], [3], [22], [35], [36], [38], etc. In these methods, MADA problems are modeled using decision matrices, in which an alternative is assessed on each criterion by either a single real number or an interval value. Unfortunately, in many decision situations, using a single number or interval to represent a judgement proves to be difficult and sometimes unacceptable. Information would have been lost or distorted in the process of preaggregating different types of information, such as a subjective judgement, a probability distribution, or an incomplete piece of information.

Concerning the fuzziness of MADA problems, a large amount of fuzzy MADA methods have been proposed in the literature, such as fuzzy hierarchical aggregation methods [25], conjunction implication methods [6], [45]–[47], weighted average aggregation methods [5], [15], [16], [40], and weighted average aggregation with criteria assessment methods [48]. Nevertheless, these pure fuzzy MADA approaches are essentially based on traditional evaluation methods and are unable to handle probabilistic uncertainties such as ignorance as modeled in the belief structure.

The ER algorithm is developed for aggregating multiple attributes based on a belief decision matrix and the evidence combination rule of the Dempster–Shafer (D-S) theory [14], [37], [49]–[53]. Different from traditional MADA approaches that describe a MADA problem using a decision matrix, the ER approach uses the belief decision matrix, in which each attribute of an alternative is described by a distribution assessment using a belief structure. The advantages of doing so is that using a distribution assessment can both model precise data and capture various types of uncertainties such as ignorance and vagueness in subjective judgments [43].

Suppose a MADA problem has M alternatives $a_l, l = 1, \ldots, M$, one upper level attribute, referred to as general attribute, and L lower level attributes $e_i, i = 1, \ldots, L$, called basic attributes. The relative weights of the L basic attributes are denoted by $W = (w_1, \ldots, w_L)$, which are supposed to be known and satisfy the conditions $0 \le w_i \le 1$ and $\sum_{i=1}^{L} w_i = 1$.

Suppose all M alternatives are assessed using the same set of N assessment grades $H_n, n = 1, \ldots, N$, which are required to be mutually exclusive and collectively exhaustive for the assessment of all attributes. The following N assessment grades formulate the frame of discernment in the D-S theory of evidence:

$$H = \{H_1, \ldots, H_N\}. \tag{1}$$

If alternative a_l is assessed to a grade H_n on an attribute e_i to a belief degree of $\beta_{n,i}$, this assessment will be denoted by $S(e_i(a_l)) = \{(H_n, \beta_{n,i}(a_l)),\ n = 1, \ldots, N\}$.

The individual assessments of the M alternatives on the L basic attributes can be represented by the belief decision matrix $D_g = (S(e_i(a_l)))_{L \times M}$.

Based on the earlier belief decision matrix and the evidence combination rule of the D-S theory, both the recursive and analytical ER algorithms have been developed to aggregate the L basic attributes. The ER approach provides a nonlinear attribute aggregation process in nature. In the rest of this section, we briefly introduce the analytical ER algorithm to pave the way for the later development of the new ER-interval-based model.

The ER algorithm first transforms the original belief degrees into basic probability masses by combining the relative weights and the belief degrees using the following equations:

$$m_{n,i} = m_i(H_n) = w_i \beta_{n,i}(a_l), \quad n = 1, \ldots, N, \quad i = 1, \ldots, L \tag{2}$$

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w_i \sum_{n=1}^{N} \beta_{n,i}(a_l), \quad i = 1, \ldots, L \tag{3}$$

$$\bar{m}_{H,i} = \bar{m}_i(H) = 1 - w_i, \quad i = 1, \ldots, L \tag{4}$$

$$\tilde{m}_{H,i} = \tilde{m}_i(H) = w_i \left(1 - \sum_{n=1}^{N} \beta_{n,i}(a_l)\right), \quad i = 1, \ldots, L \tag{5}$$

with $m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i}$ and $\sum_{i=1}^{L} w_i = 1$.

Note that the probability mass assigned to the whole set H, $m_{H,i}$, which is currently unassigned to any individual grades, is split into two parts: $\bar{m}_{H,i}$ and $\tilde{m}_{H,i}$, where $\bar{m}_{H,i}$ is caused by the relative importance of the attribute e_i and $\tilde{m}_{H,i}$ by the incompleteness of the assessment on e_i for a_l.

Next, the basic probability masses on the L basic attributes are aggregated into the combined probability assignments by using the following analytical formulas:

$$\{H_n\} : m_n = k \left[\prod_{i=1}^{L} (m_{n,i} + \bar{m}_{H,i} + \tilde{m}_{H,i}) - \prod_{i=1}^{L} (\bar{m}_{H,i} + \tilde{m}_{H,i}) \right], \quad n = 1, \ldots, N \tag{6}$$

$$\{H\} : \tilde{m}_H = k \left[\prod_{i=1}^{L} (\bar{m}_{H,i} + \tilde{m}_{H,i}) - \prod_{i=1}^{L} \bar{m}_{H,i} \right] \tag{7}$$

$$\{H\} : \bar{m}_H = k \left[\prod_{i=1}^{L} \bar{m}_{H,i} \right] \tag{8}$$

where

$$k = \left[\sum_{n=1}^{N} \prod_{i=1}^{L} (m_{n,i} + \bar{m}_{H,i} + \tilde{m}_{H,i}) - (N-1) \prod_{i=1}^{L} (\bar{m}_{H,i} + \tilde{m}_{H,i}) \right]^{-1}. \tag{9}$$

Finally, the combined probability assignments are normalized into overall belief degrees by using the following equations:

$$\{H_n\} : \beta_n = \frac{m_n}{1 - \bar{m}_H}, \quad n = 1, \ldots, N \tag{10}$$

$$\{H\} : \beta_H = \frac{\tilde{m}_H}{1 - \bar{m}_H} \tag{11}$$

where β_n and β_H represent the overall belief degrees of the combined assessments, assigned to the assessment grades H_n and H, respectively. The combined assessment is also a distribution assessment, which can be denoted by $S(y(a_l)) = \{(H_n, \beta_n(a_l)),\ n = 1, \ldots, N\}$.

The formulas (1)–(11) together constitute a complete ER analytical algorithm. Compared with the evidence combination rule of the D-S theory, the ER algorithm has at least the following features: 1) taking into account the relative importance of evidence; 2) modeling ignorance clearly by breaking down unassigned probability mass into two parts and treating them differently; and 3) generating rational conclusions in the combination of multiple pieces of conflict evidence [28] by employing the two normalization operations on both the attribute weights and the combined probability assignments.

However, the basic ER algorithm mentioned before does not consider the uncertainty caused by interval-valued evaluations, which are common in real MADA problems. So, in recent years, the basic ER algorithm is extended to model two kinds of interval-valued evaluations, interval grades and interval assessment in possibilities, separately.

B. ER Extensions to Interval-Valued Evaluations

1) ER Extensions to Interval Possibility Assignments: The ER methodology can be extended to model interval-valued distribution assessments [19], [43] in capturing ambiguity and diversity in individual or group assessments. If alternative a_l is assessed to a grade H_n on an attribute e_i to a belief degree interval of $[\beta^-_{n,i}, \beta^+_{n,i}]$, or $\beta_{n,i} \in [\beta^-_{n,i}, \beta^+_{n,i}]$, with $\beta^+_{n,i} \geq \beta^-_{n,i} \geq 0$, and ignorance is also given in interval values $[\beta^-_{H,i}, \beta^+_{H,i}]$, or $\beta_{H,i} \in [\beta^-_{H,i}, \beta^+_{H,i}]$, with $1 \geq \beta^+_H \geq \beta^-_H \geq 0$, we denote this by $S(e_i(a_l)) = \{(H_n, [\beta^-_{n,i}(a_l), \beta^+_{n,i}(a_l)]),\ n = 1,\ldots,N;\ (H, [\beta^-_{H,i}(a_l), \beta^+_{H,i}(a_l)])\}$, which is an interval-valued distribution assessment vector. Note that precise belief degree is a special case of interval belief degree with $\beta^-_{n,i} = \beta^+_{n,i}$ for every $n = 1,\ldots,N$ and $\beta^-_{H,i} = \beta^+_{H,i}$, $i = 1,\ldots,L$.

If the original belief decision matrix $D_g = (S(e_i(a_l)))_{L\times M}$ contains interval belief degrees, the following ER nonlinear optimization models can be used to aggregate multiple interval belief structures:

$$\max/\min \beta_n(a_l) \quad (\text{for each}\, n = 1,\ldots,N) \quad \text{and} \quad \beta_H(a_l) \tag{12}$$

$$\text{s.t.: } \beta^-_{n,i} \leq \beta_{n,i} \leq \beta^+_{n,i}, \quad n = 1,\ldots,N, \quad i = 1,\ldots,L \tag{13}$$

$$\beta^-_{H,i} \leq \beta_{H,i} \leq \beta^+_{H,i}, \quad i = 1,\ldots,L \tag{14}$$

$$\sum_{n=1}^{N} \beta_{n,i} + \beta_{H,i} = 1, \quad i = 1,\ldots,L \tag{15}$$

where $\beta_n(a_l)$ (for $n = 1,\ldots,N$) and $\beta_H(a_l)$ are the functions of $\beta_{n,i}$ and $\beta_{H,i}$ for $n = 1,\ldots,N,\ i = 1,\ldots,L$, generated using the analytical ER algorithm, as shown in formulas (6)–(11) or the equivalent expressions shown in (16) and (17) at the bottom of this page.

2) ER Extensions to Interval Grades Evaluations: According to Xu *et al.* [44], the performance of alternatives can be assessed to an individual grade or a grade interval. The complete set of all individual grades and grade intervals, denoted by $\hat{H}$, for assessing each attribute can be represented by

$$\hat{H} = \left\{ \begin{array}{ccccc} H_{11} & H_{12} & \cdots & H_{1(N-1)} & H_{1N} \\ & H_{22} & \cdots & H_{2(N-1)} & H_{2N} \\ & & \ddots & \vdots & \vdots \\ & & & H_{(N-1)(N-1)} & H_{(N-1)N} \\ & & & & H_{NN} \end{array} \right\} \tag{18}$$

where H_{pp} for $p = 1,\ldots,N$ is equivalent to H_p for convenience in the expressions. H_{pq} for $p = 1,\ldots,N,\ q = p+1,\ldots,N$, denotes the local uncertainty set that is the union of the basic grade p to grade q, i.e., $H_{pq} = H_{pp} \cup H_{p+1,p+1} \cup \cdots \cup H_{qq}$. And H_{1N} denotes the overall unknown set, which is equivalent to the whole set H in formula (1). Note the difference between the sets given by (1) and (18). The former is used in the basic ER algorithm and is a subset of the latter.

Based on the earlier assumption, the assessment of an alternative on attribute a_l is then given by

$$S(a_l) = \{(H_{pq}, \beta_{pq,i}),\ p = 1,\ldots,N,\ q = p,\ldots,N,\ i = 1,\ldots,L\} \tag{19}$$

where $\sum_{p=1}^{N}\sum_{q=p}^{N} \beta_{pq,i} = 1$ holds.

Similar to the basic ER algorithm, the mass functions are defined as follows:

$$m_{pq,i} = w_i \beta_{pq,i}, \quad p = 1,\ldots,N, \quad q = p,\ldots,N, \quad i = 1,\ldots,L \tag{20}$$

$$m_{H,i} = 1 - w_i, \quad i = 1,\ldots,L. \tag{21}$$

According to the basic ER aggregation rules, the recursive aggregation algorithms can be obtained as follows:

$$m_{pq,I(1)} = m_{pq,1} \tag{22}$$

$$m_{H,I(1)} = m_{H,1} \tag{23}$$

$$\begin{aligned} m_{pq,I(i+1)} = \frac{1}{1-K_{I(i+1)}} \Bigg[& - m_{pq,I(i)} m_{pq,i+1} \\ & + \sum_{k=1}^{p}\sum_{l=q}^{N} (m_{kl,I(i)} m_{pq,i+1} + m_{pq,I(i)} m_{kl,i+1}) \\ & + \sum_{k=1}^{p-1}\sum_{l=q+1}^{N} (m_{kq,I(i)} m_{pl,i+1} + m_{pl,I(i)} m_{kq,i+1}) \\ & + m_{H,I(i)} m_{pq,i+1} + m_{pq,I(i)} m_{H,i+1} \Bigg] \end{aligned} \tag{24}$$

$$\beta_n(a_l) = \frac{\prod_{i=1}^{L}(w_i\beta_{n,i} + 1 - w_i + w_i\beta_{H,i}) - \prod_{i=1}^{L}(1 - w_i + w_i\beta_{H,i})}{\sum_{q=1}^{N}\prod_{i=1}^{L}(w_i\beta_{q,i} + 1 - w_i + w_i\beta_{H,i}) - (N-1)\prod_{i=1}^{L}(1 - w_i + w_i\beta_{H,i}) - \prod_{i=1}^{L}(1 - w_i)} \tag{16}$$

$$\beta_H(a_l) = \frac{\prod_{i=1}^{L}(1 - w_i + w_i\beta_{H,i}) - \prod_{i=1}^{L}(1 - w_i)}{\sum_{q=1}^{N}\prod_{i=1}^{L}(w_i\beta_{q,i} + 1 - w_i + w_i\beta_{H,i}) - (N-1)\prod_{i=1}^{L}(1 - w_i + w_i\beta_{H,i}) - \prod_{i=1}^{L}(1 - w_i)}. \tag{17}$$

and the probability mass at large in H is given by

$$m_{H,I(i+1)} = \frac{m_{H,I(i)} m_{H,i+1}}{1 - K_{I(i+1)}} \quad (25)$$

where $K_{I(i+1)}$ is the combined probability mass assigned to the empty set $\{\Phi\}$

$$K_{I(i+1)} = \sum_{p=1}^{N} \sum_{q=i}^{N} \sum_{k=1}^{p-1} \sum_{l=k}^{p-1} (m_{kl,I(i)} m_{pq,i+1} + m_{pq,I(i)} m_{kl,i+1}). \quad (26)$$

The scaling factor $1/(1 - K_{I(i+1)})$ is used to make sure that $\sum_{p=1}^{N} \sum_{q=i}^{N} m_{pq,I(i+1)} + m_{H,I(i+1)} = 1$.

The earlier aggregation process is applied recursively until all the L basic attribute assessments are aggregated, and the overall assessment of an alternative a_l can be expressed as

$$S(a_l) = \{(H_{pq}, \beta_{pq}(a_l)),\ p = 1, \ldots, N,\ q = i, \ldots, N\}$$

with

$$\beta_{pq} = \frac{m_{I(L)}(H_{pq})}{1 - m_{I(L)}(U)}, \quad p = 1, \ldots, N, \quad q = p, \ldots, N. \quad (27)$$

Note that $\beta_H = \beta_{1N}$.

C. ER Extensions to Both Interval Grades and Possibility Assignments

1) Combined Modeling Methodology of Both Interval Grades and Possibility Assignments: If alternative a_l is assessed to a grade H_{pq} on an attribute e_i to a belief degree interval of $[\beta^-_{pq,i}, \beta^+_{pq,i}]$, or $\beta_{pq,i} \in [\beta^-_{pq,i}, \beta^+_{pq,i}]$, with $\beta^+_{pq,i} \geq \beta^-_{pq,i} \geq 0$, we denote this by $S(e_i(a_l)) = \{(H_{pq}, [\beta^-_{pq,i}(a_l), \beta^+_{pq,i}(a_l)]),\ p = 1, \ldots, N,\ q = p, \ldots, N\}$, which is an interval-valued distribution assessment vector. Note that precise belief degree is a special case of interval belief degree with $\beta^-_{pq,i} = \beta^+_{pq,i}$ for every $p = 1, \ldots, N, q = p, \ldots, N, i = 1, \ldots, L$.

If the original belief decision matrix $D_g = (S(e_i(a_l)))_{L \times M}$ contains interval belief degrees, the following ER nonlinear optimization models can be used to aggregate multiple interval belief structures:

$$\max/\min \beta_{pq} \quad (\text{for each } p = 1, \ldots, N,\ q = p, \ldots, N) \quad \text{and} \quad \beta_H \quad (28)$$

$$\text{s.t.: } \beta^-_{pq,i} \leq \beta_{pq,i} \leq \beta^+_{pq,i}, \quad p = 1, \ldots, N, \quad q = p, \ldots, N, \quad i = 1, \ldots, L \quad (29)$$

$$\sum_{p=1}^{N} \sum_{q=p}^{N} \beta_{pq,i} = 1, \quad i = 1, \ldots, L \quad (30)$$

where β_{pq} (for each $p = 1, \ldots, N,\ q = p, \ldots, N$) and β_H are the functions of $\beta_{pq,i}$, $\beta_{H,i}$ for $p = 1, \ldots, N$, $q = p, \ldots, N$, $i = 1, \ldots, L$, generated using the analytical Interval-based Evidential Reasoning (IER) algorithm, as shown in formulas (20)–(27).

2) Utility Estimation Models for Our Methodology: For ranking alternatives, expected utility values can be calculated. Suppose $u(H_{pp})$ is the utility value of the grade H_{pp} with $u(H_{p+1,p+1}) > u(H_{pp})$ as it is assumed that the grade $H_{p+1,p+1}$ is preferred to H_{pp}. Because of interval uncertainty, the maximum, minimum, and average expected utilities are calculated. As the belief degree β_{pq} could be assigned to the best grade in the interval H_{pq}, which is H_{qq}, if the uncertainty turned out to be favorable to the assessed alternative, then the utility value could be calculated as $\sum_{p=1}^{N} \sum_{q=p}^{N} \beta_{pq} u(H_{qq})$. However, if alternative a_l is assessed to a grade H_{pq} on an attribute e_i to a belief degree interval of $[\beta^-_{pq,i}, \beta^+_{pq,i}]$, the result of β_{pq} will also appear in interval, so the maximal utility value could be calculated as follows:

$$u_{\max}(a_l) = \max \sum_{p=1}^{N} \sum_{q=p}^{N} \beta_{pq} u(H_{qq}) \quad \text{s.t. formulas (29) and (30).} \quad (31)$$

Similarly, in the worst case, if the uncertainty turned out to be against the assessed alternative, i.e., the belief degree β_{pq} assigned to H_{pp}, the worst grade in the interval H_{pq}, then the minimum value would be given by

$$u_{\min}(a_l) = \min \sum_{p=1}^{N} \sum_{q=p}^{N} \beta_{pq} u(H_{pp}) \quad \text{s.t. formulas (29) and (30).} \quad (32)$$

The average of the two is given by

$$u_{\text{avg}}(a_l) = \frac{u_{\max}(a_l) + u_{\min}(a_l)}{2}. \quad (33)$$

III. NPD Assessment

A. Product Design Assessment Model

Facing the global competition, the trend of the industry is moving toward the design and manufacture of more sophisticated products with better and safer performance, higher quality and reliability, more environmental friendliness, and shorter time. Such multiple criteria have to be considered and assessed at the early product design stage. The difficulty in conducting the assessment at early design stage comes from the fact that limited reliable data are available to measure and evaluate decision criteria, though vague information or subjective judgements are often used [12], [21], [26].

Previous researches have identified criteria for assessing product design and measuring product development performance [1], [4], [11], [12], [17], [18], [20], [27], [30], which provides a gauge for companies to assess design approaches and, in turn, select the most suitable design. Most of the studies employ simple qualitative assessment methods [13], [20], [27], [41], in which a single value is assigned to assess product performance. Another approach is to employ knowledge-based or case-based support, which is based on qualitative judgment with experience of historical product design projects [8], [9], [54]. The approaches, however, are not able to address the problem of uncertainty and the involvement of both qualitative and quantitative data that are common in NPD. Thus, this study is dedicated to dealing with the deficiencies of the current assessment methods. On the basis of the literature, this research proposes

TABLE I
HIERARCHICAL PRODUCT DESIGN ASSESSMENT MODEL

Criteria		
Level 1	Level 2	Level 3
1. Product cost	1.1 Research and development cost	1.1.1 Product design cost 1.1.2 Process design cost 1.1.3 Equipment/tool cost 1.1.4 Physical prototyping cost
	1.2 Manufacturing cost	1.2.1 Production cost 1.2.2 Material cost
	1.3 Quality cost	1.3.1 Inspection and testing cost 1.3.2 Internal failure cost
	1.4 After sale services cost	1.4.1 Technical support/inquiry cost 1.4.2 Maintenance cost
2. Project risk	2.1 Research and development risk	2.1.1 Similarity of the product technology 2.1.2 Complexity of the product technology 2.1.3 R&D capability
	2.2 Supply risk	2.2.1 Similarity of the major supply 2.2.2 Supplier performance of the major supply
	2.3 Production risk	2.3.1 Similarity of the production process 2.3.2 Complexity of the production process 2.3.3 Production capability
3. Customer satisfaction	3.1 Product functions	3.1.1 Product performance 3.1.2 Product features
	3.2 Product appearance	3.2.1 Ergonomics design 3.2.2 Aesthetic
	3.3 Product availability	3.3.1 Product reliability 3.3.2 Product maintainability

a hierarchal product design assessment model that constitutes three categories of criteria, namely product cost, project risk, and customer satisfaction, as depicted in Table I. The model elements are described in the following sections.

1) Product Cost: Product cost covers the cost of NPD project activities, which has four components. The first component is research and development cost that is associated with the activities that realize the design idea and make it feasible for subsequent production. The activities include developing product design, process design, new equipment, and tools development or purchase, as well as physical prototyping. The second component is manufacturing cost that is associated with the manufacturing of the product, which includes production and material costs. Quality cost is the third component, which is associated with evaluating the quality of the raw materials/components/parts/products, and the activities resulting from the failure of products in meeting quality requirements discovered prior to product delivery. The fourth component is after-sale-services cost. It is the expense of providing services to the customers after product sale.

2) Project Risk: Project risk is the likelihood that the new product development project will not be successfully completed within specified time constraints, which is evaluated in three aspects: research and development risk, supply risk, and production risk. Research and development risk is the probability that product requirements will not be realized on schedule due to the insufficiency of research and development. Supply risk deals with the chance that the suppliers will not be able to delivery qualified raw materials/components/parts on schedule, while production risk is the probability that the production requirements will not be met within the specified time constraint.

3) Customer Satisfaction: Customer satisfaction evaluates the degree to which the product design can meet customer requirements and expectation in terms of three subcriteria, namely product functions, product appearance, and product availability. Product functions assess both the product's primary operating characteristics, which deliver basic product functions, and the product's secondary operating characteristics, which supplement the basic functions. Product appearance deals with the visible characteristics of the product, which considers the beauty or art of the product (aesthetic) and the extent to which the design fits the customers' human characteristics so that the customers will use the product comfortably and safely (ergonomics). Another indicator of customer satisfaction is product availability that is defined as the probability that the product will be available and capable of performing its intended functions for a given period of time after the product delivery. Product availability is evaluated in terms of product reliability, the probability that the product will perform its intended functions for a given period of time, and product maintainability, which is the probability that the product will retain or can be restored to a specified condition within a given period of time when maintenance is performed.

The assessment model constitutes critical criteria for product design. However, in practice, the criteria may not be of equal importance. The importance weightings of the criteria may vary depending on such factors as companies' marketing strategies and financial ability. Thus, companies need to determine the importance weightings of the model criteria according to their own companies' situations.

B. Product Design Decision-Making Process

This study also develops a decision-making process for conducting the product design assessment. As depicted in Fig. 1, the process begins with the collection of information that covers all the criteria of the proposed assessment model to assess product design. The proposed assessment methodology is capable of handling various types of information inputs, viz., precise numbers, interval numbers, belief structures, and comparison numbers. Precise numbers are single or exact values, for example, 3 out of a 1–7 Likert scale. Interval numbers express judgments in ranges, for instance, estimated quality cost ranges from \$50 000 to \$60 000. The third type of inputs is belief structures that represent an assessment as a distribution. For example, an assessor judges supply risk to be 3 (probability = 40%) or 4 (probability = 60%) using a 1–7 scale. It should be noted that the sum of the probability could be between 0 and 1. If sum = 1, it indicates a complete assessment that the assessor is 100% sure about the judgment. It is an incomplete assessment when sum $<$ 1, which may reveal that the assessor is not fully confident about the assessment due to a lack of evidence/understanding. The fourth type of input is comparisons between design options, for example, production risk of design A is at least 50% of that of design B. Moreover, the proposed assessment methodology is able to cater for judgments that constitute the natures of the four types of inputs. For instance, an assessment on quality cost could be \$20 000–\$22 000 (50%), \$25 000–\$26 000 (30%). This feature well addresses the imprecise and vague natures of assessment judgments, which can significantly help improve assessment accuracy without having to making unnecessary assumptions for incomplete or missing information.

The next step of the decision-making process is assessment transformation. Inputs of different formats are transformed to the ER format for subsequent assessment aggregation. Then, the

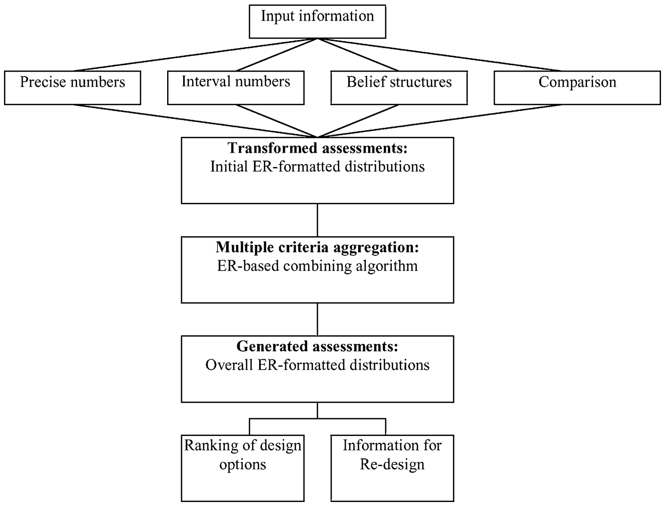


Fig. 1. NPD decision-making process.

transformed inputs of all the assessment criteria are aggregated using the ER algorithm to generate assessment results. Last, based on the results, two sets of useful information can be obtained: ranking of design options and information for redesign. Companies can prioritize and select design options based on their overall assessment scores. Moreover, the proposed methodology can also provide a distributed assessment structure that depicts the performance of the design options in all the aspects (criteria) of the assessment model. On the basis of the structure, companies can readily identify areas where the design can be improved.

In short, based on the proposed decision-making process, we can use the assessment methodology to systematically and rationally assess product design in order to prioritize design options and obtain information for design improvement.

IV. Validation Case

A. Case Background

This section presents the validation of the developed ER-interval-based assessment methodology, presented in Section II, for assessing design options rationally and systematically. A case study in a Hong Kong electrical appliance manufacturer was conducted to demonstrate the applicability and potential of the developed assessment methodology. The company is an original design manufacture (ODM) manufacturer of high-end torch products. Identifying customer needs is an integral part of its concept development phase of the product development process. The resulting customer needs are used to guide the product designers establishing specifications, generating product concepts, and selecting a product concept for further development. It develops around only 20 new products per year, but it needs to generate nearly 100 product concepts a year. Assessing and selecting alternative product concepts are thus critical to the company.

The developed ER-interval-based assessment methodology was validated in the task of assessing alternative product design concepts during the early product design stage. The design alternatives 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, manufacturing processes, optional functional and aesthetic features, expected quality and 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 consists of two steps. The first step is to determine the importance weightings with the AHP approach. With the AHP, each assessment criterion of the developed hierarchical model, shown in Table I, is determined by the collaborating company. The weightings reflect the company's strategies and emphasis on the product design evaluation, which may vary from company to company. The second step is to assess the product design alternatives by collecting the expert judgments of each criterion, which, in turn, is transformed to a composite index. The judgments are associated with uncertainties that may be a combination of precise, imprecise, and vague information from domain-specific knowledge. As discussed in Section II, the developed methodology is able to deal with uncertain data and information in forms of both qualitative and quantitative nature, data expressed in interval and range, judgment with probability functions, judgment in a comparative basis, unknown embedded, etc.

B. Importance Weightings of Criteria

In determining the importance weightings of assessment criteria, the AHP approach method is used. AHP is a well-recognized decision-making technique developed by Saaty [31]–[33] to tackle the complex problems of choice and prioritization, which enables better accuracy and consistency compared to conventional scoring methods [29]. The AHP is designed to decompose a complex, multicriteria problem into multiple levels of hierarchy. Experts are interviewed and pairwise comparison judgments are applied to pairs of homogeneous criteria, eventually to generate the overall priorities for ranking the alternatives [34]. The AHP is extensively applied in different areas with different applications [42]. Priority and ranking is one of the applications widely used in different areas, such as manufacturing and engineering, and is applied in this study [10], [39]. The Product Development Director of the company, who was qualified and experienced in both strategic and technical areas, provided the expert opinion to determine the importance weightings. The AHP results are depicted in Table II.

In level 1, the AHP result shows that when the company evaluates different product design alternatives, they put more emphasis on the project risks (0.429) and customer satisfaction (0.429), rather than the product cost (0.142). Actually, it does not imply that the cost element is not important in new product development. As mentioned before, all the alternatives to be evaluated are within the targeted cost range. Otherwise, they should have been screened out earlier. The result reflects that the company, within the acceptable cost range, pays more attention to risks and customers aspects.

TABLE II
IMPORTANCE WEIGHTING OF THE EVALUATION CRITERIA

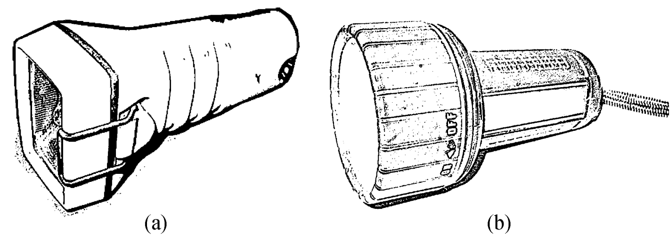
Criteria		
Level 1	Level 2	Level 3
1. Product cost =.142	1.1 Research and development cost=.021	1.1.1 Product design cost=.002 1.1.2 Process design cost=.002 1.1.3 Equipment/tool cost=.015 1.1.4 Physical prototyping cost=.002
	1.2 Manufacturing cost=.056	1.2.1 Production cost=.014 1.2.2 Material cost=.042
	1.3 Quality cost=.056	1.3.1 Inspection and testing cost=.014 1.3.2 Internal failure cost=.042
	1.4 After sale services cost=.009	1.4.1 Technical support/inquiry cost=.007 1.4.2 Maintenance cost=.002
2. Project risk =.429	2.1 Research and development risk=.231	2.1.1 Similarity of the product technology.115 2.1.2 Complexity of the product technology=.058 2.1.3 R&D capability=.058
	2.2 Supply risk=.127	2.2.1 Similarity of the major supply=.095 2.2.2 Supplier performance of the major supply=.032
	2.3 Production risk=.071	2.3.1 Similarity of the production process=.035 2.3.2 Complexity of the production process=.018 2.3.3 Production capability=.018
3. Customer satisfaction =.429	3.1 Product functions=.137	3.1.1 Product performance=.046 3.1.2 Product features=.091
	3.2 Product appearance=.240	3.2.1 Ergonomics=.080 3.2.2 Aesthetic=.160
	3.3 Product availability=.052	3.3.1 Product reliability =.042 3.3.2 Product maintainability=.010

The weightings are further established to the criteria in levels 2 and 3 respectively. In the product cost category, manufacturing cost (0.056) and quality cost (0.056) are more important than others, such as research and development cost (0.021) and after-sale-service cost (0.009). This is typical in consumer product manufacturing as the production is relatively in large volume. In project risks category, research and development risk (0.231) is of the highest importance, followed by supply risk (0.127) and production risk (0.071). This reflects that the company is strong in production and comparatively has more concern in research and development than the supply aspect. In customer satisfaction category, product appearance (0.240) is more important than the other two factors, product functions (0.137) and product availability (0.052). Torch is in a typical consumer household product market, in which the availability is not as important as the industrial product market. As mentioned before, all the alternatives to be evaluated are more or less able to meet the basic performance and functional requirements. Product appearance, comparatively, is more influential to the customer satisfaction in the torch market.

C. Evaluation on Product Design Alternatives

Having determined the importance weightings of assessment criteria as described in Section IV-B, the developed ER assessment methodology was used to assess two product design alternatives of a 2AA minisport torch, as shown in Fig. 2. The 2AA torch is operated by two AA size batteries with a major product requirement of minimum 5-m waterproof-ability.

There are two product concepts generated, one which is of a rectangular shape, while another is cylindrical. The rectangular one is a novel design of waterproof torch, while the cylindrical design is traditional and well-proven in similar models in the company. The waterproofness and manufacturability of the rectangular design are not yet proved in mass production, so more risks may be associated. Since there are fewer common components available in the company, as compared with the cylindrical design, the process design and equipment/tooling



(a) (b)

Fig. 2. Product design alternatives of a 2AA minisport. (a) Concept 1: rectangular shape. (b) Concept 2: cylindrical shape.

costs, as well as production costs for the rectangular design, are higher. Nevertheless, as indicated from a preliminary market survey, the rectangular design is more favorable because of its novel appearance. The selection between these two product concepts is thus a complex decision-making problem in which we have to simultaneously evaluate many interrelated criteria of both quantitative and qualitative nature. It is also noted that uncertainties are incurred due to a lack of evidence of the novel rectangular design at the early design stage.

According to the developed product design evaluation model, as shown in Table II, and the developed ER-interval-based assessment methodologies, described in Section II, data and expert judgment for the two design alternatives on each criterion were collected from the design teams of the company. The judgments are associated with uncertainties that are a combination of precise, imprecise, and vague information in various forms from domain-specific knowledge. Comparatively, more uncertainties are noticed in the evaluation of the rectangular concept than the cylindrical as the company does not have the experience with the novel rectangular design as much as the cylindrical one. Typical examples of the various formats of data and information are described next.

1) The judgment is shown in a precise number, e.g., the estimated process design cost of the cylindrical concept is \$30 000.
2) The judgement is in interval value, e.g., the estimated product design cost of the rectangular concept is \$50 000–\$70 000, and the R&D capability rating of the cylindrical concept is in the interval of 6–7 out of the 1–7 scale.
3) The judgment is presented in a belief structure, e.g., the estimated unit production cost of the rectangular concept is \$12 of 30% probability, \$12.5 of 50% probability, while \$13 of 20% probability. The sum of the probability is 1, indicating that the assessor is fully confident about the judgment.
4) The judgement is presented in a comparison basis. For instance, in the product features aspect, the maximum waterproofness of the cylindrical concept, based on the performance of similar design in existing product lines, is estimated to be 100% probability with 10 m, 80% probability with 12 m, and 20% with 15 m. The company does not have the direct experience with this novel rectangular design, but its performance can be estimated by a comparison with the cylindrical one. The maximum waterproofness of the rectangular concept is estimated to be 100% probability with at least 50% of the performance of

cylindrical concept, 20% probability with 60% of cylindrical performance, and 5% probability with 70% or more of cylindrical performance.

According to the various formats of the collected data and expert judgements about these two design alternatives, some transformation techniques have to be established to convert all the forms into the developed ER-based assessment methodology. In the following section, we will discuss the proposed transformation techniques and the data processing results.

V. Data Processing Procedures and Results

A. Data Processing Procedures

1) Transformation Techniques for Quantitative Data:

a) In the subfactor "product design cost," the evaluation scale corresponding to seven evaluation grades are given as 20 000–80 000, where 20 000 corresponds to the best grade (H_7), 30 000 to $H_6, \ldots$, and 80 000 to the worst grade (H_1) (see Fig. 3). Since the evaluation values of "rectangle light" is 50 000–70 000, the corresponding grades interval is $H_{2,4}$, so these evaluations can be expressed in ER formats as follows:

$$\{H_{2,4} : 100\%\}$$

$$\text{or} \quad \beta_{pq,i} = 0, \quad \text{for } p = 1, \ldots, N, \quad q = p, \ldots, N,$$

$$\text{except for } \beta_{2,4,i} = 1.$$

b) In the subfactor "inspection and testing cost," the evaluation scale corresponding to the seven evaluation grades are given as \$0.2–\$0.6 per unit, where \$0.2 corresponds to the best grade (H_7), ..., \$0.4 to average H_4, ..., and \$0.6 to the worst H_1. Since the evaluation value of "rectangle light" is \$0.5 with 100% certainty, which is between grade H_2 (\$0.534) and grade H_3 (\$0.467), the possibility value 100% should be assigned to H_2 and H_3 properly. According to Yang [49], the distances between the quantitative evaluation and the two nearest grades are considered in the transformation as follows.

For example, in Fig. 4, we have

$$\beta_2 = \frac{x_2}{x_1 + x_2} = 0.5 \quad \beta_3 = 1 - \beta_2 = 0.5.$$

So the transformed result for \$0.5 in terms of grades is given by H_2: 50% and H_3: 50%.

c) In the subfactor "product features," the original evaluation of cylindrical torchlights is given in the following formats:

cylindrical waterproof >10 m of 100% probability;
>12 m of 80% probability;
>15 m of 20% probability;

which are equivalent to the following three interval assessments with uncertainty:

cylindrical waterproof = [10, 12] meters of 20% probability;
[12, 15] meters of 60% probability;
[15, 18] meters of 20% probability.

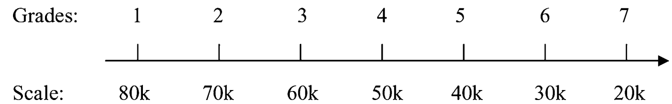


Fig. 3. Transformation from quantitative scale to evaluation grades.

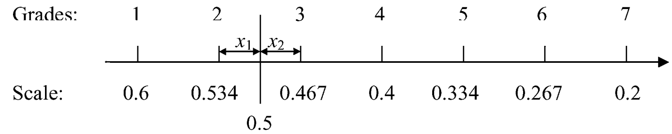


Fig. 4. Transformation for single quantitative evaluation.

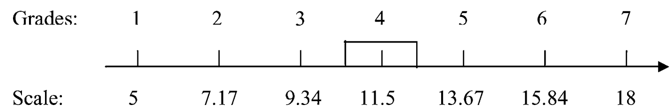


Fig 5. Transformation for quantitative interval evaluation.

However, these intervals are between the grades defined in Fig. 5. For example, in the interval [10, 12] meters, 10 m is between H_3 and H_4, while 12 is between H_4 and H_5. So the interval [10, 12] belongs to grades H_3, H_4, and H_5 to certain degrees. According to the interval information transformation technique proposed by Wang *et al.* [43], the interval [10, 12] can be equivalently transformed to the following interval beliefs:

$$\beta^-_{3,i} = 0 \quad \text{and} \quad \beta^+_{3,i} = I_{1,1} \times \frac{11.5 - 10}{11.5 - 9.34} \times 20\%$$

$$\beta^-_{4,i} = \min\left(\frac{10 - 9.34}{11.5 - 9.34}, \frac{13.67 - 12}{13.67 - 11.5}\right) \times 20\% \quad \text{and}$$

$$\beta^+_{4,i} = (I_{1,1} + I_{2,1}) \times 20\%$$

$$\beta^-_{5,i} = 0 \quad \text{and} \quad \beta^+_{5,i} = I_{2,1} \times \frac{12 - 11.5}{13.67 - 11.5} \times 20\%$$

with $I_{1,1} + I_{2,1} = 1$ and $I_{1,1} \times I_{2,1} = 0$, or

$$\{(H_{33}, [0, 0.139 I_{1,1}]),\ (H_{44}, [0.061, 0.2]),\ (H_{55}, [0, 0.046 I_{2,1}])\}.$$

Similarly, waterproof of 12–15 m of 60% probability can be transformed to

$$\beta^-_{4,i} = 0 \quad \text{and} \quad \beta^+_{4,i} = I_{1,2} \times \frac{13.67 - 12}{13.67 - 11.5} \times 60\%$$

$$\beta^-_{5,i} = \min\left(\frac{12 - 11.5}{13.67 - 11.5}, \frac{15.84 - 15}{15.84 - 13.67}\right) \times 60\% \quad \text{and}$$

$$\beta^+_{5,i} = (I_{1,2} + I_{2,2}) \times 60\%$$

$$\beta^-_{6,i} = 0 \quad \text{and} \quad \beta^+_{6,i} = I_{2,2} \times \frac{15 - 13.67}{15.84 - 13.67} \times 60\%$$

with $I_{1,2} + I_{2,2} = 1$ and $I_{1,2} \times I_{2,2} = 0$, or

$$\{(H_{44}, [0, 0.462 I_{1,2}]),\ (H_{55}, [0.138, 0.6]),\ (H_{66}, [0, 0.368 I_{2,2}])\}.$$

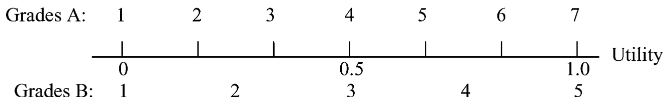


Fig. 6. Transformation between two different sets of evaluation grades.

And waterproof of 15–18 m of 20% probability can be transformed to

$$\beta_{5,i}^{-} = 0 \quad \text{and} \quad \beta_{5,i}^{+} = I_{1,3} \times \frac{15.84 - 15}{15.84 - 13.67} \times 20\%$$

$$\beta_{6,i}^{-} = \min\left(\frac{15 - 13.67}{15.84 - 13.67}, 0\right) \times 20\% \quad \text{and}$$

$$\beta_{6,i}^{+} = (I_{1,3} + I_{2,3}) \times 20\%$$

$$\beta_{7,i}^{-} = 0 \quad \text{and} \quad \beta_{7,i}^{+} = I_{2,3} \times \frac{18 - 15.84}{18 - 15.84} \times 20\%$$

with $I_{1,3} + I_{2,3} = 1$ and $I_{1,3} \times I_{2,3} = 0$, or

$$\{(H_{55}, [0, 0.077I_{1,3}]),\ (H_{66}, [0, 0.2]),\ (H_{77}, [0, 0.2I_{2,3}])\}.$$

According to the uncertain information transformation technique proposed by Yang [49], the uncertain assessments of the waterproof performance for cylindrical torchlights can be equivalently represented by the following interval belief structure:

$$\begin{aligned}&\{(H_{33}, [0, 0.139I_{1,1}]),\ (H_{44}, [0.061, 0.2 + 0.462I_{1,2}]),\\ &(H_{55}, [0.138, 0.046I_{2,1} + 0.6 + 0.077I_{1,3}]),\\ &(H_{66}, [0, 0.368I_{2,2} + 0.2]),\ (H_{77}, [0, 0.2I_{2,3}])\}\end{aligned}$$

with $I_{1,1} + I_{2,1} = 1$, $I_{1,1} \times I_{2,1} = 0$, $I_{1,2} + I_{2,2} = 1$, $I_{1,2} \times I_{2,2} = 0$, $I_{1,3} + I_{2,3} = 1$, and $I_{1,3} \times I_{2,3} = 0$.

2) Transformation Techniques for Qualitative Data: Transformation between two different sets of evaluation grades can be done based on the utility values of the grades. For example, for the subfactor "product maintainability," the original evaluation data are given using the five grades from 1 to 5, where 1 stands for the worst grade and 5 for the best grade. However, this scale must be transformed to the overall evaluation grades between 1 and 7, as shown in Fig. 6. The two scale systems can be transformed using the following formulas:

Grades 1–5	Grades 1–7
1	1
2	2: 50%; 3: 50%
3	4
4	5: 50%; 6: 50%
5	7

3) Transformation for Pairwise Comparison Data: For the subfactor "product features," the original data for evaluation of rectangle light are more complicated. It is originally stated that if a sample of cylindrical torchlights is taken and if it has the waterproof of 10 m, then the decision maker (DM) can evaluate the waterproof for rectangle torchlights as follows.

a) The designers are 100% sure that rectangle torchlights have at least 50% of the waterproof performance of cylindrical torchlights. In other words, 100% of rectangle torchlights have the waterproof performance of more than 5 m.
b) The designers are 20% sure that rectangle torchlights have at least 60% of the waterproof performance of cylindrical torchlights. In other words, 20% of rectangle torchlights have the waterproof performance of more than 6 m.
c) The designers are 5% sure that rectangle torchlights have at least 70% of the waterproof performance of cylindrical torchlights. In other words, 5% of rectangle torchlights have the waterproof performance of more than 7 m.

These original statements mean that:

80% of rectangle torchlights have waterproof performance of [5, 6] meters;
15% of rectangle torchlights have waterproof performance of [6, 7] meters;
5% of rectangle torchlights have waterproof performance of more than 7 m.

However, the evaluation of the waterproof performance for cylindrical torchlight is not as simple as the above sample (10 m), but is in more complicated uncertain interval formats. So, we need to find the probability distribution for the waterproof performance of rectangle torchlights from the given evaluation of the waterproof performance for cylindrical torchlight, as shown in the following.

The original data were given by:

100% sure that rectangle torchlights have at least 50% of cylindrical waterproof;
20% sure that rectangle torchlights have at least 60% of cylindrical waterproof;
5% sure that rectangle torchlights have at least 70% of cylindrical waterproof.

This is equivalent to the following statements:

80% sure that rectangle torchlights have 50%–60% of cylindrical waterproof;
15% sure that rectangle torchlights have 60%–70% of cylindrical waterproof;
5% sure that rectangle torchlights have 70%–100% of cylindrical waterproof.

However, as discussed earlier, the cylindrical waterproof is given by the following three uncertain intervals with different probabilities:

cylindrical waterproof = [10, 12] meters of 20% probability;
cylindrical waterproof = [12, 15] meters of 60% probability;
cylindrical waterproof = [15, 18] meters of 20% probability.

In the following, we transform the earlier comparison data for evaluation of rectangle waterproof with respect to cylindrical waterproof to uncertain interval assessments of different probabilities. First, we transform the following uncertain assessment:

80% sure that rectangle torchlights have 50%–60% of cylindrical waterproof.

Note that 50%–60% of cylindrical waterproof means that rectangle waterproof is:

[10 × 0.5, 12 × 0.6] meters of 20% probability;
[12 × 0.5, 15 × 0.6] meters of 60% probability;
[15 × 0.5, 18 × 0.6] meters of 20% probability;

or:

[5.0, 7.2] meters of 20% probability;
[6.0, 9.0] meters of 60% probability;
[7.5, 10.8] meters of 20% probability.

So, the earlier uncertain assessment can be equivalently transformed to the following three intervals with different probabilities, where "⇒" means "is equivalent to":

80% sure that rectangle torchlights have 50%–60% of cylindrical waterproof
⇒ rectangle waterproof is
[5.0, 7.2] meters of 16% (20% × 80%) probability;
[6.0, 9.0] meters of 48% (60%×80%) probability;
[7.5, 10.8] meters of 16% (20%×80%) probability.

Similarly, we can equivalently transform each of the following two uncertain assessments into three intervals with different probabilities as follows:

15% sure that rectangle torchlights have 60%–70% of cylindrical waterproof
⇒ Rectangle waterproof is
[6.0, 8.4] meters of 3% (20% × 15%) probability;
[7.2, 10.5] meters of 9% (60% × 15%) probability;
[9.0, 12.6] meters of 3% (20% × 15%) probability.

And:

5% sure that rectangle torchlights have 70%–100% of cylindrical waterproof
⇒ Rectangle waterproof is
[7.0, 12.0] meters of 1% (20% × 5%) probability,
[8.4, 15.0] meters of 3% (60% × 5%) probability,
[10.5, 18.0] meters of 1% (20% × 5%) probability.

In summary, rectangle waterproof can be equivalently assessed using the following nine intervals with different probabilities summed to one, i.e.

Rectangle waterproof is
[5.0, 7.2] meters of 16% probability;
[6.0, 8.4] meters of 3% probability;
[6.0, 9.0] meters of 48% probability;
[7.0, 12.0] meters of 1% probability;
[7.2, 10.5] meters of 9% probability;
[7.5, 10.8] meters of 16% probability;
[8.4, 15.0] meters of 3% probability;
[9.0, 12.6] meters of 3% probability;
[10.5, 18.0] meters of 1% probability.

The earlier uncertain interval assessments for rectangle waterproof can be further transformed to an equivalent interval belief assessment using the grades defined in Fig. 5, as shown in the Appendix. In summary, the interval belief assessment of the waterproof performance for rectangle torchlights can be represented as follows:

$$\begin{aligned}
&\{(H_{11}, [0, 0.16I_{1,1} + 0.016I_{1,2} + 0.259I_{1,3} + 0.0008I_{1,4}]),\\
&(H_{22}, [0.088, 0.16 + 0.03 + 0.48 + 0.01(I_{1,4} + I_{2,4})\\
&\qquad + 0.089I_{1,5} + 0.136I_{1,6} + 0.013I_{1,7} + 0.0047I_{1,8}]),\\
&(H_{33}, [0.003, 0.002I_{2,1} + 0.017I_{2,2} + 0.405I_{2,3}\\
&\qquad + 0.01(I_{2,4} + I_{3,4}) + 0.09 + 0.16 + 0.03(I_{1,7} + I_{2,7})\\
&\qquad + 0.03(I_{1,8} + I_{2,8}) + 0.0046I_{1,9}]),\\
&(H_{44}, [0, 0.01(I_{3,4} + I_{4,4}) + 0.048I_{2,5} + 0.108I_{2,6}\\
&\qquad + 0.03(I_{2,7} + I_{3,7}) + 0.03(I_{2,8} + I_{3,8})\\
&\qquad + 0.01(I_{1,9} + I_{2,9})]),\\
&(H_{55}, [0, 0.0023I_{4,4} + 0.03(I_{3,7} + I_{4,7}) + 0.0152I_{3,8}\\
&\qquad + 0.01(I_{2,9} + I_{3,9})]),\\
&(H_{66}, [0, 0.018I_{4,7} + 0.01(I_{3,9} + I_{4,9})]),\\
&(H_{77}, [0, 0.01I_{4,9}])\}
\end{aligned}$$

with

$$\begin{aligned}
&I_{1,1} + I_{2,1} = 1 \quad I_{1,1} \times I_{2,1} = 0\\
&I_{1,2} + I_{2,2} = 1 \quad I_{1,2} \times I_{2,2} = 0\\
&I_{1,3} + I_{2,3} = 1 \quad I_{1,3} \times I_{2,3} = 0\\
&I_{1,4} + I_{2,4} + I_{3,4} + I_{4,4} = 1\\
&I_{1,4} \times (I_{2,4} + I_{3,4} + I_{4,4}) + I_{2,4} \times (I_{3,4} + I_{4,4}) + I_{3,4} \times I_{4,4} = 0\\
&I_{1,5} + I_{2,5} = 1 \quad I_{1,5} \times I_{2,5} = 0\\
&I_{1,6} + I_{2,6} = 1 \quad I_{1,6} \times I_{2,6} = 0\\
&I_{1,7} + I_{2,7} + I_{3,7} + I_{4,7} = 1\\
&I_{1,7} \times (I_{2,7} + I_{3,7} + I_{4,7}) + I_{2,7} \times (I_{3,7} + I_{4,7}) + I_{3,7} \times I_{4,7} = 0\\
&I_{1,8} + I_{2,8} + I_{3,8} = 1 \quad I_{1,8} \times (I_{2,8} + I_{3,8}) + I_{2,8} \times I_{3,8} = 0\\
&I_{1,9} + I_{2,9} + I_{3,9} + I_{4,9} = 1\\
&I_{1,9} \times (I_{2,9} + I_{3,9} + I_{4,9}) + I_{2,9} \times (I_{3,9} + I_{4,9}) + I_{3,9} \times I_{4,9} = 0.
\end{aligned}$$

B. Results

By applying the ER nonlinear maximizing and minimizing optimization models shown in formulas (28)–(30), evaluations based on the 24 criterions shown in Table II can be aggregated into the final evaluations β_{pq} for each $p = 1, \ldots, 7,\ q = p, \ldots, 7$, which also appears in $\min - \max$ intervals, i.e., β_{pq} is between $[\min \beta_{pq}, \max \beta_{pq}]$, and they are shown in Tables III and IV for the two alternative products, respectively.

It is observed that the overall evaluation of rectangle light is mostly distributed in H_{11}, H_{33}, H_{55}, and global unknown H_{17} is about 0.6%–0.7%, while local unknown appears in H_{12}, H_{23}, H_{24}, H_{34}, H_{56}.

For cylindrical light, it is observed that most of the possibility is distributed in H_{33}, H_{66}, while local unknown appears in H_{45}, H_{67}.

TABLE III
β_{pq} FOR RECTANGLE LIGHT

β_{pq} \ q / p	1	2	3	4	5	6	7
1	[0.104, 0.119]	[0.011, 0.132]	0	0	0	0	[0.006, 0.007]
2		[0.027, 0.093]	[0.141, 0.161]	[0.001, 0.002]	0	0	0
3			[0.106, 0.205]	[0.090, 0.103]	0	0	0
4				[0.035, 0.063]	0	0	0
5					[0.167, 0.196]	[0.008, 0.009]	0
6						[0.096, 0.110]	0
7							[0.041, 0.048]

TABLE IV
β_{pq} FOR CYLINDRICAL LIGHT

β_{pq} \ q / p	1	2	3	4	5	6	7
1	0	0	0	0	0	0	0
2		[0.069, 0.081]	0	0	0	0	0
3			[0.135, 0.171]	0	0	0	0
4				[0.061, 0.127]	[0.012, 0.014]	0	0
5					[0.029, 0.081]	0	0
6						[0.442, 0.542]	[0.058, 0.067]
7							[0.050, 0.058]

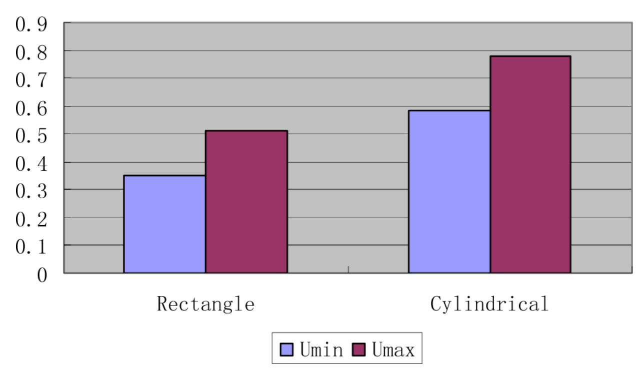


Fig. 7. Utility comparisons.

From Tables III and IV, the preference order of cylindrical and rectangle light is not easy to be observed, so the utility analysis procedures are used to compare the two alternatives.

Given the utility scale

$$U = [0 \quad 0.17 \quad 0.34 \quad 0.5 \quad 0.67 \quad 0.84 \quad 1]$$

where H_{11} has the utility value of zero and H_{77} has utility value of one, we can obtain the minimum utility value $u_{\min}$ and maximum utility value $u_{\max}$ of rectangle light as 0.3525 and 0.5132, and for cylindrical light, as 0.5840 and 0.7791.

It can be found that cylindrical light performs dominantly better than rectangle light, for

$$u_{\min}(\text{cylindrical}) = 0.5840 > u_{\max}(\text{rectangle}) = 0.5132.$$

So we can conclude that cylindrical light is strictly better than rectangle light (see Fig. 7).

The final result gives the product designers support to make the choice between two designs. It is, however, noted that, in some cases, the result may be not so clear because of the uncertainties of initial NPD data, such as unknown, imprecise both in interval grades and possibility uncertainties. For example, if the minimum and maximum utility value of rectangle light are 0.3525 and 0.6, and that of cylindrical light are 0.5840 and 0.7791, then

$$u_{\min}(\text{cylindrical}) = 0.5840 > u_{\max}(\text{rectangle}) = 0.6.$$

We cannot conclude that cylindrical light is strictly better than rectangle, although with large possibility, that the former is better than the latter. If this possibility is not big enough to be accepted by the DM or the DM wants the strictly dominant result, the initial evaluation data should be reevaluated by the DM, and then the earlier ER aggregating methods should be applied again to obtain a better or dominant result. For more detail, refer to the work of Guo *et al.* [19].

VI. CONCLUSION

The product design process becomes an increasingly complex decision-making problem in which one must simultaneously cater, in a rational way, for many interrelated criteria of both quantitative and qualitative nature. It is also noted that the design decision analysis has to be conducted on the basis of both precise numbers and subjective judgments that are imprecise and vague (fuzzy) in nature. Such uncertainties can be incurred due to a lack of evidence and understanding or human's inability of providing accurate judgments at early design stage of novel new products. This paper presents the authors' new development of a novel rigorous assessment methodology to improve the decision analysis in the complex multiple-attribute environment of NPD assessment in early product design stage.

The authors extend the basic ER algorithm to consider the uncertainties caused by interval-valued evaluations, which happen in several MADA problems, such as product design assessment. The developed ER-interval methodologies could improve the decision analysis on the basis of taking into account both two kinds of interval-valued evaluations, interval grades and interval assessment in possibilities. As shown in the case study, the industrial experts' judgments are associated with uncertainties that are a combination of precise, imprecise, and vague information in various forms. The typical formats of data and information employed in the industry are described in, namely, a precise number, an interval value, a belief structure, and a comparison scale. The ER-interval methodology is able to deal with these uncertain data and information in various forms with probability functions, in a comparative basis, unknown embedded, etc.

To illustrate the contribution of this research to the practice, the authors formulate an NPD assessment framework incorporated with the ER-interval methodology for the implementation through a case study. A hierarchal product design assessment model that constitutes three categories of criteria, namely product cost, project risk, and customer satisfaction, is proposed. The model consists of 24 evaluation factors in three levels. An AHP-based methodology is also proposed to determine the relative importance weightings of individual factor. This provides a way of thinking about the implementation of the ER-interval-based product design assessment methodology to be conducted, and helps product designers understand and assess the alternative new product concepts.

The development of the ER-interval-based NPD assessment methodology is motivated by practicing product designers trying to make decisions about choices of alternative new product concepts. The authors have demonstrated the applicability of the methodology through a case study. This case study, however, is not a full validation of the methodology, as it demonstrates its applicability only in one company. Therefore, for future work, the methodology will be validated in more companies and even in different industries. In addition, to facilitate the use of the methodology in real-life situation, a software assessment system based on the developed modeling techniques and assessment methodology is recommended.

Appendix

Transformation of the Following Uncertain Interval Assessments to an Equivalent Interval Belief Assessment Within the ER Framework

The uncertain interval assessments are given as follows:

Rectangle waterproof is
- [5.0, 7.2] meters of 16% probability;
- [6.0, 8.4] meters of 3% probability;
- [6.0, 9.0] meters of 48% probability;
- [7.0, 12.0] meters of 1% probability;
- [7.2, 10.5] meters of 9% probability;
- [7.5, 10.8] meters of 16% probability;
- [8.4, 15.0] meters of 3% probability;
- [9.0, 12.6] meters of 3% probability;
- [10.5, 18.0] meters of 1% probability.

According to the uncertain information transformation technique proposed by Yang [49] and the interval information transformation technique proposed by Wang *et al.* [43], the earlier information can be equivalently transformed to an interval belief assessment as follows. For the first interval [5.0, 7.2] of 16% probability, we have

$$\beta_{1,i}^{-}=0 \quad \text{and} \quad \beta_{1,i}^{+}=I_{1,1}\times\frac{7.17-5.0}{7.17-5.0}\times 16\%$$

$$\beta_{2,i}^{-}=0 \quad \text{and} \quad \beta_{2,i}^{+}=(I_{1,1}+I_{2,1})\times 16\%$$

$$\beta_{3,i}^{-}=0 \quad \text{and} \quad \beta_{3,i}^{+}=I_{2,1}\times\frac{7.2-7.17}{9.34-7.17}\times 16\%$$

with $I_{1,1}+I_{2,1}=1$ and $I_{1,1}\times I_{2,1}=0$, or

$$\{(H_{11},[0,0.16I_{1,1}]),(H_{22},[0,0.16]),(H_{33},[0,0.002I_{2,1}])\}.$$

For the interval [6.0, 8.4] of 3% probability, we have

$$\beta_{1,i}^{-}=0 \quad \text{and} \quad \beta_{1,i}^{+}=I_{1,2}\times\frac{7.17-6.0}{7.17-5.0}\times 3\%$$

$$\beta_{2,i}^{-}=\min\left(\frac{6.0-5.0}{7.17-5.0},\frac{9.34-8.4}{9.34-7.17}\right)\times 3\% \quad \text{and}$$

$$\beta_{2,i}^{+}=(I_{1,2}+I_{2,2})\times 3\%$$

$$\beta_{3,i}^{-}=0 \quad \text{and} \quad \beta_{3,i}^{+}=I_{2,2}\times\frac{8.4-7.17}{9.34-7.17}\times 3\%$$

with $I_{1,2}+I_{2,2}=1$ and $I_{1,2}\times I_{2,2}=0$, or

$$\{(H_{11},[0,0.016I_{1,2}]),(H_{22},[0.013,0.03]),(H_{33},[0,0.017I_{2,2}])\}.$$

For the interval [6.0, 9.0] of 48% probability, we have

$$\beta_{1,i}^{-}=0 \quad \text{and} \quad \beta_{1,i}^{+}=I_{1,3}\times\frac{7.17-6.0}{7.17-5.0}\times 48\%$$

$$\beta_{2,i}^{-}=\min\left(\frac{6.0-5.0}{7.17-5.0},\frac{9.34-9}{9.34-7.17}\right)\times 48\% \quad \text{and}$$

$$\beta_{2,i}^{+}=(I_{1,3}+I_{2,3})\times 48\%$$

$$\beta_{3,i}^{-}=0 \quad \text{and} \quad \beta_{3,i}^{+}=I_{2,3}\times\frac{9.0-7.17}{9.34-7.17}\times 48\%$$

with $I_{1,3}+I_{2,3}=1$ and $I_{1,3}\times I_{2,3}=0$, or

$$\{(H_{11},[0,0.259I_{1,3}]),(H_{22},[0.075,0.48]),(H_{33},[0,0.405I_{2,3}])\}.$$

For the interval [7.0, 12.0] of 1% probability, we have

$$\beta_{1,i}^{-}=0 \quad \text{and} \quad \beta_{1,i}^{+}=I_{1,4}\times\frac{7.17-7.0}{7.17-5.0}\times 1\%$$

$$\beta_{2,i}^{-}=0 \quad \text{and} \quad \beta_{2,i}^{+}=(I_{1,4}+I_{2,4})\times 1\%$$

$$\beta_{3,i}^{-}=0 \quad \text{and} \quad \beta_{3,i}^{+}=(I_{2,4}+I_{3,4})\times 1\%$$

$$\beta_{4,i}^{-}=0 \quad \text{and} \quad \beta_{4,i}^{+}=(I_{3,4}+I_{4,4})\times 1\%$$

$$\beta_{5,i}^{-}=0 \quad \text{and} \quad \beta_{5,i}^{+}=I_{4,4}\times\frac{12.0-11.5}{13.67-11.5}\times 1\%$$

with

$$I_{1,4}+I_{2,4}+I_{3,4}+I_{4,4}=1$$

$$I_{1,4}\times(I_{2,4}+I_{3,4}+I_{4,4})+I_{2,4}\times(I_{3,4}+I_{4,4})+I_{3,4}\times I_{4,4}=0$$

or

$$\{(H_{11},[0,0.0008I_{1,4}]),\ (H_{22},[0,0.01(I_{1,4}+I_{2,4})]),$$
$$(H_{33},[0,0.01(I_{2,4}+I_{3,4})]),\ (H_{44},[0,0.01(I_{3,4}+I_{4,4})]),$$
$$(H_{55},[0,0.0023I_{4,4}])\}.$$

For the interval [7.2, 10.5] of 9% probability, we have

$$\beta_{2,i}^{-}=0 \quad \text{and} \quad \beta_{2,i}^{+}=I_{1,5}\times\frac{9.34-7.2}{9.34-7.17}\times 9\%$$

$$\beta_{3,i}^{-}=\min\left(\frac{7.2-7.17}{9.34-7.17},\frac{11.5-10.5}{11.5-9.34}\right)\times 9\% \quad \text{and}$$

$$\beta_{3,i}^{+}=(I_{1,5}+I_{2,5})\times 9\%$$

$$\beta_{4,i}^{-}=0 \quad \text{and} \quad \beta_{4,i}^{+}=I_{2,5}\times\frac{10.5-9.34}{11.5-9.34}\times 9\%$$

with $I_{1,5} + I_{2,5} = 1$ and $I_{1,5} \times I_{2,5} = 0$, or

$\{(H_{22}, [0, 0.089 I_{1,5}]), (H_{33}, [0.001, 0.09]), (H_{44}, [0, 0.048 I_{2,5}])\}$.

For the interval [7.5, 10.8] of 16% probability, we have

$$\beta_{2,i}^- = 0 \quad \text{and} \quad \beta_{2,i}^+ = I_{1,6} \times \frac{9.34 - 7.5}{9.34 - 7.17} \times 16\%$$

$$\beta_{3,i}^- = \min\left(\frac{7.5 - 7.17}{9.34 - 7.17}, \frac{10.8 - 10.5}{11.5 - 9.34}\right) \times 16\% \quad \text{and}$$

$$\beta_{3,i}^+ = (I_{1,6} + I_{2,6}) \times 16\%$$

$$\beta_{4,i}^- = 0 \quad \text{and} \quad \beta_{4,i}^+ = I_{2,6} \times \frac{10.8 - 9.34}{11.5 - 9.34} \times 16\%$$

with $I_{1,6} + I_{2,6} = 1$ and $I_{1,6} \times I_{2,6} = 0$, or

$\{(H_{22}, [0, 0.136 I_{1,6}]), (H_{33}, [0.002, 0.16]), (H_{44}, [0, 0.108 I_{2,6}])\}$.

For the interval [8.4, 15.0] of 3% probability, we have

$$\beta_{2,i}^- = 0 \quad \text{and} \quad \beta_{2,i}^+ = I_{1,7} \times \frac{9.34 - 8.4}{9.34 - 7.17} \times 3\%$$

$$\beta_{3,i}^- = 0 \quad \text{and} \quad \beta_{3,i}^+ = (I_{1,7} + I_{2,7}) \times 3\%$$

$$\beta_{4,i}^- = 0 \quad \text{and} \quad \beta_{4,i}^+ = (I_{2,7} + I_{3,7}) \times 3\%$$

$$\beta_{5,i}^- = 0 \quad \text{and} \quad \beta_{5,i}^+ = (I_{3,7} + I_{4,7}) \times 3\%$$

$$\beta_{6,i}^- = 0 \quad \text{and} \quad \beta_{6,i}^+ = I_{4,7} \times \frac{15.0 - 13.67}{15.84 - 13.67} \times 3\%$$

with

$$I_{1,7} + I_{2,7} + I_{3,7} + I_{4,7} = 1$$

$$I_{1,7} \times (I_{2,7} + I_{3,7} + I_{4,7}) + I_{2,7} \times (I_{3,7} + I_{4,7}) + I_{3,7} \times I_{4,7} = 0$$

or

$$\{(H_{22}, [0, 0.013 I_{1,7}]), (H_{33}, [0, 0.03(I_{1,7} + I_{2,7})]), (H_{44}, [0, 0.03(I_{2,7} + I_{3,7})]), (H_{55}, [0, 0.03(I_{3,7} + I_{4,7})]), (H_{66}, [0, 0.018 I_{4,7}])\}.$$

For the interval [9.0, 12.6] of 3% probability, we have

$$\beta_{2,i}^- = 0 \quad \text{and} \quad \beta_{2,i}^+ = I_{1,8} \times \frac{9.34 - 9.0}{9.34 - 7.17} \times 3\%$$

$$\beta_{3,i}^- = 0 \quad \text{and} \quad \beta_{3,i}^+ = (I_{1,8} + I_{2,8}) \times 3\%$$

$$\beta_{4,i}^- = 0 \quad \text{and} \quad \beta_{4,i}^+ = (I_{2,8} + I_{3,8}) \times 3\%$$

$$\beta_{5,i}^- = 0 \quad \text{and} \quad \beta_{5,i}^+ = I_{3,8} \times \frac{12.6 - 11.5}{13.67 - 11.5} \times 3\%$$

with

$$I_{1,8} + I_{2,8} + I_{3,8} = 1 \quad \text{and}$$

$$I_{1,8} \times (I_{2,8} + I_{3,8}) + I_{2,8} \times I_{3,8} = 0$$

or

$$\{(H_{22}, [0, 0.0047 I_{1,8}]), (H_{33}, [0, 0.03(I_{1,8} + I_{2,8})]), (H_{44}, [0, 0.03(I_{2,8} + I_{3,8})]), (H_{55}, [0, 0.0152 I_{3,8}])\}.$$

For the interval [10.5, 18.0] of 1% probability, we have

$$\beta_{3,i}^- = 0 \quad \text{and} \quad \beta_{3,i}^+ = I_{1,9} \times \frac{11.5 - 10.5}{11.5 - 9.34} \times 1\%$$

$$\beta_{4,i}^- = 0 \quad \text{and} \quad \beta_{4,i}^+ = (I_{1,9} + I_{2,9}) \times 1\%$$

$$\beta_{5,i}^- = 0 \quad \text{and} \quad \beta_{5,i}^+ = (I_{2,9} + I_{3,9}) \times 1\%$$

$$\beta_{6,i}^- = 0 \quad \text{and} \quad \beta_{6,i}^+ = (I_{3,9} + I_{4,9}) \times 1\%$$

$$\beta_{7,i}^- = 0 \quad \text{and} \quad \beta_{7,i}^+ = I_{4,9} \times \frac{18.0 - 15.84}{18.0 - 15.84} \times 1\%$$

with

$$I_{1,9} + I_{2,9} + I_{3,9} + I_{4,9} = 1$$

$$I_{1,9} \times (I_{2,9} + I_{3,9} + I_{4,9}) + I_{2,9} \times (I_{3,9} + I_{4,9}) + I_{3,9} \times I_{4,9} = 0$$

or

$$\{(H_{33}, [0, 0.0046 I_{1,9}]), (H_{44}, [0, 0.01(I_{1,9} + I_{2,9})]), (H_{55}, [0, 0.01(I_{2,9} + I_{3,9})]), (H_{66}, [0, 0.01(I_{3,9} + I_{4,9})]), (H_{77}, [0, 0.01 I_{4,9}])\}.$$

So, the interval belief assessment of the waterproof performance for rectangle torchlights can be equivalently represented by summarizing the earlier results as follows:

$$\begin{aligned}
&\{(H_{11}, [0, 0.16 I_{1,1} + 0.016 I_{1,2} + 0.259 I_{1,3} + 0.0008 I_{1,4}]),\\
&(H_{22}, [0.088, 0.16 + 0.03 + 0.48 + 0.01(I_{1,4} + I_{2,4})\\
&\qquad + 0.089 I_{1,5} + 0.136 I_{1,6} + 0.013 I_{1,7} + 0.0047 I_{1,8}]),\\
&(H_{33}, [0.003, 0.002 I_{2,1} + 0.017 I_{2,2} + 0.405 I_{2,3}\\
&\qquad + 0.01(I_{2,4} + I_{3,4}) + 0.09 + 0.16 + 0.03(I_{1,7} + I_{2,7})\\
&\qquad + 0.03(I_{1,8} + I_{2,8}) + 0.0046 I_{1,9}]),\\
&(H_{44}, [0, 0.01(I_{3,4} + I_{4,4}) + 0.048 I_{2,5} + 0.108 I_{2,6}\\
&\qquad + 0.03(I_{2,7} + I_{3,7}) + 0.03(I_{2,8} + I_{3,8})\\
&\qquad + 0.01(I_{1,9} + I_{2,9})]),\\
&(H_{55}, [0, 0.0023 I_{4,4} + 0.03(I_{3,7} + I_{4,7}) + 0.0152 I_{3,8}\\
&\qquad + 0.01(I_{2,9} + I_{3,9})]),\\
&(H_{66}, [0, 0.018 I_{4,7} + 0.01(I_{3,9} + I_{4,9})]),\\
&(H_{77}, [0, 0.01 I_{4,9}])\}
\end{aligned}$$

with

$$I_{1,1} + I_{2,1} = 1 \quad I_{1,1} \times I_{2,1} = 0$$

$$I_{1,2} + I_{2,2} = 1 \quad I_{1,2} \times I_{2,2} = 0$$

$$I_{1,3} + I_{2,3} = 1 \quad I_{1,3} \times I_{2,3} = 0$$

$$I_{1,4} + I_{2,4} + I_{3,4} + I_{4,4} = 1$$

$$I_{1,4} \times (I_{2,4} + I_{3,4} + I_{4,4}) + I_{2,4} \times (I_{3,4} + I_{4,4}) + I_{3,4} \times I_{4,4} = 0$$

$$I_{1,5} + I_{2,5} = 1 \quad I_{1,5} \times I_{2,5} = 0$$

$$I_{1,6} + I_{2,6} = 1 \quad I_{1,6} \times I_{2,6} = 0$$

$$I_{1,7}+I_{2,7}+I_{3,7}+I_{4,7}=1$$

$$I_{1,7}\times(I_{2,7}+I_{3,7}+I_{4,7})+I_{2,7}\times(I_{3,7}+I_{4,7})+I_{3,7}\times I_{4,7}=0$$

$$I_{1,8}+I_{2,8}+I_{3,8}=1 \quad I_{1,8}\times(I_{2,8}+I_{3,8})+I_{2,8}\times I_{3,8}=0$$

$$I_{1,9}+I_{2,9}+I_{3,9}+I_{4,9}=1 \quad I_{1,9}\times(I_{2,9}+I_{3,9}+I_{4,9})+I_{2,9}\times(I_{3,9}+I_{4,9})+I_{3,9}\times I_{4,9}=0.$$

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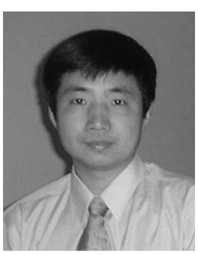
Kwai-Sang Chin received the Ph.D. degree in industrial and manufacturing system engineering from The University of Hong Kong, Hong Kong, China, in 1996.

He is an Associate Professor and the Chair of Postgraduate Teaching in the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong. He has authored or coauthored more than 100 papers published in international refereed journal in the fields of industrial engineering, quality management, and product development. His current research interests include decision makings in new product development, quality management in supply chain environment, and international technology transfer between West and East.



Jian-Bo Yang received the B.Eng. and M.Eng. degrees in control engineering from North Western Polytechnic University, Xi'an, China, in 1981 and 1984, respectively, and the Ph.D. degree in systems engineering from Shanghai Jiao Tong University, Shanghai, China, in 1987.

He is a Professor of decision and system sciences at the Manchester Business School, the University of Manchester, Manchester, U.K., where he is also the Director of the Decision Sciences Research Centre. He is also a Changjian Specially Appointed Chair Professor at the School of Management, Hefei University of Technology, Hefei, China. He has been widely engaged in the areas of design decision making, risk modeling and analysis, quality modeling and evaluation, supply chain modeling and supplier assessment, and the integrated evaluation of products, systems, projects, policies, etc.

Min Guo received the Ph.D. degree in systems engineering from Huazhong University of Science and Technology, Wuhan, China, in 2002.

He is currently an Associate Professor in the Department of Control Science and Control Engineering, Huazhong University of Science and Technology. He is also with the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong. His current research interests include the fields of evidential reasoning, supply chain contract, and optimization.

James Ping-Kit Lam is currently working toward the Ph.D. degree at the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong.

His current research interests include lean manufacturing approaches and methodologies in new product design and development.