International Journal of Database Theory and Application
Vol.7, No.5 (2014), pp.239-252
http://dx.doi.org/10.14257/ijdta.2014.7.5.18

Reliability Analysis and Prediction for Product Design Based on Feature Similarity

Tao Yang, Yu Yang* and Yao Jiao
State Key Laboratory of Mechanical Transmission, Chongqing University, 400030, Chongqing, China
Department of Industrial Engineering, College of Mechanical Engineering, Chongqing University, Chongqing 400030, China
*yangtao061@sina.cn; *yuyangcqu@cqu.edu.cn; jiaoyao7@hotmail.com*

Abstract

During product design phase, aiming at the problem of lacking reliability data, lower of product reliability, feature similarity-based new product design reliability analysis and prediction model were proposed. Putting the new product features as an evaluation objectives, an approach named Technique for Order Preference by Similarity to Ideal Solution(TOPSIS) was established firstly for selecting similar features products; Then, in order to realize the reliability analysis relational mapping with the new product design, the failure structure of the similar features products was quantified and the product failure structure matrix (FSM) was established, respectively; Afterwards, the Group Decision Making Method (GDMM) was presented for determining the improvement factor of the similar features products failure causes, on that basis, the new product features failure structure was generated to predict the reliability of new designing products. Finally, feasibility and effectiveness of the model were verified through an example of new Smart Mobile Phone product design.

Keywords: *New Product Design; Feature Similarity; Reliability Prediction*

1. Introduction

During product design, manufacture and using phases, modern production experience shows that the product design phase mainly determined the level of reliability, and the other two phases are mainly implementation and verification of the product reliability index. Therefore, in order to meet consumer demand for the purchased product quality, stability, and reliability requirements to enhance the market competitiveness of new product, enterprises should address the new product features, shape, materials and other product features in the design phase and find a more reasonable and complete way to improve the reliability of its product design significantly[1-2]. The similarity-based new products design can access and reuse existing product design results and the reliability data of design phase to achieve the relational mapping of reliability analysis with the new product, and effectively compensate the new product design phase for data shortcoming[3-4].

At present, scholars have proposed a variety of reliability design techniques and methods, such as Test-in Reliability (TIR)[5], Accelerated Degradation Testing (ADT)[6], Wafer Level Reliability (WLR)[7], Reliability Growth Technology (RGT)[8], etc. However, these methods are mainly from the perspective of product life cycle(PLC) by prototype testing, product/part life testing and other methods to record, analyze and optimize the product malfunction/failure behaviors, thus increasing product design

ISSN: 2005-4270 IJDTA

reliability, but the drawback is the testing cost is too high and the analysis process is too complicated, and it would not obtain useful reliability information if the initial tests were wrong. Case-based reasoning [9] (CBR) is a solving strategy to new problems by analogizing and associating the empirical knowledge, but this method focuses more on instance representation, case retrieval and storage, *etc*., less on reasoning research, also the retrieval process of CBR is sometimes not as accurate as the human observation, like expert decision making. Product reliability simulation technology (PRST) [10-11] to some extent reduces test cycle time and the resource consumption by using parameter characterization method, but PRST is insufficient to some degree mainly in (1) complex simulation modeling and needs experts with specialized knowledge in simulation process, which restricts the application of PRST. (2)The existing data-driven simulation modeling techniques cannot well express the large number of semantics and relationships between decision making work and simulation parameters. (3) Simulation parameters are commonly selected from engineering experience, which is not very accurate.

Built-in reliability[12](BIR) and design for reliability[13](DFR) both emphasize the need to consider and control the factors and variables affecting product reliability in early stages of product design, and take measures to optimize the reliability design. This paper based on the research results analyzing of design reliability home and abroad, combined with the theories and methods of BIR/DFR and product feature similarity, to analyze and predict the design reliability in product design phase.

2. Reliability Analysis and Prediction Model

2.1. Evaluating and selecting of the feature similarity products

Feature is the entity or abstraction with a specific meaning which can be expressed in a particular field. In practice, the same type products have similar features in function, structure, materials, etc., but the differences exist between product features according to the product design goals. In this paper, a product feature similarity level evaluation criteria has been build (shown as Table1) to evaluate the degree of feature similarity between products. The purpose of feature similarity product evaluation is to select an object more closely to the target product features from multiple evaluation objects, the evaluation and selecting methods are AHP, Fuzzy Comprehensive Evaluation Method (FCEM), SVM, Rough Kernel Distance Model (RKDM), *etc.*, of which the Technique for Order Preference by Similarity to Ideal Solution[14](TOPSIS) is a commonly evaluation method in multi-objective decision making, compared to other methods, it also takes into account the pros and cons value of each evaluation objects, making the evaluation results fully reflect the group feature of objects, more closely to actual results, and with higher reliability.

Table 1. Evaluation Criteria for Product Features Similarity Assessment

Similarity level	Category	Description
1	very strong	very strong similarity between product characteristics
0.8	strong	strong similarity between product characteristics
0.6	medium strong	similarity relationship exists between product characteristics
0.4	general	product feature similarity is not obvious
0.2	weak strong	weak similarity between product characteristics
0	no	no Similarity relationship between product characteristics

Based on TOPSIS, the specific steps to select the existing products which are similarity to the new product features are as follows:

Step1 Collecting the enterprise product designers, experts in relevant fields and customer knowledge and describing the new product design features, so we can obtain the new product features set: $X=(X^1,\dots,X^N)$, $X^n=\{x_1^n,x_2^n,\cdots,x_e^n\}$, N represents the number of features and $n\in[1,N]$, e represents the number of features decomposition.

Step2 Counting existing products $Y=(y_1,y_2,\dots,y_m)$ which are similar to new product features, and putting as the evaluation objectives. Based on the product feature similarity evaluation criteria, using experts grading method to give the similar evaluation value v_{kij} ($k=1,2,\dots,\eta$; $i=1,2,\dots,m$; $j=1,2,\dots,e$) and constructing evaluation decision matrix $V=\left[\overline{v_{ij}}\right]_{m\times e}$ and weighted standardization matrix $S=\left[s_{ij}\right]_{m\times e}$ under the following formulas:

$$s_{ij}=\omega_j^n\times v_{ij}^* \tag{1}$$

$$v_{ij}^*=\overline{v_{ij}}\Big/\sqrt{\sum_{i=1}^{m}\overline{v_{ij}}^2}\quad i\in[1,m],\ j\in[1,e] \tag{2}$$

$$\overline{v_{ij}}=\sum_{k=1}^{\eta}\gamma_k v_{kij} \tag{3}$$

$$\sum_{j=1}^{e}\omega_j^n=1 \tag{4}$$

where, γ_k represents the weight of expert k, η represents the number of experts, ω_j^n represents the weight of feature j.

Step3 Determine the positive and negative idea solutions of weighted standardization matrix. Positive idea solution $A^+=\{s_{1^+}^*,s_{2^+}^*,\cdots,s_{e^+}^*\}$ and negative idea solution:

$A^-=\{s_{1^-}^*,s_{2^-}^*,\cdots,s_{e^-}^*\}$, Where $s_{j^+}^*=\{\max\limits_i(s_{ij}),\ j=1,2,\cdots,e;\}$ and $s_{j^-}^*=\{\min\limits_i(s_{ij}),\ j=1,2,\cdots,e;\}$.

Step4 Calculating the Euclidean distance. For evaluation object y_i, its Euclidean distance to positive and negative ideal solution: $d_{i^+}^n$ and $d_{i^-}^n$ can be calculated as:

$$d_{i^+}^n=\sqrt{\sum_{j=1}^{e}\left(s_{j^+}^*-s_{ij}\right)^2}\quad i=1,2,3,\dots,m;\ n=1,2,\cdots,N \tag{5}$$

$$d_{i^-}^n=\sqrt{\sum_{j=1}^{e}\left(s_{j^-}^*-s_{ij}\right)^2}\quad i=1,2,3,\dots,m;\ n=1,2,\cdots,N \tag{6}$$

Step5 Calculate the coefficient C_i^n for each alternative. Calculate it according to the results of Step 4.

$$C_i^n=\sqrt{\left(d_{i^+}^n-\min\left(d_{i^+}^n\right)\right)^2+\left(d_{i^-}-\max\left(d_{i^-}^n\right)\right)^2},\quad i=1,2,\cdots,m;\ n=1,2,\cdots,N \tag{7}$$

The calculation of C_i^n is accomplished by firstly set the optimized idea reference point: $\left(\min\left(d_{i^+}^n\right),\max\left(d_{i^-}^n\right)\right)$, and then calculate the distance from each objective to that point, the smaller distance value indicates that the evaluation objects farther from the negative ideal solution, while more nearly to the positive ideal solution ($0\le C_i^n\le 1$).

Step6 Sorting the results of **Step5**, the best alternative is the one that having the TOPSIS coefficient C_i^n nearest to 0.

Step7 The decision-makers repeat **Step1-Step6** to evaluate the products with an optimal TOPSIS coefficient of feature similarity products, and select the more optimal C_i^n value as the reference object of new product reliability design analysis, and finally find out the feature similarity products set: $SX = \{SX^{I}, SX^{II}, \cdots, SX^{T}\}$ which corresponding to the new product design feature X^n.

2.2. Feature similarity product failure structure analysis

Product features failure structure contains two aspects: failure causes and failure modes [15,16]. Failure causes indicate the factors that cause the product features failure, such as impact, component fatigue damage, etc.; failure modes indicate the representation of product features failure caused by relevant failure factors, such as distortion, leakage, *etc*.. Most of the new product design is the improvement or design enhance of existing products, the new product failure structure would be mainly depended on the feature similarity product analysis, if no new failure modes are introduced to the improvement or enhancement process. This paper assumes that the new product feature failure structure relationship is same to the existing product, though collecting the similar products information and reliability information as the input for the new product failure structure analysis. The practical experience shows that the failure factors are not the same importance for the occurrence of failure modes, in other words, the influence degree of failure factors causing failure modes is not even. If every factor that causes product feature failure can be quantified, it may have a great importance to optimize and improve product reliability design for product features.

In 1969, Birnbaum[15]considered the influence degree of basic events failure to the top events, and established a relative importance degree index $I_i^B(t)$, shown as Formula (8), which reflects the ratio of reliability of internal parts *I* to the system reliability.

$$I_i^B(t) = \frac{\partial R_S(t)}{\partial R_i(t)} = \frac{\partial F_S(t)}{\partial F_i(t)} \tag{8}$$

Based on Birnbaum importance degree analysis, the relative importance index I_{ij}^n was proposed in this paper, which represents the product feature failure factors fc relative to product feature failure modes fm . If the product feature failure structure relationship is known, e.g. in the case of a known failure structure depicted by an Failure Tree Analysis(FTA), the failure causes represent the basis events in FTA, the failure modes is the top events. Then the probability importance degree I_{ij}^n of failure factors c_i^n relative to failure modes m_j^n can be calculated as formula (9) shows:

$$I_{ij}^n = \frac{\partial F\left(fc_1^n, fc_2^n, \cdots, fc_r^n\right)}{\partial fc_i^n} \quad i = 1, 2, \cdots, r \tag{9}$$

In formula (9), $F\left(fc_1^n, fc_2^n, \cdots, fc_r^n\right)$ represents the function of probability of each failure mode m_j^n of product feature x_i^n to each failure factors $c_1^n, c_2^n, \ldots, c_r^n$.

If the product feature failure structure relationship is unknown, the probability importance degree I_{ij}^n of failure factors c_i^n relative to failure modes m_j^n can be calculated as formula (10):

$$I_{ij}^n = \frac{fm_j^n}{fc_i^n} q_{ij} \tag{10}$$

$$\sum_{i=1}^{e} q_{ij} = 1 \tag{11}$$

In formula (10) and (11), q_{ij} represents the standardized frequency of failure cause fc_i^n when failure mode fm_j^n occurs.

The calculation of importance degree shown above is based on the determination of each failure causes probability or failure rate. This paper assumes that each feature failure structures were subjected to exponential distribution with parameters λ_{c_i} and λ_{m_i}, then the product failure probabilities can be calculated as formula (12) and (13) as below:

$$fc_i^n = 1 - e^{-\lambda_{c_i} t} \tag{12}$$

$$fm_i^n = 1 - e^{-\lambda_{m_i} t} \tag{13}$$

In the formulas, λ_{c_i} and λ_{m_i} represent the occurrence times of failure structure per unit time; t represents per unit operation time.

According to formula (10), transform the FTA model into the product feature failure structure matrix (FSM). FSM is a comprehensive expression between product feature failure factors c_i^n and failure modes m_j^n, it can describe the relationship of similar products feature failure factors to failure modes, also can be used in new product design process. By building the FSM I^n (shown as formula (14)) can clearly understanding the importance degree of each failure factors relative to failure modes.

$$I^n = \begin{array}{c} \\ c_1^n \\ c_2^n \\ \vdots \\ c_r^n \end{array} \begin{array}{c} \begin{array}{cccc} m_1^n & m_2^n & \cdots & m_p^n \end{array} \\ \begin{bmatrix} I_{11}^n & I_{12}^n & \cdots & I_{1p}^n \\ I_{21}^n & I_{22}^n & \cdots & I_{2p}^n \\ \vdots & \vdots & \ddots & \vdots \\ I_{r1}^n & I_{r2}^n & \cdots & I_{rp}^n \end{bmatrix} \end{array} \tag{14}$$

In matrix I^n, lines represent the failure causes c_i^n and rows represent the failure modes m_j^n.

In summary, the failure structure analysis of the feature similarity products mainly concludes the following steps:

Step 1 Determining the analysis object. Based on the selecting results of feature similarity products, determine the analysis object of each design feature failure structures: $SX = \{SX^{\mathrm{I}}, SX^{\mathrm{II}}, \cdots, SX^{T}\}$.

Step 2 Quantifying the feature similarity product failure structure. Calculate the occurrence frequency q_{ij} of failure causes fc_i^n when failure modes fm_j^n occur, then solving the occurrence probability of failure causes fc_i^n and failure modes fm_j^n.

Step 3 Outputting the product FSM. Calculate the importance degree I_{ij}^n of failure causes c_i^n by using formula (10). On this basis, output the product FSM I^n.

2.3. New product design reliability analysis and prediction

The purpose to analyze feature similarity products is to determine the relationship expression between product failure factors and failure modes, to optimize and improve the causes that influence the feature similarity product failure, in order to guide the new product reliability design. In the practical product improvement implementation, the corporation intends to choose the economical, reasonable and practical solutions due to the restriction of fund, technology, environment, reliability, etc., that is to say, there are many optimization and improvement forms to some extent. Given this, this paper proposes the group decision making method (GDMM) to judge quantifiably the significant degree of product feature failure structure parameters (the failure rate λ_{c_i}) improvement. Then analyzing the improvement degree of each feature failure mode, and calculating the occurrence probability of new product failure modes, to achieve the prediction of new product design reliability.

In the experts decision making process, due to the uncertain information, allowing experts to make fuzzy decision, that is to say, the experts can use the three-point estimate method, namely e_{ik}^{a} , e_{ik}^{b} , e_{ik}^{m} , to evaluate the effective degree of the improvement to the failure causes c_i^n , and then we can get:

$$\tilde{e}_{ik} = \frac{e_{ik}^{a} + 4e_{ik}^{m} + e_{ik}^{b}}{6} \tag{15}$$

In formula (15), $\tilde{e}_{ik}$ represents the estimate value of improvement effective degree, e_{ik}^{a} represents the most positive estimate value of improvement effective degree, e_{ik}^{b} represents the most negative value, while the e_{ik}^{m} represents the most possible value.

The ω_k represents the importance of each expert due to their preferences, where $k = 1, 2, \cdots, d$, and d represents the number of experts, the value of ω_k can be obtained by AHP, fuzzy comprehensive evaluation method and so on. Then the improvement effective index value e_i of group decision is:

$$e_i = \sum_{k=1}^{d} \omega_k \tilde{e}_{ik} \tag{16}$$

$$\sum_{k=1}^{d} \omega_k = 1 \tag{17}$$

After determining the improvement effective index value e_i of feature similarity product failure causes fc_i^n , the product failure structure quantified analysis can be achieved during the new product design process, so the failure occurrence frequency fc_i^n of new product failure factors c_i^n can be transformed as:

$$\begin{cases} fc_i^{n*} = 1 - e^{-\lambda^* t} \\ \lambda^* = e_i \lambda \end{cases} \tag{18}$$

So the probabilities of failure modes m_j^{n*} from the probabilities of failure causes fc_i^{n*} can be calculated as:

$$fm_j^{n*} = \sum_{i=1}^{n} I_{ij}^{n} fc_i^{n*} \quad Or \quad fm^* = I^T \times fc^* \tag{19}$$

And the reliability value $R_{X^n}^*$ of new product design feature X^n is:

$$R_{X^n}^* = \sum_{j=1}^{e} \omega_j^n \left(1 - fm_j^{n*}\right) \tag{20}$$

In summary, the procedures of new product design analysis and predicting are as follows:

Step1 Analyze and improve the product feature failure causes c_i^n .

Step2 Using the three-point estimate method to evaluate the effective degree of the improvement to the failure causes c_i^n , and recorded as e_{ik}^{a} , e_{ik}^{b} , e_{ik}^{m} , then calculate the improvement effective index value e_i by using the formula (15) and (16).

Step3 Calculating the probabilities of failure cause fc_i^n of product feature failure causes c_i^n by using the formula (18).

Step4 Calculate the probabilities of failure modes fm_j^{n*} by using formula (19)·

Step5 Repeat the ***Step 1*** to ***Step 4*** and complete the calculation of probabilities of other feature failure modes, then the reliability value $R_{X^n}^*$ of new product design feature X^n can be obtained from formula (20)·

3. Computational Study

To verifying the feasibility and effectiveness of the proposed method, product development of a new type smart phone was analyzed in Business Group C in F Company, where our research team stayed for 7 months. To simplify the analysis process, 4 features including 16 sub-features has been selected, they are function features X^{I}, shape features X^{II}, structure features X^{III} and material features X^{IV}, details are shown in Table 2.

Table 2. Features Description for New Designing Product

Product features	Symbol	Sub-features	Product features	Symbol	Sub-features
X^{I}	x_1^{I}	Communication functions	X^{III}	x_1^{III}	Screen structure features
	x_2^{I}	Web browsing functions		x_2^{III}	Speaker structure features
	x_3^{I}	Battery life functions		x_3^{III}	External interface design features
	x_4^{I}	Camera functions		x_4^{III}	Notebook expansion
X^{II}	x_1^{II}	Key design features	X^{IV}	x_1^{IV}	Packaging material features
	x_2^{II}	LED screen functions		x_2^{IV}	Faceplate material features
	x_3^{II}	Dimensions features		x_3^{IV}	Leather material features
	x_4^{II}	Battery size features		x_4^{IV}	Battery material

Though counting the existing products on the market, selected Product 1(P1) to Product 6 (P6) as the feature similarity evaluation objects, based on the evaluation criteria in Table 1, 5 professional product designers from Business Group C made up the experts team to evaluate the similarity degree, and calculate the relative proximity of alternatives under each product features by using the TOPSIS method, the results are shown in Table 3, 4 and 5.

Table 3. Decision Matrix V for Product Features Similarity Assessment

	X^{I}				X^{II}				X^{III}				X^{IV}			
	x_1^{I}	x_2^{I}	x_3^{I}	x_4^{I}	x_1^{II}	x_2^{II}	x_3^{II}	x_4^{II}	x_1^{III}	x_2^{III}	x_3^{III}	x_4^{III}	x_1^{IV}	x_2^{IV}	x_3^{IV}	x_4^{IV}
ω_j^n	0.25	0.25	0.25	0.25	0.3	0.2	0.25	0.15	0.3	0.3	0.2	0.2	0.25	0.2	0.15	0.4
P1	0.90	0.66	0.90	0.50	0.42	0.80	0.74	0.54	0.84	0.68	0.66	0.88	0.86	0.74	0.66	0.60
P2	0.88	0.96	0.74	0.64	0.50	0.70	0.90	0.82	0.72	0.70	0.50	0.84	0.40	0.80	0.62	0.72
P3	0.82	0.82	0.80	0.80	0.68	0.54	0.72	0.80	0.74	0.60	0.60	0.70	0.60	0.70	0.92	0.80
P4	0.86	0.60	0.48	0.76	0.80	0.90	0.60	0.00	0.62	0.70	0.80	0.40	0.64	0.42	0.74	0.64
P5	0.80	0.00	0.80	0.74	0.34	0.50	0.60	0.80	0.72	0.74	0.62	0.66	0.80	0.90	0.80	0.80
P6	0.74	0.78	0.90	0.70	0.50	0.80	0.78	0.60	0.80	0.74	0.60	0.74	0.80	0.70	0.80	0.60

Table 4. Weighted Matrix of Normalized Values for Product Features Similarity Assessment

	X^{I}				X^{II}				X^{III}				X^{IV}			
	x_1^{I}	x_2^{I}	x_3^{I}	x_4^{I}	x_1^{II}	x_2^{II}	x_3^{II}	x_4^{II}	x_1^{III}	x_2^{III}	x_3^{III}	x_4^{III}	x_1^{IV}	x_2^{IV}	x_3^{IV}	x_4^{IV}
P1	0.11	0.10	0.12	0.07	0.09	0.09	0.10	0.05	0.14	0.12	0.08	0.10	0.13	0.08	0.05	0.14
P2	0.11	0.14	0.10	0.09	0.11	0.08	0.13	0.08	0.12	0.12	0.06	0.10	0.06	0.09	0.05	0.17
P3	0.10	0.12	0.10	0.12	0.15	0.06	0.10	0.07	0.12	0.11	0.08	0.08	0.09	0.08	0.07	0.19
P4	0.11	0.09	0.06	0.11	0.17	0.10	0.08	0.00	0.10	0.12	0.10	0.05	0.09	0.05	0.06	0.15
P5	0.10	0.00	0.10	0.11	0.07	0.06	0.08	0.07	0.12	0.13	0.08	0.07	0.12	0.10	0.06	0.19
P6	0.09	0.11	0.12	0.10	0.11	0.09	0.11	0.06	0.13	0.13	0.08	0.08	0.12	0.08	0.06	0.14

Table 5. Calculation of the Relative Proximity of Alternatives under Features X^{n}

	X^{I}			X^{II}			X^{III}			X^{IV}		
	$d_{i^+}^{I}$	$d_{i^-}^{I}$	C_i^{I}	$d_{i^+}^{II}$	$d_{i^-}^{II}$	C_i^{II}	$d_{i^+}^{III}$	$d_{i^-}^{III}$	C_i^{III}	$d_{i^+}^{IV}$	$d_{i^-}^{IV}$	C_i^{IV}
P1	0.064	0.141	0.035	0.088	0.065	0.055	0.022	0.068	0.000	0.057	0.076	0.037
P2	0.036	0.148	0.006	0.064	0.104	0.011	0.046	0.055	0.027	0.076	0.050	0.067
P3	0.030	0.136	0.012	0.054	0.108	0.000	0.040	0.041	0.032	0.045	0.069	0.032
P4	0.079	0.100	0.069	0.086	0.108	0.032	0.065	0.041	0.051	0.065	0.033	0.073
P5	0.142	0.057	0.144	0.119	0.070	0.075	0.041	0.040	0.034	0.042	0.093	0.018
P6	0.041	0.129	0.022	0.065	0.084	0.026	0.030	0.051	0.019	0.024	0.068	0.025

According to the calculation results in table 5, the set of feature similarity products can be obtained. Then analyze the product failure structure of feature similarity products. Take the function features X^{I} of product 2 as an example, according to the information of products maintenance, failure complaints record and product reliability database, the product failure rate is shown in table 6.

Table.6 Statistical Analysis of the Product Failure Structural

Symbol	Failure structure	Failure parameters	Failure probabilities
fm_1^{I}	Call failures	$\lambda_{m_1} = 0.047$	0.046
fm_2^{I}	Network connection failure	$\lambda_{m_2} = 0.061$	0.059
fm_3^{I}	Battery failures	$\lambda_{m_3} = 0.019$	0.019
fm_4^{I}	Camera failures	$\lambda_{m_4} = 0.026$	0.026
fc_1^{I}	Cable damaged	$\lambda_{c_1} = 0.035$	0.034
fc_2^{I}	CPU damaged	$\lambda_{c_2} = 0.026$	0.026
fc_3^{I}	Lower battery capacity	$\lambda_{c_3} = 0.042$	0.041
fc_4^{I}	Signal receiver failures	$\lambda_{c_4} = 0.037$	0.036
fc_5^{I}	Lower amplifier efficiency	$\lambda_{c_5} = 0.082$	0.079

According to statistical analysis results, the occurrence frequency q_{ij} of failure factors fc_i^{n} when failure modes fm_j^{n} occur is shown as below:

$$q_{ij} = \begin{bmatrix} 0.714 & 0.275 & 0.375 & 0.250 \\ 0.320 & 0.350 & 0.125 & 0.150 \\ 0.500 & 0 & 0.450 & 0.300 \\ 0.230 & 0.500 & 0.350 & 0 \\ 0.753 & 0 & 0 & 0 \end{bmatrix}$$

Construct the product function feature FSM for I^1 as below:

$$I^1 = \begin{bmatrix} 0.953 & 0.477 & 0.21 & 0.191 \\ 0.566 & 0.794 & 0.058 & 0.15 \\ 0.561 & 0 & 0.209 & 0.19 \\ 0.294 & 0.819 & 0.185 & 0 \\ 0.438 & 0 & 0 & 0 \end{bmatrix}$$

Meanwhile, for those feature failure factors listed above, combined with the actual situation of F Company, optimizing and improving the failure factors respectively from the man, machine, material, method, measurement and environment (5M1E) aspects, using the GDMM to quantifiably judge the effective degree of product failure factors improvement, and determining the product design improvement parameters e_i , where $e_i > 0$ means the improvement percentage of feature similarity product function feature failure factor *i*, the greater value the better improvement, the results are shown in Table 7.

Table 7. Expert Decision Table for the Product Features Failure Factor Improvement

Failure causes	Improving index	value	expert1	expert 2	expert 3	expert 4	expert 5
			0.2	0.15	0.15	0.3	0.2
fc_1^1	e_1 =0.848	e_{1k}^a	1.2	1	1.3	1	1.1
		e_{1k}^b	0.8	0.5	0.7	0.5	0.5
		e_{1k}^m	1	0.75	0.9	0.8	0.8
fc_2^1	e_2 0.549	e_{2k}^a	0.6	0.85	0.8	0.75	0.7
		e_{2k}^b	0.4	0.35	0.2	0.4	0.3
		e_{2k}^m	0.5	0.5	0.5	0.6	0.65
fc_3^1	e_3 =0.565	e_{3k}^a	0.9	0.9	0.9	0.95	0.8
		e_{3k}^b	0.5	0.6	0.5	0.5	0.2
		e_{3k}^m	0.7	0.85	0.8	0.65	0.5
fc_4^1	e_4 =0.481	e_{4k}^a	0.85	0.7	0.8	0.9	0.8
		e_{4k}^b	0.3	0.3	0.3	0.5	0.45
		e_{4k}^m	0.6	0.5	0.5	0.6	0.5
fc_5^1	e_5 =0.779	e_{5k}^a	1.3	1.2	1.3	1	0.9
		e_{5k}^b	1	0.9	1.1	0.8	0.6
		e_{5k}^m	1.2	1	1.2	0.9	0.8

According to the data in table 7, calculating the shift of the occurrence rate of failure cause by using the formula (17), the results are:

$$fc_i^{1*} = (0.005, 0.012, 0.018, 0.019, 0.018)^T$$

Then according to formula (18), the probabilities of product failure modes fm_j^{1*} are calculated as below:

$$fm_j^{1*} = \begin{bmatrix} 0.953 & 0.477 & 0.21 & 0.191 \\ 0.566 & 0.794 & 0.058 & 0.15 \\ 0.561 & 0 & 0.209 & 0.19 \\ 0 & 0.819 & 0.185 & 0 \\ 0.438 & 0 & 0 & 0 \end{bmatrix}^T \square \begin{pmatrix} 0.005 \\ 0.012 \\ 0.018 \\ 0.019 \\ 0.018 \end{pmatrix}$$

$$fm_j^{1*} = (0.03, 0.027, 0.009, 0.005)^T$$

So the reliability predicting value $R^*_{x^{\text{I}}}$ of new product design feature x^{I} is:

$$R^*_{x^{\text{I}}} = \sum_{j=1}^{4} \omega_j^n \square (1 - fm_j^{n*}) = 0.9825$$

Similarly, reliability predicting value $R^*_{x^n}$ for the rest product design features x^{II}, x^{III}, x^{IV}, and Table 8 present the resultant estimates for the new product design.

Table 8. Reliability Predicting for the New Product $R^*_{x^n}$

	x^{I}	x^{II}	x^{III}	x^{IV}
P_2	0.9625	0.9071	0.9253	0.8750
New product's $R^*_{x^n}$	0.9825	0.9852	0.9647	0.9822
Reliability increase rate	2%	7.81%	3.94%	10.72%

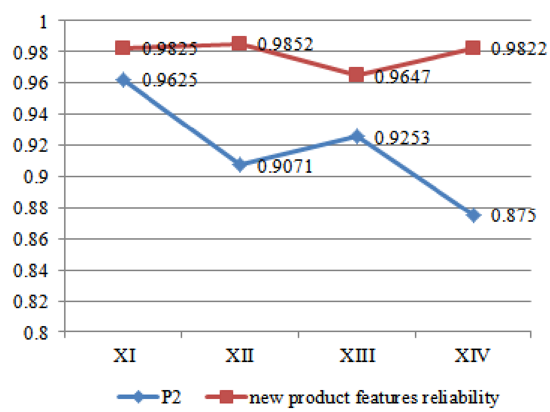

Figure 1. Features Reliability $R^*_{x^n}$ Comparison between New Product and Similar Product

As shown in Figure 1, we can conclude that, compared to the similar features product P_2, the reliability value of new product features are increased 2%, 7.81%, 3.94%, 10.72%, respectively. It indicates that the new product design reliability analysis method based on feature similarity has a certain validity and practicability. Moreover, according to this analysis and forecasting techniques, the reliability engineer has a preliminary estimation of failure mode probabilities under the new Smart Mobile Phone product design, these probabilities bring out the visibility of the impact of design changes on product reliability at the product's early design stage, so managers and engineers can plan for future reliability improvements when the cost does not pose a major constraint.

4. Conclusion

In this paper, we propose a reliability analysis and prediction method for new product design reliability problem, the key idea is to utilize the reliability information of products that already existed in a warranty database or information recorded system. The relationships between failure modes and failure causes can be found from these historical data. Experts' opinions on the effects of design changes on individual failure cause are elicited. The main contributions are as follows:

(1) For the uncertainty of similarity measure between features and the weight of evaluation objects, the feature similarity product evaluation selection algorithm based on the improvement of TOPSIS was proposed, which lays foundation for analyzing and selecting of the feature similarity products.

(2) Based on the analysis of the feature similarity product failure structure, the product FSM model was constructed, and the relational mapping from feature similarity products to new product design reliability analysis was finally achieved.

(3) Combined with GDMM technology, the effective degree of the improvement to the failure causes was evaluated, and the reliability prediction for the new product design was finally realized.

Acknowledgments

This research is funded by the National Nature Science Foundation of China (No. 71071173) and (No. 71301176), Supported by MOE (Ministry of Education of the PRC) Project of Humanities and Social Sciences (11XJC630014), and joint supported by Natural Science Foundation Project of CQ CSTC (cstcjjA90014), Guizhou Province Soft Scientific Research Project, China (Department of Guizhou Chimeric R word [2013]LKC2030).

References

[1] Y. l. Li, W. Zhao and X. Y. Shao, "A process simulation based method for scheduling product design change propagation", "Advanced Engineering Informatics", vol. 26, **(2012)**, pp. 525-538.

[2] M. Fajdiga, T. Jurejevcic and J. Kernc, "Reliability prediction in early phases of product design", Journal of Engineering Design, vol. 7, no. 2, **(1996)** , pp. 107-128.

[3] Y. Liu, H. Z. Huang and D. Ling, "Reliability prediction for evolutionary product in the conceptual design phase using neural network-based fuzzy synthetic assessment", International Journal of Systems Science, vol. 44, no. 3, **(2013)**, pp. 545-555.

[4] Z. Xu and H. B. Li, "Assessing performance risk for complex product development", "A simulation-based model", Quality and Reliability Engineering International, vol. 29, no. 2, **(2013)**, pp. 267-275.

[5] M. Krasich, "Test design and acceleration for product lifetime reliability demonstration", SAE Technical Papers, **(2004)**.

[6] W. Luo, C. H. Zhang, X. Chen and Y. Y. Tan, "Reliability demonstration based on accelerated degradation testing for unknown model parameters", Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, vol. 227, no.2, **(2013)**, pp.162-172.

[7] T.E. Timothy, "Wafer Level Reliability: Process control for reliability", Microelectronics Reliability, vol. 36, no. 11-12, **(1996)**, pp. 1839-1846.

[8] R. Hodge, J. Quigley, I. James and J. Marshall, "Integrating reliability improvement modeling into practice-challenges and pitfalls", IEEE Proceedings of the Annual Reliability and Maintainability Symposium, **(2002)**, pp. 158-164.

[9] Z. Y. Bao, G. Xiao, F. Gao and S. F. Ruan, "Evaluation method of individualized products based on case reasoning", Transactions of the Chinese Society for Agricultural Machinery, vol. 42, no. 9, **(2011)**, pp. 197-201+196.

[10] Z. Y. Guo, W. Q. Wang, J. Chen and Z. H. Ma, "Modern product design based on integrated simulation technology", Computer Integrated Manufacturing Systems, vol. 11, no. 1, **(2005)**, pp. 12-16.

[11] I. Jardine and D. Jackson, "Risk assessment and optimization of a safety system using the maros simulation package", Quality and Reliability Engineering International, vol. 5, no. 2, **(1989)**, pp. 131-141.
[12] M. T. Cher, "Customer-focused build-in reliability: a case study", International Journal of Quality & Reliability Management, vol. 20, no. 3, **(2003)**, pp. 378-397.
[13] T. S. Njindam and K. Paetzold, "Design for reliability: An event-and function-based framework for failure behavior analysis in the conceptual design of cognitive products", ICED 11-18th International Conference on Engineering Design - Impacting Society Through Engineering Design, vol. 5, **(2011)**, pp. 228-235.
[14] P. Urban and P. Igor, "Evaluating construction project success with use of the M-TOPSIS method", Journal of Civil Engineering and Management, vol. 19, no. 1, **(2013)**, pp. 16-23
[15] M. S. Luis and R. Pan, "An Enhanced Parenting Process: Predicting Reliability in Product's Design Phase", Quality Engineering, vol. 23, no. 4, **(2011)**, pp. 378-387.
[16] Y. L. Liu and Z. X. Liu, "An integration method for reliability analyses and product configuration", International Journal of Advanced Manufacturing Technology, vol. 50, no. 5-8, **(2010)**, pp. 831-841.

Authors

Tao Yang was born in Anhui Province, China, in 1985. He received the B.E. degree in Industrial Engineering from Shandong Institute of Business and Technology in 2010. Currently, he is pursuing his Ph.D. degree in Mechanical Engineering at Chongqing University. His research interests include network and system reliability, industrial engineering, and collaborative product development.

Yu Yang received his M.E. and Ph.D. degrees from Chongqing University, China, in 1995 and 1999, respectively. Now, he has been a professor in School of Mechanical Engineering, Chongqing University since 2003. During the year 2005-2006, he studies at Purdue University, USA. In 1997, he was selected for the New Century Excellent Talents in University program in China.

He is currently working on customer collaborative product development, system reliability, product process management and so on. He is also the leader of National Natural Science Foundation of China (No. 71071173).

Yao Jiao was born in 1989, Hubei Province, China, and received the B.E. degree in Industrial Engineering from Chongqing University in 2012. Currently, he is pursuing his Ph.D. degree in Mechanical Engineering at Chongqing University. His research interests include Reliability Management, Industrial Engineering(IE), and Collaborative Product Development(CPD).

