

This article was downloaded by: [University of Electronic Science and Technology of China]

On: 27 December 2012, At: 05:08

Publisher: Taylor & Francis

Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK



International Journal of Systems Science

Publication details, including instructions for authors and subscription information:
<http://www.tandfonline.com/loi/tsys20>

Reliability prediction for evolutionary product in the conceptual design phase using neural network-based fuzzy synthetic assessment

Yu Liu^a, Hong-Zhong Huang^a & Dan Ling^{a,b}

^a School of Mechanical, Electronic, and Industrial Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, P.R. China

^b Key Laboratory of Manufacture and Test Techniques for Automobile Parts, Chongqing University of Technology, Ministry of Education, Chongqing 400050, P.R. China

Version of record first published: 28 Sep 2011.

To cite this article: Yu Liu, Hong-Zhong Huang & Dan Ling (2013): Reliability prediction for evolutionary product in the conceptual design phase using neural network-based fuzzy synthetic assessment, International Journal of Systems Science, 44:3, 545-555

To link to this article: <http://dx.doi.org/10.1080/00207721.2011.617887>

PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: <http://www.tandfonline.com/page/terms-and-conditions>

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The accuracy of any instructions, formulae, and drug doses should be independently verified with primary sources. The publisher shall not be liable for any loss, actions, claims, proceedings, demand, or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

Reliability prediction for evolutionary product in the conceptual design phase using neural network-based fuzzy synthetic assessment

Yu Liu^a, Hong-Zhong Huang^{a*} and Dan Ling^{ab}

^aSchool of Mechanical, Electronic, and Industrial Engineering, University of Electronic Science and Technology of China, Chengdu, Sichuan 611731, P.R. China; ^bKey Laboratory of Manufacture and Test Techniques for Automobile Parts, Chongqing University of Technology, Ministry of Education, Chongqing 400050, P.R. China

(Received 30 May 2009; final version received 22 July 2011)

Reliability prediction plays an important role in product lifecycle management. It has been used to assess various reliability indices (such as reliability, availability and mean time to failure) before a new product is physically built and/or put into use. In this article, a novel approach is proposed to facilitate reliability prediction for evolutionary products during their early design stages. Due to the lack of sufficient data in the conceptual design phase, reliability prediction is not a straightforward task. Taking account of the information from existing similar products and knowledge from domain experts, a neural network-based fuzzy synthetic assessment (FSA) approach is proposed to predict the reliability indices that a new evolutionary product could achieve. The proposed approach takes advantage of the capability of the back-propagation neural network in terms of constructing highly non-linear functional relationship and combines both the data sets from existing similar products and subjective knowledge from domain experts. It is able to reach a more accurate prediction than the conventional FSA method reported in the literature. The effectiveness and advantages of the proposed method are demonstrated via a case study of the fuel injection pump and a comparative study.

Keywords: reliability prediction; evolutionary product; fuzzy set; neural network; fuzzy synthetic assessment

1. Introduction

Reliability is a critical measure of the performance of engineered products. Generally speaking, reliability analysis is needed at the conceptual design stage, where the reliability performance can be assessed based on all information available at that point. In addition, it needs to be continuously conducted throughout the entire lifecycle of products, including design, manufacturing, testing, operation and maintenance (Blischke and Murthy 2000; Wang, Huang, and Du 2010).

Reliability prediction has been used as a tool to determine as early as possible whether the product will be reliable enough or whether it needs further improvement to function successfully for the company (Dupow and Blount 1997). It has been applied in various fields, such as software engineering (Kumar and Misra 2008), mechanical system (Avontuur and Werff 2001; Hu, Si, and Yang 2010), etc. In most cases, an achievable reliability value, which serves as a target across the entire development and management process of a new product, must be predicted at the conceptual design stage. Based upon the anticipated reliability, relevant analyses and decision-making exercises can be executed before the prototype and

product are physically made and/or put into use (Blischke and Murthy 2000). Such exercises include risk analysis, maintenance planning, marketing and warranty policy, and they provide insights on the risk of cost and profit for manufacturers. On the other hand, technical efforts from various aspects, such as design, manufacturing and management, will be made to improve the product reliability with the aim of achieving the anticipated reliability target. To make the predicted reliability meaningful and reasonable in the early design phase, information from various sources should be taken into account and appropriately incorporated into the prediction exercise. Either optimistic or pessimistic reliability goal may mislead the manufacturers and customers, and will further have an impact on the risk and cost analysis. Since product reliability depends on many factors, its accurate prediction is a challenging task, especially when the new design is still at its conceptual design stage.

MIL-HDBK-217 (reliability prediction of electronic equipment) documents the formulations well for reliability prediction of electronic devices based on their failure physics (MIL-HDBK-217 1991). Denson (1998) provides a review of the history of reliability prediction. Bowles (1992) surveys six reliability

*Corresponding author. Email: hzhuang@uestc.edu.cn

prediction procedures for microelectronic devices, and the 64K DRAM is studied as an illustrative case. Jones and Hayes (1999) summarise many electronic reliability prediction models and report some comparative studies. However, the aforementioned reliability prediction models deal with reliability prediction for individual electronic devices. They are not suitable for complicated mechanical products since failure mechanisms of the components in the product are unique and there exist interactive faults among components. Additionally, the components to be used, detailed configuration of the new product, as well as working stress may be unknown at the conceptual design stage. Understanding the underlying failure physics completely is difficult, and it is therefore impossible to apply the aforementioned methods directly or build a mathematical model to characterise the potential failure mechanism and further assess the product reliability.

At the conceptual design stage of a new product, many alternative design schemes may be devised to meet the customer requirements and pre-determined objectives. The essential design and manufacturing techniques are usually distinct from one scheme to another. By evaluating and comparing these candidate schemes, an optimal scheme for the new product can be identified to realise the reliability target. As a matter of fact, many factors influence the product reliability. Due to the lack of sufficient test data, as well as the complicated interactive impacts among factors, it is often difficult, even impossible, to assess the exact weights and impacts imposed by these factors (Hu, Wu, and Yi 2008). On the other hand, uncertainties resulting from the lack of sufficient knowledge of underlying failure physics and subjective judgements from domain experts widely exist at the conceptual design stage. Both subjective and objective information would get involved in reliability prediction activity (Zadeh 1979; Cai 1991; Wang, Yam, Zuo, and Tse 2001; Huang, Zuo, Fan, and Tian 2005; Levitin 2007). Some commonly used methods for reliability prediction are (Blischke and Murthy 2000): (1) *Parts count method* where the reliability of a product is associated with the number of components (Bowles 1992; Blischke and Murthy 2000); (2) *Part stress analysis method* which evaluates reliability of a new product by comparing the predicted strength to the anticipated stress (Bowles 1992; Blischke and Murthy 2000); (3) *Similarity method* in which the reliability prediction of a new product is based upon the 'known' reliability of an existing product with similar attributes, and these attributes could be the type of design and manufacturing technology, system configuration, complexity of components and comparable operating environment (Bowles 1992; Blischke and Murthy 2000);

(4) *Fuzzy synthetic assessment (FSA) method* which incorporates the experts' experiences and judgements via fuzzy set theory (Zhao, Wen, and Duan 2004a; Hu et al. 2008). Other reliability prediction methods have also been proposed in recent years. For example, Bazu (1995) proposes a combined fuzzy-logic and physics-of-failure approach. Zhao, Wen, and Duan (2004b) introduce a multi-stage FSA approach to predict the reliability of aeroengines. Yang, Lin, He, and Chen (2003) develop a similarity-based reliability prediction method via combining both qualitative and quantitative fuzzy similarity approaches. Ling, Song, and Sun (2011) develop a reliability prediction method which incorporates the product defect information from the failure mode and effects analysis (FMEA). Mamtani, Green, and McDonald (2006) apply the analytic hierarchy process to predict the relative reliability risk index of a new product in the conceptual design phase. In the case where the failure rates of components and subsystems are partially known, Ormon, Cassady, and Greenwood (2002) propose reliability prediction models by using both simulation and analytic techniques. It is noteworthy that selecting a suitable reliability prediction method depends on the kind of information available at the conceptual design stage.

In this article, a novel approach is introduced to predict the reliability of a new evolutionary product at the conceptual design stage. Since the new evolutionary product inherits a majority of technologies used by existing similar products, the reliability information of similar products can provide useful insights into the new product reliability prediction. In consideration of such a situation, the proposed method utilises not only subjective knowledge and judgements from domain experts, but also reliability information from existing similar products. Due to the high degree of non-linearity between the influence factors and the product reliability, it is difficult to describe such highly non-linear relationship via a mathematic formulation. The back-propagation (BP) neural network, a model free approach, is proposed to characterise the complex input-output relationship between the influence factors and the product reliability. By treating the results from FSA as inputs of the proposed BP neural network, the reliability of the new evolutionary product can be predicted via the trained neural network.

The remainder of this article is organised as follows. Section 2 introduces FSA method. The structure of BP neural network, together with the flowchart of the proposed method is provided in Section 3. An illustrative study of reliability prediction for the fuel ejection pump of a diesel engine is provided in Section 4, and it is followed by a comparative study.

Brief remarks and conclusions are presented in Section 5.

2. FSA method

The influence factor set, comment set, single factor assessment (or called fuzzy relation matrix) and evaluation set are the four key elements in FSA method (Zhao et al. 2004a,b; Hu et al. 2008). The influence factor set is a finite discrete crisp set containing various possible factors that affect the product reliability, and it is denoted by:

$$U = \{u_1, u_2, \dots, u_n\}, \tag{1}$$

where u_i represents a certain influence factor i and n is the total number of possible influence factors. It should be noted that there would be many factors that can impact the product reliability. However, only the most significant ones will be contained in the influence factor set U . Sensitivity analysis can be first conducted to identify these influence factors according to their importance rankings, and the less important factors can be ignored to reduce the complexity (Sobol 1993; Saltelli et al. 2008; Reedijk 2000; Liu, Yin, Arendt, Chen, and Huang 2010).

The comment set consists of a finite number of levels associated with each influence factor. The purpose of the comment set is to classify the infinite amount of the possible values of each influence factor into several levels, from the highest to the lowest, and this classification is often provided by domain experts. Due to the lack of sufficient data, fuzzy linguistic variables can be used to characterise the possible levels of each factor. The comment set is therefore expressed as a fuzzy vector:

$$\tilde{V} = \{\tilde{V}_1, \tilde{V}_2, \dots, \tilde{V}_n\}, \tag{2}$$

where \tilde{V}_i is a sub-set of the fuzzy linguistic variables for the i th influence factor, and it can be further denoted as:

$$\tilde{V}_i = \{\tilde{v}_{i1}, \tilde{v}_{i2}, \dots, \tilde{v}_{ik_i}\}, \tag{3}$$

where \tilde{v}_{ij} is the j th fuzzy linguistic variable for the i th influence factor and k_i is the total number of fuzzy linguistic variables for the i th influence factor. In this article, the trapezoid fuzzy number is used to represent the fuzzy linguistic variable \tilde{v}_{ij} , and its membership function is mathematically expressed as:

$$\mu_{\tilde{v}_{ij}}(x) = \begin{cases} 0, & x \leq a \\ (x - a)/(b - a), & a < x \leq b \\ 1, & b < x \leq c \\ (d - x)/(d - c), & c < x \leq d \\ 0, & x > d \end{cases} \tag{4}$$

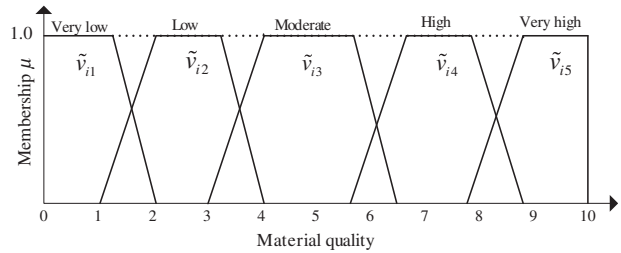


Figure 1. The fuzzy comment set of the influence factor ‘material quality’.

This trapezoid fuzzy number can be denoted by $\tilde{v}_{ij}(\delta_L, b, c, \delta_R)$, where $\delta_L = (b - a)$ is the left parameter and $\delta_R = (d - c)$ is the right parameter. When $\delta_L = \delta_R = 0$, \tilde{v}_{ij} degenerates to a crisp interval. A larger δ_L and/or δ_R indicates that \tilde{v}_{ij} is more imprecise and ambiguous. Thus, \tilde{v}_{ij} is able to describe the linguistic variable, such as ‘high’, ‘very high’, ‘moderate’, etc., and it is more realistic than a crisp value, especially when sufficient information is not available at the early design stage. In addition to the trapezoid fuzzy number, the triangular or other types of fuzzy numbers may also be used to represent the fuzzy linguistic variable \tilde{v}_{ij} . The type and parameters of the fuzzy linguistic variables will be determined on the basis of the experts’ perception of the subjective terms. For example, an expert could be asked what his perception is of the term ‘low material quality’, and his response could be ‘the material quality is somewhere between 1 and 4’. These sorts of judgements can be collected and represented by fuzzy numbers (Gupta and Bhattacharya 2007).

A sample of the fuzzy comment set for the influence factor, say ‘material quality’, is presented in Figure 1, where the values of the influence factors are classified into five categories, represented by five fuzzy linguistic variables.

According to the fuzzy comment set of each influence factor, the membership of the product with respect to the fuzzy linguistic variables of the influence factors can be identified based on the scores given by the domain experts. However, in the case where the experiences of experts cannot be precisely transformed into a crisp score located in the horizontal axis, a fuzzy number can be used to quantify this kind of uncertainty. On the other hand, if there are multiple crisp scores from several experts, only using the mean value of the multiple scores could not fully characterise the variation (or uncertainty) due to the subjective judgements from different experts. To illustrate the general idea of our proposed method, we use a triangular fuzzy number $\tilde{L}(a, m, b)$ depicted in Figure 2 to represent the score given by domain experts.

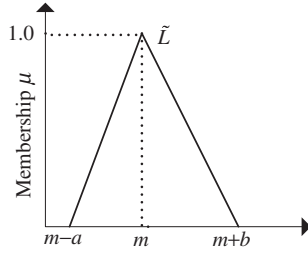


Figure 2. A triangular fuzzy number.

If the fuzzy scores are from more than one expert, they can be integrated together to get a final fuzzy score. Suppose $\tilde{L}_i(a_i, m_i, b_i)$ represents the fuzzy score given by the i th expert on a certain influence factor. If the α -level set of \tilde{L}_i is denoted by $\tilde{L}_i^\alpha = [a_i^\alpha, b_i^\alpha]$, and then one has the average α -level set for the total scores given by N experts:

$$\tilde{L}^\alpha = \frac{1}{N} \sum_{i=1}^N \tilde{L}_i^\alpha = \left[\frac{1}{N} \sum_{i=1}^N a_i^\alpha, \frac{1}{N} \sum_{i=1}^N b_i^\alpha \right], \quad (5)$$

and then the final fuzzy score is given by (Chen 1994):

$$\tilde{L}(a, m, b) = \left(\frac{1}{N} \sum_{i=1}^N a_i, \frac{1}{N} \sum_{i=1}^N m_i, \frac{1}{N} \sum_{i=1}^N b_i \right), \quad (6)$$

which is also a triangular fuzzy number according to the fuzzy number composition rule (Chen 1994). Thus, the final fuzzy scores on all influence factors given by domain experts can be denoted by the fuzzy matrix \tilde{Z} :

$$\tilde{Z} = [\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_n], \quad (7)$$

where \tilde{z}_i is the final fuzzy score for the i th influence factor. Some alternative approaches to integrating multiple expert opinions into a single fuzzy number can be found in Bardossy, Duckstein, and Bogardi (1993). However, it should be kept in mind that we should stick to applying the same integration rule for all the data sets.

Based on the final fuzzy scores and the fuzzy linguistic variables, the membership degree that the product belongs to each fuzzy linguistic variable of the influence factors can be computed as follows:

$$\max(u_{\tilde{z}}(x) \wedge u_{\tilde{v}}(x)), \quad (8)$$

where $u_{\tilde{z}}(x)$ denotes the membership degree of the final fuzzy score, $u_{\tilde{v}}(x)$ represents the membership degree of each fuzzy linguistic variable and \wedge is a fuzzy arithmetic operator which is to find the minimum membership degree between $u_{\tilde{z}}(x)$ and $u_{\tilde{v}}(x)$. An example of this manipulation is illustrated in Figure 3.

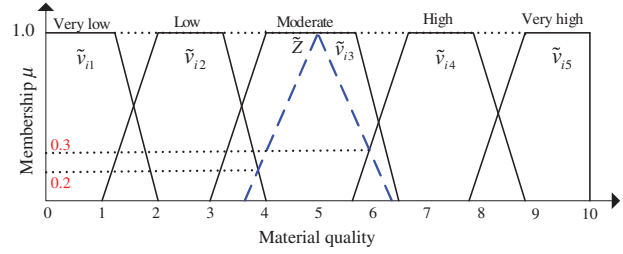


Figure 3. The membership degree of the final fuzzy score belonging to the fuzzy linguistic variables.

From Figure 3, we conclude that the membership degree of the material quality of the product is 0.2 for the fuzzy linguistic variable to be at the ‘Low’ level, 0.3 at the ‘High’ level and 1.0 at the ‘Moderate’ level.

The evaluation set is a set containing possible results of synthetic assessment. It is often represented by a set of crisp values as follows:

$$E = \{e_1, e_2, \dots, e_k\}, \quad (9)$$

where e_i is the i th possible evaluation option and k is the total number of possible options. In reliability prediction, E contains the possible values of product reliability, and the membership degree is used to represent the degree to which the product reliability belongs to each possible value.

For existing similar products, it is possible to evaluate the product reliability based on their field and experiment data. Reasons such as insufficient statistical data, subjective judgements from experts will result in the imprecise assessment of product reliability (Cai 1991; Verma, Srividya, and Gaonkar 2004; Huang, Lin, and Ke 2008; Liu, Huang, and Levitin 2008; Liu and Huang 2010; Lin, Ke, and Huang 2010). Thereby, the product reliability is presented as a fuzzy number \tilde{R} rather than a crisp value. Several methods have been introduced in the literature to construct the membership function based on the sparse failure data and subjective judgements from experts (Nikolaidis, Chen, Cudney, Haftka, and Rosca 2004; Du, Choi, and Youn 2006). The membership degree d_i of the product reliability belonging to each evaluation option e_i can be computed by (Figure 4):

$$d_i = \max(u_{\tilde{R}}(e_i)), \quad (10)$$

where e_i is the i th possible reliability value and \tilde{R} is the reliability value of the existing product. We will assume that \tilde{R} is a triangular fuzzy number to demonstrate the general idea of our proposed method.

The synthetic assessment method establishes an analytical relationship among the influence factors,

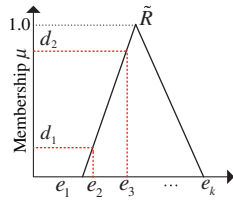


Figure 4. Membership degree of the fuzzy product reliability with respect to the evaluation set.

fuzzy linguistic variables and the evaluation sets, and it can be formulated as:

$$f(\tilde{Z})_{\tilde{U} \times \tilde{V}} \rightarrow E \tag{11}$$

Conventional synthetic assessment methods set up the relationship through fuzzy operators (say ‘ \times ’ or ‘ $+$ ’ operator), the fuzzy relation matrix and a weight set. The latter two indicate the importance of the influence factors and the associated levels. Nevertheless, the relationship between the product reliability and the influence factors is highly non-linear. Assessing the fuzzy relation matrix and the weight set is therefore not straightforward. In this article, the BP neural network is adopted to learn and approximate the complicated relationship between the product reliability and its influence factors.

3. The proposed neural network

Artificial neural networks, which mimic a complex non-linear system by a mass of neurons, are widely utilised in pattern recognition, identification and classification because of their favourable characteristics including self-learning, self-organising capacity, fault tolerance and model-free (Rojas 1996). It could provide a pretty accurate mapping between the inputs and outputs through learning from a set of samples. In recent years, the neural network technique has been successfully applied to different sorts of reliability engineering problems (Liu, Zuo, and Meng 2003; Lin and Tseng 2005; Rajpal, Shishodia, and Sekhon 2006; Hu, Xie, Ng, and Levitin 2007; Liu, Li, Huang, Zuo, and Sun 2010).

In general, BP neural network is a multi-layer feed-forward network with an input layer, an output layer and one or more hidden layers in between. The weights of connections between pairs of neurons in the neighbour layers are trained through the given samples. The deviations between the outputs of the neural network and the actual outputs of the samples will approach to zero once the neural network converges after a proper iterative training process. Therefore, the

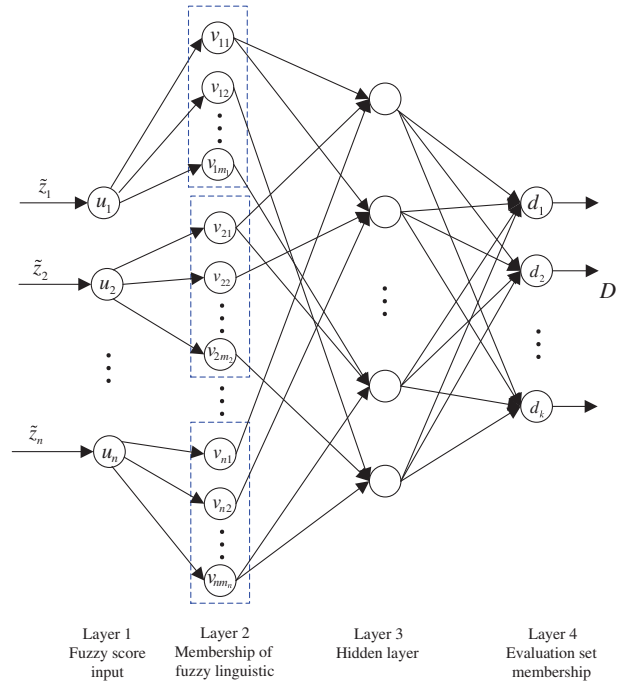


Figure 5. The structure of the proposed BP neural network.

trained neural network can act as a function approximator to predict the possible outputs for given inputs.

By treating the final fuzzy scores from experts as inputs and the product reliability values as the outputs, a BP neural network can be built to memorise the non-linear relationship between the influence factors and the product reliability. After training the neural network via the data sets from existing similar products, the neural network can be used to predict the reliability of a new evolutionary product based on the final fuzzy scores given by the domain experts. In most cases, the new evolutionary product inherits some relationship between the influence factors and the product reliability from existing similar products (Ling et al. 2011). The basic structure of the proposed BP neural network is shown in Figure 5.

The proposed neural network contains four layers. The first layer is the input layer where the inputs are the triangular final fuzzy scores of influence factors given by domain experts, as shown in Equation (6). The number of the inputs equals the number of the influence factors. The second layer is the membership degree generating layer, where the inputs from the first layer are transformed into the membership degree based on the fuzzy linguistic variables of each individual influence factor (Equation (8)). The total number of nodes in the second layer is $\sum_{i=1}^n k_i$, determined by the number of the fuzzy linguistic variables and the number of the influence factors being considered.

However, there are no weights between the first and second layers since the inputs of the second layer are purely computed by Equation (8). The third layer is called the hidden layer. The exact number of hidden neurons is difficult to estimate theoretically (Rojas 1996). In most cases, the number of hidden neurons should be in the range between the size of the input layer and that of the output layer. The fourth layer is the output layer, and the number of the output nodes is k , exactly the same as the number of evaluation options in the evaluation set. The outputs represent the membership degree of each evaluation option, and they are denoted by:

$$D = [d_1, d_2, \dots, d_k]. \quad (12)$$

The reliability of a new product can be expressed either by the crisp form of:

$$\bar{e} = \frac{\sum_{i=1}^k e_i d_i}{\sum_{i=1}^k d_i}, \quad (13)$$

or by the fuzzy form as follows:

$$\tilde{e} = \frac{d_1}{e_1} + \frac{d_2}{e_2} + \dots + \frac{d_k}{e_k}, \quad (14)$$

which denotes the degree to which the new product belongs to each possible reliability value.

By using the reliability values of existing similar products as outputs and the corresponding final fuzzy scores given by domain experts as inputs, the neural network can be trained and further used to predict the reliability of a new evolutionary product. The basic flowchart of the proposed method is shown in Figure 6.

Before predicting the reliability of a new product, the trained neural network needs to be validated (Twomey and Smith 1998). In this article, the leave-one-out cross-validation, a process of estimating errors by training the neural network with one of the existing samples left out and using this sample as the validation data, is utilised to validate the predictive capability of the trained neural network (Twomey and Smith 1998; Setiono 2001). The $Error_{CV}$, namely cross-validation error, is defined as follows:

$$Error_{CV} = \frac{1}{M} \sum_{j=1}^M \sum_{i=1}^k (\hat{d}_{(j)i} - d_{(j)i})^2, \quad (15)$$

where M is total number of existing sets of samples, i.e. the number of existing similar products, $\hat{d}_{(j)i}$ is the predicted membership degree (output) for the i th evaluation option when the neural network is trained without the j th set of data and $d_{(j)i}$ is the membership degree of the actual product reliability of the existing

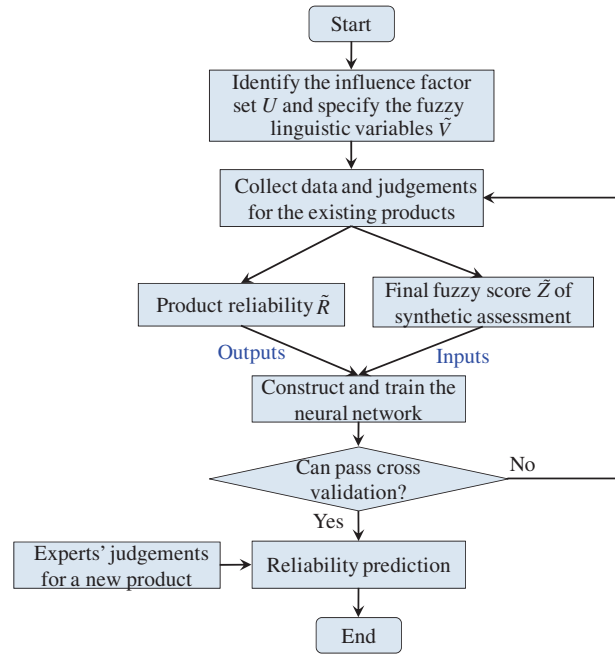


Figure 6. The flowchart of reliability prediction for a new evolutionary product.

product j with respect to the i th evaluation option, computed by Equation (10). As shown in the flowchart, the training data sets need to be continuously collected until the cross-validation error of the trained neural network is less than a pre-specified threshold, and then the trained neural network can be further used to predict the reliability of a new evolutionary product.

4. An illustrative case study

In this section, the proposed method is applied to the reliability prediction problem for the fuel injection pump of a diesel engine to demonstrate its effectiveness. The physical function of the fuel injection pump is to deliver an exact metered amount of fuel, under high pressure, to the injector at the right time. It is one of the most important parts of diesel engines, and its reliability is crucial to the reliability of the entire engine system. Therefore, predicting the reliability of the fuel injection pump accurately at the conceptual design stage will facilitate the business decision-making for manufacturers before the product is physically produced.

At the conceptual design stage, three factors, i.e. design technique, material quality and manufacturing technique, were identified as the most important influence factors that impact the reliability of the fuel

Table 1. The comment sets of each influence factor.

Factor	Level 1	Level 2	Level 3
Design	High(1.5, 8.0, 10.0, 0)	Moderate(1.5, 4.0, 6.0, 1.5)	Low(0, 0, 2.5, 1.0)
Material	High(1.0, 8.0, 10.0, 0)	Moderate(1.5, 4.5, 6.5, 1.0)	Low(0, 0, 2.5, 1.5)
Manufacturing	High(1.5, 8.5, 10.0, 0)	Moderate(1.5, 4.5, 6.5, 1.5)	Low(0, 0, 3.0, 1.5)

injection pump. These factors compose the influence factor set U :

$$U = \{u_1, u_2, u_3\} = \{\text{Design, Material, Manufacturing}\}.$$

Based on the experts' perceptions, each influence factor was classified into three levels from the highest achievable level to the lowest one. However, it should be noted that different influence factors might have different measuring units. It is necessary to unify the values of the influence factors into a uniform scale. For methods to convert a fuzzy linguistic variable to a scaled fuzzy number, readers can refer to Chen and Hwang (1992). In our case, all the measurements were scaled into the range 0–10. The value 10 represents the maximum value of each influence factor, whereas 0.0 is the lowest value. The real numbers between 0 and 10 indicate the intermediate values of each influence factor. For example, if the maximum value of the influence factor 'design technique' is D_{\max} and the fuzzy linguistic variable for the 'moderate' design technique is denoted by the unscaled fuzzy trapezoid fuzzy number $\tilde{v}(\delta_L, b, c, \delta_R)$; then, the scaled trapezoid fuzzy number in this case can be expressed as:

$$\tilde{v}' = (10 \times \delta_L / D_{\max}, 10 \times b / D_{\max}, 10 \times c / D_{\max}, 10 \times \delta_R / D_{\max}).$$

In the same manner, the scales of material quality and manufacturing technique were also unified to the range of [0, 10]. The three levels of each influence factor after unified scaling are tabulated in Table 1 from high to low. This classification composes the comment sets of the FSA method.

There are eight sets of synthetic assessment data from existing similar products, as listed in Table 2. Each set of data contains the final fuzzy scores of the three influence factors and the fuzzy reliability values represented by triangular fuzzy numbers. It is noted that the method proposed in Gupta and Bhattacharya (2007) was followed to develop the membership function of the triangular fuzzy number from the experts' judgements.

Based on Tables 1 and 2, the membership degree that the existing products belong to each fuzzy linguistic variable can be computed by Equation (8). The evaluation set in this case is defined as the

achievable reliability value of the fuel injection pump, which can be written as:

$$\begin{aligned} E &= \{e_1, e_2, \dots, e_8\} \\ &= \{0.94, 0.90, 0.86, 0.82, 0.78, 0.74, 0.70, 0.66\} \end{aligned}$$

The basic settings for the neural network are listed in Table 3. To determine the optimal number of the hidden nodes, we tested the neural network via changing the number of nodes from 5 to 20. For each tested number of the hidden nodes, the neural network was trained 10 times. It has been observed that when the number of the hidden nodes is 10, the associated average error between the actual reliability and the ones generated by the neural network is minimal. By using the cross-validation method for the eight existing sets of data from similar products, the validity of the trained neural network can be quantified. The average cross-validation error of 10 tests is 0.4833, meaning that the average cross-validation error of each output node is around 0.06 which is acceptable in the conceptual design stage. Given the final fuzzy scores for a new fuel injection pump product as shown in Table 4, the reliability can be predicted through the trained neural network.

The predicted outputs are:

$$\begin{aligned} D &= [d_1, d_2, \dots, d_8] \\ &= [0, 0, 0.526, 0.998, 0.923, 0, 0, 0]. \end{aligned}$$

Therefore, the associated reliability of the new product can be written in fuzzy form as:

$$\begin{aligned} \tilde{e} &= \frac{0}{0.94} + \frac{0}{0.90} + \frac{0.526}{0.86} + \frac{0.998}{0.82} + \frac{0.923}{0.78} \\ &\quad + \frac{0}{0.74} + \frac{0}{0.70} + \frac{0}{0.66}, \end{aligned}$$

or in crisp form:

$$\bar{e} = \sum_{i=1}^8 e_i d_i / \sum_{i=1}^8 d_i = 0.8135.$$

It is noteworthy that compared with the conventional FSA method, the proposed method has two important merits. First, in the conventional FSA-based reliability prediction approach, a fuzzy relation matrix between the fuzzy linguistic variable levels of the influence factors and the evaluation set has to be

Table 2. Final fuzzy scores and reliability values of existing similar products.

Product model	Design	Material	Manufacturing	Reliability
6108ZQ	(1.5, 8.0, 1.0)	(1.0, 8.2, 1.5)	(1.2, 8.5, 1.2)	(0.08, 0.92, 0.05)
6108Q	(1.2, 7.5, 1.0)	(1.0, 8.0, 1.0)	(0.8, 8.1, 0.8)	(0.06, 0.87, 0.06)
6112ZLQ	(1.5, 7.2, 1.0)	(1.2, 7.5, 1.0)	(1.2, 7.6, 1.0)	(0.07, 0.83, 0.05)
6105QC	(1.5, 6.0, 1.2)	(1.0, 6.2, 1.2)	(0.8, 7.0, 0.6)	(0.05, 0.79, 0.05)
4108ZQ	(1.2, 5.6, 1.2)	(1.0, 5.6, 1.5)	(0.9, 6.2, 0.8)	(0.08, 0.75, 0.06)
4108Q	(1.2, 5.0, 1.0)	(1.0, 5.0, 1.0)	(1.0, 5.0, 0.5)	(0.04, 0.72, 0.03)
4110ZQ	(1.0, 4.2, 1.0)	(1.2, 4.5, 1.5)	(1.0, 4.2, 0.8)	(0.05, 0.70, 0.03)
4110Q	(1.5, 3.0, 1.2)	(0.8, 3.5, 1.5)	(1.2, 3.5, 1.2)	(0.04, 0.67, 0.05)

Table 3. The configuration of the proposed BP neural network.

Parameters	Value
Total sample size	8
Number of input nodes	3
Number of output nodes	8
Number of hidden nodes	10
Learning rate	0.01
Performance goal	10E-5
Training epochs	1500
Training function	TRAINLM
Adaption learning function	LEARNGDM
Transfer function	PURELIN/TANSIG

Table 4. Final fuzzy scores of new product.

Product model	Design	Material	Manufacturing
6114ZQH	(1.2, 7.2, 1.2)	(1.0, 7.0, 1.2)	(1.1, 8.0, 0.8)

specified by the domain experts (Zhao et al. 2004a,b). Without completely understanding the underlying physics behind the influence factors and product reliability, it is really subjective to determine this fuzzy relation, and would bring more uncertainties in the new product reliability prediction. However, in our proposed method, the relation can be learned from existing similar products by the proposed neural network. It can reduce the additional uncertainty from experts' perceptions. Second, the neural network is capable of approximating any non-linear relationship between inputs and outputs. Therefore, it is able to characterise a more complicated relation between the influence factors and product reliability than the conventional FSA method. A comparative study is given below to illustrate this point.

In order to ensure that the comparative study between the proposed and the conventional FSA methods be comparable and the amount of available information is identical, we assume that in the FSA method, the relationship between the influence factors and product reliability can be modelled by a weighted

function rather than introducing an extra fuzzy relation matrix for the fuzzy linguistic variable levels and evaluation set as used in (Zhao et al. 2004a,b). The weighted function can be written as:

$$\tilde{R} = w_1 \cdot \tilde{z}_1 + w_2 \cdot \tilde{z}_2 + w_3 \cdot \tilde{z}_3 + w_4 \cdot \tilde{z}_1 \cdot \tilde{z}_2 + w_5 \cdot \tilde{z}_2 \cdot \tilde{z}_3 + w_6 \cdot \tilde{z}_1 \cdot \tilde{z}_3 + w_7 \cdot \tilde{z}_1 \cdot \tilde{z}_2 \cdot \tilde{z}_3,$$

where w_i is the weight to be determined by the data sets from existing similar products and \tilde{z}_i is the final fuzzy scores of influence factor i . This relationship indicates that the product reliability is a linear function of the final fuzzy scores of the influence factors and their interactions. Since there are seven unknown weights in the function, they can be evaluated based on the seven out of eight data sets presented in Table 2, and the one left out will be used to compute the associated cross-validation error. The average cross-validation error is 2.21, much larger than that of the proposed method. It proves that the proposed neural network-based FSA approach has a more accurate reliability prediction than the conventional FSA method.

5. Remarks and conclusions

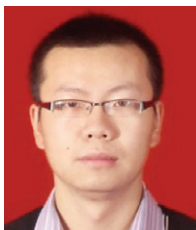
Reliability prediction deals with the evaluation of the achievable reliability of a new product design prior to its development and manufacturing. It is an important and useful tool to guide the business decision-making process before the system is assembled and/or put into use. However, reliability prediction in the conceptual design stage faces some challenging issues. The first one is that due to the lack of sufficient statistical data, the traditional reliability modelling and analysis methods, which need precise data set, become infeasible. On the other hand, the subjective information from experts' judgements and perceptions may be useful to facilitate the reliability prediction when the experiment data are not available. The second issue is that at the early design stage, it is difficult to mathematically formulate the relationship between the influence factors and the product reliability due to the lack of knowledge of the underlying physics.

To address these two issues, a neural network-based FSA approach is proposed here in which the uncertainty from the experts' subjective judgements and imprecise data are represented by the fuzzy number, and the highly non-linear relationship between the influence factors and the product reliability is learned by the tailored neural network. The benefit of this proposed method is that without providing the fuzzy relation between the fuzzy linguistic variable levels and evaluation set as it is in the conventional FSA method, the neural network can be trained to approximate this complicated relationship by the data sets of existing similar products. The effectiveness of the proposed method is illustrated by a case study of the fuel injection pump. The advantage of the method in terms of accuracy of reliability prediction is demonstrated by a comparative study with the conventional FSA method.

Acknowledgements

The constructive comments and suggestions from reviewers, the associate editor are very much appreciated. This research was supported by the National Natural Science Foundation of China under contract number 51075061, Specialized Research Fund for the Doctoral Program of Higher Education of China under contract number 20090185110019, and the Open Project Program of the Key Laboratory of Manufacture and Test Techniques for Automobile Parts (Chongqing University of Technology) under contract number 2009KLMT04, Ministry of Education, Chongqing, 400050, P.R. China.

Notes on contributors



Yu Liu received his PhD in Mechatronics Engineering from the University of Electronic Science and Technology of China. He is currently a Faculty in the School of Mechanical, Electronic, and Industrial Engineering, at the University of Electronic Science and Technology of China. He was a Visiting Pre-doctoral

Fellow in the Department of Mechanical Engineering at Northwestern University, Evanston, USA from 2008 to 2010. His research interests include design under uncertainty, reliability of multi-state systems, maintenance decisions and optimisation.



Hong-Zhong Huang is a Professor and the Dean of the School of Mechanical, Electronic, and Industrial Engineering, University of Electronic Science and Technology of China. He has held visiting appointments at several universities in the USA, Canada and Asia. He received his PhD degree in Reliability Engineering from Shanghai Jiaotong University, China, and has published 150

journal papers and 5 books in fields of reliability engineering, optimisation design, fuzzy sets theory and product

development. He is a Fellow of ISEAM (International Society of Engineering Asset Management), and a member of ESRA (European Safety and Reliability Association) Technical Committee on System Reliability, a Regional Editor of *International Journal of Reliability and Applications*, an Editorial Board Member of *International Journal of Reliability, Quality and Safety Engineering*, *International Journal of Quality, Statistics, and Reliability*, *International Journal of Reliability and Quality Performance*, *International Journal of Performability Engineering*, *Advances in Fuzzy Sets and Systems*, and *The Open Mechanical Engineering Journal*. He received the William A.J. Golomski Award from the Institute of Industrial Engineers in 2006, and the Best Paper Award of the 8th International Conference on Frontiers of Design and Manufacturing in 2008. His current research interests include system reliability analysis, warranty, maintenance planning and optimisation, computational intelligence in product design.



Dan Ling is an Associate Professor of the School of Mechanical, Electronic, and Industrial Engineering at the University of Electronic Science and Technology of China. She received her PhD degree in Mechatronics Engineering from the University of Electronic Science and Technology of China. Her research interests

include system reliability analysis and computational intelligence in product design.

References

- Avontuur, G.C., and Werff, K.V. (2001), 'An Implementation of Reliability Analysis in the Conceptual Design Phase of Drive Trains', *Reliability Engineering and System Safety*, 73, 155–165.
- Bardossy, A., Duckstein, L., and Bogardi, I. (1993), 'Combination of Fuzzy Numbers Representing Expert Opinions', *Fuzzy Sets and Systems*, 57, 173–181.
- Bazu, M. (1995), 'A Combined Fuzzy-logic & Physics-of-failure Approach to Reliability Prediction', *IEEE Transactions on Reliability*, 44, 237–242.
- Blischke, W.R., and Murthy, D.N.P. (2000), *Reliability Modeling, Prediction and Optimization*, New York: John Wiley & Sons.
- Bowles, J.B. (1992), 'A Survey of Reliability Prediction Procedures for Microelectronic Devices', *IEEE Transactions on Reliability*, 41, 2–12.
- Cai, K.Y. (1991a), 'Fuzzy Reliability Theories', *Fuzzy Sets and Systems*, 40, 510–511.
- Chen, S.M. (1994), 'Fuzzy System Reliability Analysis Using Fuzzy Number Arithmetic Operations', *Fuzzy Sets and Systems*, 64, 31–38.
- Chen, S.J., and Hwang, C.L. (1992), *Fuzzy Multiple Attribute Decision-Making: Methods and Applications*, New York: Springer-Verlag.
- Denson, W. (1998), 'The History of Reliability Prediction', *IEEE Transactions on Reliability*, 47, 321–328.

- Du, L., Choi, K.K., and Youn, B.D. (2006), 'Inverse Possibility Analysis Method for Possible-based Design Optimization', *AIAA Journal*, 44, 2682–2690.
- Dupow, H., and Blount, G. (1997), 'A Review of Reliability Prediction', *Aircraft Engineering and Aerospace Technology*, 69, 356–362.
- Gupta, S., and Bhattacharya, J. (2007), 'Reliability Analysis of a Conveyor System Using Hybrid Data', *Quality and Reliability Engineering International*, 23, 867–882.
- Hu, C.H., Si, X.S., and Yang, J.B. (2010), 'Dynamic Evidential Reasoning Algorithm for Systems Reliability Prediction', *International Journal of Systems Science*, 41, 783–796.
- Hu, Y., Wu, B., and Yi, P. (2008), 'Fuzzy Synthetic Evaluation Approach of Reliability for Condition Monitoring System', *Intelligent Robotics and Applications, Lecture Notes in Artificial Intelligence*, 5315, 582–592.
- Hu, Q.P., Xie, M., Ng, S.H., and Levitin, G. (2007), 'Robust Recurrent Neural Network Modeling for Software Fault Detection and Correction Prediction', *Reliability Engineering and System Safety*, 92, 332–340.
- Huang, H.I., Lin, C.H., and Ke, J.C. (2008), 'Two-unit Repairable Systems with Common-cause Shock Failures and Fuzzy Parameters: Parametric Programming Approach', *International Journal of Systems Science*, 39, 449–459.
- Huang, H.Z., Zuo, M.J., Fan, X.F., and Tian, Z. (2005), 'Quantitative Analysis of Influence of Fuzzy Factor on Fuzzy Reliability of Structure', in *Proceedings of the European Safety and Reliability Conference (ESREL2005)*, Tricity, Poland, 27–30 June, pp. 27–30.
- Jones, J., and Hayes, J. (1999), 'A Comparison of Electronic-reliability Prediction Models', *IEEE Transactions on Reliability*, 48, 127–134.
- Kumar, K.S., and Misra, R.B. (2008), 'An Enhanced Model for Early Software Reliability Prediction Using Software Engineering Metrics', in *Proceedings of the 2nd International Conference on Secure System Integration and Reliability Improvement*, Yokohama, Japan, 14–17 July, pp. 177–178.
- Levitin, G. (2007), *Computational Intelligence in Reliability Engineering, New Metaheuristics, Neural and Fuzzy Techniques in Reliability*, London: Springer.
- Lin, C.H., Ke, J.C., and Huang, H.I. (2010), 'Reliability-based Measures for a System with an Uncertain Parameter Environment', *International Journal of Systems Science*, DOI:10.1080/00207721.2010.545489.
- Lin, C.C., and Tseng, H.Y. (2005), 'A Neural Network Application for Reliability Modelling and Condition-Based Predictive Maintenance', *Journal of Advanced Manufacturing Technology*, 25, 174–179.
- Ling, D., Song, W., and Sun, R. (2011), 'A Reliability Prediction Method for Diesel Engine Components Based on FMEA', *Eksplotacja i Niezawodność - Maintenance and Reliability*, 49, 63–67.
- Liu, Y., and Huang, H.Z. (2010), 'Reliability Assessment for Fuzzy Multi-state System', *International Journal of Systems Science*, 41, 365–379.
- Liu, Y., Huang, H.Z., and Levitin, G. (2008), 'Reliability and Performance Assessment for Fuzzy Multi-state Element', *Journal of Risk and Reliability*, 222, 675–686.
- Liu, Y., Li, Y.F., Huang, H.Z., Zuo, M.J., and Sun, Z.Q. (2010), 'Optimal Preventive Maintenance Policy Under Fuzzy Bayesian Reliability Assessment Environments', *IIE Transactions*, 42, 734–745.
- Liu, Y., Yin, X., Arendt, P., Chen, W., and Huang, H.Z. (2010), 'A Hierarchical Statistical Sensitivity Analysis Method for Multilevel Systems with Shared Variables', *Journal of Mechanical Design*, 132, 021006.
- Liu, P.X., Zuo, M.J., and Meng, M.Q.H. (2003), 'Using Neural Network Function Approximation for Optimal Design of Continuous-state Parallel-series Systems', *Computers and Operations Research*, 30, 339–352.
- Mamtani, G., Green, G., and McDonald, S. (2006), 'Relative Reliability Risk Assessment Applied to Original Designs During Conceptual Design Phase', *Journal of Engineering Manufacture*, 220, 917–927.
- MIL-HDBK-217 (1991), *Reliability Prediction of Electronic Equipment*, Washington, DC: US Department of Defense.
- Nikolaïdis, E., Chen, S., Cudney, H., Haftka, R.T., and Rosca, R. (2004), 'Comparison of Probability and Possibility for Design Against Catastrophic Failure Under Uncertainty', *Journal of Mechanical Design*, 126, 386–394.
- Ormon, S.W., Cassady, C.R., and Greenwood, A.G. (2002), 'Reliability Prediction Models to Support Conceptual Design', *IEEE Transactions on Reliability*, 51, 151–157.
- Rajpal, P.S., Shishodia, K.S., and Sekhon, G.S. (2006), 'An Artificial Neural Network for Modeling Reliability, Availability and Maintainability of a Repairable System', *Reliability Engineering and System Safety*, 91, 809–819.
- Reedijk, C.I. (2000), 'Sensitivity Analysis of Model Output: Performance of Various Local and Global Sensitivity Measures on Reliability Problems', M.S. dissertation, Delft University of Technology, Delft, The Netherlands.
- Rojas, R. (1996), *Neural Networks: A Systematic Introduction*, London: Springer.
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., and Tarantola, S. (2008), *Global Sensitivity Analysis: The Primer*, New York: John Wiley & Sons.
- Setiono, R. (2001), 'Feedforward Neural Network Construction Using Cross Validation', *Neural Computation*, 13, 2865–2877.
- Sobol, I.M. (1993), 'Sensitivity Analysis for Nonlinear Mathematical Models', *Mathematical Modeling and Computational Experiment*, 1, 407–414.
- Twomey, J.M., and Smith, A.E. (1998), 'Bias and Variance of Validation Method for Function Approximation Neural Networks Under Conditions of Spares Data', *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 28, 417–430.
- Verma, A.K., Srividya, A., and Gaonkar, R.P. (2004), 'Fuzzy Dynamic Reliability Evaluation of a Deteriorating System Under Imperfect Repair', *International Journal of Reliability, Quality and Safety Engineering*, 11, 387–398.

- Wang, Z., Huang, H.Z., and Du, X. (2010), 'Optimal Design Accounting for Reliability, Maintenance, and Warranty', *Journal of Mechanical Design*, 132, 011007.
- Wang, Y., Yam, R.C.M., Zuo, M.J., and Tse, P. (2001), 'A Comprehensive Reliability Allocation Method for Design of CNC Lathes', *Reliability Engineering and System Safety*, 72, 247–252.
- Yang, M.S., Lin, Z.H., He, B.W., and Chen, K. (2003), 'Reliability Prediction of Mechanical Product Based on Similarity', *Machine Tool and Hydraulics*, 1, 63–65 (in Chinese).
- Zadeh, L.A. (1979), 'Fuzzy Sets as a Basis for a Theory of Possibility', *Fuzzy Sets and Systems*, 1, 3–28.
- Zhao, D.Z., Wen, W.D., and Duan, C.M. (2004a), 'A Model of Aeroengine Reliability Prediction Based on Fuzzy Number', *Journal of Aerospace Power*, 19, 320–325 (in Chinese).
- Zhao, D.Z., Wen, W.D., and Duan, C.M. (2004b), 'Application of Mechanical Reliability Prediction Based on Fuzzy Theory', *Transactions of Nanjing University of Aeronautics and Astronautics*, 21, 76–80.