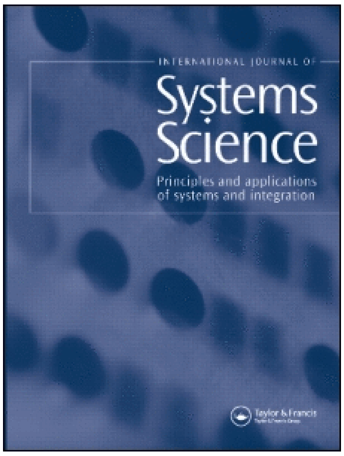

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Dynamic evidential reasoning algorithm for systems reliability prediction

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In this article, dynamic evidential reasoning (DER) algorithm is applied to forecast reliability in turbochargers engine systems and a reliability prediction model is developed. The focus of this study is to examine the feasibility and validity of DER algorithm in systems reliability prediction by comparing it with some existing approaches. To build an effective DER forecasting model, the parameters of prediction model must be set carefully. To solve this problem, a generic nonlinear optimisation model is investigated to search for the optimal parameters of forecasting model, and then the optimal parameters are adopted to construct the DER forecasting model. Finally, a numerical example is provided to demonstrate the detailed implementation procedures and the validity of the proposed approach in the areas of reliability prediction.

Keywords: reliability; dynamic evidential reasoning; nonlinear optimisation; forecasting; utility

1. Introduction

The safe and reliable operation of technical systems is of great significance, for the protection of human life and health, the environment and of the vested economic value. The correct functioning of those systems also has a profound impact on production cost and product quality. Reliability analysis is a significant direction of safety management and great importance has been attached. Many researchers have paid significant attention to this field.

As an important aspect of reliability analysis, the early prediction of systems reliability is critical in avoiding performance degradation and damage to the machinery or human life. Accurate prognosis then helps us to make the right decisions on emergency actions and repairs in advance and take follow-up actions timely. In reality, practically most systems are repairable and their reliability measures change with time. By considering this change as a time series process, the 'growth' or 'deterioration' of the system can be estimated. However, reliability prediction from the failure data is often subjective due to a lack of suitable models and a number of assumptions, which are difficult to validate, have to be made in the modelling process (Ho and Xie 1998; Liang 2007).

At present, many prediction mechanisms and mathematical models have been proposed to complete reliability prediction by a large community of researchers. The existing prediction methods can be broadly classified into three categories. The first is to determine an appropriate probability model as the reliability growth model, then use this model to predict future system reliability (Ascher and Feingold 1987). As a premise, the system model must be known *a priori* and accurate for these methods to be highly effective. Unfortunately, uncertainty widely exists in system models, and it is often difficult for a reliability engineer to select an appropriate probability model from many existing mathematics probability functions (Liang and Afzel 2005, 2006; Tong and Liang 2005). This can easily degrade the quality of prediction and cause false alarms of systems. The second is to utilize time series analysis techniques to construct a model representing reliability versus time, then to predict future reliability (Singpurwala 1978; Singh, Chrys, and Frishwick 1994; Liang and Tong 2001). However, the application of this kind of modelling methods is severely limited due to the fact that these methods are heavily dependent on the assumptions of linearity in time series. The third is to utilize machines learning technique for reliability prediction, such as neural networks (Ho and Xie 1998; Xu, Xie, Tang, and Ho 2003) and support vector machines (SVM) (Pai 2006; Chen 2007). However, for neural networks, it is difficult to determine the networks structure. As such, different people may design different networks and choose different parameters for training and testing. Therefore, they may get different results on the same subject. Another significant

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drawback of neural networks is that its connection weights are not easy to be explained (Chen 2007; Wang and Elhag 2007). For SVM, the selection of three positive parameters σ, ε and C of a SVM model is important for the accuracy of prediction, yet there is no united method to achieve this aim.

In reality, for a complex engineering system, many reliability analysis problems involve both quantitative data and qualitative information, as well as various types of uncertainties, such as incompleteness and fuzziness. Under this circumstance, there is a clear need to develop a new reliability analysis method which can deal with various types of uncertainties efficiently.

Evidential reasoning (ER) algorithm has been developed by Yang et al. for MADA under uncertainty (Yang and Singh 1994; Yang and Xu, 2002a, b). This approach is developed on the basis of decision theory and the Dempster–Shafer (D–S) theory of evidence (Dempster 1967; Shafer 1976). Due to the capability of ER approach in handling and representing uncertainties, so far, it has been applied to many areas, such as environmental impact assessment (Wang, Yang, and Xu 2006), pipeline leak detection (Xu et al. 2007) and bridge condition assessment (Wang and Elhag 2008). In addition, ER approach has been applied to conduct safety analysis. For instance, in safety analysis and assessment, system reliability can be described linguistically due to its easy interpretation. One may choose to use such linguistic terms as '*very low*,' '*low*,' '*average*,' '*high*' and '*very high*'. So it is common to assess a reliability level by degrees to which it belongs to linguistic variables, such as '*very low*,' '*low*,' '*average*,' '*high*' and '*very high*' that are referred to as reliability expression. For example, an expert may state that he is 20% sure that system reliability is low and 80% sure it is high. In the statement, '*high*' and '*low*' denote distinctive evaluation grades, and the percentage values of 20 and 80 are referred to as the degrees of belief, which indicate the extents that the corresponding grades are assessed to. The above assessment can be expressed as the following expectation: $S(reliability) = \{(low, 0.2), (high, 0.8)\}$, where $S(reliability)$ stands for the state of the system reliability and the real numbers 0.2 and 0.8 denote the degrees of belief of 20% and 80%, respectively. As such, we can conclude that ER approach is applied to reliability analysis and further forecasting is possible and the analysis results can provide a panoramic picture about the system's reliability state.

The above representation of reliability is a belief distribution structure in fact. The ER algorithm is very suitable to model belief distribution structure (Yang 2001; Yang and Xu 2002a; Yang, Liu, Wang, Sii, and Wang 2006; Yang, Liu, Xu, Wang, and Wang 2007). Some researchers have paid attention to safety analysis and reliability assessment using the ER approach (Wang et al. 1995, 1996; Liu, Yang, Wang, Sii, and Wang 2004; Liu, Yang, Ruan, Martinez, and Wang 2008). However, no attempt has been directly made to address the issue of how to deal with system reliability prediction problems. This research has been conducted to fill the gap.

Due to the static nature of original ER approach, yet in engineering practice, system performance is constantly changed over time, and this limits the application of ER approach to dynamic systems. According to the viewpoint of Smets (2007), dynamic fusion means that evidence credibility is decreasing with time. Although a dynamic evidential reasoning (DER) approach has been developed by Peddle (1995) and Sanz (2001), this approach does not incorporate time information and aims at dealing with classification problems. Thus, it is not suitable for reliability prediction. As such, there is a need to develop a supporting mechanism that can be used to conduct dynamic fusion with time, and establish a prediction model to trace and predict system performance. To solve this problem, Hu, Si, Yang, and Zhou (2008) developed a DER approach to realize dynamic fusion. The new method takes account of time effect by introducing belief decaying factor, which reflects the nature that evidence credibility is decreasing with time. The new method has been applied to deal with fault prediction problem. However, there is no attempt to apply DER algorithm for systems reliability prediction. This research has been conducted to develop a new application field.

In this article, we developed a new application for reliability prediction using DER algorithm. The central purpose of this study is to examine the feasibility and validity of DER algorithm in systems reliability prediction. Firstly, the outline of DER algorithm will be reviewed. Secondly, the DER approach is applied to reliability prediction problems, and a reliability prediction model, which is focused on the analysis of the present system reliability and the prediction of the systems reliability at some future time, is established based on the DER approach and utility theory. In the DER prediction model, input data, attribute weights and belief decaying factor are combined to generate appropriate conclusions using the DER algorithm. Thirdly, due to the difficulty to accurately determine the parameters of the DER prediction model accurately, a generic nonlinear optimisation models for training the parameters of the DER prediction model and other knowledge representation parameters in the DER approach are investigated in brief. Finally, the proposed model is applied to forecast turbochargers' reliability. The experimental results demonstrate the validity and potential of the DER model in reliability forecasting field.

The rest of this article is organized as follows. Section 2 gives a brief description of the DER algorithm. In Section 3, a reliability prediction model based on the DER approach is constructed. Section 4 investigates a generic optimal learning model for training the parameters of the DER prediction model. In Section 5, a numerical example is provided to demonstrate the detailed implementation procedures and the validity of the proposed approach in the areas of reliability prediction. Finally, Section 6 presents some concluding remarks.

2. Outline of the DER algorithm

The current ER approach is of a static fusion style in nature and does not take account of time information in fusion. In static fusion, all belief functions are combined simultaneously, the credibility of evidence source is unchanged over time, and static combination takes no account of time effect, while time information has no influence in combining results. However, in engineering practice, system performance changes significantly with time. Moreover, system reliability is decreasing with time. As such, in order to trace system state accurately in time, the DER approach has been developed by Hu et al. (2008), which extended the original ER approach and aggregated time information into the evidence combination process by incorporating belief decaying coefficient. As such, first a brief description of DER algorithm is given. Detailed descriptions of DER algorithm can be found in Hu et al. (2008).

To begin with, suppose there are L basic attributes $e_i (i = 1, \dots, L)$ associated with system state y. Define a set of L basic attributes as evidence source as follows:

$$E = \{e_1, \dots, e_L\}. \tag{1}$$

Suppose the weights of the attributes are given by $w = \{w_1, \dots, w_i, \dots, w_L\}$ where w_i is the relative weight of the i-th basic attribute e_i, and the weights of the attributes are normalized to satisfy the following constraints:

$$0 \le w_i \le 1 \quad \text{and} \quad \sum_{i=1}^{L} w_i = 1 \tag{2}$$

Define N distinctive reliability state evaluation grades as represented by

$$F = \{F_1, \dots, F_N\} \tag{3}$$

where F_n is the n-th reliability state evaluation grade. It is worth noting that F provides a complete set of standards for assessing attributes.

Mathematically, a given assessment for $e_i (i = 1, \dots, L)$ may be represented as the following distribution:

$$S(e_i(t_i)) = \{(F_n, \beta_{n,i}(t_i)), n = 1, \dots, N\}, \quad i = 1, \dots, L \tag{4}$$

where $\beta_{n,i}(t_i) \ge 0$, $\sum_{n=1}^{N} \beta_{n,i}(t_i) \le 1$, and $\beta_{n,i}(t_i)$ denotes a degree of belief at time t_i. The above distributed assessment reads that the attribute e_i is assessed to the grade F_n with the degree of belief $\beta_{n,i}(t_i)$ at time t_i, $n = 1, \dots, N$. An assessment $S(e_i(t_i))$ is complete if $\sum_{n=1}^{N} \beta_{n,i}(t_i) = 1$ and incomplete of $\sum_{n=1}^{N} \beta_{n,i}(t_i) < 1$. $\beta_{n,i}(t_i)$ could be generated using various methods, depending on the nature of the attribute and data available such as a quantitative attribute using numerical values or a qualitative attribute using linguistic values.

Let $m_{n,i}(t)$ be a basic probability mass representing the degree to which the i-th basic attribute e_i at time t_i supports the hypothesis that the system reliability state is assessed to the n-th grade at time t. Let $m_{F,i}(t)$ be a remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the system reliability state as far as e_i is concerned at time t. The basic probability mass can be calculated at time t as follows:

$$m_{n,i}(t) = w_i \alpha_i \beta_{n,i}(t_i) \cdot n = 1, \dots, N \cdot i = 1, \dots, L \tag{5}$$

$$m_{F,i}(t) = 1 - \sum_{n=1}^{N} m_{n,i}(t) = 1 - w_i \alpha_i \sum_{n=1}^{N} \beta_{n,i}(t_i), \quad i = 1, 2, \dots, L \tag{6}$$

$$\bar{m}_{F,i}(t) = 1 - w_i \alpha_i, \quad i = 1, 2, \dots, L \tag{7}$$

$$\tilde{m}_{F,i}(t) = w_i \alpha_i \left(1 - \sum_{i=1}^{N} \beta_{n,i}(t_i)\right), \quad i = 1, 2, \dots, L \tag{8}$$

$$m_{F,i}(t) = \bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t) \tag{9}$$

where $\alpha_i = e^{-\gamma \mathrm{d}t_i}$ is the discount rates, $\mathrm{d}t_i = t - t_i$.

From (5) to (9) and $\alpha_i = e^{-\gamma \mathrm{d}t_i}$, it can be seen that a new parameter γ is introduced, named the belief decaying coefficient. The meaning of γ and the reason for introducing γ in reliability prediction can be given as follows:

(1) In the process of evidence collection, considering that the credibility of evidence themselves is decaying over time, this decaying concept can be translated by claiming that every basic probability mass is discounted with time, as shown in (5)–(9). In other words, the longer the time since the basic probability mass functions were collected, the stronger the discounting is.

(2) In the DER algorithm, the belief decaying coefficient γ expressed the time effect of the credibility of engineering system. Generally, the credibility of evidence resource is diminishing over time. So γ reflects the fact that more recent evidence has greater influence in combination results. This is one of the distinctive features of the DER approach from the ER approach.

(3) In engineering practice, system reliability is decreasing with time. As such, time effect should be taken into account in reliability prediction to trace system state accurately in time. So the meaning to reliability is that the longer the time since reliability data are collected, the lower the reliability of system is.

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

Next, the basic probability masses on the L basic attributes are aggregated into the combined probability assignments by using the following analytical formulae developed by Wang et al. (2006):

$$\{F_n\} : m_n(t) = K_L(t)\left[\prod_{i=1}^{L}\left(m_{n,i}(t) + \bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t)\right) - \prod_{i=1}^{L}\left(\bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t)\right)\right] \tag{10}$$

$$\{F\} : \tilde{m}_F(t) = K_L(t)\left[\prod_{i=1}^{L}\left(\bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t)\right) - \prod_{i=1}^{L}\bar{m}_{F,i}(t)\right] \tag{11}$$

$$\{F\} : \bar{m}_F(t) = K_L(t)\prod_{i=1}^{L}\bar{m}_{F,i}(t), \quad n = 1, \ldots, N \tag{12}$$

with

$$K_L(t) = \left[\sum_{n=1}^{N}\prod_{i=1}^{L}\left(m_{n,i}(t) + \bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t)\right) - (N-1)\prod_{i=1}^{L}\left(\bar{m}_{F,i}(t) + \tilde{m}_{F,i}(t)\right)\right]^{-1}. \tag{13}$$

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

$$\{F_n\} : \beta_n(t) = \frac{m_n(t)}{1 - \bar{m}_F(t)} \tag{14}$$

$$\{F\} : \beta_F(t) = \frac{\tilde{m}_F(t)}{1 - \bar{m}_F(t)}. \tag{15}$$

$\beta_n(t)$ and $\beta_F(t)$ represent the belief degrees of the aggregated assessment, to which the general attribute is assessed to the grades F_n and F, respectively. The combined assessment can be denoted by $S(y(t)) = \{(F_n(t), \beta_n(t)),\ n = 1, 2 \ldots, N\}$. It provides a panoramic view about the assessment state of system reliability, from which one can tell which grades the system reliability is assessed to, and what belief degrees are assigned to the defined reliability assessment grades. In order to understand the DER algorithm (5)–(15) easily, a numerical example is provided in Table 1.

Table 1 presents an example of application of the DER algorithm. In this numerical example, the belief decaying coefficient γ is set to 0.15 and the attribute weights of $e_i (i = 1, 2, 3)$ are all set to be equivalent. The second row is the times (1, 3 and 4 time units) at which the given assessments for $e_i (i = 1, 2, 3)$ are collected, the time delays between two successively collected assessments. The third row is the given assessments to system state y. When the belief distribution $S(e_i(t_i)),\ i = 1, \ldots, 3$ are combined to obtain the final assessment $S(y(t))$ at time $t = 5$, the discount rates are 0.5488 at $t_1 = 1$, 0.7408 at $t_2 = 3$, and 0.8607 at $t_3 = 4$.

Table 1. A numerical example for DER algorithm.

	Basic attribute e_1		Basic attribute e_2		Basic attribute e_3	
Time	$t_1 = 1$		$t_2 = 3$		$t_3 = 4$	
Belief distribution $S(e_i(t_i))$	$\{(F_1, 0.45), (F_2, 0.4), (F_3, 0.15)\}$		$\{(F_1, 0.6), (F_2, 0.3), (F_3, 0.1)\}$		$\{(F_1, 0.8), (F_2, 0.15), (F_3, 0.05)\}$	
Basic probability mass $m_{n,i}$	$\{(F_1, 0.0823), (F_2, 0.0732), (F_3, 0.0274), (\mathrm{F}, 0.8171)\}$		$\{(F_1, 0.1482), (F_2, 0.0741), (F_3, 0.0247), (\mathrm{F}, 0.7530)\}$		$\{(F_1, 0.2295), (F_2, 0.0430), (F_3, 0.0143), (\mathrm{F}, 0.7132)\}$	
Combined probability assignments $m(t)$	$m_1(t)$	$m_2(t)$	$m_3(t)$	$\bar{m}_F(t)$	$\tilde{m}_F(t)$	$m_F(t)$
	0.3192	0.1348	0.0445	0.5015	0	0.5015
Final assessment $S(y(t))$	$\beta_1(t)$	$\beta_2(t)$	$\beta_3(t)$		$\beta_F(t)$	
	0.6403	0.2704	0.0893		0	

As such, the basic probability mass $m_{n,i}$ can be obtained by using (5)–(9), corresponding to the fourth row in Table 1. Then the final assessment $S(y(t))$ can be calculated using (10)–(15).

It has been shown that the original ER algorithm was a special case of DER algorithm with $\alpha(t)=1$, that is $\gamma=0$ (Hu et al. 2008). In this case, time factor has no influence on belief decaying and the reliability of evidence source is not decreasing with time.

3. Reliability prediction model based on DER algorithm

3.1. *Prediction model structure and representation*

In this section, reliability prediction model is investigated in the DER framework. In most situations, the reliability of engineering systems changes with time. Therefore, the changes can be treated as a time series process (Liang and Afzel 2006). It is assumed that a set of observed data is provided in the form of time series $y(t_m), m=1,\dots,M$, with $y(t_m)$ being a scalar representing the corresponding reliability value or subjective distribution value of the actual system at time t_m.

For prediction problems, the inputs used in a prediction model are the past input vector and the lagged observations of the current time, while the outputs are the future values. Each set of input patterns is composed of any moving fixed-length window within the time series of the input data. The general reliability prediction model can be represented as

$$\hat{y}(t+k-1)=f(y_{t-1},y_{t-2},\dots,y_{t-p}) \tag{16}$$

where $\hat{y}(t+k-1)$ is a scalar representing the predicted value at time $t+k-1$, $(y_{t-1},y_{t-2},\dots,y_{t-p})$ is a vector of lagged variables and p represents the dimensions of the input vector (number of input nodes) or the number of past inputs related to the future value. In reliability prediction, it is reasonable to assume that the current output value y_t is related to the most recent input vector y_{t-1} or even extended into the past values $y_{t-2},\dots,y_{t-p}$. This is because the next output value is dependent on the current output value to a certain extent which is in turn related to the current inputs. The pattern of training data set is described in Table 2 (Chen 2007). In Table 2, the first column to the p-th column can be considered to be the evidence sources associated with the predicted output.

From Section 2, it is clear that the DER approach is on the basis of Dempster combination rule. As such, in order to apply the DER approach, assume p evidence sources are independent, similar to the method used by Petit-Renaud and Niu (Petit-Renaud and Denoeux 2004; Niu and Yang 2009).

In the above equation, if $k=1$, the prediction is a one-step-ahead prediction; if $k>1$, the prediction is a multi-step prediction. Although multi-step forecasting may capture some system dynamics, the performance may be poor due to the accumulation of errors. In practice, one-step-ahead prediction results are more useful since they provide timely information for preventive and corrective maintenance plans (Xu et al. 2003). In addition, according to Wang, the more the step ahead is, the less reliable the forecasting operation is because multi-step prediction is associated with multiple one-step prediction operation (Wang 2007). Thus, this study only considers one-step-ahead prediction. In the following, for simplicity, let $\mathbf{X}(t)=(y_{t-1},y_{t-2},\dots,y_{t-p})$ denotes the input vector of the prediction model.

3.2. *Reliability prediction model based on DER approach*

In order to apply the DER approach, suppose $(y_{t-1},y_{t-2},\dots,y_{t-p})$ are p basic attributes associated with system prediction output $\hat{y}_t$, and the DER approach attempts to identity the appropriate internal representation between $(y_{t-1},y_{t-2},\dots,y_{t-p})$ and $\hat{y}_t$. In such a case, the number of the basic attribute L is equal to p, that is $L=p$. The key for solving the prediction problem is how to approximate the function $f(\cdot)$.

In reliability prediction problems, the DER prediction model can be trained first to learn relationships between past historical data and the corresponding targets, and then future output values can be predicted if the new inputs are available. Due to the fact that the input data $\mathbf{X}(t)$ may be a numerical value or a subjective distribution, there is a need to transform such data into the belief structure as the format of (4). Rule-based equivalence transformation techniques can be used in this case, and more discussions on this issue can be found in the following section. As a result, each input can be represented as a distribution on referential values using a belief structure. The main advantage of doing so is that precise data, random numbers and

Table 2. The pattern of training data set.

X				Y
y_1	y_2	$\cdots$	y_p	y_{p+1}
y_2	y_3	$\cdots$	y_{p+1}	y_{p+2}
y_3	y_4	$\cdots$	y_{p+2}	y_{p+3}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
y_{M-p}	$\cdots$	$\cdots$	y_{M-1}	y_M

subjective judgments with uncertainty can be consistently modelled under the same framework.

On the basis of the rule equivalence transformation techniques, the input vector $\mathbf{X}(t)$, that is, the p basic attributes $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ can be represented with the belief structure as follows:

$$S(y_{t-i}) = \{(F_n, \beta_{n,i}(y_{t-i})), n = 1, \ldots, N\}, \quad i = 1, \ldots, p. \tag{17}$$

Having represented each attribute using (17), the DER approach can be directly applied to combine all attributes and generate final conclusions. Using the DER analytical algorithm (5)–(15), the final prediction result $O(\hat{y}(t))$ that is generated by aggregating all attributes $\mathbf{X}(t) = (y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ can be represented as follows:

$$O(\hat{y}(t)) = \left\{\left(F_n, \hat{\beta}_n(t)\right), \left(F, \hat{\beta}_F(t)\right), n = 1, \ldots, N\right\} \tag{18}$$

where $\hat{\beta}_n(t)$ can be obtained by the analytical DER algorithm as follows:

$$\hat{\beta}_n(t) = \left\{\prod_{i=1}^{L}\left(w_i\alpha_i\hat{\beta}_{n,i}(y_{t-i}) + 1 - w_i\alpha_i + w_i\alpha_i\beta_{F,i}(y_{t-i})\right) - \prod_{i=1}^{L}\left(1 - w_i\alpha_i + w_i\alpha_i\beta_{F,i}(y_{t-i})\right)\right\} / D(t) \tag{19}$$

$$\hat{\beta}_F(t) = \left\{\prod_{i=1}^{L}\left(1 - w_i\alpha_i + w_i\alpha_i\beta_{F,i}(y_{t-i})\right) - \prod_{i=1}^{L}(1 - w_i\alpha_i)\right\} / D(t) \tag{20}$$

$$D(t) = \sum_{n=1}^{N}\prod_{i=1}^{L}\left(w_i\alpha_i\beta_{n,i}(y_{t-i}) + 1 - w_i\alpha_i + w_i\alpha_i\beta_{F,i}(y_{t-i})\right) - \prod_{i=1}^{L}(1 - w_i\alpha_i) - (N-1)\left(1 - w_i\alpha_i + w_i\alpha_i\beta_{F,i}(y_{t-i})\right) \tag{21}$$

where $L = p$, p denotes the number of lagged variables of the prediction model (16).

3.3. *Rule-based information transformation technique for quantitative data*

In the above method, $\beta_{n,i}(y_{t-i}), n = 1, \ldots, N$, $i = 1, \ldots, L$ could be generated using various ways, depending on the nature of an attribute and data available such as a qualitative attribute using linguistic values. In order to facilitate data collection, a scheme for handling various types of input information has been summarized by Yang (2001) and Yang et al. (2006, 2007). In the proposed scheme, there is an important technique, i.e. rule-based information transformation technique (Yang 2001), which is used to deal with the input information which includes qualitative assessment and quantitative data. In this article, we will only consider the quantitative input. So we first review this technique for quantitative data in this subsection.

Suppose that the input of a quantitative attribute is given by numerical values. In this case, equivalence rules need to be extracted from the decision maker. This can be used to transform a value to an equivalent expectation, thereby relating a particular value to a set of referential values (Yang et al. 2006). Therefore, a quantitative value $\gamma_j (j = 1, \ldots, N)$ can be judged to be a referential value F_j in the ER approach, or

$$\gamma_j \text{ means } F_j, \quad j = 1, \ldots, N. \tag{22}$$

Suppose that a larger value γ_{j+1} is preferred over a smaller value γ_j. Let γ_N and γ_1 be the largest and smallest feasible values, respectively. Then, an input value y_{t-i} is represented using the following equivalent expectation:

$$S(y_{t-i}) = \left\{(\gamma_j, \beta_{j,i}(y_{t-i}))\ i = 1, \ldots, L;\ j = 1, \ldots, N\right\} \tag{23}$$

where $\beta_{j,i}(y_{t-i})$ can be calculated by

$$\beta_{j,i}(y_{t-i}) = \frac{\gamma_{j+1} - y_{t-i}}{\gamma_{j+1} - \gamma_j} \quad \text{if} \quad \gamma_j \le y_{t-i} \le \gamma_{j+1}, j = 1, \ldots, N-1 \tag{24}$$

$$\beta_{j+1,i}(y_{t-i}) = 1 - \beta_{j,i}(y_{t-i}) \quad \text{if} \quad \gamma_j \le y_{t-i} \le \gamma_{j+1}, \quad j = 1, \ldots, N-1 \tag{25}$$

$$\beta_{s,i}(y_{t-i}) = 0 \quad \text{for} \quad s = 1, \ldots, N,\ s \ne j, j+1. \tag{26}$$

The quantitative attribute, y_{t-i}, may also be a random variable and may not always take a single value but several values with different probabilities. In order to solve this problem, the corresponding rule-based information transformation technique has also been proposed by Yang (2001).

3.4. *Construction of numerical output*

From (18), we can clearly see that the aggregated distributed assessment

$$O(\hat{y}(t)) = \left\{\left(F_n, \hat{\beta}_j(t)\right), \left(F, \hat{\beta}_F(t)\right), n = 1, \ldots, N\right\}$$

represents the overall assessment of reliability. It provides a panoramic view about the reliability state at time t, from which one can tell which assessment grades the reliability is assessed to, and what belief degrees are assigned to the defined reliability grades $F_n, n = 1, \ldots, N$. However, if the output value $\hat{y}(t)$ is a numerical value, it is desirable to generate numerical values equivalent to the distributed assessments (18) in a sense. The concept of expected utility is used to define such values (Yang 2001; Xu et al. 2007; Yang et al. 2007). Suppose $u(F_i)$, $i = 1, \ldots, N$ are the utilities of the reliability grade $F_i, i = 1, \ldots, N$, respectively, with $u(F_i) < u(F_j)$. If for reliability prediction problem, F_j is preferred to F_i. $u(F_i)$, $i = 1, \ldots, N$ may be estimated using prior expert knowledge or by constructing optimisation models, in this article, we select the latter.

$$\hat{y}(t) = u_{avg}(O(\hat{y}(t))) = \sum_{n=1}^{N} \hat{\beta}_n(t)u(F_n) + \frac{u(F_1) + u(F_N)}{2}\hat{\beta}_F(t) \tag{27}$$

where $\hat{y}(t)$ represents the prediction outcome. If the distributed reliability assessments are complete and precise, then $\hat{\beta}_F(t) = 0$ and the prediction outcome $\hat{y}(t)$ is reduced to

$$\hat{y}(t) = \sum_{n=1}^{N} \hat{\beta}_n(t)u(F_n). \tag{28}$$

The DER approach is a nonlinear aggregation method in nature. Therefore, the functional relationship between outputs and inputs in the DER prediction model is nonlinear in nature. As such, the above method can complete nonlinear systems reliability prediction.

However, it is difficult to determine the parameters of the DER model accurately. In addition, a change in attribute weight or belief decaying factor may lead to changes in the performance of the DER prediction model. As such, there is a need to develop a method that can optimally learn parameters using observed input and output information. This is exactly the topic for the rest of this article.

4. Optimal learning algorithm of DER prediction model

For reliability prediction model discussed above, the relative weights of attributes $w_i, i = 1, \ldots, L$, the utility of assessment grades $u(F_n)$, $n = 1, \ldots, N$ and the coefficient of belief decaying γ are all unknown. In order to train parameters from input–output pairs, the optimisation model needs to be constructed.

In this section, a generic optimisation models and procedures are investigated in the DER framework to help search for optimally trained belief decaying factor and weights and expected utilities simultaneously. Figure 1 shows the process of training a DER prediction model, where $\mathbf{X}(t)$ is a given input represented as $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$; $y(t)$ is the corresponding actual observed output, either measured using instruments or assessed by experts; $\hat{y}(t)$ is the simulated output that is generated by the DER prediction model; and $\xi(P)$ is the difference between $y(t)$ and $\hat{y}(t)$, as defined later.

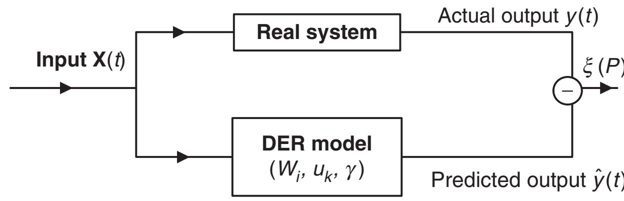

Figure 1. Illustration of optimal learning process for DER prediction model.

It is desirable that $\xi(P)$ is as small as possible where P is the vector of training parameters including $w_i, i = 1, \ldots, L$, $u(F_n)$, $n = 1, \ldots, N$. and γ. This objective is difficult to achieve if the DER prediction model is constructed using expert judgments only. Several learning models are designed to adjust the parameters in order to minimize the difference between the observed output $y(t)$ and the simulated output $\hat{y}(t)$ generated by (27), i.e. $\xi(P)$. In the previous work, these learning models are constructed by minimising the mean square error (MSE) criterion. After training, such an optimally trained DER model may then be used to predict the behaviours of the system. In general, the optimal learning problem can be represented as the following generic nonlinear optimisation model:

$$\begin{aligned} &\min\ f(P) \\ &\text{s.t. } A(P) = 0,\ B(P) > 0 \end{aligned} \tag{29}$$

where $f(P)$ is the objective function, P is the training parameter vector, $A(P)$ is the equality constraint functions and $B(P)$ is the inequality constraint functions.

In the learning process, a set of observations on the system inputs and outputs is required. In the following, we assume that a set of observation pairs $(\mathbf{X}(t_m), y(t_m))$, $m = 1, \ldots, M$ is available, where $\mathbf{X}(t_m)$ is an input vector and $y(t_m)$ is the corresponding output. Both $\mathbf{X}(t_m)$ and $y(t_m)$ can be either numerical, judgmental or both. The format of the objective function is important for the parameter optimisation. Depending on the types of input and output, the optimal learning models can be constructed in different ways, as discussed in detail in Yang et al. (2007) and Hu et al. (2008), in which optimal learning models under numerical output and belief distribution output and mixed output are investigated deeply by minimising the MSE between the predicted outputs $\hat{y}(t)$ and the observed outputs $y(t)$.

Since the reliability data of turbocharger is numerical, we only investigate the case in which $y(t_m)$ is numerical in this section.

For a reliability prediction problem, the relative weight of attribute $w_i, i = 1, \ldots, L$, the utilities of assessment grades $u(F_n), n = 1, \ldots, N$ and the coefficient of belief decaying γ are all unknown. In order to train and learn these parameters from input–output pairs, the optimisation model is constructed to minimize the MSE criterion as follows:

$$\min J = \xi(P) = \frac{1}{M}\sum_{i=1}^{M}(y(t_i) - \hat{y}(t_i))^2 \tag{30}$$

where $y(t_i)$ denotes the actual output data of a system at time t_i and $\hat{y}(t_i)$ denotes the predicted output data of the system at time t_i from the DER prediction model, which can be obtained from (27). $w_i, \gamma, u(F_n), i = 1, \ldots, L, \quad n = 1, \ldots, N$ are the relative weights of attributes, the belief decaying factor and the utilities of reliability assessment grades to be estimated, respectively. P is the parameter vector including w_i, $u(F_n)$, $i = 1, \ldots, L$, $n = 1, \ldots, N$ and γ. M is the number of training data in the input–output pairs. $(y(t_i) - \hat{y}(t_i))$ is the residual of training data at time t_i.

The construction of the constraints of the learning model is given as follows.

(1) An attribute weight is normalized, so that it is between zero and one and the total weights will be equal to one, for example

$$0 \le w_i \le 1, \quad i = 1, \ldots, L \tag{31}$$

$$\sum_{i=1}^{L} w_i = 1. \tag{32}$$

(2) The belief decaying factor is a nonnegative number, for example

$$\gamma \ge 0. \tag{33}$$

(3) For numerical data, the utility of the reliability state evaluation grade is a nonnegative number, for example

$$u(F_n) \ge 0, \quad n = 1, \ldots, N \tag{34}$$

and if F_j is preferred to F_i, then

$$u(F_j) > u(F_i). \tag{35}$$

Therefore, all generations of the optimisation algorithm are used to obtain the minimal MSE. In (30), it is a multi-variable constrained nonlinear single-objective optimisation problem and can be solved using MATLAB optimisation toolbox. Once the weights, the utilities of grades and the belief decaying factor are learnt, the DER prediction model can be used for reliability prediction.

5. Experimental study

Turbochargers are a critical component in turbo-charged diesel engines. Since reliability is one of the most important considerations in diesel engine system design, an accurate forecast of reliability can provide a good assessment of engine performance and help make correct decisions for follow-up maintenance actions.

5.1. *Problem description of the turbochargers' reliability prediction*

In this study, the systems reliability data are the same data sets as in Xu et al. (2003). The data sets include the time-to-failure data for 40 suits of turbochargers. When analysing ungrouped failure data, the cumulative failure distribution can be estimated from generating the median plotting positions for the i-th ordered failures (Xu et al. 2003). Since the cumulative failure distribution is skewed for values of i close to zero and close to the sample size n, the reliability estimates $R(T_i)$ can thus be calculated based on the following formula via Benard approximation (Nelson 1988; Chen 2007).

$$R(T_i) = 1 - \frac{i - 0.3}{n + 0.4}. \tag{36}$$

In this study, the reliability data of turbocharger were employed as the data set to train and test the DER prediction model.

5.2. *Prediction model based on DER approach for turbochargers*

As analysed above, it indicates that the systems reliability data of turbochargers is a time series. So it is reasonable to assume that the current reliability value y_t is related to the most recent y_{t-1} or even extended into the past values $y_{t-2}, \ldots, y_{t-p}$. This is because the next reliability value is dependent on the current level of system state to a large extent. As such, the proposed DER prediction model can be applied to accomplished turbochargers' reliability prediction. Let $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$ be the input vector of the DER prediction model, so (16) can be represented as follows:

$$\hat{y}(t) = \hat{y}_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) \tag{37}$$

where $\hat{y}(t)$ is a scalar representing the predicted turbochargers reliability at time t.

In this study, the reliability data of turbochargers were employed as the data set to train and test the DER prediction model. This study is conducted with a relatively larger number $p=4$ for the order of autoregressive terms. Therefore, we can transform 40 observation values to 36 input patterns. So (37) can be represented below:

$$\hat{y}(t) = \hat{y}_t = f(y_{t-1}, y_{t-2}, y_{t-3}, y_{t-4}). \quad (38)$$

In (38), the original input and output data were all provided as numerical numbers, so there is a need to equivalently transform the numerical value into the belief distribution structures.

5.3. *Referential values of turbochargers' reliability state*

For the turbochargers' reliability prediction problem, suppose turbochargers' reliability state is classified into several categories like '*high*' (F_1), '*average*' (F_2) and '*low*' (F_3). Define the following discernment framework of turbochargers' reliability state:

$$F = \{F_j, j = 1, 2, 3\} = \{High, Average, Low\}.$$

All related factors to turbochargers' reliability may then be assessed with reference to this framework using the rule-based information transformation technique. Note that the referential values of an attribute and the types of input information are problem specific, thus, their definitions depend on the problems in hand.

Through analysing the characteristic of turbochargers' reliability data, similar to Yang's method (Yang 2001; Yang et al. 2007), it is assumed that equivalence rules can be acquired. Three equivalence rules could be acquired as follows:

(1) If turbochargers' reliability is 1.0, then system reliability state is ranked to be '*high*' with belief degree 1.0, that is, F_1 is equivalent to the referential value 1.0.
(2) If turbochargers' reliability is 0.75, then system reliability state is ranked to be '*average*' with belief degree 1.0, that is, F_2 is equivalent to the referential value 0.75.
(3) If turbochargers' reliability is 0.5, then system reliability state is ranked to be '*low*' with belief degree 1.0, that is, F_3 is equivalent to the referential value 0.5.

The quantified results above are listed in Table 3.

On the basis of the rule-based information transformation technique, the given values for the input vector $\mathbf{X}(t) = (y_{t-1}, y_{t-2}, \ldots, y_{t-4})$ can be transformed into the belief structures with respect to the defined three referential points using the information transformation technique. Take the 10th input vector $(0.8735, 0.8835, 0.8934, 0.9034)$ for example. For $y_{t-1} = 0.8735$, this can be equivalently transformed to belief distribution structure by using (24)–(26) as follows:

Table 3. The referential values of turbochargers' reliability.

Linguistic terms	High (F_1)	Average (F_2)	Low (F_3)
Numerical values	1.0	0.75	0.5

$$S(y_{t-1} = 0.8735) = \{(F_1, 0.494), (F_2, 0.506), (F_3, 0)\}.$$

Similarly, $y_{t-2} = 0.8835$ can be equivalently transformed to

$$S(y_{t-2} = 0.8835) = \{(F_1, 0.534), (F_2, 0.466), (F_3, 0)\}, \ldots$$

$$S(y_{t-4} = 0.9034) = \{(F_1, 0.5736), (F_2, 0.4264), (F_3, 0)\}.$$

The other given input training data sets can be transformed in a similar way.

5.4. *Illustration of the DER prediction approach*

For training and testing, there are many different ways of dividing the data set into two sub-sets for training and testing. In this section, for illustration, the first 31 sets of data are used as the training data for parameters estimation and other division will be considered in the end. In this case, the output value $\hat{y}(t)$ in (38) is a numerical value. After training, the remaining 5 sets of data are used for testing the trained DER prediction model. The initial parameter vector P is given by experts. The initial attribute weights of $y_{t-1}, y_{t-2}, y_{t-3}$ and y_{t-4} are all set to be equivalent. The initial parameter vector P is set to:

$$P = [w_1, w_2, w_3, w_4, u(F_1), u(F_2), u(F_3)] \\ = [0.25, 0.25, 0.25, 0.25, 1.0, 0.8, 0.5, 0.3].$$

In order to solve nonlinear optimisation model (30), FMINCON function in MATLAB is used, the error tolerance is set to 0.000001, and the maximum iteration is set to 60. After training, the trained parameter vector P is obtained as follows:

$$P = [0.2511, 0.2500, 0.2495, 0.2494, 0.9782, \\ 0.7761, 0.4804, 0.3051]$$

where $w_1 > w_2 > w_3 > w_4$ denotes that y_{t-1} has the most influence on the prediction results $\hat{y}_t$ and y_{t-4} has the least influence on $\hat{y}_t$, and the utilities $u(F_1) > u(F_2) > u(F_3)$ denoting F_1 is preferred to F_2

and F_2 is preferred to F_3. The belief decaying coefficient γ is adjusted to 0.3051 after training.

After searching for the optimal parameter sets with nonlinear optimisation model, the DER forecasting models were built. The forecasting simulation was performed against the testing data. The graphical comparisons between the actual and predicted reliability are shown in Figures 2 and 3. It shows the predicted and actual values of the systems reliability and relative prediction error in the data sets. It is observed that the proposed DER model fits this particular data set very well.

5.5. *Comparison with the existing methods*

It is of interest to compare the results generated by the DER prediction model with some existing reliability forecasting methods. In this section, the traditional ARIMA models, and the neural network approaches, and support vector regression model with genetic algorithm (GA-SVR) are used for the comparative study, such as the experiment results of Xu et al. (2003), Chang, Lin, and Pai (2004) and Chen (2007).

Table 4 shows that the forecasting performance from DER and GA-SVR and various neural network approaches are all excellent.

In order to evaluate the performance of the above prediction methods, we use the mean absolute percentage error (MAPE) as the evaluation criteria in this study. It is defined as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \quad (39)$$

where y_t and $\hat{y}_t$ are actual and predicted values, respectively. The MAPE generated results with small values, indicating extremely small deviations between the predicted and actual values.

As shown in Table 4, generally speaking, the results made by the DER model and GA-SVR model were superior to those from the other models. Furthermore, the difference between the DER model and GA-SVR model with respect to the predicted precision is small and the predicted precision of DER and GA-SVR is at the same order of magnitude. However, in the experiment, the training process of GA-SVR model is time-consuming. Generally, it takes about 67.4 s for model training. Fortunately, our modelling process is more efficient and the training time is about 1.83845 s.

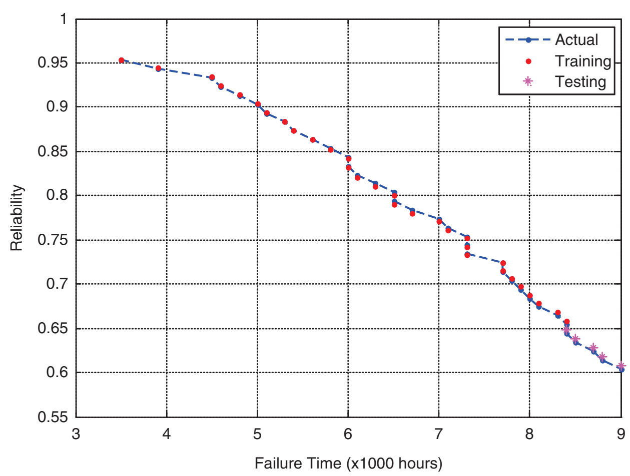

Figure 2. Reliability prediction results with DER.

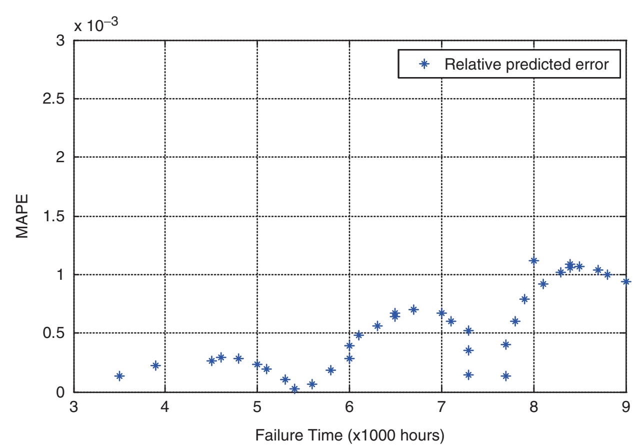

Figure 3. Reliability prediction error with DER.

Table 4. Comparison of the prediction results.

No.	Actual value	DER	GA-SVR	NF	GRNN	MLP	RBF	ARIMA
36	0.6444	0.6450	0.6446	0.6845	0.6533	0.6515	0.6466	0.6460
37	0.6345	0.6343	0.6346	0.6344	0.6389	0.6446	0.6369	0.6392
38	0.6245	0.6246	0.6248	0.6236	0.6270	0.6383	0.6270	0.6338
39	0.6145	0.6140	0.6148	0.6163	0.6049	0.6328	0.6170	0.6294
40	0.6046	0.6034	0.6049	0.6070	0.5989	0.6287	0.6072	0.6256
MAPE (%)		0.0841	0.0387	0.2972	0.9960	2.3437	0.3914	1.6753

This is very important when there is a high level of real-time requirement for system reliability forecasting.

In order to deeply explore the performance of the DER prediction model, one special case should be considered. If there is no such belief decaying coefficient, that is $\gamma = 0$, then the unknown parameters of the prediction model are the relative weights of attributes $w_i, i = 1, \ldots, L$, the utility of assessment grades $u(F_n), n = 1, \ldots, N$. Similar to the case that there is such belief decaying coefficient γ as above, the predicted results can be obtained as shown in Figure 4, from which it is clear that the performance of prediction model without γ is worse than with γ. Furthermore, the MAPE is 15.2% in this case. This demonstrates that the performance of prediction model is significantly improved by introducing belief decaying coefficient γ.

5.6. *Influence on the predicted results with the way of data division*

In the previous sections, the first 31 sets of data are used as the training data for parameters estimation. There are many different ways of dividing the data set into two sub-sets for training and testing. For simplicity, we only consider two cases that are the size of training data and different way of division to study their effect to the predicted results.

Case 1: The size of training data is different.

In this case, the first 15 and 34 sets of data are used as the training data, respectively. By using DER prediction model, the experimental results are shown in Figure 5.

From Figure 5, it can be clearly seen that the size of training samples have significant influence on the predicted results. Also, the MAPEs with 15 samples and with 34 samples are 0.1870 and 0.0792, respectively. Obviously, the more training samples, the better predicted results. As such, for this case study, it is recommended that more than 80% sample should be used as the training sample. Of course, the size of training sample is determined by researchers on a case-by-case basis.

Case 2: The ways of data division are different.

In this case, for illustration, the 16th–20th sets data and the 25th–30th sets data are used as the testing data, respectively. The remaining data can be used to train the DER prediction model. The experimental results are shown in Figure 6.

From Figure 6, it is observed that the proposed DER model fits this case very well. Also, the MAPEs are 0.0823 and 0.0835 corresponding to the 16th–20th sets data and the 25th–30th sets data, respectively. As such, it can be concluded that the ways of data division under the condition that the size of training sample are constant, have minor influence on the

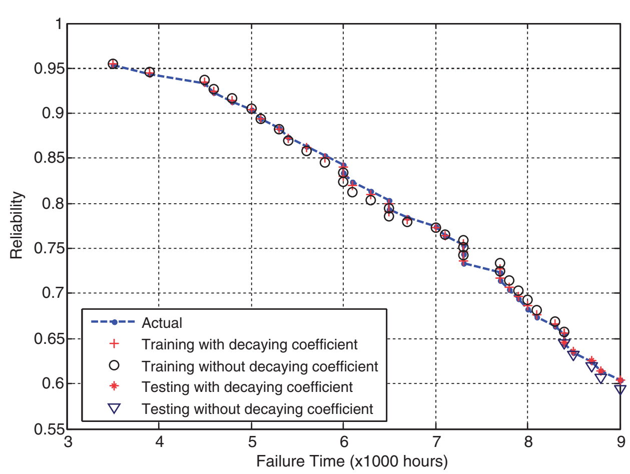

Figure 4. Reliability prediction results with γ or not.

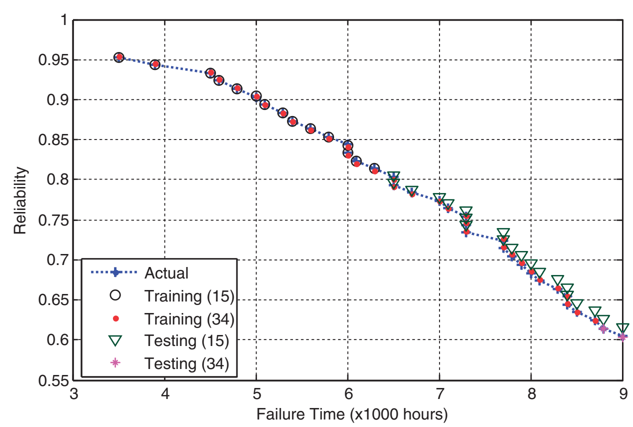

Figure 5. The predicted results under *Case 1*.

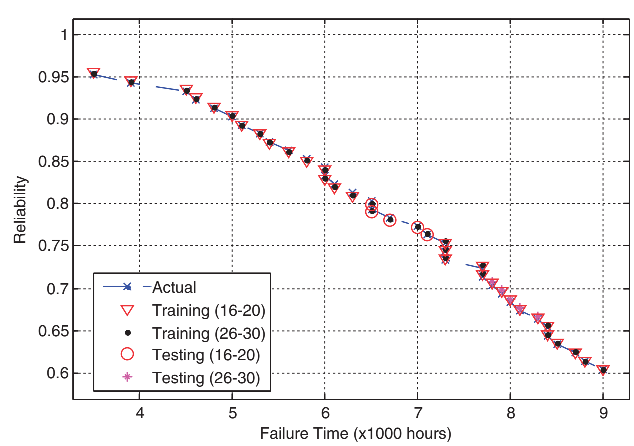

Figure 6. The predicted results under *Case 2*.

predicted results of DER prediction model in this case study.

On the basis of the above analysis and comparison, it shows that the prediction performance of DER model outperforms the existing prediction methods in terms of prediction accuracy and speed for the turbochargers' reliability prediction. Further, the experimental results demonstrate the potential of the DER model in reliability forecasting field.

6. Conclusions

In this article, a novel reliability prediction technique is developed and applied to forecast reliability in turbochargers engine systems. This research yielded the following conclusions:

(1) A novel reliability prediction technique that can be used to predict the reliability of turbochargers engine systems has been developed, tested and validated. The new method that is discussed is based on DER algorithm.
(2) Compared with the existing method, the proposed method is superior in predicting future reliability of repairable systems in terms of the prediction accuracy and speed.
(3) Although the reliability prediction model used in this article is focused on turbochargers engine systems, it can be changed to suit a different domain.
(4) The methodology presented in this article can be improved. In this article, the size of training data set is a bit small, thus the performance of the proposed algorithm may not be completely exploited. As such, one further research should be pay attention to the large sample case. On the other hand, the exact characteristic of the model and the details of its implementation have not been discussed completely: the influence of the number of input nodes is not analysed and the original number of input nodes is determined by expert knowledge subjectively. Thus, to develop a technique available to determine the number of input nodes in DER prediction model will be a significant direction for future development.

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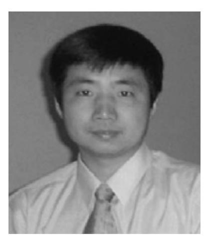

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