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Sustainable Manufacturing Oriented Prognosis for Facility Reuse Combining ANN and Reliability

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Reuse is considered as one of the most reasonable strategies in realizing sustainability, because it enables longer useful life of facilities. This article presents an effective methodology of artificial neural network–based prognosis combined with reliability methods to evaluate and guarantee the reusability of a facility. The methodology provides the assessment of the degradation trend and prediction of the remaining life of facilities based on online condition monitoring data and historical data utilizing back propagation artificial neural networks. In addition, the corresponding reliability of a facility is calculated by fitting suitable life distribution against the in-house time-to-failure data. Furthermore, maintenance decision is made by predicting the time when reliability or remaining life of a facility reaches the threshold, as determined by the facility's reusability. Application results show that the proposed methodology provides sufficient condition information for reuse decision making from both historical and online perspectives; a facility can be reused for many times during its lifetime until its reuse is no longer economic, which can assist in the achievement of the goal of manufacturing with fewer resources and assets. Copyright © 2011 John Wiley & Sons, Ltd.

Keywords: sustainable manufacturing; reusability; maintenance; prognosis; reliability

1. Introduction

Since the end of the last century, sustainable development (SD) has been undoubtedly becoming the major topic of this heavy-loaded world. SD aims for a future where products are 100% recyclable and manufacturing itself has a zero net impact on the environment[1]. Therefore, sustainable manufacturing (SM) has been widely considered as a main enabler of SD[2].
To realize SM, it is crucial to analyze the whole life cycle of a product. One of the most significant stages, which have great influences on the environment, of a product's life cycle is evaluating the product's potential for reuse (i.e., reusability) and reusing the product as far as possible[3]. In addition, the legislation mandates that manufacturers bear the economic burden of collection and disposal of products at the end of their useful lives, which means that reuse of some components might be more cost-effective than disposal and provide an opportunity for recovery of their economic value[4].

According to Organisation for Economic Co-operation and Development (OECD)/Euro stat Joint Questionnaire on waste, reuse shall mean any operation by which end-of-life products and equipment (e.g., electrical and electronic equipment) or its components are used for the same purpose for which they were conceived. RREUSE (the network for Reuse and Recycling European Union Social Enterprises) argues that reuse is also a set of activities including refurbish/reconditioning and repair, without entailing the remanufacturing or upgrade of the product or its components.

Although reuse without repair and remanufacturing are environmentally and economically superior to the other methods such as recycling[5], the uncertain quality and reliability of used products at the end of the first lifetime tend to reduce the attractiveness of reuse[6], and hence, it is commonly agreed that the reliability of facilities is the main concern when they are reused[7]. Technically, reliability is often defined as the probability that a system, vehicle, machine, device, and so on could perform their intended functions under operating conditions, for a specified period[8]. Anityasari *et al.*[6] proposed that in the reuse strategy, reliability of a used facility must be assessed based on the probability of its survival during the second life, and only facilities that fall within an "acceptable" reliability are worth reusing. A mathematical model of reusability was defined by Murayama *et al.*[7] based on the reliability theory. Ohta *et al.*[9] proposed a method for reliability predicting of reused electronic circuit board to realize its reuse.

Traditional approaches of reliability estimation are based on the distribution of historical time-to-failure data of a population of identical facilities obtained from in-house test. Many parametric failure models, such as Poisson, Exponential, Weibull, and log-normal distributions have been used to model machine reliability. However, these approaches only provide overall estimates for the entire population of identical facilities, which is of less value to an end user of a facility [10]. In other words, reliability reflects only the statistical

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quality of a facility, which means that it is likely that this certain facility does not necessarily obey the distribution that is determined by a population of tested facilities of the same type.

Therefore, it is recommended that condition monitoring data should also be used to reflect the quality and degradation severity of this certain facility so that the reusability of used facilities can be estimated more specifically.

Prognosis, which is defined as a systematic approach that can continuously track health indicators to predict risks of unacceptable behavior over time[11], can just serve the purpose of assessing the degradation of facility's quality based on acquired online condition monitoring data. Most of the existing prognostics models can be divided into two main categories, *mechanism-based models* and *data-driven models*, although the real-life system mechanism is often too stochastic and complex to model, and hence, physics-based model might not be the most practical solution. Artificial neural network (ANN) is currently the most commonly found data-driven technique in the prognostics researches[10]. Yan *et al*.[12] developed two Elman neural networks for fatigue severity assessment and trend prediction correspondingly. Satish *et al*.[13] have made an attempt to combine neural networks and fuzzy logic to form a fuzzy back propagation network for identifying the present condition of the bearing and estimating the remaining life of the motor.

Artificial neural network–based prognosis is fast in handling multivariate analysis and can provide nonlinear projection without requiring *a priori* knowledge. However, ANN-based prognosis cannot work well when the training sample set is small or when there are fast dynamic fluctuations, such as during the chipping of gear tooth surface material[10], and it is also true that the estimation of remaining useful life often fluctuates dramatically when multiple-step-ahead prediction is performed. Therefore, it is not feasible to evaluate the reusability of used facility based on only ANN-based prognosis.

Because the evaluation of the reusability gains no satisfying result based solely on either reliability methods, which analyze historical in-house test data or ANN-based prognosis, which exploits the online condition monitoring data, it is reasonable to combine these two approaches to reflect both the population characteristics and the state of individual operating facilities.

This article presents an efficient methodology of ANN-based prognosis combined with reliability methods, which predicts the remaining useful life of facility through mining the online condition monitoring data by utilizing back propagation ANNs and supports the decision making of maintenance by referring to the reliability of facility that is calculated through fitting suitable life distribution against the in-house time-to-failure data. Two thresholds are defined for both remaining useful life and the reliability of facility to obtain the time of maintenance and guarantee enough reusability. The reliability improvement of the used facility after maintenance is modeled by adopting Malik's proportional age reduction (PAR) model for imperfect maintenance. The creditability of the prediction results obtained by ANN is defined and calculated through analyzing the fluctuation of the prediction results, which reduces the impact of the fluctuation and makes the result more reliable. Utilizing the proposed methodology of prognosis, the performance of facility can be evaluated dynamically based on both historical and online monitoring information and maintenance can be carried out at the right time so that the reuse of facility can be guaranteed.

The rest of the article is organized as follows. The method of reliability estimation and modeling of reliability improvement after maintenance are presented in "Section 2"; an ANN-based prognosis method is presented in "Section 3"; the methodology of ANN-based prognosis combined with reliability methods is presented in "Section 4"; and a case study is presented in "Section 5" to verify that the proposed methodology of prognosis can guarantee reusability of facility better and realize reusing facility many times until its reuse is no more profitable. Finally, conclusions and an outlook of future work are given.

2. Reliability modeling

2.1. Reliability estimation

To estimate the reliability of a facility, a collection of time-to-failure data of a population of identical facilities should be available. The estimation is conducted by fitting the data to suitable life distribution.

In this article, reliability is modeled utilizing widely used distributions in their standard forms. Among these distributions, normal, exponential, gamma, and Weibull distributions are the most commonly applied in reliability engineering. One of the four distributions is selected so that the deterioration process can be modeled with satisfaction. Hence, the four distributions are fitted to the in-house test data, and analysis and comparison on the fitting result are carried out to select the optimal distribution.

As it is unknown which distribution fits the data best, one-sample nonparametric test methods are needed. At present, the commonly used methods include chi-square test, K–S test, binomial test, Wilcoxon signed ranks test, sign test, and run test, etc. However[14,15], binomial test, Wilcoxon signed ranks test, sign test, and run test cannot be applied within the analysis in this article. The binomial test works well only when the data are dichotomous; the sign test is used to test the hypothesis that there is "no difference" between two continuous distributions, which requires a known distribution; Wilcoxon signed ranks test works in the assumption that the population probability distribution is symmetric; and the run test is developed to determine the randomness of the data. Then, we choose the chi-square test and the K–S test because both the two methods can be applied to test the goodness of fit of the normal, exponential, gamma, and Weibull distributions and provide comparable results, which lead to identical evaluation criterion.

The one-sample K–S test is designed to test the null hypothesis in favor of the alternative hypothesis. It uses a statistic known as D-stat to test the hypothesis. The K–S test's appeal is its straightforward computation of the test statistic and the distribution-free characteristic. Similarly, the chi-square test can be used to test the significant difference between the sample data and the presumed distribution.

The K–S test and the chi-square test are used to determine the goodness-of-fit of the four distributions mentioned earlier. These two tests can provide results in two aspects: first, whether the null hypothesis that a certain distribution fits the sample data is

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rejected at a significance level of 5%; second, the probability (referred as p value), under assumption of the null hypothesis, of observing the given statistic. The result will be analyzed comprehensively to select a distribution to be used for reliability modeling with the characteristics of the distributions taken into account.

In addition, because of the fact that exponential distribution is a special case of Weibull distribution when the slope parameter $\beta=1$, goodness-of-fit test is only performed on normal, gamma, and Weibull distributions.

Among these distributions, Weibull distribution is most widely utilized in reliability modeling of machinery facilities. 'The distribution is characterized by two parameters, a scale (η) and a slope (β). The scale parameter (η) is defined as the life of the product at which 63.2% of all facilities will fail, while the slop parameter (β) is defined as the mode of failure. Referring to the well-known bathtub curve, $\beta<1$ indicates an infant mortality, $\beta=1$ a random failure, and $\beta>1$ a wear out failure.'[16] If t represents the lifetime, the reliability of facility can be calculated by Eq. (1), which is

$$R(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{1}$$

The parameters of the distributions are estimated using maximum likelihood estimation (MLE) method. MLE is a popular statistical method used for fitting a statistical model to data and providing estimates for the model's parameters.

2.2. *Modeling the improvement of reliability after maintenance*

After the first life of a facility, it can only be reused if its reliability is still above a threshold below which remanufacturing or overhauling should be performed to restore the facility to a usable state. Therefore, it is crucial to maintain the facility before its reliability reaches the threshold.

According to Lie *et al.*[17], maintenance should be described by two major categories, corrective or preventive. Corrective maintenance is any maintenance that occurs when the system is failed. Preventive maintenance is any maintenance that occurs when the system is operating.

The corrective maintenance should be divided into two categories:

- Minimal repair restores the system to the reliability it had when it failed. This is often called *bad as old*.
- Corrective replacement restores the system time to zero; the reliability curve is that of a new system. This is often called *good as new*.

The preventive maintenance should also be divided into two categories:

- Simple preventive maintenance improves the reliability of a facility to a higher level, but not all the way to *good as new*.
- Preventive replacement, like corrective replacement, restores the reliability to like new.

In this article, only simple preventive maintenance is taken into consideration on the assumption that the maintenance is always implemented before any failure happens. This assumption is reasonable because prognosis serves the purpose of failure prevention. In addition, the facility is intended to be reused, and hence, no preventive replacement will be carried out.

To model the reliability improvement after preventive maintenance, Malik's PAR model is employed. According to Malik's model[18], the *kth* effective maintenance is presumed to reduce the last operation time (t_k-t_{k-1}) to $(1-I_k)\cdot(t_k-t_{k-1})$.

In this model, the improvement factor I_k denotes the effect of the *kth*maintenance and is set between 0 and 1. If I_k goes to 0, the state of the maintained facility is as *bad as old*, if I_k goes to 1, the maintenance renews the facility to the state *good as new*.

For example, if the simple preventive maintenance is carried out at t_1 when reliability decreases to 0.8, the theoretical operation time that has elapsed is reduced to $(1-I_1)\cdot t_1$, which is a portion of the actual operation time t_1. Therefore, the reliability of the facility is elevated to the level at time $(1-I_1)\cdot t_1$. If the second simple preventive maintenance is carried out at t_2 when reliability decreases to 0.7, the theoretical operation time that has elapsed between t_1 and t_2 is reduced to $(1-I_2)\cdot(t_2-t_1)$, as is shown in Figure 1, where $I_1=0.5$ and $I_2=0.2$.

It is also assumed that the improvement by the *kth* maintenance has no effect on that by the $(k-1)$*th* maintenance. If the reliability is modeled using Weibull distribution, after the *kth* maintenance is carried out, the reliability of a facility between t_k and t_{k+1} can be calculated by Eq. (2), which is

$$R_k(t) = \exp\left[-\left(\frac{t+T_k}{\eta}\right)^{\beta}\right] \tag{2}$$

where

$$T_k = -t_k + (1-I_1)\cdot t_1 + \sum_{i=2}^{k}(1-I_i)\cdot(t_i-t_{i-1}) \tag{3}$$

The improvement factor I_k could be estimated either by using statistical methods[19] or by analyzing all the possible simple preventive maintenance activities and their improvement effect on a facility[20]. As to the latter, the simple preventive maintenance activities are categorized into six types, which are lubricating, cleaning, calibrating, tightening, simple repairing, and consuming material resupplying. The improvement effect of these activities on the reliability of a facility is measured by improvement effect E_i, and the probability of a certain type of activity being taken is measured by P_i. Both of the two parameters have their values limited between 0 and 1. The improvement factor could be calculated by Eq. (4), which is

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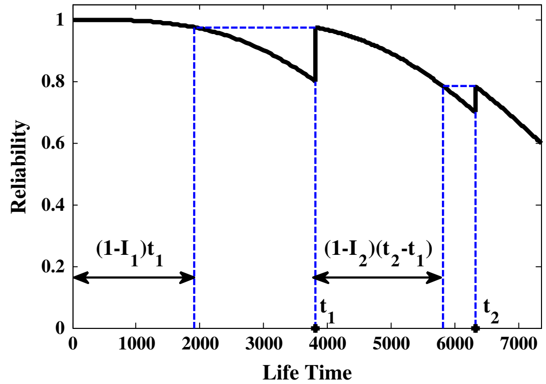

Figure 1. The illustration of proportional age reduction model

$$I = \frac{1}{\sum_{i=1}^{6} P_i} \cdot \sum_{i=1}^{6} P_i E_i \tag{4}$$

In this article, it is assumed that the improvement factor is estimated by the maintainer who is experienced and, without any written calculation, able to give a relatively proper estimation of the improvement effect of maintenance works he or she carries out. In addition, it is reasonable to assume that the value of improvement factor decreases with the number of maintenance increasing.

Even if the maintenance can be carried out when the reliability of facility reaches a threshold below which the reliability is not acceptable for reuse, the facility cannot be maintained indefinitely, and hence the facility cannot be reused indefinitely. The fact is that after several times of maintenance, the reliability of the facility cannot be improved to a relatively high level and the reuse of the facility is less profitable than purchasing a new one. Therefore, when this situation occurs, it is recommended that maintenance should not be carried out any more. In other words, then the reuse of the facility should cease and the remanufacturing or recycle of the facility should be implemented.

3. ANN-based prognosis

An ANN is a system which simulates biological neural network. With several layers of neurons, the basic information process units, connected with each other, ANN possesses promising ability to model complex nonlinear relationships between input and output variables. ANN has hence been widely applied to implement predictions, especially the prediction of remaining useful life of facilities. In this article, the remaining life of a facility is predicted with back propagation feed-forward ANN.

3.1. The architecture of the ANN-based prognosis

The architecture of ANN-based prognosis is composed of *network training* and *real-time prognosis*, as is shown in Figure 2. Network training involves sample data preprocessing, feature extraction, performance-evaluation network training, and remaining-life-prediction network training, after which a performance-evaluation neural network N_{PE} and a remaining-life-prediction network

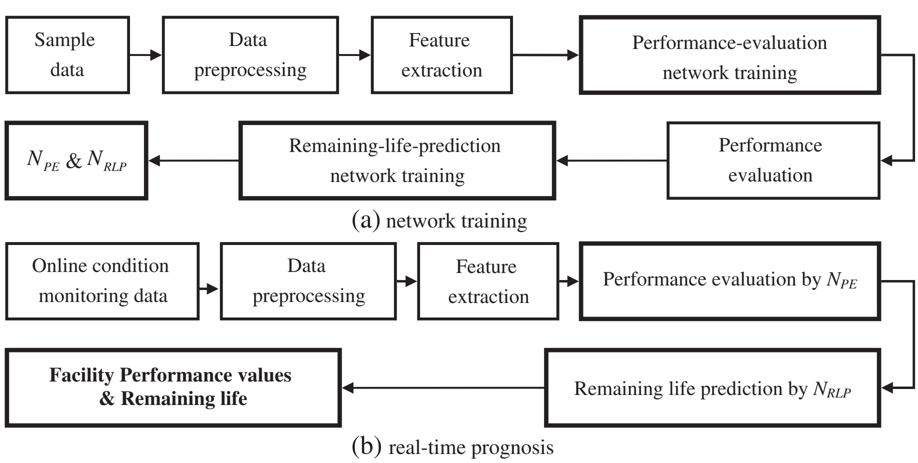

Figure 2. Architecture of the artificial neural network–based prognosis

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N_{RLP} are obtained, as shown in Figure 2(a). Real-time prognosis involves online condition monitoring data collection, data preprocessing, feature extraction, performance evaluation, and dynamic remaining life prediction, as is shown in Figure 2(b).

3.2. Data preprocessing and feature extraction

One of the key procedures of prognosis is transforming the condition monitoring data into feature data that can be used for performance evaluation and remaining life prediction. Data transforming involves data preprocessing and feature extraction.

The data collection, whether sample data or online conditioning monitoring data, is acquainted through multiple sensors and usually contaminated by noises. Therefore, it has to be preprocessed, usually classified and filtered, so that it can be used for feature extraction.

Generally, feature extraction is carried out using two different approaches. For low-frequency signal data, mechanism modeling and expert experience are used, whereas for high-frequency signal data, fast Fourier transform and wavelet packet transform are used.

3.3. The architecture of the ANNs

Back propagation feed-forward ANN with biases, a hidden layer, and an output layer are capable of approximating any function with a finite number of discontinuities. In this article, the proposed architecture of the networks is a two-layer back propagation feed-forward neural network, as is shown in Figure 3, where *I*is the input vector to this network; *M* is the intermediate result of the network; *O* is the output; N_i is the element number of input vector; N_h is the number of neuron in hidden layer; N_o is the number of neuron in output layer; W_{hi} and W_{oh} are the weights matrices from input layer to hidden layer and from hidden layer to output layer, respectively; and b_h and b_o are the bias vectors of hidden layer and output layer, respectively.

3.4. The performance-evaluation network training and parameter selection

After extracted from sample data, features are normalized and feature vectors at several given data collection times would serve as the training sample set together with corresponding performance values that are estimated by experts. For each training sample, input vector is composed of normalized features at a given data collection time and the output (target) is a corresponding performance value, which is between 0 and 1. Therefore, the neuron number of the output layer is 1. However, the neuron number of the hidden layer cannot be easily set because there is no mature method to refer to.

In this article, the range of neuron number of the hidden layer, N_h, is first calculated utilizing Eq. (5) according to Yuan[21]

$$N_h = \sqrt{N_o + N_i} + \alpha \tag{5}$$

where α is a constant between 1 and 10. For each network with certain neuron number of hidden layer, it is trained with a large part of the sample set and simulated with the entire sample set. Because different initial values of biases and weights result in different simulation results, network with certain neuron number of hidden layer is trained for several times, and the simulation results are averaged to get the final simulation result. Then, the simulation result is compared with the actual value in sample set, and mean square error is calculated. Through comparing the mean square errors, the optimal neuron number that results in the least error is chosen.

Different training algorithms make dramatic differences to convergence time of training and generalization of a network. The gradient descent algorithm is widely used for its simplicity, although it may cause overfitting and is often too slow for practical problems. In this article, conjugate gradient algorithm is utilized as it converges fast and is immune to overfitting.

Transfer function has significant impact on convergence time of training and accuracy of a network. Sigmoid functions are characterized by the fact that their slopes approach zero as the absolute value of input gets larger. For log-sigmoid function, $y=1/(1+e^{-x})$, if its input *x* is very close to the center point 0, the gradient in conjugate gradient algorithm is of large magnitude and performance of the network improves fast; however, if the absolute value of *x* gets larger, the gradient gets too small to make any significant improvement in weights and bias value, and hence, a long convergence time is needed. To avoid this situation, tan-sigmoid function, $y=(1-e^{-2x})/(1+e^{-2x})$, is chosen to be the transfer function of the hidden layer. For tan-sigmoid function, the gradient is larger than log-sigmoid function, and hence, the convergence time is shortened. Because the output value of the performance-evaluation network (i.e., the performance value) is between 0 and 1, log-sigmoid function is chosen to be the transfer function of the output layer.

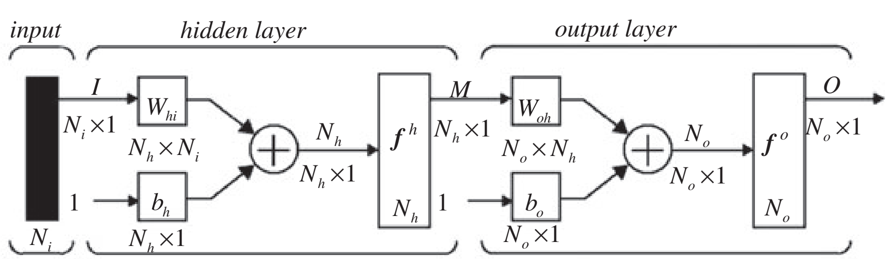

Figure 3. Proposed architecture of the artificial neural networks

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3.5. The remaining-life-prediction network training and optimization

The training sample set of the remaining-life-prediction network is derived from the performance values at all the data collection times, which are the output of the performance-evaluation network, with its input being the feature vectors at all data collection times. The training sample set is prepared by arranging these performance values in the following way. For each training sample, the input vector consists of performance values at N sequential data collection times, and the output is the performance value at the next data collection time. As Figure 4 shows, the input vector is performance value at time from $(t_0 - N \cdot \Delta t)$ to $(t_0 - \Delta t)$, where Δt is a data collection interval, and the output is the performance value at time t_0.

To train the network on this sample set is to make the network be able to predict the performance value at time $t_0$with the performance values at the previous N times from $(t_0 - N \cdot \Delta t)$ to $(t_0 - \Delta t)$.

The remaining life prediction at time t is performed by following steps.

- Step 1: Predict the performance value at t with the performance value from time $(t - N \cdot \Delta t)$ to $(t - \Delta t)$, utilizing the performance-evaluation network.
- Step 2: Compare the predicted performance value with the threshold of performance, which is preset with expertise. If the performance value is lower than or equal to the threshold, Δt is the predicted remaining life and the prediction process is over; otherwise, continue the next steps.
- Step 3: Predict the performance value at $(t + \Delta t)$ with the performance values from time $(t - (N-1) \cdot \Delta t)$ to t, where the performance value at time t is predicted in step 1.
- Step 4: Compare the predicted performance value with the threshold of performance. If the performance value is lower than or equal to the threshold, $2\Delta t$ is the predicted remaining life and the prediction process is over; otherwise, continue the next steps.
- Step 5: Continue the prediction process as above steps until the predicted performance value is lower than or equal to the threshold of performance.

The remaining lives at time 0 to $(N-1) \cdot \Delta t$ cannot be predicted by the said steps because performance values at less than N times are obtained. Therefore, the average remaining life of specimen facilities at those times should be used as the predicted value of remaining life.

The same rules and Eq. (5) as mentioned in "Section 3.4" are followed to choose the neuron number of the hidden layer, the training algorithm, and the transfer functions. It is the same with the network initializing. The only difference is that the mean absolute deviation (MAD) instead of mean square error is employed to evaluate the performance of the trained network, because the remaining life is predicted with a sequence of performance values being predicted. The MAD, denoted as $\bar{E}$, is calculated with Eq. (6), which is

$$\bar{E} = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \tag{6}$$

where $\hat{y}_i$ and y_i are the predicted value and the actual value of the ith remaining life prediction, respectively; n is the total number of life prediction performed from the beginning to the end of a facility's life.

3.6. Dynamic remaining life prediction

It is on the basis of the sample data set that the remaining-life-prediction network is trained to predict the performance of facility. However, the specimen facilities from which the sample data set is derived are not exactly the same with a specific facility in use,

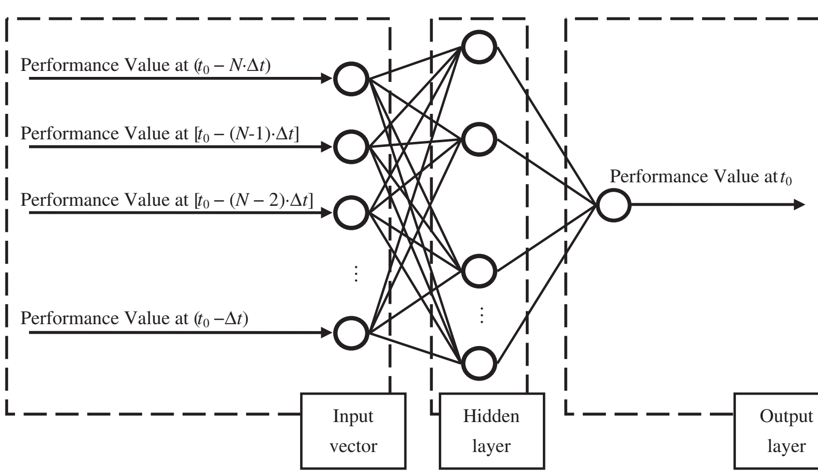

Figure 4. Architecture of remaining-life-prediction network

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and hence, unexpected error would occur when the trained network is used to predict its remaining life. Therefore, the dynamic life prediction which adjusts the weights and bias of the fully trained network with online condition monitoring data is proposed.

The adjustment is carried out by retraining the remaining-life-prediction network on the basis of real-time sample set derived from the real-time performance values, which are the output of performance-evaluation network. The input of the performance-evaluation network is real-time features extracted from online condition monitoring data. If the remaining-life-prediction network is retrained at time t, the real-time performance values from time $(t-K_d \cdot \Delta t)$ to t are arranged in the same way as described in "Section 3.5" to get the retraining sample set, where $K_d > N$.

Overfitting is apt to occur because the retraining sample set is relatively small, with only $(K_d - N+1)$ samples in it, which makes the prediction unreliable. Therefore, smaller learning rate and lower training epoch number are set to realize slight adjusting in remaining-life-prediction network so that the network is more practical.

4. ANN-based prognosis combined with reliability methods

The reliability methods that analyze historical in-house test data reflect only the population characteristics of facilities of the same type, whereas the ANN-based prognosis that exploits the online condition monitoring data reflects merely the state of individual operating facility. Because the traditional approaches to evaluate the reusability gain no satisfying result, it is reasonable to combine these approaches. Therefore, the ANN-based prognosis combined with reliability methods is proposed to evaluate the performance of facility from both population and individual facility view.

4.1. Definitions and rules

For the methodology, three parameters have been defined, namely, the threshold of reliability T_r, the threshold of actual value of remaining life T_l and the credibility level C_l.

The parameter T_r and T_l are the thresholds of reliability and the actual value of remaining life. Because low reliability and small actual value of remaining life have adverse impact on reusability, the facility should be maintained when its reliability is equal to or very close to T_r or when its actual remaining life is equal to or very close to T_l to guarantee its reusability.

However, the predicted value of remaining life is not exactly equal to the actual value. The fact is that when the predicted value of remaining life is lower than T_l, the actual value is unavailable, and hence, whether it is lower or higher or equal to T_l is not clear at all. In this article, the parameter C_l is proposed to evaluate the credibility of the predicted value of remaining life. The calculation method of C_l is presented in "Section 4.2".

If the predicted value of remaining life has been lower than T_l for three times in succession, and C_l of the three predicted values totals more than 1 or equal to 1, then it is very probable that the actual value of remaining life has already reached or crossed T_l. Meanwhile, if reliability of the facility is relatively close to T_r , for example, the inequation $|R(t)-T_r| \leq 10\%$ is satisfied, then the actual value of remaining life is considered as equal or very close to T_l, and then the maintenance should be carried out.

4.2. The estimation of the parameters

To set the value of T_r, the risk of failure and the reusability should both be taken into consideration. If the risk of failure is high, then the value of T_r should be set high, for example, 0.9; if the risk is moderate, the value should be set moderate, for example, 0.8; if the risk is low, the value should be set low, for example, 0.7. In addition, to avoid the situation that the reliability of a facility is so low that the reuse of facility is not economic or possible, the value of T_r should be set relatively high. However, if the value is too high, the facility could be shut down for maintenance too frequently, which makes the abrasion during maintenance so serious that maintenance does more harm than good to the facility. Besides, frequent maintenance has inverse impact on economic profit as well.

In most cases, the value of T_r can be easily determined if compromise is made in either risk of failure or reusability. However, when it comes to certain key facilities, the determination of its value becomes a little more complex. For facilities that carry out important manufacturing processes, they should always work in high reliability condition because huge lost may possibly occur otherwise. Then, regular maintenances should be carried out. These maintenances are carefully done, and they do not result in serious abrasion because they do not involve disassembly or replacement of key components. Meanwhile, the maintenance cost is minor compared with the high potential lost caused by these facilities' failure. In this case, the threshold should be set high, for example, 0.9.

The value of T_l should be estimated according to T_r. First, with the absence of maintenance, the time when the reliability of facility reaches T_r should be calculated. Denote the time as t_{reach}, then the average remaining life of the specimen facilities at t_{reach} can be calculated as a rough estimation of T_l, which serves as T_l before the first maintenance. After the first maintenance, to get a relatively accurate estimation of T_l, the rough estimation should be adjusted. If reliability reaches T_r while the predicted value of remaining life is still much higher than T_l at the first maintenance, chances are the value of T_l is set too low. On the contrary, if the predicted value of remaining life reaches T_l while reliability is still much higher than T_r at the first maintenance, chances are the value of T_l is set too high.

By analyzing the remaining life prediction carried out utilizing ANN, some typical characteristics can be concluded. The mean square error of remaining life prediction between time points 1 and 30 is more than 200, whereas the mean square error between time points 31 and 52 is 9.8. This indicates that the accuracy of prediction is getting higher with time. As shown in Figure 5, the bold straight line is the actual remaining life and the polyline with asterisks is the predicted value of remaining life. The change rate of predicted value, denoted as C_r, can partly reflect the credibility of the prediction. If the change rate is of large value, namely if the

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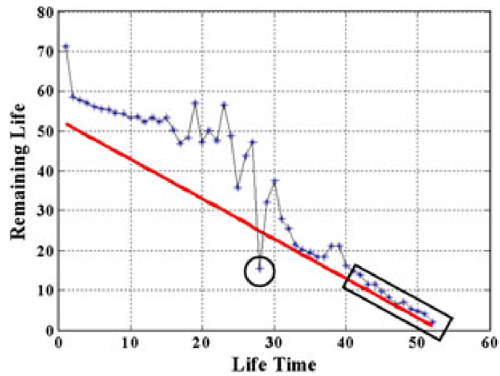

Figure 5. A typical remaining life prediction utilizing artificial neural network

predicted value changes dramatically, the prediction is less credible. Especially when the predicted value decreases abruptly for more than 15 prediction intervals, the false alarm is opt to occur, as the circled point shows in Figure 5. If the change rate is of minor value, namely the predicted value changes slightly, the prediction is more credible. Especially when the slope keeps close to 1, which is the change slope of the actual value, for more than five prediction intervals in succession, the prediction is very credible, as the points in the square shown in Figure 5. It is also true that at the beginning, the prediction value changes slightly while the prediction error is notable. However, the actual value of remaining life is by far higher than T_r then, so the notable error in practice makes no significant difference to the decision making of maintenance.

The value of C_l is calculated based on the following rules referring to the value of C_r.

Rule 1. If $15 \leq |C_r|$, then $C_l = -1$;
Rule 2. If $4 < |C_r| < 15$, then $C_l = 0$;
Rule 3. If $2 < |C_r| \leq 4$, then $C_l = 1$;
Rule 4. If $0 \leq |C_r| \leq 2$ and it is the case for more than five prediction intervals in succession, then for the predictions at the corresponding five time points, their $C_l = 2$.
Rule 5. If $0 \leq |C_r| \leq 2$ and Rule 4 is not satisfied, $C_l = 1$.

4.3. Improvement in reusability

The threshold T_r guarantees that facility can get maintained before its reliability is below an acceptable level so that the facility is reusable in terms of its population characteristics. The threshold T_l and credibility level C_l guarantee that the facility can get maintained before its actual remaining life is below an acceptable level so that the facility is reusable in terms of its specific situation. In other words, more reasonable maintenance decision is made so that the performance of a facility would not degrade to the situation where it can only be remanufactured or recycled rather than reused.

In addition, only facilities with enough potential to survive during their second (or third and so on) life fall within an "acceptable" reliability and are reusable, which means the survival of used facility during its reusing period is crucial to its reuse[6]. After maintenance, the reliability of a facility improves to an acceptable level. By modeling the improvement of reliability after maintenance, the reliability of a facility during the reusing periods can be calculated so that the proposed methodology can be implemented. Then, maintenance decision can also be made at the right time during the reusing periods, and the survival of the facility can be guaranteed. Therefore, the reusability of the facility is enhanced, and the facility can be reused for many times.

Utilizing the methodology of ANN-based prognosis combined with reliability methods, the performance of the facility can be evaluated dynamically based on both historical and online monitoring information, and maintenance can be carried out at right time so that the reusability of the facility can be guaranteed.

5. Case study

In this section, the proposed methodology is validated through a case study of blade material specimens. The validation procedure of the proposed methodology is as follows:

1. Data acquisition. Life test should be carried out on a number of identical specimens to obtain their life spans for reliability modeling. Meanwhile, performance data should be collected from these specimens to train the performance-evaluation network and the remaining life prediction network. The data collected should be divided into two parts: one part for modeling and training and the other part for validation of the proposed method.
2. Modeling and training. To carry out reliability modeling, lifetime data should be fitted into a suitable distribution selected by referring to the employed indices. In addition, ANN should be trained to obtain the ability of predicting remaining useful life of specimens.

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3. Validation and result analysis. Data for validation contain inputs of the reliability model and the remaining useful life prediction network and the actual remaining useful life, which should be compared with the output of the remaining useful life prediction network. To validate the effectiveness of the proposed method, both the accuracy of the remaining useful life prediction and the reuse situation should be analyzed.

5.1. Data acquisition

In this article, the data are derived from the in-house test of blade material specimens, which are tested under a cyclic strain of range $\pm 0.45\%$. For every test cycle, the strain goes from $+0.45\%$ to -0.45% and goes back to $+0.45\%$ again. Referring to GB/T 15248–1994, the fatigue failure occurs when the amplitude of stress is less than or equal to 20% of the amplitude at the 20th test cycle, and then the test is ceased. This test is carried out in the Harbin Turbine Company ltd, with 13 blade material specimens. For each test, stress values of at only about 58 test cycles are recorded for analysis because of limited memory capacity of test bed MTS810. Also, the maximum cycles of each specimen are recorded as their lifetime. An example of the fatigue hysteresis loops is shown in Figure 6, where the loops of specimen one in brand new situation and fatigued situation are presented. It can be concluded that the stress amplitude of the fatigued specimen is much smaller than that of the brand new specimen, which implies that the performance of the specimen degrades with time.

Thirteen sets of data are obtained in the test. Eight of them are used for life distribution fitting and network training as historical data; and the other five sets are used as online condition monitoring data.

5.2. Reliability estimation

With MATLAB, we fit the in-house test data to normal, gamma, and Weibull distributions using the MLE method and apply the K–S test to determine their goodness of fit. The result is shown in Table I. With the same method, the chi-square test is carried out. The result is shown in Table II.

As shown in Tables I and II, the K–S test and the chi-square test provide similar results. Normal distribution has the best goodness of fit; gamma, second; and Weibull, last. However, the results show no remarkable difference between the distributions.

First, the difference between normal and Weibull distribution is merely 0.0486 through the K–S test and 0.0850 through the chi-square test.

Second, the P–P chart, as shown in Figure 7, demonstrates the difference between the distributions to be very slight as well.

Now that there is no remarkable difference of goodness of fits between distributions, we choose Weibull to carry out the reliability modeling considering some of its advantages as follows.

1) Weibull can well approximate normal when its slope parameter ranges from 3.25 to 3.61. Especially when the slope parameter equals to 3.60232, the percentiles of the two distributions are very close to each other.
2) Compared with gamma and normal, the form of Weibull is easier to use. Moreover, Weibull has a simple, useful, and informative graphical plot of failure data[22], which is extremely important to engineering.
3) Weibull is more widely applied in reliability engineering of machinery equipment. As the data used in this article comes from the torsion test of the blade material, Weibull is more suitable.
4) The data present in this article form a relative small sample. Weibull analysis can offer reasonably accurate failure analysis and failure forecasts with extremely small samples[22].

With all the considerations mentioned, Weibull is used in reliability modeling.

To estimate the reliability of the specimens, the time-to-failure data, that is, the maximum test cycles, of 8 out the 13 material specimens are used to carry out the Weibull fitting. The parameters are calculated and the result is η=3798.5 and β=4.2.

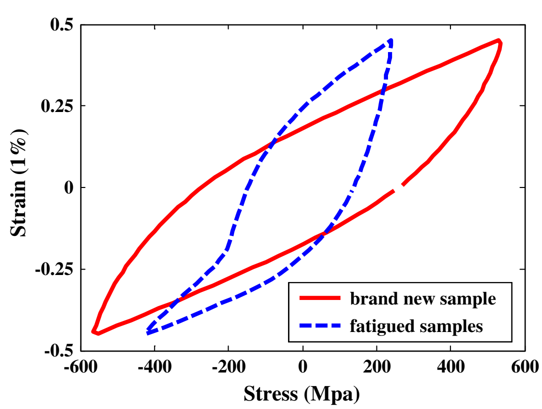

Figure 6. The fatigue hysteresis loops of the material specimen one

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Table I. Result of the K–S test			
	Normal	Gamma	Weibull
Null hypothesis	Rejected	Rejected	Rejected
p	.7599	.7472	.7113

Table II. Result of the chi-square test			
	Normal	Gamma	Weibull
Null hypothesis	Rejected	Rejected	Rejected
p	0.6089	0.5794	0.5239

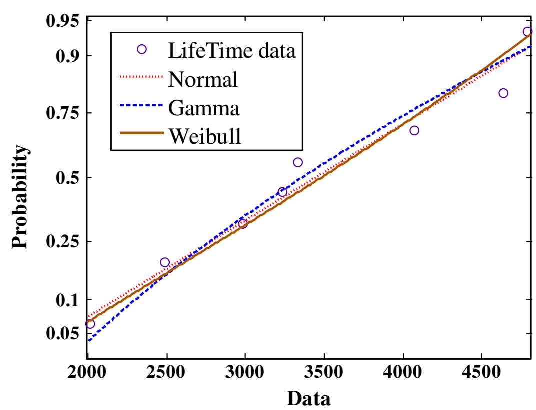

Figure 7. P–P chart of lifetime data

5.3. ANN network training sample set

The data preprocessing such as signal filtering and the test are carried out simultaneously. Because the data of material fatigue are low-frequency signal data, the feature extraction is implemented by examining the stress data manually. From Figure 6, it can be concluded that as the fatigue develops, the amplitude of the stress decreases. It has also been proved[23] that stress amplitude of materials and their fatigue life is closely connected. Therefore, the maximum stress, minimum stress, and the sum of their absolute values are selected as the features of blade performance. At each data collection time point, the three features compose a feature vector. For each material specimen, the feature vectors at seven given cycles are made a part of the entire input vectors of the sample set. The seven given data collection time points are the 1st, 5th, 10th, the middle, the last but 10, the last but 5, and the last ones. The performance values at these seven time points are 0.99, 0.97, 0.94, 0.75, 0.1, 0.05, and 0.01, respectively, which make a part of the entire outputs of the network training sample set. These data samples from 8 out of 13 material specimens, the same 8 ones as mentioned in "Section 5.2", are put together to be the entire training sample set of the performance-evaluation network. For the remaining-life-prediction network, its training sample set is derived from the output of performance-evaluation network whose input vectors are feature vectors at all the data collection time points from the 8 material specimens.

In this research, the Neural Network toolbox in MATLAB is used for network training. According to the default setting of the toolbox, 15% of the training sample data are used for validation and another 15% are used for testing.

5.4. ANN network parameters

For the performance-evaluation network, the element number of its input vector, N_i, is 3 and the neuron number of output layer, N_o, is 1. According to Eq.(5), the neuron number of its hidden layer, N_h, ranges from 3 to 12. By comparing the performance of the networks with different N_h, N_h is set as 11.

For the remaining-life-prediction network, N is set as 5, which means the element number of its input vector, N_i, is 5, and the neuron number of output layer, N_o, is 1. According to Eq.(5), the neuron number of its hidden layer, N_h, ranges from 3 to 12 as well. By comparing the performance of networks with different N_h, its N_h is set as 11.

For the dynamic remaining life prediction, the parameter K_d is set as 8, the learning rate as 0.01, and training epoch number as 10.

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5.5. Validation and result analysis

To verify the effectiveness of the method proposed in this article, historical data collected from the in-house test were used. Historical data are composed of feature data, the same type of data as online monitoring data, and actual remaining life. Feature data from one of the five earlier mentioned material specimens are used as input. As the material specimen underwent no maintenance during the in-house test, the final validation result is obtained by reorganizing the actual value and predicted value of the specimen's remaining life.

The result is shown in Figure 8 where the four dots represent four maintenance activities. In Figure 8(a), the horizontal line represents T_r, which is 0.8. The material specimen is maintained for three times and hence reused for three times. The improvement factor of the first maintenance is 0.7; the second, 0.6; and the third, 0.35. At the end of the fourth life (i.e., at the end of the third reusing life) period, the reliability of the specimen cannot be improved to an acceptable level, so it is considered more suitable to be remanufactured or recycled.

In Figure 8(b), the dashed line represents the actual remaining life, which is obtained by joining four pieces of actual remaining life data of the specimen according to the improvement of its reliability after maintenance activities, and the polyline with asterisks represents the predicted value of the remaining life, which is obtained by joining the corresponding pieces of predicted remaining life that is predicted utilizing four different remaining-life-prediction networks trained on the same training sample set. The unit of lifetime and remaining life here is converted from data collection interval into test cycle so that the unit of lifetime here conforms to the unit in reliability estimation. The horizontal line represents T_l, which stands for 2129 test cycles. The cause of the second shutdown is that the value of the remaining life is predicted to be lower than T_l. The cause of the other shutdowns is that the reliability of the material specimen is very close to T_r even if the value of the remaining life is not predicted to be lower than T_l.

The accuracy of remaining life prediction is analyzed utilizing MAD defined in "Section 3.5", and mean forecast error (MFE). MAD reflects the accuracy of prediction, whereas MFE reflects the unbiasedness of prediction. MAD, denoted as $\bar{E}$, and MFE, denoted as $\bar{e}$, can be calculated referring to Eqs. (6) and (7).

$$\bar{e} = \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)}{n} \tag{7}$$

where $\hat{y}_i$ and y_i are the predicted value and the actual value of the ith remaining life prediction; n is the total number of life prediction performed from the beginning to the end of a facility's life. In addition, the prediction accuracy of the remaining-life-prediction network has to be calculated in unit of data collection interval instead of test cycles because it was trained and used with the data collected in certain interval.

According to the validation result, the overall MAD and MFE of the prediction are 14 and -10.6806, respectively. Also, the MAD and MFE of the prediction are 16.2653 and -12.0204 respectively for the earlier 50 predictions and 8.6087 and -7.8261 respectively for the later 22 predictions. Therefore, it can be concluded that the prediction methods perform better in the later fatigue stage than in the initial stage. In fact, it is just because of the low accuracy in the early prediction that ANN is combined with reliability methods to carry out the remaining life prediction.

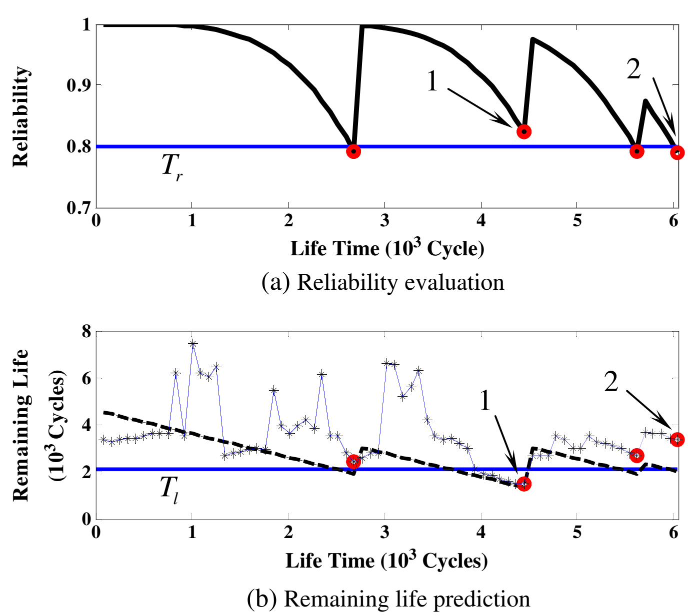

Figure 8. Validation result

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If reliability method and T_r are solely used to make maintenance decision, chances are that the degradation of the facility cannot be detected and maintenance cannot be carried out in time. As point 1 in Figure 8 shows, the reliability is still far higher than T_r, whereas the actual remaining life of the material specimen is lower than T_l. The facility may not be maintained until its remaining life is far lower than T_l by referring to reliability only, which means that the reusability cannot be guaranteed.

If prognosis method and T_l are solely used, the reliability information is totally ignored. As point 2 in Figure 8 shows, the actual value of remaining life is very close to T_l, whereas the predicted value is still far higher than T_l. If the reliability information is ignored, the maintenance would not be carried out until the actual remaining life is far lower than T_l, which means that the performance would degrade to an unacceptable level and the facility is not reusable.

The result shows that this methodology can guarantee the reusability of facility efficiently. In addition, the facility can be reused for many times during its lifetime until its reuse is not profitable anymore.

6. Summary

A methodology of ANN-based prognosis combined with reliability methods is proposed to evaluate and guarantee the reusability of a facility from both historical and online perspectives. For a specific facility, its reliability is calculated by fitting proper distribution to the time-to-failure data obtained from the in-house test, and its remaining life is predicted by the ANN-based prognosis method, which is realized with two ANNs, the performance-evaluation network and the remaining-life-prediction network. As the facility is online monitored, the condition monitoring data are preprocessed. Then, the features are extracted to evaluate the performance of facility and predict its remaining life dynamically; meanwhile, the reliability of facility is calculated. Two thresholds and a credibility level are defined to make maintenance decisions so that the facility can be maintained at the right time to guarantee enough reusability. It is validated that the proposed methodology provides effective condition information for reuse decision making from both historical and online perspectives. The reliability improvement after maintenance is modeled by employing Malik's PAR model so that the reliability of facility in reusing life periods can be calculated. The fact is the modeling method of the reliability improvement after maintenance is not limited to Malik's PAR model; any other reasonable methods or models can be adopted to realize the modeling. In addition, other prognosis methods can be adopted to realize the performance evaluation and life prediction only if the condition monitoring data can be well analyzed. This means that the methodology proposed in this article is flexible.

Further works should focus on the validation of the methodology using more data collections from other facility to verify its generalization capability. In addition, the reliability calculation should be improved utilizing more advanced distribution, such as the three-parameter Weibull, and more precise methods.

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