An Artificial Neural Network Approach for Remaining Useful Life Prediction of Equipments Subject to Condition Monitoring

Zhigang TIAN
Concordia Institute for Information Systems Engineering
Concordia University
Montreal, Quebec, H3G 2W1, Canada

***Abstract*— Accurate equipment remaining useful life prediction is critical to effective condition based maintenance for improving reliability and reducing overall maintenance cost. An artificial neural network (ANN) based method is developed for achieving more accurate remaining useful life prediction of equipment subject to condition monitoring. The ANN model takes the age and multiple condition monitoring measurement values at the present and previous inspection points as the inputs, and the life percentage as the output. Techniques are introduced to reduce the effects of the noise factors that are irrelevant to equipment degradation. The proposed method is validated using real-world vibration monitoring data.**

Keywords- remaining useful life; prediction; artificial neural network; accurate; bearing.

I. INTRODUCTION

Condition based maintenance (CBM) aims at achieving reliable and cost-effective operation of engineering systems such as aircraft systems, wind turbine generators, hydro power plants and manufacturing systems [1]. In CBM, condition monitoring data, such as vibration data, oil analysis data and acoustic data, are collected and processed to determine the equipment health condition; Future health condition and thus the remaining useful life (RUL) of the equipment is predicted; And optimal maintenance actions are scheduled based on the predicted future equipment health condition, so that preventive maintenance actions can be performed to prevent unexpected failures and minimize total maintenance costs. Accurate health condition prediction is the critical to effective implementation of condition based maintenance.

Existing equipment health condition and RUL prediction methods can be roughly classified into model-based (or physics-based) methods and data-driven methods. The model-based methods predict the remaining useful life using damage propagation models based on damage mechanics [2]. Data-driven methods utilize collected condition monitoring data for RUL prediction. Jardine et al developed the Proportional Hazards Model approach for CBM, where health condition indicators are predicted using the transition probability matrix [1, 3]. However, in order to ensure the CBM optimization efficiency, each health condition indicator, or covariate, has to be divided into a small number of bands, which affects the health condition indicator prediction accuracy. Moreover, the state transition rates are hard to accurately predict if a large amount of condition monitoring data is not available. Artificial neural networks (ANNs) have been considered to be very promising tools for equipment health condition and RUL prediction due to their adaptability, nonlinearity, and arbitrary function approximation ability [4]. Neural network methods do not assume the analytical model of the damage propagation, but aim at modeling the damage propagation process, or degradation process, based on the collected condition monitoring data using neural networks and perform health condition prediction. Lee et al [5] proposed to extract an overall health indicator based on the collected condition data, and predict future health indicator values using the autoregressive moving average (ARMA) method and Elman neural networks. Gebraeel et al [6] developed ball bearing remaining life prediction methods based on feedforward neural networks. The output of the ANN model was a condition monitoring measurement, such as overall vibration magnitude. However, the failure threshold values are typically hard to clearly define in many practical applications. Wu et al [7] proposed another RUL prediction method based on ANN, where the ANN output was the life percentage, or in another word, one minus the remaining life percentage. The accuracy and robustness of this method, though, can be further improved.

In this paper, we propose a new ANN based method for achieving more accurate RUL prediction. The ANN model takes the age and multiple condition monitoring measurement values at discrete inspection points as the inputs and the life percentage as the output. The prediction accuracy is improved mainly by reducing the effects of the noise factors that are irrelevant to the equipment degradation in the condition monitoring data, and by utilizing the validation mechanism in the ANN training process.

II. THE PROPOSED ANN REMAINING USEFUL LIFE PREDICTION METHOD

A. Issues with Using Actual Measurement Values as the Inputs to the ANN Model

Many methods use actual condition monitoring measurement values as the inputs to the ANN model [7]. However, when the measurements are collected at inspection points in practical applications, there are usually external noise

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factors that will affect the measurement values. As an example, Figure 1 shows an actual measurement series for a bearing failure history, which was collected from a pump in the field. A history refers to the period of a unit from the beginning of its life to the end, failure or suspension, of its life, and the inspection data collected during this period. The bearing failed at age 511 days. It can be seen that although the measurement shows a generally increasing trend, there are large fluctuations at multiple places. On the other hand, the deterioration of the health condition of a component, such as the propagation of a spall in a bearing or the propagation of a root crack or the surface wear in a gear, is generally a monotonic process. Therefore, directly feeding the current and the previous actual measurement values to the ANN model and mapping it to life percentage, the health condition measure, will introduce noises into the ANN model, and compromise its capability to accurately represent the health condition of the equipment.

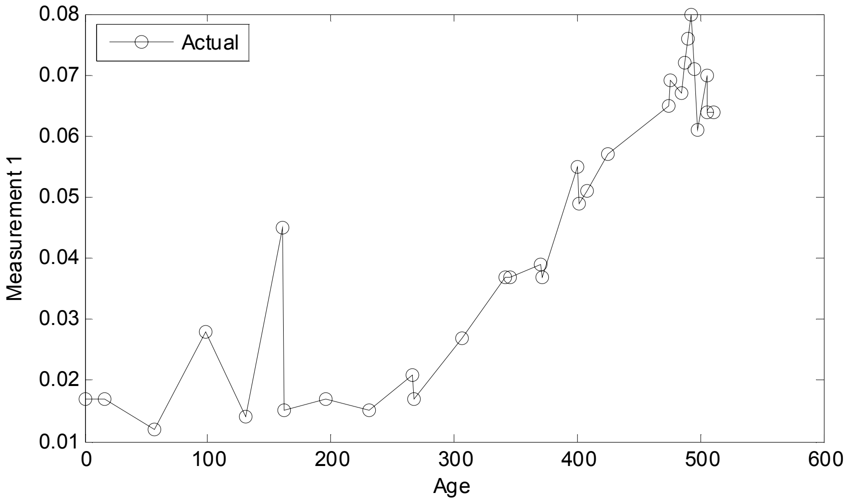

Figure 1. An actual measurement series for a sample failure history

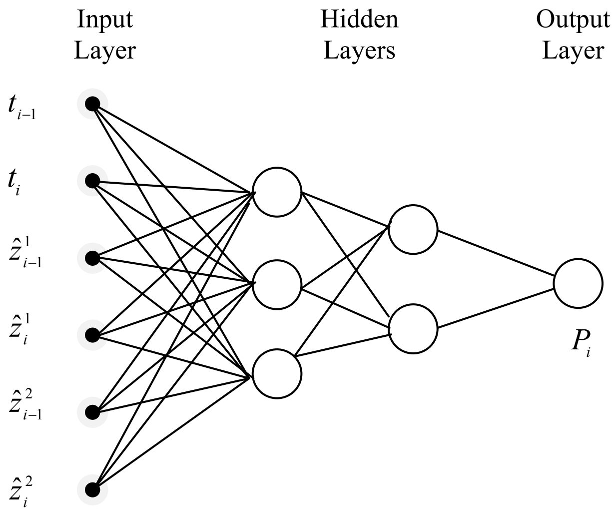

Figure 2. Structure of the proposed ANN model

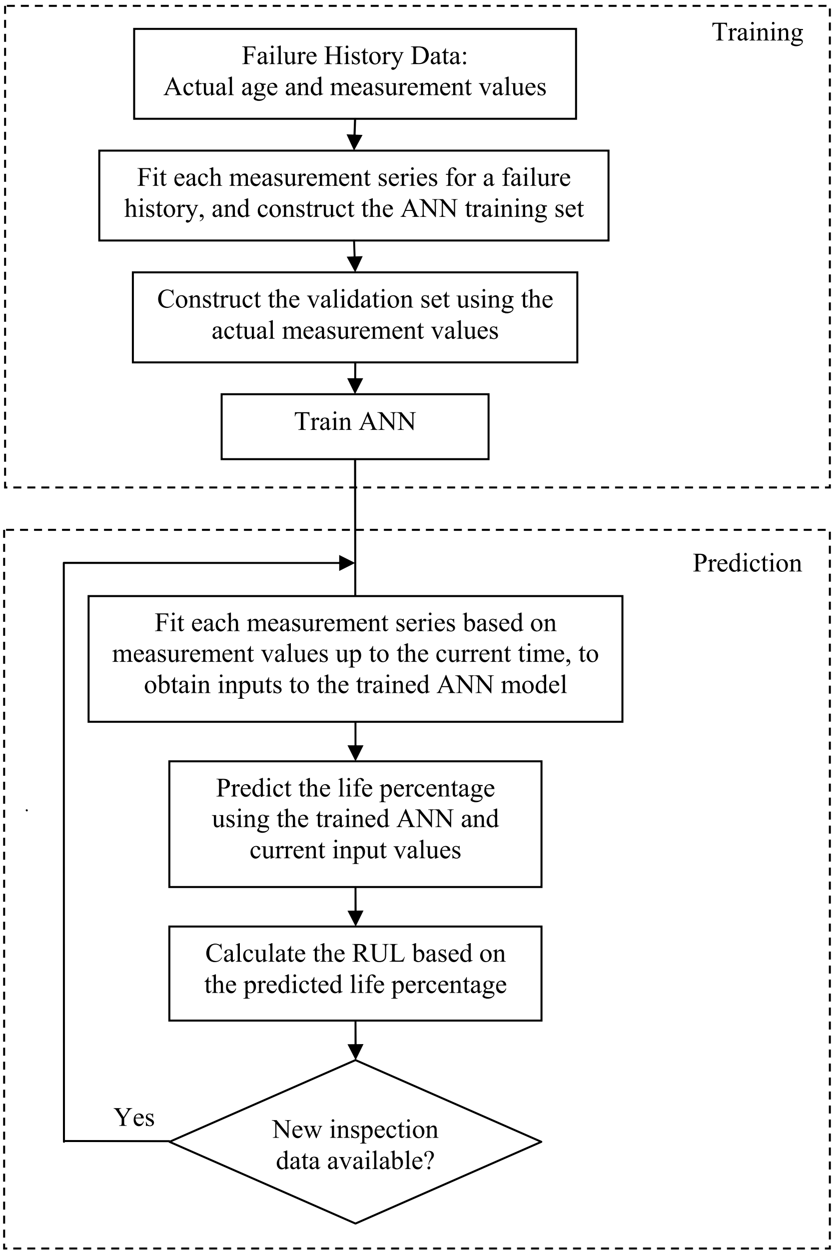

Figure 3. Procedure of the proposed ANN method

B. *Function for Fitting the Actual Measurement Series*

To address the above-mentioned issues with using actual condition monitoring measurements as the inputs to the ANN model, we propose to use an appropriate function to fit the measurement series first, and use the fitted measurement values as inputs to the ANN model, so as to better represent the deterioration of a piece of equipment. We propose a function which is generalized from the Weibull distribution failure rate function. In reliability analysis, it is the failure rate measure that indicates the health condition of a certain type of component at a given time. Weibull distribution is very powerful in representing various practical lifetime distributions, and flexible enough to represent distributions with different scales and shapes [8]. Thus, the following function generalized from the Weibull distribution failure rate function is used to fit the measurement series:

$$\hat{z}(t) = Y + K\frac{\beta}{\alpha^{\beta}}t^{\beta-1}, \tag{1}$$

where t is the age of the unit, $\hat{z}(t)$ is the fitted measurement value, α and β are the scale parameter and the shape parameter, respectively. $(\beta/\alpha^{\beta})t^{\beta-1}$ is the failure rate function for the 2-parameter Weibull distribution. Parameter K is introduced to scale the fitted measurement values to any ranges, and parameter Y is used to indicate the value when the age is 0. We refer the function in Equation (1) as the "Generalized Weibull-

FR function". Thus, the Generalized Weibull-FR function has 4 parameters, which can be determined using least-square method based on the actual measurement series. In this work, we use genetic algorithm (GA) to find the optimal values for the 4 parameters because of the good global optimization performance of GA [9]. We have tested the Generalized Weibull-FR function using many actual measurement series collected from the field, and found that the function is capable of fitting all the tested measurement series very well.

C. *The Proposed ANN Model*

The structure of the proposed ANN model is shown in Figure 2. The proposed ANN model uses the fitted measurement values instead of the actual measurement values as the inputs. Specifically, t_i and t_{i-1} are the age values at the current inspection point i and the previous inspection point $i-1$, respectively; z_i^1 and z_{i-1}^1 are the fitted values of measurement 1 at the current and previous inspection points, respectively; z_i^2 and z_{i-1}^2 are the fitted values of measurement 2 at the current and previous inspection points, respectively. With these data at the current and the previous inspection points, we take into account the age and measurement values as well as the changes of the measurement values at these points, and these important pieces of information will be processed by ANN to estimate the remaining useful life. We only use data at the two inspection time points instead of incorporating data at more past inspection points, because ANNs with less input nodes have better generalization capability, and the experiments results in this work show that adding more input nodes will not improve the RUL prediction performance.

The output of the proposed ANN model is the life percentage, denoted by P_i. As an example, suppose the failure time of a bearing is 511 days and, at an inspection point i, the age is 400 days, then the life percentage at inspection point i would be: $P_i = 400/511 \times 100\% = 78.3\%$.

D. *Training of the Proposed ANN Model*

The training set for the proposed ANN, shown in Figure 2, is formed by the age and fitted measurement values at the inspection points for the available failure histories. For example, suppose we have four failure histories, and they have 30, 30, 40, 40 inspection points, respectively. So for failure history 1, we have 29 training pairs, including the six inputs and the corresponding one output, since we need data at the current and previous inspection points in the input vector. Thus, the total number of training pairs is: . For each condition monitoring measurement in a failure history, we first use the Generalized Weibull-FR function to fit the measurement series, and then use the fitted measurement values in the ANN training set.

A critical issue of using ANN is to avoid overfitting the network. If an ANN is overfitted, noise factors will be modeled in the network, which affects the generalization capability of ANN, and thus affects the prediction accuracy. Wu et al [7] did not consider this issue in their work, thus there is no mechanism as to when to stop training so as to achieve a trained ANN that can best model the mapping relationship between the inputs and outputs without overfitting. A widely used approach for avoiding overfitting is the use of validation set. That is, during the ANN training process, the mean square error for the training set and that for the validation set are calculated. Both of the mean square errors drop early in the training process because the ANN is learning the relationship between the inputs and the outputs by modifying the trainable weights based on the training set. After a certain point, the mean square error for the validation set will start to increase, because the ANN starts to model the noise in the training set. Thus, the training process can be stopped at this point, and the trained ANN with good modeling and generalization capability can be achieved.

Another question is how to construct the validation set. One method is dividing the available failure histories into two groups, one used as the training set and the other as the validation set. The percentage of histories used in the validation set is typically around 40%. This causes a problem if we do not have a lot of failure histories, which is the case in many practical applications. As an example, there are 11 failure histories in the problem to be investigated in the case study later. If we use this method to construct the validation set, only 6-7 histories can be included in the training set. The valuable information in the other 4-5 failure histories will not be directly used to modify the trainable weights, which will affect ANN's ability to model the relationship between the inputs and output based on available data. In this paper, we propose to construct the validation set using the actual measurement data for all failure histories, and, as mentioned before, use the fitted measurement data to construct the training set. Data based on all failure histories can be taken advantage of for modifying the trainable weights in the ANN training process, and the validation process can help to avoid overfitting the network. Experiments based on practical condition monitoring data have shown that the use of such a validation process can lead to more accurate and robust predictions. Based on the training set and the validation set, the ANN is trained using the Levenberg-Marquardt (LM) algorithm.

Because of the uncertainty in the ANN training algorithms such as the LM algorithm, with the same training set and validation set, typically we will not obtain the same neural network after training. In this work, we train the ANN 5 times, and select the one with the lowest training mean square error (MSE). This is actually another advantage of using the validation mechanism in the training process. Without the validation process, a lower training MSE does not necessarily means a better network, and in many cases it is not. Thus, we can not select the best trained ANN based on the training MSE if we do not have the validation mechanism. However, if we do have the validation mechanism, as in the proposed ANN method, a lower training MSE will indicate a trained ANN with better modeling and generalization capabilities, and thus an ANN with better prediction capability.

E. *Procedure of the Proposed ANN Method*

The procedure of the proposed method is shown in Figure 3.

III. CASE STUDY

The condition monitoring data were collected from bearings on a group of Gould pumps at a Canadian kraft pulp mill company [10]. There are 11 bearing failure histories, and they are used in this work. Vibration monitoring data were collected from the pump bearings using accelerometers. Significance analysis can be used to identify the significant condition monitoring measurements, and two measurements are identified to be significant. We refer to these two measurements as Measurement 1 and Measurement 2. There are totally 310 inspection points for these 11 bearing failure histories.

We use 1 bearing failure history to construct the ANN test set to test the prediction performance, and use the remaining 10 failure histories to construct the ANN training set and the validation set to train the ANN model. After that, we can use a different failure history to construct the ANN test set to test the prediction performance and use the remaining 10 failure histories to train the ANN. We can repeat this process until we go through all the failure histories. We test the prediction performance starting from inspection point 6, since measurement values at the first several inspection points are needed to fit the measurement series and generate the fitted measurement values used as the inputs to the trained ANN model. The predicted life percentage values are obtained, and are compared with the actual life percentage values, which are calculated based on the age values at the inspection points and the bearing failure time. Each of the 11 failure histories is used to construct the test set once to test the prediction performance.

The Average Prediction Error, denoted by $\bar{e}$, is used to quantify the prediction performance:

$$\bar{e} = \frac{1}{n} \cdot \sum_{k=1}^{n} \left| P_k - \hat{P}_k \right| \cdot 100\%, \quad (2)$$

where n is the number of inspection points for testing the prediction performance, P_k is the actual life percentage at inspection point k, and $\hat{P}_k$ is the predicted life percentage at inspection point k. We investigate three Average Prediction Errors: (1) the Average Prediction Error considering all the inspection points in the test sets, $\bar{e}_{All}$, (2) the Average Prediction Error considering only the last 5 inspection points for each test history, $\bar{e}_{L5}$, and (3) the Average Prediction Error considering only the prediction results where the predicted life percentage values are between 90% and 100%, $\bar{e}_{90-100}$. The last two measures are considered because the prediction accuracy late in the life is more important than that early in its life, since this will more likely affect the decision on whether or not preventive replacement should be performed at the current inspection point.

Using the bearing failure data, we compare the prediction performance of the proposed ANN method and a modified version of the method by Wu et al [7]. The results are given in Table 1. It can be seen that the proposed ANN method can produce more accurate prediction with respect to all of the three measures.

IV. CONCLUSIONS

Accurate equipment remaining useful life prediction is critical to effective condition based maintenance for improving reliability and reducing overall maintenance cost. This paper develops an ANN method for achieving more accurate remaining useful life prediction of equipment subject to condition monitoring. The ANN model takes the age and multiple condition monitoring measurement values at the present and previous inspection points as the inputs, and the life percentage as the output. The generalized Weibull-FR function is used to fit each condition monitoring measurement series for a failure history, and the fitted measurement values are used to form the ANN training set to reduce the effects of the noise factors that are irrelevant to the equipment degradation. When the trained ANN is used for RUL prediction, the inputs to the trained ANN are generated by fitting the available measurement values for the current unit using the generalized Weibull-FR function. The validation mechanism is introduced in the ANN training process to improve the prediction performance of the ANN model. In addition, the proposed ANN method does not require the definition of a failure threshold, which is hard to clearly define in many practical applications.

The proposed ANN method is validated using the condition monitoring data collected in the field from bearings on a group of Gould pumps. Experiment results show that the proposed ANN method can produce satisfactory RUL prediction results, which will assist the condition based maintenance optimization. A comparative study is performed between the proposed ANN method and the Modified Wu's method, and the results demonstrate the clear advantage of the proposed approach in achieving more accurate predictions.

TABLE I. THE RUL PREDICTION RESULTS

	Average Prediction Error ($\bar{e}$)		
	$\bar{e}_{All}$	$\bar{e}_{L5}$	$\bar{e}_{90-100}$
The Proposed ANN method	10.6%	3.4%	3.65%
The Modified Wu's method	12.5%	4.9%	8.28%

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