Gear Remaining Useful Life Prediction Based on Grey Neural Network

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Abstract: The condition monitoring data of gears is asymmetric distributed, moreover, sampling is usually conducted discontinuously in practice. Thus makes it difficult to predict gear remaining useful life accurately considering the two reasons above. In this paper, a fusion method is proposed using Elman Neural Network to modify residual series of grey model since Elman Neural Network performs better on feeding back and accuracy than BP network. The proposed method takes the advantages of both GM (1, 1) for data mining and Elman neural network for feedback. Experimental data is used to validate the proposed method. The results illustrate that the integrated method has a high prediction capability compared with GM model. In addition the proposed method is a promising approach for life prediction in the case of small sample, incomplete and discontinuous sampling data.

Keywords: Gear, GM (1, 1) models, Elman neural network, Grey Neural Network, Remaining Useful Life (RUL) Prediction

1. Introduction

Gear is widely used in rotating machinery and transmission devices, and it is one of the most important parts in mechanical equipment. The research of L. Cohen[1] have shown that gearbox’s failure 60% source from gear. When gear failure occurs, it will lead to the suspension of work, resulting in production losses and casualties. Predicting remaining useful life of the in-service gear based on historical data has a profound significance to engineering and manufacturing, it can improve the production efficiency and reduce the accident rate.

In order to predict gear’s remaining useful life effectively, research must focus on the following two key issues.

(1) Establish an effective life prediction models. There are two main methods to predict RUL, physical based methods and data driven methods.

Currently, many of the gear RUL physical based method is based on the Cumulative Fatigue Damage Theory, in which the Linear Cumulative Fatigue Damage Theory (Miner rule) is to use the most widely [2], and the method is used to design gear transmission system and analysis gear. Tang and Cui [3]considering the influence of the residual stress on the contacting fatigue limit, predicted the fatigue life of gears by combining the fatigue life prediction technique. Zhang and Cui [4] introduced the computer aided engineering (CAE) technology into armament fields, established the cooperation simulation platform used for

fatigue life prediction of gear and predict the fatigue life of transmission gear by the integration of four kinds of commercial software.

There are also many researches focus on data driven methods, especially a variety of algorithms are applied to RUL prediction. Tian[5] developed an artificial neural network (ANN) based method for achieving more accurate remaining useful life prediction of equipment subject to condition monitoring. Liu and Miao[6] presented the Grey-Markov model to optimize the model based on the Markov and grey theory, the results showed that the prediction accuracy is improved greatly.

Many research [6-9] has been developed the life prediction method based on historical data, but majority of them are just appropriate for complete and continuous data. So for small sample, incomplete and discontinuous data, it is very necessary to develop a new method to solve the problem.

(2) Establish appropriate performance degradation index. Shao and Nezu[8] extract RMS and kurtosis index from the vibration signal in mechanical failure research as degradation index, study shown that RMS is more stable and accurate than kurtosis in monitoring the health condition, however kurtosis is more sensitive to monitor early gear failure. Ahamada and Saon[9], Liao and Zhao et al[10] also extract the RMS and kurtosis from vibration signal, and use artificial neural networks(ANN) to predict the remaining useful life of bearing. Gebraeel and Lawley [11], developed neural-network-based models for predicting bearing failures not just focused on diagnosing bearing faults, research developed to perform accelerated bearing tests where vibration information is collected from a number of bearings that are run until failure. The information is used to train neural network models on predicting bearing operating times. Vibration data from a set of validation bearings are then applied to these network models. Resulting predictions are then used to estimate the bearing failure time. Huang and Xi [12] developed a new scheme for predicted of ball bearing’s RUL based on self-organizing map and back propagation neural network, it uses the minimum quantization error (MQE) network and indicator deriving from SOM, which is trained by six vibrations features including a new designed degradation index for performance degradation assessment.

Shen and Chen [13] proposed novel prediction method based on the relative features and multivariable support vector machine (MSVM) to estimate the rolling bearing remaining life under limited condition data. The relative root mean square (RRMS) with ineffectiveness of the bearing individual difference is used to assess the performance degradation, and sensitive features are selected as input by correlation analysis.
2. Performance degradation model of gear

The normal life cycle of gears is divided into three phases, health working phase, degradation and failure phase. Assessment of performance degradation of gear is that using one or more time/frequency domain index or construct a composite index to reflect the gear’s real life cycle. The establishment of appropriate gear’s performance degradation index is one of the key issues to predict RUL of the gear.

Vibration sensors have been used widely in mechanical systems health monitoring area. Condition indicators (CIs) are obtained from vibration data and used for mechanical fault detection and diagnosis.

Wang and Jiang [14] presented a method to identifying the gradual deterioration in the components of aero-engines, a sensitivity analysis of the target performance parameters is calculated, select the performance parameters due to the largest deviation of measurement. Li Dong and Li Benwei et al [15] aiming at component performance deterioration not being recognized because of coupling with components in measured parameter, a recognition method of component performance deterioration based on performance modified factor kernel pattern analysis was presented and deviation of sensor was distinguished. David and Eric et al [16] use data mining based techniques to effectively define the degradation state transition and measurement functions using a one-dimensional health index obtained by whitening transform.

Many of methods above just suitable for big, complete and even data, but due to human factors and human factors affecting the data collection, so some monitoring data is small and uneven sample. Little and Rubin [17] divided the missing data mechanism into three categories, missing completely at random, missing at random and missing can’t be ignored. Fault monitoring data missing belong to missing can’t be ignored, because the fault trend is changing, small sample data has too limited information to use, and thus can’t confirm gear’s degradation trend and degradation thresholds. There is two way to deal with missing data, the first method is to discard the missing data segments from the total training samples, reducing the raw data to enhance completeness of the data. The second method is to ignore the vacancy data, using known data and data mining method to find alternative values for each missing value.

In this paper, we use the second theory to solve the problem because the situation is about multiple data missing. Tian [5] proposed a method using a suitable curve equation to fit the original data series, and used Weibull distribution curve to match. Many researches showed that a lot of machine degradation obey Weibull distribution, but Weibull distribution has many parameters and hard to estimate. In this paper, GM (1, 1) model be used to replace Weibull distribution function for curve fitting. There are three main reasons why adopt Grey Model, firstly, GM model is exponential increasing, which has the same trend to the gear’s degradation model. Secondly, GM model is suitable for processing sample data. And finally, the modeling process of GM is simple, the parameter is less and easy to estimate and has a better practical effect.

3. Performance degradation model of gear

3.1 Original Gray GM (1, 1) model and its residual model

Grey theory [18] proposed by Deng, is a general systems theory focus on poor, incomplete or uncertain information processing. Grey model is an important branch of grey system theory. The GM (1, 1) is one of the most frequently used grey forecasting model. The GM (1, 1) model constructing process is described below:

Denote the original data sequence by

\[ x^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(N)) \]

where \( N \) is the serial number.

The AGO formation of \( x^{(0)} \) is defined as:

\[ x^{(i)} = (x^{(i)}(1), x^{(i)}(2), x^{(i)}(3), \ldots, x^{(i)}(N)) \]

Where

\[ x^{(i)}(1) = x^{(0)}(1), \]

\[ x^{(i)}(k) = \sum_{n=1}^{k} x^{(0)}(m), \quad k = 2, 3, \ldots, m. \]

The GM (1, 1) model can be constructed by establishing a first order differential equation for \( x^{(i)}(k) \) as:

\[ \frac{dx^{(i)}}{dt} + ax^{(i)} = b \]

By using the least square method, we can get the solution of Eq. (3.1.3):

\[ x^{(i)}(k + 1) = (x^{(i)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \]

where

\[ \hat{a} = [a, b]^T \]

a is called development coefficient, b is called grey action quantity.

And,

\[ \hat{a} = (B^T B)^{-1} B^T Y \]
Applying the inverse AGO, we then have,
\[
\begin{align*}
\hat{\xi}^{(0)}(k+1) &= \hat{\xi}^{(0)}(k+1)-\hat{\xi}^{(0)}(k) \\
\hat{\xi}^{(0)}(1) &= \hat{\xi}^{(0)}(1)
\end{align*}
\] (3.1.5)

We denote the residual series as \( q^{(0)} \),
\[ q^{(0)} = (q^{(0)}(2), q^{(0)}(3), q^{(0)}(4), \ldots, q^{(0)}(n)) \] (3.1.6)

where
\[ q^{(0)}(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \]

We denote the absolute value of the residual series as \( \varepsilon^{(0)} \),
\[ \varepsilon^{(0)} = (\varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \varepsilon^{(0)}(4), \ldots, \varepsilon^{(0)}(n)) \] (3.1.7)

where
\[ \varepsilon^{(0)} = |q^{(0)}(k)|, \quad k = 2, 3, \ldots, n \]

Set up residual GM (1, 1) model, we denote the residual prediction series as \( \hat{\varepsilon}^{(0)}(k) \), we can get the solution of residual model as following,
\[ \hat{\varepsilon}^{(0)}(k) = (\varepsilon^{(0)}(2)-\frac{b_1}{a_1}a_2 \varepsilon^{(0)}(k-1), \quad k = 2, 3, \ldots \] (3.1.8)

3.2 Elman neural network

The Elman network is a local RNN that mainly consists of four layers, the input, the hidden layer, the context layer and the output, shown in Fig. 2. Compared to classical BP neural network, Elman neural network possesses massive parallel connections not only between the hidden and output, but also between the hidden and input as well as the context units [19]. This enhances its sensitivity to the historical data and processing capability of the dynamic information, which means that such network structure makes it particularly applicable for mechanical RUL prediction based on historical data modeling.

Assuming that the numbers of input units, context units and output units are \( r, n \) and \( m \), respectively, in order to achieve better prediction accuracy take Hecht-Nelson method [20] to determine the number of nodes in the hidden layer: if the number of input nodes is \( r \), the number of hidden nodes \( r \) is \( 2r+1 \). The state equations are formulated as,

Where \( W^{(1)} \), \( W^{(2)} \) and \( W^{(3)} \) are the weights of input, internal state and output, respectively, and the context layer, if \( \alpha \neq 0 \) and \( \varepsilon \) is called transfer function, almost time it is sigmoid function,
\[ f(x) = \frac{1}{1+e^{-x}}, \quad 0 \leq \alpha \leq 1 \]

3.3 Grey neural network

Due to the fact that only a few data for prediction, that is suggested that it might be reasonable to adopt an appropriate method to best utilize an incomplete and discontinuous data. In addition to the small sample problem, we adopt artificial neural network, it’s data training and error feedback feature are the important considering point of this paper to gain higher prediction accuracy. In order to gain acceptable results from the monitoring data, the Grey neural network is an appropriate method.

Grey neural network model is the combination of GM (1, 1) model and Elman neural network. A new combination form of grey neural network is proposed in this paper, and apply it to predict gear’s RUL. Firstly, use the original GM (1, 1) model to predict the input data, the input is exacted from early monitoring data of gear (normal or degradation phase). Secondly, use the residual GM (1, 1) model to eliminate the errors and fitted actual data, until connect the next section existing data and repeat the above steps until bridge all gap data. Thirdly, the combination of new sequence. Lastly, use original Elman neural network to predict the value and use modified model[21] for accuracy correction. The general framework of the integrated gear remaining useful life approach using grey neural network is shown in Fig. 3.

Elman neural network to do a two-step prediction and correction accuracy trend signal. First, we introduce a dummy variable \( d(k) \) to indicate the sign of the \( k \)th data. Assume the sign of the \( k \)th data is positive compared to the trend, then the value of is \( d(k) \) is 1, otherwise it is 0. Then, we set up an ANN model by using the values of \( d(n-1) \) and \( d(n) \) to estimate the values of \( d(n+1) \).
Let the sign of the kth series $s(k)$ be

$$s(k) =\begin{cases} +1, & \text{if } d(k) = 1 \\ -1, & \text{if } d(k) = 0 \end{cases}$$

$k = 1, 2, \ldots, n, \ldots$ 

(3.3.1)

In summary, the prediction steps of grey neural network are as follows:

Step 1: Extract gear health degradation index from incomplete and discontinuous monitoring data.

Step 2: Use original GM (1, 1) model to fit the actual series, and using residual model to bridge the gap between two disconnected data.

Step 3: Use actual series and fitted series to form a newly combined series.

Step 4: Use the combined series to predict RUL based on original Elman neural network and use modified Elman to correct error.

4. Case Study

4.1 Experimental Setup and Data Collection

In this paper, data collected from a planetary gearbox and experiments held in Gear test platform in the State Key Laboratory of Mechanical transmission.

When measure the vibration signal, place of sensor (measurement points) is different, the measurement value obtained will vary greatly. Measurement site should ensure that surface smooth and clean, and should avoid vibration attenuation caused by dirt. In this test, the experimental table and measuring point is set up and selected as shown in Fig. 4.

In this experiment, the sampling frequency choose 10 kHz, Magnification choose 1mv/g. We measured periodically to find abnormalities in the initial state, so it is necessary to choose the appropriate cycle for the detection of gear. Period too short, not conducive to detect problems timely; cycle too long, wasteful and uneconomical. Half an hour picking three groups sample, and length is set to 30s. M beginning to get the file storage, such as m-1 to m-104.

In this study, a total sampling time is over 18 hours.

We predict RUL of gear following the 4-steps method mentioned in the end of 3.3. In order to evaluate the proposed approach, we use GM (1, 1) model and presented grey neural network to predict RUL of gear. We don’t compare with Elman neural network because the original data are small sample and not fit for neural network. The prediction results are computed and shown in Table 1 and Fig. 5.

### Table 1 Model value and predict errors

<table>
<thead>
<tr>
<th>Time</th>
<th>Actual value</th>
<th>GM (1,1)</th>
<th>Error (%)</th>
<th>Grey neural network</th>
<th>Error (%)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Predicted value</td>
<td></td>
<td>Predicted value</td>
<td></td>
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<tr>
<td>2202</td>
<td>2.5716</td>
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<td>2.3</td>
<td>-0.10562</td>
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<tr>
<td>2222</td>
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<td>-0.09396</td>
<td>2.4</td>
<td>0.07692</td>
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<tr>
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<td>2.729</td>
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<td>2.59</td>
<td>-0.05093</td>
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<tr>
<td>2262</td>
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<td>2.71</td>
<td>-0.09667</td>
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<tr>
<td>2282</td>
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<tr>
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<tr>
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<tr>
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<tr>
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<td>4.3</td>
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<td>0.0829</td>
<td>4.65</td>
<td>-0.03125</td>
<td></td>
</tr>
</tbody>
</table>

Average error: -0.2368

-0.03294
As is shown in Fig. 6 grey neural network has a higher accuracy compared to grey model, and the error declines 1 orders of magnitude approximately.

5. Conclusions

In this paper, a combined method was proposed, and using the combined model predict RUL of gear for small sample, incomplete and discontinuous data situation. An experimental test verified that the prediction accuracy of the newly integrated model increased greatly. Several conclusions can be deduced based on the results presented in the previous sections:

(1) RMS as a performance degradation index do well in monitoring the degradation of gear and is suitable for the RUL prediction.

(2) Grey model fit well in exponential rise of performance degradation model.

(3) Compared to GM and Elman neural network, the combined model can greatly improve the prediction accuracy in the situation of small sample, incomplete and discontinuous data.

The next research plan is to combine GM and neural network deeply based on the present study of the neural network, and trying to combine varies model and choose the better match. Using correlation analysis to select multiple sensitive features, considering the interaction of many variables and do some information mining research to find and construct the better performance degradation indicators. On the other hand our research will use more advanced signal processing methods to extract more excellent gear performance degradation indicators.

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