A Hybrid Model For Predicting The Degradation Trend Of Hydropower Units Based On Deep Learning

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Abstract—**The degradation of hydropower units affects the safe and stable operation of hydropower stations and even the power system. Obtaining the degradation trend of hydropower units and predicting it accurately is a problem to be solved. In this paper, a framework based on healthy state model and degradation trend prediction model is developed to obtain and predict the degradation trend of hydropower units. Firstly, the healthy state model of hydropower unit considering the effect of working water head and active power was established based on particle swarm optimization and artificial neural network. Secondly, according to the healthy state model, the degradation trend of hydropower unit was deduced. Then, the degradation trend was decomposed by variational mode decomposition to obtain several modal components, and long short-term memory neural network model was constructed for each modal component for prediction. Finally, the results of prediction models were superimposed to obtain the prediction of degradation trend. In this paper, the actual data of a certain hydropower station was used for verification, and the results show that the proposed model is suitable for predicting the deterioration trend of hydropower units.**

Keywords-degradation trend prediction; hydropower units; healthy state model; VMD; LSTM; hybrid model

I. INTRODUCTION

Hydropower units are playing important roles in power generation and frequency regulation. As the age of hydropower units increases, the health status of units gradually degrades, even leads to faults. Because the fault samples of hydropower units are few, the existing fault diagnosis methods cannot meet the actual demands [1]. With more and more state monitoring data collected by the monitoring system of hydropower station, it is a new research direction to effectively mine the relationship between monitoring data and unit state and accurately predict the deterioration trend [2]. This is also of great significance for developing reasonable maintenance strategies, ensuring safe operation of hydropower units and achieving greater economic benefits.

In recent years, the research on equipment degradation trend has been widely developed, and the related research on hydropower unit is also gradually increasing. Pan et al. studied the degradation law of bearing by conducting accelerated bearing life test [3]. An index is proposed to measure the degradation of bearing based on fuzzy c-means in his paper. However, this index did not take into account the effect of different working conditions on bearing state. Caesarendra et al. used relevance vector machine and logistic regression to evaluate and predict the bearing degradation [4]. This method evaluates the degradation state of the bearing through logistic regression and predicts the failure probability of individual units of machine component through relevance vector machine. The setting of hyper-parameter in the model affects the accuracy of prediction. An et al. proposed a degradation trend prediction model for hydropower units based on radial basis function interpolation and empirical mode decomposition [5]. The model takes the influence of working conditions into consideration and establishes a degradation model through radial basis function interpolation. But this model does not analyze the degradation trend under different working conditions.

Deep learning first proposed by Hinton et al. has successfully applied in computer vision, speech recognition and other fields [6] [7]. In recent years, it has also made great progress in PHM domain. Zhang et al. proposed a new entropy index to judge the state of bearings, and predicted the degradation of bearings through the long short-term memory network and exponential model [8]. Wang et al. used the deep neural network to predict the lubricant pressure in the wind turbine gearboxes, and used the exponentially weighted moving average chart to identify their faults [9]. Yoo et al. extracted time-frequency images features of bearings by wavelet transform, and used 2-D convolutional neural network to predict the remaining useful time [10]. However, deep learning theory has rarely been used to predict the degradation trend of hydropower units.

In this paper, the relationship between monitoring data and unit state was fully mined. Firstly, the healthy state model of hydropower unit was established based on artificial neural network optimally tuned by particle swarm optimization. Secondly, according to the healthy state model, the degradation trend of hydropower unit was deduced. Then, the degradation trend was decomposed into several modal

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components by variational mode decomposition (VMD). Taking advantage of the strong feature extraction and non-linear expression ability of deep neural network, long short-term memory neural network (LSTM) model was constructed for each modal component for prediction. Finally, the result of each prediction model was composed to obtain the prediction of degradation trend. In the end, the degradation trend of a real pumped storage unit (PSU) in China was studied, the effectiveness of the prediction method is verified by comparison experiments.

II. Prediction Model of Degradation Trend of Hydropower Units

A. Model of Degradation Trend of Hydropower Units

By analyzing the massive monitoring data of hydropower units, the operation state of hydropower unit is affected by active power and working water head. In this paper, the mapping relationship between active power P, working water head H and unit state parameter F is obtained by constructing the healthy state model of hydropower unit. Furthermore, the state degradation trend of hydropower units is deduced. The steps are shown as follows:

1) Establish the healthy state model of hydropower unit.

The healthy state model of hydropower unit is established by building an Artificial Neural Network(ANN) optimally tuned by Particle Swarm Optimization (PSO). The ANN is composed of several fully connected layers. PSO is used to train the weights and bias of each layer in the ANN.

By observing and analyzing the massive state monitoring data under different active power and working water head, the healthy state of the unit is determined. The data of active power P and working water head H under healthy state are selected as the input of the ANN and the corresponding unit state parameter F is taken as the output of the ANN .The healthy state model is obtained by training the data. The mapping relationship between active power P, working water head H and unit state parameter F is shown:

$$F(t) = f(P(t), H(t)) \tag{1}$$

2) Deduce the trend of degradation of hydropower units

The active power data and working water head data in the state monitoring data are taken and input into the healthy state model of hydropower unit. The output $F(t)$ of the model is compared with the actual unit state parameters $R(t)$, and they are substituted into the following equation to obtain the unit degradation trend $D(t)$.

$$D(t) = \frac{|R(t) - F(t)|}{F(t)} \tag{2}$$

Due to the influence of different working conditions such as active power and working water head, the degradation trend of hydropower units has strong fluctuation. In order to show the degradation results of hydropower units more clearly, the degradation trend under different working conditions will be shown separately.

B. Prediction of Degradation Trend of Hydropower Unit

Due to the nonlinearity and strong fluctuation of degradation trend, simple network prediction is generally not effective. In order to obtain more accurate prediction results, the degradation trend is decomposed into several simple sequences and then predicted them using LSTM separately. LSTM can effectively process long sequence data and solve the problem of gradient disappearance in Recurrent Neural Network [12]. The steps are as follows:

First, the original degradation trend was decomposed into k sequences by VMD. VMD is used to decompose complex signals into several simple modal components with limited bandwidth and corresponding frequency centers [11].

Second, for k simple sequences, k LSTM prediction models were built. Each LSTM prediction model is composed of an LSTM layer and several fully connected layers, as shown in Fig. 1.

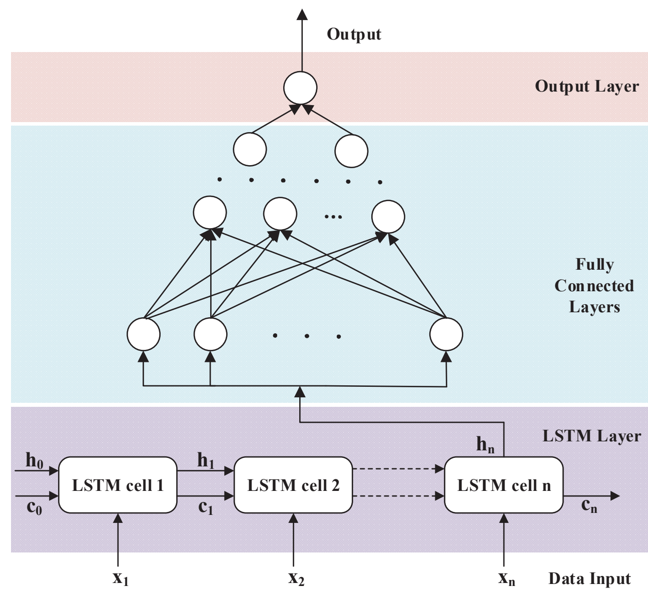

Figure 1. Structure of LSTM prediction model

The sequence data are input into the LSTM layer in chronological order. Each LSTM neuron corresponds to an input, and the dimension of input data is the same as the number of neurons in the LSTM layer. The LSTM layer can extract the basic features of the input data. The output of the last neuron in the LSTM layer serves as the input to the first fully connected layer. A one-dimensional vector, the predicted result, is output from last fully connected layer containing one neuron. Each fully connected layer utilizes the Rectified Linear Unit (ReLU) which can reduce the computation and help to solve the convergence problem in deep network as the activation function. Each degradation sequence is input into the respective LSTM model, and k predicted sequences are obtained.

Finally, the k predicted sequences are superimposed to obtain the final predicted result of degradation trend of hydropower units.

III. EXPERIMENT ON REAL DATASET

In this paper, the degradation trend prediction for a unit of a pumped storage power station were studied. Because vibration may affect the stable operation of hydropower units and even cause faults, the y-direction horizontal vibration data of the lower bracket of the unit was selected to reflect the running state of the units. The corresponding working water head data and active power data were record to construct data vectors $(F, H, P)_t$. Data of the PSU from July 24, 2008 to January 21, 2009 were selected to build the healthy state model, the degradation trend series of years later, May to December of 2011, were then deduced. Finally, the degradation trend prediction model was trained and tested.

A. *Vibration Data Analysis*

The data of the unit from December 1 to December 31 of 2008 are taken to show the relationship between the working head, active power and y-direction vibration of the lower bracket. The relationship between working water head and vibration is shown in Fig. 2. The working water head of the hydropower unit is mainly between 324 meters and 337 meters. Fig.3 shows the relationship between active power and vibration. The vibration data were mainly divided two categories: the pumping condition dataset and the generating condition dataset. The active power in pumping condition are concentrated at -250MW, while that in generating condition are concentrated at 150MW, 200MW and 250MW.

As can be seen from the figures, the vibration data is very complex and greatly affected by the working water head and active power.

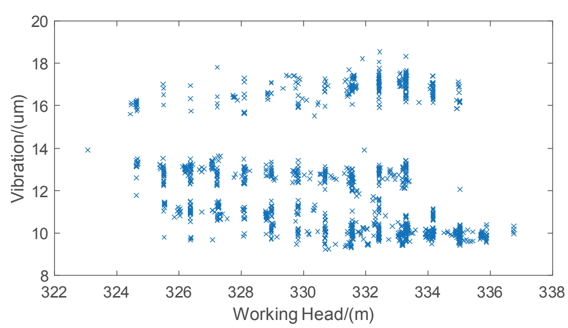

Figure 2. Working water head– Vibration

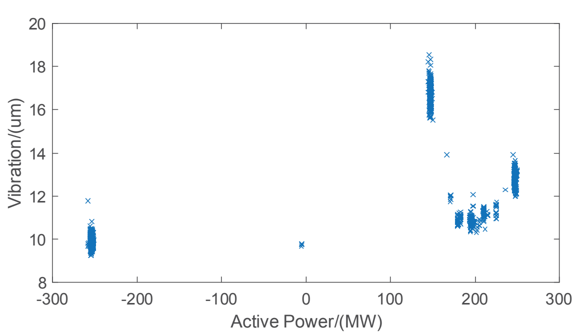

Figure 3. Active Power – Vibration

B. *Establish and Verifiy the Model of Unit Healthy State*

The standard heathy data at the initial operation stage of the unit were selected to establish and verify the effectiveness of the proposed healthy state model based on ANN optimized by PSO, and the mapping relationship between the working head, active power and vibration is obtained under the healthy state.

The 860 data samples of the PSU from July 24, 2008 to January 21, 2009 were selected. In order to consider the influence of different working conditions, all possible working water head and active power were contained in 860 data samples. 688 samples were randomly selected to train the established healthy state model, and the remaining 172 samples were used to test the effectiveness of the model.

As for the testing results, the mean absolute percentage error (MAPE) between the model outputs and the real value was 3.33%, and the root mean square error (RMSE) was 0.51. The three-dimensional surface obtained by fitting results is shown in Fig. 4.

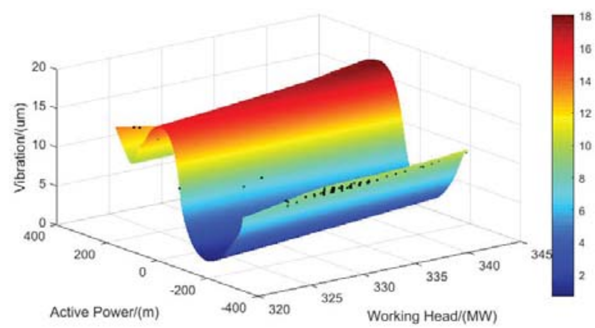

Figure 4. Fitting three-dimensional surface

C. *Obtain the Degradation Trend*

The data samples of three years later were used to deduce the degradation trend of the PSU, while data from May 12, 2011 to December 12, 2011 were adopted. By inputting H and P values into the established healthy state model, the estimated vibration values were obtained. The estimated vibration values and the measured vibration values were substituted into the equation 14 to obtain the degradation trend.

Since the PSU frequently switch between generator and pumping conditions, the heathy state is related to the working conditions. Therefore, the degradation trend of units should be discussed under different working conditions. This paper only analyzed the degradation trend under the generating condition due to the data deficiency. The degradation trend under generating condition was exhibited in Fig. 5. It can be seen that the unit has degraded after three years. The degree of degradation is fluctuating and rising. In Fig. 6, the monthly mean value of the degree of degradation shows that the overall trend is upward.

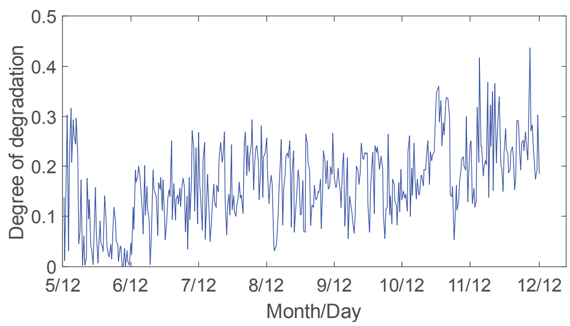

Figure 5. Degradation trend under generator condition

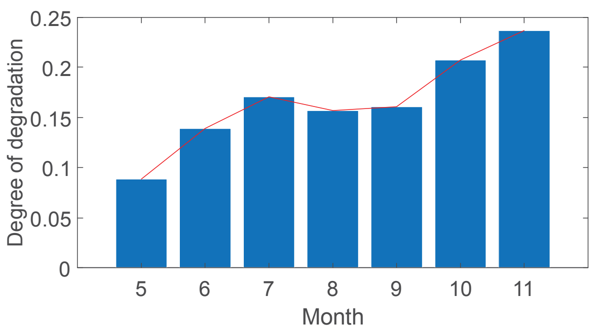

Figure 6. Monthly degradation trend under generator condition

D. *Predict Degradation Trend of Hydropower Unit*

In this part, the degradation trend shown in Fig. 5 was decomposed into five modal components by using VMD. The decomposition results were shown in Fig. 7.

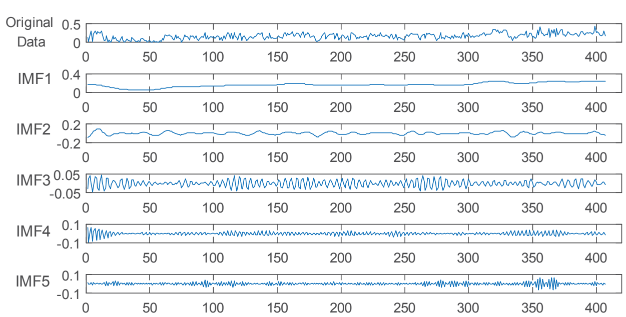

Figure 7. Decomposition results by VMD

After the decomposition, the corresponding LSTM model was established for each mode for prediction. In each LSTM model, the number of LSTM layer cell is 9, and the number of neurons in the five fully connected layers is 64, 32, 16, 4 and 1. To validate the superiority of the proposed model, VMD-LSTM, LSTM, VMD-ANN and support vector machine based on variational mode decomposition (VMD-SVM) were established to predict degradation trend for comparison. The number of network layers and neurons in LSTM and VMD-ANN are consistent with those in the proposed model. The hyper-parameter of kernel function in SVM were obtained by grid search.

In order to verify the effectiveness of the proposed prediction model, the first 320 data of the above degradation trend series were taken as the training set, and the remaining 80 data were taken as the test set. In VMD-LSTM (the proposed), VMD-SVM and VMD-ANN models, five modal components decomposed by VMD were used to train and test the sub-models. The final prediction series was composed by the predicted sub-series.

The comparison of the expected degradation trend and the predicted trend obtained by VMD-LSTM model was shown in Fig. 8. It is found that the predicted values fitted well with the expected values.

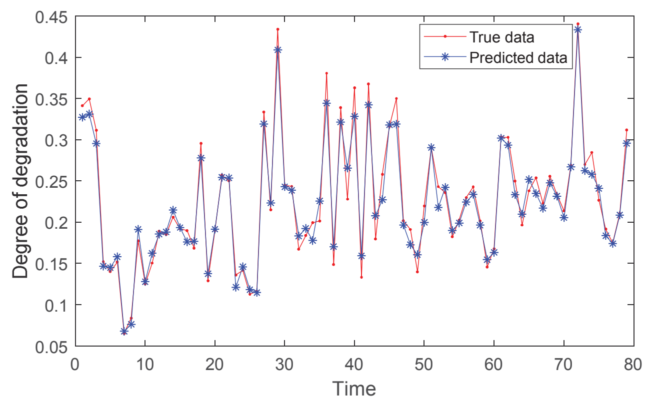

Figure 8. Predicted result based VMD-LSTM

To show the advantage of the proposed model, the mean absolute percentage error (MAPE) and the root mean square error (RMSE) results obtained by the compared models were presented in Table I. From these results, It is found that the MAPE and RMSE obtained by the proposed model is 5.44% and 0.015 respectively. Comparatively, the MAPE and RMSE of LSTM are 31.48% and 0.9636 respectively, which are far greater than the indexes of the proposed VMD-LSTM. This result indicates that it is beneficial to decompose the complicated time series by VMD. The MAPE and RMSE of VMD-ANN and VMD-SVM are also greater than those of the proposed model, which manifests that the proposed method has better prediction accuracy. The overall results have confirmed the superiority of the proposed method for predicting the degradation trend of hydropower units.

TABLE I. PERFORMANCE INDEXES COMPARISION OF FOUR MODELS

Index	**Model**			
	VMD_LSTM (proposed)	***LSTM***	***VMD_ANN***	***VMD_SVM***
MAPE(%)	5.44	31.48	7.75	6.37
RMSE	0.0150	0.9636	0.0182	0.0153

IV. CONCLUSION

As an important part of PHM, the prediction of degradation trend of hydropower units is of great significance for developing reasonable maintenance strategies, ensuring the reliable operation of hydropower units and getting more economic benefits. In this paper, firstly, the monitoring data in the healthy state was input to the ANN optimized by PSO to establish the healthy state model. Secondly, according to the output of the health model and the state parameters when the unit has degraded, the degradation trend was deduced. Finally, VMD-LSTM model was used to predict the degradation trend sequence. By comparing the results of the proposed model with those of the control group, it has been verified that the proposed model shows superiority and effectiveness for the prediction of degradation trend of hydropower units.

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