A Fault Recognition System for Gearboxes of Wind Turbines

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Abstract. Costs of maintenance and loss of power generation caused by the faults of wind turbines gearboxes are the main components of operation costs for a wind farm. Therefore, the technology of condition monitoring and fault recognition for wind turbines gearboxes is becoming a hot topic. A condition monitoring and fault recognition system (CMFRS) is presented for CBM of wind turbines gearboxes in this paper. The vibration signals from acceleration sensors at different locations of gearbox and the data from supervisory control and data acquisition (SCADA) system are collected to CMFRS. Then the feature extraction and optimization algorithm is applied to these operational data. Furthermore, to recognize the fault of gearboxes, the GSO-LSSVR algorithm is proposed, combining the least squares support vector regression machine (LSSVR) with the Glowworm Swarm Optimization (GSO) algorithm. Finally, the results show that the fault recognition system used in this paper has a high rate for identifying three states of wind turbines' gears; besides, the combination of date features can affect the identifying rate and the selection optimization algorithm presented in this paper can get a pretty good date feature subset for the fault recognition.

1. Introduction

The failure-rate of wind turbines is higher than the traditional generating units because their gearboxes suffer from irregular loads and instantaneous shock in the harsh natural environment. Therefore, costs of maintenance and loss of power generation caused by the faults are the main components of operation costs for a wind farm. Among various failures, the downtime caused by gearbox's faults is the longest, and the maintenance cost is the highest [1].

Over the past ten years, planned maintenance and corrective maintenance have been implemented in China's wind farms. Condition Monitoring Systems (CMS) for wind turbines are usually transplanted from other industrial applications, such as the Turbine Diagnosis and Management System for the thermal power plants. But their performance is not as good as they once were because of time-varying operational conditions, complicated compact gearboxes and uncertain fault characteristics. Therefore, the technology of condition monitoring and state recognition for wind turbines gearboxes is becoming a hot topic.

Here are some of the existing works in this field: Hameed2009 reviewed different techniques, methodologies and algorithms developed for the monitoring of the performance of wind turbine as well as for an early fault detection to keep away the wind turbines from catastrophic conditions due to

sudden breakdowns [2]. Yang2010 uses a continuous-wavelet-transform-based adaptive filter to analyses the generator output power and rotational speed for deriving a fault detection signal [3]. Guo2011 proposed a new condition monitoring method using temperature trend analysis for a wind turbine gearbox [4]. Nejad2014 introduced a fatigue reliability-based maintenance plan for wind turbine gearbox components [5]. Hu2015 presented a method combining ensemble intrinsic time-scale decomposition (EITD) with wavelet packet transform (WPT) and correlation dimension (CD) for decomposing non-stationary vibration signal and diagnosing wind turbine faults [6]. Santos2015 proposed a multi-sensory system for fault diagnosis in wind turbines, combined with a support vector machines (SVM) data-mining solution for the classification of the operational state of the turbine [7]. Jingling Chen2016 used empirical Wavelet Transform (EWT) to extract inherent modulation information by decomposing signal into mono-components under an orthogonal basis [8]. Xiaowang Chen2016 proposed an improvement with fine time–frequency resolution and free from interferences for highly non-stationary multi-component signals, by exploiting the merits of iterative generalized demodulation [9].

In this paper, a condition monitoring and fault recognition system (CMFRS) is presented for CBM of wind turbines' gearboxes. The vibration signals from acceleration sensors and the data from supervisory control and data acquisition (SCADA) system are collected to CMFRS. Then data features are collected, optimized and analyzed to recognize the condition of the wind turbines' gearboxes. The structure of the paper is going to be as the following: in section 2 the structure and details of the condition monitoring system will be introduced; Then the methods of feature extraction and optimization will be explained in section 3; Furthermore, in section 4 the fault recognition method based on the GSO-LSSVR algorithm is proposed; next, the identifying results of CMFRS for three kinds of health state of wind turbines' gears will be discussed in Section 5; finally, Conclusions will be given in Section 6.

2. Condition Monitoring Systems

A new CMS was developed to collect the vibration signals and SCADA data. It can also be used to monitor the wind turbine in shutdown or outage condition because it has the capacity of data storage and continuous power supply.

As shown in Figure 1, the new system includes several data acquisition units (DAU) and a wind farm central server. The data acquisition unit includes a controller, a vibration data acquisition module (VAM), some sensors, a SCADA data acquisition module (SCADAM), a data storage module (DSM), an uninterruptible power supply module (UPS), a DSP data processing module (DPM) and a data communication module (DCM).
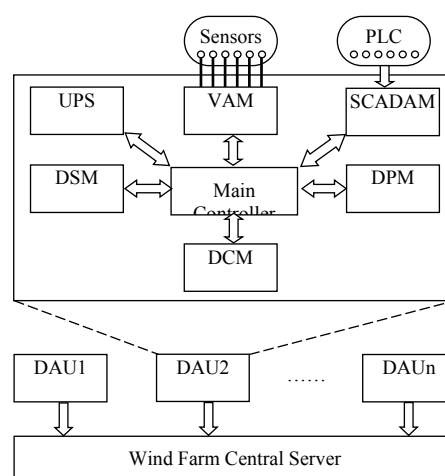

Figure 1. Structure of CMS

The VAM acquires vibration signals form sensors installed at different location of wind turbines and the SCADAM receive SCADA data from a programmable logic controller (PLC) connected with the main controlling system of wind turbines. The DPM takes charge of saving original data in the DSM according to the preset storage strategy and extracting features from the original data. The UPS ensures the CMS to collect complete data when the wind turbine is shutdown or outage. The DCM communicates with the wind farm central server through TCP/IP communication protocol. The functions of all modules are integrated in the main controller.

3. Features Extraction and Optimization

3.1. Signal Denoising and Feature Extraction

The collected signal data must be denoised to improve the signal-noise ratio because concerned fault information is often susceptible to strong background noise and signal transmission channel; in addition, the vibration signal of the wind turbine is generally nonlinear and non-stationary. It is necessary to adopt the nonlinear denoising method to suppress and eliminate the noise effectively. Common nonlinear denoising methods are: empirical mode decomposition (EMD), wavelet denoising, Kalman filter, and phase space reconstruction. The EMD method is employed in this paper because it does not need to know the priori information of the signal and the noise and it can adaptively decompose the signal into a series of different scales of Intrinsic Mode Function (IMF), then combine some modal components to form low-pass, High-pass, or band-pass filters [10].

After denoising process, the features of the vibration signal are extracted as a health state feature set in order to obtain the health information of the gearbox. In this paper, a health states feature set is composed of 23 features, including time-domain [11], frequency-domain [12] and wavelet packet energy features [13]. The time domain features are Mean, Absolute Mean (AM), Range, Standard Deviation (SD), Root Mean Square (RMS), Mean Square Amplitude (MSA), Skewness, Kurtosis, Shape Factor (SF), Crest Factor (CF), Impulse Factor (IF), and Clearance Index (CI). The frequency domain characteristic parameters mainly includes the barycenter of frequency spectrum(BFS), the mean square frequency (MSF), the root mean square frequency (RMSF), the frequency variance (FV) and the frequency standard deviation (FSD).

The wavelet packet energy features are adopted as the time-frequency features in this paper, because wavelet packet decomposition has the ability of multi-resolution analysis in which the original signal can be decomposed into different frequency bands and each signal band contains the characteristic information of original signal in different frequency range. The signal of different fault has different energy distribution in the frequency bands decomposed from wavelet packet, so the energy distribution in the frequency bands can be used as the time-frequency features of the health states of wind turbine gearboxes [13].

3.2. Optimization Algorithm of data features

The feature set extracted from signal must be optimized for reducing data redundancy and improving the computational efficiency in the health management of wind turbines. The common optimization methods include principal component analysis (PCA) [14], linear discriminant analysis (LDA) [15] and distance evaluation method [16, 17]. An improved distance evaluation method is proposed to find a features subset from the 23 extracted features in which members are linear independent and sensitive to health state classification in this paper.

The health state features set is $S=\{s_{ijk}\}$, where s_{ijk} means the ith feature under the jth state and the kth sample; i=1, 2,... M, j=1, 2,... N, k=1, 2,... K; M is the quantity of concerned health states; the sample quantity of each state is K; N is the quantity of features needing to be optimized. The process of optimization is explained as follow.

Step 1: To the ith feature, the intra-cluster distance D_{ij} (DIC) and the center of cluster C_{ij} (COC) in jth state are calculated as follow:

$$D_{ij} = \frac{1}{K(K-1)} \sum_{k_1,k_2=1}^{K} |s_{ijk_1} - s_{ijk_2}| \tag{1}$$

$$(i = 1,2,\cdots,M; \ j = 1,2,\cdots N; \ k_1 \neq k_2)$$

$$C_{ij} = \frac{1}{K} \sum_{k=1}^{K} s_{ijk} \quad (i = 1,2,\cdots,M; \ j = 1,2,\cdots N) \tag{2}$$

Step2: the average intra-cluster distance (AID)d_i^{in} and average between-clusters distance (ABD) d_i^{out} of the ith feature are obtained by the following formula:

$$d_i^{in} = \frac{1}{N} \sum_{j=1}^{N} D_{ij} \quad (i = 1,2,\cdots,M) \tag{3}$$

$$d_i^{out} = \frac{1}{N(N-1)} \sum_{j_1,j_2=1}^{N} |C_{ij_1} - C_{ij_2}| \quad (i = 1,2,\cdots,M; \ j_1 \neq j_2) \tag{4}$$

Step 3: To the ith feature, the intra-cluster constraint factor (ICF) σ_i^{in}, the between-cluster constraint factor (BCF) σ_i^{out} and the correction factor θ_i are calculated as follow:

$$\sigma_i^{in} = \frac{\max(D_{ij})}{\min(D_{ij})} \quad (i = 1,2,\cdots,M; j = 1,2,\cdots,N) \tag{5}$$

$$\sigma_i^{out} = \frac{\max(|C_{ij_1} - C_{ij_2}|)}{\min(|C_{ij_1} - C_{ij_2}|)} \tag{6}$$

$$(i = 1,2,\cdots,M; \ j_1,j_2 = 1,2,\cdots,N; \ j_1 \neq j_2)$$

$$\theta_i = \frac{1}{[log_2(\sigma_i^{in}\sigma_i^{out})]^\alpha} \quad (i = 1,2,\cdots,M) \tag{7}$$

Generally, the smaller two constraint factors are, the better the classification result is. The correction factor θ_i is defined to correct the sensitivity coefficient, where α is the attenuation factor, whose value is 0.5 or 1 or 2.

Step 4: the sensitivity coefficient e_i is defined to evaluate the sensitivity of the ith feature for the health state classification, and it is calculated as follow:

$$e_i = \theta_i \frac{d_i^{out}}{d_i^{in}} \quad (i = 1,2,\cdots,M) \tag{8}$$

Step 5: a sensitivity vector $E = [e_1, e_2, \cdots e_M]$, $(e_1 \geq e_2 \geq \cdots \geq e_M)$ is constructed after the sensitivity coefficients e_i are sorted.

Step 6: a correlation coefficients matrix $R = (r_{i_1 i_2})_{M \times M}$ is defined, where $r_{i_1 i_2}$ shows the linear correlation of two features $S_{i_1} = (s_{i_1 jk})_{N \times K}$ and $S_{i_2} = (s_{i_2 jk})_{N \times K}$ which distribute the health state of wind turbines.

$$r_{i_1 i_2} = \frac{\sum_{j=1}^{N} \sum_{k=1}^{K} (s_{i_1 jk} - \bar{S}_{i_1})(s_{i_2 jk} - \bar{S}_{i_2})}{\sqrt{\sum_{j=1}^{N} \sum_{k=1}^{K} (s_{i_1 jk} - \bar{S}_{i_1})^2} \sqrt{\sum_{j=1}^{N} \sum_{k=1}^{K} (s_{i_2 jk} - \bar{S}_{i_2})^2}} \tag{9}$$

$$(i_1 = 1,2,\cdots,M; \ i_2 = 1,2,\cdots,M; \ )$$

$$\bar{S}_i = \frac{1}{N}\frac{1}{K} \sum_{j=1}^{N} \sum_{k=1}^{K} s_{ijk} \qquad (i = 1,2,\cdots,M) \tag{10}$$

Step 7: according to the sensitivity vector $\mathbf{E}$ and correlation coefficients matrix $\mathbf{R}$, the most sensitive and linear independent state features are selected to be an optimized features set which will be used in state recognized algorithm later.

4. Fault Recognize Based on GSO-LSSVR

4.1. Least squares support vector regression

The basic idea of least squares support vector regression algorithm (LSSVR) is: to select a non-linear transformation, taking a multidimensional vector as the input vector and a one-dimensional vector as the output vector; then map from the original space to a high dimensional feature space and construct optimal linear regression function; next replace dot product in the high-dimensional feature space with the kernel function in original space, using the structural risk minimization principle; thus transform solving nonlinear estimation function into solving linear estimation function in the high dimensional feature space [18].

When the LSSVR modelling is trained, the penalty coefficient C and the kernel parameters σ will directly affect the accuracy of the model. Usually these parameters are confirmed by trial-and-error method, which is generally subject to the user's subjective experience, but in fact it is time-consuming and of no-guaranteed accuracy.

To avoid the inefficiency and aimlessness of common method, an optimization algorithm is used to search the best combination of punitive coefficient C and kernel parameter σ automatically in this paper.

4.2. GSO algorithm

The idea of glowworm swarm optimization (GSO) algorithm [19] originates from the natural phenomenon that glowworms use light-emitting to attract mates. The optimized object is represented as the position of glowworm swarm. In each iteration, the glowworm will be attracted to the companion who has more fluorescein in its perception scope, finally the best position is achieved as the optimization goal.

4.3. GSO-LSSVR algorithm

The penalty coefficient C and the kernel parameters σ of LSSVR are optimized to find an optimal combination of two parameters by using GSO algorithm.

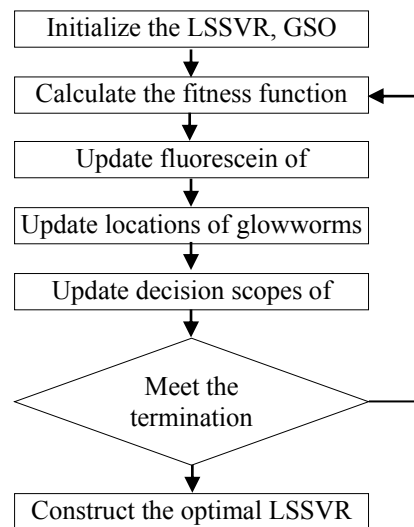The process of GSO-LSSVR is explained as follows and shown in Figure 2:

Figure 2. Flow Chart of GSOLSSVR Algorithm

Step 1: Initialize the LSSVR, GSO parameters.

The LSSVR model is constructed and penalty coefficient C and the kernel parameter σ of LSSVR model are set randomly as the initial position of the glowworm in the GSO algorithm.

Step 2: Calculate the fitness function. The fitness function in GSO algorithm is shown as follow:

$$J(C,\sigma) = \frac{1}{\sum_{i=1}^{N}|g_i - \tau| + e} \tag{11}$$

e N is the quantity of samples; g_i is the output of LSSVR; τ is the target of training; e is a real number great than 0.

Step 3: Update fluorescein, location and decision scope until the termination condition is met.

Step 4: Construct the LSSVR model with the best combination of penalty coefficient C and the kernel parameter σ exported from GSO algorithm.

5. Verification and Analysis

5.1. Raw data

Three 1.5MW wind turbines with different health status have been selected in a wind farm located in Jilin province of China. Vibration sensors of the CMS are installed in four key positions of the gear box which monitor the low speed shaft, the planetary gear, the middle shaft and the high-speed shaft. As shown in Table 1, a total of 360 groups at different speed and in different states are tested, while the sampling frequency of the vibration sensor is 8000Hz, the sampling interval is 10 minutes, and the data length is 10 seconds. Figure 3 shows the three typical vibration examples of high speed gear under different health states.

Table 1. Quantity of Vibration Samples for Testing.

Health status	Sample Size	Working Condition	State Encoding
Normal Gear	104	13	1
Worn Gear	112	14	2
Cracked Gear	114	18	3

(a) Normal state

(b) The state of worn teeth
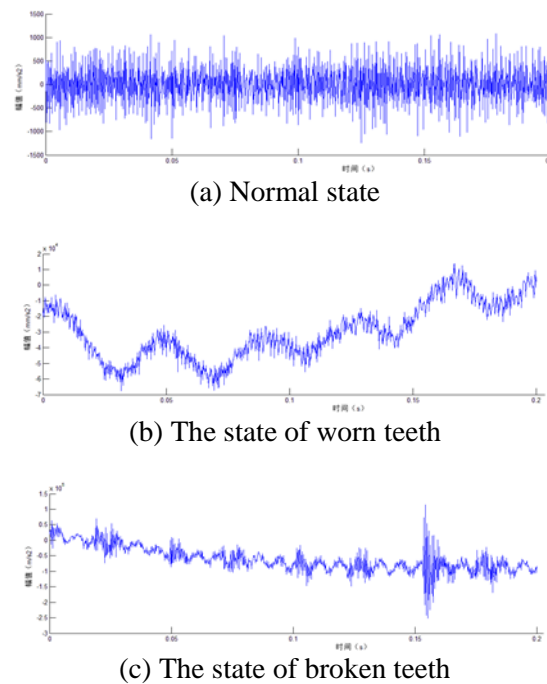

(c) The state of broken teeth

Figure 3. Radial Vibration Signals of High Speed Shaft

5.2. Data Processing

The EMD process can be equivalent to the filtering, i.e. different characteristic scale fluctuation amplitude variation can be clearly observed, because the IMF is ordered in accordance with the frequency, thus the localization effect of time domain is achieved [20]. The noise signal is usually in high frequency, and the denoised signal is obtained by denoising the decomposed high frequency IMF components. Figure 4 and Figure 5 are spectrograms of the original signal and the EMD denoising signal. From the signal spectrum, the noise reduction and detail deletion in the high frequency part of the signal can be seen clearly after noise reduction by EMD.
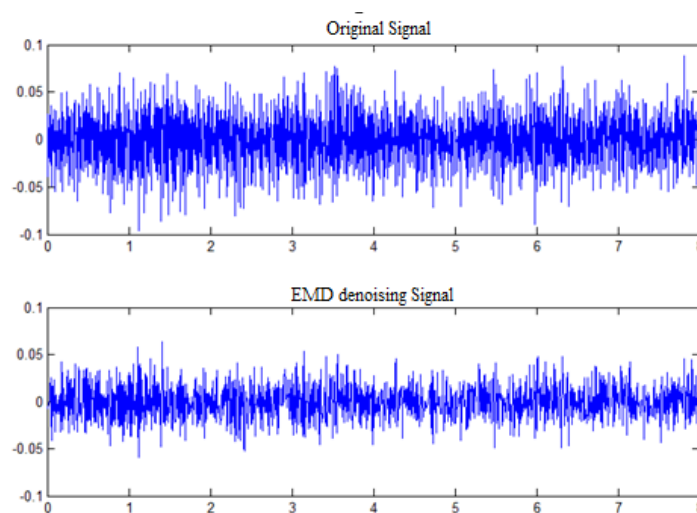

Figure 4. Time-domain diagram of the original signal and denosing signal
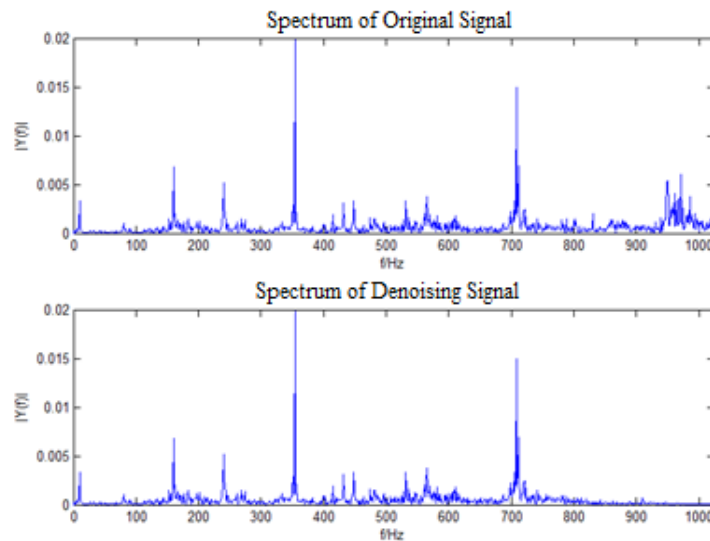
Figure 5. Spectrum of the original signal and denoising signal

5.3. Feature Extraction and Optimization

Using the data feature extraction formula, the 12 kinds of time-domain features, 3 kinds of frequency-domain characteristics and 8 groups of wavelet packet energy features are extracted.

There are some viewpoints which can be observed from the extracted features:

1) The features have different sensitivity levels with regard to rotate speeds and gear states. For example, the range and standard deviation are very sensitive to the gear states and operating modes, and the impulse index and clearance index are only different in the gear states, but not sensitive to the rotate speed, however the skewness completely unable to reflect the recognition rules.

2) Some features are more sensitive to a certain state. For example, kurtosis, crest index and wavelet packet 7 energy ratio of are more sensitive to the gear with broken tooth and BFS is more sensitive to worn teeth state.

3) Some Features values have strong correlation, such as the absolute mean, RMS and MSA.

The above analysis shows that more features are not the guarantee of accuracy in the state recognition algorithm. The state features must be selected optimally for reducing the redundancy and raising efficiency according to their sensitivity and correlation. Therefore, an optimization algorithm mentioned above is used to calculate the 23-feature's sensitivity to the gear states in this paper and figure 6 shows the sensitivity order of the 23 kinds of data features. Furthermore these 23 state features are optimally chosen by the sensitivity combined with the correlation analysis and the result is shown in Table 2. There are three groups of combinations if the optimal feature subset has two features; two groups of combination when the subset has three features; and only one set of combinations when the subset includes four or five features.
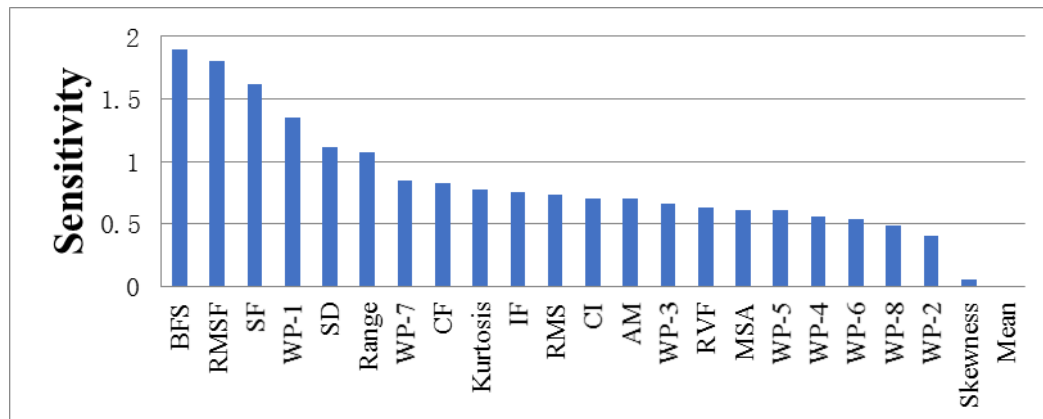
Figure 6. Sensitivity Order of Different Features

Table 2. Optimization Combination Result of Data Features.

Feature Quantity	Detail of Combination	Recognition Rate	Rank	Total
2	Shape indicator, Range	97.78%	4	253
	BFS, Range	97.22%	15	253
	RMSF, Range	97.22%	17	253
3	Absolute mean, Range, BFS	97.78%	55	1771
	BFS, Shape indicator, RMS	97.78%	110	1771
4	Absolute mean, Kurtosis, Shape indicator, BFS	98.89%	96	8855
5	Absolute mean, Range, Shape indicator, BFS, 1st wavelet packet energy ratio	98.33%	612	33649

All the combination of the 2, 3, 4 and 5 features in the all 23 features have been applied in the state recognition algorithm. The result shows that the recognizing rates of the optimal combination of the features provided in Table 2 are not the best, but they rank the top.

5.4. fault identification

The absolute mean value, range, shape indicator, BFS and 1st wavelet packet energy ratio are used as the state feature combination, and the training set is composed of 150 sets of signal data totally, which are 50 sets for 13 kinds of operational conditions in normal state, 50 sets for 14 kinds of operational conditions in worn teeth state and 50 sets for 18 kinds of operational conditions in broken teeth state. All the training sets are selected randomly, and remaining data are test sets. Then GSO-LSSVR algorithm is used for state recognition. The recognizing rates of 10 state recognition experiments are shown in Table 3.

Table 3. Recognition Rate of 10 Experiments for Gearbox in Full Operational Conditions.

	1	2	3	4	5	6	7	8	9	10
Normal	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Worn teeth	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Broken teeth	95.74%	92.55%	89.36%	85.11%	90.43%	98.94%	94.68%	96.81%	91.49%	87.23%

Data are selected randomly in half operational conditions of normal state, worn teeth state and broken teeth state, so a total of 176 sets of data are used for the training sets, and data in another half

conditions are used for the testing sets. Finally, GSO-LSSVR algorithm is used for state recognition. The recognizing rates of 10 state recognition experiments are shown in Table 4.

Table 4. Recognition Rate of the 10 Experiments for Gearbox in Different Operational Condition.

	1	2	3	4	5	6	7	8	9	10
Normal	80.36%	83.93%	100%	94.64%	89.29%	100%	100%	91.07%	100%	92.86%
Worn Teeth	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Broken Teeth	100%	98.61%	91.67%	100%	93.06%	80.56%	90.28%	84.72%	83.33%	86.11%

The table 3 and table 4 show that, the method proposed in this paper provides a better recognition rate for the worn teeth state, which is 100%, but the recognition rate for the broken teeth state is not so good. When the training set covers the whole working conditions, the recognition rate is obviously better, but the training set contains only part of the operating conditions and the test set is in different conditions, the recognition rate drop out significantly, especially for the normal state.

6. Conclusion

A condition monitoring and state recognition system (CMSRS) presented in this paper adopts a redesigned CMS for wind turbine gearboxes. The vibration signals and SCADA data are collected to CMSRS. Then 5 optimal features are selected from 23 kinds of state features through an improved distance evaluation method combined with correlation analysis. Finally, the GSO-LSSVR algorithm is applied to recognize the three kinds of health states of high speed gears of wind turbines in different operational conditions. As a result, the following conclusion can be acquired from this work.

The combination of state features can affect the recognizing rate of the state recognition method. The selection optimization algorithm presented in this paper can get a pretty good state feature subset, although it is not the best one.

The state recognition algorithm used in this paper has a high recognizing rate in the identification of three kinds of health state of gears of wind turbines and the training set composed by different operational condition has great influence on the recognizing rate.

Future works will be focus on further research for the state recognition method based on the combination of SCADA data and vibration signals.

Acknowledgments

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