Research on Fault Warning of Doubly Fed Wind Power Generator based on LS-SVM

Sheng-Yu NIU, Bo-Wen LIU, Xin-Yan ZHANG

College of Electrical Engineering, Xinjiang University, China

College of Electrical Engineering, Xinjiang University, China

Engineering Research Center of Education Ministry for Renewable Energy Power Generation and Grid Technology, Xinjiang University, China;

40468367@qq.com, xdlbwtsjk@163.com, xjcxzxy@126.com

Xin-Yan ZHANG

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Abstract. According to the problem that difficult to build accurate model of equipment due to DFIG complex operation condition and strong coupling characteristics of multi state variables , a intelligent data mining method was applied to the early fault warning and diagnosis of wind turbine equipment. The wind turbine typical operating characteristics have been analyzed and a method based on least squares support vector machine (LS-SVM) of the double fed wind turbine fault warning has been presented. Combine the history data of a wind turbine generator of unit 18 of a wind farm in Hami Xinjiang wind power line collection area, the proposed method is verified and analyzed by Matlab. The study results prove that the prediction method has high estimation accuracy, can promptly identify fault of double fed wind generator in operation, also the method is applicable to fault diagnosis of equipment of doubly fed wind generator, thus, it has certain engineering application value.

Introduction

Because of the wind turbine always works in a sparsely populated and harsh environment, frequent faults in the operation of wind turbines, and frequent maintenance of the wind farms result in higher operating costs.How to reduce the number of faults in wind power generation by intelligent monitoring methods to achieve the purpose of saving the operating costs of wind farms is the most urgent problem for wind farms. Therefore, it is of great significance to carry out intelligent method for fault warning research of wind power generator.

The operation condition of doubly fed wind power generator is complex and mutual coupling among variables are exist, so the traditional modeling method is difficult to achieve the desired results. In recent years, some fault monitoring methods have been proposed by scholars both at home and abroad. Paper [1] use Bin method to process data and obtained the new power curve by acquiring wind speed and power data from two generator, compare the operation state of wind turbine power through the difference between before and after treatment, We can come to a conclusion that the standard deviation is too large, the running state of the less stable; paper [2] aim at the fault of the yaw system and the pitch system of the wind turbine, collect the real-time data of SCADA system, and based on the power curve we establish the probability model of Copula function, then the experimental results show that we can monitor the effectiveness of the early fault; paper [3] presents a wind power generator fault diagnosis method based on RBF artificial neural network, moreover, through a lot of experiments show that this method can more effectively identify the basic typical faults of wind turbine under the same conditions; paper [4] apply Riemann manifold and the visualization of covariance matrix distribution to detect the abnormal fault of mechanical equipment, the fault of the wind turbine gearbox is taken as the experimental object to verify the diagnosis method, the result shows that this method is more reasonable and effective.

Over the years, support vector machines (SVM) have become an effective tool in nonlinear regression estimation and time series forecasting[5-6]. Based on continue to have the SVM samples of minimize the risk of retained and other characteristics, LS-SVM transform the risk function to the least square function, inequality constraints to equality constraints, and the two optimization to a set of linear equations, greatly reduce the computational complexity of the algorithm[7].

This paper presents a fault warning method for doubly fed wind power generator based on LS-SVM. Combine the historical operation data of a primary wind power generator of a wind farm in Hami Xinjiang wind line collection area, the proposed method is verified and analyzed by Matlab.

Least Squares Support Vector Machines (LSSVM) Principle

The basic principle of LSSVM the can be described as follows. Considering a training set with l data samples(x_i , y_i)($i=1,2,\cdots,l$),The input data is $x_i \in R^n$,The output data is $y_i \in R$, The linear functions in high-dimensional feature space are as follows:

$$y(x) = \omega^T \varphi(x) + b \tag{1}$$

Fitting sample set, The nonlinear mapping 5 maps the data sets from the input space to the feature space, so that the nonlinear fitting problem in the input space becomes a linear fitting problem in the high-dimensional feature space. According to the principle of structural risk minimization, considering the function complexity and the fitting error, the regression problem of the LSSVM can be expressed as a constrained optimization problem：

$$\begin{aligned} &\min \frac{1}{2}(\omega \cdot \omega) + \frac{1}{2} C \sum_{i=1}^{l} \xi_i^2 \\ &s.t. \quad y_i - \omega^T \phi(x_i) - b = \xi_i \\ &i = 1, 2, \cdots \end{aligned} \tag{2}$$

In order to solve the above optimization problem, the constrained optimization problem becomes an unconstrained optimization problem, and the Lagrange function is established:

$$L = \frac{1}{2}(\omega \cdot \omega) + \frac{1}{2} C \sum_{i=1}^{l} \xi_i^2 - \sum_{i=1}^{l} \alpha_i \left[\omega^T \phi(x_i) + b + \xi_i - y_i \right] \tag{3}$$

Formula: α_i is the Lagrange multiplier.

The derivatives of ω、b、ξ_i、α_i can be obtained respectively:

$$\begin{aligned} &\frac{\partial L}{\partial \omega} = 0 \to \omega = \sum_{i=1}^{l} \alpha_i \varphi(x_i) \\ &\frac{\partial L}{\partial b} = 0 \to \sum_{i=1}^{l} \alpha_i = 0 \\ &\frac{\partial L}{\partial \xi_i} = 0 \to \alpha_i = c \xi_i \\ &\frac{\partial L}{\partial \alpha_i} = 0 \to \omega^T \varphi(x_i) + b + \xi_i - y_i = 0 \end{aligned} \tag{4}$$

$i=1,2,\ldots,l$, Eliminated ω and ξ_i ,and the formula (4) is written in the form of a matrix:

$$\begin{bmatrix} 0 & 1^T \\ 1 & K + C^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{5}$$

Where:$Y=(y_1,y_2,\cdots,y_l)^T$; $1=(1,1,\cdots 1)^T$; $\alpha=(\alpha_1,\alpha_2,\cdots,\alpha_l)^T$; I is the unit matrix of $l \times l$;

$K_{i,j}=(\varphi(x_i)\cdot\varphi(x_j))=k(x_i, x_j)$; $k(\cdot,\cdot)$ is the kernel function. $(i,j=1,2,\cdots,l)$.

The output of the fitted function and the least squares support vector machine are:

$$f(x)=\sum_{i=1}^{l}\alpha_i k(x,x_i)+b \tag{6}$$

The number of the kernel function reflects the complexity of the model,From this aspect, radial basis kernel functions (RBF) are superior to polynomial functions and Sigmoid functions, and because of the universality of radial basis function (RBF), this study applies the support vector machines (SVM) to the Gauss kernel function, which is the most widely used radial basis function[8]:

$$K(x_i,x_j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2}\right) \tag{7}$$

Estimation of Wind Turbine Vibration by LS-SVM Model

In this study, the data of the proposed method of early warning of DFIG based on vibration detection signal LSSVM estimation is derived from the PI database of the on-line monitoring system of Xinjiang power dispatching control center of the State Grid. According to the collected real-time / historical data, the LSSVM modeling method is adopted to model the unit 18 of a wind farm unit of Hami wind line collection area, and the experimental verification is carried out.

According to the monitoring screen of PI system,in this study, 20 relative measurement points, such as wind turbine baffle opening, outlet pressure, motor-oil pressure and bearing temperature of wind turbine, were collected.In this study, the vibration velocity of the free end of No.18 wind turbine bearing is predicted.First, reduced the dimension of multiple temperature variables at the same measurement point and eliminated redundant variables.Then, the variables closely related to the vibration rate are chosen as inputs to the LSSVM model to estimate the vibration magnitude of the free end of the wind turbine bearing.In this study, correlation analysis was used to select relevant variables.In statistics, the correlation coefficient r is used to measure the intensity of the linear correlation between two variables. When x_i is not all zero, y_i is not all zero, and the correlation coefficients of the two variables are calculated as follows:

$$r=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}}=\frac{\sum_{i=1}^{n}x_i y_i-n\bar{x}\bar{y}}{\sqrt{\sum_{i=1}^{n}(x_i-n\overline{x^2})\sum_{i=1}^{n}(y_i-n\overline{y^2})}} \tag{8}$$

By calculation, the state variables associated with the vibration of the wind generator and their correlation rank are shown in table 1.

Table 1 Coefficient of correlation of state variables

Number	Parameter description	Correlation coefficient
1	Lubricating oil pressure	0.8425
2	Bearing temperature	0.6438
3	Baffle opening	0.6323
4	Outlet pressure	0.4816
5	Wind turbine current	0.2493

As shown in Table 1, this study selects lubricant oil pressure, free end bearing temperature, plate opening, and outlet pressure as inputs to the support vector machine model.

Example Analysis

Sample data selection and preprocessing

This study from the PI database to read the doubly fed wind generator of 30 days of running data from April 1, 2017 to April 30, 2017 as training data set for LS-SVM model, which includes the input pressure of lubricating oil, baffle opening degree, bearing temperature, outlet pressure, output vibration speed.

First of all, due to the different measuring point data per day is different, we need to deal with the data, taking a certain time as step length to perform data interpolation, in order to get the same time, the same amount of data data; secondly, because the different dimension of measurement points of equipment model in wind farm, and the absolute values of data from different points are very different, in order to ensure the use of nonlinear operator to measure correctly between different input vector distance of each measuring point measured values were normalized according to their extreme value, the measured value is mapped to the [0,1] range

Performance index

In this study, the average absolute percentage error e_{MAPE} and the root mean square error e_{RMSE} are used to evaluate the model. The formula is as follows:

$$e_{\mathrm{MAPE}} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{V_i - V_{pi}}{V_i}\right| \times 100 \tag{9}$$

$$e_{\mathrm{RMSE}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(V_i - V_{pi}\right)^2} \tag{10}$$

In which, V_i is actual vibration value size; V_{pi} is predict vibration value; N is sample number.

Experiment and result analysis

In order to verify the performance of LSSVM model fault prediction for doubly fed induction generator, the proposed method is evaluated by simulation experiments on Matlab platform, and neural network estimation method is used as the benchmark.

LSSVM, BP algorithm estimates the vibration speed of No. 18 doubly fed generator, as shown in Figure 1 and Figure 2.

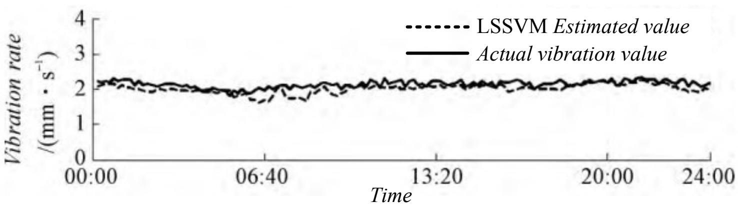

Fig. 1 Estimation of vibration speed by LS-SVM

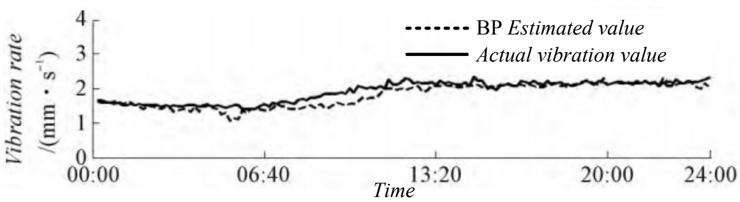

Fig. 2 Estimation of vibration speed by BP algorithm

The data were derived from operation data of wind generator No. 18 in April 1st and sampled every 10 minutes. The errors of different algorithms are compared with those shown in Table 2. It can be seen that, compared with the BP algorithm, the root mean square error is reduced by 9.86%, and the LS-SVM model estimation error is smaller, which shows that the modeling method based on LS-SVM can accurately estimate the vibration rate of doubly fed wind generator.

Table 2. Error comparison of different algorithms

Average absolute percentage error		Root-mean-square error/（%）	
LSSVM	BP	LSSVM	BP
0.0803	0.1262	12.83	22.69

When the vibration of a wind-driven generator is abnormal, the vibration intensity increases with time. At this time, the on-site monitoring personnel should pay attention to the trend of vibration changes, if the deviation continues to increase, should notify the maintenance personnel to confirm whether the wind generator is running normally, and take timely corresponding protection and maintenance measures.

Conclusion

In order to meet the safety and economical operation of wind turbines in large-scale wind generator collection area, a method of vibration fault warning for wind turbines based on LS-SVM is proposed in this paper. Through the real-time data acquisition by the field device for finding the variable sets associated with vibration of wind turbines based on linear correlation analysis, using LS-SVM to achieve real-time dynamic modeling of equipment, able to detect abnormal, and realize the fault early warning. The accuracy and effectiveness of the proposed method are verified by the simulation of a wind farm in Xinjiang, Hami.

In future work, the method proposed in this paper will continue to be improved by the data which obtained from wind power generator in operating, and the method is applied to the wind farm and other types of wind turbine, generator and hydraulic power plant generator running state analysis and fault warning. At the same time, the feature states of the incipient fault are extracted accurately, and perform the well-directed study to the identification of the degree and type of fault.

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