Fault detection of pressure sensor of blast furnace fan based on Chaos Sparrow Search Algorithm- Support vector machine regression

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Abstract: The sensor diagnosis system of the blast furnace axial fan is very important to the safety of the blast furnace fan control system. In view of the fact that the sensor fault detection of the blast furnace fan is not considered in the existing research, this paper proposes to use SVR to establish a fault detection model for the blast furnace fan outlet pressure sensor, and then use the improved chaotic sparrow algorithm to optimize the selection of the SVR penalty parameters and kernel function parameters. Find the optimal parameters. By comparing the model prediction value and the residual error of the diagnostic sensor output value, the sensor fault diagnosis is realized. When the fault is judged, the model prediction value is used instead of the fault sensor output value to be used by the blast furnace fan control system to realize the fault-tolerant control of the blast furnace fan control system. The simulation results show that this method realizes the fault detection of the pressure sensor of the blast furnace fan and improves the safety of the blast furnace production.

1. Introduction

Blast furnace axial fans are prone to surge. In order to avoid losses after surge, the fans and the motors that drive the fans must be shut down immediately, which will cause large fluctuations in the power grid and have a serious impact on the production of blast furnace steelmaking. The safety of the blast furnace fan control system relies on the accuracy of many sensors on site. Once the sensor fails, it may cause the anti-surge control system to malfunction. For this reason, fault detection, isolation and reconstruction of the sensors of the blast furnace axial flow fan are of great significance to improving the safety of the fan's anti-surge control system.

At present, the existing sensor fault detection technology has been widely studied in many fields such as aerospace, electrical machinery. The existing research has not yet conducted sensor fault diagnosis in the field of blast furnace fans. This article extends the sensor fault diagnosis technology to the field of blast furnace fans. The existing sensor fault detection methods mainly include three methods: methods based on analytical models, methods based on knowledge, and methods based on combination. Analytical model-based methods rely on the accuracy of mathematical models. The diagnosis speed of linear systems is fast, but it is difficult to establish accurate models for nonlinear models, and the model effect will inevitably decrease; The combination-based method combines the
advantages of the above two and has achieved good results. Juan-Juan Li\cite{1} first uses wavelet packet to extract the fault features, and then uses SOM neural network for fault diagnosis. Jing-Song Zhao\cite{2} of Tsinghua University combined wavelet analysis and neural network, used wavelet analysis for pre-diagnosis and screened out the sensors that may be faulty, and then used the neural network to determine whether the sensor to be diagnosed was faulty.

However, most of the existing researches propose methods for fault diagnosis and identification, and do not consider the need to repair and replace the sensor's fault data after diagnosis\cite{5}. Especially for the sensor that detects the fan operating point studied in this paper, when the fan operating point fails, the predicted value of the model can replace the fault value and be displayed on the monitoring interface to prevent the anti-surge system from starting by mistake. This article uses the correlation between the fan parameters to detect the failure of the outlet pressure sensor of the blast furnace fan. First, perform feature selection on multiple parameters that are dependent on the outlet pressure, and then input the selected parameter variable set into the support vector regression machine model after data preprocessing, and realize fault diagnosis and reconstruction. An accurate model is the key to sensor fault diagnosis. The improved sparrow algorithm is used to optimally select the parameters of the support vector regression machine, and the optimal penalty parameter c and kernel parameter g are solved, which improves the recognition rate of fault diagnosis.

2. Operating point of blast furnace fan
Axial fans are prone to surge during work. Surge will cause the blast furnace fan to stop, which will seriously affect the production of blast furnace ironmaking. It is necessary to control the blast furnace fan against surge. The operating point of the blast furnace fan shows the operating status of the fan. The anti-surge control is to monitor the operating point of the blast furnace fan to make it in a safe range, as shown in the following figure:

![Diagram](image)

Figure 1. Anti-surge control of axial flow fan

The operating point of the blast furnace fan is determined by the outlet pressure and the flow rate of the fan. When the operating point is above the anti-surge line, the anti-surge control system will be activated, and the air release valve will open to a certain degree, making the operating point return Safe place. The failure of the sensor that measures the outlet pressure and flow rate may cause the anti-surge control system to start incorrectly; for this reason, it is necessary to perform sensor failure detection on the outlet pressure and flow rate. For a steel plant, there are three throat difference sensors and one flow sensor. The literature mentions that the outlet flow is a function of the throat pressure difference \( f(\Delta p) \). It can be seen that the established outlet flow sensor fault detection model will have a high accuracy rate. It is easy to distinguish the failure of the flow sensor. For this reason, this article
mainly studies the failure detection model of the outlet pressure sensor.

3. Support vector regression machine

Support vector machine is a data mining method that replaces the principle of minimizing empirical risk in traditional machine learning methods with the principle of minimizing structural risk. Support vector regression machine is a derivative model of SVM. SVR has powerful nonlinear fitting and predictive capabilities[6].

The linear regression function can be expressed as:

\[ f(x) = w \cdot \varphi(x) + b \]  

(1)

\( \varphi(x) \) is a non-linear mapping function, \( w \) is the weight vector, \( b \) is the offset. First introduce \( \varepsilon \) linear insensitive loss function, and then because of the existence of a bit outside the interval band, slack variables are also introduced \( (\xi, \xi^*) \). The optimization problem can be expressed as:

\[
\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \\
\begin{align*}
    &y_i - (w^T x_i + b) \leq \varepsilon + \xi_i \\
    \text{s.t.} & (w^T x_i + b) - y_i \leq \varepsilon + \xi_i^* \\
    &\xi_i, \xi_i^* \geq 0, i = 1, 2, \ldots, n
\end{align*}
\]  

(2)

In the formula, \( \varepsilon \) is the insensitivity coefficient, and \( C \) is the penalty parameter. Then by introducing the Lagrange multiplier, the above problem is transformed into a dual problem, as follows:

\[
\max W(\alpha, \alpha^*) = -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) \\
K(x_i, x_j) - \varepsilon \sum_{i=1}^{n} (\alpha_i^* + \alpha_i) + \sum_{i=1}^{n} y_i (\alpha_i^* - \alpha_i^*) \\
\text{s.t.} \left\{ \begin{array}{l}
\sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0 \\
0 \leq \alpha_i, \alpha_i^* \leq C
\end{array} \right.
\]  

(3)

In the formula, \( \alpha_i \) and \( \alpha_i^* \) are Lagrange multipliers and \( K(x_i, x_j) \) are kernel functions. Here, the commonly used Gaussian kernel function with smaller deviation is used. Finally, by solving the dual problem, the regression function obtained is:

\[
f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b
\]  

(4)

4. Improved chaos sparrow optimization algorithm

4.1. Basic Sparrow Search Algorithm

The Sparrow Search Algorithm (SSA) is a new type of swarm intelligence algorithm proposed by XUE J [7] in 2019. The SSA algorithm is inspired by the foraging behavior and anti-predation behavior of sparrows in the biological world. The foraging process of sparrows can be regarded as a discoverer-adder model, and a detection and early warning mechanism is introduced. The individuals with the highest fitness value are used as discoverers, and the others as joiners. Some individuals are randomly selected as guards according to a certain proportion. The discoverers have a larger search range to be responsible for finding food, and some joiners will monitor the discoverer or even the food will be scrambled for food, and the watcher will conduct anti-predation behaviors when they find danger. The SSA algorithm updates the discoverers, joiners, and guards respectively, as follows: Discoverers with a large search range generally account for 10% to 20% of the population. The specific locations are
updated as follows:

\[ x_{i+1}^t = \begin{cases} 
    x_i^t \cdot \exp \left( \frac{-i}{\alpha \cdot \text{iter}_{\text{max}}} \right) & R_2 < ST \\
    x_i^t + Q \cdot L & R_2 \geq ST 
\end{cases} \quad (5) \]

In the formula, \( x_i^t \) represents the position of the \( i \) sparrow in the \( t \) iteration; \( \alpha \) is a random number in \((0,1)\); \( \text{iter}_{\text{max}} \) is the total number of iterations; \( R_2 \in [0,1] \) indicates the warning value; \( ST \in [0.5,1] \) indicates the safety value; \( Q \) is a random number with normal distribution. The early warning value is less than the safety value, which means that there is no predator, and the finder can search for food extensively; otherwise, the predator appears and the finder needs to move to a safe area immediately.

Taking the sparrows after the discoverer as the joiner, the position update formula is as follows:

\[ X_{i+1}^t = \begin{cases} 
    Q \cdot \exp \left( \frac{X_{\text{worst}}^t - X_{i}^t}{i^2} \right) & i > \frac{N}{2} \\
    X_{\text{best}}^t + |X_{i}^t - X_{\text{best}}^t| \cdot A^t \cdot L & i \leq \frac{N}{2} 
\end{cases} \quad (6) \]

In the formula, \( X_{\text{worst}}^t \) represents the global worst position in the previous iteration; \( X_{\text{best}}^t \) represents the best position after the discoverer updates the position.

Taking 10%-20% of the population is randomly selected as Monitor. The vigilantes can increase the global search capability of the algorithm. The specific update formula is as follows:

\[ X_{i+1}^t = \begin{cases} 
    X_{g_{\text{best}}}^t + \beta \cdot \left| X_{i}^t - X_{g_{\text{best}}}^t \right| & f_i > f_g \\
    X_{i}^t + k \cdot \left( \frac{X_{i}^t - X_{\text{worst}}^t}{f_i - f_w} + \xi \right) & f_i = f_g 
\end{cases} \quad (7) \]

In the formula, \( X_{g_{\text{best}}}^t \) represents the global optimal position; \( \beta \) is a random number that satisfies a normal distribution with a mean of 0 and a variance of 1. To prevent 0 in the denominator, \( \xi \) take \( 10E - 10 \).

### 4.2 Initialization of Chebyshev Chaos Population

The basic sparrow algorithm uses randomly initialized populations, which may lead to uneven distribution of the initialized populations, making the optimization speed slower or even falling into a local optimal solution. The chaotic variable has the characteristics of uniformity, ergodicity, and randomness. It is used to optimize the search algorithm in many studies. The chaotic mapping theory is added to the sparrow algorithm, which increases the diversity of the population and helps to jump out of the local optimum. Most of the existing researches use An mapping, Tent mapping and Logistics mapping. Studies have shown that Chebyshev mapping has better chaotic characteristics than the previous several mappings\(^8\). The function expression of Chebyshev is as follows:

\[ Y_{i+1} = \cos(k \cdot \arccos Y_i) \quad (8) \]

In the formula, \( k \) represents the order, here is 4, \( Y_i \) is a random number of \([-1,1]\), \( Y_{i+1} \) is the data after Chebyshev chaos initialization. Then use formula (9) to map the chaos to the sparrow individual. Among them, \( lb \cdot ub \) are the upper and lower boundaries of each dimension respectively.

\[ X_i = lb + (lb - ub) \cdot (Y_i + 1) \cdot 0.5 \quad (9) \]
4.3 Joiner introduces weight factor
Some joiners scrambled for food and moved towards the best overall position. This movement is jumpy, which is helpful for the convergence of the algorithm, but this mechanism is easy to make the population quickly gather near the current optimal solution in a short time, the diversity of the population is reduced, and it is easy to fall into the local optimum. In the basic sparrow algorithm, when the number of optimization parameters is 2, $A^+$ is a two-dimensional matrix composed of 0.5 or -0.5, and the moving speed of the joiner is constant; The adaptive weight factor can be introduced in the basic sparrow algorithm to add the position update of the person, so that $w$ is larger in the early stage of the iteration and gradually reduced to fully perform the global search, and in the latter stage of the iteration, $w$ is quickly reduced to perform the local search. Literature [10] introduces dynamic adaptive weight $w_1$, and literature [11] introduces cosine weight $w_2$, see formula (10) (11):

$$w_1 = \frac{e^{2(1-t/item_{max})} - e^{-2(1-t/item_{max})}}{e^{2(1-t/item_{max})} + e^{-2(1-t/item_{max})}}$$ (10)

$$w_2 = \cos(\frac{\pi \cdot t}{2 item_{max}})$$ (11)

![Figure 2. comparison of different weights](image)

The above figure shows that, compared with the dynamic adaptive weight, the cosine weight changes more slowly in the early stage of the iteration and changes faster in the later stage of the iteration. Therefore, this paper chooses the cosine weight as the weighting factor. In order to offset the influence of the numerical value, take $w = 2w_2$, and amend the position update formula of the joiner to:

$$X_i^{t+1} = \begin{cases} Q \cdot \exp \left( \frac{X_i^{t} - X_{worst}^{t}}{i^2} \right) & i > \frac{N}{2} \\ X_{best}^{t} + w \cdot \left| X_i^{t} - X_{best}^{t} \right| \cdot A^+ \cdot L & i \leq \frac{N}{2} \end{cases}$$ (12)

4.4 Improved chaotic sparrow search algorithm
The CSSA algorithm uses Chebyshev chaotic search and polynomial mutation to increase the diversity of the sparrow population, avoid falling into the local optimum, and improve the convergence speed. The specific search steps are as follows:

Step 1: Parameter settings. the maximum number of iterations $T$, the population size $N$, the
dimension $dim$ of the parameters to be optimized and the upper and lower bounds $ub, lb$, the ratio of discoverers and guards $p_1, p_2$.

Step2: population initialization. Use the Chebyshev chaotic sequence in section 3.2 to initialize the population, calculate the fitness, sort and sort, and get the best fitness and its location, as well as the worst fitness and its location.

Step3: Take the first $p_1 \cdot N$ sparrows as the discoverer, and the rest as the joiners, take the random $p_2 \cdot N$ sparrows as the guards, and update the position according to formula (5), formula (12) and formula (7).

Step4: Calculate the fitness of each sparrow after the update, and compare the fitness of each sparrow after the position change with that before the position change to obtain a better position of the sparrow itself; calculate the best position of the population and its fitness.

Step5: Adjust to Step3 until the end condition is met.

5. Axial fan outlet pressure prediction model and its sensor fault detection

5.1 Data preprocessing of blast furnace fan

For this outlet pressure sensor failure detection model, on the premise of detecting a single sensor failure, other normal sensor data is used as input, and the sensor data of outlet pressure is used as output to establish a multiple-input single-output model. The selection of feature quantities should be considered more comprehensively, and as many features as possible are selected; however, too many feature selections will increase the redundancy of the model and sacrifice the calculation time of the model[12]. In order to select better feature quantities, the Pearson correlation coefficient is introduced for feature selection, and bivariate correlation analysis $c_1$ and partial correlation $c_2$ analysis are performed in SPSS software. Among them, the partial correlation analysis is to study the closeness of the relationship between these two variables separately without considering the influence of other factors.

| Fan | Axis displacement | Number of revolutions | Inlet temperature | Valve opening | Guide vane opening | Inlet flow |
|-----|-------------------|-----------------------|-------------------|--------------|-------------------|------------|
| $C_1$ | -0.563            | 0.215                 | 0.058             | 0.592        | 0.440             | 0.427      |
| $C_2$ | -0.753            | 0.057                 | -0.546            | 0.63         | 0.282             | 0.505      |

The basic data of this article is to collect the data of a blast furnace axial fan in a steel plant. In addition to the outlet pressure, the data collected for the fans with close influence include: fan shaft displacement, fan revolutions, throat difference A, throat difference B, throat difference C, fan inlet temperature, fan inlet flow, air release valve opening ZT135, Setting of air release valve opening degree ZT136, air release valve opening degree ZT137, fan outlet temperature and guide vane opening degree. In the control system, there are three throat differences and three vent valve openings as hardware redundancy. The throat difference and the inlet flow square theoretically have a linear relationship. Take the vent valve opening ZT136 and the data of the inlet flow. In order to fully select the feature quantity, select the parameter with correlation or partial correlation greater than 0.4 as the feature quantity, but it is necessary to ensure that one of them cannot be lower than 0.1. It can be seen from Table 1 that only the number of fan revolutions in the fan data is eliminated, and the number of revolutions collected can basically be regarded as a fixed number of revolutions.

5.2 CSSA optimizes the selection of SVR optimal parameters

The accuracy of the SVR prediction model is closely related to the selection of its parameters, among which the penalty parameter $c$ and the kernel parameter $g$ have the greatest impact on it. The improved sparrow algorithm is used to optimally select the parameters of the support vector regression machine, and the optimal penalty parameter $c$ and kernel parameter $g$ are solved, and the mean square error of the trained SVR is used as the fitness function. The specific process is as shown in Figure 3:
5.3 Sensor failure detection principle

According to the strong correlation between the parameters of the blast furnace axial flow fan during the operation phase, the outlet pressure sensor to be tested is used as the output, and other parameters with strong correlation with the outlet pressure are used as the input, and the powerful fitting ability of the support vector regression machine is used to build the model. The previous work selected the optimal penalty parameter $c$ and the kernel parameter $g$ through CSSA-SVR, and substituted them into the model built above, and the offline preparation was completed. When detecting the failure of the outlet pressure sensor, input other normal sensor data as input, simulate the value $y_{\text{predict}}$ of the outlet pressure sensor, compare it with the true value of the sensor\textsuperscript{[2]}, and then judge according to the following formula:

$$\begin{align*}
\frac{|y_{\text{predict}} - y_{\text{real}}|}{y_{\text{predict}}} > \omega_p & \quad \text{Sensor failure} \\
\frac{|y_{\text{predict}} - y_{\text{real}}|}{y_{\text{predict}}} \leq \omega_p & \quad \text{No trouble}
\end{align*}$$

Take the left side of the above formula (15) as the residual rate $w_t$, $w_p$ is the threshold set by the blast furnace blower outlet pressure sensor fault detection. The setting of the threshold is extremely important, and the value should be appropriately selected according to the fitting effect of the model. After the above steps, it can be distinguished whether the outlet pressure sensor is normal disturbance or failure. The indication under normal disturbance does not undergo any processing. When a failure is detected, the predicted value is used instead of the failure value to be displayed on the monitoring interface. The specific detection principle is shown in Figure 4. The sensor failure can be detected, and the time period during which the sensor failure occurs can be detected, and the type of sensor failure can be classified according to the distribution of residual.

![Figure 3. obtain optimal parameters](image1)

![Figure 4. Principle of sensor fault diagnosis](image2)
6. Simulation and experiment

6.1 CSSA-SVR sensor fault model training and testing

Based on 4 hours of historical fan data of a blast furnace axial fan in a steel plant, the data is divided into 10 equal parts. The first 9 parts are randomly divided at a ratio of 7:3 between the training set and the test set, and the model effect is verified after the training data. The last data is used to generate the fault data set later to test the feasibility of sensor fault detection.

The simulation experiment is carried out on MATLAB2018B to build a support vector machine regression model. The parameters of the model have a great influence on the support vector machine network. The improved chaotic sparrow algorithm is used to find the optimal penalty parameters and kernel function parameters. The number of populations set by the SSA and CSSA algorithms is 50, the discoverers account for 20% of the population, the proportion of vigilant is 10%, the upper limit of the parameter is 500, the lower limit is 0.001, the maximum number of iterations is 100, and the mean square error of SVR is used. For the fitness function, the comparison chart of convergence is shown in Figure 5. It can be seen that the CSSA algorithm declines faster than the basic sparrow algorithm, and the final fitness value is better, jumping out of the local optimum. The improvement effect is shown on 30 random data in the test set. The comparison chart of the default parameters of the SVR algorithm, SSA-SVR algorithm and CSSA-SVR algorithm is shown in Figure 6. It can be seen that the CSSA-SVR algorithm has the best effect.

![Figure 5. Comparison of SSA and CSSA](image1)

![Figure 6. Comparison of relative errors](image2)

In order to verify the effect of the improved model, the average absolute percentage error (MAPE), root mean square error (RMSE) and coefficient of determination (R2) are used to evaluate the performance.

\[
MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i^* - y_i}{y_i} \right| \quad (14)
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i^* - y_i)^2} \quad (15)
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i^* - y_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2} \quad (16)
\]

In the above formula: \( n \) is the number of samples; \( y_i^* \) is the predicted value of the sample; \( y_i \) is the true value of the sample; \( \overline{y} \) is the mean value of the actual value. It can be seen from Table 2 that
the SVR model optimized by the improved Sparrow algorithm is compared with the SVR model with default parameters and the SVR model optimized by the Sparrow algorithm. The average absolute percentage error and root mean square error are smaller, and the coefficient of determination is larger. Which shows that the accuracy of the CSSA-SVR model is relatively high, and the model fit is better.

### Table 2. Comparison of prediction results of different methods

| Algorithm          | MAPE       | RMSE       | $R^2$     |
|--------------------|------------|------------|-----------|
| SVR                | 0.0014716  | 0.91996    | 0.83560   |
| SSA-SVR            | 0.0007614  | 0.49461    | 0.95743   |
| CSSA-SVR           | 0.0006938  | 0.42290    | 0.97066   |

#### 6.2 Experiment of CSSA-SVR sensor fault diagnosis model

Taking into account the problem that the sensor failure data on site is small and difficult to obtain, a sensor failure simulation experiment is carried out to obtain a failure data set, and the effect of the sensor failure real-time detection model is verified with the failure data set. Sensor faults are divided into hard faults and soft faults. Hard faults include open circuit faults and short circuit faults; soft faults include impact faults, drift faults, periodic interference faults, and bias faults. Open-circuit faults and short-circuit faults can be regarded as more serious bias faults. Therefore, this paper studies impact faults, drift faults, bias faults and periodic interference. The simulation principles of different sensor faults can be found in the literature. In order to better verify the effect of the fault detection model, the fault amplitude set below in this paper is too small. The specific simulated pressure sensor fault data set is shown in Figure 7. The failure detection principle of the outlet pressure sensor is shown in Figure 4 above. The setting of the threshold will seriously affect the accuracy of the failure detection. According to the CSSA-SVR, the average absolute percentage error is 0.0006735, which means that the prediction accuracy is much less than 1%. After a large number of random simulated faults, the faults are detected through the above model, and the normal fluctuations and sensor faults are distinguished. Finally, the fault detection threshold $w_p$ is set to 0.015, and the fault detection recognition rate reaches 98.56%.

Figure 8-12 is the residual signal change curve of the blast furnace fan detection outlet pressure sensor under five states of normal, impact, offset, drift and periodic noise. It can be seen that when the sensor has a small impact, offset, drift, and periodic noise failure, the residual has obvious changes, and it is much larger than the set residual threshold, that is, the sensor failure can be diagnosed by this method.
7. Conclusions
This paper presents a method to detect the fault of the pressure sensor at the outlet of the axial flow fan that combines CSSA and SVR models. In the design of the CSSA-SVR model, the CSSA algorithm is used to select the optimal penalty parameter $c$ and the kernel parameter $g$ in the SVR model, which solves the problem that the basic SSA algorithm is easy to fall into the local optimum and the
convergence speed is slow. SVR's prediction model of the outlet pressure of the axial flow fan. Through the collected data of the blast furnace fan monitoring system, the prediction value of the above model is compared with the measured value of the sensor, which can effectively diagnose the bias, drift, impact, periodic noise and other faults that often occur in the pressure sensor, and replace it with the predicted value after the fault is determined. The fault measurement value is displayed on the monitoring interface to ensure the normal operation of the blast furnace fan control system.

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