

Retraction

Retracted: Application of PSO Improved Algorithm in Motor Fault Diagnosis Simulation

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Shan, "Application of PSO Improved Algorithm in Motor Fault Diagnosis Simulation," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2386523, 6 pages, 2022.

Research Article

Application of PSO Improved Algorithm in Motor Fault Diagnosis Simulation

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Aiming at the shortcomings of the traditional fault diagnosis methods of electric motors, the author proposes a method based on the application of improved PSO algorithm in the simulation of motor fault diagnosis. The method optimizes the fault diagnosis method of BP neural network by adopting the adaptive mutation particle swarm algorithm. Firstly, the fault features are extracted from the response signals of the measurable points of the motor to be tested, and wavelet packet decomposition and normalization are performed to construct a sample set; then, the particle swarm improvement algorithm is used to optimize the weights and thresholds of the BP neural network, so as to realize the training and testing of the motor to be tested. In the fault diagnosis of a certain motor, it is found that the fault diagnosis time and diagnosis rate of this method are significantly improved compared with the previous ones, and the diagnosis rate reaches 99% when the center deviation range is 0.3, the efficiency of the fault diagnosis model for parameter optimization through the improved PSO algorithm is higher, and the accuracy of the diagnosis results is further improved.

1. Introduction

Motors are important energy-driven devices in contemporary production processes. It is composed of many mechanical parts and has a complex structure, and the working conditions are generally poor, working in production environments such as high temperature, strong corrosion, and high-speed operation; the working life of the motor is limited after all; it is an inevitable process from stable operation to fatigue wear and then to failure, not to mention in the above-mentioned harsh engineering operating environment [1]. The motor has been moving with a load during long-term work, and the parts of the motor will gradually age with the extension of the working time, and the deformation caused by the severe high temperature will cause the motor to fail (Figure 1), resulting in production efficiency drops. In actual production, once the motor fails, it will basically lead to the sudden termination of the work, causing irreversible damage to the motor itself and also causing changes in the internal composition; it will even become the fuse of the entire system failure, causing the entire production operation to fail, resulting in engineering accidents and

extremely large economic losses, etc.; in this regard, it is of great significance to diagnose and explore the abnormality of electrical devices [2]. Rolling bearings are the most important components in asynchronous motors, and bearings need to keep rotating at high speed all the time; at the same time, the working environment is relatively bad, so its own structure is easily damaged, and it is also the largest number of parts in the entire system. The working state of each bearing directly affects the performance of the entire motor equipment. Almost all the faults of rotating machinery are related to rolling bearings to varying degrees, according to statistics, the faults of rotating machinery are caused by 30% of the faults of rolling bearings. Compared with other mechanical parts, rolling bearings have a prominent feature, that is, their life is discrete, that is to say, the same materials, the same processing technology, the same equipment, and the same workers that process a batch of rolling bearings; their lifespans vary greatly [3]. Therefore, by analyzing the failure mechanism of the motor rolling bearing, selecting a reasonable diagnosis method to find the early failure problem, and taking corresponding countermeasures in time, the safety and reliability of the motor operation can be

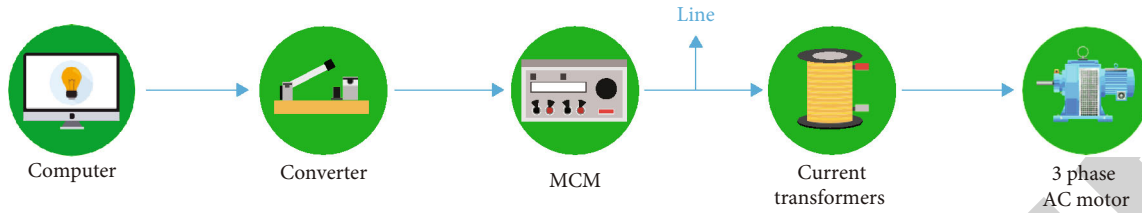


FIGURE 1: Motor failure.

ensured, thereby avoiding the occurrence of accidents and loss of life and property. On the basis of the original technology, the author improves the diagnosis method to make the analysis of motor faults clearer and more accurate, which will greatly improve the production efficiency and create huge economic benefits.

2. Literature Review

Motor fault diagnosis is based on the fault mechanism of the motor. By detecting the changes in vibration, temperature, electrical characteristics, etc. of the motor during operation, it can be judged whether the motor is in a normal operating state or whether there is a fault. Through the active research of colleagues, the theoretical method of motor fault diagnosis has been basically perfected, and a lot of experience has been accumulated over the decades, and the corresponding technology has been inherited and developed. The motor fault diagnosis process can be subdivided into three stages: signal acquisition, signal processing, and fault diagnosis. Correspondingly, these three parts have been vigorously developed through the efforts of scholars.

The research in the field of motor fault diagnosis started relatively late, but with the spirit of hard work and strong learning ability, many achievements have been achieved. Zhao Zhiguo et al. carried out fault diagnosis of dry DCT clutch brushless DC motor through dual Kalman filtering; this method adopts dual Kalman state and parameter joint estimation algorithm to effectively estimate the state and parameters of the clutch actuating motor; the potential faults of the motor that cannot be detected by the sensor can be diagnosed online in real time, which lays the foundation for the subsequent fault-tolerant control [4]. Gou Xudan et al. proposed a fault diagnosis method for rotor broken bars of induction motor based on stator current Hilbert modulus and chaotic particle swarm optimization BPNN; the method uses chaotic particle swarm optimization to optimize the weight coefficient of BPNN and improve the performance of BPNN, but this method only solves the weight initial value problem of BPNN and does not study the performance of the algorithm in the face of large data sets [5]. Zhang Fangfang et al. combined the least squares support vector machine and displacement detection to realize the fault diagnosis of the oil pump motor; this method reduces the calculation amount of the online diagnosis through sparseness, and at the same time, the fault discrimination rate and generalization ability are ensured [6]. Zhang Yapei et al. introduced the estimated value of back EMF into the stator current observation and calculation, which

improved the large jitter of the estimated value of the traditional synovial observer due to the discontinuous switching function and ensured the normal operation of the permanent magnet propulsion motor without a position sensor [7]. The large stator current when the AC motor is directly started will cause the cage winding to bear huge thermal and mechanical stress, it is easy to fatigue and fracture under strong stress, and the large starting current will also cause the deformation of the winding end and the loosening of the iron core; faults such as cage bar fracture and air gap eccentricity will be reflected by the current of the air gap magnetic field, and the stator current signal is sampled to obtain the characteristic frequency. In order to enhance the fault-tolerant performance of the five-phase motor drive system, Tian Bing et al. proposed a rotor position estimation and distribution method based on an extended observer; this method changes the previous pulse vibration high-frequency voltage injection method to track the magnetic saturation salient pole and realizes the position-free control of the five-phase motor under the single-phase open-circuit fault [8].

The author adopts the adaptive mutation to improve the particle swarm algorithm, which is to improve the inertia weight in the PSO (particle swarm algorithm), and reinitialize some variables with a certain probability, and then use the improved particle swarm algorithm to optimize the BP neural networks, and apply it to simulate motor fault diagnosis. This improvement is simple to operate, and the diagnostic effect is better [9].

3. Methods

3.1. Basic Principles of Motor Fault Diagnosis. During the operation of the motor, some structures and components will gradually deteriorate, causing the motor to appear abnormal; parameters are measured through various detection techniques; in order to identify faults, a large amount of experience must be accumulated to form a database or expert system, so as to achieve predictive maintenance without affecting production [10]. At present, the common faults of motors include two categories: mechanical faults and electrical faults.

At present, the signals collected during the operation of the motor are mostly current signals. Correspondingly, the stator current analysis method is relatively mature as a method of motor fault signal analysis. Normally, the ideal frequency of the stator current of the asynchronous motor should be the same as the frequency of the power supply, which is a single frequency [11]. The theory of some scholars

has confirmed that when the rotor circuit fails, the stator current spectrum is at a position that is twice the slip frequency ($\pm 2sf$) from the power frequency. However, the eccentricity of the air gap may cause uneven magnetic permeability along the circumferential direction of the air gap and will lead to asymmetric distribution of the magnetic field in the air gap; this asymmetric magnetic field distribution will be reflected as harmonics in the stator current. Cameron, Thomson, and Dow's research also proved that the stator current spectrum, which represents the eccentricity of the air gap, can identify this unique spectral component, and the frequency of these components is

$$f_{ag} = \left\{ (n_{rt}Z_2 \pm n_d) \frac{1-s}{p} \pm n_{ws} \right\} f_0 (HZ). \quad (1)$$

Among them, f_0 is the power frequency, $n +$ is any integer, z_2 is the number of rotor slots, s is the slip, p is the number of pole pairs, n_w is an odd integer, and na is an arbitrary integer ($na = 0$, for static eccentricity; $na = 1, 2, \dots$ for dynamic eccentricity). The current characteristic frequencies of common faults are shown in Table 1.

Nowadays, the motor structure is gradually becoming more complex, and a noninvasive signal acquisition method is required for the special determination of motor fault characteristics; in this context, the acquisition of vibration signals of motor faults gradually replaces the acquisition of current and voltage. Motor faults are often reflected in abnormal vibration, and sometimes the type of fault can be preliminarily determined by the frequency of its vibration; the following are some typical fault vibration characteristics:

- (1) Electromagnetic vibration of the stator is abnormally generated: under normal conditions, the electromagnetic vibration frequency of the stator should be the product of the rotating magnetic field frequency (f/p) multiplied by the electrodynamic series ($2p$), that is, twice the power frequency [12]. When the three-phase magnetic field of the stator is asymmetrical, the magnetic field of the stator is asymmetrical, resulting in abnormal vibration; The stator core and coil are loose, which increases the electromagnetic vibration and electromagnetic noise of the stator; in addition to the $2f$ basic component in the vibration spectrum, there are also harmonic components of $4f$, $6f$, and $8f$; the foot screws of the motor become loose, the stiffness of the frame is reduced, the motor will generate resonance in the vicinity of the frequency close to $2f$, and the vibration of the stator will increase, resulting in abnormal vibration
- (2) Electromagnetic vibration caused by the static eccentricity of the air gap: the static eccentricity of the air gap will often generate a large unilateral magnetic pulling force in the air gap of the motor, resulting in a smaller distance between the stator and the rotor or even friction with each other. The electromagnetic vibration generated by the eccentricity of the static air gap is twice the frequency of the power supply,

which is indistinguishable from the electromagnetic vibration generated by the abnormal stator [13]

- (3) Electromagnetic vibration caused by air gap dynamic eccentricity: when the rotating shaft is deflected or the iron core of the motor is not round, the air gap dynamic eccentricity will occur, and the position of the eccentricity is not fixed relative to the stator and fixed relative to the rotor. For the eccentric point, the speed of the rotating magnetic field exceeding the rotor speed is $[f/p - (1-s)f/p] * 2p = 2sf$, so the electromagnetic vibration generated is f/p frequency vibration, and $1/2sf$ is the periodic beat pulsation
- (4) Vibration caused by abnormal rotor conductor: the cage bar is broken, the electrical imbalance of the rotor circuit of the wound asynchronous motor is caused, and its properties are the same as the eccentricity of the dynamic air gap; the vibration waveforms are also similar and difficult to distinguish. When the load exceeds 50%, the phenomenon is obvious; in the spectrum diagram, the side frequency of $+2sf$ will appear on both sides of the fundamental frequency; according to the relationship between the side frequency and the fundamental frequency amplitude, the degree of the fault can be effectively judged [14]

Fault diagnosis (FD) is called condition monitoring and fault diagnosis (CMFD); it can lead to system malfunction, and this degraded state of the system is called failure. The purpose of fault diagnosis technology is to judge the system state according to the monitoring characteristic information, guide production, improve production efficiency, and stabilize production operation status. In a complex system, if a key device cannot continue to operate due to failure, it often affects the entire system and causes huge losses. Therefore, fault diagnosis technology is one of the key technologies for the safe and reliable operation of complex industrial processes and equipment and has extremely important research significance. The current fault diagnosis methods mainly include the following three categories: (1) fault diagnosis methods based on mathematical models, (2) fault diagnosis methods based on signal processing, and (3) fault diagnosis methods based on artificial intelligence [15].

- (1) Method of strong tracking filter: this method is mainly developed on the basis of the theory of strong tracking filter and is a highly systematic parameter deviation fault diagnosis method. The method can diagnose step-type, slow-drift-type, and even pulse-type faults. This method can even be combined with nonlinear suboptimal Gaussian filtering, realize the online estimation of the fault amplitude of the nonlinear system, and it creates conditions for further realizing fault-tolerant control [16]
- (2) The method of parameter tracking adaptive observer: this method abstracts the state equation

TABLE 1: Common fault current characteristic frequencies.

Dpart	Eigen frequency	Remark
Stator	$[n \pm 2k(1-s)]f_0, k = 1, 2, 3 \dots, n = 0, 1, 2 \dots$	Short circuit between stator turns
Rotor	$(1 \pm 2ks)f_0, k = 1, 2, 3 \dots$	Broken rotor bars and end rings
Bearing	$f_0 \pm mf$	Bearing failure

of the dynamic system and observes it and obtains the corresponding state deviation equation and system deviation equation. This method designs an adaptive parameter tracking observer, which makes the observer tracking insensitive to noise; the state of the actual object can be well estimated, and the system fault diagnosis can be carried out by generating the state and system residuals

3.2. Improvement and Application of PSO Algorithm. Particle swarm optimization provides a general framework for solving complex system optimization problems; it does not depend on the specific domain of the problem; it has strong adaptability to the types of problems, so it is widely used in many disciplines.

Although the particle swarm optimization algorithm has the advantages of fast convergence speed, few parameters to be set, and strong versatility, it still has shortcomings such as easy to fall into premature convergence, low search accuracy, and low iteration efficiency in the later stage; therefore, a variety of improved algorithms for particle swarm optimization have emerged. The author makes improvements in two aspects [17].

- (1) For inertia weights, if linearly decreasing weights are used, that is, linearly decreasing from a larger initial weight to another smaller value, the author adopts the adaptive weight method that is adjusted according to the global optimal point; it is to associate the magnitude of the inertia weight with its distance from the global optimum. The calculation formula used is

$$\omega = \begin{cases} \omega_{\min} - \frac{(\omega_{\max} - \omega_{\min})(f - f_{\min})}{f_{\text{avg}} - f_{\min}}, & f \leq f_{\text{avg}} \\ \omega_{\max}, & f > f_{\text{avg}} \end{cases}. \quad (2)$$

In the formula, f is the current real-time fitness value of the particle; f_{avg} and f_{\min} are the average and minimum values of all particles, respectively. That is to say, when the particle fitness value is relatively concentrated, the inertia weight is increased accordingly; and when the fitness value differs greatly, the inertia weight is correspondingly reduced; this achieves the purpose of quickly finding the global optimum.

- (2) The crossover mutation operation is introduced to improve the particle swarm algorithm. Adaptive

TABLE 2: Some parameters of the faulty platform.

Parameter	Value
Rotating speed	25HZ
Sampling frequency	1 2000HZ
Accelerometer type	IEPA
Accelerometer model	4534-B
DE	Data collected by the drive-side accelerometer
FE	The data collected by the fan-side accelerometer

mutation is an operation method used to imitate the mutation situation in the biological world; that is, the cross-mutation operation is introduced in PSO, that is, for some variables, for example, the position of the particle is re-initialized with a certain probability; this crossover mutation operation is actually based on the operation in the genetic algorithm, which is relatively simple and easy to implement [18]. The specific method is to first perform individual mutation according to the individual properties, and then cross over to obtain new particles. Its calculation formula is

$$x_n = px_{m1} + (1-p)x_{m2}, \quad (3)$$

$$v_n = \frac{v_{m1} + v_{m2}}{|v_{m1} + v_{m2}|} |v_{m2}|. \quad (4)$$

In the formula, x_n and v_n are the position and velocity of the child particle, respectively; x_m and v_m are the position and velocity of the parent particle, respectively; p is the probability of crossover variation [19]. Therefore, the introduction of the adaptive mutation operation broadens the population search space that is constantly shrinking in the iteration; this allows the particle to jump out of the previously searched optimal value position; the search is carried out in a wider space while maintaining the diversity of the population and increasing the possibility of the algorithm finding better values in the iterative optimization process.

4. Experimental Analysis

First, the standard PSO algorithm is used to optimize the parameters of the LSSVM classifier; the initial parameter settings of the standard PSO algorithm have a great influence on the optimization effect; relatively accurate parameter settings can increase the convergence speed of the particle

TABLE 3: Acceleration coefficient comparison parameter setting.

Numbering	1	2	3	4	5	6
c_1	1.4	1.6	1.05	0.5	1.5	3.05
c_2	1	3.0	2.05	1.5	0.5	2.05

TABLE 4: Comparative analysis of diagnostic results before and after optimization.

Network structure type	Training steps	Diagnosis rate of neural network with different center deviation values/%		
		Center value 0.1	Center value 0.2	Center value 0.3
Before improvement	641	89.0	95.2	96.7
After improvement	236	91.4	97.1	99.0

swarm, avoid too long particle evolution algebra, and allow particles to achieve a higher fitness in a short time, so as to obtain more suitable LSSVM penalty factors and kernel parameters and improve the accuracy of failure mode recognition [20]. Generally, the parameters of the PSO algorithm are set: the total number of particles $m = 20$, inertial weight $\omega = 1$, and evolution termination condition $T_{\max} = 100$. The value interval of the particle pair penalty factor γ is $[0, 1000]$, and the value interval of the RBF kernel parameter σ^2 is $[0, 1000]$. In order to find other suitable PSO parameters, it is necessary to carry out simulation comparison analysis. The experimental platform parameters are given in Table 2.

The acceleration coefficients c_1 and c_2 in the PSO algorithm can control the particle to approach the optimal particle position in the group or field; it can also play a balancing role for local search and global search capabilities [21]. Design experiments for the acceleration coefficients c_1 and c_2 in the standard PSO algorithm; the 6 groups of different c_1 and c_2 values are randomly selected for simulation comparison and analysis to obtain appropriate acceleration coefficients c_1 and c_2 . The 6 groups c_1 and c_2 values are shown in Table 3.

Since the output of the neural network is not absolute 0 and 1, it is necessary to perform threshold processing on the output data. When the center deviation range is 0.3, that is, the value in the range of $[0, 0.3]$ is 0, the value in the range $[0.7, 1]$ is 1. 30 groups (210) can be obtained, and only 2 of the test samples were wrong, so the diagnostic rate was 99.0%. The simulation results obtained by optimizing the BP neural network before and after the particle swarm improvement are compared as shown in Table 4.

It can be seen from Table 4 that, under the same network structure and fault feature vector, the analog circuit fault diagnosis of the BP neural network optimized by the improved particle swarm algorithm has fewer training steps than the previous improvement, and the diagnosis rate has also been improved accordingly, which shows the effectiveness of the method [22].

It can be observed from the fitness curve in Figure 2 that the improved PSO parameter optimization method based on SA hybrid has better effect; the particle swarm optimization speed becomes faster, around the 18th generation, and the average number of iterations of the standard particle swarm

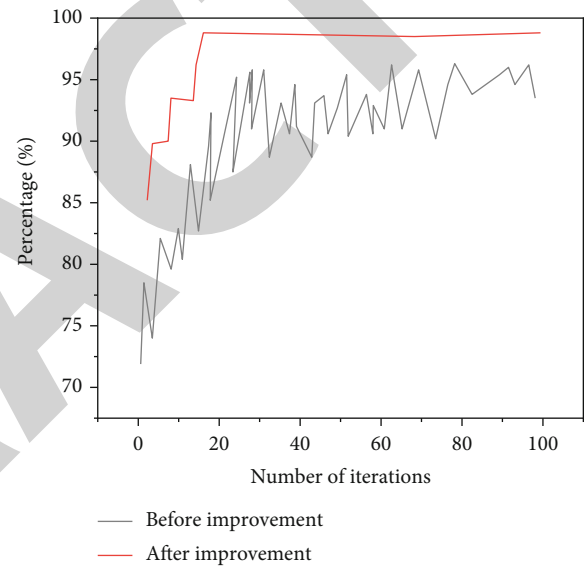


FIGURE 2: PSO-based particle fitness curve.

is 25, which reduces the time of the optimization algorithm from more than 20 seconds to 10.43 seconds and improves the diagnosis efficiency; it can be seen that the diagnosis accuracy rate has increased to 98.75%, and the number of misdiagnoses is only for 4.

5. Conclusion

When using the standard particle swarm algorithm for fault diagnosis, it is easy to fall into premature convergence, the search accuracy is not very high, and the global optimal value cannot be searched. The author chooses to optimize the weights and thresholds of the neural network through the adaptive mutation particle swarm optimization. Compared with before the improvement, the generalization ability of the BP network is enhanced, which not only reduces the number of training steps, but also improves the accuracy of fault diagnosis. The author has few types of fault diagnosis for motors, and it is not possible to diagnose every type of fault; however, in the process of using motors, faults are often not so single and ideal; therefore, the focus of scientific

research in the next part is to engage in the research of algorithm methods with higher practical value according to the needs of actual production activities and at the same time to further improve the efficiency of diagnosis.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he/she has no conflicts of interest.

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