Transformer fault diagnosis based on Improved Particle Swarm Optimization to support Vector Machine

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Abstract. Power transformer fault diagnosis exerts a vital part in the safe operation of power system. The PSO-SVM based on transformer fault diagnosis still has some shortcomings, such as slow convergence speed and easy to fall into local optimization. This dissertation proposes a transformer diagnosis method based on Improve Particle Swarm Optimization to support Vector Machine (MPSO-SVM). Adding disturbance to Particle swarm optimization (PSO) to disturb the position of such "precocious" particles, so as to get rid of local optimum. The case analysis represents that the diagnostic accuracy of MPSO-SVM is higher than that of PSO-SVM and Generalized Regression Neural Network (GRNN), and MPSO-SVM can effectively promote the fault diagnosis performance of transformer.

1. Introduction
Power transformers, a kind of facility that remains crucial in electric system, must operate safely and stably or otherwise electricity generation and transmission are beyond possibility. Economic loss arising from transformer faults cannot be underestimated. In consequence, quick and accurate diagnosis of transformer faults is indispensable [1-2].

Faults occurring in oil-immersed transformers, whose insulating oil contains a variety of different hydrocarbon molecules, can be detected through analyzing hydrocarbon gases including hydrogen, methane, ethane, ethylene, and acetylene, which dissolve in insulating oil once any fault occurs. Dissolved Gas Analysis (DGA)[3], one of the essential methods used for transformer fault diagnosis in the early days, can identify potential faults to a certain extent, appearing remarkably effective. Currently DGA-based diagnosis methods encompass several ones recommended by International Electrotechnical Commission (IEC) ranging from three-ratio method to improved three-ratio method[4], the latter of which, nonetheless, has some defects[5] comprising incomplete codes, excessively absolute boundary of codes, and uselessness in diagnosis of multiple faults. To minimize the diagnosis error that appears big in previous traditional methods, researchers have put forward DGA-based artificial intelligence algorithms containing Fuzzy Theory, Artificial Neural Network, Probabilistic Neural Network, Support Vector Machine (SVM), and Expert System [6-10,22]. Unfortunately, the aforesaid algorithms still have their own problems to resolve. Artificial neural network relies on a large number of sample data, expert system has limited knowledge base, and fuzzy theory does not apply to complex systems since it is far less systematic than expected. Therefore, this paper concentrates on SVM applicable for small samples and nonlinear problems

SVM is a machine learning algorithm that is established on the basis of statistical learning theory [11]. It features a high degree of generalization, allowing small samples, local extreme points and non-linear issues to be well handled, which helps it secure a place in transformer fault diagnosis. SVM also has its
own drawbacks, including difficulty in determining kernel parameter and low accuracy of fault diagnosis. For that reason, researchers are dedicated to optimizing kernel parameter options in SVM through optimization algorithms. Zheng Hanbo et al.[12] applied Particle Swarm Optimization (PSO) algorithm to optimize kernel function parameter $\sigma$ and penalty parameter $C$ in Least Square Support Vector Machine (LS-SVM), and enhanced the generalization performance of diagnosis models through cross validation; Jia Lijing et al.[13] focused on strengthening search capability of SVM through Differential Evolution algorithm (DE), which significantly improved the selection efficiency of SVM parameter. Among the increasing optimization algorithms are traditional ones whose diagnosis accuracy still has a plenty of room to improve due to their inherent defects. Huang Xinyi et al.[14] refined Grey Wolf Optimizer (GWO), which is in turn used to improve SVM, by utilizing DE to eliminate the problem of local optimization, contributing to a higher accuracy of transformer fault diagnosis; Min Yaqi et al.[15] proposed a diagnosis method based on PSO-optimized SVM, and Improved Particle Swarm Optimization (MPSO) through Simulated Annealing algorithm (SA) that is characteristic of error tolerance in probability, leaving optimization search no longer stuck in local area.

This study, concentrating on the “premature” convergence of PSO particle, maintains that perturbation methods can be used in PSO to perturb the position of such “premature” particle, which will get rid of local optimization. In this case, algorithm performance will be enhanced due to a more diversified population. Simulation is performed to verify the model built based on MPSO-SVM. It is demonstrated that MPSO-SVM furnishes a fault diagnosis method superior in accuracy in comparison with that based on PSO-SVM and Generalized Regression Neural Network (GRNN).

2. Basic Theory of SVM

SVM [11,16,18] is initially a binary linear classifier that identifies in two-dimensional space the optimal hyperplane that can perfectly divide any two kinds of samples. Its discriminative model is

$$f(x) = \text{sgn}(\omega^T x + b)$$

(1)

Wherein $\omega$ represents weight vector and $b$ represents deviation.

In this paper SVM is adopted in transformer fault diagnosis to deal with non-linear and multi-class matters, so the relaxation factor $\xi_i \geq 0$ is introduced to allow a slight error during classification, help threshold value extend its range of error tolerance, and form a soft margin classifier:

$$\begin{align*}
\min & \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{N} \xi_i \\
\text{s.t.} & y_i(\omega^T x_i + b) \geq 1 - \xi_i
\end{align*}$$

(2)

wherein $C$ signifies penalty factor. Lagrange multiplier $\lambda_i$ is simultaneously introduced to convert the original problem subject to constraints to a simple dual problem, namely

$$\begin{align*}
\min & \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \lambda_i \lambda_j y_i y_j \langle x_i, x_j \rangle - \sum_{i=1}^{N} \lambda_i \\
\text{s.t.} & 0 \leq \lambda_i \leq C, i = 1, 2, \ldots, n
\end{align*}$$

(3)

According to Karush-Kuhn-Tucker (KKT) conditions, the following formula must be satisfied:

$$\begin{align*}
\frac{\partial f}{\partial \omega} = 0; \frac{\partial f}{\partial b} = 0; \frac{\partial f}{\partial \lambda_i} = 0 \\
\lambda_i [1 - y_i (\omega^T x_i + b) - \xi_i] = 0 \\
1 - y_i (\omega^T x_i + b) - \xi_i \leq 0
\end{align*}$$

(4)

This formula shows that there are some cases where $\lambda_i \neq 0$. The optimum value of $\omega$ and $b$ can be obtained by solving the above partial derivative.
A decision function of classification can be obtained by plugging Formula (5) \( \omega^* \) into Formula (1):

\[
f(x) = \text{sgn}\left(\sum_{i=1}^{N} \lambda_i y_i K(x_i, x) + b^*\right)
\]

Wherein \( K(x_i, x_j) = \varphi^T(x_i)\varphi(x_j) \) is a kernel function, which in this paper specifically refers to radial basis function (RBF) that, possessing a sole parameter \( \sigma \), performs well in resisting interference and dealing with small samples, and has a high degree of generalization.

\[
K(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right)
\]

To attain the optimal penalty factor Best \( C \) and kernel parameter Best \( g \), this paper optimizes \( C \) and \( \sigma \) by utilizing MPSO which is based on perturbation method.

### 3. Improved PSO

#### 3.1. Basic theory of PSO

PSO [17,20] is a swarm intelligent optimization algorithm proposed by James Kennedy and Russell Eberhart in 1995. It, though similar to genetic algorithm (GA) which also searches the optimal solution through iteration of swarm, searches surrounding region of the optimal particle without involving the evolution process that exists in GA.

PSO is inspired by bird foraging pattern and social activities. Humans normally make their decisions based both on their own experience and that learned from others. The same holds true to a bird flock, each of which accumulates their own experience and also learns from others in the same flock, so that all of them can locate the optimal site of food source. PSO algorithm searches the optimal solution with the help of collaboration and information shared between each individual in the swarm. Specifically speaking, each individual has its velocity and position updated during each iteration through Pbest and Gbest. The concrete formulas used for adjusting are as shown below:

\[
v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1(P_{id}^t - x_{id}^t) + c_2 r_2(P_{gd}^t - x_{id}^t)
\]

\[
x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1}
\]

wherein \( v_{id}^t \) represents the velocity of particle generation \( t \); \( r_1 \) and \( r_2 \) are two random numbers ranging from 0 to 1; \( x_{id}^t \) represents the current position of particle generation \( t \); \( c_1 \) and \( c_2 \) are two learning factors, both of which normally equal 2; \( \omega \) is a inertia factor indicating inertia weight that can extend search-space; \( P_{id} \) signifies Pbest; \( P_{gd} \) represents Gbest.

#### 3.2. MPSO principle and method of improvement

Despite the fact that PSO requires less parameters and possesses not so difficult a principle as other optimization algorithms, information exchanged between PSO particles during iteration tends to be homogeneous, intensifying the clustering of particle swarms and gradually decreasing global search capability. If particles fail to shift to global area from local when searching the optimal solution, local optimization is hard to avoid.

To tackle the aforesaid weakness, this paper puts forward MPSO based on method of perturbation. The approach is to perturb the flying position of PSO particles during iteration by modifying the formula of position updating so that particles stuck in local search can get rid swiftly, leaving particles of PSO
more diversified and the search for global optima possible. The specific method to realize is as follows:
- Generating initial particle and initial velocity, and randomly generate population and velocity before calculating initial fitness;
- Identifying the extreme value and extreme point;
- Calculating the average fitness of each generation of population;
- Searching for the optimal solution through iteration, updating velocity and population, modifying the formula of position updating, setting up the period of variation $T$, and then perturbing the very position of the particle by utilizing modified formula at the time when iterative times reach $nT$, which helps the particle get rid of local optimum and maintains population diversity in the later period of iteration. The specific formula is:

$$x_{id}^t = \begin{cases} 
  x_{id}^{t-1} + v_{id}^t & t \neq nT \\
  x_{id}^{t-1}[1 + A(0.5 - \text{rand})] & t = nT
\end{cases} \quad (10)$$

Wherein $A$ is the coefficient of variation; $n = 1, 2, \cdots$; controls the range of variation; $T$ represents the period of variation ($T < $ the maximum iteration period $t_{\text{max}}$); rand represents random number evenly distributed in the range of 0 to 1;
- Constantly updating $P_{\text{best}}$ and $G_{\text{best}}$ in the entire process of iteration through variation and perturbation added in Formula (10) until the end;
- Finishing optimization search, obtaining $\text{Best } C$ and $\text{Best } g$, and training SVM with the resulting optimal parameter.

4. Transformer Fault Diagnosis Based on MPSO-Optimized SVM

This part expounds the process of transformer fault diagnosis based on MPSO-optimized SVM, which contains the following four steps illustrated in the flow chart as shown in Figure 1.

4.1. Data pre-processing

Data used to evaluate transformer faults principally refer to several gases, namely $H_2$, $CH_4$, $C_2H_6$, $C_2H_4$, and $C_2H_2$, which are required to be normalized in accordance with the following formula due to their disparity in value:

$$x_i^* = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (11)$$

Wherein $i = 1, 2, \cdots, 5$; $x_i^*$ is the fault data yielded after normalization processing; $x_i$ is the original fault data; $x_{\text{max}}$ is the maximum value in $x_i$; $x_{\text{min}}$ is the minimum value in $x_i$. 

![Figure 1. The flowchart of Fault diagnosis based on MPSO-SVM algorithm](image-url)
4.2. Classification of faults and samples

This paper classifies transformer faults in accordance with specifications in IEC60599 and the data obtained into six categories of state, namely partial discharge (PD), low-energy discharge (D\textsubscript{1}), low temperature overheating (T\textsubscript{1}), medium temperature overheating (T\textsubscript{2}), high energy discharge (D\textsubscript{2}) and high temperature overheating (T\textsubscript{3}).

The sample of fault data is divided by a fixed proportion into training set and test set pertaining to each fault type, among which the training set totals 61, accounting for 61/10 of the aggregate data, and the test set totals 40, accounting for 41/10. They are assigned specifically as shown in Table 1.

Table 1. Sample classification table

| Fault type | D\textsubscript{1} | T\textsubscript{1} | D\textsubscript{2} | T\textsubscript{2} | PD | T\textsubscript{3} |
|------------|----------------|----------------|----------------|----------------|----|----------------|
| Training set | 8             | 7             | 9             | 12            | 8  | 17            |
| Test set    | 4             | 5             | 7             | 7             | 6  | 11            |

4.3. Search process for the optimal parameter

Particle position undergoes perturbation as opposed to that before the last iteration due to MPSO which exerts variation and perturbation on the particle that is updating its population through iteration. In doing so, the constant updating of P\textit{best} and G\textit{best} thanks to the expelled particle from local optimization enables the algorithm to strengthen its capability of global optimization, eventually outputting the optimal parameter for SVM.

4.4. Fault diagnosis

Number and classify DGA-based transformer fault data in accordance with fault categories, build a model based on resulting data using the simulation tool MATLAB, debug the simulation model, output fault diagnosis categories through MATLAB, train the accuracy, and then test the accuracy, optimal parameter, and parameter relationship diagram.

5. Example Analysis

5.1. Simulation analysis of test functions

To check its performance, this paper compares MPSO with GA and PSO, and conducts a simulation test by utilizing the four typical functions as shown in Table 2. Population size of the three optimization algorithms stands at 30, while the maximum number of iterations is set to 500.

Table 2. Typical test function

| Name   | Function | Range    | \( f_{\text{min}} \) |
|--------|----------|----------|-----------------------|
| Schwefel | \( F_1(x) = \sum_{j=1}^{n} \left( \sum_{j=1}^{m} x_j^2 \right)^{1/2} \) | [-100,100] | 0 |
| Ackley  | \( F_2(x) = -20 \exp \left\{ -0.2 \sqrt{\frac{1}{n} \sum_{j=1}^{m} x_j^2} - \exp \left\{ \frac{1}{m} \sum_{j=1}^{m} \cos (2\pi x_j) \right\} + 20 + e \} \) | [-32,32] | 0 |
| Rosenbrock | \( F_3(x) = \sum_{j=1}^{n-1} \left[ 100 \left( x_{j+1} - x_j^2 \right)^2 + (x_j - 1)^2 \right] \) | [-30,30] | 0 |
| Quartic | \( F_4(x) = \sum_{j=1}^{n} x_j^4 + rand(0,1) \) | [-100,100] | 0 |
It can be observed from Figure 2 that PSO and GA are apt to get stuck in local optimization, and their excessively smooth fitness curves during iteration signifies a poor convergence; conversely, MPSO algorithm exerts variation and perturbation on any “premature” particle when updating population, which prevents the particle from being stuck in local optimization, leaving its fitness curve with a higher peak and strong convergence. Figure 2 (a) demonstrates that MPSO, unlike PSO and GA, can identify and constantly update the optimal fitness value, appearing noticeable in optimization; it can be inferred from Figure 2 (b), (c) and (d) that the ever-changing iterative curve of MPSO arises from the improvement of convergence accuracy when “premature” particle gets into the best state of optimization search after jumping out local optimum, where the functions $F_2$, $F_3$, $F_4$ has been stuck in, through variation and perturbation continuously imposed during iteration. Simulation analysis proves that MPSO is superior both to PSO and GA.

5.2. Result and analysis of transformer fault diagnosis
Simulate the three algorithms of MPSO-SVM, PSO-SVM, and GRNN based on the 101 sets of transformer fault data that have been clearly concluded, compare and analyze the simulation result, and draw an accurate conclusion.

With regard to MPSO-SVM algorithm, the parameter is chosen in the range $g \in [10^{-3}, 10^3]$ and $C \in [10^{-3}, 10^3]$, the maximum number of iterations is set to 200, the population size stands at 30, $V = 5$, $V_{MAX} = 10$, $\omega = 1$, $c1 = c2 = 1.5$, the coefficient of variation $A = 1$, and the period of variation $T = 5$.

Simulation by using PSO-SVM is conducted based on the 61 sets of normalized training data pertaining to transformer faults and 40 sets of test data. The optimized parameter and the accuracy of training and test sets are as shown in Table 3.

| Number | Best $C$ | Best $g$ | Training accuracy | Test accuracy |
|--------|----------|----------|--------------------|--------------|
| 1      | 239.0401 | 86.0807  | 98.361% (60/61)    | 77.5% (31/40) |
| 2      | 239.2028 | 85.6349  | 98.364% (60/61)    | 77.5% (31/40) |
| 3      | 239.0571 | 86.0054  | 98.364% (60/61)    | 77.5% (31/40) |
| 4      | 713.8963 | 136.592  | 100% (61/61)       | 75% (30/40)   |
| 5      | 239.0938 | 85.8657  | 98.361% (60/61)    | 77.5% (31/40) |

PSO particle tends to be stuck in local optimization search, preventing simulation accuracy of PSO-SVM algorithm from reaching a higher level than around 80%. The results in Table 3 obtained after five simulations show that the diagnosis accuracy in four times simply reaches 77.5% due to PSO’s failure to get rid of local optimum, and the other is even lower owing to the trouble of particle’s initial position, standing at 75%.

The variation and perturbation in MPSO-SVM algorithm allow particle undergoing iteration to get rid of local optimization search so as to generate an optimized SVM parameter, which is as shown in Table 4 along with the accuracy of training and test sets. The diagnosis accuracy of MPSO-SVM algorithm exceeds 80% in all the simulations, among which three times show an accuracy of 85% and...
the other two 87.5%. A high accuracy must be ensured in this algorithm, while a certain degree of
generalization is also required. That is why the training accuracy in MPSO-SVM is not sufficiently high.

### Table 4. Classification accuracy of MPSO-SVM

| Number | Best C | Best g | Training accuracy | Test accuracy |
|--------|--------|--------|-------------------|---------------|
| 1      | 210.8976 | 50.3585 | 96.721% (59/61)   | 82.5% (33/40) |
| 2      | 188.8901 | 48.9908 | 95.082% (58/61)   | 85% (34/40)   |
| 3      | 197.8235 | 48.6151 | 95.082% (58/61)   | 87.5% (35/40) |
| 4      | 452.8392 | 8.6901  | 93.443% (57/61)   | 85% (34/40)   |
| 5      | 870.1354 | 7.2347  | 93.443% (57/61)   | 87.5% (35/40) |

An effective analysis of the diagnosis performance is beyond possibility simply based on the rate of
fault diagnosis and the optimal parameter displayed in Table 3 and 4. Nevertheless, a better simulation
result is possible by comparing Figure 3 and 4, which explicitly highlight misclassified samples in the
six categories of sample data. The corresponding fault category of each number is as shown in Table 5.

Figure 3 shows that nine misclassifications occur in PSO-SVM algorithm, none of which appear in
the sample of category 1, while one appears in each of the category 2, 3 and 4, followed by category 5
and 6, which contain three incorrect classifications respectively. In other words, misclassifications in
low-energy and high-energy discharge outnumber those in other faults, whereas less occur in the fault of
partial discharge and overheating. Simulation results indicate that PSO-SVM is by no means to reach as
high a rate of fault diagnosis as expected and its diagnosis accuracy requires further improvement.

In Figure 4 MPSO-SVM algorithm is used for fault diagnosis, the result of which contains five
mistakes in classification in comparison with the actual faults. Sample 3, 4 and 6 include one
respectively, sample 5 has the most, including 2, and none appears in sample 1 and 2. Basically incorrect
classifications are evenly distributed, with one occurring in each sample. Accuracy is significantly
enhanced in comparison with that of PSO-SVM. Nonetheless, given the homogeneous data in the
diagnosis result arising from fluctuations existing in both PSO-SVM and MPSO-SVM, this paper
introduces fitness curve to analysis process as shown in Figure 5 and 6, to further validate
MPSO-SVM’s performance of optimization search and highlight its advantages:
It can be observed from Figure 5 and 6 that, the data, parameter and iterations being equal, MPSO-SVM iterates six times, during which its particle immediately jumps out when stuck in local optimum in the fifth generation and fitness value peaks in the sixth with a high convergence speed and large value; in contrast, the fitness curve of PSO-SVM changes once in the 100th generation due to algorithm defect, and starts to converge until the 105th generation with a low speed and small value.

Table 6 presents a comparative analysis of the simulation results obtained by using the three algorithms. When five DGA gases are input and smoothing parameter is set to 0.02 in simulation based on the same data by using GRNN, six fault states are output and the rate of fault diagnosis stands at 75%; in the simulation test conducted using PSO-SVM the rate of fault diagnosis stands at 77.5%; the diagnosis accuracy of MPSO-SVM is 87.5%, proving that accuracy of the improved algorithm is greatly enhanced.

6. Conclusion
This paper draws the following conclusions pertaining to the fault diagnosis method based on PSO-SVM that is proposed to eliminate PSO’s drawback of local optimization tendency and enhance the accuracy of transformer fault diagnosis:

- The algorithm suggested in this paper can diagnose transformer faults more accurately and effectively in comparison to PSO-SVM and GRNN;
- PSO possesses the drawbacks that it tends to be stuck in local optimization search and appears unstable, while GRNN fails to perform accurate diagnosis in terms of small number of sample data;
- IPSO proves more effective and superior thanks to its higher stability, convergence speed, performance of optimization search, and accuracy compared with PSO.

The upcoming research will continue to refine the optimization algorithm so that complex data can be diagnosed accurately and stably. This algorithm applies not only to transformer fault diagnosis but to other fields.

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