Research of condition based maintenance evaluation model for the on-post vacuum circuit breaker on least squares support vector machine based on particle swarm optimization algorithm

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Abstract:-With the connections between the safe operation and national economy development getting closer, the original scheduled maintenance has been unable to adapt to the current demand for electricity. The condition-based maintenance, which is an immediate and effective maintenance mode for supply equipment, achieves supply companies general concern. This paper aims at the existing problems in on-post vacuum circuit breaker, builds the device status and risk assessment index system based on actual situation, and proposes on-post vacuum circuit breaker condition-based maintenance overhaul which based on particle swarm optimization and least squares support vector machine. This paper collects 100 box transformer substation data from distribution network in a power company to do empirical analysis, the mean absolute percentage error and mean square error is 0.1296% and 0.0716, respectively. Thus, this method has high accuracy and good generalization ability, which can be applied to the evaluation of condition-based maintenance.

Key-Words: -Condition-based maintenance; On-post vacuum circuit breaker; Particle swarm optimization; Least squares support vector machine; Comprehensive evaluation

1 Introduction

With the improvement of power supply enterprise technical level and organizational capacity, the transition from regular preventive maintenance to predictability of condition-based maintenance becomes possible. Equipment condition-based maintenance is a reliability centered maintenance mode, which plays an important role in improving the reliability of the power grid, saving maintenance costs, increasing the supply of time and electricity and improving power quality of service. Currently, equipment condition-based maintenance mainly composes seven aspects, which are information gathering equipment, equipment status evaluation, risk assessment, maintenance strategies, maintenance scheduling, maintenance implementation and performance evaluation. The problems of lacking timeliness and accuracy in equipment condition-based evaluation lead to difficulty in carrying out risk assessments [1]. Therefore, evaluation of equipment status becomes a short-coming for power supply enterprises in carrying out equipment condition-based maintenance, which need to focus on [2].

Aiming at the problem in equipment condition-based maintenance, this paper follows a systematic, integrity and quantifiable indicators of system construction principles. After combining the relevant national standards and provincial standards with expert opinions and analyzing the various factors which affecting the status of the device and device data which can be accurately monitored, this paper constructs an evaluation system of on-post vacuum circuit breaker overhaul. Referring to the current evaluation theory and advanced intelligent model and combining with the state of power supply enterprise maintenance need, this paper proposes particle swarm optimization-least squares support vector machine (PSO-LSSVM) algorithm to apply least squares support vector machine (LSSVM) into comprehensive evaluation of on-post vacuum circuit breaker maintenance, thus shows the advantage of LSVVM in solving small sample and nonlinear problems. The use of particle swarm optimization (PSO) algorithm in optimizing regularization parameters and kernel width of LSSVM improves generalization ability of LSSVM. Examples of this algorithm can verify the effective application of the comprehensive evaluation of on-post vacuum circuit breaker maintenance.

2 Evaluation index system

Constructing a set of scientific and improved evaluation index system is a significant premise of evaluating equipment condition and risk evaluation and the base of making comprehensive evaluation. On the characteristics of the on-post vacuum circuit breaker, this paper builds an index system, which is shown in Table 1, consisting technical parameter, operation security, protective function and reliability through analyzing various affecting factors of the equipment condition and risk [3].

Table 1. Equipment condition evaluation index system

First-grade indexes	Second-grade indexes
Technical parameter indexes	Switch in/on position indication P_1
	Temperature of guide pole junction P_2
	Temperature of scaffold's auxiliary equipment P_3
	energy storage position indicator p_4
	Seal design differenccesP$_5$
	grounding resistance P_6
Operation security indexes	Switch itself corrosion P_7
	defection of Pole's number plate P_8
	slope of Scaffold P_9
	Crack of pole P_{10}
	Accumulated short open circuit times P_{11}
	Unsmooth stagnation of spring mechnismsP$_{12}$
	Grounding connections P_{13}
Protective function indexes	Out-taken isolation tool P_{14}
	inrush current defense function P_{15}
	Voltage transformer installation method P_{16}
Reliability indexes	Surge arrester installation P_{17}
	length of Operation P_{18}
	Family defect P_{19}
	Historical defect P_{20}

3 LSSVM

LSSVM is an improvement of SVM which is based on the statistical learning theory. It transforms the inequality constraints of traditional SVM into equality constraints, and considers sum squares error loss function as the loss experience of the training set, which transforms solving quadratic programming problem into solving linear equations problem. This method can improve the speed and accuracy of convergence [4,5].

In LSSVM model, the training set is set as $D = \{(x_i, y_i) | i = 1,2,\cdots,l\}$, where $x_i \in R^l$ is the input variable and $y_i \in R$ is its corresponding output variable. The function estimation problem in the ω-weight space can be described as follows [6]:

$$\min \quad \frac{1}{2}\omega^T\omega + \frac{1}{2}C\sum_{i=1}^{l}\xi_i^{\,2} \tag{1}$$

$$s.t. \quad y_i = \omega^T\varphi(x_i) + b + \xi_i\,,\ i = 1,2,\cdots,l \tag{2}$$

Where $\varphi(\cdot)$ is the nonlinear mapping function, which maps the training data into a highly dimensional linear feature space, C is the regularization parameter , ξ_i is the error, ω is weight, and b is bias. According to Eq.(1) and Eq.(2), the Lagrange function can be defined as follows:

$$L(\omega,b,x,a) = \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{l}\xi_i^{\,2} - \sum_{i=1}^{l}a_i\left[\omega^T\varphi(x_i) + b + \xi_i - y_i\right] \tag{3}$$

Where $a_i\ (i = 1,2,\cdots,l)$ are the Lagrange multipliers.

According to the Karush-Kuhn-Tucker (KKT) conditions, ω , b , ξ_i , a_i are taken partial derivative and required as zero. The Eq.(4) is obtained as follows:

$$\begin{cases} \omega = \sum_{i=1}^{l}a_i\varphi(x_i) \\ \sum_{i=1}^{l}a_i = 0 \\ a_i = C\zeta_i \\ \omega^T\varphi(x_i) + b + \zeta_i - y_i = 0 \end{cases} \tag{4}$$

According to Eq.(4), the optimization problem can be transformed into solving linear equations problem, which is shown as follows:

$$\begin{bmatrix} b \\ a_1 \\ \vdots \\ a_l \end{bmatrix} = \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(x_1,x_1)+\frac{1}{C} & \cdots & K(x_1,x_l) \\ 1 & \vdots & \vdots & \vdots \\ 1 & K(x_1,x_l) & \cdots & K(x_l,x_l)+\frac{1}{C} \end{bmatrix} \times \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_l \end{bmatrix} \tag{5}$$

The final form of LSSVM model is obtained as follows:

$$y(x) = \sum_{i=1}^{l}a_iK(x,x_i) + b \tag{6}$$

Where $K(x,x_j) = \varphi(x)^T \cdot \varphi(x_j)$ is the symmetric function which satisfies Mercer’s condition and it is called kernel function in general. In this paper, we choose the radial basis function (RBF) as the kernel function, which is shown in Eq.(7):

$$K(x,x_i) = e^{-\frac{(x-x_i)}{2\sigma^2}} \tag{7}$$

Where σ^2 is the width of the kernel parameter.

For LSSVM with RBF, the parameters conclude penalty parameter C and core width σ. The penalty parameter C is made between the structure and the risk of sample error compromise. The value of C is related to the tolerable error. A larger value allows small error and the smaller value allows larger errors. Core width σ is related to the input space of learning sample or the width. If the extent of the input sample is large, the value is large. On the contrary, if the extent of the input sample is small, the value is also small.

4 PSO algorithm

PSO was developed by Kennedy and Eberhart in 1995 based on the swarm behavior, such as fish and bird schooling in nature, which has generated much interest in the ever-expanding area of swarm intelligence [7].

PSO algorithm uses N particles, ie individual, composed of PSO in D -dimensional problem space iterative way to search for the optimal solution. Particles by tracking two " extremes " to update themselves, one is the optimal location of the particle itself $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$, and the other is the entire population of the current optimal position $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$. Particles in space flight, with the position and speed of the two characteristics. In each iteration, j -dimensional velocity of this particle updated v_{ij} and x_{ij} according to the following expression:

$$v_{ij}^{t+1} = \omega \cdot v_{ij}^t + c_1 r_1 (p_{ij} - x_{ij}^t) + c_2 r_2 (p_{gD} - x_{ij}^t) \quad (8)$$

$$x_{ij}^{t+1} = x_{ij}^t + v_{ij}^{t+1} \quad (9)$$

Where t is the current number of iterations, $i = 1,2,\cdots,N$, $j = 1,2,\cdots,D$,. $v_{ij} \in [-v_{\max}, v_{\max}]$, $v_{\max}$ is a constant. $x_{ij} \in \lfloor X_{\min,j}, X_{\max,j} \rfloor$, $X_{\min,j}$ and $X_{\max,j}$ are also constant. c_1 and c_2 are as a learning factor , respectively, to adjust the maximum step to global best particle and individual optimal particle direction of flight length, usually, $c_1 = c_2 = 2$. r_1 and r_2 is a random number between 0 to 1 [8]. w is the inertia weight which is on behalf of the particle inherits its parent particle velocity extent. It has a greater impact on the PSO algorithm convergence speed and accuracy , the expression of w is as follows:

$$w = (w_s - w_e)(t_m - t)/t_m + w_e \quad (10)$$

Where w_s and w_e are the initial inertia weight and end weights. t_m is the maximum allowed number of iterations [9,10].

5 The LSSVM based on PSO model

The regularization parameters C and kernel width σ in LSSVM have a greater impact on its accuracy. The parameter space of the exhaustive search method is commonly used to optimize the two parameters mentioned above, but the drawback is difficult to determine a reasonable range of parameters. To a certain extent this method affected the training samples of speed and accuracy. This paper uses the PSO algorithm to optimize the parameters of LSSVM ,which can quickly find the optimal solution , the steps of the LSSVM based on PSO model (PSO-LSSVM) is as follows:

(1) PSO is initialized on the settings, including particle dimension, population size , number of iterations , the initial position and velocity of particles.

(2) Separately in each particle vector of the LSSVM model to forecast the learning samples, get the prediction error of each particle current location value as a fitness value of each particle, and the fitness funcion is as follows:

$$f_i(C,\sigma^2) = 1 - \frac{1}{n}\sum_1^n \left| \frac{R_i(C,\sigma^2) - F_i(C,\sigma^2)}{R_i(C,\sigma^2)} \right| \quad (11)$$

Where R_i is the actual value and F_i is predicted value.

(3) The current fitness value of each particle are compared with the particle 's own best fitness value. If better, then the current position of the particle will be regarded as the optimal location of the particle.

(4) The fitness value of each particle best position itself to adapt to the optimal position are compared with the group values. If better, then the optimal position of the particle will be regarded as the optimal position groups.

(5) Inertia weight is calculated according to Eq.(10), and the use of Eq.(8) and Eq.(9) update the velocity and position of the particles.

(6) Check whether meet the termination conditions, if not satisfied return Step 2 to calculate, if meet the calculation and the output end.

6 Specific example and results analysis

This paper selects 100 sets of variable data in the distribution network of a certain power supply company,and each set contains 20 indicators described above. Particle swarm optimization is used to optimize least squares support vector machine model to evaluate the status. Then the former 80 sets among total data are taken as training samples, the rest as test samples. Thus, the specific evaluation process is as follows:

(1) Parameter optimization

Use particle swarm optimization algorithm to optimize the regularization parameter C and kernel width σ of least squares support vector machine, and the parameters of PSO is set in Table 2, and the process of particle swarm optimization can be seen in Fig 1.

Table 2. The parameter settings of PSO

Parameters	N	t_m	c_1	c_2	w_s	w_e	V_{max}
Value	20	200	1.5	1.7	0.3	0.9	1

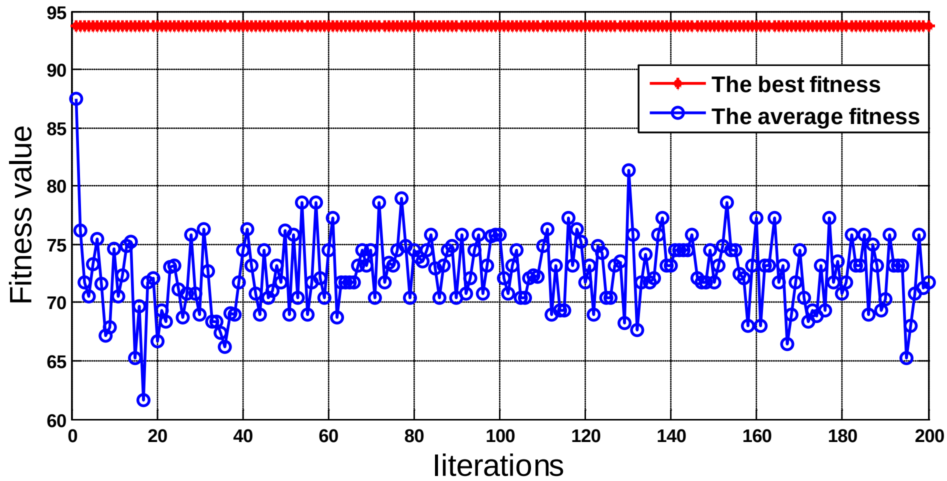

Fig 1. The iterative process of PSO

As seen from Fig 1, the best fitness value for each generation of PSO is maintained at 94, and the average is at 73,which indicates that PSO maintains high efficiency in the optimization process. The final parameters through particle swarm optimization are determined that $C = 86.47$ and $\sigma = 21.96$ respectively.

(2) Training and testing

Set the parameters of least squares support vector machines: $C = 86.47$ and $\sigma = 21.96$. Then take the 80 groups of training samples into the least square support vector machine training, the results of which are shown in Fig 2.

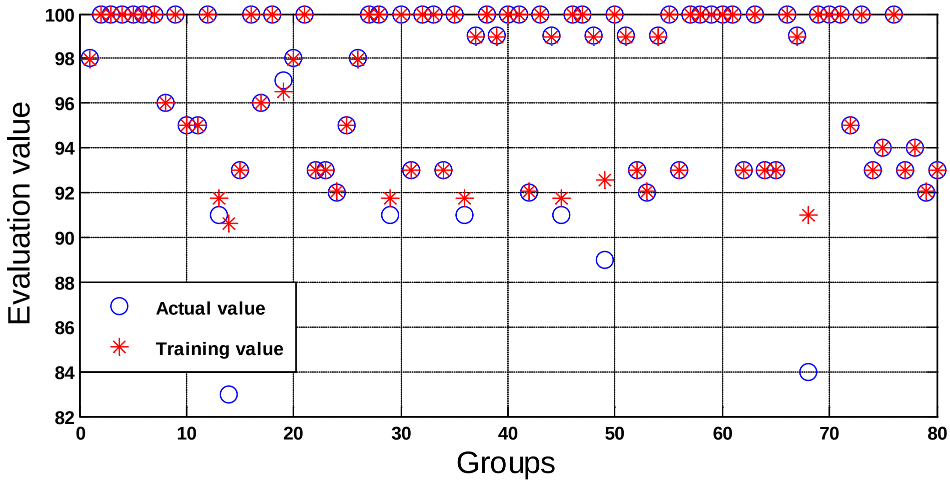

Fig 2. The training result of LSSVM

It can be seen from Fig 2 that in the 80 training samples, the training result errors of 72 groups are zero basically while the remaining 8 groups are kept within 1%, indicating a satisfactory training result.

20 groups of test samples are taken into the least squares support vector machine model which has been trained well for prediction. In order to reflect a higher accuracy and better generalization ability of the proposed method-least squares support vector machine optimized by particle swarm optimization more objectively. This paper chooses the widely-used grid search optimization least squares support vector machine (GS-LSSVM) for the same test as a contrast. And this paper introduces three kinds of error calculation methods:

$$RE_i = \frac{P_i - R_i}{R_i} \times 100\% \tag{12}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(R_i - P_i)^2 \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{P_i - R_i}{R_i}\right| \times 100\% \tag{14}$$

Where R_i is the actual value and F_i is predicted value.

The testing results can be seen in Table 3.

Table 3. The testing results

Training sample number	Actual value	PSO-LSSVM		GS-LSSVM	
		Output value	RE (%)	Output value	RE (%)
1	98	97.7958	-0.2084	97.9896	-0.0106
2	100	99.9899	-0.0100	99.9895	-0.0105
3	99	98.9899	-0.0100	98.9904	-0.0097
4	91	91.6804	0.7477	91.7321	0.0805
5	95	95.0099	0.0105	95.0096	0.0101
6	100	99.9899	-0.0100	99.9895	-0.0105
7	100	99.9899	-0.0100	99.9895	-0.0105
8	93	93.0100	0.0108	93.0101	0.0109
9	100	99.9899	-0.0100	99.9895	-0.0105
10	100	99.9899	-0.0100	99.9895	-0.0105
11	94	94.6804	0.7238	95.1589	1.2328

12	92	92.0099	0.0109	92.0502	0.0546
13	100	99.9899	-0.0100	99.9895	-0.0105
14	93	93.0100	0.0108	93.0101	0.0109
15	100	99.9899	-0.0100	99.9895	-0.0105
16	100	99.9899	-0.0100	99.9895	-0.0105
17	99	98.9899	-0.0101	98.9904	-0.0097
18	100	99.9899	-0.0100	99.9895	-0.0105
19	91	91.6804	0.7477	91.7321	0.0805
20	92	92.0099	0.0109	92.0502	0.0546
MSE		0.0716		0.1211	
MAPE (%)		0.1296		0.1554	
Elapsed time (s)		63.9579		21.2252	

(3) Results analysis

As can be seen from Table 3,for 20 groups of test samples, the relative errors (RE) of PSO-LSSVM model are controlled within 1%, among which the minimum is 0.0100% and maximum is 0.7477%, while GS-LSSVM model has a relative error more than 1%, where in the minimum is 0.0097% and the maximum is 1.2328%. On the whole,predictive errors of 16 sample points of PSO-LSSVM are smaller than that of GS-LSSVM. The mean absolute percentage error (MAPE) of PSO-LSSVM is 0.1296, lower than 0.1554 of GS-LSSVM, which can clarify that PSO-LSSVM has a higher prediction accuracy. In addition, the mean square error(MSE) of PSO-LSSVM model is 0.0716, lower than 0.1211 of GS-LSSVM, indicating the error floating degree of PSO-LSSVM model is less than GS-LSSVM,which means the former has a better generalization capacity. Although the run time of PSO-LSSVM model is longer than that of GS-LSSVM, it does not affect the advantages of this model when applied.

7 Conclusions

In this paper, according to the existing problems in state evaluation,evaluation index system of condition-based maintenance for on-post vacuum circuit breaker is constructed and least square support vector machine model optimized by particle swarm optimization is applied for this evaluation. Through example analysis,the model is clarified that it has a good performance in the evaluation precision and generalization ability,better than traditional evaluation model. Moreover, it has practical application and reference theory to some degree, to perfect the state overhaul process, standardize state overhaul operation and improve state overhaul performance.

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