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An unknown fault identification method based on PSO-SVDD in the IoT environment

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Abstract When a new fault occurs, how to determine whether the new fault is a known fault or an unknown fault outside the fault pattern base. If a new unknown fault is identified, adding the unknown fault to the fault pattern base for adaptive updating the fault diagnosis model has become a new problem in the field of fault diagnosis. In order to solve this problem, we take Box transformer substation (BTS) widely used in power distribution equipment as an example, propose an unknown fault identification method. First, through the construction of the IoT framework including the perception layer, transmission layer and application layer, real-time data collection and online monitoring for the BTS can be realized. Then, using Support Vector Data Description (SVDD) as the unknown fault identification method, and optimizing the relevant parameters by Particle Swarm Optimization (PSO) algorithm, so that BTS can identify unknown faults with a timely and effective manner. Meanwhile, through the retraining of the model, the adaptive update of the existing fault diagnosis model is achieved. Finally, the validity of the designed method is verified by an example.

1. Introduction

Equipment fault diagnosis generally involves establishing a fault diagnosis model, and then integrating all possible fault types into a fault mode library, using the model to reason based on the equipment's operating status data, and matching specific fault types from the fault mode library, and completing the diagnostic process. However, with the vigorous development of sensors, the Internet of Things and other technologies, the working environment of the equipment is becoming more and more complex, the working conditions are changing rapidly, the equipment will fail at any time, and the forms of failure are becoming more and more diverse, and is likely to happen for the fault mode library outside the new and unknown type of fault, to the existing fault diagnosis method is put forward new problems and challenges. Therefore, we take the fault diagnosis of distribution network equipment as an example to carry out related research and explore the method of unknown fault identification.

In view of the existing problems of central network cabinet, box transformer substation and other equipment in distribution network, using IoT technology, intelligent algorithms, and machine learning algorithms to collect internal information and data in the cabinet of the distribution equipment, perform timely quantitative and qualitative analysis to

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understand the distribution and the operation status of electrical equipment, monitor online status and fault identification, in order to prevent system fluctuations and catastrophic accidents. This is an important technical means to improve the level of distribution operation management [1,2].

Box transformer substation (BTS), as an important power distribution equipment, transform electric energy from high-voltage system above 10 kV to low-voltage system. Most of the BTS are installed outdoors, the working environment is changeable, the conditions are complicated, and natural disasters and external forces are seriously damaged. In the long-term operation process, various failure problems will occur [3]. When a fault occurs, relying on the manual troubleshooting method, the workload is large, the accuracy is low, and the fault diagnosis state of the BTS cannot be diagnosed and processed in real time, which may cause major safety accidents such as large-scale blackouts and explosions [4].

Many scholars have also done a lot of research work on the fault diagnosis of power distribution equipment. Methods for troubleshooting oil-immersed transformers have been proposed such as three-ratio method [5], characteristic gas method [6]. Aiming at the defects of three ratio method, Yu et al. [7] used probabilistic neural network algorithm to predict the internal fault of transformer. Mileta and Zlatan [8] designed a fuzzy controller, calculated the probability of transformer faults through the expert system, and tested it in the Serbian system, which proved the result to be feasible; Tang et al. [9] developed an intelligent technology of small pulse fault diagnosis for distribution transformer by using expert system.

In terms of fault diagnosis of other power distribution equipment, scholars have also made a lot of research results. Wang lei et al. [10] proposed a power grid fault tracking method based on big data platform to find the fault components and give the fault reasons; Xu et al. [11] used Petri net to establish fault diagnosis model for a large power station, so that monitors could accurately diagnose faults; Di et al. [12] proposed a method to systematically study the power converter fault prediction, which can effectively predict the fault of the power converter; According to other feature map based on multi-sensor data, Wang et al. [13] constructed a corresponding convolutional neural network to diagnose different types of faults. In order to avoid the problems that no-training samples of unknown type are recognized as the normal samples or wrong types of known fault, Huang et al. [14] proposed a new method for monitoring and diagnosing the mechanical state fault of circuit breaker. Hierarchical hybrid classifier method proposed can not only identify the mechanical state and fault type of circuit breaker accurately, but also identify the unknown fault type without training samples effectively. He et al. [15] propose a visualization approach and apply it to unknown fault isolation. The detection and isolation rules are proposed for diagnosing both the known faults and the unknown faults This approach maintains the fault isolability so that engineers will be able to diagnose the faults more reasonably.

From the present research, the current stage of the Internet of Things technology has been basically mature, scholars for the distribution network and distribution equipment fault diagnosis have carried out a lot of research, and achieved a lot of results. However, most of the researches have established the fault diagnosis model based on box transformer substation based on theory and method, and trained the model with a large amount of historical fault data, enabling it to reason about fault types based on real-time monitoring data. Moreover, the fault diagnosis models built in these studies face the rapidly changing new situations and problems during the actual operation of the equipment, especially new and unknown fault types, which often cannot be identified in a timely and effective manner, and the diagnosis model cannot be sustained updated and optimized, greatly reducing the self-learning and adaptive ability of the model.

Therefore, in addition to the existing fault diagnosis model, a new model needs to be built to determine whether the device produces a new, unknown fault type. For unknown faults, in addition to supplementing the fault mode library, unknown fault data should also be input into the existing fault diagnosis model for model training, so that the fault diagnosis model has the ability to continuously learn new knowledge and adapt to new situations. We take the widely used power distribution equipment as an example to conduct research, proposes Particle Swarm Optimization - Support Vector Data Description (PSO-SVDD) method to identify unknown faults in box transformer substation, which aims to identify the unknown fault of box transformer substation effectively, and then continuously optimizing and updating the existing fault diagnosis model, so as to improve the fault diagnosis level of box transformer substation and ensure the stable and reliable operation of urban power supply system.

2. Box transformer substation real-time monitoring and unknown fault identification IOT architecture

The application of Internet of things technology in power system is generally called electric Internet of things. It combines computer, network, sensing, communication, automation and other technologies to realize the safe and reliable transmission of power information, and has four characteristics of comprehensive perception, IP interconnection, reliable transmission, and intelligent processing. The electric Internet of Things is generally divided into three layers: perception layer, transport layer and application layer [1]. The perception layer is responsible for the overall perception and correct collection of data, which is the core base layer; the transport layer mainly uses the various wired and wireless methods to perform reliable near and long distance data transmission according to the agreed protocol; The application layer provides intelligent monitoring and diagnosis services by establishing a dedicated mathematical model, using the ubiquitous power data of the perception layer, and using data mining and machine learning methods.

The proposed method for identifying unknown faults in box-type substations is based on the three-tier architecture of the electric IoT, the specific frame diagram is shown in Fig. 1. First, according to the needs of data collection and data communication of box transformer substation, a gateway of Internet of things is designed to collect and analyze the internal operating parameters of box transformer substation; Then, the data is transmitted to the application layer cloud server through the GPRS network; Finally, in the application layer, the on-line monitoring of the box transformer substation is completed. At the same time, real-time data and historical data of box transformer substation monitoring are utilized to realize the unknown fault identification of the box transformer substation by using PSO-SVDD method.

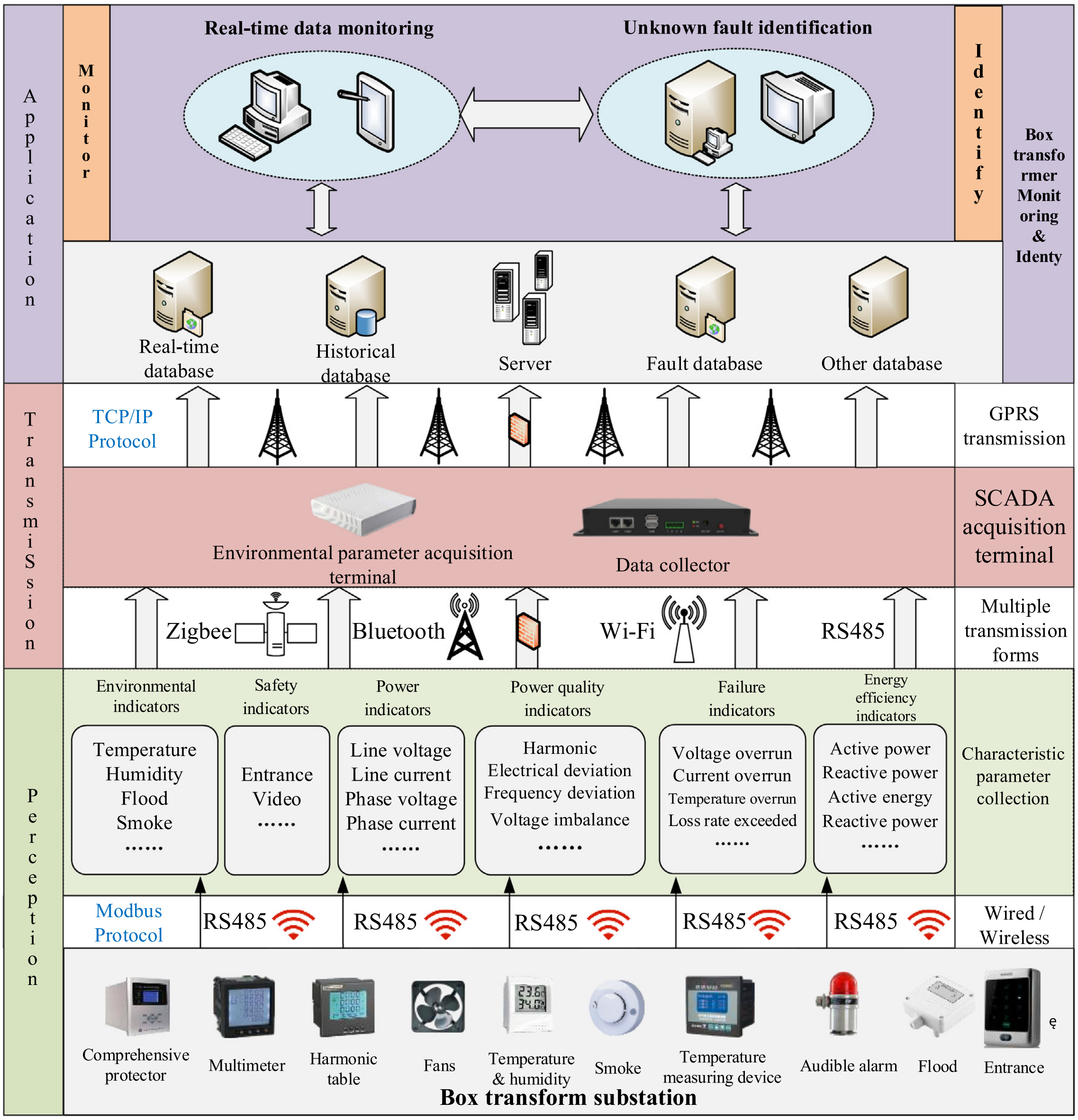

Fig. 1 Systematic overview of the proposed approach.

3. Unknown fault identification method of box transformer substation based on PSO-SVDD algorithm

Unknown fault identification method of box transform substation is a supplement to existing fault diagnosis model. By studying the unknown fault identification method, when a new fault occurs, the classification algorithm of the model is used to identify whether the fault is in the original fault mode library. If an unknown fault type is generated, the model is retrained so that the existing fault diagnosis model has the ability to identify the new unknown fault during subsequent diagnosis.

3.1. Principle of PSO-SVDD

The key of unknown fault identification method is the establishment of boundary condition judgment mechanism. Generally, methods such as support vector machines are used. However, when using support vector data description for calculation, the selection of relevant parameters becomes particularly important. Reasonable parameters can greatly enhance the classification recognition ability of the method, speed up the classification speed, simplify the calculation complexity, and improve the calculation accuracy.

3.1.1. Principle of SVDD

SVDD is a description method based on boundary data. It’s main idea is to map the target sample point of a nonlinear mapping to a high-dimensional inner product space to form a hyper sphere containing all the target samples [16]. This characteristic makes SVDD widely used in the field of unknown fault detection, so the SVDD method can be used as the judgment mechanism of the box transformer substation fault diagnosis model.

For the traditional SVDD method, the structure of the hyper sphere is mainly determined by the penalty coefficient C and the kernel parameter bf. Penalty coefficient C determines the upper bound of the Lagrangian multiplier, so increasing the penalty coefficient C can make the SVDD method have a larger range containing training samples. However, if the sample deviation phenomenon is individual, it will make a large blank space to contain all the samples, which will cause the accuracy of SVDD to be greatly reduced. A reasonable penalty coefficient value will balance the complexity and classification ability of the hypersphere. The kernel parameter bf is used to determine the radial range of the model, also known as the generalization ability. The smaller the value of bf, the more accurate classification boundary will be obtained. When bf approaches 0, there are only training samples in the SVDD model, the model does not have any generalization ability, which means it cannot identify new failure samples.

The principle of SVDD algorithm is that in the data space $X \subset R^d$ (d is the sample dimension), there is a known training sample set $\{x_i | x_i \in R^d, i = 1,2,3...n\}$, the training sample set needs to find a minimum hyper sphere with a spherical center of a and a radius of R in the high-dimensional feature space F through nonlinear mapping, and this hyper sphere includes all the training sample sets. Therefore, the goal of this SVDD problem is to minimize the radius of the hyper sphere R, and at the same time, in order to reduce the influence of the singular value, introduce a relaxation variable ξ_i, in order to control the trade-off between the volume of the sphere and the error rate, introduce a penalty coefficient C. Then consider the following convex quadratic planning:

$$\min_{R,a,\xi_i} F(R,a,\xi_i) = R^2 + C\sum_{i=1}^{n}\xi_i \quad s.t.\{\|x_i - a\|^2 \le R^2 + \xi_i, i = 1,...,n, \xi_i \ge 0 \tag{1}$$

The above optimization problem can be solved by Lagrange equation, introducing Lagrange function can transform Eqs. (1) into (2), in the equation, α_I, λ_I is Lagrange multiplier.

$$L(R,a,\xi_i,\alpha_i,\lambda_i) = \mathrm{R}^2 + \mathrm{C}\sum_{\mathrm{i}=1}^{\mathrm{n}}\xi_\mathrm{i} - \sum_{i=1}^{n}\xi_i\lambda_i - \sum_{\mathrm{i}=1}^{\mathrm{n}}\alpha_\mathrm{i}\left(\mathrm{R}^2 + \xi_\mathrm{i} - \|\mathrm{x_i} - \mathrm{a}\|^2\right) \tag{2}$$

Take the partial of this equation with respect to R, a, ξ_I, and let the partial derivative result be 0, the following results can be obtained:

$$\sum_{i=1}^{n}\alpha_i = 1 \tag{3}$$

$$a = \sum_{i=1}^{n}\alpha_i x_i \tag{4}$$

$$C - \lambda_i - \alpha_i = 0 \rightarrow 0 \leqslant \alpha_i \leqslant C \tag{5}$$

Bringing Eqs. (3)–(5) into the original plan, the dual form of Eq. (1) can be obtained as follows:

$$\max_{\alpha_i} L(R,a,\xi_i,\alpha_i,\lambda_i) = \sum_{i=1}^{n}\alpha_i(x_i,x_i) - \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j(x_i,x_j) \quad \mathrm{s.t.}\sum_{\mathrm{i}=1}^{\mathrm{n}}\alpha_\mathrm{i}, 0 \leqslant \alpha_\mathrm{i} \leqslant \mathrm{C}, \mathrm{i} = 1,....\mathrm{n} \tag{6}$$

The inner product x_i, x_j can be replaced by the new inner product $K(x_i, x_j)$ of the Mercer 's theorem. Eq. (2) is converted into:

$$\max_{\alpha_i} L(R,a,\xi_i,\alpha_i,\lambda_i) = \sum_{i=1}^{n}\alpha_i K(x_i,x_i) - \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j K(x_i,x_j) \quad s.t.\sum_{\mathrm{i}=1}^{\mathrm{n}}\alpha_\mathrm{i}, 0 \leqslant \alpha_\mathrm{i} \leqslant \mathrm{C}, \mathrm{i} = 1,....\mathrm{n} \tag{7}$$

This dual form satisfies the KKT condition, that is $(R^2 + \xi_i - ||x_i - a||^2)\alpha_i = 0$, $\xi_i\lambda_i = 0$.

Solving dual Eq. (7) gives three conditions about α_i:

$$\begin{gathered}\| x_i - a \|^2 < R^2 \Rightarrow \alpha_i = 0 \\ \| x_i - a \|^2 = R^2 \Rightarrow 0 < \alpha_i < C \\ \| x_i - a \|^2 > R^2 \Rightarrow \alpha_i = C\end{gathered} \tag{8}$$

According to formula (8), when $\alpha_i = 0$, the corresponding training samples are in the hyper sphere; when $0 < \alpha_i < C$, the corresponding training sample is on the hyper sphere interface; when $\alpha_i = C$, the corresponding training sample point is outside the hyper sphere. In order to determine whether the test point is inside the hyper sphere, the distance from the test point to the center of the hyper sphere needs to be calculated. This distance function is:

$$d^2(x) = K(x,x) - 2\sum_{i=1}^{n}\alpha_i K(x_i,x) + \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j K(x_i,x_j) \tag{9}$$

The judgment function is:

$$f(x) = sgn\left(R^2 - \| x - a \|^2\right) = sgn\left(R^2 - d^2(x)\right) \tag{10}$$

If $f(x) \ge 0$, the sample is inside the super sphere, otherwise it is outside the super sphere.

3.1.2. Principle of PSO

PSO algorithm is a group from birds foraging behavior back to evolutionary algorithm, using the individual in the group of information sharing of the whole group of movement in the problem solves space evolution process from disorderly to orderly, each particle in the community through continuous iterative optimization search, to modify the movement speed and direction, thus to seek the optimal group [17]. In order to make the SVDD method optimal, the PSO algorithm is integrated into the SVDD method to optimize its key parameters, so as to find the optimal parameter selection value, which can well avoid the problem of improper parameter selection in the original SVDD method.

The principle of the PSO algorithm is that in H-dimensional space, particle i is used to abstractly express the individual bird, each particle i uses two parameters to represent its state in H space: the current position x_i, the current speed v_i. Particles through the change of these two parameters to search the optimal point in space, to prevent particle blind search, all particles have a fitness value determined by the objective function, and to search the optimal position of the p_i for record, clearly recorded in the group at the same time other particles to search the optimal position of the p_g, namely the global optimal position. x_i, v_i, p_i. p_g, the fitness function is expressed as:

$$\begin{cases} x_i = (x_{i1}, x_{i2}, \cdots x_{id}) \\ v_i = (v_{i1}, v_{i2}, \cdots v_{id}) \\ p_i = (p_{i1}, p_{i2}, \cdots p_{id}) \\ p_g = (p_{g1}, p_{g2}, \cdots p_{gd}) \end{cases} \tag{11}$$

$$p(f) = \frac{1}{n}\sum_{i=1}^{n} L(f_k(x_k), y_k) \tag{12}$$

The fitness function uses the leave-one-out method, where f_k is a classifier composed of n-1 training samples, $f_k(x_k)$ is the result of the sample x_k under the current classifier, and y_k is the actual classification result. If the classification is correct, $L(f_k(x_k), y_k)$ is taken as 1, and classification is incorrectly taken as 0.

Particles in space use their searched optimal position p_i and global optimal position p_g to optimize their current position and current speed. The optimization formula is:

$$v_{id}^{k+1} = v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k}\right) \tag{13}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k} \tag{14}$$

In the formula, $i = 1, 2, \ldots, n$, n is the total number of particles generated, c_1 and c_2 are acceleration factors, usually $c_1 = c_2 = 2$, r_1 and r_2 are distributed in [0,1] random number, k is the current number of iterations. In order to make the particles have better optimization performance, the inertia factor ω is introduced. The inertia factor can determine the degree to which the particles inherit the speed before iteration to obtain a balanced exploration ability for the particles. After introducing ω, the formula (13) becomes:

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k}\right) + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k}\right) \tag{15}$$

The larger ω, the faster the PSO convergence speed, but it is hard to get an accurate solution; the smaller ω, the slower the PSO convergence speed, the easier it is to fall into a local optimum. For ω, the recommended linear decreasing inertial weighting strategy is generally used to balance the performance of global search and local search. The formula is:

$$\omega^k = (\omega_{start} - \omega_{end})(k_{\max} - k)/k_{\max} + \omega_{end} \tag{16}$$

In the formula, ω_{start} is the initial inertia weight, ω_{end} is the inertia weight at the maximum number of iterations, and k_{max} is the maximum number of iterations.

3.2. Unknown fault identification process

We propose to use the SVDD method as the fault type identification method. In order to optimize the method, the PSO algorithm is selected to optimize the parameters in the SVDD method, and finally an unknown fault identification algorithm of PSO-SVDD is formed. The specific flow of the proposed method is shown in Fig. 2.

Step1: Initial parameter setting. Initialize the parameters involved in the algorithm;

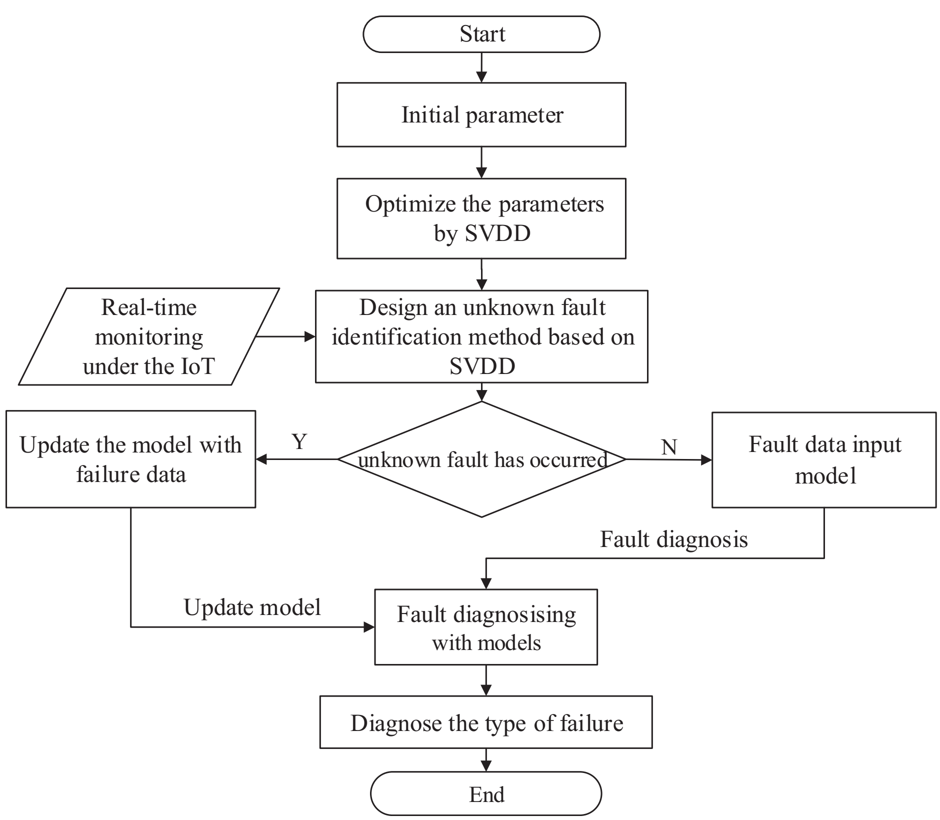

Fig. 2 Process of Unknown Fault Identification Based on PSO-SVDD.

Step2: PSO algorithm is used to optimize the parameters of SVDD method. It mainly involves the penalty parameter C and kernel parameter b_f, C and b_f were taken as the combination of iterative optimization variables in PSO, and the input algorithm was used to obtain the optimal combination of variables;

Step3: Design an unknown fault identification method based on SVDD. The optimal variable combination value obtained in the PSO algorithm is taken as the initial parameter of SVDD, and the known fault data is selected as the training data of SVDD, while the unknown fault data is taken as the test data of SVDD;

Step4: Update fault diagnostic model. For the new fault types identified by the SVDD method, input them into the diagnostic model to learn and obtain a new fault diagnostic model.

3.3. PSO-SVDD algorithm process

The basic idea of the PSO-SVDD algorithm is to use the particle swarms optimization algorithm to encapsulate the feature subset selection of the sample data set and the parameter optimization of the kernel function as a whole of the particles to jointly optimize, that is, to find an optimal combination of

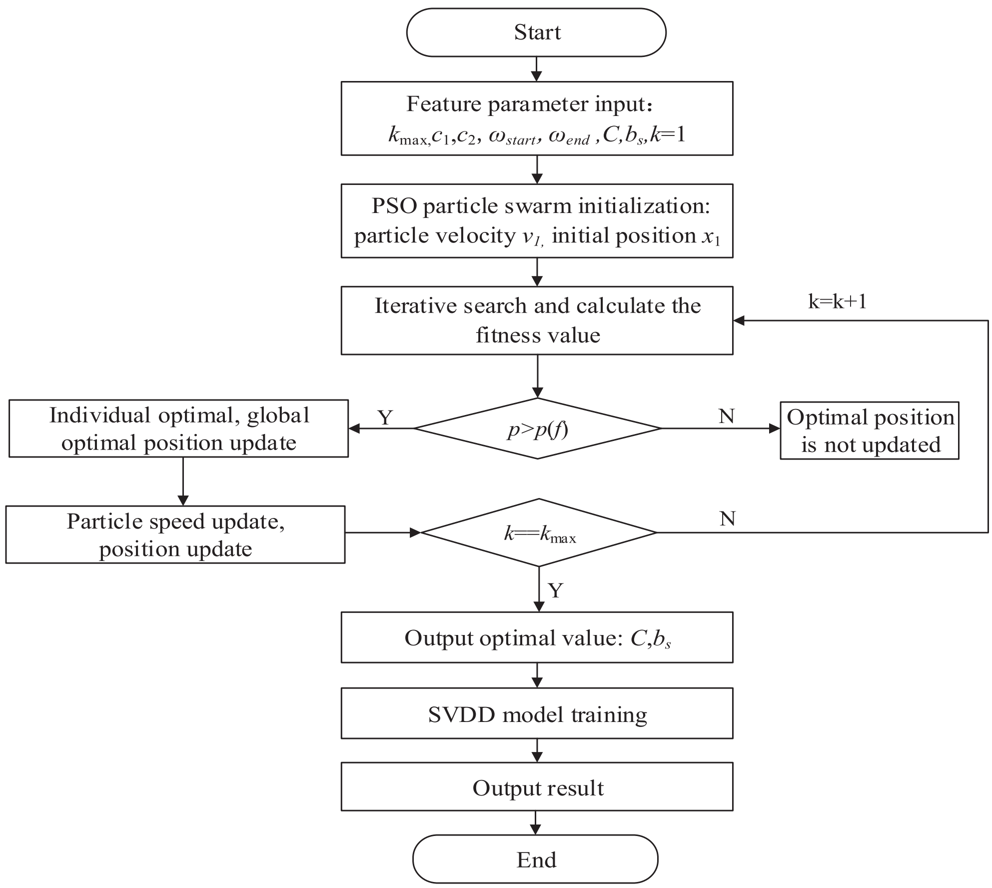

Fig. 3 Flow Chart of PSO-SVDD.

Table 1 Fault characteristic parameter of BTS.

serial number	characteristic parameter	serial number	characteristic parameter	serial number	characteristic parameter	serial number	characteristic parameter
1	temperature	7	partial discharge	13	high voltage	19	bus temperature
2	humidity	8	dielectric loss ratio	14	high voltage current	20	neutral line current
3	water immersion	9	winding absorption ratio	15	Low voltage incoming line voltage	21	action rejection information
4	smoke detector	10	core ground current	16	Low voltage outgoing voltage	22	trip information
5	dewing	11	iron core temperature	17	Low voltage incoming current	23	contact temperature of circuit breaker
6	contact resistance	12	frequency	18	Low voltage outgoing current	24	current at both ends of circuit breaker

Table 2 Original decision table.

Object	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	Failure mode
Y1	16	32	25	0.15	3	111	60	0.32	1.41	0	50	50.1	6.64	2.45	224	221	1.5	13	54	0	0	0	44	21	D1
Y2	25	49	13	0	11	234	21	0.44	1.52	0.02	33	49.9	6.54	2.34	223	220	1.2	17	48	1.4	0	0	50	23	D1
Y3	35	23	7	0.03	2	336	111	0.57	1.28	0.70	62	50.1	8.89	1.28	225	222	1.4	22	45	0.9	0	0	34	20	D2
Y4	40	15	2	0.60	0	517	735	0.88	1.55	0.51	44	50.1	6.77	2.56	221	221	1.4	24	40	0	0	0	47	25	D2
Y5	29	31	8	0.23	4	275	838	0.95	1.40	0.04	50	50.4	6.23	2.48	224	222	1.3	18	43	1.8	0	0	30	18	D2
Y6	34	10	1	0.11	1	212	95	0.94	1.35	0.20	42	50.2	7.58	0.89	222	221	1.5	32	55	2.5	0	0	32	24	D2
Y7	31	80	33	0.04	94	654	234	1.20	2.00	0.30	66	50.1	6.11	2.89	222	224	1.7	42	66	1.1	0	0	41	37	D2
Y8	37	11	20	0.35	0	156	18	0.12	1.25	0.01	34	49.8	9.34	0.22	220	220	1.6	35	42	0.4	0	1	68	10	D3
Y9	29	33	4	0.55	1	333	123	0.55	1.30	0.22	41	50.3	8.88	0.14	221	222	1.5	42	35	0	1	0	33	19	D3
Y10	32	12	3	0.32	1	96	566	1.23	1.10	0.11	34	49.9	6.88	1.56	221	223	1.7	36	41	0.2	0	1	62	28	D3
Y11	45	92	21	0	13	38	936	1.34	0.89	0.27	35	50.0	9.75	0.11	223	221	1.8	44	47	0.4	0	1	54	15	D3
Y12	36	27	0	0.11	0	75	123	0.48	0.44	0.03	31	50.1	6.34	2.35	220	220	1.9	29	37	0.3	0	1	22	0	D3
Y13	29	94	56	0.33	96	58	35	0.36	0.15	0.01	30	51.2	6.21	2.47	221	222	1.4	25	38	21	0	0	35	25	D4
Y14	30	95	48	0.17	94	68	48	0.38	0.21	0.02	35	51.0	6.23	2.46	220	221	1.5	24	40	28	0	0	34	21	D4
Y15	32	90	50	0.22	90	53	88	0.12	0.14	0.05	36	50.8	6.74	2.45	220	221	1.6	30	36	30	0	0	31	20	D4
Y16	34	91	51	0.12	91	75	74	0.13	1.40	0.04	37	50.9	6.21	2.12	221	223	1.7	25	48	34	0	0	34	22	D4
Y17	31	93	53	0	92	88	100	0.11	1.56	0.05	34	50.9	6.37	2.28	222	221	1.8	27	38	35	0	0	36	26	D4
Y18	34	14	10	0.01	2	99	121	0.08	0.11	0.01	38	49.1	6.31	2.15	224	258	1.4	6	65	12	0	1	50	24	D5
Y19	35	20	8	0.34	1	114	95	0.06	1.34	0.08	37	49.2	6.22	2.43	221	274	1.5	2	54	13	1	0	52	12	D5
Y20	36	25	4	0.37	4	88	252	0.09	1.10	0.02	37	49.0	6.17	2.21	223	293	1.6	3	56	11	1	0	54	11	D5
Y21	37	31	6	0.55	2	98	114	0.05	1.23	0.03	38	50.7	6.28	2.23	220	288	1.7	4	53	15	0	1	56	21	D5
Y22	31	19	1	0.47	1	109	103	0.01	1.24	0.05	38	50.1	6.12	2.24	221	269	1.8	6	58	18	0	1	58	0	D5
Y23	36	17	1	0.88	1	86	103	0.64	1.52	0.01	40	50.2	6.22	2.55	288	221	0.1	21	38	2	0	1	40	24	D6
Y24	37	29	2	0.42	2	75	98	0.76	1.19	0.02	41	49.3	6.32	2.26	276	220	0.5	23	39	12	1	0	42	26	D6
Y25	36	26	2	0.38	2	62	56	0.52	1.74.	0.01	38	49.8	6.16	2.24	294	223	0.1	28	35	3	0	1	43	31	D6
Y26	39	31	3	0.71	3	34	38	0.39	1.31	0.09	39	50.0	6.15	2.55	265	224	0.3	27	37	8	0	1	40	0	D6
Y27	40	94	51	0.80	91	88	678	0.17	1.43	0.02	40	50.0	6.38	2.38	220	220	1.8	29	39	41	0	0	38	28	D7
Y28	41	96	49	0.86	90	56	742	0.66	0.58	0.06	38	50.7	6.47	2.64	221	223	1.7	26	42	50	0	0	36	26	D7
Y29	42	92	62	0.64	90	39	655	0.58	1.10	0.07	37	49.8	6.66	2.33	223	224	1.6	27	43	53	0	0	39	32	D7
Y30	40	93	53	0.52	92	47	831	0.72	0.62	0.08	39	50.3	6.52	2.49	220	221	1.5	31	42	38	0	0	40	12	D7
Y31	56	24	54	0.94	3	24	54	0.34	0.48	1.12	34	54.8	6.32	2.33	221	220	1.3	22	41	52	0	0	37	49	*
Y32	52	23	33	0.31	0	10	31	0.12	0.22	1	35	52.3	6.77	2.41	222	221	1.2	21	43	52	0	0	35	47	*
Y33	51	27	32	0.22	2	12	36	0.33	0.47	0.98	36	56.7	9.12	2.44	222	220	1	20	48	54	0	0	44	44	*
Y34	54	28	10	25	4	21	24	0.13	0.63	0.54	37	53.3	9.32	2.53	221	221	1.1	23	49	54	0	0	43	21	*

data feature subset and kernel function parameter values, and finally establish the optimal SVDD model. The specific implementation process is shown in Fig. 3.

Step1: Feature parameter input. Let the initial variables be $c_1 = c_2 = 1.495$, the number of evolutions maxgen = 1000, the population size sizepop = 100, $V_{max} = 1$, $V_{min} = -1$, popmax = 5, popmin = -5, $\omega_{start} = 0.9$, $\omega_{end} = 0.4$, $k_{max} = 300$;

Step2: PSO particle swarm initialization. Generate initial particle velocity v_1 and initial position x_1, and generate *size* parameter combinations;

Step3: Iterative search to calculate the fitness value $p(f)$ of each particle;

Step4: Global optimal location update;

Step5: Update the speed and position of particles according to formula (10) and formula (11);

Step6: Judge whether the algorithm has reached the termination condition of precision. If so, output the optimal parameter combination as the optimal SVDD model parameter; otherwise, return Step3;

Step7: Use the optimal parameter combination to train the SVDD model, and determine whether the sample is in the hyper sphere according to formula (5) and output the SVDD judgment result.

4. Example verification and results analysis

4.1. Fault feature parameter selection

The fault diagnosis data of the box transformer substation comes from the data collection under the Internet of Things technology, in order to fully obtain the status data of the box transformer substation operation, select important monitoring data related to key faulty equipment to collect, environmental parameters such as temperature and humidity, electrical characteristic parameters such as contact resistance and partial discharge, and insulation characteristic parameters such as dielectric loss rate. Therefore, a total of 24 fault characteristic parameters were selected as the source information of the box transformer substation fault, as shown in Table 1.

4.2. Data preparation

According to the fault characteristic parameters selected from Table 1, 34 sets of data were extracted from the database and expressed as Y_i (i = 1–34) to establish the original fault decision table of box transformer substation, use X_j (j = 1–24) to represent 24 condition attributes, D_k (k = 1–7) represents the fault type, meaning respectively, D1: no fault; D2: dry transformer fault; D3: high voltage circuit breaker fault; D4: fault of capacitor arrester; D5: fault of low-voltage outgoing circuit breaker; D6: fault of low-voltage incoming circuit breaker; D7: fault of high voltage arrester. In the data, the first 30 sets of fault history data of Y1-Y30 have known fault types, and are used for the establishment and training of unknown fault models. The last four sets of data are unknown faults, which are temporarily indicated by *, and are used to test the unknown fault recognition capability of the established unknown fault recognition model. The selected decision table of 34 sets of data is shown in Table 2.

4.3. PSO-SVDD algorithm and model verification

The PSO algorithm is used to calculate the fitness parameters for the penalty parameter C and kernel parameter b_f in the SVDD algorithm according to fitness function Eq. (11). The results are shown in Fig. 4.

It can be seen from Fig. 4 that the optimal fitness of the function is 80.6. Under this optimal fitness, the optimal parameter point value is taken. The result is shown in Fig. 5. The obtained optimal parameter combination result is $C = 0.05$, $b_f = 8$.

The first 30 sets of data from y1-y30 in Table 2 were taken as training samples of known fault types. The training sample data were input into the SVDD algorithm optimized by PSO, and the SVDD training model of known fault types was obtained through training. In this SVDD training model, the corresponding relationship between fault data and characteristic parameters is shown in Fig. 6.

According to the correspondence between the training fault data and the characteristic parameters, it can be known that under the SVDD model, each characteristic parameter of the training data is distributed in range between [-4, 4], and the discrete results are shown in Fig. 7.

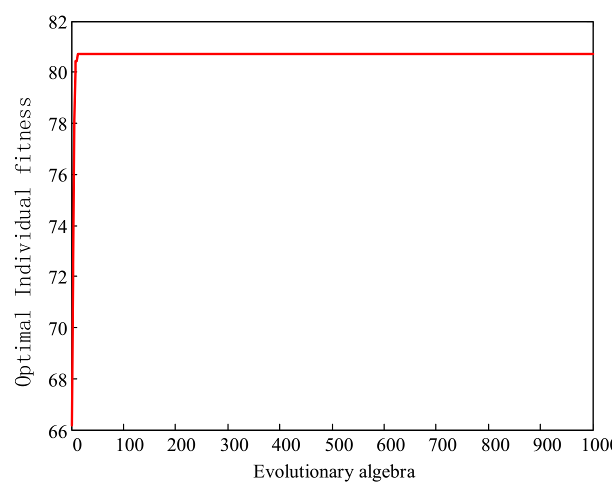

Fig. 4 Optimal individual fitness.

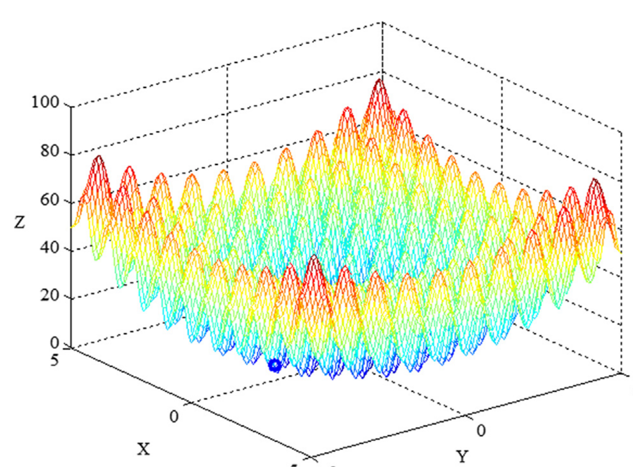

Fig 5 Optimal Point Value.

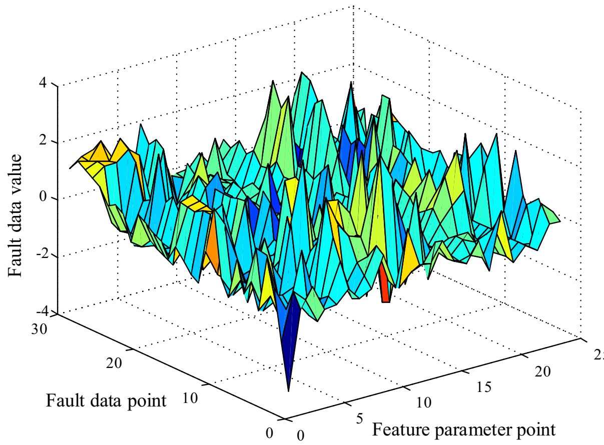

Fig. 6 Corresponding results of fault data and characteristic parameters.

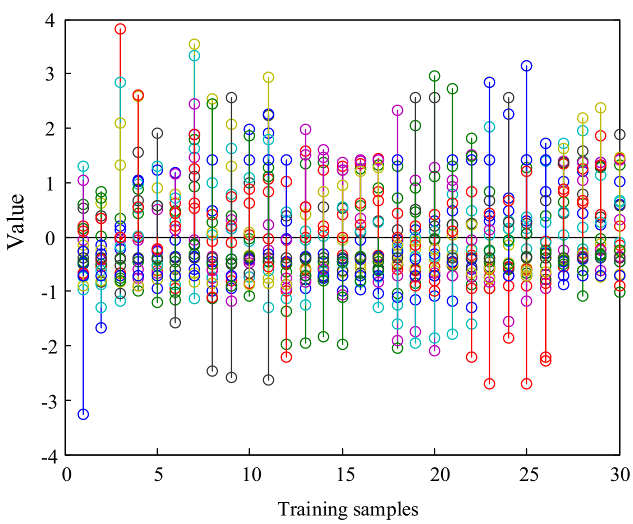

Fig. 7 Discrete situation of training data.

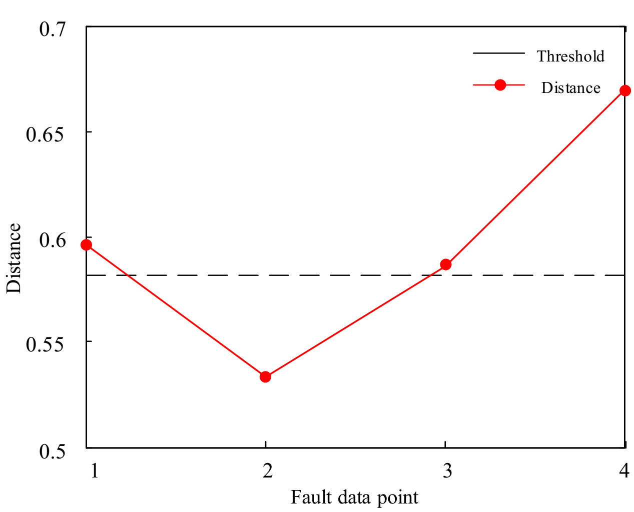

Fig. 8 Test result of unknown fault type.

The training data is used to train the SVDD algorithm model optimized by the PSO algorithm. The four sets of test data after Y_{31}-Y_{34} in Table 2 are input into the PSO-SVDD model. The results are shown in Fig. 8.

It can be seen from Fig. 8 that when four sets of test data are input into the PSO-SVDD model, all four sets of data exceed the threshold range. The model judges that the four sets of data cannot match the known fault types in the model and belong to unknown fault types. The four unknown fault types are defined as D8 fault, D9 fault, D10 fault and D11 fault. Therefore, it can be concluded that during the operation of the box transform substation, new fault types have appeared. The four sets of data and the four new fault types need to be input into the fault diagnosis model for adaptive update.

5. Conclusion and future work

Considering that the general fault diagnosis model does not consider the occurrence of unknown fault types, based on the standard power IoT perception layer, transmission layer and application layer three-layer framework, we propose the PSO-SVDD method to identify unknown types of faults in box-type substations, and adaptively update the fault diagnosis model based on the recognition results. In order to obtain the SVDD model with the best combination of parameters, the parameters are optimized using the PSO method. The SVDD model under PSO optimization is trained using training data, and the validity of this unknown fault identification method is verified by test data. This method adds the ability to identify unknown fault types to the fault diagnosis model and the ability to learn new knowledge to adaptively update the model, so as to better meet the needs of model changes caused by sample accumulation and improve the fault diagnosis level of box transformer substation. In order to realize the pre-warning of the box transformer substation failure, the follow-up research will be based on the big data-based box transformer substation failure warning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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