A MODEL BASED ON SVM-GDPSO FOR THE VOLTAGE STABILITY FORECASTING OF LARGE POWER SYSTEM

Q. Li[*], *Y. Qiang*[†], *D. Kong*[‡], *X. Liu*[§]

Abstract: The stability assessment of a large power system in real-time is very necessary after it encounters fault. The paper proposes a new model (SVM-GDPSO) for assessing the large power system. In order to enhance SVM, taking tangent vector of power flow Jacobian (PFJ) as the goal of machine learning was used for improving the precision. Besides, particle swarm optimization (PSO) with Gaussian disturbance (GD) is taken for setting the key parameters of SVM, and meta-learning was utilized to decrease the search space of PSO. The experiment on the standard test system of IEEE 118-bus demonstrated that this model could reflect the status of large power system in time. Besides, the method could locate the fault area and rank the fault level by the observation of critical bus. The proposed method has the reliability rate 97.22 %, which is superior to the back propagation neural network (BPNN) and SVM-GA, as well as determines the fault area with the success rate of 96.61 %.

Key words: *power flow, PSS, SVM, voltage stability assessment, meta-learning, gaussian disturbance, GDPSO*

Received: February 12, 2020 **DOI:** 10.14311/NNW.2022.32.008
Revised and accepted: June 30, 2022

1. Introduction

People have paid much effort to avoid the system exceptions, since the accidents of power grid happened occasionally and lead to an amount of cost. Practically, system stability could take the risk of impaction [1].

PMUs are very practical tools for monitoring system status in real-time, since it can provide valuable hint beforehand before system collapse [2].

A large number of methods on the assessment after disturbance have been reported. Where, the nonlinear differential formulas are used to show the system

[*]Qiang Li; Information Institute, Shan Xi Finance & Taxation College, Taiyuan City, 030024, P. R. China, E-mail: 122824940@qq.com

[†]Yan Qiang – Corresponding author; College of Information and Computer, Tai Yuan University of Technology

[‡]De-jin Kong; College of Finance, Tai Yuan University of Technology, Taiyuan City, 030024, P. R. China

[§]Xiao-feng Liu; College of Data Science, Tai Yuan University of Technology, Taiyuan City, 030024, P. R. China

status directly, but they need whole network information and their time-cost is larger [3].

Practically, the index is the one easiest way to monitor system performance. Voltage collapse proximity indicator (VCPI) is a useful tool to observe system status [4]. Dynamic voltage collapse indicator (DVCI) has been used to describe the system limited status in real-time. Where, PTSI was considered as one better DVCI [5]. The paper [6] proposed a new method regarded as a VSI, which is "the components of tangent vector of the power flow jacobian". This method could present voltage collapse as L index does. Additionally, it has a wider application range and more precise than L index does.

AI has been utilized to assess the system status and can control system successfully in recent years. Decision trees (DT) is a good example for establishing expert system [7]. This technology is helpful to decide the system status quickly, but it is usually very difficult to construct a trees structure for complicated system beforehand. Some experts have used the fuzzy algorithm to enhance the recognition [8]. It was reported that BP network was applied successfully for electrical fault identification. However, this method still needs a large number of data and time for training [9].

Support vector machine (SVM) has developed quickly for nearly twenty years. Comparing with BP network, SVM has much less training data and time [10, 11]. Nevertheless, some parameters influence its performance greatly the same as they does for ANN.

The simplest way to set these parameters is artificial by experience so that the precision and performance is very limited. There are grid search method and gradual gradient search method about the parameter automatic-setting algorithms for SVM. Grid search method need to search in the problem space by the presetting interval, however it is time-cost and precision depends on the interval. Gradual gradient search can execute quickly in the space of smooth boundary surface, but the search space exists much less practically.

The paper [12] proposed a method based on the "quasi-Monte Carlo" theory, called MOUD, for reducing the search scope. Genetic algorithm (GA) and PSO were used to set the combination parameters automatically, at same time it was also demonstrated in the experiment that PSO has better precision and performance than others does [13–15].

In fact, PSO algorithm falls into local minima easily, thus Gaussian disturbance was taken for improving PSO in this paper, called "GDPSO". The method not only obtains the parameters, but also resolves the problem that they were contradictory.

An amount of data is produced by power flow computation in real-time, thus some technologies were utilized, that network simplication for the large power system was carried out for saving time and the computation performed on a distribution system, and a novel model used SVM to compute the tangent vector (TV) of PFJ in order to assess the system security in this paper.

In our model, an enhanced PSO algorithm was used to compute the optimum combination parameters for SVM. Furth more, the meta-learning technology was applied for supporting PSO initial seeds. The last test decided the parameters as well.

This paper is divided six Sections. Section 2 describes the technology of the tangent vector of power flow Jacobian. The algorithms of support vector machine (SVM) and particle swarm optimization with Gaussian disturbance (GDPSO) are shown in next part. Network optimization and experiment model in Section 4. The analyses of experimental result in Section 5. The conclusion is drawn in last part.

2. The definition of tangent vector

Practically, the L index is a PVSI (popular voltage stability indicator), which is used to assess the system status popularly. The reference [6] demonstrated that the method applies in direct-connected system limitedly but other systems, such as radial distribution system, as well as it only can express relative value.

The equation (1) expresses the equilibrium relationship including active power and reactive power about i-th node in power flow computation.

$$P_{Gi} - P_{Li} - P_{Ti} = 0, P_{Ti} = \sum_{j=1}^{n} V_i V_j \left[G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}\right],$$

$$Q_{Gi} - Q_{Li} - Q_{Ti} = 0, Q_{Ti} = \sum_{j=1}^{n} V_i V_j \left[G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}\right], \tag{1}$$

where P is an active power and Q is a reactive power, $\cos \delta_{ij}$ is power factor.

The Eq. (2) defines the matrix of power flow jacobian (PFJ) at any operating node which is derived from above Eq. (1).

$$J_{\text{powerflow}} = \begin{pmatrix} \frac{\partial Q_{Ti}}{\partial \delta_j} & \frac{\partial P_{Ti}}{\partial \delta_j} \\ \frac{\partial Q_{Ti}}{\partial V_j} & \frac{\partial P_{Ti}}{\partial V_j} \end{pmatrix} \tag{2}$$

The tangent vector (TV) is obtained from the matrix of power flow jacobian in Eq. (3).

$$TV = \begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} = J_{\text{powerflow}}^{-1} \begin{bmatrix} P_{Gi} - P_{Li} \\ Q_{Gi} - Q_{Li} \end{bmatrix} \tag{3}$$

In the above formula, voltage amplitude is represented absolutely by the element $\Delta|V|$ at any load bus, and in the range of 0 and 1 for stable state, otherwise for instable state. Furthermore, it can be applied in any network topology structure including radial distribution system, thus it is considered as a better replacement for L index [6].

In practice, it is very difficult to obtain the tangent vectors at all operating points in real-time, because it still needs amount of computation. In order to resolve the above problem, this paper suggests that SVM-GDPSO model is used for simulating the component $\Delta|V|$.

The subfigure (A) in Fig. 1 shows that L index and tangent vector have the same behaviors when system in security state. Nevertheless, when the load reachs 150 % (load rate $\beta = 1.5$) for standard 14-bus system in subfigure (B), L index failed to note the critical bus when system collapsed. From the above oberservation, TV is superior to L index in the respects of accuracy and reliability.

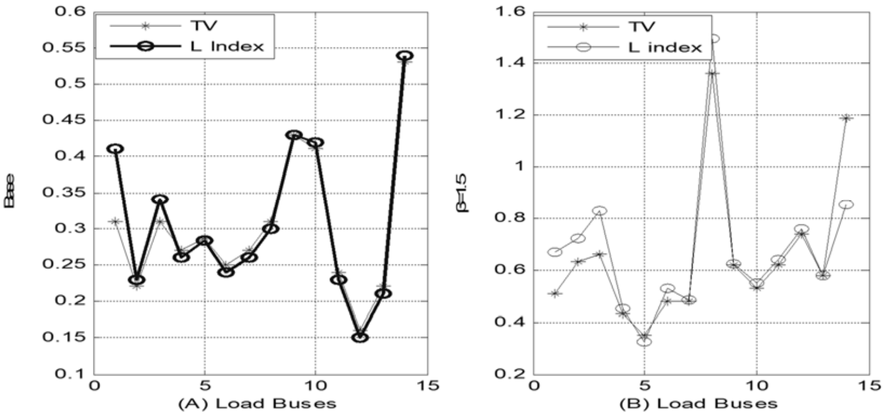

Fig. 1 *Tangent vector on standard IEEE 14-bus system.*

3. SVM-GDPSO model

3.1 SVM model

SVM is a promising method in the respects of regression and classification, and successfully applied in prediction.

Assuming a set of training samples, $\{u_j, v_j\} = 1, 2, \ldots, n$, with $u_j \in \mathbb{R}^s$ and $v_j \in \mathbb{R}$, where u_j and v_j are respectively input and output value. A linear function in SVM is defined which can divide the space into two parts, that is binary classification.

In Eq. (4), the weight factor is represented by ω, as well as the deviation done by β.

$$f(u) = \omega \cdot u + \beta \tag{4}$$

A large number of nonlinear spaces exists practically, thus $\phi(u)$ is a mapping function that change the nonlinear space into a linear space in order to take the Eq. (5) [19]. The Eq. (5) redefines the regression function $f(u)$ as bellow.

$$f(u) = (\omega \cdot \phi(u)) + \beta \tag{5}$$

There are two slack factors η_j, η_j^* to describe the amplitude of deviation where the samples are beyond band. The above Eq. (5) takes optimization as bellow.

$$\min \frac{1}{2} \|\omega\|^2 + T \sum_{j=1}^{n} \left(\eta_j + \eta_j^*\right), T > 0 \tag{6}$$

$$\text{s.t.} \begin{cases} v_j - \omega \cdot \phi(u) - \beta \leq \tau + \eta_j, \\ \omega \cdot \phi(u) + \beta - v_j \leq \tau + \eta_j^*, \end{cases} \eta_j, \eta_j^* \geq 0, j = 1, 2, \ldots, n \tag{7}$$

In constraint condition of the Eq. (6), the nonsensitive lose is presented by τ, as well as the penalty factor T describes the punishment level of sample deviating from the error.

In order to simplify the above problem, extreme value problem with constrained conditions is mapped into the dual problem by Lagrange method. And the Lagrange multipliers α_i, α_i^* are introduced in Eq. (8) for transformation expression.

$$\begin{aligned} & \max \sum_{i=1}^{n} v_i(\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^{n} (\alpha_i + \alpha_i^*), \\ & -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(u_i, u_j), \\ \text{s.t.} \quad & \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0, \qquad C \geq \alpha_i, \alpha_i^* \geq 0 \\ & K(u_i, u_j) = \varphi(u_i) \cdot \varphi(u_j). \end{aligned} \tag{8}$$

For reducing the huge scale of computation, kernel function $K(u_i, u_j)$ takes the place for dot product operation in high dimensional space. In other words, the kernel $K(u_i, u_j)$ achieves function in the input space and prevents dimensional disaster.

As a kernel, the function needs to meet the Mercer's principle that the function should be positive and semi-definite. There are several usual kernels such as linear, polynomial and Gaussian RBF. In our experiment, Gaussian RBF kernel is selected for SVM. This kernel with a parameter γ is shown as bellow, and γ is the width of function distribution.

$$\text{Gaussian RBF: } K(u_i, u_j) = \exp(-\frac{\|u_i - u_j\|^2}{2\gamma^2}). \tag{9}$$

The Eq. (10) describes the final SVM regression model.

$$f(u) = \sum_{i=1}^{m} (\alpha_i - \alpha_i^*) K(u_i, u_j) + b. \tag{10}$$

SVM classification for stability assessment is as shown in reference [10].

To validate the model, a k-fold cross-validation will be carried out in the experiment, which uses $k-1$ folds for training the model and one fold for testing. This procedure is repeated k times, such as each fold is used for testing.

3.2 PSO algorithm

The main idea of particle swarm optimization (PSO) algorithm is from the observation of foraging behavior of birds, swarm intelligence discovery in other words. In the algorithm, each bird is abstracted as an independent particle with individual position and independent movement velocity. Meanwhile, every particle is guided by the group. Besides, the group has one uniform movement velocity and position, that the calculation is integrated according to the velocity and position of all the particles. At same time, the "elite" in the group will also affect the direction of the dominant movement of the whole. Finally, the group of birds would obtain the optimal solution in problem space through evolutionary process.

The system will firstly produce a group of particles to represent the birds according to the setting at beginning. During movement, the particles will tend to the two goals: The one is the best position of the whole, which is the best solution of group p_g; the other is the best position of single individual, namely p_i. In the iterative process of the algorithm, each particle will update its position and movement parameters according to the Eq. (11).

$$\begin{aligned} v_{i,j}^k &= \rho \cdot v_{i,j}^{k-1} + \delta_1 \beta_1 (p_{i,j}^{k-1} - x_{i,j}^{k-1}) + \delta_2 \beta_2 (p_{g,j}^{k-1} - x_{i,j}^{k-1}), \\ x_{i,j}^k &= x_{i,j}^{k-1} + \gamma \cdot v_{i,j}^k, \end{aligned} \tag{11}$$

where the coefficient ρ records the capability of previous movement. The variables of x and v are on behalf of position and velocity respectively. Moreover, δ_1 and δ_2 are random between 0 and 1, β_1 and β_2 are accelerating factors by manual, γ is weight factor that controls velocity. Additionally, k is iteration number.

3.3 Improvement with Gaussian disturbance

The basic particle swarm algorithm provides excellent means, a kind of swarm intelligence, to solve the combinatorial optimization problems, but the algorithm easily falls into the local minima during optimization process. As a result, the solution is limited to local optimal solution rather than the global optimal solution [12]. In order to avoid this situation, we take the Gaussian disturbance technology to improve the basic PSO.

$$\begin{aligned} v_{i,j}^k &= w \cdot v_{i,j}^{k-1} + c_1 \beta_1 (p_{i,j}^{k-1} + \beta_3 g^k - x_{i,j}^{k-1}) + c_2 \beta_2 (p_{g,j}^{k-1} - x_{i,j}^{k-1}), \\ x_{i,j}^k &= x_{i,j}^{k-1} + \gamma \cdot v_{i,j}^k, \end{aligned} \tag{12}$$

$$g^k = \beta_4 \, gaussian \, (\mu, \sigma^2). \tag{13}$$

The Gaussian disturbance particle swarm optimization (GDPSO) enhances the updating capability of the individual velocity by Gaussian disturbance In above Eqs. (12), (13), β_3 and β_4 are all a random value between 0 and 1, μ and σ are the sample mean and variance respectively.

The specific steps of GDPSO shown in Fig. 2 are as follows:

First step: Initiate seeds and set system parameters.

Second step: Evaluate the fitness of each individual particle by fitness function.

Third step: Calculate the best positions of each individual and the group in history. Additionally, generate the disturbance offset by Gaussian disturbance.

Fourth step: Update the velocity and position.

Fifth step: Determine whether to meet the terminal conditions, if satisfied, then end the program, output the particle swarm optimization and the corresponding fitness; otherwise, go to the second step and continue to execute.

The fitness function (14) is taken for assessing the quality of the parameter setting during the training. Where, $y_i(x)$ is the target that needs the computation of SVM and $y_i'(x)$ is the real value. The $g(x)$ is utilized to assess the setting of

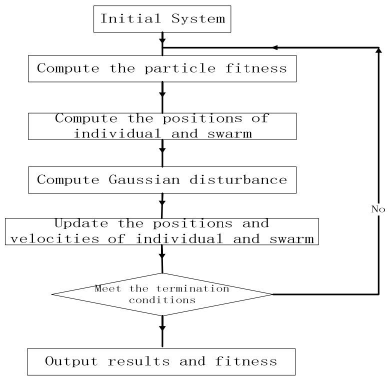

Fig. 2 *Optimization process of GDPSO.*

the whole model, and the value of which is smaller, the model is better. When it meets the conditions, the program ends.

$$\mathrm{g}(x) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i(x) - y_i'(x)\right)^2}. \tag{14}$$

3.4 Model selection & initial seed

The paper [16] suggests that prior experience could help to enhance the capability of machine learning. Furthermore, the paper [17] proposed a meta-learning model for how to utilize the experience. A lot of experience that the similar experiments and methods performed on other standard systems has been accumulated. Based on the above thought, we create a meta-database to select the initial parameters and kernel type for SVM.

Meta-learner module retrieves a predefined number of past meta-examples stored in a database (DB), selected on the basis of their similarity to the input problem.

The algorithm of constructing the meta-leaner:

Given a problem, its input can be represented by a vector $x = (x_1, \ldots, x_n)$, A function was defined to calculate the distance between the meta-attributes of the input and meta-examples in meta-base. The meta-learner searches the k most similar meta-examples by the function.

$$dis(x, x') = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(x_i - x_i')^2}. \tag{15}$$

400 datasets in SVM exist in the database, and each includes algorithm name, experiment system, kernel type, the success rate for each kernel, and optimized parameters etc. [11]. Kernel types include linear kernel, polynomial kernel, and RBF kernel.

In our experiment, RBF kernel is selected for SVM because the RBF kernel is superior to other kernels in the respects of performance and accuracy in history. The initial seeds of PSO were also selected from the database.

Combined multiple parameters may be competing so balance point of multi-object based on "ROC front" technique determines was presented in the paper [18]. At same time, the paper also proved that the point cannot be found in time since the decided condition is difficult to obtain at runtime, and the only left way is the last testing.

The initial parameters for particle swarm optimization were selected from the database and recombined. As we known, PSO could produce multiple results. Thus those should be tested further and decided for the goal.

4. Experiment

4.1 Test system

This experiment carried out on IEEE standard 118-bus test system, which has 50 generators and 118 Load buses.

4.2 Network simplication

Many main factors influence the voltage amplitude including the generator status, system level, bus load, etc. In the basic formula of power flow computation, it can be found that active power, reactive power and bus load are the main impacting factors [6]. Thus, input sample should contain these variables. 118 nodes exist and 354 parameters for input in the standard IEEE 118-bus system. A large number of computation produce in short-time so that the SVM algorithm difficultly reaches convergence in time. So, it is very necessary to simplify the network scale.

Keeping boundary condition including geographical and electrical characteristic is an important principle during the process of simplifying. In each sub-area, the power flow computation executes alone and it retains stability relatively. In addition, mutual influence between areas is reflected by the link-line bus between the both [20].

The simplication principle is:

- Calculation independent: the part with less links with other parts as possible and can do power flow computation alone.
- Electrical and spatial locality: the target node and its neighbors keep in same area geographically and electrically. Additionally, the whole structure can't be changed.

The Fig. 3 shown that the system is divided into 3 parts by the dotted line, containing part A, part B and part C. Each part contains fewer nodes and keeps the whole structure.

4.3 Experimental model

There are four SVMs in our experiment. The three SVMs of them were employed for identifying the fault area and the other was utilized to simulate the tangent vector of PFJ that indicated the whole system status simultaneously. So five outputs exits

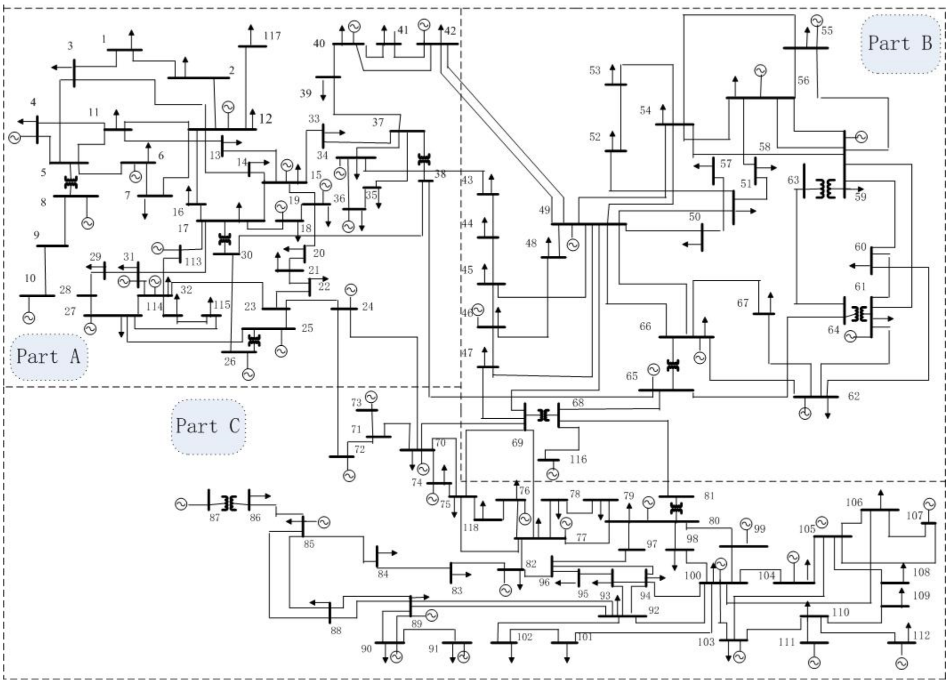

Fig. 3 *Network simplication of IEEE standard 118-bus system.*

in the model in Fig. 4 Out 1, out 2 and out 3 represent the stable status of each part respectively and out 4 is the status of the whole power system. Besides, out 5 is the output of simulation of the *VSI* which is the component of tangent vector of power flow jacobian.

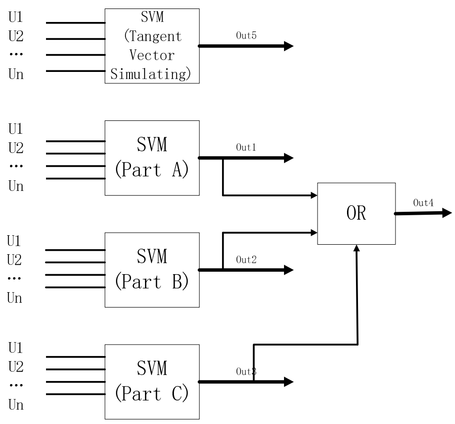

Fig. 4 *System model.*

4.4 Experimental tools and generation of data

This algorithm is the enhancement of libsvm and particle swarm algorithm in MATLAB. Besides, the PSO is an improvement with Gaussian disturbance by custom-programmed.

Power system analysis toolbox (PSAT) is used to produce all data in simulation [21].

There were 1000 loading cases that the load of each bus was changed randomly in four degrees ($\pm 25\,\%$, $\pm 50\,\%$). 472000 data were produced (1000×472).

The producing principle for data is:

1. Change the three parameters including (active power, reactive power, and load) at all buses; Change the three parameters at individual bus; Change each parameter alone at each bus.

2. Calculate power area parameters through link-link between the adjacent parts and other parts considered as an equivalent system.

In order to response in real-time, the program was deployed on a distributed system. The job of each areas and a job of simulation ran on four parallel nodes as shown in Fig. 5. Besides, a master node was in charge of management.

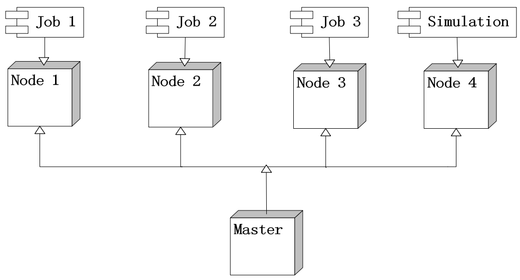

Fig. 5 *Jobs running model.*

4.5 The configuration of system

Before running, the parameters of system need to be set as in Tab. I.

The Gaussian RBF was considered as the best kernel type by meta-database.

500 data were used for the total seeds, where 400 of the total recombining records from meta-database for initial seeds, and several values produced randomly between 0 and 2^{16} for the left.

The configuration of three hyper-parameters is set as in Tab. II.

4.6 Training and testing data

A 5-fold cross validation was selected to train and test data set in this experiment.

The simulation tools produced 472000 data for the model totally. $80\,\%$ of the total data was for training and the left ($20\,\%$ of the total) for testing.

Name	Value	Role	Description
R_l	12	Real-coding length	6 bits for integer
S_N	500	Initial seeds number	
ρ	0.5	Record coefficient	
γ	0.75	Velocity control factor	
β_1	0.65	Accelerating factors	
β_2	0.23	Accelerating factors	
loop	100000	Max loop number	Max loop number
MSE	0.5e-5		Max loop number

Tab. I *System parameters.*

Parameter	Begin	End	Step size
C	0	20	0.01
σ	-2	2	0.00001
ε	-2	2	0.00001

Tab. II *Hyper-parameters range and precision.*

4.7 Experimental procedure

The steps of SVM-GDPSO algorithm is defined by the following description.

1. Run the standard IEEE 118-bus system on the tool of PSAT and produce the simulation data.
2. Use 80 % data as training sample; Decide the input and output data
3. Decide initial seeds of PSO from meta-database.
4. Compute the parameters for SVM by GDPSO.
5. Adjust the weights by the fitness function as the Eq. (14).
6. Satisfy the end conditions and generate the candidates, otherwise go back to the step (iv).
7. Determine the best candidates by the last test.
8. Output result.

5. Result and analysis

5.1 SVM parameters

37 candidates were generated by SVM-GDPSO algorithm. Then they were decided trough the last test and their presentation as bellow in Tab. III.

Algorithms	The average number of iterations	The average convergence time (ms)	The global optimal probability [%]
GDPSO	179	145	92.55
GA	235	189	87.53
Grid-search	22980	232791	73.31
Gradient-search	1151	535	32.37

Tab. III *Algorithms for the parameters of SVM.*

It can be found in the Tab. III that the proposed method is superior to the others including GA, Grid-search and Gradient-search in the aspects of performance and global optimal probability. Thus, GDPSO is recognized as the better solution for the automatic configuration of SVM.

By comparing the MSEs of different algorithms in Tab. IV and Tab. III, the proposed algorithm has the higher accuracy than the others do, whose MSE is 1.03371e-005, and the best candidates for SVM parameters (C, σ, ε) are 9.231377, 0.512323 and 0.003717 respectively.

Parameters	GDPSO	GA	Grid-search	Gradient-search
C	9.231377	12.250011	16.17231	22.32872
σ	0.512323	0.472312	0.01434	0.57432
ε	0.003717	0.003432	0.22481	0.003226

Tab. IV *Parameters and accuracy.*

5.2 Algorithm performance

There are four algorithms for simulating the TV respectively and their performances presents as bellow Tab. V. The learning time includes only the time required to train the model after performing the hyper-parameters selection.

Model	Learning time (s)	Testing time (ms)	Mean squared error (MSE)
SVM-GDPSO	437	72	0.83731e-006
GA-SVM	752	104	2.03749e-006
SVM	1221	254	3.41237e-006
BPNN	4781	421	4.92743e-006

Tab. V *The performances of simulations.*

The Tab. V shows that the training time for SVM-GDPSO, GA-SVM, SVM and BPNN are 437 s, 752 s, 1221 s and 4781 s respectively. Besides, the testing times for the different algorithms are 72 ms, 104 ms, 254 ms and 421 ms respectively. Simultaneously, it can be seen that SVM-GDPSO is superior to the others in respect of accuracy. Besides, the spending time during the evolutionary task was only 210 s. By the above analysis, SVM-GDPSO is more suited to assess the large power system in real-time.

5.3 Algorithm test

20 % (94400) of total data is used for testing, 25 % of it (23600) used for unstable case and the left (70800) used for stable case.

The Tab. VI shows that the accuracy of data classified as stable in stable case can reach 100 %, but the data of less than 3 % in unstable case are wrongly assigned in stable case.

Cases	Classified as stable [%]	Classified as unstable [%]
Stable case	100 (70800/70800)	0 (0/70800)
Unstable case	2.783 (657/23600)	97.216 (22943/23600)

Tab. VI *Classification accuracy.*

5.4 Identifying unstable area

The status classifier in each area outputs the value 0 or 1, 0 for instability and 1 for stability. For identifying the critical bus, it firstly generates the error of locating area, when each bus increase 50 % of load alone and the others keep constant.

The Tab. VIII presents that 4 buses are identified wrongly for SVM-GDPSO, but 6 buses for GA-SVM.

Bus No.	Area No.	SVM-GDPSO	GA-SVM	Bus No.	Area No.	SVM-GDPSO	GA-SVM
24	1	3	3	69	2	3	3
34	1	2	2	70	3	3	2
49	2	1	1	81	3	3	2

Tab. VII *Error of identifying unstable area.*

Method	Error No.	Correct rate [%]
SVM-GDPSO	4	96.61
GA-SVM	6	94.91

Tab. VIII *Locating accuracies.*

The Tab. VIII demonstrates that the suggested method locates the area with the correct rate of 96.61 % and GA-SVM with the rate of 94.91 %. Thus, SVM-GDPSO has higher success rate in locating fault area.

5.5 Locating critical buses

When system subjects to a fault, the weakness point is firstly critical bus. Identifying the critical buses of system will help to management and reduce the cost of risk. Thus, in order to find them, each bus raises the load with rate of 150 % ($\lambda = 1.5$) alone and the others remains constant respectively.

It was observed in Tab. IX that 13 critical buses exist in the system whose value is greater than 1. Meanwhile, some non-sensitive buses can be seen in Fig. 6 whose values between 0 and 1. Besides, there are some buses whose value is near to 1 and less than 1. For ease of management, they can be ranked as three levels. The first level in which the value of buses is above 1 needs to be focused on. The buses, the value of which is between 0.6 and 1, need to pay less attention and be arranged to the second level. In addition, the left buses for the third level.

Bus No.	Area	Value of TV
12	1	1.77
15	1	1.38
17	1	1.89
37	1	1.33
49	2	1.58
56	2	1.28
68	2	1.30
69	2	1.33
70	3	1.32
77	3	1.78
80	3	1.63
100	3	1.43
105	3	1.32

Tab. IX *Identifying critical buses.*

6. Conclusion

The paper provided the novel method of SVM-GDPSO for assessing the status of large power system in real-time. In the model, particle swarm optimization was used to set the parameters for support vector machine, and the approach of Gaussian disturbance was applied for improving PSO by enhancing the capability of global search. Additionally, meta-learning technology was taken in order to reduce the search space of PSO, thus a large number of parameters on similar experiments was accumulated for setting the initial seeds of PSO. Besides, the component of tangent vector taken as the learning goal of SVM is helpful to improve the range and precision in application.

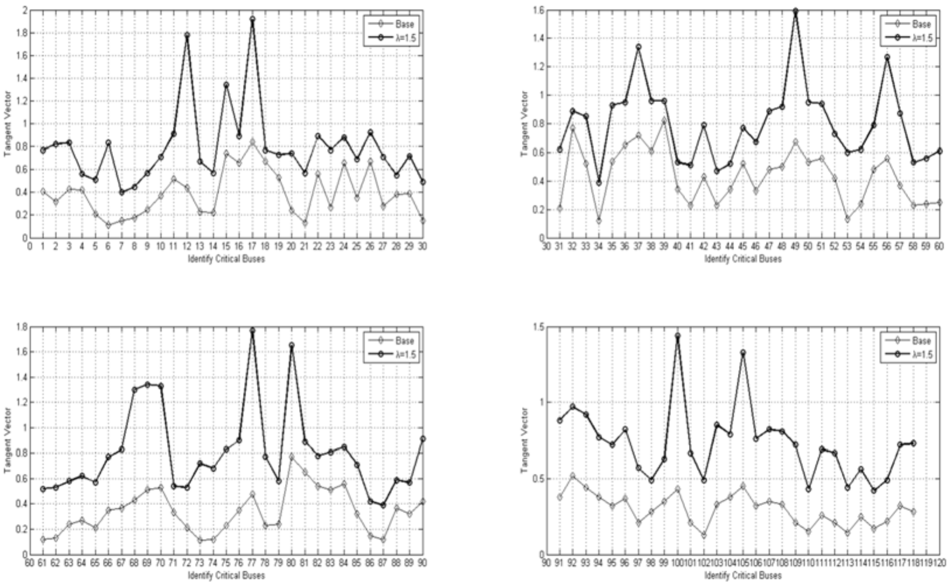

Fig. 6 *Find critical buses.*

The research of the voltage security assessment of large power system based on the SVM- GDPSO notes that the prediction of reliability could reach to 97.216 %. Meanwhile, it is also indicated that this model is able to decide the system status in real-time and provides the alert information for protection system. The observation of critical buses based on the model tends to focus on the weak point of system and maintain the complex system.

Besides, it is very interesting to find the more information of specific position and fault equipment which is our next research spot.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (61502330) and Science and Technology Innovation Project of Shanxi Province (2020L0743) and Project of Soft Science Project of Shanxi Province (2016041008-5).

Statement We declare that there is no conflict of interest regarding the publication of this paper

References

[1] KARLSSON D., LINDAHL S. *Wide area protection and emergency control,In Proc. IEEE Power Eng. Soc. General Meeting,* 2004, 1, p. 5.

[2] PHADKE A.G. *Synchronized phasor measurements in power systems, IEEE Comput, Appl. Power*, 1993, 6(2), pp. 10–15.

[3] ANDERSON P.M. *A. Fouad, Power System Control and Stability, 2nd ed. Piscataway,* NJ: IEEE, 2003.

[4] KESSEL P., GLAVITCH H. *Estimating the voltage stability of power systems, IEEE Trans. on Power Delivery*, 1986, 1(3), pp. 346–354.

[5] NIZAM M., MOHAMED A. *Hussain. Performance evaluation of voltage stability indices for dynamic voltage collapse prediction, Journal of Applied Science,* 2006, 6(5), pp. 1104–1113.

[6] ACHARYA N.V., RAO P.S.N. A new voltage stability index based on the tangent vector of the power flow jacobian, ISGT Asia (978-1-4799-1346-6), 2013, IEEE, pp. 1–6.

[7] KAI S., LIKHATE S., VITTAL V., KOLLURIV V.S., MANDAL S. An online dynamic security assessment scheme using phasor measurements and decision trees,IEEE Trans. Power Syst., 2007, 22(4), pp. 1935–1943.

[8] GAVOYIANNIS A.E., VOGIATZIS D.G., GEORGIA D.R., HATZIARGYRIOU N.D. Combined support vector classifiers using fuzzyclustering for dynamic security assessment, In Proc. IEEE Power Eng. Soc. Summer Meeting, 2001, 2, pp. 1281–1286.

[9] HAN X., ZHENG Z., TIAN N., HOU Y. Voltage stability assessment based on BP neural network, Asia-Pacific Power & Energy Engineering Conference (978-1-4244-2486-3), 27-31 March 2009, pp. 1–4.

[10] GOMEZ F.R., RAJAPAKSE A.D., ANNAKKAGE U.D. Support Vector Machine-Based Algorithm for Post-Fault Transient Stability Status Prediction Using Synchronized Measurements, IEEE Transactions on Power Systems, 2011, 26(3), pp. 1417–1483.

[11] LI Q. Analysis and assessment of voltage stability based on GA-SVM, Journal of system simulation, 2014, 26(11), pp. 2369–2373+2406. ISSN:1004-731X.

[12] LI W., LIU L., GONG W. Multi-objective uniform design as a svm model selection tool for face recognition, Expert Syst. Appl., 2011, 38(6), pp. 6689–6695.

[13] LI Q, LIU X.F. Voltage Stability Assessment of Complex Power System Based on GA-SVM, Nerual network world, 2019, 29(6), pp. 447–463.

[14] YUAN R., GUANGCHEN B. Determination of Optimal SVM Parameters by Using GAPSO, journal of computers, 2010, 5(8), pp. 1160–1168.

[15] LORENA A.C., DE CARVALHO A.C., Evolutionary tuning of SVM parameter values in multiclass prolems, Neurocomputing, 2008, 71(16–18), pp. 3326–3334.

[16] MIRANDA B.C., PRUDENCIO R.B.C., CARVALHO A.C.P.L.F., SOARES C. Combining meta-learning with multi-objective particle swarm algorithms for svm parameter selection: an experimental analysis. In: Proceedings of the 2012 Brazilian Symposium on Neural Networks, SBRN '12, IEEE Computer Society, Washington, DC, USA, 2012, pp. 1–6.

[17] MIRANDA B.C., PRUDENCIO R.B.C., CARVALHO A.C.P.L.F., SOARES C. Multi-objective optimization and meta-learning for svm parameter selection. In: The 2012 International Joint Conference on Neural Networks (IJCNN), 2012, pp. 1–8.

[18] CHATELAIN C., ADAM S., LECOURTIER Y., HEUTTE L., PAQUET T. A multi-model selection framework for unknown and/or evaluative misclassification cost problems, Pattern Recognit, 2010, 43(3), pp. 815–823.

[19] AN J.L., YANG Q.X., MA Z.P. Study on SVM on-line function regression method for mass data, Machine Learning and Cybernetics, 2007 International Conference, 2007, (978-1-4244-0973-0), 5, pp. 2773–2777.

[20] LI X., SONG Y., LIU J., FU Y., ZENG M. Post-fault voltage security assessment of complex power system based on ANN, Proceedings of the Chinese Society of Electrical Engineering, 1996, 16(3), pp. 147–150.

[21] Power System Test Archive-UWEE (University of Washington) Available-online, http://www.ee.washington.edu/research/