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PSO-MSVR Based Prediction Approach for Unstable Equilibrium Points of Disturbed Power System

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***Abstract*—With expansion of power system and continuous proliferation of renewable energy generation, the transient stability characteristics of power system become more complicated, and online transient stability assessment faces severe challenges. The calculation of unstable equilibrium point (UEP) is a critical step in the direct method of power system transient stability assessment. This paper presents a new method for predicting transient UEPs of power systems based on PSO-MSVR. Instead of complicated calculation, UEPs can be obtained by steady state measurement date. Firstly, UEPs are calculated by BCU method under different operating conditions of the system to provide sample data for the prediction model. Then the voltage amplitude and phase angle of the steady state operating conditions are taken as the sample characteristics, and the mapping relationship between the measured data and UEPs is constructed by multi support vector regression (MSVR). In the meantime, the penalty and kernel parameters in MSVR are optimized by particle swarm optimization (PSO) algorithm. Finally, fast prediction of the transient UEPs based on the steady state operating information of the system is achieved. Case study on IEEE 9-bus system shows that the proposed approach has high prediction accuracy through a small amount of training data.**

Keywords—transient stability, UEP, PSO-MSVR, BCU, prediction model

I. INTRODUCTION

Currently electric power systems operate under more stressful conditions because of the need to increase the transmission capacity of transmission lines at the lowest cost [1]. These operating conditions make power systems more susceptible to large disturbances because of the increased possibility of loss of stability. Once the stability of the power system is destroyed, it will not only lead to power failure, but form some very serious accidents [2]. After the fault occurs, the fast and accurate prediction of the unstable equilibrium point (UEP) can provide the basis for the stability discrimination in time, which is of great significance to the security prevention and control of the power system [3].

One method of power system transient stability analysis and control is the direct method or energy based method [4]. The algorithm relies on the identification of the UEP of the given transient energy function. Several methods have been proposed to compute the closet UEP [5]-[7]. In [7], homotopic-based algorithm combined with the singular fixed-point strategy is proposed to find a set of UEPs containing the closest UEP. However, the computational speed of the above-mentioned mechanism based UEP algorithm is slow, which cannot meet the requirements of online fast calculation. With the development of artificial intelligence, a large number of artificial intelligence algorithms are applied to transient stability prediction [8]-[10]. Compared with the traditional neural network, the support vector machine (SVM) method can better solve the practical problems such as small sample size, nonlinearity, high dimension and local minima [11]. In view of this, the mapping relationship between steady-state operation information and UEPs is established by using multi support vector regression (MSVR) for multi-input and multi-output (MIMO) system in this paper. And in order to determine the optimal values of the kernel width and penalty factor in MSVR model, particle swarm optimization (PSO) algorithm is used to optimize the kernel function.

The rest of the paper is structured as follows. Section II gives boundary of stability region based controlling UEP (BCU) methods for solving UEPs. In the Section III, PSO-MSVR is used to construct the mapping relationship between steady-state operation information and UEPs, in the meantime, penalty and kernel parameters in MSVR are optimized by PSO algorithm. The UEPs of the system can be quickly and accurately predicted by the voltage and phase angle of the steady-state operation node. Section IV solves UEPs of IEEE 9-bus system using the potential energy boundary surface (PEBS) and BCU methods respectively, and validates the PSO-MSVR prediction model. The conclusion is provided in Section V.

II. THE BCU METHOD

For a multi machine system, a classical model of n-machine is considered, load is simulated with constant impedance, assuming that the network shrank to the node inside the generator, ignoring the transfer conductance of the network. The system equation after fault is:

$$\begin{cases} \dot{\delta}_i = \omega_i \\ M_i \dot{\omega}_i = P_{mi} - \sum_{\substack{j=1 \\ j \neq i}}^{n} E_i E_j B_{ij} \sin(\delta_i - \delta_j) \end{cases}, \quad i = 1, 2, ..., n \quad (1)$$

where δ_i and ω_i are the rotor angle and its angular velocity of i^{th} generator, respectively; P_{mi}, M_i and E_i are the mechanical power, inertia constant and internal potential amplitude of i^{th} generator, respectively; B_{ij} is the network transfer admittance between bus i and bus j.

Take the n^{th} generator as the reference machine. Define relative angle and relative angular velocity as follows:

$$\delta_{\mathrm{in}} = \delta_{\mathrm{i}} - \delta_{\mathrm{n}},\ \omega_{in} = \omega_i - \omega_n,\ i = 1, 2, ..., n-1 \tag{2}$$

The system equation (1) can be abbreviated as:

$$\begin{cases} \dot{\boldsymbol{\delta}} = \boldsymbol{\omega} \\ \dot{\boldsymbol{\omega}} = \boldsymbol{f}(\boldsymbol{\delta}) - \dfrac{D}{M}\boldsymbol{\omega} \end{cases} \tag{3}$$

where $\boldsymbol{\delta}$ and $\boldsymbol{\omega}$ are n-1 dimensional vectors; $\boldsymbol{f}$ is n-1 dimensional vector function and have the following components:

$$f_i(\boldsymbol{\delta}) = \frac{1}{M_i}P_{\mathrm{m}i} - \frac{1}{M_n}P_{mn} - \frac{1}{M_i}\sum_{\substack{j=1 \\ j\neq i}}^{n} E_i E_j B_{ij}\sin(\delta_{in} - \delta_{jn}) + \frac{1}{M_n}\sum_{j=1}^{n-1} E_n E_j B_{nj}\sin\delta_{nj} \tag{4}$$

The equilibrium point of the system (3) is the solution of $\boldsymbol{\omega} = 0$ and $f(\boldsymbol{\delta})=0$ .The corresponding transient energy function $V(\delta,\omega)$ of the above systems can be written as the sum of the transient kinetic energy $V_{KE}(\omega)$ and the transient potential energy $V_{PE}(\delta)$:

$$V(\boldsymbol{\delta},\boldsymbol{\omega}) = V_{KE}(\boldsymbol{\omega}) + V_{PE}(\boldsymbol{\delta}) = \frac{1}{2}\sum_{i=1}^{n} M_i\omega_i^2 - \sum_{i=1}^{n} P_{\mathrm{m}i}(\delta_i - \delta_i^s) - \sum_{i=1}^{n}\sum_{j=i+1}^{n+1} E_i E_j B_{ij}(\cos\delta_{ij} - \cos\delta_{ij}^s) \tag{5}$$

where the superscript s represents the state variable at the stable equilibrium point.

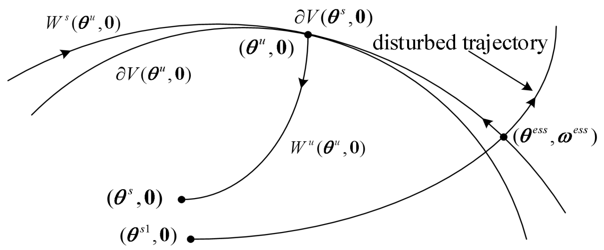


Fig. 1. The BCU method

The BCU method is an analysis method based on the theory of modern non-linear dynamic system. UEP under a specific fault whose stable manifold contains the exit point (EP) of the trajectory during fault, called the controlling UEP (CUEP).Generally, it is very difficult to determine the EP of a critical unstable trajectory, while the manifolds of SEP and UEP are not explicitly represented. It is easier to replace the stable manifold of UEP with an energy function, so it can be said that the BCU method approximates the locally stable boundary with a constant energy surface passing through CUEP, as shown in Fig. 1. In the figure, $(\boldsymbol{\theta}^{s1},\mathbf{0})$ and $(\boldsymbol{\theta}^{s},\mathbf{0})$ represent the SEPs of the system before and after the fault, $(\boldsymbol{\theta}^{ess},\boldsymbol{\omega}^{ess})$ represents the EP of the trajectory during fault, and $(\boldsymbol{\theta}^{u},\mathbf{0})$ represents the CUEP. It can be seen that the energy function value of any point on the stable manifold $W^s(\boldsymbol{\theta}^u,\mathbf{0})$ of $(\boldsymbol{\theta}^{u},\mathbf{0})$ is always greater than or equal to the constant energy surface $\partial V(\boldsymbol{\theta}^u,\mathbf{0})$.

The main steps to obtain the UEPs using the BCU method are as follows:

1) Using the PEBS method, find the EP $\boldsymbol{\delta}^*$ of projected trajectory of the fault trajectory $(\boldsymbol{\delta}(t),\boldsymbol{\omega}(t))$ in angular space through PEBS;

2) Set $\boldsymbol{\delta}^*$ as the EP of the shrinkage system and $\boldsymbol{\delta}^*$ as the initial condition, integrate the shrinkage system after fault to find the point $\boldsymbol{\delta}_0^*$ where $\sum_{i=1}^{\mathrm{n}} f_i^2(\boldsymbol{\delta})$ first reaches the minimum value.

3) With $\boldsymbol{\delta}_0^*$ as the initial value, the equation $f(\boldsymbol{\delta})=0$ is solved iteratively to obtain the UEP $\hat{\boldsymbol{\delta}}$.

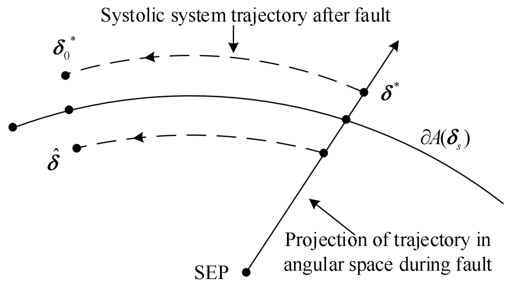


Fig. 2. The solving process of the UEPs

In Fig. 2, $\partial A(\boldsymbol{\delta}_{\mathrm{s}})$ is stable boundary of the primitive system. As shown in Fig. 2, the distance from $\boldsymbol{\delta}^*$ to $\hat{\boldsymbol{\delta}}$ is far away, but the distance from $\boldsymbol{\delta}_0^*$ to $\hat{\boldsymbol{\delta}}$ are close enough that $\hat{\boldsymbol{\delta}}$ can be quickly found using iterative method.

III. UEP Prediction Model Based PSO-MSVR Algorithm

A. The MSVR algorithm

To solve the multivariable output problem, the MSVR algorithm for MIMO systems is used to predict the UEPs. For a regression problem of n-dimensional input and m-dimensional output, assume given training samples $\{\boldsymbol{x}_i,\boldsymbol{y}_i\}_{i=1}^{L}$, where L is the number of samples, $\boldsymbol{x}\in\boldsymbol{R}^n$ is the input data, and $\boldsymbol{y}\in\boldsymbol{R}^m$ is the output data. Construct the regression function to be $\boldsymbol{F}(\boldsymbol{x}) = \boldsymbol{\Phi}(\boldsymbol{x})^T\boldsymbol{W} + \boldsymbol{B}$, where $\boldsymbol{\Phi}(\boldsymbol{x})$ is a non-linear mapping of high-dimensional space, $\boldsymbol{W}=[\omega^1,...,\omega^m]$, $\boldsymbol{B}=[b^1,...,b^m]$. In the case of multiple outputs, the minimization structure belongs to the following constrained optimization problem:

$$\min L(\boldsymbol{W},\boldsymbol{B}) = \frac{1}{2}\sum_{j=1}^{m}\left\|\omega^j\right\|^2 + C\sum_{i=1}^{L} L(u_i) \tag{6}$$

where C is the penalty factor and $L(u_i)$ is the loss function defined on the hypersphere, which is expressed as $L(u_i) = \begin{cases} 0 & u_i < \varepsilon \\ u_i^2 - 2u_i\varepsilon + \varepsilon^2 & u_i > \varepsilon \end{cases}$; $u_i = \left\|\boldsymbol{e}_i\right\| = \sqrt{\boldsymbol{e}_i\boldsymbol{e}_i^T}$, $\boldsymbol{e}_i = \boldsymbol{y}_i - \boldsymbol{\Phi}(\boldsymbol{x}_i)^T\boldsymbol{W} - \boldsymbol{B}$; ε is a hypersphere insensitive domain. When $\varepsilon = 0$, the problem is a least-squares regression of each output component. When $\varepsilon \neq 0$, the regression of output function is solved by taking into account the fitting effects of other output components, so that the problem will be an optimal solution for overall fitting.

By introducing Lagrange multipliers, the estimation function of MSVR is obtained after partial derivative processing of the related parameters as follows:

$$\boldsymbol{F}(\boldsymbol{x})=\sum_{i=1}^{L}(\alpha_i-\alpha_i^*)\boldsymbol{K}(x_i,x)+\boldsymbol{B} \tag{7}$$

where $\alpha_i,\alpha_i^*\geq 0(i=1,2,...,L)$ are Lagrange multipliers and $\boldsymbol{K}(x_i,x)$ is a kernel function.

In the construction of MSVR, the selection of kernel is the most important. Generally, Gaussian kernel is chosen as the kernel in MSVR model, and its expression is:

$$K(x_i,x_j)=\exp(-\frac{\left\|x_i-x_j\right\|^2}{2\sigma^2}),\sigma>0 \tag{8}$$

where σ is kernel width which controls the range of the Gaussian kernel function.

B. The PSO algorithm

Generally, the kernel width σ and penalty factor C are set artificially in MSVR model construction, and it is not possible to determine the optimal value of these two parameters. For this reason, this paper uses PSO algorithm to find the optimal combination of parameters in MSVR model, and then the optimal combination of parameters is assigned to MSVR for model building.

The PSO algorithm is a population-based random optimization technique. The quality of each particle is determined by the fitness function. The position and speed of each particle are updated by learning global and local optimal solutions to achieve global optimization. The particle positions and velocities are $\boldsymbol{X}_i=(x_{i1},x_{i2},...,x_{id})$ and $\boldsymbol{V}_i=(v_{i1},v_{i2},...,v_{id})$, respectively. The speed of particles directly affects the global convergence of PSO algorithm. When approaching the optimal solution, particles lack effective control and constraints, and do not have strong local search ability. Therefore, effective control and adjustment of particle flight speed can be achieved by introducing inertial weights. The strategy they update is:

$$\begin{aligned}
&\mathrm{v}_{id}^{(t+1)}=w\cdot\mathrm{v}_{id}^{(t)}+c_1r_1(p_{id}^{(t)}-x_{id}^{(t)})+c_2\mathrm{r}_2(p_{gd}^{(t)}-x_{id}^{(t)})\\
&x_{id}^{(t+1)}=x_{id}^{(t)}+\mathrm{v}_{id}^{(t+1)}\\
&w=w_{\max}-\frac{w_{\max}-w_{\min}}{t_{\max}}\cdot t
\end{aligned} \tag{9}$$

where $p_{id}^{(t)}$ and $p_{\mathrm{gd}}^{(t)}$ are individual and globally optimal solutions for particles at time t, $w_{\max}$ and $w_{\min}$ are maximum and minimum values of inertial weights, r_1 and r_2 are random numbers evenly distributed between (0,1), c_1 and c_2 are positive learning factors, $t_{\max}$ and t are maximum and current iterations.

C. UEP prediction model based PSO-MSVR algorithm

The UEPs of the system after a fault are related to the parameters of each component in the power grid, the topology, the current operation condition of the power grid and the characteristics of the fault. In a specific power grid, the UEPs of a single fault under the same operation condition are only related to the operation condition of the system, and there is a mapping relationship from steady-state operation information to the UEPs. When $\boldsymbol{X}=[\boldsymbol{X}^{(1)},\boldsymbol{X}^{(2)},...,\boldsymbol{X}^{(p)}]$ is used to represent the steady-state operation information of a power grid, the UEP can be expressed as $\boldsymbol{P}_{\mathrm{UEP}}=f(\boldsymbol{X})$. In this paper, the node voltage and phase angle are selected as sample characteristics to represent the steady-state operation information of the system.

In order to eliminate the influence of different dimensions and units of the input and output, the input and output dates of the samples should be normalized before training to satisfy the following formula:

$$\begin{cases}\dfrac{1}{L}\sum\limits_{i=1}^{L}x_i=0\\ \sum\limits_{i=1}^{L}x_i^2=1\end{cases} \tag{10}$$

In the offline training stage, the topology of the power grid and the actual operating environment are considered to generate the set of expected accidents. For each fault, the training sample was generated under different operating conditions considering the load fluctuation in the power network and the power of the generation. Then, the training was conducted through PSO-MSVR to obtain the UEP prediction model of each expected fault. In the online application stage, after a fault occurred, according to the stable operation information and the specific fault number of the current operation condition of the power network, the power network's UEP could be quickly calculated through the UEP prediction model, which provided a basis for the temporary stability assessment and a more reasonable and effective security control for the system.

The process of model building is shown in Fig. 3. The steps of UEP prediction based on PSO-MSVR are as follows:

1) Determine the range of combinatorial optimization parameters (σ,C) , and set the basic parameters in MSVR, mainly including particle size M, positive learning factor c_1 and c_2 ; maximum and minimum of inertial weights, maximum number of iterations $t_{\max}$ and finally initialize the speed and location of each particle in the population.
2) The sample set of UEPs calculated by BCU method is input into MSVR model for training and learning, and the target function value of each particle, i.e. the fitness, is calculated according to the following formula:

$$fit=\sum_{i=1}^{L}(y_i-\hat{y}) \tag{11}$$

3) Find the individual and global optimal position p_d and p_g of each particle according to the fitness value.
4) Update the velocity and position of particles and their inertial weights according to the formula (4).
5) Recalculate the fitness of each particle after location updates, and reupdate p_d and p_g .

6) Check the termination condition of the PSO and output the optimal solution location if the maximum number of iteration or the optimal solution has been stopped; otherwise, return to step 4).

7) Construct the MSVR prediction model of UEP by the corresponding value of the optimal solution location and training samples, and calculate test sample set.

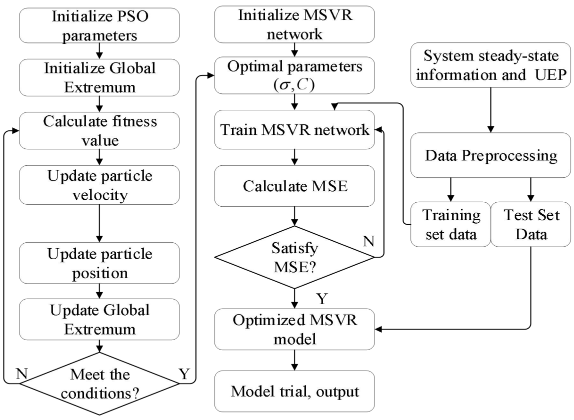


Fig. 3. PSO-MSVR based UEP prediction model

IV. Simulation Results and Analysis

A. Test system

To verify the validity of the proposed method in this paper, the IEEE 9-bus system is set as the test system. There are 3 synchronous generators, 3 loads and 9 lines in the whole system. The role of exciters is considered in all the generators. The three-phase short-circuit fault occurred on line 5-7 will be analyzed, and the fault location is near bus 5. The method to clear the fault is to cut off line 5-7.

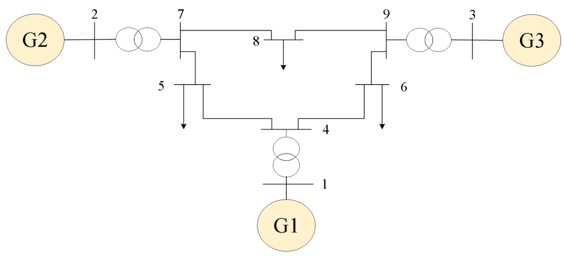
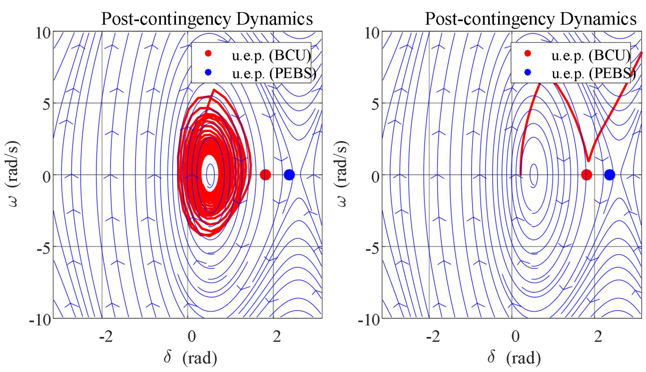


Fig. 4. IEEE 9 bus test system

B. UEP calculation results



(a) Fault clearing time: 0.15s (b) Fault clearing time: 0.18s

Fig. 5. Family of phase planar curves and UEPs

The blue line in the figure above corresponds to a series of unstable trajectories on the plane from closed to unclosed trajectories with increasing fault clearing time; the red line is the trajectory after fault calculated by BCU method. And the red and blue points are UEPs calculated by BCU method and PEBS method, respectively. After calculating the UEPs, the equipotential energy curves of the system and the transient energy at each time can be obtained, as shown in Fig. 6, Fig. 7, respectively. Table I compares the results of critical transient energy, critical fault clearing time (CCT), and calculation time calculated by time domain method, PEBS and BCU methods.

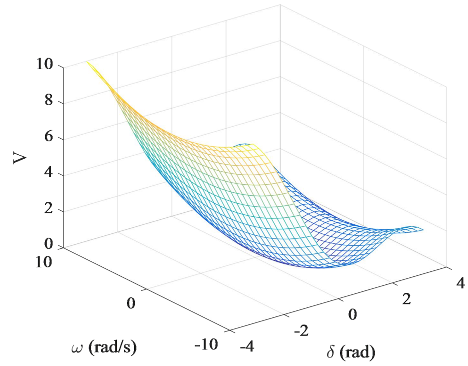


Fig. 6. Equipotential energy curve

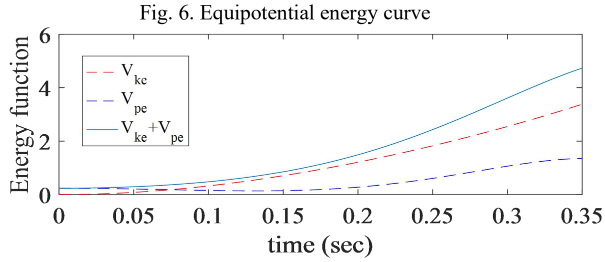


Fig. 7. Transient energy curve after fault

It can be seen that PEBS method will mistakenly judge stability when the system is unstable. Therefore, BCU method is selected to construct the sample set of PSO-MSVR prediction model. Compared with time domain method, BCU method is faster and more in line with the purpose of the UEP fast prediction.

TABLE I. Performance of different UEP calculation methods

Method	Time domain method	PEBS	BCU
Critical transient energy	0.843	1.250	0.973
CCT(s)	0.178	0.184	0.162
Calculation time(s)	0.85	0.53	0.71

C. Prediction model results

All the loads (both active and reactive) change randomly within 80% to 120% of basic load level, independently; and the generator output is adjusted accordingly. Then, the UEPs under different operation conditions can be calculated by BCU method so that 729 sets of sample date are obtained. The rotor angles of three generators representing UEPs are taken as sample output, and considering the difficulty of data acquisition in practical application, the node voltage and phase angle are selected as the sample characteristics. 510 sets of date are selected as training set and 219 groups are used as test set. The data in the test set is different from that in the training set, which can be used to test the generalization ability of the training model.

The initial particle swarm size M is set to 20, dimension set as 3; acceleration factor c_1 and c_2 are 1.5 and 1.7 respectively; inertia weight w_{max} and w_{min} are 1.0 and 0.1 respectively; maximum iteration time is 200; the kernel width σ and penalty factor C optimized by PSO algorithm both range from 0.001 to 1000. The change of fitness curve in the process of optimizing MSVR model by PSO algorithm is shown in Fig. 8, and the optimal combination parameters σ and C are 1.933 and 807.509 respectively. Finally, the optimal combination parameters are substituted into MSVR model for test sample experiment.

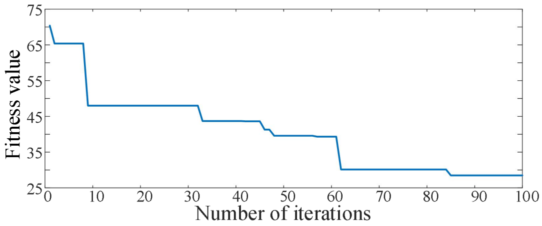
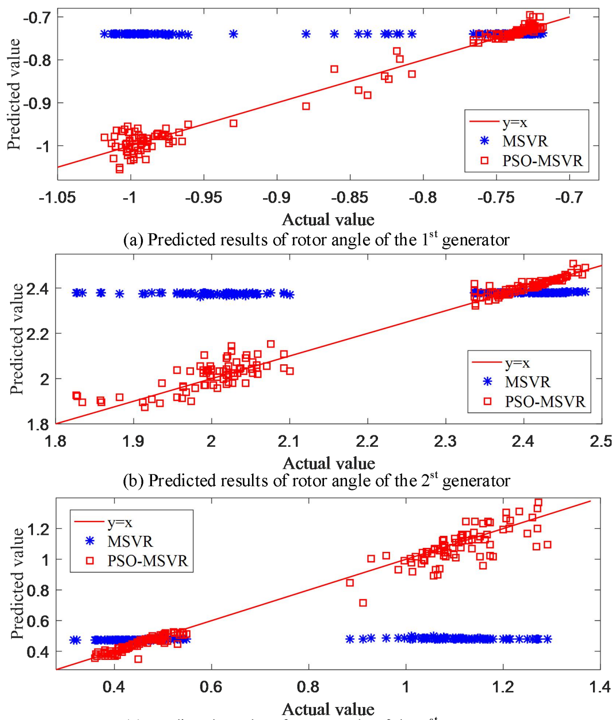


Fig. 8. PSO-MSVR fitness curve

In order to visually display the prediction accuracy of the model for the test samples, the prediction overlap charts of the test samples of the model are made. From the comparison of the models in Fig.9, it can be seen that the prediction values of the test samples in the PSO-MSVR model proposed in this paper are closer to the actual values. To further quantitatively compare the accuracy of the model predictions, the mean square error (MSE) of the model predictions are calculated.

$$E_{\mathrm{MSE}} = \frac{1}{M}\sum_{k=1}^{M}(y_k - \hat{y}(k))^2 \qquad (12)$$

where M is the number of samples in the test data set; y_k is the output data in the test data set; and $\hat{y}(k)$ is the output value of the MSVR prediction model.



(a) Predicted results of rotor angle of the 1st generator

(b) Predicted results of rotor angle of the 2st generator

(c) Predicted results of rotor angle of the 3st generator

Fig. 9 . The results of prediction model

TABLE II. Different sample set prediction performance

	MSE_train	MSE_test
MSVR	0.2437	0.2535
PSO-MSVR	0.0437	0.0645

It can be seen from Table II that the prediction accuracy of MSVR optimized by PSO algorithm is greatly improved.

TABLE III. Calculation time of different UEP calculation methods

	Time domain method	PEBS	BCU	PSO-MSVR
Calculation time(s)	183.28	115.64	153.49	21.89

In aspect of computing efficiency, Table III shows that PSO-MSVR method is much faster than other traditional methods. In this paper, high prediction accuracy is achieved by using only the voltage and phase angle of each node in steady state operation, and the model is simple, the calculation speed is fast. This prediction model can meet the requirements of practical application.

V. Conclusion

This paper presents a PSO-MSVR based method for predicting transient UEPs of power systems. First, compared with PEBS, the UEPs calculated by BCU are more accurate and there is no aggressive result. Then, PSO-MSVR is used to construct the mapping relationship between steady-state operation information and UEPs, where penalty parameters and kernel parameters in MSVR are optimized by PSO algorithm. Therefore, the UEPs of the system can be quickly and accurately predicted by the voltage and phase angle of each node in steady state operation. The results of simulation examples show that the proposed method can accurately predict the UEPs of the systems under different operating conditions through a small amount of training data, and has a certain generalization ability.

Acknowledgment

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