

Voltage Security Operation Region Calculation Based on Improved Particle Swarm Optimization and Recursive Least Square Hybrid Algorithm

Saniye Maihemuti, Weiqing Wang, Haiyun Wang, and Jiahui Wu

Abstract—Large-scale voltage collapse incidences, which result in power outages over large regions and extensive economic losses, are presently common occurrences worldwide. To avoid voltage collapse and operate more safely and reliably, it is necessary to analyze the voltage security operation region (VSOR) of power systems, which has become a topic of increasing interest lately. In this paper, a novel improved particle swarm optimization and recursive least square (IPSO-RLS) hybrid algorithm is proposed to determine the VSOR of a power system. Also, stability analysis on the proposed algorithm is carried out by analyzing the errors and convergence accuracy of the obtained results. Firstly, the voltage stability and VSOR-surface of a power system are analyzed in this paper. Secondly, the two algorithms, namely IPSO and RLS algorithms, are studied individually. Based on this understanding, a novel IPSO-RLS hybrid algorithm is proposed to optimize the active and reactive power, and the voltage allowed to identify the VSOR-surface accurately. Finally, the proposed algorithm is validated by using a simulation case study on three wind farm regions of actual Hami Power Grid of China in DlgSILENT/PowerFactory software. The error and accuracy of the obtained simulation results are analyzed and compared with those of the particle swarm optimization (PSO), IPSO and IPSO-RLS hybrid algorithms.

Index Terms—Voltage stability, renewable energy, improved particle swarm optimization (IPSO), recursive least square (RLS), voltage security operation region (VSOR).

I. INTRODUCTION

WITH the continuous expansion of power grid interconnection, large-scale grid connection of high-penetration renewable energy as well as power flow distribution randomness and other problems, power system operation risks are aggravated and system voltage stability is difficult to esti-

mate the hidden danger [1]-[3]. Therefore, it is of utmost importance in this field to study the voltage stability in the background of high-penetration renewable energy connected to power grid [4], [5].

The security stability region is used to describe the system interval to maintain the safe operation. Its stability region can be defined as the hypergeometry, which can ensure that the system can meet all kinds of static security constraints in the node injection space. For a given network topology, the set of system operation balance points can ensure that the node voltage does not exceed the limit, and the equipment and line are not overloaded. The research of stability region can be divided into three categories: static stability region, dynamic stability region and transient stability region. Among them, the static stability region can be divided into three parts: active stability region, reactive stability region and voltage stability region. This article is concerned only with the analysis on static aspects of voltage stability. Voltage stability is defined as the ability to retain the steady-state voltage at every bus in a power system in normal operation conditions and after a disturbance. In the normal operation condition, the voltage profile of a power system is kept within the stable range. But when a fault or disturbance occurs in the system, the voltage becomes unstable and it leads to a progressive and uncontrollable decline in voltage. Voltage instability problems have been one of the utmost concerns of electric utilities, which are closely related to the reactive power distribution and heavy load in the wind power transmission system [6]-[11]. The effect of the large-scale penetration and the power output from different types of variable renewable energy systems on the system stability and reliability of distribution and sub-transmission networks is discussed by using different optimization and control approaches in [12]-[16]. A stability index that considers both the active and reactive loads is presented in [17]-[19], which is based on the voltage stability operation region (VSOR). VSOR shows the voltage stability index with a three-dimensional space, which considers voltage instability as a function of both the active and reactive loads/voltages. To build the VSOR, it is necessary to employ proper optimization algorithm to control power, voltage and frequency [20] to search

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its stability region boundary accurately and quickly. Recently, many traditional and nature-inspired optimization algorithms are different aspects of the voltage stability problems, such as genetic algorithm (GA) [21]-[23], particle swarm optimization (PSO) algorithm [24]-[28], artificial neural network (ANN) [29], [30], Tabu search [31], dynamic programming [32], [33], differential evolution [34], gravity search algorithm (GSA) [35]-[37], etc. Some of these methodologies show excellent performance in reaching a near-global optimum while greatly prevailing over the difficulty arises due to the nonlinearity nature of such problems. However, due to the excessive number of iterations, large amount of off-line computation and slow speed of some algorithms, the global accuracy of the VSOR boundary cannot be guaranteed. Besides, the selection of different key parameters has a great impact on the topology of VSOR boundary, so it is difficult to use the unified analytical expression to describe and obtain the general conclusion. Therefore, it is still a difficult problem to construct VSOR considering the accuracy and efficiency of the calculation.

The main aim of this paper is to develop a new hybrid algorithm consisting of two naturally-inspired metaheuristic algorithms, namely the improved particle swarm optimization (IPSO) and recursive least square (RLS) algorithms. And then the complexity and nonlinearity of the voltage stability problem are solved and optimized, and are used properly on three different wind farms in Hami Power Grid to search the VSOR-surface of the system. The IPSO algorithm is an evolutionary metaheuristic algorithm that imitates the complex social behavior of flocking birds or fish schooling firstly introduced by Kennedy and Eberhard [38]. It utilizes a set of potential solutions (known as particles) to explore the search space, where every possible solution (or particle) modifies its position via the learning-by-experience concept from the history of its position and the positions of its neighboring particles. The application of the IPSO algorithm, either as a stand-alone algorithm or in combination with another metaheuristic algorithm [39]-[44], has been extensively considered to solve complex problems in various engineering disciplines, including those related to voltage stability.

In the least-square (LS) problems, unknown parameters of a linear model are calculated by minimizing the sum of the squares of the differences between the computed values and the actual values. To optimize such LS problems, a closed-form solution is used. Since the focus is on a real-time calculation, it is computationally more efficient to update the estimates recursively as new data becomes available online. For this purpose, the RLS algorithm, which is a popular algorithm used in adaptive control, adaptive filtering, and system identification [45] can be employed. The RLS algorithm achieves an excellent convergence rate, especially for highly correlated input data, which is regarded as the optimal solution in practice. Recent literature shows the powerful capabilities of the RLS algorithm, both as a stand-alone algorithm and in combination with other algorithms [46]-[49] in solving various kinds of problems, which demonstrates that the RLS algorithm can exhibit solid search performance and fast convergence advantages. The overall goal is to produce an

intact algorithm that combines the global search capabilities of the IPSO algorithm with the strong local exploratory search performance of the RLS algorithm while improves the convergence characteristics of the IPSO algorithm. The IPSO algorithm exhibits flexible and wide-range search features that enhance its global population diversity, which provides a high search accuracy and fast convergence combined with the RLS algorithm. After developing the mathematical representation of each algorithm, we validate the performance of the combined algorithm on three wind farms of Hami Power Grid of China and conduct a comprehensive simulation study.

The rest of the paper is organized as follows. Section II introduces the mathematical representation and the model of the voltage stability and VSOR-surface. Section III describes the mathematical representation and framework for the IPSO, RLS, and hybrid IPSO-RLS algorithms, and the process in searching the VSOR-surface. Section IV presents the simulation results and discussions. Section V provides the analysis and comparison of the results regarding the accuracy. Section VI concludes the paper and provides suggestions on future studies to be conducted in this area.

II. VOLTAGE STABILITY CURVES ON A VSOR-SURFACE

A simple algorithm of assessing the static voltage stability of a power system is presented. The circuit diagram used to explain the mechanism of static voltage stability is shown in Fig. 1.

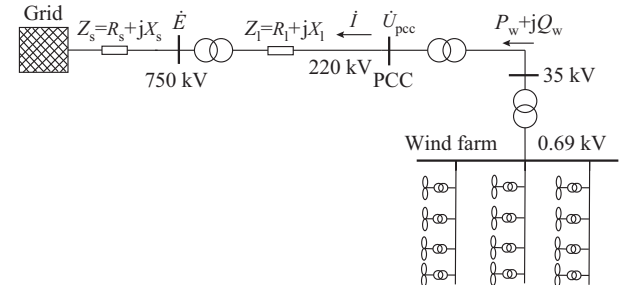


Fig. 1. Schematic diagram of wind farm connection to system.

As shown in Fig. 1, $\dot{E}$ is the voltage of system balance point; $\dot{U}_{pcc}$ is the voltage of the wind farm at point of common coupling (PCC); $Z_s = R_s + jX_s$ is the system equivalent impedance; $Z_l = R_l + jX_l$ is the line equivalent impedance between the PCC and $\dot{E}$; $P_w + jQ_w$ is the output apparent power of the wind farm; and $\dot{I}$ is the current injected from the wind farm.

For a given load $P_w + jQ_w$ at the bus, the load current $\dot{I}$ and $\dot{U}_{pcc}$ can be expressed as [17]-[19]:

$$\dot{I} = \frac{P_w - jQ_w}{\dot{U}_{pcc}^*} \quad (1)$$

$$\dot{U}_{pcc} = \dot{E} + (R_s + jX_s)\dot{I} \quad (2)$$

The relationship between the receiving-end voltage E and sending-end voltage U_{pcc} , active power P_w and reactive power Q_w can be expressed as:

$$U_{pcc}^4 + U_{pcc}^2 [2(R_s P_w + X_s Q_w) - E^2] + (R_s^2 + X_s^2)(P_w^2 + Q_w^2) = 0 \quad (3)$$

To plot the VSOR-surfaces, solutions for active and reac-

$$\begin{cases} P_{1,2} = -\frac{R_s U_{pcc}^2 \mp \sqrt{-Q_w^2 (R_s^2 + X_s^2)^2 + (R_s^2 + X_s^2)(U_{pcc}^2 - 2Q_w X_s)U_{pcc}^2 - X_s^2 U_{pcc}^4}}{R_s^2 + X_s^2} \\ Q_{1,2} = -\frac{X_s U_{pcc}^2 \pm \sqrt{-P_w^2 (R_s^2 + X_s^2)^2 + (R_s^2 + X_s^2)(U_{pcc}^2 - 2P_w R_s)U_{pcc}^2 - R_s^2 U_{pcc}^4}}{R_s^2 + X_s^2} \\ U_{1,2} = \sqrt{-(P_w R_s + Q_w X_s) + \frac{U_{pcc}^2}{2} \pm \sqrt{\frac{U_{pcc}^4}{4} - (P_w R_s - Q_w X_s)^2 - U_{pcc}^2 (P_w R_s + Q_w X_s)}} \\ U_{3,4} = -\sqrt{-(P_w R_s + Q_w X_s) + \frac{U_{pcc}^2}{2} \pm \sqrt{\frac{U_{pcc}^4}{4} - (P_w R_s - Q_w X_s)^2 - U_{pcc}^2 (P_w R_s + Q_w X_s)}} \end{cases} \quad (4)$$

In (4), the entire VSOR-surface is described by two solutions for active and reactive power, and four solutions for voltage. The negative value of P corresponds to a maximum power generation, and the positive value of P corresponds to a maximum load power with a given power transportation. The solutions of $U_{3,4}$ give negative values of the voltage without physical meaning. Therefore, $U_{3,4}$ is not of interest in this work. The solutions of $U_{1,2}$ are positive values of the voltage used in the following derivations.

III. MATHEMATICAL FRAMEWORK OF METAHEURISTIC ALGORITHMS

A thorough discussion on the IPSO and RLS algorithms and their combination are presented in this section.

A. IPSO Algorithm

The PSO algorithm is a population-based, bio-inspired metaheuristic algorithm established by Kennedy and Eberhart in 1995 [38]. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space based on simple mathematical formula over the particle's position and velocity. Furthermore, each particle's movement is influenced by its local best-known position P_{best} but is also guided toward the best-known positions in the search-space, which are found by other particles as the global best position G_{best} . To conclude, the search process is aimed at accelerating each particle toward its P_{best} and the swarm's G_{best} . The velocity and updated equations of the particles are given by:

$$v_i(j+1) = \omega v_i(j) + c_1 r_1 (P_{best}(j) - x_i(j)) + c_2 r_2 (G_{best}(j) - x_i(j)) \quad (5)$$

$$x_i(j+1) = x_i(j) + v_i(j+1) \quad (6)$$

$$\omega = \omega_{max} - \left(\frac{\omega_{max} - \omega_{min}}{i_{ter, max}} \right) i_{ter} \quad (7)$$

where ω is an inertia weight factor; i is the sequence of particle numbers ($i=1, 2, \dots, n$), and n is the number of particles; j and $j+1$ are the previous and current iteration numbers ($j=1, 2, \dots, m$), and m is the maximum number of population iterations; c_1 and c_2 are the learning factors which are

tive power and the voltage need to be determined. For rearranging and solving the active and reactive power, four solutions for voltage are obtained as follows:

usually in the range $[0, 2]$; r_1 and r_2 are two independent random numbers uniformly distributed in the range $[0, 1]$; ω_{max} and ω_{min} are the initial and final weights, respectively; i_{ter} is the current iteration number; and $i_{ter, max}$ is the maximum number of iterations.

The searching criteria in standard PSO algorithm is shown in Fig. 2.

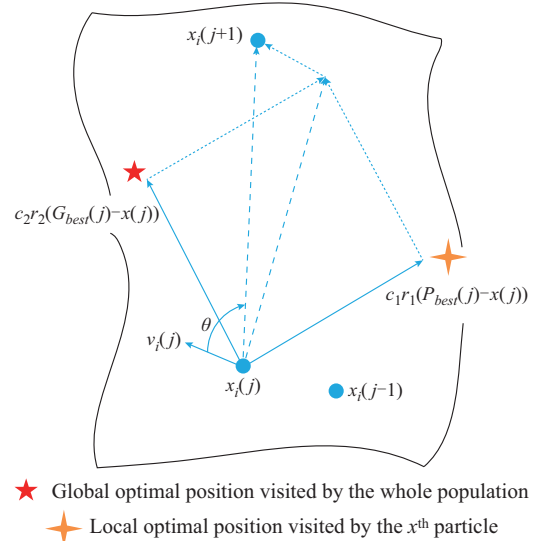


Fig. 2. Searching criteria in standard PSO algorithm.

B. RLS Algorithm

The least square method (LSM) is the most basic and the most widely-used method proposed by K. F. Gauss in his research on orbital motion orbit prediction [50]. The RLS algorithm is a new algorithm developed on the basis of the LSM, which overcomes the shortcomings of occupying large memory and failing to realize the online identification. Also, it can realize numerical predictions and be widely used [51], [52]. The RLS algorithm corrects the parameter estimation every time when new observation data is obtained, and a satisfactory identification result is guaranteed over time. The RLS algorithm can be obtained as follows [53].

For an observable system, the L -group input and output observations are expressed as $\{y(k), u(k), k=1, 2, \dots, L\}$, and

L is the group size.

The iterative equation of the RLS algorithm is given by:

$$\begin{cases} \hat{\theta}(k) = \hat{\theta}(k-1) + \mathbf{K}(k)(y(k) - \varphi^T(k)\hat{\theta}(k-1)) \\ \mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\varphi^T(k))\mathbf{P}(k-1) \\ \mathbf{K}(k) = \frac{\mathbf{P}(k-1)\varphi(k)}{1 + \varphi^T(k)\mathbf{P}(k-1)\varphi(k)} \end{cases} \quad (8)$$

where $\hat{\theta}(k)$ is the estimate of the parameter; $\mathbf{P}(k)$ is the error covariance matrix; $\mathbf{K}(k) = \mathbf{P}(k)\varphi(k)$ is the gain vector; and $\mathbf{I}$ is the identity matrix.

C. Parameter Identification Based on IPSO-RLS Hybrid Algorithm

Although it is difficult to ensure the accuracy of the range in the IPSO algorithm, its global optimization ability supports to narrow the solution range and approximate an optimal solution. The main drawback of the RLS algorithm is its sensitivity to the selection of the initial value of iterations. However, when the initial value of an iteration is close to the real solution, the convergence speed and accuracy of the RLS algorithm are high. Therefore, it can provide desired results by combining the global optimization ability of the IPSO algorithm with the fast convergence ability of the RLS algorithm in the global optimal neighborhood solution. The pseudocode of the IPSO-RLS hybrid algorithm is as follows.

Step 1: input the original data and necessary parameters. Input all the relevant electrical data of the system, including the system's nodes, branch information, control parameters and all kinds of constraints. Further, set the operation parameters of the optimization algorithm.

Step 2: use the specifications from *Step 1*, and perform the power flow calculation for the given network.

Step 3: initialize a group of particles (group size is N) including their random positions and velocity vectors.

Step 4: evaluate the fitness of each particle.

Step 5: for each particle, compare its fitness value (P) with its P_{best} . If the obtained P is smaller than P_{best} , update its fitness value to the current P_{best} .

Step 6: update the particle velocity and position by (5) and (6).

The velocity is updated by (5), while the upper and lower limits are defined as follows:

$$v_{i,j}(t+1) = \begin{cases} v_{j,\max} & v_{i,j}(t+1) > v_{j,\max} \\ v_{i,j}(t+1) & v_{i,j}(t+1) \in [v_{j,\min}, v_{j,\max}] \\ v_{j,\min} & v_{i,j}(t+1) < v_{j,\min} \end{cases} \quad (9)$$

where $v_{i,j}(t+1)$ is the velocity of the j^{th} iteration of the i^{th} particle at the time of $t+1$; $v_{j,\max}$ is the maximum velocity of the j^{th} iteration; and $v_{j,\min}$ is the minimum velocity of the j^{th} iteration.

Besides, the position is updated by (6), while the upper and lower limits are defined as follows:

$$x_{i,j}(t+1) = \begin{cases} x_{j,\max} & x_{i,j}(t+1) > x_{j,\max} \\ x_{i,j}(t+1) & x_{i,j}(t+1) \in [x_{j,\min}, x_{j,\max}] \\ x_{j,\min} & x_{i,j}(t+1) < x_{j,\min} \end{cases} \quad (10)$$

where $x_{i,j}(t+1)$ is the position of the j^{th} iteration of the i^{th} particle at the time of $t+1$; $x_{j,\max}$ is the maximum position of the j^{th} iteration; and $x_{j,\min}$ is the minimum position of the j^{th} iteration.

cle.

This procedure is followed to obtain G_{best} .

Step 7: take the global extreme value G_{best} from the L -group of the IPSO algorithm as the initial value of the RLS iteration.

Step 8: if it is the first iteration of the calculation, initialize $\mathbf{P}(0)$ and $\hat{\theta}(0)$, and proceed with the iteration; otherwise, read $\mathbf{P}(k-1)$ and $\hat{\theta}(k-1)$ as $\mathbf{P}(k)$ and $\hat{\theta}(k)$.

Step 9: if $\max_i (\hat{\theta}_i(k) - \hat{\theta}_i(k-1)) / \hat{\theta}_i(k-1) < \varepsilon$, the maximum number of iteration is reached, update the global optimum and end the process; otherwise, continue the next iteration.

Step 10: based on the parameter identification result obtained by (4), the VSOR-surface is plotted for the three wind farms. The calculation errors are compared and analyzed regarding the root mean square error (RMSE) given by (11).

$$\begin{cases} e_{RMSE,P} = \sqrt{\frac{\sum_{i=1}^n (P_i - \bar{P}_i)^2}{n-1}} \\ e_{RMSE,Q} = \sqrt{\frac{\sum_{i=1}^n (Q_i - \bar{Q}_i)^2}{n-1}} \\ e_{RMSE,U} = \sqrt{\frac{\sum_{i=1}^n (U_i - \bar{U}_i)^2}{n-1}} \end{cases} \quad (11)$$

where $e_{RMSE,P}$, $e_{RMSE,Q}$ and $e_{RMSE,U}$ are the RMSEs of active power, reactive power and voltage, respectively; P_i , Q_i and U_i are the G_{best} of active power, reactive power and voltage, respectively; and $\bar{P}_i$, $\bar{Q}_i$ and $\bar{U}_i$ are the average G_{best} of active power, reactive power and voltage, respectively.

In practice, for a given system topology, there is a well-defined relationship between the active power, reactive power, and voltage. This relationship can be visualized with a three-dimensional VSOR-surface, which represents the voltage stability margin of an access point and how they all operate at any wind turbine output after a wind farm is connected to the grid. Hence, it is suitable for the voltage stability analysis of a grid-connected wind power system with fluctuated wind power. The VSOR-surface can be used to estimate the available margin (active power, reactive power, voltage sensitivity, and other margins) of a grid-connected wind power system, and to formulate the wind power scheduling strategy. When disturbances occur in the system, the power margin requirements to be met can be determined based on its VSOR-surface, and the corresponding measures should be taken to increase the margin.

IV. SIMULATION RESULT AND DISCUSSION

A. Introduction to Hami Power Grid

In this subsection, the proposed hybrid algorithm is tested considering the actual specification of Hami Power Grid of China, which is a mainland city with a wealth of wind and coal energy resources. The Hami Power Grid of China, located in the eastern part of Xinjiang Power Grid of China, is not only an important part of Xinjiang Power Grid but also acts as a hub in connecting Xinjiang Power Grid with Central China Power Grid. Moreover, Hami is one of the largest

coal bases in China. It is the first cross-regional ultra-high voltage (UHV) transmission channel to absorb wind power and other renewable energies in Xinjiang. Also, it facilitates the first renewable energy and thermal power bundled through the ultra-high voltage direct current (UHVDC) power transmission project in China. The Hami Power Grid is designed and tested by using DlgSILENT/PowerFactory software.

The three wind farm stations in this power grid are Santanghu station, Hami station and Yandun station, as shown in Fig. 3. In this paper, three cases of Hami Power Grid of China are analyzed based on the geographical locations of wind farms.

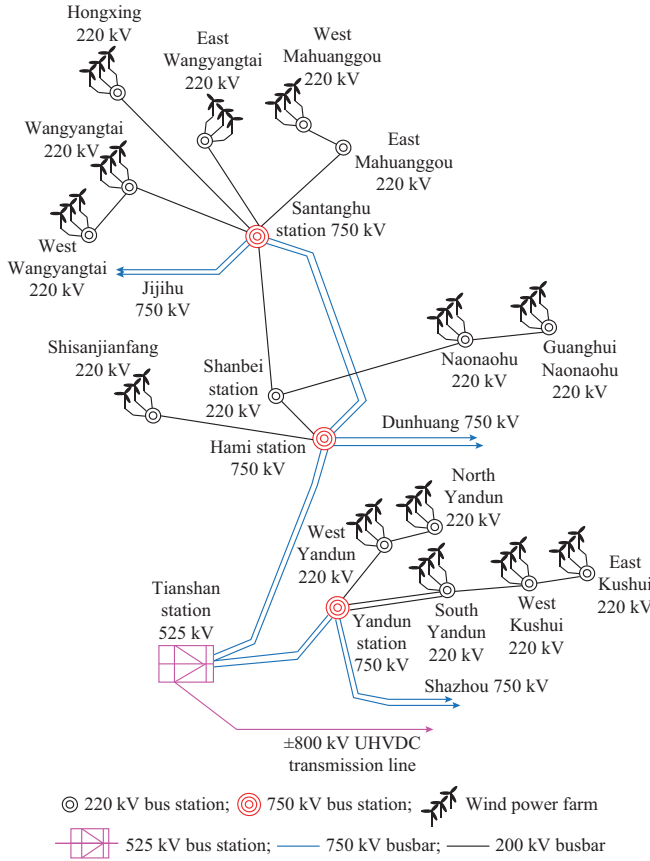


Fig. 3. Schematic diagram of Hami Power Grid.

1) Case 1: Santanghu station considers six wind farms, and employs 220 kV lines for connecting the wind farms to the 750 kV Santanghu station.

2) Case 2: central Hami station contains of three main wind farms (220 kV) connected to the 750 kV central Hami station.

3) Case 3: Yandun station consists of five main wind farms (220 kV) connected to the 750 kV Yandun station.

Thus, the three wind farms associated with the Hami Power Grid of China are discussed in the following text.

B. Calculation of VSOR-surface of Hami Power Grid

Firstly, based on the time-domain simulation results obtained by DlgSILENT/PowerFactory software, the operation power at various nodes is obtained. When the wind power

penetration is increased, the static safe operation areas for three cases are obtained by using the power flow results of Hami Power Grid of China and the reactive power of wind farm groups as constraint conditions, i.e., the comprehensive static characteristic sample data of the wind farm. Then, (4) is used to describe the wind farm three-dimension comprehensive static characteristics of the model, the parameters of which are identified by using the pseudocode of the IPSO-RLS hybrid algorithm presented in the Section III-C. The IPSO-RLS is coded by DlgSILENT/PowerFactory software using DPL language. While implementing the proposed algorithm, the size of the population is set as 30, and the maximum number of iterations is set as 100. The parameter identification for the three considered cases are shown in Fig. 4. The P , Q , V of the VSOR-surface are the active power, reactive power and voltage at the security region, respectively.

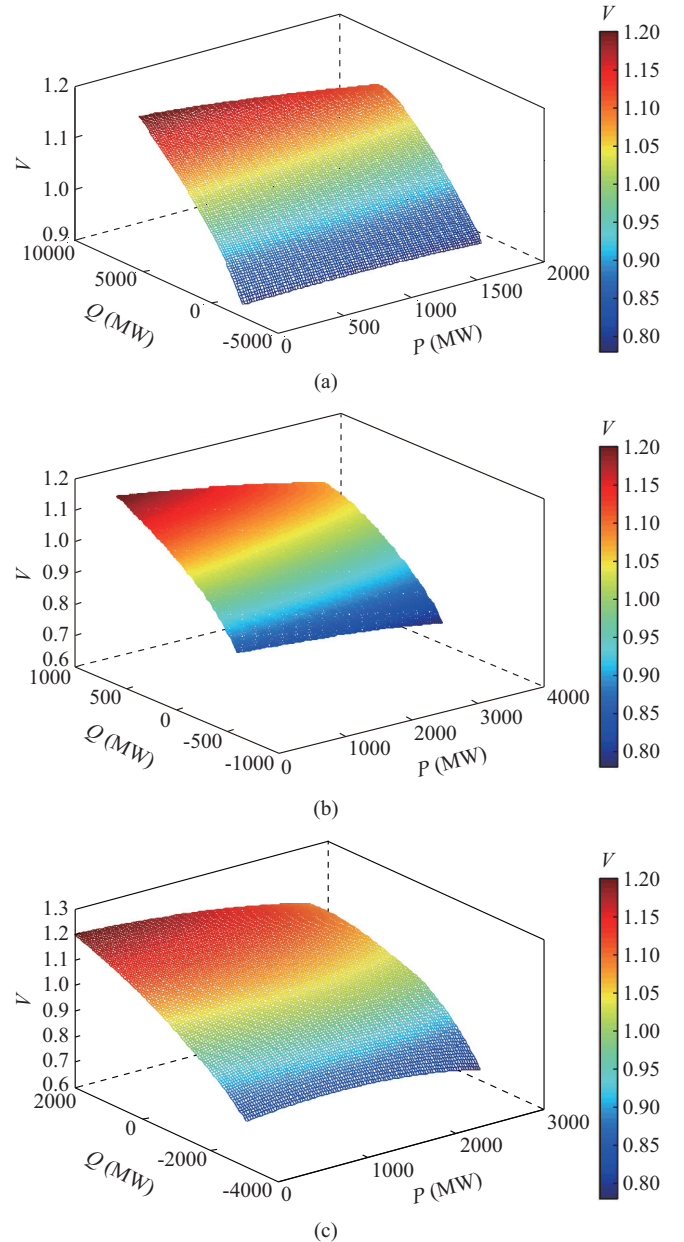


Fig. 4. VSOR-surface of wind power system at different stations. (a) Case 1: Santanghu 750 kV. (b) Case 2: Hami 750 kV. (c) Case 3: Yandun 750 kV.

From the viewpoint of the static voltage stability, it is clear that the bus with a larger VSOR-surface would indicate a higher voltage stability margin. While the bus is operating near or at the voltage collapse point, the VSOR-surface would be approaching zero. The ranking of voltage weak nodes susceptible to voltage instability can be done by the VSOR-surface as the index truly present the physical meaning of the voltage stability margin. Since the voltage collapse problem starts at the critical bus, its identification in time can be used for the mitigation of the voltage collapse. The VSOR-surface for the three considered cases with different wind power penetrations at bus junction is shown in Fig. 4. With a decrease in the reactive power or an increase in the active power injected into the wind farm, the critical voltage of the grid-connected bus increases, thus further enhances the stability of the grid-connected wind power system. As shown in Fig. 4, the increase in the active power injected from the wind farm has less effects on the critical voltage instability of the grid-connected bus but has a greater influence on the voltage stability of the wind power system compared with the reactive power. Further, the critical voltage, critical active and reactive power, and minimum distance to voltage collapse (MDVC), i. e., voltage stability boundary can be obtained by Fig. 4 for the three cases. MDVC is the shortest distance from the coordinate origin to the tangent plane of the VSOR-surface, which is a parameter that determines the size of the critical value.

Comparing the VSOR-surface parameters of the three wind farms in Table I, it can be seen that the critical value of bus voltage U_{cr} in Case 1 is the highest; hence, the voltage margin is the lowest in this area. The critical values of the active power P_{cr} in Case 1 and Case 3 are approximately equal, but the critical value of the reactive power Q_{cr} in Case 3 is twice larger than that in Case 1. Therefore, comparing the parameters of the VSOR-surface, it is found that the stability is the highest in Case 3, followed by Case 2 and Case 1, respectively. In Case 1, the maximum penetration and the transmission capacity of the wind power generation results in the lowest margins of the active and reactive power as well as the lowest stability.

TABLE I
INDEXES OF INTEGRATING BUSBAR OF THREE CASES

Case	U_{cr} (p.u.)	Q_{cr} (p.u.)	P_{cr} (p.u.)	MDVC (p.u.)
Case 1	1.0408	0.9736	1.8372	1.826
Case 2	0.8034	4.8361	3.0613	2.422
Case 3	0.7829	1.7320	1.9744	2.656

V. RESULT ANALYSIS AND COMPARISON

The PV and QV curves of 220 kV wind farms in Hami Power Grid of China could be obtained from Fig. 4. The PV and QV curves of the wind farms describe the influence of wind power generation on the static voltage stability of the system with different wind power output levels. With the increase of the number of wind turbine units connected to each wind farm, the voltage critical points and active and reactive limits of each 220 kV wind power grid-connected bus

in three main stations of the Hami Power Grid are shown in Fig. 5.

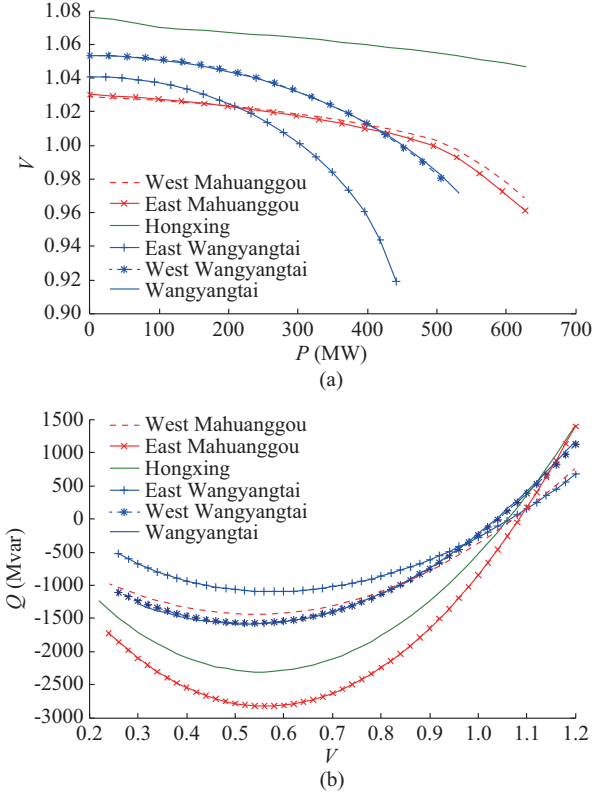


Fig. 5. PV and QV curves of Santanghu station. (a) PV curves. (b) QV curves.

As can be seen in Fig. 5, the average active power output limit of the six wind farms in Santanghu station is 500 MW. With the increase of the number of wind turbines, the PV curves of this area will reach the collapse edge when the number of wind turbines approaches to 420.

In Fig. 6, the average active power output limit of the three wind farms in Central Hami is 250 MW, and when the number of wind turbines approaches 200, the PV curves of this region will reach the edge of collapse.

The average active power output limit of the six wind farms in Yandun station is about 800 MW, and when the number of wind turbines approaches to 600, the PV curves of this region will reach the edge of collapse.

From the QV curves of each region in Fig. 5 to Fig. 7, with the increase of the number of wind turbine units, the wind power penetration is also increasing. The reactive margin of 220 kV bus at the grid point of the wind farm is increasing when the wind power system is in a stable state, which shows that the power injected into the original grid from wind power plays a supporting role in the grid voltage.

When MDVC is becoming longer, the stability boundary values of the system are greater and the system is more stable. MDVC in Table I is obtained from the VSOR-surface in Fig. 4. Therefore, in order to verify the validity and superiority of the MDVC values, the obtained simulation results are compared with that of the standard PSO and IPSO algorithms.

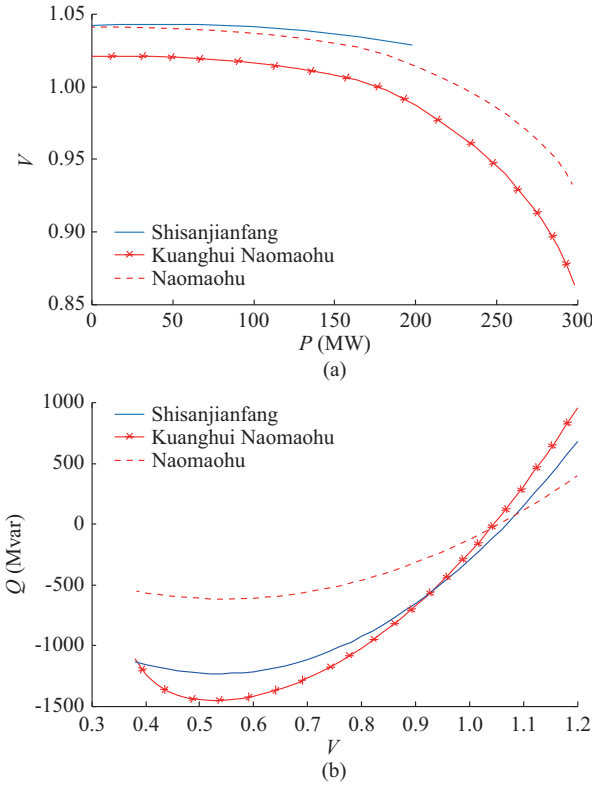


Fig. 6. PV and QV curves of central Hami station. (a) PV curves. (b) QV curves.

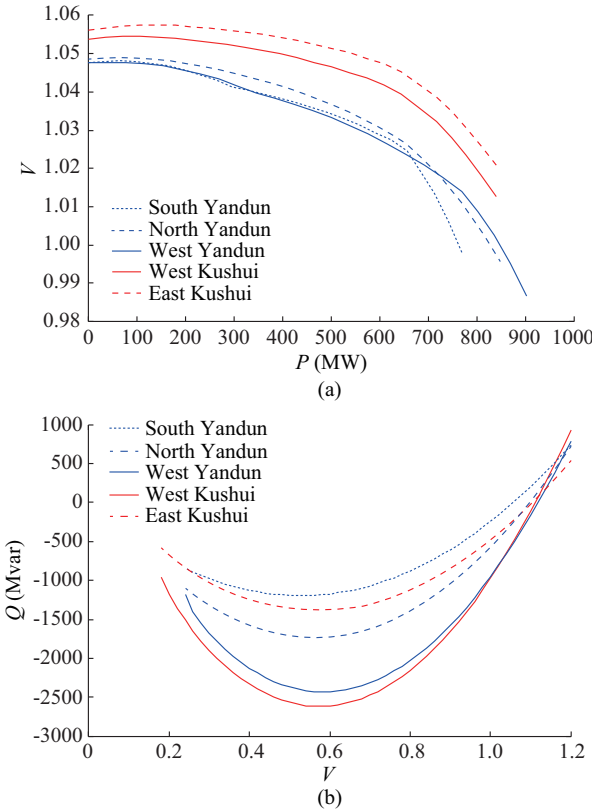


Fig. 7. PV and QV curves of Yandun station. (a) PV curves. (b) QV curves.

Therefore, in Table II and Fig. 8, it can be seen that with

the difference of the optimization algorithm, when the distance of MDVC is becoming longer, the system stability boundary values would be larger. Then, it not only can obtain the VSOR-surface more precisely during the iteration, but also can ensure system operation stability.

TABLE II
COMPARISON OF VSOR-SURFACE PARAMETERS OF DIFFERENT ALGORITHMS
IN THREE CASES

Case	Algorithm	U_{cr} (p.u.)	Q_{cr} (p.u.)	P_{cr} (p.u.)	MDVC (p.u.)
Case 1	PSO	0.7794	0.6785	1.3115	1.452
	IPSO	0.9195	0.7529	1.6387	1.599
	IPSO-RLS	1.0408	0.9736	1.8372	1.826
Case 2	PSO	0.5185	3.7169	2.6012	1.912
	IPSO	0.7228	4.3085	2.9887	2.178
	IPSO-RLS	0.8034	4.8361	3.0613	2.422
Case 3	PSO	0.6026	1.4287	1.6012	1.951
	IPSO	0.6974	1.5857	1.8107	2.201
	IPSO-RLS	0.7829	1.7320	1.9744	2.656

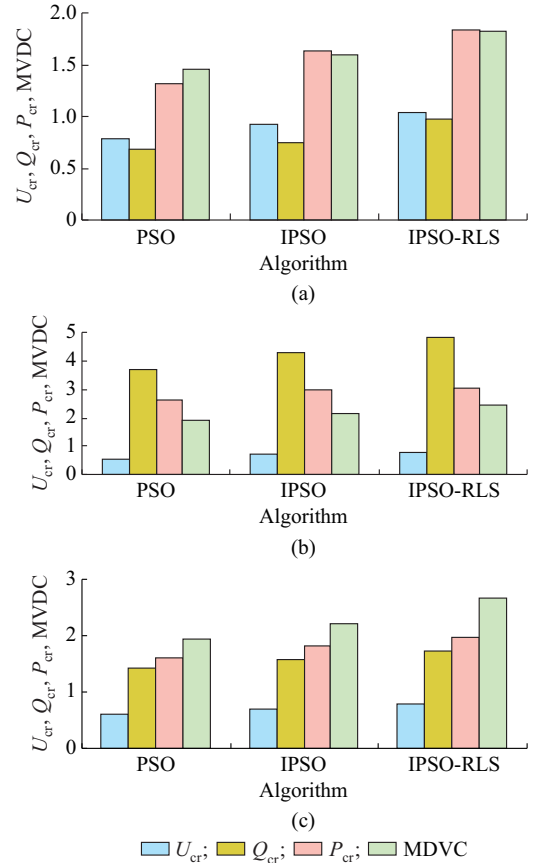


Fig. 8. Comparison of VSOR-surface parameters of different algorithms in three cases. (a) Case 1: Santanghu 750 kV. (b) Case 2: Hami 750 kV. (c) Case 3: Yandun 750 kV.

To verify the feasibility of the proposed algorithm, the error and convergence accuracies of the three algorithms are compared and analyzed by using the simulation results. The errors of the three algorithms are defined by (11).

As can be seen in Fig. 9, except for few minor differenc-

es, the obtained results in the three cases are quite close. The error accuracy of the PSO and IPSO algorithms is beyond our expectations, but the stability of these algorithms is not ideal. This can be clearly observed from the error curves of the PSO and IPSO algorithms, which increase sharply indicating that the algorithms are tracking a local optimum value during the parameter identification. On the other hand, the IPSO-RLS hybrid algorithm not only identifies the target parameters accurately but also maintains the diversity of particles while improving the global search speed and avoiding the local extremum at the later stage of the search. Therefore, compared with the PSO and IPSO algorithms, the IPSO-RLS hybrid algorithm can obtain lowest identification errors and error fluctuation ranges, as well as more accurate and stable model parameters.

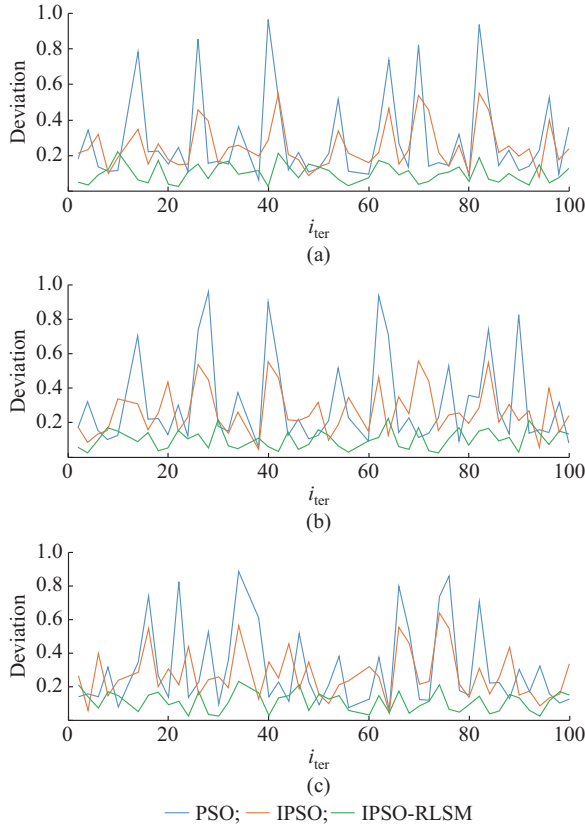


Fig. 9. Comparison of parameter identification errors of three algorithms. (a) Case 1: Santanghu 750 kV. (b) Case 2: Hami 750 kV. (c) Case 3: Yandun 750 kV.

During the iterations, the PSO algorithm is more likely to miss the optimal solution in the process of fast search because of its relatively faster convergence speed in the early stages, and the phenomenon of “premature convergence” easily leads to a local optimum. Moreover, for a higher-dimensional system such as the one presented in this paper, the convergence accuracy of the PSO algorithm is not high, and it can easily fall into a local extremum. Therefore, in order to further emphasize the superiority of the proposed algorithm, it is necessary to compare and analyze the convergence accuracies of the three algorithms for the following proposed cases.

It can be seen in Fig. 10 that the results of the PSO and IPSO algorithms are quite different from that of the IPSO-RLS hybrid algorithm in the three considered cases. With an increase in the number of iterations, the convergence accuracy of the three algorithms is increasing slightly. However, it should be noted that the convergence accuracy of the IPSO-RLS is always higher than that of the PSO and IPSO algorithms. Considering the smaller fitting errors of the IPSO-RLS hybrid algorithm, it can be concluded that the convergence speed and accuracy are highest in this case compared to the other two algorithms.

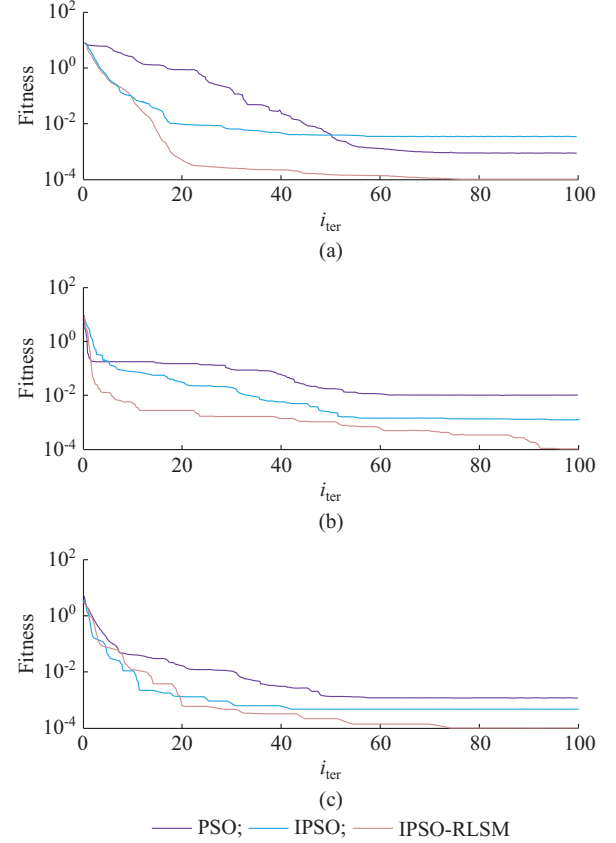


Fig. 10. Comparison of convergence accuracy of three algorithms. (a) Case 1: Santanghu 750 kV. (b) Case 2: Hami 750 kV. (c) Case 3: Yandun 750 kV.

The iteration time of the algorithm is also one of the important indicators for evaluating its performance. The iteration time of the three algorithms is shown in Fig. 11. It can be seen that the iteration time becomes longer as the algorithm complexity and the number of iterations increase.

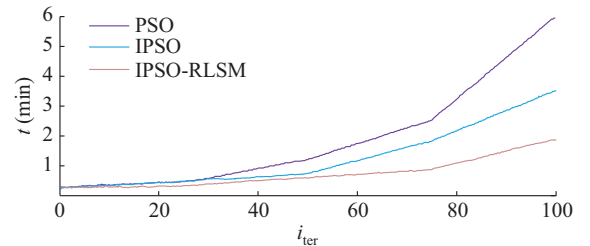


Fig. 11. Total iteration time of three algorithms.

VI. CONCLUSION

One of the important goals of power system planning, operation, and control, if not the main goal in recent time, is achieving a secure power system that is less prone to voltage collapse. In this paper, we have investigated the improvement of power system static operation region by tracking the global optimal value of active and reactive powers and voltage. The goal is to enhance the voltage stability condition of the whole power system by maintaining the stability margin of all the transmission lines above a secure level. Compared with the traditional construction method for static VSOR based on CPF, the VSOR-surface constructed by the proposed method not only has higher accuracy and calculation efficiency, but also greatly reduces the calculation time and significantly improves the construction efficiency of voltage stability operation region in power system. In the future, we plan to carry out the influence of renewable energy access with different penetration rates on the system stability region, and consider to propose a more general stability region construction method to solve the transient stability region, dynamic stability region and thermal stability region of the system, which will be the focus of the next research stage.

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