Reactive Power Multi-objective Optimization for Multi-terminal AC/DC Interconnected Power Systems Under Wind Power Fluctuation

Qian Hui, Yun Teng, *Member, IEEE*, Hao Zuo, and Zhe Chen, *Fellow, IEEE*

***Abstract*—In view of the reactive power coordination difficulties caused by reactive power strong coupling, the provincial power grids in the interconnected system are formed by the multi-AC/DC transmission. Wind power channels are under the conditions of large-scale long-distance transmission of wind power and other forms of renewable power generation. The AC-DC hybrid power flow equation of the interconnected system, including the AC-DC tie lines, is presented in this paper, along with the robust dynamic evolutionary optimization of the reactive power system in interconnected systems under fluctuating and uncertain wind power conditions. Therefore, the rapid collaborative optimization of reactive power flow and the exchange of reactive power between tie lines between provincial power grids are realized. The analysis was made by taking four interconnected large-scale provincial power grids of Eastern Mongolia, Jilin, Liaoning and Shandong as an example. The simulation results demonstrate the effectiveness and superiority of the proposed reactive power dynamic multi-objective optimization method for interconnected power grids.**

***Index Terms*—Multi-objective robust evolution, multi terminal AC/DC interconnection, reactive power optimization, wind power transmission.**

I. Introduction

Several provincial power grids have been interconnected by large-capacity, long-distance UHV, AC-DC transmission lines for transferring the wind power generated due to the rapid development of wind power in the western and northern regions of China. This causes the voltage stability problems to become more and more prominent with a greater threat to the safe and stable operation of the power system. A great deal of work has been done [1]–[4] in order to improve the voltage stability level. References [5]–[8] used the fuzzy clustering method to solve the partition problem in secondary voltage control, and complete the fuzzy clustering partition through the composing index of control effect of reactive power source to nodes. In [9], [10], a coordinated control strategy of nonelectric voltage in the area with wind farms is proposed for solving the voltage instability problem caused by centralized access of large-scale wind power. Reference [11] considered the control of the voltage when the wind power is integrated and guarantees the normal and safe operation within the area, based on the voltage control. Reference [12] constructed a fitness function suitable for multi-objective optimization by taking the weight setting as the standard of quantization partitioning, which has a good effect in partitioning a single provincial power grid, however, the applicability for multi-area interconnected systems still requires further study. Reference [14] introduced the differential game theory to solve the problem of multi-controller dynamic coordination in power systems. On the basis of this, reference [15] used a dynamic game approach to solve the problem of conflicts among multiple control subjects of regional voltage and obtained a Nash equilibrium solution by applying two-layer iterations, rather than conducting optimization analysis to the voltage control in multiple large areas; moreover, the Nash equilibrium in the game does not mean an overall optimal state of two sides of the game; therefore, the real optimal strategy may not be obtained through the game.

At present, the research primarily focuses on the centralized or decentralized control within a specific provincial power grid, and little has been done about the voltage coordination control among multiple provincial power grids. Meanwhile, with the development of large-scale interconnected power grids, the connection between the provincial power grids is intensively increasing, and the inter-regional interactions have become inevitable and important. Especially in an emergency, the reactive power weak coupling between adjacent regions often no longer exists. Neglecting reactive power coupling between regions can cause voltage fluctuations and even oscillations [16]. In a complex multi-area interconnected power grid coupled by multi-end AC-DC tie lines, local voltage disturbances may cause instability of the interconnected systems due to lack of reginal reactive power coordination [17]. On the other hand, the reactive power exchange caused by wind power fluctuation in the sending-end grid may not only have an impact on the voltage stability of the sending-end gird but it may even cause a voltage stability problem in the entire interconnected system. Therefore, achieving reactive dynamic optimization control in AC-DC interconnected multi-provincial power grids is of great importance to all provincial power grids and the entire interconnected system [18].

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In order to solve the problem of reactive power coordination optimization in different regions, this paper analyzed the dynamic multi-objective evolutionary optimization theory based on traditional reactive power and voltage control, and proposed a multi-terminal coordinated control method for improving voltage stability, using the robust optimization model. The decomposed multi-objective evolutionary algorithm is used to realize the dynamic reactive power control strategy to deal with the impact caused by uncertain wind power. The simulation analysis of the interconnected system, consisting of the four grids of Eastern Mongolia, Jilin, Liaoning and Shandong provinces, shows that the proposed multi-objective reactive power optimization method is robust and can better coordinate the inter-regional interconnections reactive power distribution, and the relationship between the reactive power balance and wind power fluctuations.

II. Multi-end AC-DC Interconnected Power Grid Reactive Power Control Model

The reactive power voltage control of each provincial power grid in the AC/DC interconnected system is a complex multi-objective optimization problem. A reactive power flow model is first established. When performing multi-terminal AC-DC interconnection grid reactive power control, set the sending and receiving areas of the AC and DC lines to A and B respectively. The frequency deviation of the inertia center angle between the two regions of the DC transmission line and the receiving end is equal to zero. The specific circuit diagram is shown in Fig. 1.

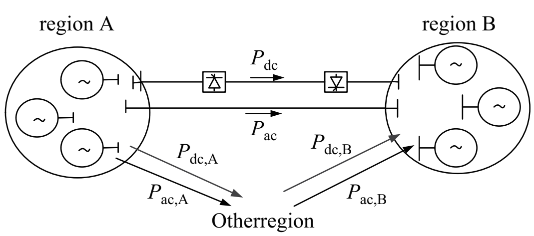

Fig. 1. AC and DC transmission line sending and receiving line diagram.

The power flow equation of the AC-DC combined power system is:

$$\begin{cases} P_i^{\mathrm{s}} - \sum\limits_{j\in i} P_{ij}(U_i, U_j, \theta_i, \theta_j) + \alpha P_{di} = 0 \\ Q_i^{\mathrm{s}} - \sum\limits_{j\in i} Q_{ij}(U_i, U_j, \theta_i, \theta_j) - Q_{di} = 0 \end{cases} \tag{1}$$

where P_i^{s} and Q_i^{s} are respectively the active power and reactive power in flow of the node I in AC network; P_{ij} and Q_{ij} are respectively the active and reactive power of the outflow node i; U_i and θ_I are respectively the voltage amplitude and voltage phase angles of the node i; U_j and θ_j are respectively the voltage amplitude and phase angles at node j; α is the signal variable of the rectifier or inverter accessing; take -1 while node i connecting the rectifier and 1 while connecting the inverter.

The constraint equation of the DC transmission line is:

$$P_{\mathrm{d}R} - P_{\mathrm{d}I} - I_{\mathrm{d}}^2 R = 0 \tag{2}$$

It can be seen from equations (1), (2) that the AC-DC hybrid system power flow correction equation [2] is:

$$\begin{bmatrix} \Delta \boldsymbol{P}_{\mathrm{d}} \\ \Delta \boldsymbol{P} \\ \Delta \boldsymbol{Q} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial \boldsymbol{P}_{\mathrm{d}}}{\partial \boldsymbol{I}_{\mathrm{d}}} & \dfrac{\partial \boldsymbol{P}_{\mathrm{d}}}{\partial \boldsymbol{U}}\boldsymbol{U} & 0 \\ \dfrac{\partial \boldsymbol{P}_{\mathrm{d}}}{\partial \boldsymbol{I}_{\mathrm{d}}} & \dfrac{\partial \boldsymbol{P}}{\partial \boldsymbol{U}}\boldsymbol{U} + \dfrac{\partial \boldsymbol{P}_{\mathrm{d}}}{\partial \boldsymbol{U}}\boldsymbol{U} & \dfrac{\partial \boldsymbol{P}}{\partial \boldsymbol{\theta}} \\ \dfrac{\partial \boldsymbol{P}_{\mathrm{d}}}{\partial \boldsymbol{I}_{\mathrm{d}}} & \dfrac{\partial \boldsymbol{Q}}{\partial \boldsymbol{U}}\boldsymbol{U} + \dfrac{\partial \boldsymbol{Q}_{\mathrm{d}}}{\partial \boldsymbol{U}}\boldsymbol{U} & \dfrac{\partial \boldsymbol{P}}{\partial \boldsymbol{\theta}} \end{bmatrix} \begin{bmatrix} \Delta \boldsymbol{I}_{\mathrm{d}} \\ \dfrac{\Delta \boldsymbol{U}}{\boldsymbol{U}} \\ \Delta \boldsymbol{\theta} \end{bmatrix} \tag{3}$$

where $\boldsymbol{P}_{\mathrm{d}}$ and $\Delta \boldsymbol{P}_{\mathrm{d}}$ are respectively the vectors of the DC active power and the unbalanced power vector of the DC active power in the DC transmission unit; $\boldsymbol{Q}_{\mathrm{d}}$ is the vector of the reactive power in the DC transmission lines; $\boldsymbol{P}$ and $\boldsymbol{Q}$ are the vectors of the active power and reactive power of the nodes; $\Delta \boldsymbol{P}$ and $\Delta \boldsymbol{Q}$ are the vectors of the unbalanced active power and reactive power; $\boldsymbol{I}_{\mathrm{d}}$ and $\Delta \boldsymbol{I}_{\mathrm{d}}$ are the vectors and correction vectors of the DC current in the DC transmission line; $\Delta \boldsymbol{U}$ and $\Delta\theta$ are respectively the voltage amplitude and phase angle correction vectors of the nodes; $\boldsymbol{U}$ is the voltage amplitude vector of the nodes.

It is a well-known fact that the reactive power balance of the total system means that the total reactive power generation is equal to the total reactive power load consumption in the interconnected power grid interconnected by multi-end AC-DC channels. For the reactive power control of the interconnected power grid, the change of reactive power in any provincial power grid will cause the change of reactive power distribution and reactive power balance in the interconnected system. Meanwhile, the fluctuation in total wind power output of the interconnected system will also cause the changes in the reactive power at the provincial power grids and AC-DC tie lines in the interconnected power grid. Therefore, the goal of reactive power optimization control for interconnected power grids is to ensure the reactive power balance under the certain voltage level of provincial power grids during the fluctuation of wind power on the premise of the minimum reactive power exchange in the tie line.

The reactive power control model of the interconnected grid can be obtained:

$$\begin{cases} \min\{f(\Delta Q_{ij}, \Delta Q_i, \Delta P_{ij}, \Delta P_{iW})\} \\ s.t.\ g(Q_{\mathrm{G1}}, Q_{\mathrm{G2}}, \cdots, Q_{Gn}, Q_{\mathrm{L1}}, Q_{\mathrm{L2}}, \cdots, Q_{Ln}) = 0 \end{cases} \tag{4}$$

where ΔQ_{ij} is the reactive power change of the lines transferring wind power; ΔP_{ij} is the active power exchange of wind power transmission line; ΔQ_i is the provincial power grid reactive power of interconnected system; ΔP_{iW} is the amount of wind power fluctuation in the interconnected system; and $i, j = 1, 2, \cdots, n$.

III. Reactive POWER Multi-objective Optimization Model of AC-DC Interconnected Power Grid

The reactive power control problem in interconnected systems is a multi-agent multi-objective dynamic optimization control problem. The optimization of reactive power in the interconnected power grids includes the output of reactive power at each provincial level, the voltage stability index, reactive power exchange capacity between grids, etc.; constraints include the active power of the AC-DC tie line, and the wind power capacity and load levels of provincial power grids. However, the number of parameters for the reactive power optimization and the dimensionalities and parameters of the variables of the objective function will change dynamically with grid operational status and wind power output, which results in the change of the optimal solution of reactive power control in the interconnected system. Therefore, the problem of reactive power optimization in a multi-area power system is actually a kind of dynamic multi-objective optimization problem (DMOP).

In this paper, the dynamic multi-objective optimization problem, which deals with the reactive power optimization in the power grids interconnected by multiple AC-DC lines of provincial power girds under the changes with the wind power output, was primarily considered. This problem can be described as:

$$\begin{cases}\min F(x,\alpha(t)) = \{f_1(x,\alpha(t)),\cdots,f_M(x,\alpha(t))\} \\ s.t. \quad x \in S\end{cases} \tag{5}$$

where x is a decision variable; $S \subset R^N$ is a decision-making space; $F : (x, \alpha(k)) \rightarrow R^M$ is a multi-objective reactive optimization function that contains M objective functions; R^M is the objective space; and $\alpha(t)$ is the wind power related dynamic parameters.

It is generally considered that wind power changes discretely according to the time, that is, wind power changes only occur at some non-continuous time points, corresponding dynamic parameters can be discretized and satisfy:

$$\forall \alpha(k), \alpha(k) \neq \alpha(k+1)$$

For all wind power outputs, if $\alpha(k)$ is kept unchanged, then the corresponding objective function is unchanged. Thus, the above dynamic multi-objective optimization problem is transformed into K static multi-objective optimization problems and denoted as:

$$\langle \min F(x,\alpha(1)),\cdots,\min F(x,\alpha(K))\rangle$$

For any static multi-objective optimization problem of wind power output, the Pareto optimal solution set obtained is denoted as: $PS(k), k = 1, 2, \cdots K$. The corresponding Pareto front end is denoted as: $PF(k), k = 1, 2, \cdots K$.

The goal of dynamic multi-objective optimization is to find the Pareto optimal solution $PS(k)$ satisfying $\min F(x, \alpha(k))$ quickly before the dynamic change of wind power output, in order to perform on the line control, in other words, before the occurrence of $\alpha(k + 1)$.

The idea of robust optimization [19] was proposed by the statistician Wald in 1950. This paper presents the concept of robust optimization overtime (ROOT) based on the time-varying characteristics of wind power output of the sending-end gird. Its core idea is to find a set of robust solutions for determining the reactive power of provincial power grids; each robust solution can be applied to the case where wind power output dynamically changes in several consecutive times with a certain degree of satisfaction. The robust Pareto optima over time (RPOOT) model describing the adaptability of Pareto solutions to wind power output changes is proposed for the dynamic multi-objective optimization of complex power grids interconnected by AC-DC wind power transmission lines across multiple provincial power grids, and the description about lifetime and average fitness of Robust Pareto Solutions are also established.

The RPOOT solution for reactive power at each provincial grid in the interconnected power grid should consider two aspects: first, it is necessary to optimize two objectives, reactive power and voltage of several grids at the same time, which are contradictory in the usual case. The single-objective optimal solution for one provincial power grid is generally the reactive power boundary. When taking into account the reactive power and voltage indexes of multiple girds, it is necessary to compromise the optimal solution of a single power network, but the compromised solution generally cannot completely satisfy the optimal reactive power objective of all provincial grids at the same time. Therefore, the robustness of a certain optimal solution should not only consider the fitness value of a certain objective under continuous dynamic wind fluctuations, but also needs to measure the relative changes of all its sub-targets. Secondly, in the process of solving dynamic multi-objective robust solutions of multiple grids, it is often necessary to predict the fitness of solutions under future continuous dynamic wind fluctuations. Because of multi-objective optimization problems, all of each other's non-dominant solutions will become the optimal solutions and constitute the Pareto optimal solution set, so in RPOOT, the objective time series of multiple non-dominant solutions constitutes a multi-time series prediction problem.

Aiming at the frequent changes of wind power output of multi-AC/DC transmission lines, especially during small and fast fluctuation of wind power, the change of reactive power optimization solutions among provincial power grids may result in big reactive power exchanges and increase security and stability costs. However, the traditional dynamic multi-objective optimization method usually obtains the Pareto optimal solution that accommodates wind power fluctuations through searching for re-optimized solutions under every new wind power output. Meanwhile, changing the optimal solution of the multi-objective will result in large power exchanges in the entire interconnected power grid and even failure in finding the multi-objective optimal solution for reactive power over the entire grid during rapid changes of wind power in each time interval. The key idea of the dynamic multi-objective robust evolutionary optimization method presented in this paper is to find a set of robust Pareto solutions, in which each robust Pareto solution can be applied to a number of continuous dynamic wind speeds with a certain degree of satisfaction, thus to avoid the time delay and the increase in scheduling cost caused by the frequent calculation of the Pareto optimal solution under each dynamic wind power output.

IV. Reactive Multi-objective Robust Evolutionary Optimization Algorithm for interconnected Power Grids

A. Reactive Multi-objective Robust Evolutionary Algorithm Model for Interconnected Power Grids

The core of reactive multi-objective optimization of multi-provincial interconnected power systems as shown in (5) is to find a set of robust pare to optimal solution sets, and the robust Pareto optimal solution denoted as:

$$RPS = RPS(1), \cdots, RPS(LS), LS \leq K \tag{6}$$

where each robust Pareto optimal solution $RPS(i)$ can be applied to multiple continuous dynamic wind power output fluctuations. Traditional dynamic multi-objective optimization problems often only consider the convergence and distribution under the dynamic changes of a certain grid parameter, without considering the applicability of the Pareto solution under the continuous dynamic fluctuation of wind power output in the future. How to evaluate the adaptability of wind power fluctuation of every reactive Pareto solution and how to approximate the convergence of the real Pareto front under every dynamic fluctuation are crucial in the robust multi-objective reactive power optimization for interconnected power systems.

In dynamic multi-objective robust optimization, RPOOT obtains the robust Pareto optimal solution $PS(k)$ of each dynamic wind power output, rather than seeking a Pareto optimal solution $PS(k)$. When the wind power fluctuates, the method not only needs to approximate convergence to the real Pareto optimal solution, but also should approximate the real Pareto optimal solution as much as possible, while the subsequent wind power output continues to fluctuate dynamically. In this way, it is necessary to know the current fitness of the Pareto solution $PS(k)$ and its fitness value under future possible wind power fluctuations during evolutionary optimization. The following model is constructed for the dynamic robust Pareto optimization.

$$\begin{cases} \min F^{\text{ave}}(x, \alpha(k)) = (f_1^{\text{ave}}(x, \alpha(k)), \cdots, f_M^{\text{ave}}(x, \alpha(k))) \\ \text{s.t. } \dfrac{\|F^{\text{ave}}(x, \alpha(k)) - \hat{F}(x, \alpha(k+q))\|}{\|F^{\text{ave}}(x, \vec{\alpha}(k))\|} \leq \eta, \\ q = 0, \cdots, T-1 \end{cases} \tag{7}$$

where x is the reactive power optimal solution for the interconnected grid; k is the corresponding moment of wind power output; T is the wind power fluctuation time window of sending-end grid; $F^{\text{ave}}(x, \alpha(k))$ is the average fitness value of solution x within a fixed time window T under the dynamic wind power output moment k; η is the stability threshold of the standard deviation of the current fitness function of solution x and the fitness value at T-1adjacent wind power output moments.

While $q = 0$ in $\hat{F}(x, \alpha(k+q))$, the result is $\hat{F}(x, \alpha(k+q)) = F(x, \alpha(k))$.

Equation (7) guarantees the approximation ability of solution x to the real Pareto front under the continuous constraints within the time window.

B. Evolutionary Optimization Algorithm of Reactive Power Multi-objective RPOOT Based on Decomposition

In the above robust evolutionary algorithm model, two types of robustness metrics in the dynamic multi-objective robust optimization problem are transformed into the performance robustness under the fixed-time robustness, that is, the average fitness value of a certain solution under current wind power output and future T-1 wind power output continuous fluctuations [20]–[22]. Therefore, for this type of transformation model, the core of the optimization process is to find a robust Pareto optimal solution with good convergence to current and future dynamic wind power output within the time window. Being different from the traditional DMOPs, on the one hand, the optimization objective is the average fitness of each solution in the time window T; on the other hand, the fitness value of the solution under unknown conditions is unknown in the future, the estimation should be made by applying the time series prediction method. In order to solve the model, the traditional multi-objective evolutionary algorithm based on decomposition (MOEA/D) is adopted, in which, the decomposition method uses the penalty-based boundary intersection (PBI). The algorithm flow is shown in Fig. 2.

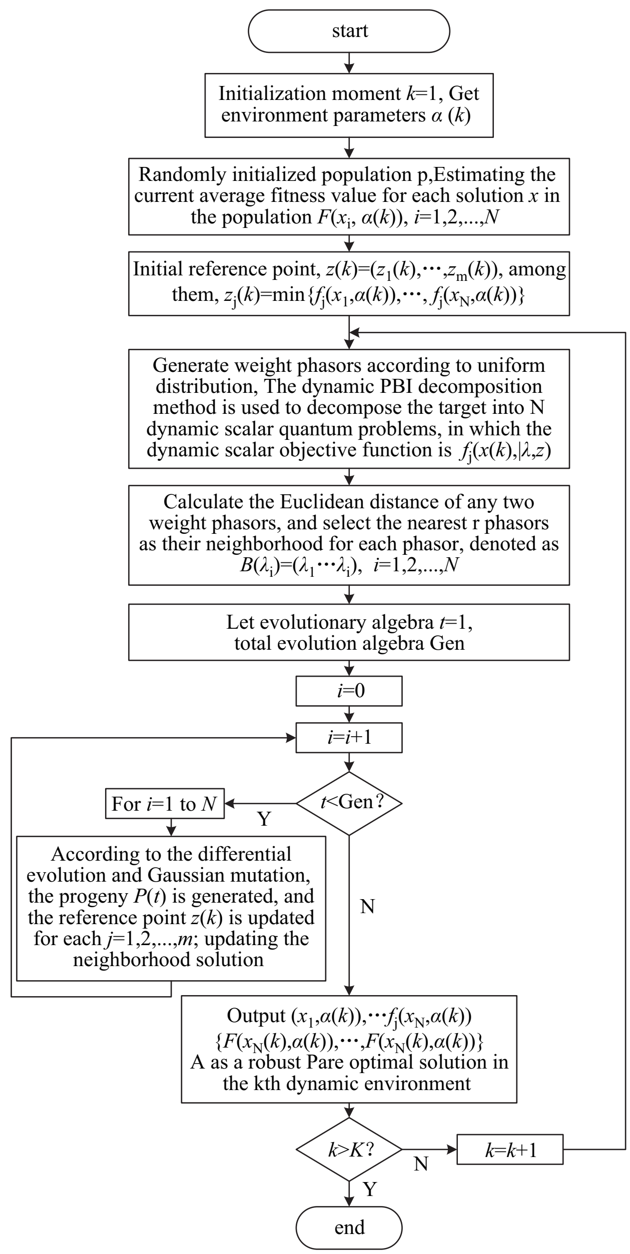

Fig. 2. Flow chart of dynamic multi-objective robust optimization algorithm.

In the process of evolution, the core of constraint processing lies in the determination of constraint satisfaction. As seen in (7), due to the influence of the prediction error and the dynamic change of wind power output, with the increase of T, the feasible solution that satisfies constraints at T will be greatly reduced. Therefore, the above constraints are transformed into the degree of constraint satisfaction, and individuals are compared by using the weakened constraint after being transformed.

$$\begin{cases} g_{\mathrm{q}}(x,\alpha(k)) = \dfrac{\|F^{\mathrm{ave}}(x,\alpha(k)) - \hat{F}(x,\alpha(k+q))\|}{\|F^{\mathrm{ave}}(x,\vec{\alpha}(k))\|} \leq \eta, \\ -\eta \leq 0, q = 0,\cdots,T-1 \end{cases} \tag{8}$$

Based on the above transformation of constraints, the definition of the constraint satisfaction function is:

$$V_{\mathrm{s}}(x,\alpha(k)) = \sum_{q=0}^{s} \max\{g_{\mathrm{q}}(x,\alpha(k)),0\} \tag{9}$$

where $s = 0,\cdots,T-1$.

When $V_{\mathrm{s}}(x,\alpha(k)) = 0$ is satisfied, the individual x is a weak feasible solution that satisfies the first s constraints in (9); otherwise, x is not a weak feasible solution.

C. Reactive Multi-objective Prediction Mechanism

In the process of solving the dynamic multi-objective optimization problem, the prediction mechanism can effectively improve the evolutionary efficiency of the algorithm. In RPOOT, the robustness of the robust Pareto solution should be considered to determine its applicability to dynamic wind power output in the future. Therefore, the fitness value of the robust Pareto solution under future dynamic wind power output should be used. For the actual dynamic optimization problem on line, the fitness value of the solution under future dynamic wind power output is unknown and needs to be estimated by the prediction method [23]. Therefore, the essence of prediction in RPOOT is to estimate the fitness value of the current solution under future continuous wind power output based on historical information and trends of dynamic wind power output. In the robust evolutionary algorithm model, the optimization goal is the average fitness function value $F^{\mathrm{ave}}(x,\alpha(k))$. It can be determined from (7) that the average fitness of x in the case of continuous fluctuation of wind power output in the time window depends on the fitness value of x in the future continuous fluctuation of wind power output. Therefore, in the process of dynamic multi-objective robust optimization, the future fitness value of all solutions in each generation population needs to be predicted on multiple objectives, so that the RPOOT prediction problem is transformed into a multi-dimensional time series prediction problem with a dimension of $N \times M$. To reduce the computational complexity, the design of the prediction method needs to be considered from the following two aspects: first, the space complexity of the prediction method can't be too high; second, the time complexity of the prediction method can't be too large; otherwise real-time performance of the dynamic multi-objective optimization algorithm will be greatly affected.

The moving average (MA) prediction model is applied in this paper. MA is a simple and effective time series prediction model. First, supposing that a time series with a length of m for each solution x in the population under the k^{th} dynamic wind power output is constructed:

$$(\boldsymbol{F}(x,\alpha(k-m+1)),\cdots,\boldsymbol{F}(x,\alpha(k))) \tag{10}$$

where, $\boldsymbol{F}(x,\alpha(i))$, $k-m+1 \leq i \leq k$ is the vector of fitness of solution x under the wind power output, which is composed of $f_j(x,\alpha(k))$, $1 \leq j \leq M$. The purpose of the prediction is to estimate $F(x,\alpha(k+i))$, $1 \leq i \leq T-1$ under the future dynamic wind power output based on the above time series.

The MA model is defined as follows:

$$\hat{F}(x,\alpha(k+i)) = b + \varepsilon(k) \tag{11}$$

where $\varepsilon(k) \sim U(0,\sigma^2)$ is the Gaussian of the white noise variance σ^2. b is the average estimate of the first m data points adjacent in the time series.

$$b = \frac{1}{m}\sum_{j=1}^{m} F(x,\alpha(k+i-j)) \tag{12}$$

Variance σ^2 is estimated by the following equation:

$$\hat{\sigma}^2 = \frac{1}{m}\sum_{j=1}^{m} (F(x,\alpha(k+i-j)) - b)^2 \tag{13}$$

It can be seen that the fitness value of $\hat{F}(x,\alpha(k+i))$ under continuous fluctuations of future wind power output can be predicted as a value with mean b and variance σ^2.

V. Simulation and Result Analysis

To verify the feasibility and superiority of the proposed control method, modeling and simulation are carried out in a MATLAB based on the dynamic reactive power multi-objective robust evolutionary optimization model for interconnected power grids mentioned above. The example of an interconnected power system is shown in Fig. 3.

In Fig. 3, the Jilin Power Grid is connected to the Eastern Mongolia Power Grid via three 500 kV AC transmission lines, while the Liaoning Power Grid is connected to the Eastern Mongolia Power Grid via one 500 kV AC transmission line, while the Shandong Power Grid is connected to the Eastern Mongolia Power Grid via one 500 kV DC transmission line. The four provincial power grids are connected by 5 lines, 4 AC lines and 1 DC line, forming a large interconnected power grid. Wind power in Jilin, Liaoning and Eastern Mongolia grids are collected in the Zhalute AC and DC station in Eastern Mongolia, which is sent out to the Shandong Power Grid via DC channels. 5 and 2 sets of thermal power units are respectively arranged in the Eastern Mongolia Power Grid and Jilin Power Grid to stabilize the wind power fluctuations.

The interconnected system model parameters used in this paper are as follows: the load of the Eastern Mongolia Power Grid is 5,000 MW, the load of the Liaoning Power Grid is 20,000 MW, the load of the Jilin Power Grid is 15,000 MW and the load of the Shandong Power Grid is 50,000 MW. The operational conditions of the interconnected systems in

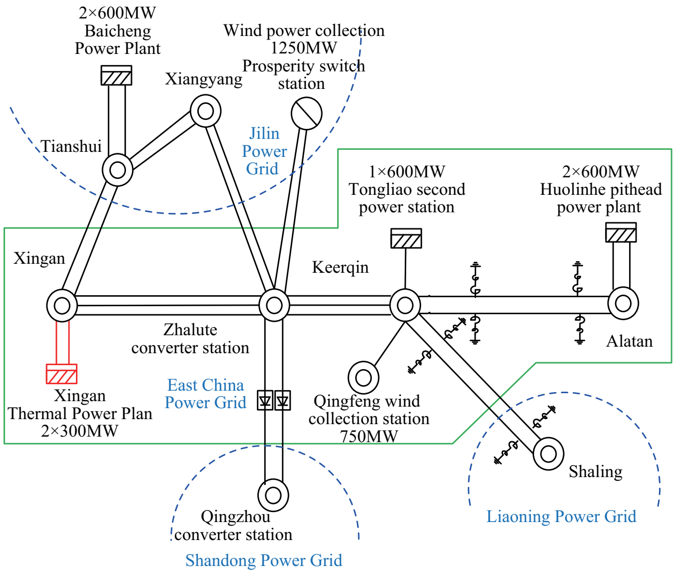

Fig. 3. Topological structure of interconnected power system.

the simulation are as follows: Eastern Mongolia Wind Power delivers 7,000 MW, Jilin Wind Power delivers 1,500 MW and the Liaoning Wind Power delivers 1,500 MW. The total wind power transmission capacity in the interconnected system is 1,000 kW. With 25% uncertainty added to the output of wind power and a sudden increase in total wind power output in the interconnected grid, two cases of simulation analysis have been made, one with dynamic robust optimization control and the other one without dynamic robust optimization control. Reactive power curves in the interconnected system are shown in Fig. 4.

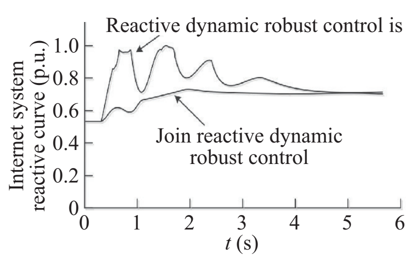

Fig. 4. Dynamic robust optimization of reactive power.

As can be seen from Fig. 4, after adding the reactive dynamic robust optimization control, the reactive power response speed of the system is significantly increased, and reactive power fluctuations and overshoot are significantly reduced.

In the simulation system, the reactive multi-objective dynamic robust evolutionary optimization model of the interconnected power grid established in this paper is used; the wind power fluctuation of $-30 \sim 30\%$ is added to the typical daily load curve of multiple power grids in the whole system, and 25% uncertainty of the wind power output disturbance is added at 17:00 to optimize reactive power control of the interconnection system. The simulated calculation about voltage fluctuation of the 500 kV system in 4 provincial power grids is as shown in Figs. 5–8.

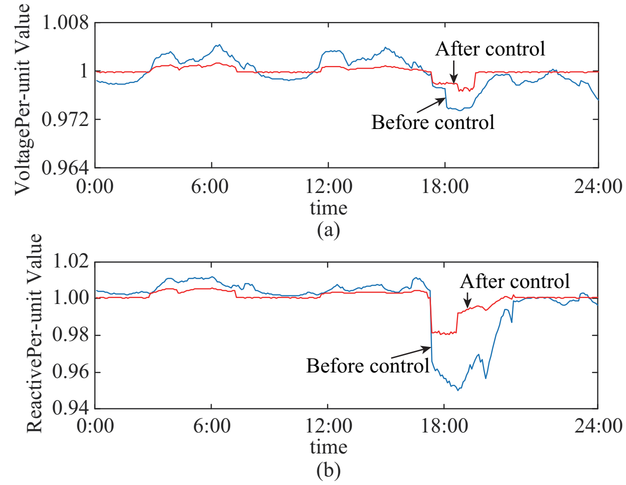

Fig. 5. Voltage and reactive power level under multi-objective robust optimization (Eastern Mongolia Grid). (a) Uncertainty of the wind power is 0. (b) Uncertainty of the wind power is 25%.

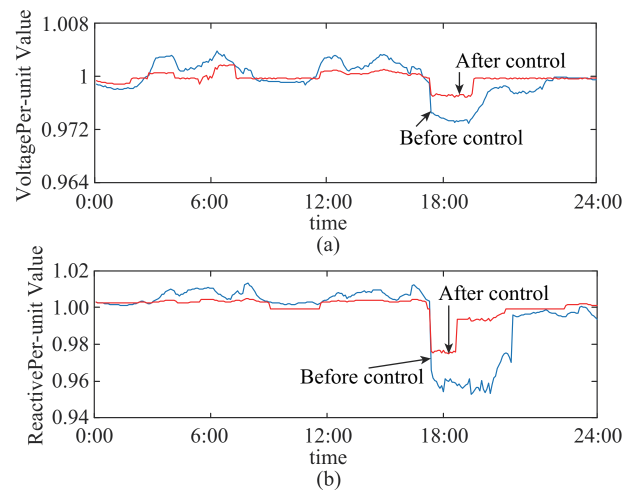

Fig. 6. Voltage and reactive power level under multi-objective robust optimization (Jilin Grid). (a) Uncertainty of the wind power is 0. (b) Uncertainty of the wind power is 25%.

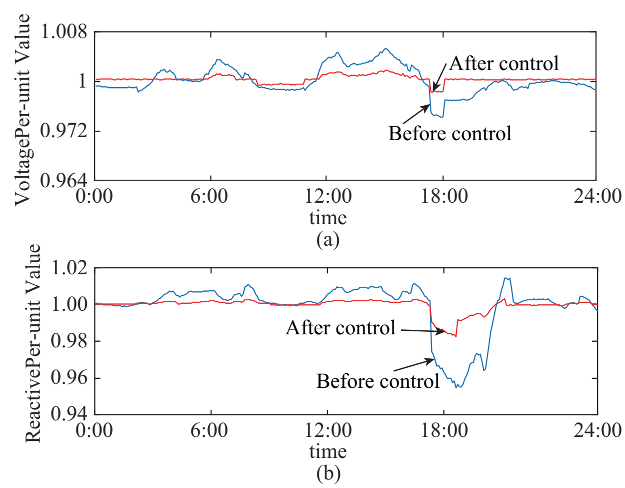

Fig. 7. Voltage and reactive power level under multi-objective robust optimization (Liaoning Grid). (a) The uncertainty of the wind power is 0. (b) The uncertainty of the wind power is 25%.

TABLE I
COMPARISON OF VOLTAGE FLUCTUATION INDEXES BEFORE AND AFTER REACTIVE MULTI-OBJECTIVE ROBUST OPTIMIZATION

Reginal power grid	Average daily Peak Valley Difference (kV)		Valley Difference Drop (%)	Daily Average Standard Deviation (kV)		Standard deviation decrease (%)
	No control	With control		No control	With control	
Eastern Mongolia	35.55	25.35	28.69	15.01	10.94	27.12
Liaoning	33.28	27.24	18.15	16.09	10.83	32.69
Jilin	32.29	24.75	23.35	12.17	10.69	12.16
Shandong	36.11	22.99	36.33	15.12	10.67	29.43

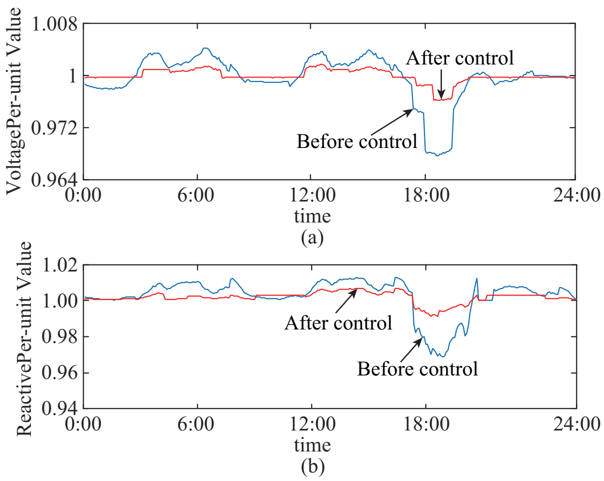

Fig. 8. Voltage and reactive power level under multi-objective robust optimization (Shandong Grid). (a) Uncertainty of the wind power is 0. (b) Uncertainty of the wind power is 25%.

It can be seen from Figs. 5–8 that the fluctuation of reactive power and voltage of all the grids after the inputting control are obviously smaller than those without control. There is an obvious voltage drop in the contact node of each grid at 17:00. After the reactive power multi-objective optimization of the interconnected power grid, voltage and reactive power of all the provincial power grids in the entire interconnected power grid could stay stable to suppress the voltage fluctuation effectively, even if the wind power output experiences severe change.

To further prove the effectiveness of the control, two long periods of time were chosen for comparative analysis. In view of the uncertainties of the output fluctuation of various wind power sources in the interconnected system, 3–5 periods of time with small wind power fluctuations and 3–5 periods of time with large wind power fluctuations are selected for model verification. The time period of about 20–30 days has good representativeness.

Under the two types of wind power fluctuation conditions, the reactive power voltage controls of the interconnected grid were carried out respectively with the dynamic multi-objective robust algorithm and without the algorithm to verify the effectiveness of the model. Data analysis and comparison results are shown in Table I. The data comparison results show that the dynamic multi-objective robust optimization model for interconnected power grids has a good effect on voltage and reactive power control over a long time scale.

VI. CONCLUSION

For solving the robust optimization problem during strong nonlinear transient processes in the interconnected power grid, are active power optimization method based on finding the robust dynamic Pareto optimal solution sets of interconnected provincial power grids was proposed in this paper for large-scale power grids interconnected by multi-terminal wind power AC-DC transmission lines.

1) The reactive dynamic multi-objective optimization problem of multiple provincial grids was transformed into two types of robust optimization models. The decomposition-based multi-objective evolutionary optimization method was applied to construct a reactive dynamic multi-objective decomposition robust evolutionary optimization method.

2) According to the characteristics of wind power output fluctuation, a fitness prediction algorithm was established for the dynamic fluctuation of future wind power output to restrain reactive power exchange caused by wind power output fluctuation.

3) The results of simulation analysis about large-scale interconnected power grids formed by four provincial power grids showed that reactive power voltage control based on the reactive power dynamic multi-objective fast robust evolutionary optimization model of interconnected power grids has obtained favorable control effect.

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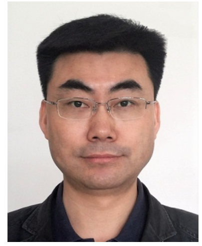

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