Research Article

Multiobjective Synergistic Scheduling Optimization Model for Wind Power and Plug-In Hybrid Electric Vehicles under Different Grid-Connected Modes

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In order to promote grid's wind power absorptive capacity and to overcome the adverse impacts of wind power on the stable operation of power system, this paper establishes benefit contrastive analysis models of wind power and plug-in hybrid electric vehicles (PHEVs) under the optimization goal of minimum coal consumption and pollutant emission considering multigrid connected modes. Then, a two-step adaptive solving algorithm is put forward to get the optimal system operation scheme with the highest membership degree based on the improved ε constraints method and fuzzy decision theory. Thirdly, the IEEE36 nodes 10-unit system is used as the simulation system. Finally, the sensitive analysis for PHEV's grid connected number is made. The result shows the proposed algorithm is feasible and effective to solve the model. PHEV's grid connection could achieve load shifting effect and promote wind power grid connection. Especially, the optimization goals reach the optimum in fully optimal charging mode. As PHEV's number increases, both abandoned wind and thermal power generation cost would decrease and the peak and valley difference of load curve would gradually be reduced.

1. Introduction

With the promotion of the national energy conservation policy, implementing energy-saving generation scheduling in power system has been already put in the process. This means renewable energies are facing excellent development opportunities. With wind power's scale increasing, in 2013, wind power newly increased installed capacity was 16093.3 MW and the gross installed capacity reached 92038.49 MW. Both of the two indicator values rank first in the world. Currently, China is planning to build 8 million level wind power bases. The gross installed capacity of wind power will reach one hundred million in 2020 MW [1].

However, because of wind power output volatility, power sources away from the load centers, uncoordinated grid construction, and other factors, wind power absorptive problem has become the bottleneck of wind power in China. According to the statistical data released by The National Energy Board, in 2012, the total abandoned wind power

reaches 20TW·h in China. The average equivalent utilization hours of wind power units are 1890 h and less than that in 2011. In Mongolia East, Jilin, Qinghai, and other wind resource-rich regions, the average equivalent utilization hours of wind power units are 1400 h and the abandoned wind power problem is very serious. To achieve the target, that renewable energy proportion in primary energy reaches 15% [2], abandoned wind problem should be solved mainly by improving the wind power absorptive capacity and efficiency of the grid.

There are already many researches focused on improving the wind power absorptive problem. Optimization methods are mainly aimed at optimizing wind power's backup service. They could be divided into four categories, namely, wind power-AGC collaborative grid connection [3–6], wind power and adjustable units collaborative grid connection [4–7], wind power and energy storage devices collaborative grid connection [8, 9], and wind power and demand side response collaborative grid connection [10–13]. Although all

the optimization methods could bring some benefits, they also have certain deficiencies. For example, the adjustment capability of backup service is weak, and backup service cost is too high [14, 15], which promote power system to search for new backup service for wind power.

Plug-in hybrid electric vehicles (PHEVs) have chargeable and dischargeable capacity, which makes PHEV have the potential to be the backup service for wind power grid connection. PHEV's orderly grid connection can bring multiple benefits such as achieving energy conservation by using electricity rather than oil, smoothing the load curve by controlling charging and discharging behavior, and promoting wind power grid connection. However, if PHEV's grid connection behavior is not under control, its arbitrary charging and discharging behavior would exacerbate the volatility of system load, which would decrease wind power consumption capacity. To solve these problems, wind power-PHEV synergistic scheduling optimization method needs to be studied.

Researches on wind power-PHEV synergistic scheduling optimization are mainly focused on two aspects, namely, model building and solution algorithm. As for model building, literature [16–18] established PHEV-thermal power synergistic scheduling optimization model and taxonomic studies on 4 kinds of charging modes' influence on the optimal combination of thermal power. In those literatures, there are only thermal units in the assumed system. Literature [19, 20], respectively, established PHEV-wind power synergistic scheduling stochastic optimization model. Literature [21] put forward a PHEV-wind power synergistic scheduling optimization model in multiple time scales. And using the model, the literature studied wind power-PHEV synergistic scheduling's influence on the grid under free-charging mode. However, literature [19–21] assumes that PHEVs are in the free-charging mode, ignoring the elasticity relationships between user's electricity consumption behavior and electricity price.

In terms of solution algorithm, minimizing pollution emission becomes another optimization objective of wind power-PHEV synergistic scheduling under energy conservation requirements. This makes the optimization problems become multiobjective problems. Multiobjective problems need suitable solution algorithms to get the optimal solution sets. Literature [22, 23] and literature [24], respectively, use POS, the simulated annealing, differential evolution, and other intelligent algorithms to solve unit commitment problems in wind power-PHEV synergistic scheduling. Conventional solution algorithms generally have difficulties in determining parameters and transforming constraints, which make their optimization levels not high [25, 26]. Intelligent algorithms can avoid these problems. But when individual extremes do not meet the multiobjective planning principles, intelligent algorithms are easy to fall into the local extreme point, limiting the search abilities [27–29].

Based on the analysis above, to overcome the deficiencies of the study on wind power-PHEV synergistic scheduling, this paper mainly contains 7 sections. Section 2 analyzed PHEV's charging and discharging characteristics and put forward the PHEV charging and discharging power output

model. Section 3 simulates the uncertainty of wind power and constructs wind power scenarios simulation and scenario reduction strategy. Section 4 considered system demand and supply balance and units' output and backup service constraints, established wind power-PHEV synergistic scheduling models, respectively, and set the minimum coal cost and pollution emission cost as the optimization objectives during power generation. Section 5 puts forward a two-step solution algorithm based on the improved ε constraints and fuzzy decision theory. Section 6 introduced the solving progress of the solution algorithm. Section 7 used the improved IEEE36 points system as the simulation system to analyze the optimization results in different charging and discharging modes and then made a sensitive analysis for the grid connection PHEV's number.

2. PHEV Charging and Discharging Models

2.1. Charging Modes. In terms of charging model, there are some research results. PHEV's charging modes can be divided from two aspects, namely, ordered or disordered charging, distinguish time periods, or continue charging. In this way, its charging modes can be classified into 3 kinds as follows: the no-control charging mode, the continuous charging mode, and the delayed charging mode [29]. We can compare these three charging modes with the fully optimized charging mode. Their charging load curves are as shown in Figures 1, 2, and 3. Their characteristics can be described as follows.

- (1) The no-control charging mode: in this mode users' charging behaviors are not influenced by anything. They just follow their own needs and habits. So PHEV's charging load would have strong volatility. Therefore PHEV's grid connection would bring some bad effects to electric system's short term operation stability. However, in the long term operation aspect, electric system could grasp users' charging habit and formulate corresponding measures to overcome the bad effects.
- (2) The delayed charging mode: being different from the no-control charging mode, this charging mode applies time of use (TOU) and other control means to lead users' charging behaviors. Users are trend to adjust their charging behavior according to the load curve. This charging mode is usually considered to be a practical scenario, because in this mode PHEV mainly charge in the valley period and discharge in the peak period. So PHEV could play an important role in load shifting, smoothing the load curve.
- (3) The continuous charging mode: in the no-control charging mode or delayed charging mode, PHEV is supposed to charge and discharge only once a day. That can be true for individual PHEV, but it is not so practical for public PHEV. In the continuous charging mode, as long as PHEV is not in operation, it can charge or discharge. So in this mode user's charging and discharging behavior would not be limited. PHEV's grid connection would increase, which

FIGURE 1: The PHEV charging load profile in the uncontrolled charging mode [30].

FIGURE 2: The PHEV charging load profile in the continuous charging mode [30].

means gasoline consumption and CO_2 emission would decrease. However, users' casual charging and discharging behavior would bring some uncontrolled effects to electric system's operation. For example, the volatility of load curve may increase. This is not conducive to wind power grid connection.

- (4) The fully optimal charging mode: based on the delayed charging mode, the fully optimal charging mode takes measure to control users' charging behavior directly. In this mode, PHEV's charging or discharging would absolutely be in accordance with power system's supply and demand situation. If TOU is rational in the continuous charging mode, its optimization result would be almost the same with the fully optimal mode. So the load curve of the fully optimal charging mode is similar to the continuous mode.

2.2. Discharging Modes. PHEV's discharging mode is influenced by battery type, capacity, related parameters, discharging cycle, discharging loop power, and other factors. Because it is hardly to decide discharging parameters, this paper uses existing research results [11] as data basis of discharging load distribution.

PHEV is used as a kind of backup service for wind power grid connection, in a certain extent; it is determined by controlling and estimating PHEV's discharging capacity. So the uncertainty of PHEV's discharging time and number brings considerable difficulties to accurately estimate the discharge capacity. Literature [31] has already studied PHEV's battery type, capacity, discharge cycle, discharge power, and other parameters' influence on PHEV's discharging behavior. This paper uses its result to make further study. Setting the maximum discharge capacity to be 9.6 kW, PHEV's discharging time and capacity 11 curve are shown in Figure 4. In the figure, almost all PHEVs can finish their discharging work in 6 hours.

FIGURE 3: The PHEV charging load profile in the delayed charging mode [30].

FIGURE 4: Different types of PHEV discharging characteristic curves [31].

2.3. PHEV Charging and Discharging Power Model. PHEVs need storage battery as their energy storage component to achieve charging and discharging behavior. Load change of storage battery can be tracked by energy storage controller [2]. When it comes to the maximum capacity of the storage battery, the energy storage controller would stop storage battery from charging to ensure the battery life and operation safety. And when it comes to the minimum capacity, the energy storage controller would stop storage battery from discharging. Consider

$$S^{\min} \leq S_t \leq S^{\max}, \quad (1)$$

where $S^{\max}$ and $S^{\min}$ are the upper and lower limit of the storage battery capacity; S_t is the storage electricity of PHEV at time t .

(1) When PHEV is in the charging status,

$$S_{t+1}^d = S_t^d - P_t^d (1 + \rho_d). \quad (2)$$

(2) When PHEV is in the discharging status,

$$S_{t+1}^c = S_t^c + P_t^c (1 - \rho_c), \quad (3)$$

where S_t^d and S_t^c are the storage electricity at time t of PHEV d and PHEV c ; ρ_d is the self-consumed electricity during its discharging period of PHEV d ; ρ_c is the self-consumed electricity during its charging period of PHEV c ; P_t^d and P_t^c are discharging and charging power at time t of PHEV d and PHEV c .

Generally, PHEV's charging or discharging power should not exceed 20% of the maximum capacity of the storage battery [25]. The constraints can be described as

$$\begin{aligned} P_t^d &\leq \frac{0.2S_t^d}{\Delta t} \\ P_t^c &\leq \frac{0.2S_t^c}{\Delta t}. \end{aligned} \quad (4)$$

3. Simulate the Uncertainty of Wind Power

Wind power output is limited by the income-wind velocity. However, if the income-wind velocity is lower than the cut-in wind velocity or is higher than the cut-out wind velocity, the wind farm will not generate power. The relationship between output power and the income-wind velocity could be expressed as

$$g_{w,t}^* = \begin{cases} 0, & v_t \leq v_{i,w} \quad \text{or} \quad v_t > v_{o,w}, \\ \frac{g_r (v_t - v_{i,w})}{v_{r,w} - v_{i,w}}, & v_{i,w} < v_t < v_{r,w}, \\ g_r, & v_{r,w} \leq v_t \leq v_{o,w}, \end{cases} \quad (5)$$

where $g_{w,t}^*$ is the actual available output of wind power unit w at time t ; g_r is the rated output power of wind power units; $v_{i,w}$ is the cut-in speed; $v_{o,w}$ is the cut-out speed; $v_{r,w}$ is the rated wind speed; v_t is the actual speed at time t .

FIGURE 5: Discrete method for wind forecasting power.

3.1. Wind Power Scenarios Simulation. In the actual scheduling progress, wind power output can be determined through two ways, namely, forecast and simulation. In terms of wind power forecast method, there are classical forecast method [32, 33], modern forecast method [34–36], and intelligent forecast method [37–39]. The development of intelligent forecast method, especially, largely promoted wind power forecast technology. However, the practical applications show that the forecasting accuracy of these methods is still not able to reach the requirements of system scheduling. Therefore, this paper does not forecast wind farm's output power but uses scenario analysis method to simulate each power generation scenario. Assume the random variable of wind power output is $g_{w,t}$; its composition is detailed as follows:

$$g_{w,t} = g_{w,t}^f + \zeta_{w,t}, \quad (6)$$

where $g_{w,t}^f$ is the forecast power of wind power; $\zeta_{w,t}$ is the forecast error of wind power forecast. The forecast error is assumed to follow the normal distribution $\zeta_{w,t} \sim [0, \delta_{w,t}^2]$; then $g_{w,t}$ could be thought to follow the normal distribution $g_{w,t} \sim [g_{w,t}^f, \delta_{w,t}^2]$ [40].

In order to gain the wind power scenarios, interval method is used to simulate wind power output. Divide wind power output into several intervals. Set the value of a point in the interval as wind power output expectation. When the number of intervals is sufficient, the forecast value could be regarded as the real output. The details are shown in Figure 1.

According to Figure 5, in each interval, there are three statues, namely, high, normal, and low. The expectation of wind power output in each statue is $g_{w,t}^z$, where $z = 1, 2, 3$ are, respectively, corresponding with three statues. The probabilities of each output statue are p_t^z ; then the wind power output set in each scenario is $A = \{g_{w,t}^s \mid t = 1, 2, \dots, T\}$ and the scenario probability of wind power output is $p = \prod_{t \in T} p_t^z$. Figure 6 shows the wind power output forecast simulation scene scenario of three statues.

3.2. Wind Power Scenario Reduction Strategy. The basic concept of scenario reduction is comparing a scenario with other scenarios and removing the closest one. And the bigger the scenario number, the bigger the workload of scenario reduction. To overcome this problem, this paper

FIGURE 6: Wind scene tree.

introduces the Kantorovich distance [41], and set minimize the Kantorovich distance between the initial scenario and the reduced scenario as the optimize objective.

Assume $P = [\xi_{it}]_{T \times N}$ is the initial wind power scenario set and $Q = [\tilde{\xi}_{jt}]_{T \times \tilde{N}}$ is the reduced scenario set. Then the Kantorovich distance between the initial scenario set P and the reduced scenario set Q can be defined as

$$D_K(P, Q) = \inf \left\{ \sum_{k=1}^N \sum_{j=1}^{\tilde{N}} \eta_{kj} c_T(\xi_k, \tilde{\xi}_j) : \eta_{kj} \geq 0, \right. \\ \left. \sum_{k=1}^N \eta_{kj} = q_j, \sum_{j=1}^{\tilde{N}} \eta_{kj} = p_k, \forall k, \forall j \right\} \quad (7)$$

$$c_T(\xi_k, \tilde{\xi}_j) = \sum_{t=1}^T |\xi_k - \tilde{\xi}_j|. \quad (8)$$

Then the Kantorovich distance would be

$$D_K(P, Q) = \sum_{k \in J} p_k \min_{j \notin J} c_T(\xi_k, \tilde{\xi}_j). \quad (9)$$

Define q_j to be equal to the summation of the scenario's occurrence probability in the initial scenario and the closest deleted scenario. This is detailed as

$$q_j = p_j + \sum_{k \in J(j)} p_k \quad (10)$$

$$J(j) = \{k \in J : j = j(k)\} \quad (11)$$

$$j(k) \in \arg \min_{k \in J(j)} c_T(\xi_k, \tilde{\xi}_j), \quad \forall k \in J. \quad (12)$$

Then build wind farm scenario reduction optimization method based on (7)–(12). The optimized scenario reduction method can be expressed as

$$\min \left\{ \sum_{k \in J} p_k \min_{j \notin J} c_T(\xi_k, \tilde{\xi}_j) : J \subset \{1, 2, \dots, \tilde{N}\}, S = N - \tilde{N} \right\}. \quad (13)$$

According to (13), the scenario reduction mechanism would influence the reduction result directly. To set an appropriate scenario deleted number, this paper puts forward the maximum reduction strategy:

$$\sum_{k \in J} p_k \min_{j \notin J} c_T(\xi_k, \tilde{\xi}_j) \leq \beta, \quad (14)$$

where (14) is to ensure the similar degree of the reduced scenario set and the initial scenario set in the required range. The scenario reduction model consists of (7)–(14). To solve this model, this paper uses the multistage heuristic algorithm, referring to literature [42].

4. Wind Power-PHEV Synergistic Scheduling Optimization Model

4.1. Objective Functions

4.1.1. Minimize Power Generation Coal Consumption Cost Objective Function. For thermal units, coal consumption cost mainly includes power generation coal consumption cost and startup-shutdown coal consumption cost; the objective function is

$$\min F_1 = \sum_{t=1}^T \sum_{i=1}^I [u_{it} f_1(g_{it}) + u_{it} (1 - u_{i,t-1}) N_{it}], \quad (15)$$

where I is the quantity of power generation units; T is the total optimization period and, in this paper, $T = 24$; u_{it} is a 0-1 variable and when $u_{it} = 1$ it means that unit i is in operation at time t and $u_{it} = 0$ means unit i is shutdown at time t ; N_{it} is the startup-shutdown cost of unit i at time t ; g_{it} is the output of unit i at time t ; $f_1(g_{it})$ is the generation coal consumption cost function of unit i at time t . Consider

$$f_1(g_{it}) = a_i + b_i g_{it} + c_i g_{it}^2, \quad (16)$$

where a_i , b_i , c_i are coal cost coefficients of unit i determined by the regression of historical data of power generation. Consider

$$N_{it} = \begin{cases} N_i^h, & T_{d,i}^{\min} < T_{it}^{\text{off}} \leq H_i^{\text{off}} \\ N_i^c, & T_{it}^{\text{off}} > H_i^{\text{off}} \end{cases} \quad (17)$$

$$H_i^{\text{off}} = T_{d,i}^{\min} + T_{s,i}^c, \quad (18)$$

where N_i^c is the cold-start cost of unit i ; N_i^h is the hot-start cost of unit i ; $T_{d,i}^{\min}$ is the allowed minimum downtime; T_{it}^{off} is the continuous downtime of unit i at time t ; $T_{s,i}^c$ is the cold-start time of unit i ; H_i^{off} is the summation of minimum downtime and cold-start time of unit i .

4.1.2. Minimize Pollutant Emission Cost Objective Function. Pollutant emission cost of power generation can be calculated by the least squares method using historical pollutant emission data. The objective function is

$$\min F_2 = \sum_{t=1}^T \sum_{i=1}^I \sum_{k=1}^K u_{it} f_2(g_{it}) \quad (19)$$

$$f_2(g_{it}) = \alpha_i^k + \beta_i^k g_{it} + \gamma_i^k g_{it}^2,$$

where K is the number of pollutant types; in this paper $K = 3$ and $k = 1, 2, 3$, respectively, means that the pollutant is CO_2 , SO_2 , and NO_x ; α_i^k , β_i^k , and γ_i^k are pollutant emission parameters of unit i .

4.2. Constraints

4.2.1. Load Balancing Constricks. Consider

$$\sum_{i=1}^I g_{it} u_{it} (1 - \theta_i) + \sum_{d=1}^D P_t^d + \sum_{w=1}^W g_{w,t} (1 - \varphi_w) = L(t) + \sum_{c=1}^C P_t^c, \quad (20)$$

where D is the number of all PHEVs; C is the number of PHEVs in charging; $L(t)$ is the load demand before PHEVs' grid connection at time t ; W is the number of wind power units; θ_i is the self-consumption rate of unit i ; $g_{w,t}$ is the output of wind power at time t ; φ_w is the power consumption rate of the wind farm.

4.2.2. Thermal Units Output Constraints. Thermal power output constraints include power generation upper and lower constraints, power climbing constraints, and the minimum startup and downtime constraints, as described in formulas (14)–(17). Consider

$$u_{it} g_i^{\min} \leq g_{it} \leq u_{it} g_i^{\max}, \quad (21)$$

where $g_i^{\max}$ and $g_i^{\min}$ are the upper and lower power generation limitation of thermal unit i . Consider

$$\Delta g_i^- \leq g_{it} - g_{i,t-1} \leq \Delta g_i^+, \quad (22)$$

where Δg_i^+ and Δg_i^- are the upper and lower power climbing limitation of thermal unit i . Consider

$$(T_{i,t-1}^{\text{on}} - M_i^{\text{on}})(u_{i,t-1} - u_{it}) \geq 0, \quad (23)$$

where M_i^{on} is the minimum startup time of thermal unit i ; $T_{i,t-1}^{\text{on}}$ is the continuous operation time of thermal unit i at time $t - 1$. Consider

$$(T_{i,t-1}^{\text{off}} - M_i^{\text{off}})(u_{it} - u_{i,t-1}) \geq 0, \quad (24)$$

where M_i^{off} is the minimum downtime of thermal unit i ; $T_{i,t-1}^{\text{off}}$ is the continuous downtime of thermal unit i at time $t - 1$.

4.2.3. Wind Power Output Constraints. Consider

$$0 \leq g_{w,t} \leq g_{w,t}^*, \quad (25)$$

wherein $g_{w,t}^*$ is the upper output limitation of wind power units at time t .

4.2.4. PHEV Charging and Discharging Constraints. Consider

$$\begin{aligned} C_t &\leq C_t^{\max} \\ D_t &\leq D_t^{\max}, \end{aligned} \quad (26)$$

where C_t and D_t are, respectively, the number of charging and discharging PHEVs and are, respectively, the maximum number of chargeable and dischargeable PHEVs.

4.2.5. System Spinning Reserve Capacity. Consider the following:

(1) During the charging period, system's spinning reserve capacity is

$$\begin{aligned} \sum_{i=1}^I u_{it} (g_i^{\max} - g_{it}) &\geq R_c + R_w^{(1)}(g_{w,t}) \\ \sum_{i=1}^I u_{it} (g_i^{\max} - g_{it}) &\geq R_w^{(2)}(g_{w,t}), \end{aligned} \quad (27)$$

where R_c is the spinning reserve capacity before wind power's grid connection; $R_w^{(1)}(g_{w,t})$ and $R_w^{(2)}(g_{w,t})$ are, respectively, increased upper and lower limitation of spinning reserve capacity after wind power's grid connection.

(2) During the discharging, system's spinning reserve capacity is

$$\begin{aligned} \sum_{i=1}^I u_{it} (g_i^{\max} - g_{it}) + \sum_{d=1}^D (P_d^{\max} - P_t^d) &\geq R_c + R_w^{(1)}(g_{w,t}) \\ &+ R_d^{(1)}(P_t^d) \\ \sum_{i=1}^I u_{it} (g_{it} - g_i^{\min}) + \sum_{d=1}^D (P_t^d - P_d^{\min}) &\geq R_w^{(2)}(g_{w,t}) \\ &+ R_d^{(2)}(P_t^d), \end{aligned} \quad (28)$$

where $R_d^{(1)}(P_t^d)$ and $R_d^{(2)}(P_t^d)$ are, respectively, increments of upper and lower limitation of spinning reserve capacity after PHEV's grid connection

4.3. Linearization

4.3.1. Objective Function Linearization. To simplify the solving process, we need to do a linearization for the quadratic objective function. Here we divide unit i 's power limit $[g_i^{\min}, g_i^{\max}]$ into N segments, so that quadratic functions

$f_1(g_{it})$ can be expressed as piecewise functions. When $g_{it} \in [g_i^{\min} + n\Delta, g_i^{\min} + (n+1)\Delta]$,

$$f'_c(g_{it}) = f'_c(g_i^{\min} + n\Delta) + (g_{it} - g_i^{\min} - n\Delta) \cdot [b_i + (2n+1)c_i\Delta + 2c_i g_i^{\min}], \quad (29)$$

where $n = 0, 1, \dots, N-1$; $\Delta = (g_i^{\max} - g_i^{\min})/N$.

4.3.2. Contracts Linearization. To facilitate solving, we need to do linearization of formula (10) and formula (11).

(1) Initial state constraints are as follows:

$$\sum_{t=1}^L (1 - u_{it}) = 0 \quad (30)$$

$$\sum_{t=1}^F (u_{it}) = 0, \quad (31)$$

where L is the number of operating thermal units at initial state and if there is no initial state, then $L = 0$; F is the number of thermal units in shutdown statue at initial state. Set U^0 as the period of operating thermal units at initial state; then

$$L = \min \{T, (M_i^{\text{on}} - U^0) u_{it}\} \quad (32)$$

$$F = \min \{T, M_i^{\text{off}} (1 - u_{it})\}.$$

(2) Startup and shutdown constraints are as follows:

$$\sum_{\tau=t}^{T_1} u_{i\tau} \geq T_{i\tau}^{\text{on}} M_i^{\text{on}}, \quad T_1 = t + M_i^{\text{on}} - 1, \quad \forall t = L+1, \dots, T - M_i^{\text{on}} + 1$$

$$\sum_{\tau=t}^{T_2} [1 - u_{i\tau}] \geq T_{i\tau}^{\text{off}} M_i^{\text{off}}, \quad T_2 = t + M_i^{\text{off}} - 1, \quad \forall t = F+1, \dots, T - M_i^{\text{off}} + 1 \quad (33)$$

$$\sum_{\tau=t}^T [u_{i\tau} - T_{i\tau}^{\text{on}}] \geq 0, \quad \forall t = T - M_i^{\text{on}} + 2, \dots, T$$

$$\sum_{\tau=t}^T [1 - u_{i\tau} - T_{i\tau}^{\text{off}}] \geq 0, \quad \forall t = T - M_i^{\text{off}} + 2, \dots, T.$$

5. Two-Step Adaptive Solving Algorithm

5.1. The Improved ε Constraints. When solving multiobjective models, if a solution x can make all objective functions $f_i(x)$ ($i = 1, 2, \dots, m$) achieve optimum, we could define x as an absolutely optimal solution. However, general contradictions exist between objectives and there is no absolutely optimal solution, but a set of optimal solutions, called Pareto optimal solution set [21].

This paper selects the improved constraints method to calculate multiobjective optimization problems. And then it uses the determination method in literature [43] to select feasible solutions. That means if $x_e \in X$ meets $f_s(x) > f_s(x_e)$, $f_i(x) > f_i(x_e)$ and $i \neq s$, then x_e is a feasible solution. The constraints method has many advantages. But there are the following two big problems: (1) this method can only be used in the range of feasible solutions, which makes optimization results easy to fall into partial optimum; (2) results may not satisfy Pareto optimal solution's feasibility and are nondominant. According to literature [44, 45], lexicographic optimization [33] and enhanced ε constraints method can overcome these problems [29].

However, the enhanced ε constraints method does not take different important degrees of each objective into consideration during its solving progress. This paper combines the enhanced ε constraints method, lexicographic optimization method, and weight coefficient to get an improved ε constraints method. And by defining an iteration parameter, e_j^{ω} , we can get the feasible solution for the multiobjective problem, as shown in formula (31). Consider

$$\max / \min F_1(x) + \left(\frac{\psi_j r_1}{\chi_1} \right) \sum_{j=2}^J \frac{\chi_j \varsigma_j^{\omega}}{r_j} \quad (34)$$

$$e_j^{\omega} = \frac{f_j^{\min}(\psi_j + 1)}{2} - \frac{f_j^{\max}(\psi_j - 1)}{2} + \frac{\psi_j r_j \omega}{j}, \quad \varsigma_j \in \mathbf{R}^+, \quad j = 2, 3, \dots, J, \quad \omega = 0, 1, \dots, j, \quad (35)$$

where ψ_i is the direction of objective i ; ψ_i equals -1 means that objective i needs to be minimized, while ψ_i equals $+1$ means that objective i needs to be maximized. To avoid objectives' scale expand problems we pull $\chi_j \varsigma_j / r_j$ into objective functions. χ_j is the weight of objective I ; ς_j is the residual variables of constraints; r_j is the range of objective function, which is determined by the decision attribute table and its determination progress is detailed in literature [46]. Different from conventional weighting method, the improved ε constraints method regards weights as the optimization variable. And the iteration parameter would update the weights during the solving progress.

5.2. Fuzzy Decision Theory. To meet decision-makers' demand, this paper chooses fuzzy decision method to calculate membership degrees of the Pareto optimal solution set. Define membership function u_n^r , which stands for the optimal degree of objective j in the Pareto optimization scheme r .

Then the membership degree function of Pareto optimization scheme r can be described as

$$u_j^r = \begin{cases} 1, & F_j^r \leq \min(F_j) \\ \frac{\max(F_j) - F_j^r}{\max(F_j) - \min(F_j)}, & \min(F_j) \leq F_j^r \leq \max(F_j) \\ 0, & F_j^r \geq \max(F_j) \end{cases}$$

$$u^r = \frac{\sum_{j=1}^J \varphi_j \cdot u_j^r}{\sum_{r=1}^R \sum_{j=1}^J \varphi_j \cdot u_j^r}, \quad (36)$$

where φ_j is the weight of objective j in (35); B is the number of elements in Pareto solution set; F_j^r and u_j^r , respectively, stand for the value and membership degrees of objective j and in Pareto optimization scheme r . The membership functions of the optimization objective are shown in Figure 7.

6. Solving Progress

Based on the two-step adaptive solving algorithm, we can analyze different wind power-PHEV effectiveness in multi-grid connected mode. Its solving steps are as follows.

- (1) Input the original data of the model. The objectives $F_1(x)$ and $F_2(x)$ are, respectively, set as a single-objective optimization model and it could get objective values under different optimization objectives. The results form a decision attribute table of the objectives, as shown in Table 1.
- (2) Based on step (1), objective functions $F_1(x)$ and $F_2(x)$ would adjust the maximum value of each objective function ($F_1^{\max}$, $F_2^{\max}$) according to decision makers' wishes and preferences as follows:

$$\begin{aligned} 0 &\leq F_1^{\max} - F_1^{\min} \leq F_1^{(2)} - F_1^{\min} \\ 0 &\leq F_2^{\max} - F_2^{\min} \leq F_2^{(1)} - F_2^{\min}. \end{aligned} \quad (37)$$

- (3) Based on step (1) and step (2), the value range of objective function $F_2(x)$ can be determined. And the improved ε constraints method would help to solve the model and get the optimal solution sets.
- (4) Based on step (3), formula (36) could get the Pareto solutions and membership degrees of the objective functions. Choosing the solution set with the highest membership degree can get the satisfactory solution for the optimization model. Figure 8 shows the details.

7. Simulation

7.1. Basic Data. This paper uses IEEE36 nodes 10-unit system as a simulation base. Add in wind farms at nodes 10, 15, and 24, respectively. The installed capacities of those wind farms are 200 MW, 300 MW, and 150 MW. Power generation

FIGURE 7: The corresponding membership function of optimization objective.

TABLE 1: The input-output tables of objective function.

Objective function	F_1	F_2
F_1^*	$F_1^{\min}$	$F_1^{(2)}$
F_2^*	$F_2^{(1)}$	$F_2^{\min}$

Remark: * indicates that the objective function is the target to solve.

coal consumption and pollutant emission parameters are listed in Table 3. The emission parameters are referenced from paper [28]. Based on wind power scenario simulation method, MATLAB is used to simulate 100 wind power output scenarios. Then the scenarios are reduced according to (7)–(14). Finally we got 20 basic scenarios and wind power output, use the average output value of wind power in 20 basic scenarios as its available output power. The details are listed in Table 2. Load demand of a typical load day is also listed in Table 2.

Currently, there are three main types of PHEV, namely, BEVs, V2G, Triple-VG2 (equivalent to three V2G), and PCEV. Compared with other types, V2G has the advantage of being rechargeable and dischargeable, which makes it have better prospects. Therefore, this paper chooses 50000 V2G cars and studies V2G cars grid connection influence on wind power consumption. Assume that their average charging power is 1.8 kW and the maximum charging power is 2.4 kW. Charging period lasts for 6 hours and total charged electricity is 10.8 kWh [11]. The number of PHEVs in charging period is equal to that in the discharging period. PHEV's power discharging consumption occupies 5.6% of its total electricity capacity, which means it can discharge 10.2 kWh. The discharging behavior is limited in 6 hours.

7.2. Simulation Results. The simulation has been implemented in GAMS optimization software using CPLEX 11.0 linear solver from ILOG solver. The CPU time required for solving the problem for different case studies with a VAIO E series laptop computer powered by core i3 processor and 2 GB of RAM was less than 10 s. Firstly, we verified the validity and applicability of the solving algorithm in Section 7.2.1 to ensure the reliability of the result. And then the optimization schemes for different charging modes are compared.

7.2.1. Verification of Algorithm's Validity and Applicability. This paper sets the no-control charging mode as the basic simulation scenario and chooses improved multiobjective nondominated sorting genetic algorithm-II (NSGA-II) [47] to solve the wind power-PHEV synergistic scheduling optimization model, where the maximum iterations time of

FIGURE 8: Flowchart of the solving progress.

NSGA-II algorithm is 10000, population size is 100, genetic operations crossover probability is 0.95, and mutation probability is 0.05. Results comparing the two algorithms are shown in Table 4.

According to Table 4, compared with the NSGA-II algorithm, the algorithm put forward by this paper could get a better optimal solution with lower iteration number and solving time. The grid-connected electricity of wind power is also more than that in the NSGA-II algorithm.

Analyzing the solution of the algorithm put forward by this paper can verify its applicability of solving wind power-PHEV synergistic scheduling optimization model under multiobjective functions. Figure 9 shows charging and discharging load distribution in the no-control charging mode. PHEV's charging time is concentrated in low load periods (1:00–5:00, 16:00–17:00, and 23:00–24:00). Its discharging time is concentrated in peak load periods (9:00–12:00 and 19:00–21:00). So the optimization result shows that PHEVs tend to

TABLE 2: Wind power output and power load demand.

Period	Wind power output/MW	Power demand/MW·h
1	286	900
2	513.5	1000
3	533	1100
4	559	1200
5	520	1500
6	435.5	1700
7	383.5	1900
8	305.5	2100
9	182	2300
10	188.5	2500
11	169	2600
12	195	2700
13	169	2500
14	143	2300
15	214.5	2100
16	260	1800
17	240.5	1700
18	188.5	1900
19	136.5	2100
20	130	2500
21	214.5	2300
22	292.5	1900
23	423.8	1300
24	370.5	1000

charge in low load period and discharge in high load period, consistent with the expectation.

7.2.2. Comparison between Different Charging Modes. In this section, we will compare thermal units' output structure, wind power grid connection status, power generation cost, and pollutant emission after PHEV's grid connection under 4 charging modes. Table 5 lists Pareto sets in different charging modes. According to Table 4, (32) is applied to get the optimal result with the highest membership degree.

(1) *Thermal Units' Output Structure.* After PHEV's grid connection, thermal units' total output decreased. The output structure is significantly optimized. For example, 7# and 8# units no longer generate power and 6# unit only generates power in the unrestricted charging mode. And 3# and 4# units generate less while units 1# and 2# generate more. In terms of the output structure, consider the following.

- (1) Compared with the no-control charging mode, in the other 3 charging modes, 1# unit achieved full capacity operation and the large capacity generators' output increased, namely, 2# and 3# units.
- (2) In the continuous charging mode, charge and discharge times are not limited. Therefore, PHEV's grid

FIGURE 9: Electric vehicle charging and discharging time distributions in the no-control charging mode.

connection is the maximum, which makes thermal units' output decrease. But for units with small installed capacity, like 4# and 5# units, their output would be more than that in the delayed charging mode or the fully optimal charging mode.

- (3) In the fully optimal charging mode, thermal units' output allocation is determined by their installed capacity. That means units with big installed capacity would output much more than the small ones. In this way, the output structure comes to the optimal. Table 5 shows output allocation of thermal power units in four modes.

According to Table 6, thermal units' output before and after PHEV grid connection can be compared. The output allocation in the fully optimal charging mode is described as Figure 10 and that before PHEV grid connection is described as Figure 11. From these two figures, we can see the characteristics of the output allocation in the fully optimal charging mode as follows.

- (1) Thermal units' output decreased obviously and the output curve is relatively smooth.
- (2) In section of the base load, unit 1# and unit 2# supply the basis load demand.
- (3) In section of the waist load, units 3# and 6# supply the waist load demand before PHEV grid connection and that changed to be unit 3# and unit 4# in the fully optimal charging mode.
- (4) In section of the peak load, units 7# and 8# supply the peak load demand before PHEV grid connection.

TABLE 3: Coefficients of coal-fired power units.

ft	a_i	b_i	c_i	M_i^{on}/h	$M_i^{\text{off}}/\text{h}$	N_i/tce	$g_i^{\text{min}}/\text{MW}$	$g_i^{\text{max}}/\text{MW}$	$\Delta g_i^+/\text{MW}\cdot\text{h}$	$\Delta g_i^-/\text{MW}\cdot\text{h}$
1#	11.6	0.260	$1.88E-05$	8	8	25.6	250	600	280	-280
2#	9.7	0.259	$6.55E-06$	8	8	23.1	200	500	240	-240
3#	8.8	0.268	$9.44E-06$	7	7	22.3	200	450	210	-210
4#	8.4	0.273	$1.65E-05$	7	7	19.6	180	400	180	-180
5#	7.2	0.28	$2.17E-05$	6	6	16.2	150	350	150	-150
6#	6.1	0.285	$3.39E-05$	5	5	15.4	150	300	150	-150
7#	5.2	0.292	$3.42E-05$	4	4	12.3	120	300	120	-120
8#	4.6	0.304	$4.13E-05$	4	4	8.1	100	250	100	-100
9#	3.5	0.306	$3.63E-05$	3	3	4.3	70	150	70	-70
10#	1.4	0.314	$8.35E-05$	2	2	2.1	30	100	50	-50

TABLE 4: Results comparing the two algorithms.

Algorithms	Coal consumption/tce	Pollutant emission/t	Grid-connected electricity/MW·h		Iteration number	Solving time
			Thermal power	Wind power		
The proposed	9341.2	40016.13	40425.32	5728.66	485	5.2
The NSGA-II	9438.5	40298.24	40921.47	5432.51	642	7.1

TABLE 5: Best Pareto-optimal solution in different modes.

Number	No-control charging		Continuous charging		Delayed charging		Fully optimal charging	
	F_1	F_2	F_1	F_2	F_1	F_2	F_1	F_2
1	9341.32	40016.13	8622.48	38576.44	8565.85	38803.84	8492.16	38480.11
2	9424.81	33955.16	8719.04	32034.96	8652.33	32776.17	8585.55	31897.44
3	9653.03	27894.19	9000.33	25493.48	8885.29	26748.50	8871.93	25314.62
4	10074.93	21833.21	9541.44	18951.98	9321.98	20720.82	9429.48	18731.95
5	11099.96	15772.26	11553.41	12410.50	10414.55	14693.17	11435.41	12149.31

TABLE 6: Output allocation of thermal power unit in four modes (MW).

Unit	Before PHEV grid connection	After PHEV grid connection			
		No-control charging	Continuous charging	Delayed charging	Fully optimal charging
1#	14 388	14 380	14 400	14 400	14 400
2#	10 105	10 877	11 563	11 424	11 512
3#	6052	6539	14400	14400	14400
4#	4626	4372	11324	11463	11512
5#	3197	2090	7228	7621	7891
6#	2200	2167	0	0	0
7#	480	0	0	0	0
8#	400	0	0	0	0
Total output	41 448	40 425	38796	39070	38967

And that changed to be unit 5# in the fully optimal charging mode.

(2) *Wind Power Grid Connection Situation.* Before PHEV's grid connection, abandoned wind was 1511.39 MW. But after PHEV's grid connection, abandoned wind decreased obviously. It is because in delayed charging mode or fully optimal charging mode, users' charging behaviors are influenced by

the load curve. That makes load curve gentler and provide a stronger backup for wind power. In these two charging modes, the abandoned winds are, respectively, 233 MW·h and 26 MW·h. Wind power output in 4 charging modes is shown in Figure 12.

(3) *Economic and Environmental Benefits.* PHEV's economic and environmental benefits in 4 modes are shown in Table 7.

TABLE 7: System optimization results contrast in different modes.

	Startup and shutdown cost/tce	Coal consumption cost/tce	Abandoned wind/MW·h	Emission/t		
				CO ₂	SO ₂	NO _x
Before connection	177.29	9783.80	1511.40	40743.09	132.63	155.43
Uncontrolled	153.44	9187.88	1325.14	39735.20	129.35	151.58
Delayed	103.36	8519.12	232.86	38305.61	124.70	146.13
Continuous	153.36	8412.49	545.40	38531.42	125.43	146.99
Fully optimal	98.65	8393.51	25.64	38209.95	124.39	145.77

FIGURE 10: Thermal units' output allocation in the fully optimal charging mode.

FIGURE 11: Thermal units' output allocation before PHEV grid connection.

FIGURE 12: The output of wind power in four modes.

After its grid connection, both economic and environmental benefits increased. In the fully optimal charging mode, thermal units' startup and shutdown costs decreased by 50%, coal consumption cost decreased by 14%, emission of CO₂, SO₂, and NO_x, respectively, decreased by 7%, 6%, and 6%, and abandoned wind decreased to 25.64 MWh. PHEV's grid connection would bring, obviously, economic and environmental benefits. To achieve the maximum benefit, electric enterprise should take relative incentive mechanisms to guide PHEV users' rational charging and discharging.

7.2.3. Sensitive Analysis. As government's support to develop PHEV is increasing, PHEV's number grows. This means the charging and discharging behaviors of PHEV would influence power system's load curve directly. To verify the influence of PHEV's grid connection on power system's load curve economic benefit and environmental benefit, this paper sets 25, 50, 75, and 1000 thousand PHEVs in succession to do system simulation. The results are shown in Figures 13 and 14 and peak and valley differences of different PHEV number are listed in Table 8.

As the number of PHEVs increases, system's load curve becomes gentler, which means more obvious load shifting effect. When PHEV number is 25 thousand, the peak load is 2700 MW and the valley load is 1700 MW. And when PHEV

TABLE 8: Sensitive analysis result on PHEV number.

PHEV number	Peak load	Valley load	Peak and valley difference
25000	2700.5	1700	1000.5
50000	2615	1790	825
75000	2580	1772.5	807.5
10000	2545	1830	715

FIGURE 13: Demand load curve comparison.

number is 100 thousand, the peak and valley loads changed to 2545 MW and 1830 MW. Their difference decreased by 29%.

According to Figure 14, as the number of PHEVs increases, abandoned wind decreases. When PHEV number is 100 thousand, abandoned wind is 72.5 MW, 77% less than that of 315.4 MW when PHEV number is 25 thousand. Furthermore, part of the PHEV would use wind power to charge at the valley time and discharge at the peak time. Thermal power's generation cost decreased when the number of PHEVs increased.

8. Conclusions

To analyze PHEV's grid connection benefits, this paper established a wind power-PHEV synergistic scheduling optimization model and put forward a two-step adaptive solving algorithm based on improved ε constraints theory and fuzzy decision theory. According to the simulation results, there are some conclusions as follows.

- (1) This paper uses the improved ε constraints method to get Pareto optimal solution set and fuzzy decision theory to select a satisfactory solution with the highest membership degree. This two-step adaptive algorithm can be more suitable to solve the multi-objective wind power-PHEV synergistic scheduling optimization model.
- (2) PHEV's grid connection can help in load shifting, decrease abandoned wind and power generation cost,

FIGURE 14: Economic and environmental benefits comparison.

and obviously bring economic and environmental benefits. And in delayed charging pattern and fully optimal charging pattern, system would get the optimal benefits.

- (3) Compared with the no-control charging mode, the delayed charging mode has the maximum grid connection electricity amount, the least thermal power generation, and little abandoned wind. However, since users' casually charging behavior, PHEV grid connection can bring big impact on system's safe and stable operation. So the abandoned wind in this mode is higher than that in the delayed charging mode or fully optimal charging mode.
- (4) In the fully optimal charging mode, abandoned wind comes to be the least. That is because in this mode users would adjust their charging behavior according to the load curve. Then the load shifting effect would be increased and PHEV grid connection can help wind power grid connection, increasing economic and environment benefits.
- (5) Based on the conclusions above, to make full use of PHEV grid connection, we need to commence from two aspects. On one hand, use incentive policies to promote the development of electric vehicles. And on the other hand, use reasonable demand side electricity to guide users' charging behavior, which would be an important research direction on wind power-PHEV synergistic scheduling.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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