A Bi-Level Particle Swarm Optimization Algorithm for Solving Unit Commitment Problems with Wind-EVs Coordinated Dispatch

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Abstract. Nowadays, the grid faces much more challenges caused by wind power and the accessing of electric vehicles (EVs). Based on the potentiality of coordinated dispatch, a model of wind-EVs coordinated dispatch was developed. Then, A bi-level particle swarm optimization algorithm for solving the model was proposed in this paper. The application of this algorithm to 10-unit test system carried out that coordinated dispatch can benefit the power system from the following aspects: (1) Reducing operating costs; (2) Improving the utilization of wind power; (3) Stabilizing the peak-valley difference.

1. Introduction

With the improvement of public awareness of environmental protection, the penetration level of wind power generation and electric vehicles (EVs) have kept rapidly growing in recent years. According to the study [1], a high penetration of wind power may bring many challenges to the grid; besides, the unordered access to grid by a large amount of EVs could significantly impact the power system [2].

In this work, a model of coordinated dispatch was proposed. Then added it into the conventional Unit Commitment (UC) problem and solve it by bi-level particle swarm optimization algorithm. The outer level is based on Quantum-inspired Binary Particle Swarm Optimization (QBPSO) [3] to solve the UC problem; The inner level adopts conventional Particle Swarm Optimization (PSO) [4] to distribute the load between thermal units, simultaneously, calculate the accepted wind power and schedule EVs charging demand. According to the characteristics of QBPSO, this paper also proposed a novel mutation strategy to prevent the algorithm from falling into premature too early.

2. Model of Wind-EVs Coordinated Dispatch

2.1. Forecasting of EVs charging demand and wind power
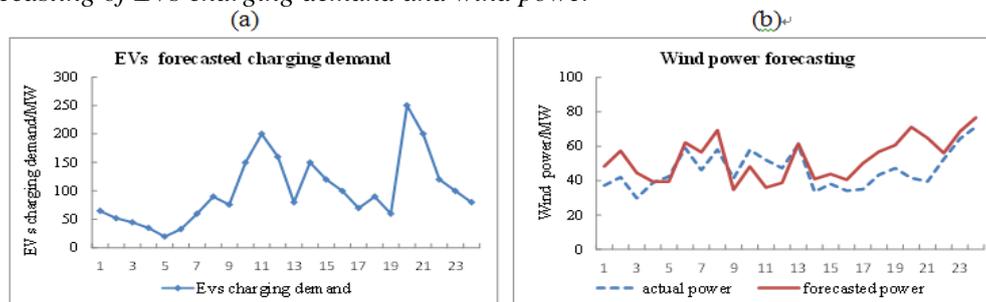

Figure 1. Forecasting of EVs charging demand and wind power

Figure 1 (a) shows the forecasted demand of EVs based on [5]. And according to Ouammi's work [6], taking the operating data of a certain wind farm in Northern China Power Grid as an example, the forecasted wind power curve is shown in figure 1 (b).

2.2. Wind-EVs Coordinated Dispatch

In this work, the forecasted wind power is regarded as a variable that can be scheduled. When discussing the grid's ability of accepting wind power, first of all, it is necessary to examine whether the thermal unit ramp-rate can cover the fluctuation of the load and wind power. Second, research the relationship between the economic benefit that brought by wind power and the amount of the wind power that the grid accepted. The wind power acceptance region is bound to following constrains:

$$(\sum_{g}^{G} -r_{d,g} \cdot u_g^t)\Delta T \le \Delta P_W^t + \Delta P_L^t \le (\sum_{g}^{G} r_{u,g} \cdot u_g^t)\Delta T \tag{1}$$

$$\Delta C_G - \Delta C_W < 0 \tag{2}$$

where $-r_{d,g}$ and $r_{u,g}$ are decent rate and rising rate respectively of gth unit; ΔP_W^t and ΔP_L^t are the variation of the wind power and load respectively in tth interval; u_g^t is the status of ith unit in tth interval; ΔC_G means the variation of coal consumption caused by wind power; ΔC_W is the coal conserved by wind power. Constraint (2) narrows the region of the wind-power-acceptance which determined by constraint (1). When the accepted wind power exceed this region, the increased ΔC_G will counteract the ΔC_W, because the wind power will cause many uneconomical problems such as increasing reserve capacity and making the thermal units deviate from economic operation point [7].

The wind power acceptance region can be extended by scheduling EVs charging demand. In order to ensure a basic charging demand can be satisfied, for each time interval, we set 30% of the forecasted charging demand as basic demand, and the rest 70% as variable that can be scheduled. The strategy can be expressed as follows:

$$P_{EV}^t = P_{EV,base}^t + \Delta P_{EV,ed}^t \tag{3}$$

where P_{EV}^t is the EVs charging demand after scheduling; $\Delta P_{EV,ed}^t$ is the variation according to the coordinated dispatch; EVs basic charging demand $P_{EV,base}^t = 30\% \times P_{EV,pre}^t$; $P_{EV,pre}^t$ is the forecasted demand of EVs.

Then, the total demand of EVs charging should obey constraint (4):

$$\sum_{t=1}^{T} P_{EV}^t = \sum_{t=1}^{T} P_{EV,pre}^t \tag{4}$$

The total EVs charging demand after scheduling of all intervals shouled be equal to the total forecasted demand.

3. A bi-level particle swarm optimization algorithm for solving unit commitment problems with wind-EVs coordinated dispatch

3.1. Application of QBPSO to UC problem

QBPSO adopts quantum-bit (Q-bit) to contain information, kind of like the chromosome encode mode in Genetic Algorithm (GA). And "Quantum Rotation Gate", which is a more efficient way for particle to update itself, is introduced into QBPSO. Given that, all possible combinations of decision variables can be derived from a single representation.

For a UC problem with T intervals and G thermal units, the outer-level particles should be initialized as a $1 \times T$ matrix as:

$$x = [x_1^1 x_2^1 \cdots x_N^1, x_1^2 x_2^2 \cdots x_N^2, \cdots, x_1^T x_2^T \cdots x_G^T] \tag{5}$$

where $(t-1) \times G + g$ is the index of gth unit in tth interval.

The generation for probability matrix and rotation angle adjustment is mainly based on [8].

When to decide the value of the rotation angle, a linear-decreasing-weighted method is proposed by this work, this method can expand the searching space in prophase, and accelerate the convergence in final phase, just as follow:

$$\theta = \theta_{max} - (\theta_{max} - \theta_{min}) \times \frac{k}{k_{max}} \tag{6}$$

where k is number of iterations; θ_{max} and θ_{min} can be found in table 1.

3.2. Application of PSO to economic dispatch and coordinated dispatch

3.2.1. Initialization.

Corresponding to the outer level, the inner level particles should also be initialized as a $1 \times T$ matrix. For thermal units, their particles are defined as:

$$p = [p_1^1 p_2^1 \cdots p_N^1, p_1^2 p_2^2 \cdots p_N^2, \cdots, p_1^T p_2^T \cdots p_N^T] \tag{7}$$

The Initialization of the initial position for thermal-unit particles is mentioned in equation (18).

$$[P_{wind}^1, P_{wind}^2, \cdots, P_{wind}^T] \tag{8}$$

$$P_{wind}^t = \min(P_{wind,forecasted}^t, P_{wind,accepted}^t) \tag{9}$$

Equation (8) is the initialization for wind power particles. The $P_{wind,accepted}^t$ in equation (9) is determined by equation (1) and (2). The initial positions for wind-power particles are set as the minimum value between the forecasted wind power and the margin of acceptance region in every interval, considered that the wind power has the highest priority to be put into the grid.

The particles of EVs charging demand are initialized according to (10). The initial positions for EVs-charging-demand particles are set as the basic charging demand as mentioned in equation (3).

$$[P_{EV}^1, P_{EV}^2, \cdots, P_{EV}^T] \tag{10}$$

3.2.2. Update.

The inner-level particles share the same pattern of update. The equation is as follow:

$$\begin{cases} v_{id} = \omega \times v_{id} + c_1 \times r_1 \times (P^{id} - P) + c_2 \times r_2 \times (P^{gd} - P) \\ P = P + v_{id} \end{cases} \tag{11}$$

where ω is inertia weight; c_1 and c_2 are acceleration constants; r_1 and r_2 are acceleration-weighted coefficient; v_{id} is the velocity of the particle, as its value gets smaller, the solution gets more accurate; P^{id}, P^{gd} and P can be replaced according to the type of particles.

3.3. Objective function and constraints for UC problem with wind-EVs coordinated dispatch.
- Objective function:

$$\min \sum_{t=1}^{T} [\sum_{i=1}^{N} (u_{i,t} F_i(P_{i,t}) + S_i u_{i,t} (1 - u_{i,t-1}))] \tag{12}$$

where $u_{i,t}$ is the ON/OFF status of ith unit in tth interval; F_i is the cost function of ith unit; S_i is the start-up cost of ith unit.
- Constraints:
  - Generation limit constraint:

$$P_{i,min} \leq P_{i,t} \leq P_{i,max} \tag{13}$$

  - Ramp-rate constraint:

$$-r_{di} \Delta T \leq P_{i,t} - P_{i,t-1} \leq r_{ui} \Delta T \tag{14}$$

  - Minimum up-time/down-time constraints:

$$\begin{cases} (T_{i,t-1}^{on} - T_{\min,i}^{on})(u_{i,t-1} - u_{i,t}) \geq 0 \\ (T_{i,t-1}^{off} - T_{\min,i}^{off})(u_{i,t} - u_{i,t-1}) \geq 0 \end{cases} \tag{15}$$

- Spanning reserve constraints:

$$\begin{cases} \sum_{i=1}^{N} P_{i,\max} - \sum_{i=1}^{N} P_{i,t} \geq \alpha P_W + \beta(P_D + P_{EV}) \\ \sum_{i=1}^{N} P_{i,t} - \sum_{i=1}^{N} P_{i,\min} \geq \alpha P_W + \beta(P_D + P_{EV}) \end{cases} \tag{16}$$

- Load balance constraint:

$$\sum_{i=1}^{G} P_{i,t} + P_W^t = P_{EV}^t + P_L^t \tag{17}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum power and maximum power of ith unit respectively; $P_{i,t}$ is the output power of ith unit in tth interval; $T_{i,t-1}^{on}$ and $T_{i,t-1}^{off}$ are the continuous time of ON/OFF in t-1th interval respectively; $T_{\min,i}^{on}$ and $T_{\min,i}^{off}$ are minimum continuous time of ON/OFF of ith unit respectively; $u_{i,t-1}$ is the status of ith unit in t-1th interval; α / β is the coefficient of reserve for wind / load.

3.4. Some improvements on the algorithm
- The advanced initialization for particles of thermal units

The thermal units with a higher priority should bear the load as much as possible, and the unit should remain above its minimum rated power once it is decided to be put into operation. So, for all the units, its initial position can be initialized by:

$$p_g^t = x_g^t \times [P_{\min}^g + (1 - \frac{g - rand()}{G}) \times (P_{\max}^g - P_{\min}^g)] \tag{18}$$

g is unit number after priority-ordering, and as g gets smaller, the priority of this unit gets higher, so the value of $(1 - \frac{g - rand()}{G})$ is more close to 1, then p_g^t is close to its maximum rated power, and vice versa. After that, the particles of unit can be generated in a proper position which closed to the final solution. Obviously, this method can accelerate the convergence of the algorithm.
- The Mutation Strategy in outer-level algorithm

Applied with the concept of "mutation" in GA, a new evolution strategy can be modeled. According to the features of the 10-unit test system, unit 9 and 10 are regarded as base-load units and they are operated at full load in the most of intervals. So the "mutation" can be applied only to from unit 1 to unit 8. The procedures are demonstrated as follows:
- To select a Q-bit with a certain probability. For example, if the 5th bit is selected, then calculate the total power can be provided according to the status of units from 5th bit to the final bit.
- If the total power calculated by step (1) exceed the demand, then retrace step (1); otherwise, calculate the power shortage.
- Selecting a certain Q-bit or few Q-bits before the 5th bit, set its/their value to 1, others are set to 0. Examine if the units selected in step (3) can meet the shortage calculated in step (2).
- Putting the new particle into inner algorithm.

The mutation can not only change the value of a certain bit, but also change the evolution path for this bit. Different from the mutation in GA, the mutation here keeps the population diversity. The mutation can operated as many times as needed. If the fitness after mutation is better than before, then save this individual and put it into the next iteration; otherwise, try again or quit the mutation. If the algorithm gets no better results beyond continuous 100 iterations, the mutation strategy will be introduced automatically.

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4. Case studies

The proposed algorithm was programmed with Matlab and tested with 10-unit test system in 24-hour horizon. The parameters were set as table 1:

Table 1. Parameters for the algorithm.

Population size	Maximum iteration	θ_{max}	θ_{min}	ω	c_1	c_2	r_1	r_2
60	1000	0.05π	0.01π	1	[1,2]	[1,2]	[0,1]	[0,1]

According to the forecasted data, the penetration of wind power is 4.32%, and the penetration of EVs charging load is 8.15%.

Figure 2 shows that the algorithm fell into premature since around 100th iteration. After the "mutation" proposed by this work, the algorithm continued the search in solution-space. The mutation procedure was introduced into the algorithm for the second time in around 300th iteration. The result proved that the "mutation" procedure can prevent the algorithm from falling into premature and improve the accuracy of the solution.
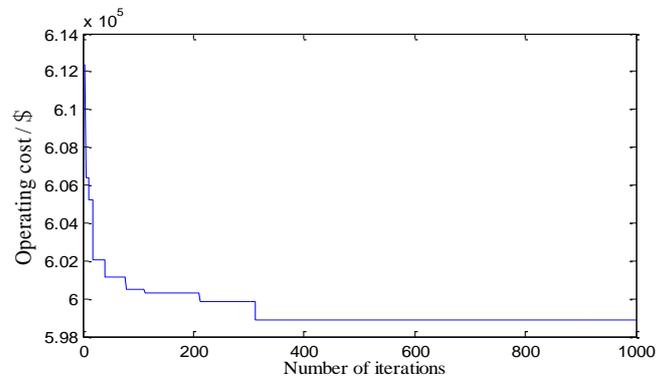
Figure 2. The convergence curve of the algorithm

The two vallies of wind acceptance region in figure 3 (a) are mainly because that the load has reached the peak, which led to the insufficient capacity for covering the fluctuation. After the coordinated dispatch, not only the acceptance region has been expanded, but also the actual wind power follow closely with the forecasted power, in other words, the utilization of wind power is improved, just as figure 3 (b) demonstrated.
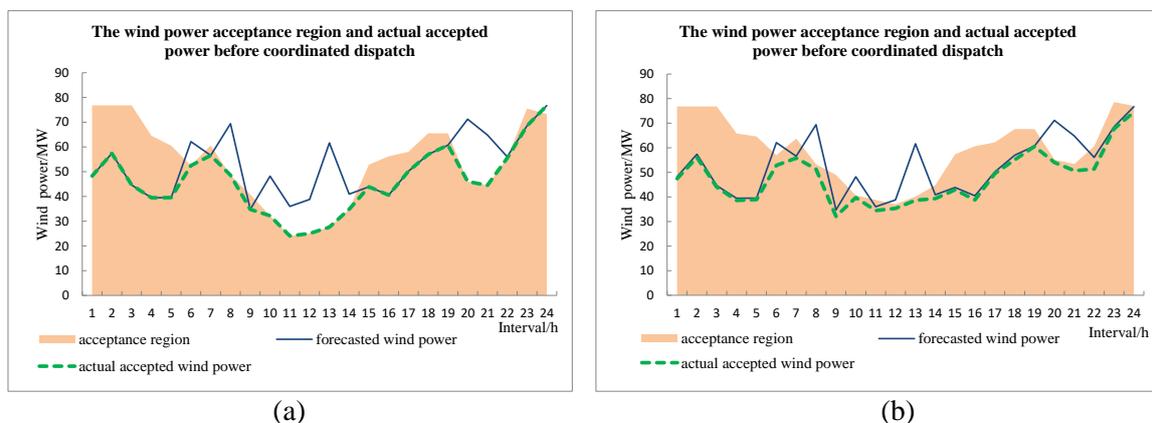

Figure 3. Wind-acceptance region and accepted wind before/after coordinated dispatch

(a)   (b)
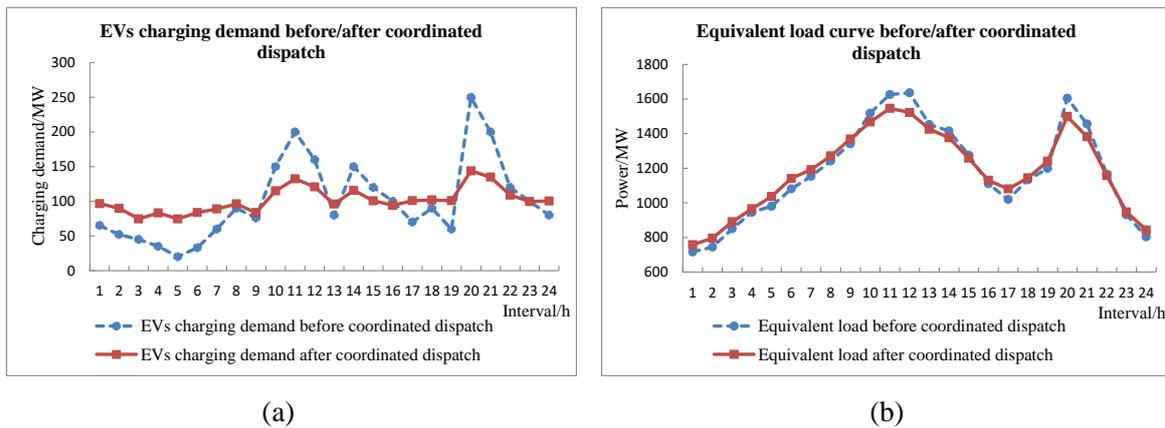
Figure 4. EVs charging demand and equivalent load before/after coordinated dispatch

Moreover, the superposition of power demand on account of the participation of EVs charging is no longer severe as before, because that the coordinated dispatch can smooth the load curve to reduce frequent output-adjustments between thermal units. The curve of EVs charging demand and equivalent load before/after coordinated dispatch are shown in figure 4 .

Figure 5 demonstrates the results of unit commitment problem and the generation plan.

Figure 5. Results of UC problem and generation plan

5. Conclusion

The data demonstrated in table 2 can be obtained by analyzing the information in figure 3 and figure 4.

Table 2. The benefits to grid in contrast with the data before coordinated dispatch

	Total operation cost /\$	Peak-valley difference / MW	Utilization of wind	EVs utilization of electricity at night
Before coordinated dispatch	612761	918.26	86.8%	16.5%
After coordinated dispatch	598846	787.7	90.7%	25.8%

where the night period is defined as 23:00 to 5:00 the next day.

By compared the results after coordinated dispatch with before, the conclusion can be drawn that the total operation cost has reduced by 2.27%, the peak-valley difference of equivalent load has decreased

by 14.22%, and the utilization of wind power has risen nearly 4%. Besides, the EVs charging demand can be partly transferred to the night-off-peak period to let EVs use more power at this period which can benefit both the grid and the EVs users.

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