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Bi-Level Real-Time Economic Dispatch of VPP Considering Uncertainty

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ABSTRACT In this paper, we propose a bi-level, real-time economic dispatch method of a virtual power plant (VPP), including various distributed energy resources (DERs). Considering the different interests of VPPs and a system operator, the real-time economic dispatch of VPPs is described as a bi-level programming problem, where a system operator dispatches VPPs based on the price incentive mechanism on the upper level, and the VPPs provide response according to the optimal control of their DERs on the lower level. Considering the uncertainties of DERs and loads, the decision risks of a system operator on the upper level and VPPs on the lower level are further dealt with by the fuzzy chance constrained programming, such that they can make reasonable decisions according to their own preferred risks. The mapping method and the bi-level optimization method are also presented as the solutions for the proposed model. In this way, the fuzzy chance constraints and objective functions of both levels are transformed into deterministic forms and, then, are calculated dispersedly. As a result, the calculation burden of a system operator and the information privacies of VPPs all can be treated availably. The case studies verify the effectiveness of the proposed method in the end.

INDEX TERMS Virtual power plant, real-time economic dispatch, price incentive scenario, uncertainty, hybrid algorithm.

I. INTRODUCTION

The rapid development of distributed energy resources (DERs) is playing an increasingly important part in the economic dispatch of power systems, particularly in the real-time economic dispatch affected significantly by the uncertainty of DERs [1]–[3]. If they excessively generate or consume power, the real-time balance of power systems will bear too much pressure. On the contrary, the DERs will play a positive role when they are managed and controlled appropriately.

However, as DERs are generally the small power plants and controllable loads belonging to common users, they are prohibited from interacting directly with the electric network [4], [5]. In order to solve this problem, the virtual power plant (VPP) concept, which aggregates DERs either for trading electric energy or providing system support services, can be adopted [6], [7]. VPP was proposed conceptually in 1997 [8], and was then investigated in some projects, such as the Europe union project [9], the Fenix project [10], and others. As the aggregation of DERs can be guided by different functional needs and geographical locations, there is no consensus regarding the components, geographical locations, generation technologies, and control architectures of VPP [11]–[13]. From the perspective of a control strategy, VPP can be controlled in a distributed or centralized manner. In the distributed control manner, each DER unit of VPP decides its strategy respectively, while the VPP with the centralized control manner always controls DER units as a whole generating system. The advantages and requirements of these two control manners are analyzed in [14]. Comparatively speaking, the centralized control manner of VPP has been applied in more fields [15], e.g., the Fenix VPP project and the European VPP project mentioned above all adopted the centralized control strategies.

In order to offer a path for VPP to interact with the electric network, the bidding method is addressed in [16] and [17]. A bid should contain information on how much power and at which price VPP is willing to sell, such that VPPs can bid at the prices with their preferences. However, this scenario would frustrate the small VPPs with weak market power. In this respect, the price incentive scenario can be used as an alternative [18]. In this scenario, a system operator gives an initial electricity price, and then VPPs will offer their own price-based power responds. If a power shortage occurs, the system operator will raise the price to encourage VPPs to offer more power and vice-versa regarding lowering the price. After several rounds of adjustment, a power balance can be achieved. In this way, each VPP is able to maximize its profit at the given price, no matter the size. Furthermore, during this process, the calculation is undertaken by each VPP, and no private information from the VPP needs to be unloaded to the system operator. These features all ensure its valid implication, especially when the calculation burden and information privacy of a large number of participants are considered. However, the price incentive scenario is still a method framework rather than the strict mathematical model. The uncertainties associated with DERs and loads are also unexploited in this process.

The objective of this paper is to propose a method for real-time economic dispatch of VPPs, whereby individual DERs can gain more visibility and accessibility to the distribution network. The distribution network can also benefit from the optimal use of available resources. Specifically, the dispatch strategy is carried out under a bi-level dispatch structure. On the upper level, the system operator dispatches VPPs based on the aforementioned price incentive mechanism, in which electricity price is used to provide incentive to VPPs and so adjust their outputs. On the lower level, the control center of each VPP is responsible for controlling DERs in a centralized manner. The control centers also handle the interactions between VPPs and the distribution network. When electricity price is posted by the system operator, the VPPs with control centers should make optimal responses to maximize profits.

The bi-level dispatch structure mentioned above is described as a bi-level programming model in this paper. Furthermore, taking the uncertainties of DERs and loads into consideration, it is necessary to weigh the profits and the risks no matter when the system operator incentivize VPPs or when VPPs respond to the system operator in the bi-level programming model. For instance, what is the probability of realizing the objective values? What is the probability of satisfying the constraints? Hence, the fuzzy chance constrained programming is further embedded into the above bi-level programming. For the solution of the proposed model, it is first transformed into a deterministic form by the crisp equivalent method and the mapping method. This helps to avoid massive computation caused by the fuzzy simulation. Then, the bi-level optimization method comprising of the pattern search (PS) algorithm and the particle swarm optimization (PSO) algorithm is used for solving the bi-level real-time economic dispatch model with the deterministic form. Since the optimization problem on the lower level is executed by every VPP, problems like calculation burden and information privacy can be solved efficiently.

This paper is organized as follows: Section II establishes the bi-level real-time economic dispatch model of VPP considering uncertainty, namely the price incentive model for system operator and the power respond model for VPPs. Section III proposes the solution method of the proposed model. Section IV provides the simulation analysis results which demonstrates the effectiveness of the method presented in this paper. The conclusion is drawn in Section V.

II. BI-LEVEL REAL-TIME ECONOMIC DISPATCH MODEL OF VPP CONSIDERING UNCERTAINTY

A. BRIEF INTRODUCTION OF BI-LEVEL PROGRAMMING

Consider a decision system with a leader and several followers. The leader can't control the follower directly, and what it can do is to influence the responses of followers through his decision, while the followers have full authority to optimize their own decisions. Thus, the leader and the followers have the decision variables and objective functions, respectively, being described by the following bi-level programming as

$$\begin{cases} \min_{x} F\left(\boldsymbol{x}, \boldsymbol{y}_1^*, \boldsymbol{y}_2^*, \cdots \boldsymbol{y}_m^*, \boldsymbol{\xi}_0\right) \\ \text{s.t. } G\left(\boldsymbol{x}, \boldsymbol{y}_1^*, \boldsymbol{y}_2^*, \cdots \boldsymbol{y}_m^*, \boldsymbol{\xi}_0\right) \le 0 \\ \boldsymbol{y}_i^* \text{ is solved by} \\ \max_{y_i} f_i\left(\boldsymbol{x}, \boldsymbol{y}_1, \boldsymbol{y}_2, \cdots \boldsymbol{y}_m, \boldsymbol{\xi}_i\right) \\ \text{s.t. } g_i\left(\boldsymbol{x}, \boldsymbol{y}_1, \boldsymbol{y}_2, \cdots \boldsymbol{y}_m, \boldsymbol{\xi}_i\right) \le 0 \end{cases} \tag{1}$$

where F and f_i are the objective functions of the upper level and the lower level, respectively; G and g_i are the constraint functions of the upper level and the lower level, respectively; $\boldsymbol{x}$ and $\boldsymbol{y_i}$ are the decision vectors of the upper level and the lower level, respectively; $\boldsymbol{\xi_0}$ and $\boldsymbol{\xi_i}$ are the uncertainty vectors of the upper level and the lower level, respectively.

Since the price incentive scenario has a system operator and multiple VPPs, and the system operator can adjust the price for motivating VPPs, while the VPPs respond to the price for maximizing their profits, it can be modeled by the bi-level programming felicitously.

B. DESCRIPTION OF UNCERTAINTY

As shown in equation (1), the uncertainty variables existing on the upper level and the lower level also affect their decisions to some extent. For the rational decisions of both levels, the uncertainty should be described at first.

In the VPPs with centralized control strategies, the output of DERs should be scheduled within a certain range. Considering the uncertainties of wind farms, the upper and lower limits are described as the fuzzy variables in this paper. As for conventional loads, since they cannot be controlled by VPPs, they are described as fuzzy variables directly.

When the commonly used trapezoidal number is adopted, fuzzy variables can be described as:

$$w_{\max,i,j} = \left(r_{\mathrm{w},\max,i,j}^1, r_{\mathrm{w},\max,i,j}^2, r_{\mathrm{w},\max,i,j}^3, r_{\mathrm{w},\max,i,j}^4\right) \tag{2}$$

$$w_{\min,i,j} = \left(r_{\mathrm{w},\min,i,j}^1, r_{\mathrm{w},\min,i,j}^2, r_{\mathrm{w},\min,i,j}^3, r_{\mathrm{w},\min,i,j}^4\right) \tag{3}$$

$$L = \left(r_{\mathrm{L}}^1, r_{\mathrm{L}}^2, r_{\mathrm{L}}^3, r_{\mathrm{L}}^4\right) \tag{4}$$
$$l_i = \left(r_{l,i}^1, r_{l,i}^2, r_{l,i}^3, r_{l,i}^4\right) \tag{5}$$

where $w_{\max,i,j}$ and $w_{\min,i,j}$ are the upper limit and the lower limit of power of wind farm j in VPP i, respectively; L and l_i represent the conventional loads in the distribution system and VPP i, respectively.

Then the membership function of fuzzy variables described in equations (2)-(5) can be calculated as follows:

$$\mu(\xi) = \begin{cases} \dfrac{\xi - r^1}{r^2 - r^1} & r^1 \le \xi < r^2 \\ 1 & r^2 \le \xi < r^3 \\ \dfrac{r^4 - \xi}{r^4 - r^3} & r^3 \le \xi < r^4 \\ 0 & else \end{cases} \tag{6}$$

where ξ represents the fuzzy variables described in equations (2)-(5); $\mu(\xi)$ is the membership function of ξ.

C. PRICE INCENTIVE MODEL OF SYSTEM OPERATOR ON THE UPPER LEVEL

1) OBJECTIVE FUNCTION ON THE UPPER LEVEL

The objective of system operator is to minimize the cost of distribution systems as:

$$\min \ \bar{F} \tag{7}$$
$$F = \sum_{i=1}^{N} p \times q_i + F' \tag{8}$$

where p is the electricity price; q_i is the power of VPP i supplied to the distribution system; N is the number of VPPs; F' is the imbalance cost of distribution system; F is the total cost of distribution system; $\bar{F}$ is the α_0-pessimistic value of F in the chance constrained programming.

The imbalance power and the imbalance cost of distribution system can be written as:

$$\Delta D = L - \sum_{i=1}^{N} q_i \tag{9}$$
$$F' = \begin{cases} k_1 \Delta D^2, & \Delta D > 0 \\ k_2 \Delta D^2, & \Delta D < 0 \\ 0, & \Delta D = 0 \end{cases} \tag{10}$$

where ΔD is the imbalance power of distribution system; k_1 and k_2 are the cost coefficients when the power of distribution system is insufficient and excessive, respectively.

2) CONSTRAINTS ON THE UPPER LEVEL

The constraints on the upper level include the upper and lower limit constraints of electricity price and the chance constraints of objective cost and imbalance power, which are given as:

$$p_{\min} \le p \le p_{\max} \tag{11}$$
$$Cr\left\{F \le \bar{F}\right\} \ge \alpha_0 \tag{12}$$
$$\mathrm{Cr}\{S_{\min} \le \Delta D \le S_{\max}\} \ge \beta_0 \tag{13}$$

where $p_{\max}$ and $p_{\min}$ are the upper limit and the lower limit of price, respectively; $S_{\max}$ and $S_{\min}$ are the upper limit and the lower limit of imbalance power, respectively; α_0 and β_0 are the confidence level of objective cost and the confidence level of imbalance power, respectively.

D. POWER RESPOND MODEL OF VPP ON THE LOWER LEVEL

1) OBJECTIVE FUNCTION ON THE LOWER LEVEL

The objective of VPP is to maximize its profit by selling power to the power system. It can be written as:

$$\max \ \bar{f}_i \tag{14}$$
$$f_i = p \times q_i - \sum_{j=1}^{N_{\mathrm{g},i}} f_{i,j}^{\mathrm{g}} - \sum_{j=1}^{N_{\mathrm{v},i}} f_{i,j}^{\mathrm{v}} + \sum_{j=1}^{N_{\mathrm{e},i}} f_i^{\mathrm{e}} - f_i^{\mathrm{d}} \tag{15}$$

where $f_{i,j}^{\mathrm{g}}$ is the cost of micro gas turbine j in VPP i; $f_{i,j}^{\mathrm{v}}$ is the cost of electric vehicle j in VPP i; f_i^{e} is the comfort utility of air conditioning j in VPP i; f_i^{d} is the imbalance cost of VPP i; $N_{\mathrm{g},i}$, $N_{\mathrm{v},i}$ and $N_{\mathrm{e},i}$ are the numbers of micro gas turbines, electric vehicles, and air conditionings in VPP i, respectively; f_i is the objective profit of VPP i; $\bar{f}_i$ is the α_i-optimistic value of f_i in the chance constrained programming.

The costs and the utility functions in formula (15) can be described as follows:

(1) Operation cost of micro gas turbine

The cost of micro gas turbine can be represented by the following quadratic function:

$$f_{i,j}^{\mathrm{g}} = b_{i,j}'' x_{i,j}^2 + b_{i,j}' x_{i,j} + b_{i,j} \tag{16}$$

where $b_{i,j}''$, $b_{i,j}'$ and $b_{i,j}$ are the cost coefficients of the micro gas turbine j in VPP i; $x_{i,j}$ is the output of micro gas turbine j in VPP i.

(2) Dispatching cost of electric vehicle

As a typical controllable load, the dispatching cost of electric vehicle can be described by the quadratic function, which is convex and non-decreasing within the dispatching range [19], [20]. In this paper, the dispatching cost of electric vehicle is formulated as:

$$f_{i,j}^{\mathrm{v}} = a_{i,j}\left(v_{i,j}^2 + g_{i,j} v_{i,j}\right) \tag{17}$$

where $v_{i,j}$ is the output of electric vehicle j in VPP i; $v_{i,j} > 0$ represents the electric vehicle discharges power, vice versa; $a_{i,j}$ and $g_{i,j}$ are the cost coefficients of electric vehicle j in VPP i; $g_{i,j}$ is set to be $2\left|v_{\min,i,j}\right|$, such that $f_{i,j}^{\mathrm{v}}$ is non-decreasing within $\left[v_{\min,i,j}, v_{\max,i,j}\right]$; $v_{\max,i,j}$ and $v_{\min,i,j}$ are the upper limit and the lower limit of power of electric vehicle j in VPP i, respectively.

In (17), $f_{i,j}^{\mathrm{v}}$ is positive when the electric vehicle discharges power. Conversely, $f_{i,j}^{\mathrm{v}}$ is negative if it is in the charge state.

(3) Comfort utility of air conditioning

Similar to the electric vehicle, the comfort utility of air conditioning can be described by the quadratic function formulated as:

$$f_i^{\mathrm{e}} = c_{i,j}\left(\left(t_{0,i,j} - t_{\mathrm{s},i,j}\right)^2 - \left(t_{i,j} - t_{\mathrm{s},i,j}\right)^2\right) \tag{18}$$

where $c_{i,j}$ is the utility coefficient of air conditioning j in VPP i; $t_{i,j}$, $t_{0,i,j}$, and $t_{s,i,j}$ are the setting temperature, initial temperature, and optimum temperature of air conditioning j in VPP i, respectively.

In equation (18), when the temperature $t_{i,j}$ set by air conditioning equals to the optimum temperature $t_{s,i,j}$, the comfort utility f_i^e obtains the largest value. If $t_{i,j}$ turns farther away from $t_{s,i,j}$, the value of f_i^e decreases correspondingly.

(4) Imbalance cost of VPP

The imbalance power of VPP is:

$$\Delta d_i = q_i + l_i + \sum_{j=1}^{N_{e,i}} e_{i,j} - \left(\sum_{j=1}^{N_{g,i}} x_{i,j} + \sum_{j=1}^{N_{w,i}} w_{i,j} + \sum_{j=1}^{N_{v,i}} v_{i,j} \right) \tag{19}$$

$$e_{i,j} = \begin{cases} \lambda'_{i,j} \left(t_{i,j} - t_{0,i,j}\right), & t_{i,j} \geq t_{0,i,j} \\ \lambda''_{i,j} \left(t_{0,i,j} - t_{i,j}\right), & t_{i,j} < t_{0,i,j} \end{cases} \tag{20}$$

where Δd_i is the imbalance power of VPP i; $e_{i,j}$ is the power consumed by air conditioning j in VPP i; $w_{i,j}$ is the output of wind farm j in VPP i; $N_{w,i}$ is the number of wind farms in VPP i; $\lambda'_{i,j}$ and $\lambda''_{i,j}$ are the power consumption coefficients of air conditioning j in VPP i.

Then the cost due to the imbalance power of VPP i can be described as:

$$f_i^d = \begin{cases} k_3 \Delta d_i^2, & \Delta d_i > 0 \\ k_4 \Delta d_i^2, & \Delta d_i < 0 \\ 0, & \Delta d_i = 0 \end{cases} \tag{21}$$

where k_3 and k_4 are the cost coefficients when the power of VPP i is insufficient and excessive, respectively.

2) CONSTRAINTS ON THE LOWER LEVEL

There are three types of chance constraints in VPPs, including the constraint of objective profit, the constraint of imbalance power, and the limit of output of wind farm:

$$Cr\left\{f \geq \overline{f_i}\right\} \geq \alpha_i \tag{22}$$
$$Cr\left\{s_{\min,i} \leq \Delta d_i \leq s_{\max,i}\right\} \geq \beta_{1,i} \tag{23}$$
$$Cr\left\{w_{\min,i,j} \leq w_{i,j} \leq w_{\max,i,j}\right\} \geq \beta_{2,i} \tag{24}$$

where $s_{\max,i}$ and $s_{\min,i}$ are the upper limit and the lower limit of imbalance power, respectively; α_i, $\beta_{1,i}$, and $\beta_{2,i}$ are the confidence levels of chance constraints of VPPi.

The deterministic constraints should also be satisfied as:

$$t_{\min,i,j} \leq t_{i,j} \leq t_{\max,i,j} \tag{25}$$
$$x_{\min,i,j} \leq x_{i,j} \leq x_{\max,i,j} \tag{26}$$
$$v_{\min,i,j} \leq v_{i,j} \leq v_{\max,i,j} \tag{27}$$

where $t_{\max,i,j}$ and $t_{\min,i,j}$ are the upper temperature limit and the lower temperature limit of air conditioning j in VPP i, respectively; $x_{\max,i,j}$ and $x_{\min,i,j}$ are the upper output limit and lower output limit of micro gas turbine j in VPP i, respectively.

III. SOLUTION METHODOLOGY

For the solution of the above model, two issues should be handled: 1) how to deal with the uncertainties, namely, transforming the fuzzy chance constraints and the objective functions into deterministic forms; and 2) how to optimize the models in two levels which interact each other deeply.

A. DEALING WITH UNCERTAINTY

1) TRANSFORMATION OF FUZZY CHANCE CONSTRAINT

For translating the fuzzy chance constraints of the proposed model into deterministic forms, the crisp equivalent method is used in this paper.

Assume that $g(x, \xi)$ is written as:

$$g(x, \xi) = h_1(x)\xi_1 + h_2(x)\xi_2 + \cdots + h_t(x)\xi_t + h_0(x) \tag{28}$$

If $a \geq 0.5$, the fuzzy chance constraint $Cr\{g(x, \xi) \leq 0\} \geq a$ can be converted to:

$$(2-2a)\sum_{k=1}^{t}\left[r_{k3}h_k^+(x) - r_{k2}h_k^-(x)\right] + (2a-1) \cdot \sum_{k=1}^{t}\left[r_{k4}h_k^+(x) - r_{k1}h_k^-(x)\right] + h_0(x) \leq 0 \tag{29}$$

$$h_k^+(x) = \begin{cases} h_k(x), & h_k(x) > 0 \\ 0, & \text{else} \end{cases} \tag{30}$$

$$h_k^-(x) = \begin{cases} -h_k(x), & h_k(x) < 0 \\ 0, & \text{else} \end{cases} \tag{31}$$

where ξ_k is the trapezoidal fuzzy variable determined by the quadruplet $(r_{k1}, r_{k2}, r_{k3}, r_{k4})$, and $k = 1, 2 \ldots t$.

In order to use the crisp equivalent method described in (29)-(31), the fuzzy chance constraints in this paper should be rewritten as $Cr\{g(x, \xi) \leq 0\} \geq a$ at first. Taking equation (13) for example, it can be divided into two chance constraints:

$$Cr\{-\Delta D \leq -S_{\min}\} \geq \beta_0 \tag{32}$$
$$Cr\{\Delta D \leq S_{\max}\} \geq \beta_0 \tag{33}$$

Then according to formula (29)-(31), they can be transformed into:

$$\sum_{i=1}^{N} q_i \leq -S_{\min} + (2-2\beta_0) \times r_L^2 + (2\beta_0 - 1) \times r_L^1 \tag{34}$$
$$\sum_{i=1}^{N} q_i \geq -S_{\max} + (2-2\beta_0) \times r_L^3 + (2\beta_0 - 1) \times r_L^4 \tag{35}$$

In this way, the fuzzy chance constraint of imbalance power on the upper level is transformed into a deterministic constraint as other fuzzy chance constraints in this paper.

2) TRANSFORMATION OF FUZZY OBJECTIVE FUNCTION

The fuzzy objective function can be deal with by the fuzzy simulation method [21]. The procedures are as follows:

Step 1) Generate θ_k from the ε-level set of fuzzy variable ξ randomly, namely $\mu(\theta_k) \geq \varepsilon, k = 1, 2, \ldots N$, where ε and N are the sufficiently small positive number and the sufficiently large number, respectively.

Step 2) Denote $v_k = \mu(\theta_k), k = 1, 2, \cdots N$.

Step 3) Set the credibility measure $H(\bar{F}) = Cr\{F(\xi(\theta_k)) \leq \bar{F}\}$, then for any given $\bar{F}$

$$H(\bar{F}) = \frac{1}{2} \max_{1 \leq k \leq N} \{v_k | F(\xi(\theta_k)) \leq \bar{F}\} + \frac{1}{2} \min_{1 \leq k \leq N} \{1 - v_k | F(\xi(\theta_k)) > \bar{F}\} \quad (36)$$

Step 4) Find the minimum $\bar{F}$ satisfying $H(\bar{F}) \geq \alpha_0$.

Since $H(\bar{F})$ in Step 4) is monotonic, the minimum $\bar{F}$ satisfying $H(\bar{F}) \geq \alpha_0$ is just the $\bar{F}$ satisfying $H(\bar{F}) = \alpha_0$. It can be optimized by dichotomy.

However, the fuzzy simulation is very time-consuming, particularly when carried out during the process of real-time economic dispatch. To address this problem, a mapping method based on the fuzzy simulation and the radical basis function (RBF) neural network is proposed in this paper. That method gives multiple groups of decision vectors in the decision space randomly, and calculates their pessimistic objective values by the fuzzy simulation. Next, it trains the RBF neural network with the decision vectors and the pessimistic objective values as inputs and outputs, respectively. Since the fuzzy simulation is approximated by the RBF neural network in advance, it should not be executed during the optimization process in the following.

The flowchart of the mapping method based on the fuzzy simulation and the RBF neural network is shown in Fig.1.

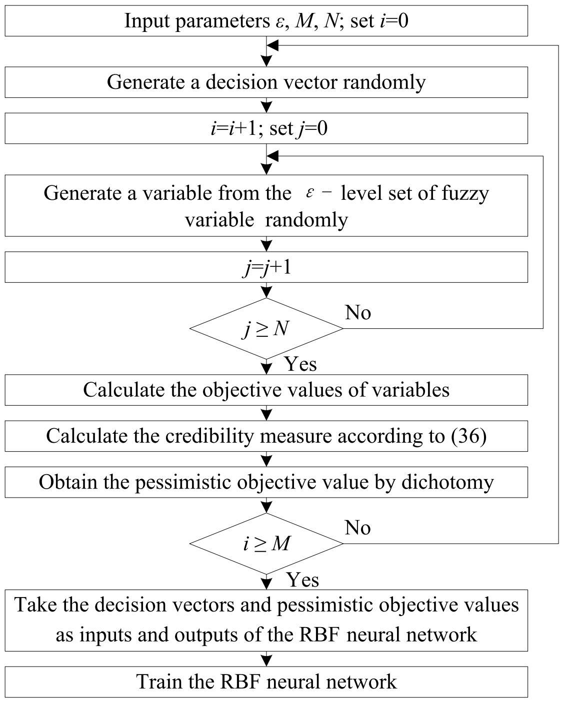

FIGURE 1. Flowchart of the mapping method.

3) BI-LEVEL OPTIMIZATION METHOD

When the proposed bi-level real-time economic dispatch model is transformed into deterministic form, its mathematical property is no longer clear. Thus, the optimization algorithm based on derivative information cannot be used as its solution. In this paper, a hybrid algorithm comprising of the PS algorithm (see in [22]) and the PSO algorithm (see in [23]) is presented. The steps are as follows:

Step 1) An initial electricity price p^n is given randomly by the system operator on the upper level.

Step 2) The PSO algorithm is employed to solve the respond models of VPPs on the lower level dispersedly, then the optimum power response q_i^n of each VPP at p^n is obtained.

Step 3) Calculate the pessimistic value of system cost $\bar{F}(p^n)$ on the upper level based on p^n and q_i^n.

Step 4) Make $p^{new} = p^n \pm \Delta p$, respectively; return to step 2) and step 3) for calculating the pessimistic values of system costs on either hand of p^n. Denote the better one as $\bar{F}(p^{new})$.

Step 5) If $\bar{F}(p^{new}) < \bar{F}(p^n)$, the searching is successful, go to step 6); else go to step 7).

Step 6) Let $p^n = p^{new}$, $\Delta p = \Delta p \cdot \lambda(\lambda > 1)$, and return to step 4).

Step 7) Let $\Delta p = \Delta p \cdot \tau$ $(\tau < 1)$, and return to step 4).

Step 8) Repeat step 4) - 7) until Δp is small enough.

IV. CASE STUDIES

A. TEST SYSTEM

A test system is given in Fig. 2, which consists of three VPPs; each one includes the micro gas turbine, wind farm, electric vehicles, air conditionings, and conventional loads. In order to demonstrate the feasibility of the proposed method, the accuracy of the mapping method, the calculation speed of the solution algorithm, the incentive of the system operator and the response of VPPs, and the impact of coefficients, uncertainty and risk preference are tested respectively in the following. The computer with the Intel Core i5 M480 CPU 2.67GHz is used in these tests.

B. TEST RESULTS

(1) Accuracy test of the mapping method. Take the pessimistic value of system cost on the upper level as an example. Assume that the electric price is 48.4$/MWh, generate 3000 groups of outputs of VPPs randomly, and calculate the pessimistic values of system costs by the fuzzy simulation. Then regard 2,000 groups of outputs of VPPs for training the RBF neural network, and the rest are used for testing the mapping accuracy. The tests are carried out at different confidence levels, and the results are shown in Table 1.

Table 1 shows that no matter which value the confidence level is, the maximum error of 1,000 groups of test data is smaller than 1 percent. This verifies the accuracy of mapping method adequately.

(2) Calculation speed of the solution algorithm. In order to test the calculation speed of the bi-level optimization method, we carry out the test once randomly. The changes of price and system cost during the iteration process of the PS algorithm

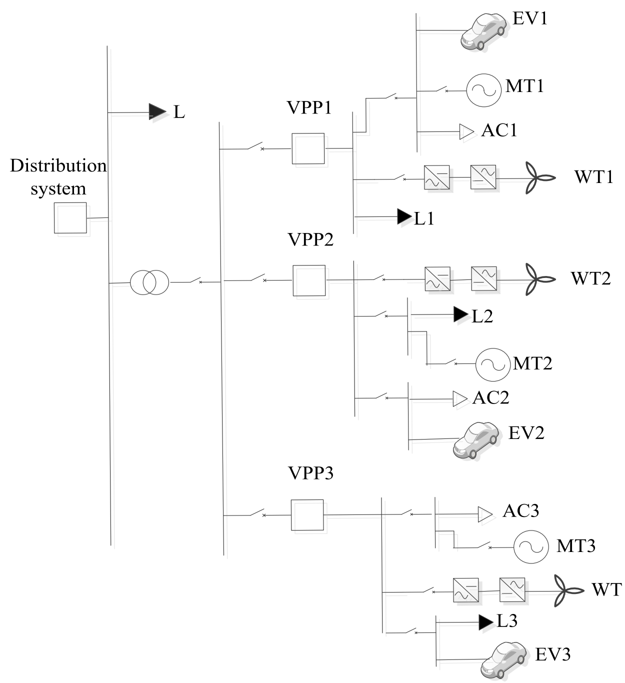

FIGURE 2. Test system.

TABLE 1. Maximum error at different confidence levels.

Confidence level	Pessimistic value of system cost when the error is maximum ($)		Maximum error (%)
	Fuzzy simulation	Mapping method	
0.6	1035.08	1039.62	0.44
0.7	1060.74	1058.80	0.18
0.8	1083.13	1086.22	0.29
0.9	1112.20	1108.31	0.35
1	1132.28	1134.82	0.22

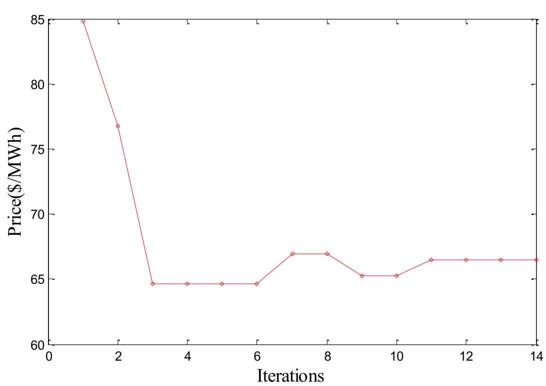

FIGURE 3. Change of price during iteration process on the upper level.

on the upper level are shown in Fig. 3 and Fig. 4, respectively. It is found that the system cost decreases sharply in the beginning. When the PS algorithm reaches the third iteration, the price and the system cost are already close to the final values. In order to gain better price and smaller system cost,

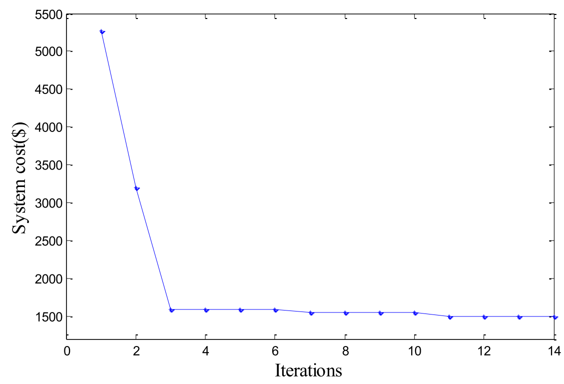

FIGURE 4. Change of system cost during iteration process on the upper level.

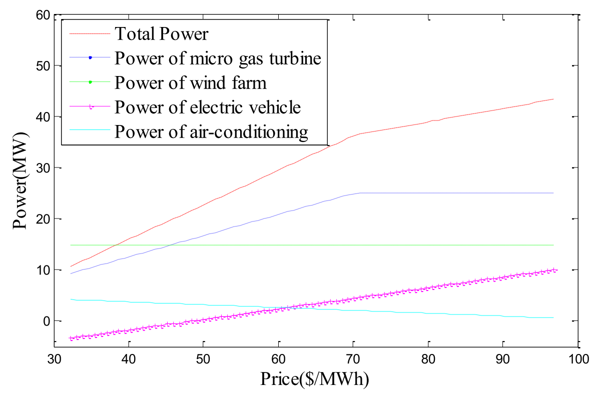

FIGURE 5. Optimal response of DERs of VPP 1 to electricity price.

the iteration continues and reaches the termination condition (which is set to be the change of price is smaller than 0.30$ /MWh in this paper) at the fourteenth iteration.

As for the PSO algorithm on the lower level, it is run at each iteration of the PS algorithm in the proposed bi-level optimization method. However, since the PSO algorithm can be utilized by each VPP dispersedly, the total calculation time of the bi-level optimization method is just 17.28s in this case. Furthermore, the calculation speed is almost unaffected by the number of VPPs. Thus, the requirement of calculation speed of real-time economic dispatch can be met effectively.

(3) The incentive of system operator and the response of VPPs. By changing the electricity price from 32$/MWh to 97$/MWh, each VPP optimizes its power response at every price, while the system operator calculates the system cost correspondingly. The results are shown in Fig. 5 and Fig. 6.

Fig. 5 provides the optimal outputs of DERs of VPP 1 at different prices. It can be seen that the power of wind farm stay maximum no matter how much the price is because the cost of wind power is not considered in this paper. When the price is low, the total output of electric vehicles is negative, indicating they are charging power at such circumstances. However, with the increase of electricity price, the electric vehicles reduce the charge power and even change to discharge state gradually; the air conditionings also decrease their consuming power to rise the total power of VPP 1

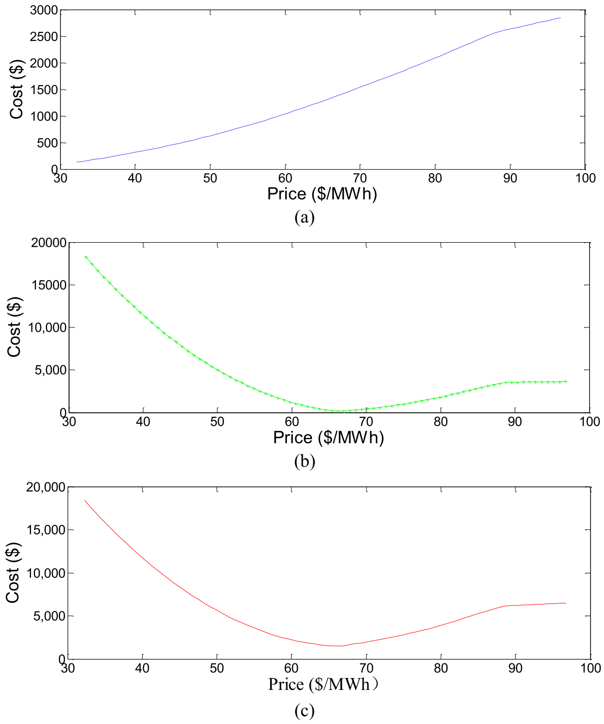

FIGURE 6. Change of system cost with different prices: (a) Power purchase cost; (b) Power imbalance cost; (b) Total cost.

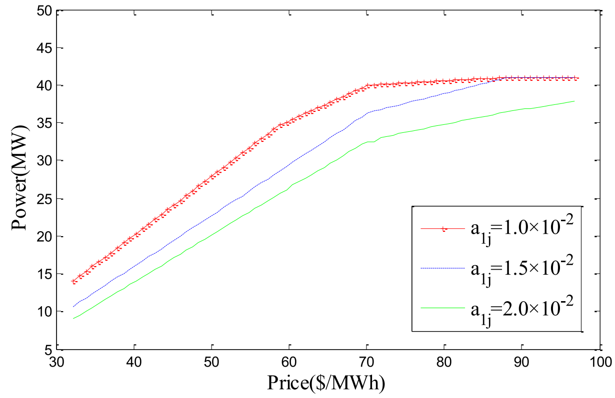

FIGURE 7. Impact of cost coefficient of electric vehicle on the total power of VPP 1.

TABLE 2. Impact of coefficient of electric vehicle on the result of real-time economic dispatch.

a_{1j}	Profit of VPP($)			System cost
(10^{-2})	VPP1	VPP2	VPP3	($)
1	218.77	231.97	211.09	1438.49
1.5	207.95	244.57	227.43	1481.46
2	209.94	253.92	239.62	1507.34

supplied to the distribution system. When the micro gas turbine and the electric vehicles reach the upper limits of outputs and the air conditionings reach the lower limits of consumed power, VPP 1 gets the maximum power as well.

Fig. 6 shows the change of power purchase cost, power imbalance cost, and total cost of the distribution system with the increase of electricity price, respectively. For the power purchase cost, it increases gradually as the price rises. But the imbalance cost decreases at first and then increases as the price increases. In a combination, the total cost also decreases at first and increases later. When the total cost reaches the minimum, the corresponding price should be the optimal price.

(4) The impact of coefficients. The costs or profits of electric vehicles, air conditionings and so on are considered in the method proposed in this paper, which is the basis of optimal operation of DERs. In the practical applications, the coefficients of cost or profit functions should be provided in advance according to the specific condition of each participant. To make clear the impact of these coefficients on the real-time economic dispatch, the cost coefficient a_{1j} of electric vehicle in VPP1 is studied as an example in the following, and the results are shown in Fig. 7 and Table 2.

Fig. 7 indicates that the smaller a is, the bigger the output of VPP 1 is. This indicates that the small cost coefficients of DERs would promote the output of VPP to some extent.

The change of profits of VPPs and system cost in Table 2 are more complex. As the increase of a, VPP1 will reduce its output at the same price. In order to realize the real-time balance, the system operator must raise price to give more incentive to VPPs. Thus, it pays more when a_{1j} increase. For VPP2 and VPP3, their profits also increase due to the rise of price. However, the change of the profit of VPP1 is non-unilateral. On one hand, the selling income will increase with the rise of price; on the other hand, the costs of electric vehicles will also increase correspondingly. Therefore, the profit of VPP1 decreases and then increases with the increase of a_{1j} in this case.

(5) The impact of uncertainty. Two cases are tested to study the impact of the number of fuzzy variables at first. In case 1, the fuzzy variable set, including the fuzzy variables described in equations (2)-(5) are considered. While in case 2, the fuzzy variables about the wind farm are removed from the fuzzy variable set of case 1. The results are shown in Fig. 8. The profit of VPP1 in case 1 is always less than that in case 2 because more fuzzy variables means greater uncertainties, which will lead to less profit of VPP when other conditions are the same.

Secondly, the impact of confidence level on the profit of VPP is studied. As shown in Fig. 9, the lower the confidence level is, the bigger the profit of VPP is. The main cause is that the lower confidence level means the VPP bears more risk, which is conducive to better profit as a result.

The impact of uncertainty due to different descriptions is also studied. The uncertainty of conventional load on the upper level is described by trapezoidal fuzzy variable and triangle fuzzy variable respectively, then the system costs in these two cases are calculated, and the results are shown in Fig. 10. It can be seen that when the trapezoidal fuzzy

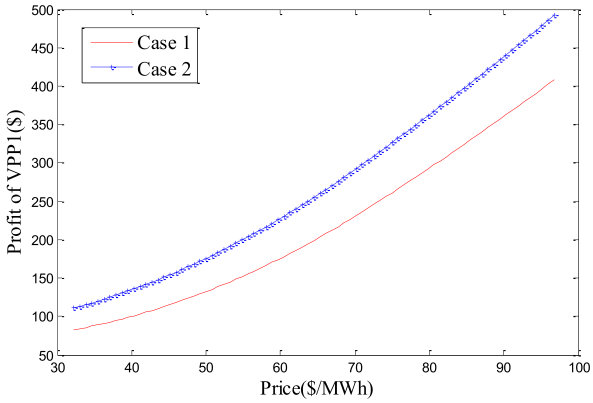

FIGURE 8. Impact of number of fuzzy parameters on the profit of VPP.

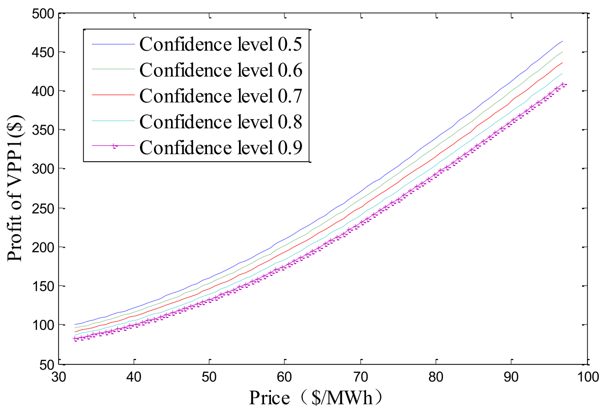

FIGURE 9. Impact of confidence level on the profit of VPP.

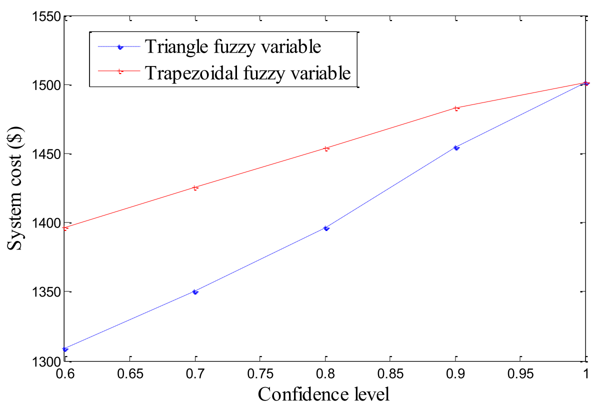

FIGURE 10. Impact of uncertainty description method on the system cost.

method is chosen, the system cost is more than that when the triangle fuzzy method is chosen. It indicates that the shape of fuzzy membership function has a certain impact on the optimization results. However, this impact becomes smaller and smaller as the confidence level rises.

In the proposed method, each participant can choose the confidence level according to its risk preference. In order to reveal this feature of the proposed method, three scenarios with different confidence levels for the participants are provided in Table 3, then the real-time economic dispatch is executed respectively, showing the results in Table 4.

TABLE 3. Confidence level of participants in different scenarios.

Scenario	Confidence level			
	Distribution system	VPP 1	VPP 2	VPP 3
1	1.0	1.0	1.0	1.0
2	0.9	0.9	1.0	1.0
3	0.9	0.9	0.9	0.9

TABLE 4. Comparison of results in different scenarios.

Cost or profit of participant	Scenario1	Scenario2	Scenario3
System cost ($)	1523.20	1509.23	1481.46
Profit of VPP1($)	206.31	212.40	207.95
Profit of VPP2($)	239.34	235.38	244.57
Profit of VPP3($)	222.52	217.09	227.43

By comparing scenario 2 with scenario 1, we found that as the confidence level of the distribution system and VPP 1 decrease from 1.0 to 0.9. The system cost, profits of VPP 2, and VPP3 all decrease while the profit of VPP1 increases correspondently. The main reason is that the system operator and VPP1 take higher risks as their confidence levels decline. But for VPP2 and VPP3, their profits decrease due to the decline of optimal price given by the system operator. When scenarios 2 and 3 are compared, the system cost decreases as the confidence levels of VPP2 and VPP3 decrease from 1.0 to 0.9. Considering the influence of price and output together, the profits of VPP2 and VPP3 increase, while the profit of VPP1 decreases to some extent.

V. CONCLUSION

A novel bi-level real-time economic dispatch method of VPP is proposed in this paper. The main conclusions are as follows:

1) By describing the real-time economic dispatch of VPP as the bi-level programming model, both the interaction between the distribution system and VPPs, and the operation of DERs inside VPPs can be optimized simultaneously.

2) Considering the uncertainties of DERs and conventional loads, the fuzzy chance constrained programming is further embedded into the above model. Through this method, the system operator and VPPs in different levels can make decisions according to their risk preferences effectively.

3) The proposed bi-level real-time economic dispatch model considering uncertainty is converted to deterministic form through the mapping method. This way, massive computation caused by the fuzzy simulation can be avoided in the process of real-time solution of the proposed model, while the error of the mapping method is quite small.

4) The bi-level optimization method is proposed to solve the bi-level real-time economic dispatch model. As the PSO algorithm on the lower level can be utilized by each VPP

dispersedly, the requirement of calculation speed of the real-time economic dispatch can be met availably.

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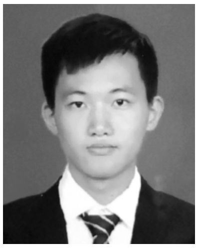

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