A Bi-level Stochastic Scheduling Optimization Model for a Virtual Power Plant Connected to a Wind-Photovoltaic-Energy Storage System Considering the Uncertainty and Demand Response

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Abstract: To reduce the uncertain influence of wind power and solar photovoltaic power on virtual power plant (VPP) operation, robust optimization theory (ROT) is introduced to build a stochastic scheduling model for VPP considering the uncertainty, price-based demand response (PBDR) and incentive-based demand response (IBDR). First, the VPP components are described including the wind power plant (WPP), photovoltaic generators (PV), convention gas turbine (CGT), energy storage systems (ESSs) and demand resource providers (DRPs). Then, a scenario generation and reduction frame is proposed for analyzing and simulating output stochastics based on the interval method and the Kantorovich distance. Second, a bi-level robust scheduling model is proposed with a double robust coefficient for WPP and PV. In the upper layer model, the maximum VPP operation income is taken as the optimization objective for building the scheduling model with the day-ahead prediction output of WPP and PV. In the lower layer model, the day-ahead scheduling scheme is revised with the actual output of the WPP and PV under the objectives of the minimum system net load and the minimum system operation cost. Finally, the independent micro-grid in a coastal island in eastern China is used for the simulation analysis. The results illustrate that the model can overcome the influence of uncertainty on VPP operations and reduce the system power shortage cost by connecting the day-ahead scheduling with the real-time scheduling. ROT could provide a flexible decision tool for decision makers, effectively addressing system uncertainties. ESSs could replace CGT to provide backup service for the WPP and PV, to smooth the VPP output curve and to improve the WPP and

PV grid connection by its charging-discharging characteristics. Meanwhile, IBDR and PBDR could smooth the load curve to the maximum extent, link the generation side with the demand side to minimize abandoned power value and reach the optimum benefit of VPP operation.

Key words: Virtual Power Plant; Energy Storage System; Uncertain; Demand Response; Bi-level Model

1 Introduction

Since energy and environmental problems become very serious, distributed energy resources (DERs), especially wind power and solar photovoltaic power, are playing increasingly important roles in the energy structure. However, constraints of small installed capacity, intermittence, uncertainty and other characteristics, make entrance and operation of the power market difficult for DERs[1]. Thus, the virtual power plant (VPP) was proposed as a new technology for DERs in the power market[2]. Without changing the DERs grid connection method, VPP integrates different types of DERs, such as distributed power sources, energy storage systems and controllable loads, by using advanced control, calculation and communication technology [3]. In recent years, smart grid technology has gained significant attention. The government performs a series of policies to improve smart grid development, and to accelerate the construction of ultra-high voltage power networks and distribution networks to promote resource reasonable configuration, to enhance interactions among the power grid, power resources and energy consumers, and to provide solid support for VPP development.

VPP pilot projects are underway at home and abroad. In 2007, Cassell University integrated a wind turbine, solar photovoltaic system, biogas power station and hydro power plant into a VPP with the maximum installed capacity in the world [4]. In 2009, the electric vehicle grid connection project in Denmark used VPP technology to control electric vehicle smart charging-discharging considering large-scale wind power output uncertainty [5]. In 2008, a distributed energy power plant was operated at China Guangdong University City, including a gas-steam combined cycle unit to meet the electric power demand and heat demand [6]. In 2011, the China Zhangbei wind-photovoltaic-storage-transmission project began operation, which is a new energy comprehensive utilization platform to integrate wind power, photovoltaic power, a storage system, and power transmission [7]. In 2014, the Xiaozhongdian wind-photovoltaic-hydro distributed demonstration project of China National Electric Power Group Corporation successfully connected into the grid and started its business operations in Yunnan province

[8].

Research on VPP generally begins from the VPP itself, and focuses on how to realize optimal VPP operation based on the capacity configuration and coordinate operation. Morteza et al.[9] have defined the concept and control mode of VPPs and summarized the essential status and development prospects. Then, mathematical models were constructed for VPP scheduling. Hrvoje et al.[10] have presented a mixed integer linear programming based on the optimum operation of a wind-hydro VPP. João et al.[11] have applied VPP to manage the day-ahead energy resource scheduling in the smart grid, considering the intensive use of distributed generation and Vehicle-To-Grid. Tiago et al.[12] have proposed a methodology for day-ahead energy resource scheduling for smart grids considering the intensive use of distributed generation and Vehicle-to-Grid managed by a virtual power player (VPP). Spyros et al.[13] have optimized the installed capacity and control generation mode to realize VPP economical scheduling. Zapata et al.[14] have proposed an optimization model to improve VPP operation income by making use of a controllable load to reduce the influence of wind power output uncertainty. Saeed et al.[15] have analyzed the coordination problem among wind power, solar photovoltaic power and hydro power.

To overcome the uncertainty problem among different powers, controllable units [16] energy storage systems [17] and controllable loads [18] were used to coordinate VPP operation and to ensure the stability of the VPP output. Hrvoje et al.[19] have casted a two-stage, stochastic, mixed-integer, linear programming model with uncertain parameters, including the power output of the intermittent source and the market prices. Seyyed et al.[20] have integrated distributed generation units and demand response loads (DRL) into the VPP, and proposed a stochastic formulation for power scheduling. By introducing the DRL programs and using the proposed modeling, one can select the best DRL program for each VPP in a scheduling procedure. Wang et al.[21] have proposed interactive dispatch modes and a bidding strategy of multiple VPPs, and discussed day-ahead and real-time scheduling result. However they did not analyze the difference between the two scheduling stages. Tascikaraoglu et al.[22] have proposed an adaptive load dispatching and forecasting strategy for VPP, which is mainly used in real-time scheduling.

The power consumption mode has improved with the development of the smart grid and the extension of two-way interactive technology, which can provide a technological foundation for demand side participating in the operation scheduling optimization on generation side [23]. The introduction of related user guidance measures could optimize customer behavior to respond to system power generation

optimization scheduling. Wang et al.[24] have defined the basic concept of demand response (DR), divided it into price-based demand response (PBDR), and incentive-based demand response (IBDR). DR could result in load peak-valley shifting and reduce the uncertainty caused by renewable energy grid connections[25], which is conducive to promote VPP power generation and grid connections. Some literature discusses how IBDR participates into VPP power generation scheduling. Stjepan et al.[26] have discussed the operation modes of VPP with interruptible loads. Spyros et al.[27] have discussed how to allocate power output in energy scheduling, and to reserve scheduling to maximize VPP operation income. Erdinc[28] has analyzed the economic impacts of small-scale own generating and storage units and electric vehicles under different demand response strategies for smart households.

Note that there are some insufficiencies on the optimization of VPP operation. Firstly, some studies took the uncertainty of wind power and solar photovoltaic power into consideration and analyzed the influence of uncertainty on VPP operation with the prediction value or simulation value of wind power and solar photovoltaic power as a determined variable and without the volatility characteristics. Secondly, the demand response could guide reasonable power consumption on the demand side to provide more capacity for wind power and solar photovoltaic power by grid connections such that we can optimize the VPP operation result. Some literature has discussed how IBDR participates in VPP power generation scheduling. But there are few studies on how to utilize PBDR to optimize customer distribution, and to improve VPP grid connections. Thirdly, most models proposed in previous studies are used for day-ahead scheduling. The study of real-time scheduling of VPP is essential because the output of intermittent renewable energy has strong fluctuation characteristics. However, the previous literature rarely discussed real-time scheduling of the VPP. To link the day-ahead scheduling and real-time scheduling, Tan et al.[29] have introduced two-stage optimization theory to build the linkage optimization mode for day-ahead scheduling and hour-ahead scheduling, which could be used in VPP optimization scheduling. All analysis above motivates us to consider a bi-level stochastic scheduling model for VPP considering DR and uncertainty. The main contributions of this work are summarized as follows:

- A wind power plant (WPP), photovoltaic generators (PV), a conventional gas turbine (CGT), energy storage systems (ESSs) and demand resource providers (DRPs) are integrated into a virtual power plant. The interval method and the scenario tree technique are introduced to construct the scenario generation method. The Kantorovich distance is introduced to construct the scenario reduction method.

The typical scenario of the WPP output and PV output could be obtained by the proposed method.

- A bi-level scheduling optimization model for VPP is proposed. In upper layer model, the maximum VPP operation income is taken as the optimization objective. The day-ahead scheduling scheme can be obtained with the day-ahead prediction output of the WPP and PV. In the lower layer model, the minimum system net load and the minimum system operation cost are taken as the optimization objectives to revise the day-ahead scheduling scheme with the actual output by adjusting the outputs of the ESS and DRPs.

- Robust stochastic optimization theory is introduced to overcome the uncertainties of the output of the WPP and PV. Robust coefficients for the output of the WPP and PV are introduced to provide a flexible decision tool for decision makers with different risk attitudes and to reach the optimal balance point between risk and income.

- Multiple scenarios are utilized to compare the optimization effects of the DR and ESSs on VPP operation. The influence of the DR and ESSs on VPP operation is analyzed. The optimization difference between PBDR and IBDR is discussed to propose the coordination between DR and ESSs.

The rest of this paper is organized as follows: In Section 2 the demand response models are presented, including the PBDR model and IBDR model. In Section 3 the basic structure of the VPP is described, the inner uncertainty of the VPP is analyzed, and a simulation method and scenario reduction strategy for wind power and solar photovoltaic generation are proposed. In Section 4 a bi-level scheduling optimization model for VPP is proposed which is our main contribution. In Section 5 robust stochastic optimization theory is introduced to overcome the uncertainties of the output of the WPP and PV. Thus, a robust stochastic scheduling model is proposed. To simplify the solution progress, the non-linear objective function and constraints are linearized. The model is transformed into a mixed integer linear programming model (MILP). Four simulation scenarios of ESSs and DR with the real data of an island in East China for the proposed model are given in Section 6. Finally, highlights the contributions and conclusions are given in the last section.

2 Demand response model

2.1 Price-based DR model

PBDR optimizes customer behavior by performing time-of-use (TOU) price, and transfers demand

load from the peak load time to the valley load time. Load shifting and load curtailment can occur both in the PBDR model. The influence of PBDR on customers' power consumption can be described by demand-price elastic, as equation (1)

$$e_{st} = \frac{\Delta L_s / L_s^0}{\Delta P_t / P_t^0} \begin{cases} e_{st} \leq 0, \text{ if } s = t \\ e_{st} \geq 0, \text{ if } s \neq t \end{cases} \quad (1)$$

where s is index for time, $s=1,2,\dots,T$.

If the electricity price changes in diverse periods, customers could respond in two ways. The first way: they could be only on or off in the case that some loads are not able to move from one period to another (e.g., illuminating loads). Such loads have sensitivity in a single period called "self-elasticity", which always has a negative value[30]. The second way: some consumption could be transferred from the peak period to the off-peak or low periods (e.g., process loads). Such behavior is called multi-period sensitivity and evaluated by "cross-elasticity", which is always positive [31]. The detailed mathematical description is as follows:

1) When $s=t$, e_{st} is called self-elasticity. Only demand curtailment could occur, with which e_{st} is always negative. Then, load change is always a negative amount.

2) When $s \neq t$, e_{st} is called cross-elasticity. Demand shifting could occur. In this case, e_{st} is always positive. Then, the load change is always a positive amount.

The load change after PBDR has been calculated in [32], without discussions of the detailed calculation method. The load change L_t after PBDR is shown in equation (2).

$$L_t = L_t^0 \times \left\{ 1 + e_{tt} \times \frac{[P_t - P_t^0]}{P_t^0} + \sum_{\substack{s=1 \\ s \neq t}}^{24} e_{st} \times \frac{[P_s - P_s^0]}{P_s^0} \right\}. \quad (2)$$

The introduction of PBDR changes power sale income. The PBDR cost π_t^{PB} is defined as the power sale income difference before and after PBDR.

$$\pi_t^{\text{PB}} = P_t^0 L_t^0 - (P_t^0 + \Delta P_t) L_t. \quad (3)$$

2.2 Incentive-based DR model

The IBDR program is provided by demand response Providers (DRPs) and large individual consumers with free controllable load. Only load change can occur in IBDR without load shifting. IBDR programs can participate in energy scheduling by load reduction and reserve scheduling by reserve

capacity [33]. Customer loads mainly consist of residential load, industrial load and commercial load. Residential loads mainly participate in the IBDR programs by reducing power consumption. Industrial loads mainly participate in the IBDR programs by adjusting the power consumption plan for increasing or decreasing power consumption. Commercial loads mainly participate in the IBDR programs by taking some energy-savings measures to reduce electricity consumption [33]. Since price directly influence DRPs' DR revenue, DPRs participate in IBDR programs step-by-step according to DR price and form step-wise DR price-demand curves, as shown in Fig. 1. Hence, DPRs submit different reduction offers at different price-quantity offer packages [34].

Figure 1 Step-wise DR price-demand curve

It follows from Fig. 1 that the load reduction of DPRs in energy scheduling is described in Eq. (4)-Eq. (7):

$$D_i^{j,\min} \leq \Delta L_{i,t}^j \leq D_i^j, j = 1, \quad (4)$$

$$0 \leq \Delta L_{i,t}^j \leq (D_i^j - D_i^{j-1}), j = 2, 3, \dots, J, \quad (5)$$

$$\Delta L_{i,t}^E = \sum_{j=1}^J \Delta L_{i,t}^j. \quad (6)$$

Consider a DPR participating in reserve scheduling. The DR program should meet the following constraints:

$$\Delta L_{i,t}^E + \Delta L_{i,t}^{R,dn} \leq D_i^{\max}, \quad (7)$$

$$\Delta L_{i,t}^E - \Delta L_{i,t}^{R,up} \geq D_i^{\min}. \quad (8)$$

Finally, the costs of DPRs participating in energy scheduling and reserve scheduling could be calculated by Eq. (9).

$$\pi_t^{\text{IB}} = \sum_i \rho_{i,t}^E \cdot \Delta L_{i,t}^E + \sum_i \rho_{i,t}^{R,dn} \cdot \Delta L_{i,t}^{R,dn} + \sum_i \rho_{i,t}^{R,up} \cdot \Delta L_{i,t}^{R,up}. \quad (9)$$

In Eq. (9), the first term is the cost of DPRs participating in energy scheduling. The second and third

terms are the costs of DPRs participating in down/up reserve scheduling.

3 VPP description and uncertainty analysis

3.1 VPP Assumption

The VPP model consists of the WPP, PV, CGT, ESS and DRPs. DRPs only provide IBDR because the PBDR cannot be directly scheduled by the VPP controller. The structure of the VPP is shown in Fig. 2.

Figure 2 The structure of the VPP

In the VPP, the output of the WPP and PV is stochastic, but system scheduling is pre-scheduling, which has to achieve a determined system scheduling scheme before knowing the actual output of the WPP and PV. To overcome the uncertainty of the WPP and PV, in day-ahead scheduling, we use a scenario simulation method to determine the day-ahead prediction output result of the WPP and PV to determine the day-ahead scheduling plan. In the hour-ahead scheduling, we use the real-time output of the WPP and PV to revise the day-ahead scheduling scheme. The VPP can transfer part of the energy from some hours to others according to the load demanded by the ESSs, which could improve market incomes, reduce power shortage costs, and realize extra income. DPRs could participate in energy scheduling by transferring power consumption periods and gain backup service income by participating in up/down reserve scheduling.

3.2 Uncertainty analysis

The VPP model has two sources of uncertainty, namely, the WPP output and the PV output. The WPP

output is mainly influenced by wind speed with stochastic characteristics. The PV output mainly depends on external weather, especially cloudiness. Therefore, to analyze the uncertainties, the probability density functions (PDF) for the WPP output and PV output should be proposed.

3.2.1 WPP output

The stochastics of the WPP output depends on the stochastic nature of wind speed. Although wind speed is intermittent in the short and long terms, the literature proves that the Rayleigh PDF could be used as a proper expression model of wind speed behavior [35]. The Rayleigh PDF is also the special case of the Weibull PDF, as shown in Eq. (10)

$$f(v) = \frac{\varphi}{g} \left(\frac{v}{g} \right)^{\varphi-1} e^{-(v/g)^{\varphi}}. \quad (10)$$

The probability of wind speed state v can be calculated by Eq. (11)

$$P(v) = \int_{v_a}^{v_b} f(v) dv. \quad (11)$$

If the average value of each interval is used as the input wind speed, then the WPP output can be calculated by Eq. (12)

$$g_{w,t} = \begin{cases} 0, & 0 \leq v_t < v_{in}, \quad v_t > v_{out} \\ \frac{v_t - v_{in}}{v_{rated} - v_{in}} g_R, & v_{in} \leq v_t \leq v_{rated} \\ g_R, & v_{rated} \leq v_t \leq v_{out} \end{cases} \quad (12)$$

where v_t is the actual speed of the wind turbine, equal to $(v_{a,t} + v_{b,t})/2$ at time t .

3.2.2 PV output

The PV output mainly depends on solar irradiance. Literature [36] proves that the Beta PDF can be used to describe the distribution of irradiance at a particular location.

$$f(\theta) = \begin{cases} \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha)+\Gamma(\beta)} \theta^{\alpha-1} (1-\theta)^{\beta-1}, & 0 \leq \theta \leq 1, \alpha \geq 0, \beta \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

The mean and standard deviation of the irradiance is introduced to calculate the parameters of the Beta PDF by Eq. (12) and Eq. (13) as follows

$$\beta = (1-\mu) \times \left(\frac{u \times (1+\mu)}{\sigma^2} - 1 \right), \quad (14)$$

$$\alpha = \frac{\mu \times \beta}{1-\mu}. \quad (15)$$

After Eq. (13) and Eq. (14), the probability of solar irradiance state θ can be calculated by Eq. (16)

$$P(\theta) = \int_{\theta_c}^{\theta_d} f(\theta) d\theta. \quad (16)$$

Then, by applying the irradiance-to-power conversion function in [32], we can calculate the PV output by Eq. (16) to get

$$g_{PV,t} = \eta_{PV} \times S_{PV} \times \theta_t. \quad (17)$$

3.3 Uncertainty simulation

The uncertainty simulation includes two steps: scenario generation and scenario reduction. Eq. (11) and Eq. (16) can be used to calculate the WPP output and PV output, respectively. Then, the interval method is utilized to simulate the output scenarios of the WPP and PV. The method divides the WPP output and PV output into several intervals, and takes the value of a point in the interval as the power output's expectation. When the number of intervals is sufficient, the simulation output value can be regarded as the real output. Assume that there is no correlation between the WPP output and PV output. Thus, there exist two different states at each scenario, namely, the WPP output and PV output. Considering the different states of the output functions in all periods, we apply the scenario tree technology to divide the power output into three statuses, namely, high, mean and low. Then, the different output statuses of the WPP and PV can be calculated. Taking the output of the WPP as an example, if the wind speed distribution is divided into several intervals, we obtain the value of the wind speed belonging to interval $[a, b]$ at time t as $(v_{a,t} + v_{b,t})/2$. In this way, the values of wind speed and solar irradiance at different intervals can be calculated. Then, the scenario weights (γ_s) can be calculated by $\gamma_s = P(v) \times P(\theta)$. The detailed procedures of the simulation method based on the interval method and the scenario tree technique can be found in [29].

The number of scenarios generated by the method above is huge and redundant, which is expensive for solving the VPP scheduling model considering all simulation scenarios. Therefore, it is necessary to construct a scenario reduction method to delete the scenarios with high similarity for saving computational cost. The basic concept of scenario reduction is to choose a reference scenario, compare this scenario with other scenarios, and remove the closest scenario. Here, the Kantorovich distance (K-distance) is introduced to calculate the distance among the different scenarios under the objective function of the minimum K-distance between the initial scenario and the reduced scenario. The scenario with the minimum K-distance is deleted. The probability of a deleted scenario should be added to the reference scenario.

Then, the final simulation scenarios and the probability of all scenarios can be calculated. The scenario reduction model is described in [29]. To solve the model, the multi-stage heuristic algorithm is used, referring to [37]. Fig. 3 is the scenario simulation flowchart of the WPP and PV.

Figure 3. The scenarios simulation flowchart of WPP and PV

4 Bi-level stochastic scheduling optimization model for VPP

4.1 Model assumption

When stochastic variables exist in constraint conditions or objective functions, the expectation values of the objective functions are usually taken as the optimal objective, called the expectations model[29]. In the VPP, the output of the WPP and PV have stochastic characteristics, but the system must make the scheduling arrangement before knowing the actual output of the WPP and PV based on their prediction results, which is called advanced decision. The scenario simulation method is proposed to obtain the simulation scenarios and scenario weight. The expectation values of the objective functions can be calculated as the sum of multiplying the objective function value and weight in each scenario. Therefore, the expectations model can be applied to construct the VPP scheduling model. To solve the model, a bi-level optimization method is introduced, which divides the stochastic variables into the prediction stage and the realization stage. In the VPP scheduling model, the stochastic variables of the WPP output and PV output are divided into the day-ahead prediction stage and the ultra-short-term forecast stage (hour-ahead scheduling stage). In the second stage, the prediction can be regarded as the actual value of the stochastic variables. After the division, the system can arrange the scheduling plan in advance and revise the plan according to the actual value of the stochastic variable, which could reduce the stochastic influence of the WPP output and PV output on system scheduling.

Based on the analysis above, we construct a bi-level stochastic scheduling model for the VPP considering uncertainties and the DR. The upper layer model refers to the day-ahead scheduling model.

Load demand, WPP output and PV output are predicted before the next day. The output scenarios of the WPP and PV are simulated, and the scheduling plan is arranged with the simulation scenarios. Because the difference between the prediction value and the actual value of the WPP output and PV output may be large, in order to promote the adjustment capability of the VPP, IBDR is not considered in the upper layer model. IBDR can be used for scheduling in the lower layer model to revise the day-ahead scheduling plan after knowing the actual output of the WPP and PV. In the upper layer model, the maximum revenue of the VPP operation is taken as the optimization objective function considering the system operation constraints, e.g., supply and demand balance constraints, CGT operation constraints, WPP and PV output constraints, especially the reserve service constraints. The time for day-ahead scheduling plan is sufficient. All simulation scenarios can be considered for units scheduling schemes in each period.

In the lower layer model, the actual output of the WPP and PV are known, and the day-ahead scheduling plan is revised according to the actual output. Because DRPs are generated by customers, if they are scheduled in the layer model, the prediction for the DRPs output is necessary, which will generate another uncertainty factor. Therefore, IBDR should be scheduled in the lower layer model to promote the adjustment capability of the VPP. The DRPs output can also be scheduled without considering its uncertainty. For the maximum utilization of the WPP and PV, the minimum system net load and the minimum system generation cost power are taken as the objective functions, respectively. The first objective function is used for the optimal operation of the ESSs and DRPs to achieve the maximum output of the WPP and PV. The second objective function is used for the optimal CGT operation plan to achieve the minimum generation cost. The DRPs are performing the scheduling in this model and can participate in energy scheduling by load reduction and reserve scheduling by reserve capacity, which is better for realizing the optimum system operation scheduling scheme. Fig. 4 is the structural frame diagram for VPP scheduling model.

Figure 4 The structural frame diagram for the VPP scheduling model

4.2 Upper layer scheduling model

The WPP, PV, CGT and ESSs of the VPP are scheduled with the day-ahead prediction output result in the upper layer model. To promote the development of the VPP, set the maximum VPP operation revenue as the optimal objective function for the day-ahead scheduling plan of the VPP. The objective function is as follows:

$$\max R = \sum_{t=1}^T \sum_{k=1}^k \gamma_k (R_{W,t} + R_{PV,t} + R_{ESS,t} + R_{CGT,t})_k, \quad (18)$$

$$R_{W,t} = \rho_{W,t} g_{W,t}, \quad (19)$$

$$R_{PV,t} = \rho_{PV,t} g_{PV,t}, \quad (20)$$

$$R_{ESS,t} = \rho_{ESS,t}^{dis} g_{ESS,t}^{dis} - \rho_{ESS,t}^{chr} g_{ESS,t}^{chr}, \quad (21)$$

$$R_{CGT,t} = \rho_{CGT,t} g_{CGT,t} - \pi_{CGT,t}^{pg} - \pi_{CGT,t}^{ss}. \quad (22)$$

298 The generation cost and startup-shutdown cost of the CGT can be calculated by Eq. (22)-Eq. (24) as

$$\pi_{CGT,t}^{pg} = a_{CGT} + b_{CGT} g_{CGT} + c_{CGT} (g_{CGT,t})^2, \quad (23)$$

$$\pi_{CGT,t}^{ss} = [u_{CGT,t}(1-u_{CGT,t})] D_{CGT,t}, \quad (24)$$

$$D_{CGT,t} = \begin{cases} N_{CGT}^{hot} \square T_{CGT}^{\min} < T_{CGT,t}^{\text{off}} \leq T_{CGT}^{\min} + T_{CGT}^{cold} \\ N_{CGT}^{cold} \square T_{CGT,t}^{\text{off}} > T_{CGT}^{\min} + T_{CGT}^{cold} \end{cases}, \quad (25)$$

299 Where binary variable $u_{CGT,t}$ is the operation status of the CGT at time t , and $u_{CGT,t} = 1$ means the CGT
300 is in operation, whereas $u_{CGT,t} = 0$ means the CGT is not in operation.

301 The WPP, PV, CGT and ESSs are considered in the model. IBDR provided by DRPs is not considered,
302 but PBDR can occur in day-ahead scheduling. Therefore, constraints for the upper layer model include the
303 supply and demand balance constraint, the CGT operation constraints, the WPP and PV output constraints,
304 PBDR constraints and reserve constraints. The details are as follows.

305 (1) Supply and demand balance constraint

$$\underbrace{g_{W,t}(1-\varphi_W) + g_{PV,t}(1-\varphi_{PV}) + (g_{ESS,t}^{dis} - g_{ESS,t}^{chr}) + g_{CGT,t}(1-\varphi_{CGT}) + g_{GC,t}}_{WPP \text{ output in day-ahead scheduling}} = L_t - u_{PB,t} \Delta L_{PB,t}, \quad (26)$$

306 where the binary variable $u_{PB,t}$ is the status of the PBDR operation, $u_{PB,t} = 1$ means the PBDR is
307 implemented, whereas $u_{PB,t} = 0$ means PBDR is not implemented. When $\Delta L_{PB,t}$ is positive, the load is
308 shifting or curtailing, otherwise, the load is increasing from other hours of load shifting.

309 (2) CGT operation constraints

$$u_{CGT,t} g_{CGT}^{\min} \leq g_{CGT,t} \leq u_{CGT,t} g_{CGT}^{\max}, \quad (27)$$

$$u_{CGT,t} \Delta g_{CGT}^- \leq g_{CGT,t} - g_{CGT,t-1} \leq u_{CGT,t} \Delta g_{CGT}^+, \quad (28)$$

$$(T_{CGT,t-1}^{\text{on}} - M_{CGT}^{\text{on}})(u_{CGT,t-1} - u_{CGT,t}) \geq 0, \quad (29)$$

$$(T_{CGT,t-1}^{\text{off}} - M_{CGT}^{\text{off}})(u_{CGT,t} - u_{CGT,t-1}) \geq 0. \quad (30)$$

310 (3) ESSs operation constraints

311 In the whole scheduling period, the relationship of the charge power and discharge power meet the
 312 following constraint:

$$\sum_{t=1}^T (Q_0 + g_{ESS,t}^{chr} - Q_t)(1 - \rho_{ESS}) = \sum_{t=1}^T g_{ESS,t}^{dis}. \quad (31)$$

313 When the ESS is discharging,

$$Q_{t+1} = Q_t - g_{ESS,t}^{dis} (1 + \rho_{ESS,t}^{dis}). \quad (32)$$

314 When the ESS is charging,

$$Q_{t+1} = Q_t + g_{ESS,t}^{chr} (1 + \rho_{ESS,t}^{chr}). \quad (33)$$

315 Assuming the ESS cannot discharge and charge at the same time, the constraint is as follows

$$g_{ESS,t}^{chr} \cdot g_{ESS,t}^{dis} = 0. \quad (34)$$

316 Then, to protect ESS's lifetime, the charging or discharging power cannot exceed its maximum
 317 capacity, as shown in Eq. (34) and Eq. (35)

$$0 \leq g_{ESS,t}^{chr} \leq \bar{g}_{ESS,t}^{chr}, \quad (35)$$

$$0 \leq g_{ESS,t}^{dis} \leq \bar{g}_{ESS,t}^{dis}. \quad (36)$$

318 (4) PBDR operation constraints

319 Since load shifting and load curtailment can both occur in the PBDR, to smooth the load demand
 320 curve, the load change produced by the PBDR should meet the following constraints

$$|\Delta L_{PB,t}| \leq u_{PB,t} \Delta L_{PB,t}^{\max}, \quad (37)$$

$$u_{PB,t} \Delta L_{PB} \leq \Delta L_{PB,t} - \Delta L_{PB,t-1} \leq u_{PB,t} \bar{\Delta L}_{PB}, \quad (38)$$

$$\sum_{t=1}^T \Delta L_{PB,t} \leq \Delta L_{PB}^{\max}. \quad (39)$$

321 (5) System reserve constraints

$$g_{VPP,t}^{\max} - G_{VPP,t} + \Delta L_{PB,t} \geq r_1 \cdot L_t + r_2 \cdot g_{W,t} + r_3 \cdot g_{PV,t}, \quad (40)$$

$$g_{VPP,t} - g_{VPP,t}^{\min} \geq r_4 \cdot g_{W,t} + r_5 \cdot g_{PV,t}. \quad (41)$$

322 4.3 Lower layer scheduling model

323 In the lower layer model, the actual output of the WPP and PV are known. The day-ahead scheduling
 324 plan should be revised according to the actual output, especially the operation plan of the ESSs and CGT.
 325 The IBDR produced by the DRPs is scheduled to provide up/down reserves. Two optimization objective
 326 functions are utilized to revise the day-ahead scheduling plan, namely, the minimum system net load and
 327 the minimum system operation cost. At time $t-1$ on the scheduling day, the lower layer model is used to

revise the day-ahead scheduling generation plan at time t according to the actual output by revising the ESSs output and introducing DPRs to provide IBDR, which can be realized by the following two steps:

(1) ESSs output revise model

The minimum system net load is taken as the optimization objective. The optimization goal of this model is to improve the grid connection of the WPP and PV by adjusting the operation of the ESSs and IBDR. Because DRPs are introduced in the lower layer model, the system can also utilize DRPs to provide up/down reserves for the WPP and PV while revising the ESSs output plan. The details are as follows

$$\min N_t = \left| -\left(g_{ESS,t}^{dis} - g_{ESS,t}^{chr}\right) - g_{PV,t} - g_{W,t} + \left(g_{ESS,t}^{dis} - g_{ESS,t}^{chr}\right)^* + g'_{PV,t} + g'_{W,t} + \Delta L_{IB,t} \right|, \quad (42)$$

$$\Delta L_{IB,t} = \sum_{i=1}^I \left(\Delta L_{i,t}^E + \Delta L_{i,t}^{R,dn} - \Delta L_{i,t}^{R,up} \right), \quad (43)$$

Where $\left(g_{ESS,t}^{dis} - g_{ESS,t}^{chr}\right)^*$ is the revised output of the ESSs, which should meet the constraints from Eq. (31)-Eq. (35). Meanwhile, the revised energy storage system output at time t should not influence the output plan after time t . This requires that ESSs operation meet Eq. (44)-Eq. (45):

When the ESS is discharging,

$$Q_{t'+1} = Q_{t'} - g_{ESS,t'}^{dis} \left(1 + \rho_{ESS,t'}^{dis}\right). \quad (44)$$

When the ESS is charging,

$$Q_{t'+1} = Q_{t'} + g_{ESS,t'}^{chr} \left(1 + \rho_{ESS,t'}^{chr}\right). \quad (45)$$

Where t' is the index for time, $t' = t + 1$. Then, when the DPRs are introduced, the system supply and demand balance constraint should be revised as follows:

$$\left\{ \underbrace{\left[g'_{W,t} (1 - \varphi_W) + g'_{PV,t} (1 - \varphi_{PV}) + \left(g_{ESS,t}^{dis} - g_{ESS,t}^{chr} \right)^* + g_{CGT,t} (1 - \varphi_{CGT}) \right]}_{VPP\ revisd\ output} \right\} + g_{GC,t} + \sum_{i=1}^I \left(\Delta L_{i,t}^E + \Delta L_{i,t}^{R,dn} \right) = L_t - u_{PB,t} \Delta L_{PB,t} + \sum_{i=1}^I \left(\Delta L_{i,t}^{R,up} \right). \quad (46)$$

Then, like PBDR, the load curtailment produced by IBDR should also meet the maximum load change constraints and the pickup/drop off rate of load, as shown in Eq. (37)-Eq. (39). The load curtailment produced by IBDR is more flexible than PBDR, which could be regarded as a virtual generation unit. The virtual generation unit should also meet the following constraints:

$$[X_{t-1}^{on} - T_U](u_{IB,t-1} - u_{IB,t}) \geq 0, \quad (47)$$

$$[X_t^{off} - T_D](u_{IB,t} - u_{IB,t-1}) \geq 0, \quad (48)$$

Where the binary variable $u_{IB,t}$ is the status of the IBDR operation: 1 means the IBDR in operation, 0 the

IBDR not in operation.

(2) DRPs operation revise model

The implementation of DR smooths the load demand curve and reduces the system power shortage loss costs. But the cost of implementing DR affects the system. The optimization goal of this model is to minimize the system operation cost. For a customer, the price of power consumption is the lowest when the system operation cost reaches the minimum. Therefore, the minimum system operation cost is taken as the objective function as follows

$$\min \pi = \sum_{t=1}^T \sum_{s=1}^S \gamma_s \left[\left(\pi_t^{\text{PB}} + \pi_t^{\text{IB}} \right) + \left(\pi_{\text{CGT},t}^{\text{pg}} + \pi_{\text{CGT},t}^{\text{ss}} \right) + \rho_{\text{GC},t} g_{\text{GC},t} + \rho_{\text{SP},t} g_{\text{SP},t} \right]. \quad (49)$$

The revised CGT's output should meet the following constraint:

$$\left\{ \underbrace{\left[g'_{W,t}(1-\varphi_W) + g'_{PV,t}(1-\varphi_{PV}) + \left(g_{\text{ESS},t}^{\text{dis}} - g_{\text{ESS},t}^{\text{chr}} \right)^* + g_{\text{CGT},t}^*(1-\varphi_{\text{CGT}}) \right]}_{\text{VPP revised output}} + g_{\text{GC},t} + \sum_{i=1}^I \left(\Delta L_{i,t}^{*E} + \Delta L_{i,t}^{*R,dn} \right) \right\} = L_t - u_{PB,t} \Delta L_{PB,t} + \sum_{i=1}^I \left(\Delta L_{i,t}^{*R,up} \right). \quad (50)$$

The revised output and operation of the CGT and IBDR should also meet the constraints of Eq. (27) to Eq. (30), Eq. (37)-Eq. (39) and Eq. (47)-Eq. (48). In the lower layer model, the statuses of the CGT and ESSs are known by the upper layer model. In the lower layer model, assume that only the output of the CGT and ESSs can be adjusted to maintain the VPP steady operation. The power contract for GC signing in the upper model could be changed without paying any default cost. After the model above, the final output of WPP, PV, CGT, ESSs and DRPs can be calculated to obtain the VPP scheduling scheme.

In total, when the two-level models are both considered, the system operation reaches the optimum. The first model can improve the grid connection of the WPP and PV without undertaking the extra operation cost of the CGT. The second model can minimize the cost of system operation and reduce the price of customer power consumption.

5 Robust Stochastic-MILP model

5.1 Robust stochastic optimization model

The model proposed in Section 4 can help to ease the output stochastics of the WPP and PV on VPP optimization scheduling. The upper layer model provides the initial scheduling scheme based on the day-ahead prediction result. The lower layer model revises the scheduling scheme with the actual output of the WPP and PV. Since the statuses of the CGT and ESSs are certain, to realize the optimization

scheduling of the VPP, the stochastic influence of the WPP and PV on VPP scheduling should be considered in depth. The model directly takes the prediction results as the model input parameters without considering the prediction error, which may have a significant influence on the VPP operation if the error is large. Therefore, to consider the prediction error, robust stochastic optimization theory is introduced. The detailed application steps are as follows.

Assume that the absolute value of the error coefficients of WPP and PV are $e_{WPP,t}$ and $e_{PV,t}$. Then, the output of the WPP and PV may fluctuate within $\left[(1-e_{WPP,t}) \cdot g_{WPP,t}, (1+e_{WPP,t}) \cdot g_{WPP,t}\right]$ and $\left[(1-e_{PV,t}) \cdot g_{PV,t}, (1+e_{PV,t}) \cdot g_{PV,t}\right]$. To ensure the existence of a feasible solution, Eq. (25) is revised as follows

$$\underbrace{g_{W,t}(1-\varphi_W) + g_{PV,t}(1-\varphi_{PV}) + (g_{ESS,t}^{dis} - g_{ESS,t}^{chr}) + g_{CGT,t}(1-\varphi_{CGT}) + g_{GC,t}}_{VPP \text{ output in day-ahead scheduling}} \geq L_t - u_{PB,t} \Delta L_{PB,t}. \quad (51)$$

Assume that H_t is the system net load calculated in Eq. (51). Then,

$$H_t = (g_{ESS,t}^{dis} - g_{ESS,t}^{chr}) + g_{CGT,t}(1-\varphi_{CGT}) + g_{GC,t} - (L_t - u_{PB,t} \Delta L_{PB,t}). \quad (52)$$

Combining Eq. (50) with Eq. (50), we obtain

$$-\left[g_{WPP,t}(1-\varphi_{WPP}) \pm e_{WPP,t} \cdot g_{WPP,t}\right] - \left[g_{PV,t}(1-\varphi_{PV}) \pm e_{PV,t} \cdot g_{PV,t}\right] \leq H_t. \quad (53)$$

Eq. (53) shows that the inequality constraint becomes stricter when the influence of the stochastics is greater. To ensure that the constraints meet the requirement when the actual output reaches the prediction boundary, an auxiliary variable $\theta_{WPP,t}, \theta_{PV,t} (\theta \geq 0)$ is introduced to strengthen constraint Eq. (53). Assume that $\theta_{WPP,t} \geq |g_{WPP,t}(1-\varphi_{WPP}) \pm e_{WPP,t} \cdot g_{WPP,t}|$ and $\theta_{PV,t} \geq |g_{PV,t}(1-\varphi_{PV}) \pm e_{PV,t} \cdot g_{PV,t}|$. Thus, Eq. (53) can be changed as follows

$$-(g_{WPP,t} + e_{WPP,t} W_{WPP,t}) - (g_{PV,t} + e_{PV,t} W_{PV,t}) \leq -W_{WPP,t} + e_{WPP,t} |W_{WPP,t}| - W_{PV,t} + e_{PV,t} |W_{PV,t}|, \quad (54)$$

$$-W_{WPP,t} + e_{WPP,t} |W_{WPP,t}| - W_{PV,t} + e_{PV,t} |W_{PV,t}| \leq -W_{WPP,t} + e_{WPP,t} \theta_{WPP,t} - W_{PV,t} + e_{PV,t} \theta_{PV,t} \leq H_t. \quad (55)$$

Combining Eq. (54)-Eq. (55), Eq. (18)-Eq. (25) and Eq. (26)-Eq. (41), we can construct the stochastic optimization model with the most stringent constraints. The model has the strongest robustness, which can result in the most conservative solution. Due the occurrence probability of the extreme scenario, we introduce the robust coefficients Γ_{WPP} and Γ_{PV} , $\Gamma \in [0,1]$ to modify constraints Eq. (53) and Eq. (54) as

$$-(g_{WPP,t} + e_{WPP,t} W_{WPP,t}) - (g_{PV,t} + e_{PV,t} W_{PV,t}) \leq -W_{WPP,t} + \Gamma_{WPP} e_{WPP,t} |W_{WPP,t}| - W_{PV,t} + \Gamma_{PV} e_{PV,t} |W_{PV,t}|, \quad (56)$$

$$-W_{WPP,t} + \Gamma_{WPP} e_{WPP,t} |W_{WPP,t}| - W_{PV,t} + \Gamma_{PV} e_{PV,t} |W_{PV,t}| \leq -W_{WPP,t} + e_{WPP,t} \theta_{WPP,t} - W_{PV,t} + e_{PV,t} \theta_{PV,t} \leq H_t. \quad (57)$$

Combining Eq. (55)-Eq. (56), Eq. (17)-Eq. (24) and Eq. (25)-Eq. (40), we can construct the stochastic optimization model with the free adjustment robust coefficient. The model can be used to calculate the optimization scheduling scheme with different robust coefficients considering the different risk attitudes of the policymakers.

5.2 Mixed integer linear programming model

The proposed bi-level stochastic scheduling model is a mixed integer, nonlinear programming model (MINLP), including a nonlinear objective function and constraints, that is, Eq. (22). Eq. (26)-Eq. (29) and Eq.(46)-Eq.(47). This model costs significant time and effort, which may also cause the available commercial solvers breakdown in some special cases. To make the proposed model easily with binary variables, discrete variables and continuous variables, the linearization process method is used for the objective functions and constraints [26].

Step 1: Linearization of the nonlinear objective function. Divide the CGT's output limitation $[g_{CGT}^{\min}, g_{CGT}^{\max}]$ into N segments. Then, the objective function can be expressed as a piecewise function.

If $g_{CGT,i} \in [g_{CGT}^{\min} + n\Delta g_{CGT}, g_{CGT}^{\max} + (n+1)\Delta g_{CGT}]$, the function in this subinterval can be calculated as follows:

$$\pi'(g_{CGT}) = \pi(g_{CGT}^{\min} + n\Delta g_{CGT}) + (g_{CGT,i} - g_{CGT}^{\min} - n\Delta g_{CGT}) \times [b_{CGT} + (2n+1)c_{CGT}\Delta g_{CGT} + 2c_{CGT}g_{CGT}^{\min}] \quad (57)$$

Where $n = 0, 1, \dots, N-1$, $\Delta g_{CGT} = (g_{CGT}^{\max} - g_{CGT}^{\min})/N$. In general, as N increases, the error of the piecewise function decreases. When $N \geq 5$, the maximum error is less than 1%. Fig. 5 is the linearization process of the objective function.

Step 2: Linearization of the nonlinear constraints. For nonlinear constraints Eq. (26)-Eq. (29) and Eq. (46)-Eq. (47), we introduce the linearization process method, including the initial status variables progress and the startup-shutdown time progress [38]. After the linearization progress above, the MINLP can be transferred into the mixed integer linear programming model (MILP).

Figure.5 Linearization progress of the objective function

6 Simulation analysis

6.1 Basic data

An independent micro-grid on an island in East China (Longitude 122.40 degrees, 30.10 degrees north latitude) is utilized for the simulation analysis of the proposed model. The system contains 2×1 MW wind turbine, 5×0.2 MW solar photovoltaic powers, 1×1 MW CGT unit and 1×0.5 MW energy storage system [39]. The CGT unit contains a diesel generator, and the climbing and downhill slope speed are 01.MW/h and 0.2MW/h, respectively, the startup time and shutdown time are 0.1 h and 0.2 h, respectively, and the startup and shutdown are both 0.102 Yuan/kW·h. Referring to literature [39], we divide the cost curve into two segments and linearized the two segments. The slope coefficients of the two segments are 110 Yuan/MW and 362 Yuan/MW. The power consumption rate during the charging-discharging progress is approximately 4% [40], and the power charging price and discharging price obey the real-time electric power price.

Assume that the parameters of wind turbine are $v_{in} = 3 \text{ m/s}$, $v_{rated} = 14 \text{ m/s}$ and $v_{out} = 25 \text{ m/s}$, and the shape parameter and scale parameters $\varphi = 2$ and $g = 2\bar{v}/\sqrt{\pi}$ [39] respectively. According to the illumination intensity changing curve on the island for a week, the illumination intensity parameters α and β can be simulated as 0.3 and 8.54 [40]. The proposed scenario simulation method is used to obtain the simulation scenarios of the WPP output and PV output. 10 typical scenarios are obtained after using the K-distance to reduce the scenes. Suppose that the prediction errors of the WPP and PV are 0.08 and 0.06 and both initial robust coefficients are 0.5.

The grid connection prices of the CGT, wind power, and solar photovoltaic power are 0.52 Yuan/kW·h, 0.61 Yuan/kW·h and 1.0 Yuan/kW·h, respectively. The customer power consumption price is 0.59 Yuan/kW·h before PBDR. Twenty-four hours are divided into the peak load (12:00-21:00) period, float load (0:00-3:00 and 21:00-24:00) period, and valley load (3:00-12:00) period. After PBDR, the power demand-price elastic is set according to [29]. The power price in the float period remains the same, the peak load power price is increased by 30%, and the valley load power price is reduced by 50%. Then, set the price-quantity offer package of the DRPs referring to [34]. To avoid customer excessive demand responding to PBDR, which would cause the peak-valley to reverse, the load fluctuation caused by PBDR is limited to 10% of the original load. The daily peak load of a typical customer is 9 MW. The demand load distribution, wind power and solar photovoltaic power prediction values are shown in Fig. 6.

Figure 6. Prediction values of the load, WPP and PV output

After inputting above basic data, the model is solved by the GAMS software using the CPLEX 11.0 linear solver from ILOG_solver [29]. The CPU time required for solving the problem of different case studies with an idea pad450 series laptop computer powered by a core T6500 processor and 4 GB of RAM under the four cases is less than 20 s. When the optimization is MILP, the GAMs software obtains a satisfactory solution quickly. Fig. 7 is the bi-level optimization flowchart for the VPP scheduling model.

Figure.7 The bi-level optimization flowchart for the VPP scheduling model

6.2 Simulation scenarios

To analyze the optimization effects of the DR and ESSs on VPP operation comparatively, we used 4 simulation scenarios:

Case 1: self-scheduling of the VPP without DR and ESSs. This case is used to analyze the applicability of the bi-level scheduling model and the robust optimization theory for overcoming the VPP output stochastics.

Case 2: self-scheduling of the VPP only with DR. This case is used to discuss the optimization effect of the demand response on the VPP optimization operation.

Case 3: self-scheduling of the VPP only with ESSs. This case is used to analyze the influence of the ESSs and VPP optimization operation.

Case 4: self-scheduling of the VPP with DR and ESSs. This case is used to discuss the coordination effect of the ESSs and DR on the VPP optimization operation.

These four cases verify the proposed bi-level stochastic scheduling model and comparatively analyze the optimization effect of the ESSs and DR on the VPP grid connection.

6.3 Scheduling operation results

6.3.1 Case 1: self-scheduling of the VPP without DR and ESSs

In Case 1, the real-time outputs of wind power and solar photovoltaic power are 8.97 MW·h and 3.28 MW·h, respectively. In day-ahead scheduling and real-time scheduling, the outputs of the WPP and PV are 9.105 MW·h, 3.346 MW·h and 8.253 MW·h, and 3.018 MW·h, that is, the units' generation is arranged according to the day-ahead scheduling scheme. The system should bear the power shortage cost, which would reduce the VPP operation income. In two scheduling stages, the VPP incomes are 11,814.8 Yuan and 11,958.96 Yuan. Fig. 8 is the VPP operation optimization results in the upper/lower layer model.

Figure.8 VPP operation optimization results in the upper/lower layer model

Firstly, compare the difference between the output of the wind power and solar photovoltaic power in the two scheduling stages. In the valley load periods, the system has enough backup service. The VPP output in the real-time stage is consistent with the arranged output in the day-ahead scheduling scheme. However, in the peak load periods, to meet the balance constraint between supply and demand, the controllable unit CGT is called to output, which makes system backup service insufficient. To reduce the influence of wind power and solar photovoltaic uncertainty on the power system, the VPP reduces the output of the WPP and PV. For example, from 11:00~13:00, the solar photovoltaic power output is reduced by 98 kW·h. From 15:00 to 19:00, the wind power output is reduced by 314 kW·h, and the output of the CGT units also decreases. The results illustrate that the proposed bi-level scheduling model can relieve the punishment cost caused by the uncertainty of the wind power and solar photovoltaic power, which contributes to realizing system optimization operation.

Secondly, to analyze the applicability of robust optimization theory in solving the stochastic output of the WPP and PV, we discuss the VPP scheduling optimization results with different robust coefficients, as

shown in Table 1.

Table 1. VPP operation optimization results with different robust coefficients

$(\Gamma_{WPP}, \Gamma_{PV})$	VPP power output/MW·h			Abandoned power/MW·h		Benefit/¥
	CGT	WPP	PV	WPP	PV	
(0,0)	7.371	8.253	3.018	0.717	0.262	11958.96
(0.5,0)	7.999	7.625	3.018	1.345	0.262	11908.72
(0,0.5)	7.601	8.253	2.788	0.717	0.492	11850.86
(0.5,0.5)	8.230	7.624	2.788	1.346	0.492	11800.54

Compare the optimization results with the robust coefficient. When the robust coefficients of the WPP and PV are introduced, to reduce the uncertain influence of the WPP and PV on the system stability operation, the system reduces the output of the WPP and PV. When $\Gamma_{WPP} = 0.5$ and $\Gamma_{PV} = 0$, the WPP output is reduced by 0.628 MW·h. When $\Gamma_{WPP} = 0$ and $\Gamma_{PV} = 0.5$, the PV output is reduced by 0.23 MW·h. When $\Gamma_{WPP} = 0.5$ and $\Gamma_{PV} = 0.5$, the outputs of both the WPP and PV are reduced. The output reduction of the WPP and PV reduces the system operation risk and avoids system power shortage costs to the maximum extent. It may also reduce the VPP operation income. Fig. 9 is the VPP scheduling optimization results with $\Gamma_{WPP} = \Gamma_{PV} = 0.5$.

Figure.9 VPP power output with $\Gamma_{WPP} = \Gamma_{PV} = 0.5$

Compared with Fig. 8, when the robust coefficient is introduced, in peak load periods, the demand load is large, and the CGT units are called to meet the balance request between the power supply and demand, which makes the backup service for the grid connection of the WPP and PV. To reduce the system power shortage punishment costs, the system reduces the grid connection of the WPP and PV. In other periods, the demand load is relative small, and CGT can provide more backup service for the grid connection of the WPP and PV, which would improve the output and the grid connection of the WPP and PV, for example, in 21:00-24:00 and 0:00-4:00. To ensure the balance between power supply and demand,

the output of the CGT and WPP maintains a reverse-matching relationship, which means the CGT is the main backup service provider for the WPP and PV. We perform a sensitive analysis of the influence of Γ_{WPP} and Γ_{PV} on system operation. Fig. 10 is the CGT power output with different robust coefficients.

Figure.10 CGT power output with different robust coefficients

The system reduces the WPP and PV output and increases the CGT output to minimize the system scheduling risk, because the VPP operation risk mainly comes from the output stochastics of the WPP and PV. According to Fig. 10, from the aspect of the single robust coefficient effect, when Γ_{WPP} or Γ_{PV} is a constant, as Γ_{PV} or Γ_{WPP} increases, the CGT output also increases. From the aspect of the double robust coefficients effect, the CGT output change trend can be divided into three segments; when $\Gamma \leq 0.3$ the robust coefficient is small, which means the decision maker prefers risk, the slope of the CGT output increase does not reach the maximum point. When $\Gamma \in (0.3, 0.5)$, the robust coefficient is large, which means the decision maker hates risk, and the slope of the CGT output increase reaches the maximum point. When $\Gamma \geq 0.5$, the CGT output is close to its upper limit. To make use of wind power and solar photovoltaic power to improve the system scheduling benefits, the CGT output increase is smooth, that is, robust optimization theory provides a decision tool for decision makers with different risk attitudes.

The bi-level optimization model results in benefits for the system by arranging pre-scheduling and revising the output of the WPP and PV with their real-time outputs, which reduces the system power shortage punishment cost and improve the VPP operation income. Robust stochastic optimization provides a decision tool for decision makers with different risk attitudes. Therefore, the proposed bi-level stochastic scheduling optimization model balances VPP operation risk and income, which is better than other

methods to achieve system optimal operation. In practical applications, decision makers adjust the robust coefficient according to their own risk affordability. When their risk affordability is low, the outputs of the WPP and PV are reduced, which decreases the system power shortage punishment costs caused by the stochastics of the WPP and PV. When their risk affordability is high, the output of WPP and PV is increased, which can increase the income of the VPP operation, but the risk caused by the stochastic output should be considered.

6.3.2 Case 2: self-scheduling of the VPP only with DR

In Case 2, set $\Gamma_{WPP} = \Gamma_{PV} = 0.5$. The scheduling optimization results with PBDR, IBDR and DR (PBDR and IBDR) are discussed. The VPP operation income under the three scenarios is 11721.68 Yuan, 12888.5 Yuan and 12993.22 Yuan respectively. Fig. 11 displays the load demand curves after DR.

Figure 11. Load demand curve after DR

According to Fig. 11, compared with the original scheduling, PBDR has a load shifting effect. The peak load is 0.87 MW, which decreased by 0.03 MW. The valley load is 0.61 MW, which increased by 0.03 MW. The peak-valley ratio decreased from 1.5 to 1.38. IBDR directly reduces the demand load in the peak load period. The peak load is 0.85 MW, 0.05 less than Case 1, but the effect of the valley load is not as obvious as in PBDR and only increased by 0.01 MW. The peak-valley ratio is 1.39, which is bigger than PBDR. The introduction of both PBDR and IBDR smooths the system load to the maximum extent, and the peak load is reduced by 0.06 MW, whereas the valley load is increased by 0.05 MW. The peak-valley ratio is 1.29 and reaches the minimum. In the day-ahead scheduling, the PBDR is conducive to smoothing the demand load curve and increasing system backup service. In hour-ahead scheduling, the IBDR could call the demand side to provide up/down reserves for VPP generation, which is conducive to improving the

output of the WPP and PV. The VPP operation optimization results with/without DR are shown in Table 2.

Table 2. VPP operation optimization results with/without DR

	VPP power output/MW·h				Abandoned power/MW·h		Load demand/MW		
	CGT	WPP	PV	IBDR	WPP	PV	Peak load	Valley load	Peak-valley ratio
Origin	8.23	7.624	2.788	—	1.346	0.492	0.9	0.6	1.5
PBDR	7.255	8.073	2.952	—	0.897	0.328	0.87	0.63	1.38
IBDR	8.592	8.234	2.887	± 0.17	1.076	0.394	0.85	0.61	1.39
DR	7.470	8.592	3.018	± 0.31	0.718	0.262	0.84	0.65	1.29

According to Table 2, compared with Fig. 11, the introduction of both PBDR and IBDR allows the VPP operation result to reach the optimum. The customers' response to VPP optimization scheduling reaches the maximum. The up/down reverse capacity provided by IBDR is 0.31 MW, which is more than after introducing only IBDR. Therefore, the introduction of PBDR could promote IBDR to participate into VPP scheduling and result in a more obvious load shifting effect. The valley load in this scenario is more than the valley load in the scenario that only introduces PBDR, which means that IBDR improves PBDR's load shifting effect. Therefore, PBDR and IBDR have a coordinated optimization effect, and the abandoned energy of WPP and PV reaches the minimum, which is 0.718 MW·h and 0.262 MW·h, respectively. Fig. 12 displays the VPP scheduling optimization results in Case 2.

Figure 12. VPP operation power output in Case 2

Compared with Fig. 9, DR smooths the load demand curve. In the peak load periods, the CGT output decreases, which provides more backup services for the WPP and PV. Then, the output of the WPP and PV increases by 0.425 MW·h and 0.152 MW·h, respectively. In the valley load periods, customers' demand load increases, which increases the grid connection space for WPP and PV. The CGT provides backup service and participate in energy scheduling. The outputs of the WPP and PV increase by 0.21 MW·h and

0.08 MW·h, respectively. Then, to coordinate with the VPP output, IBDR provides down reserves in the peak load periods and up reverse in the valley load periods. Overall, compared with the original scenario, DR improves the output of the WPP and PV by 0.628 MW·h and 0.23 MW·h, respectively, and reduces the CGT output by 0.802 MW·h. Therefore, DR effectively improves the output of the WPP and PV.

Furthermore, the results of the IBDR participating in the up/down spinning reverse with different backup service prices are analyzed. The up spinning reverse price has been increased from 100 Yuan/MW·h to 220 Yuan/MW·h step-by-step, whereas the down spinning reverse price has been increased from 200 Yuan/MW·h to 500 Yuan/MW·h. From the overall trend, as the backup service increases, the system reduces the up/down backup capacity provided by IBDR. To maintain the balance between the demand and supply, the system still calls for backup service. Therefore, the backup service increases when the prices of the up/down spinning reverse increases. But the speed of the system reducing backup service capacity increases first and then decreases. When the speed reaches the inflection point, to realize system optimal operation, the system prefers to bear part of the backup service cost to avoid the power shortage punishment cost. Fig. 13 is the reserve capacity under different reserve prices.

Figure 13. Reserve capacity under different reserve prices

To optimize VPP operation, the power price and reserve price should be ensured according to the actual load demand to utilize PBDR and IBDR to the maximum extent. The load demand curve is then the smoothest. The outputs of the WPP and PV reach the maximum. The result of the VPP operation also reaches the optimum.

6.3.3 Case 3: self-scheduling of VPP only with ESSs

In Case 3, suppose that Γ_{WPP} and Γ_{PV} are the same to be 0.5. The system optimization scheduling

result with ESSs is discussed. In Case 3, the VPP operation income is 12238.22 Yuan. The outputs of the WPP and PV are 8.772 MW·h and 3.050 MW·h, respectively. The charging and discharging powers of the ESSs are 0.3 MW·h and 0.22 MW·h, respectively. The abandoned energies of the WPP and PV are 1.076 MW·h and 0.394 MW·h, respectively. Fig. 14 is the VPP operation power output in Case 3.

Figure 14. VPP operation power output in Case 3

According to Fig. 14, in the peak load periods, the ESSs charge power and replace part of the CGT output, providing backup service capacity for the WPP and PV. In the valley load periods, the ESSs discharge power and improve the demand load to expand the grid connection space of the WPP and PV. Compared with Case 1, the outputs of the WPP and PV increase obviously in the valley load periods. The abandoned energy of the WPP and PV decreased by 0.27 MW·h and 0.092 MW·h, respectively. In flat load periods, the ESSs only charge from 23:00-24:00 with small power, the WPP and PV outputs increase a little in this period and are almost the same as in other periods. The VPP operation optimization result in Case 3 is shown in Table.3.

Therefore, to optimize VPP operation, more ESSs should be integrated into the VPP. ESSs charge power in the peak load periods and discharge power in valley load periods, which smooths the load demand curve. ESSs could replace the CGT to provide up/down reserve capacity for the WPP and PV by their charging-discharging characteristics, which reduces the system generation cost.

6.3.4 Case 4: self-scheduling of VPP with DR and ESSs

In Case 4, the VPP operation income is 12355.48 Yuan, and the outputs of the WPP and PV are 8.772 MW·h and 3.050 MW·h, respectively. To coordinate with the VPP scheduling, the scheduling results of the ESSs and IBDR show a reverse distribution relationship. In the valley load periods, the ESSs charge power and IBDR provides up spinning reserve. In peak load periods, the ESSs discharge power and IBDR

provides down spinning reverse. This relationship reduces the system's demand on the CGT backup service and also expands the grid connection space of WPP and PV. With the coordination of the ESSs and the IBDR, the grid connection power of the WPP and PV reaches the maximum. The CGT output reaches the minimum in the peak load periods, which provides more backup capacity for the WPP and PV and is conducive to controlling the risk brought by the uncertainty of the WPP and PV. Fig. 15 displays the VPP operation power output in Case 4.

Figure 15. VPP operation power output in Case 4

6.4 Results comparative analysis

To analyze the influence of the DR and ESSs on VPP scheduling, this section examines the VPP optimization scheduling results under four cases. Table 3 shows VPP operation optimization results in different cases.

Table 3. VPP operation optimization of the results in different cases

	VPP power output/MW·h					Abandoned power rate/MW·h		Load demand/MW		
	CGT	WPP	PV	IBDR	ESS	WPP	PV	Peak load	Valley load	Peak-valley ratio
Case 1	8.272	7.624	2.788	-	-	1.346	0.492	0.9	0.6	1.50
Case 2	7.470	8.592	3.018	±0.31	-	0.718	0.262	0.84	0.65	1.29
Case 3	7.772	7.894	2.886	-	(-0.3,0.22)	1.076	0.394	0.86	0.64	1.34
Case 4	6.939	8.772	3.050	±0.15	(-0.21,0.18)	0.538	0.230	0.83	0.685	1.21

According to Table 3, both the DR and ESSs can improve the grid connection of the WPP and PV. The VPP operation optimization result reaches the optimal when they are both introduced. From the aspect of the demand load curve, both the ESSs and DR respond to the load demand distribution and have good load shifting effect by charging-discharging power and providing up/down spinning reverse. When introducing only the ESSs or DR, the peak-valley ratio is 1.34 or 1.29, respectively. When introducing both, the peak-valley ratio decreases by 1.21. The load demand curve in different cases is given in Fig. 16.

Figure 16. Load demand curve in different cases

Furthermore, the VPP operation outputs have different influential factors. The introduction of ESSs provides backup service for the WPP and PV by charging-discharging power, which is conducive to smoothing the VPP output power and reducing backup service for the VPP provided by CGT. This process could also improve the output of the WPP and PV. The introduction of DR could smooth the demand load curve. In peak load periods, the demand load decreases to improve the CGT backup service capacity. In valley load periods, the demand load improves to increase the backup service capacity for the WPP and PV grid connection. In this way, the introduction of DR achieves the objective of smoothing the VPP output. When both the DR and ESSs are introduced, the VPP output curve is smoothed to the maximum extent. The grid connection of the WPP and PV reaches the maximum. The abandoned energy of the WPP and PV reaches the minimum. The income of the VPP operation reaches the maximum. Fig. 17 is the VPP operation power output in different cases.

Figure 17. VPP operation power output in different cases

Finally, the VPP operation income with different robust coefficients is discussed. The sensitive analysis for the robust coefficient of WPP and PV is performed. The fluctuation scope changes from 0.1 to 0.9, and

the VPP operation benefit from different robust coefficients is given in Fig. 18.

Figure 18. VPP operation benefit with different robust coefficients

According to Fig. 18, as the robust coefficient increases, system operation income decreases. The decreasing slope occurs in three stages. When $\Gamma < 0.5$, the decision maker has a good attitude toward risk, which is a will to bear the risk of wind power and solar photovoltaic power uncertainty and gain high income brought by wind power and solar photovoltaic power. When $\Gamma \geq 0.5$, the decision maker does not wish to bear the risk of the wind power and solar photovoltaic power uncertainty, and the WPP and PV output is reduced, which influences the VPP operation income. When $\Gamma > 0.7$, the VPP needs to meet the system load demand. If the WPP and PV output is decreased rapidly, the system may bear the power shortage cost. Then, the system would slow the speed of reducing the WPP and PV output, which is in accordance with the conclusion drawn from Fig. 10.

7 Conclusions

The WPP, PV, CGT, ESSs and DRPs are aggregated in VPP in this paper. A robust optimization model is introduced to build a bi-level stochastic scheduling optimization mode for the VPP. In the upper layer model, a joint scheduling optimization model for the VPP and PBDR with the day-ahead prediction result of the WPP and PV is proposed under the objective function of the maximum VPP operation income. In the lower layer model, a model is constructed to revise the day-ahead scheduling scheme with the actual output of the WPP and PV under the objective functions of the minimum system net load and the minimum system operation cost. A case analysis is performed with the real data of an independent micro-grid on an island in East China. The conclusions can be summarized as follows:

(1) The proposed bi-level optimization model helps the system make a pre-scheduling plan and revise

the scheduling scheme considering the WPP and PV real-time output, which is conducive to reducing the system power shortage punishment cost and improving the VPP operation income. Robust stochastic theory provides decision tools for decision makers with their own risk affordability. When their risk affordability is low, the output of the WPP and PV will decrease, which would decrease the system power shortage punishment cost. When their risk affordability is high, the output of WPP and PV will increase, which could increase the income of the VPP operation, but the decision makers must address the risk brought by the output stochastics.

(2) When both IBDR and PBDR are introduced, IBDR provides backup service for the WPP and PV. PBDR guides customers to coordinate the VPP power generation scheduling, which could achieve the linkage optimization between the power generation side and demand side. PBDR has good load shifting effect. PBDR's effect to reduce the peak load is weaker than IBDR, but its effect to increase the valley load is stronger than IBDR. The demand load curve is smoothed to the maximum extent if both PBDR and IBDR are introduced. To optimize the VPP operation, the power price and reserve price should be ensured according to the actual load demand, which would utilize PBDR and IBDR to the maximum extent.

(3) ESSs could coordinate the output of the WPP and PV by charging-discharging power. ESSs charge power in the peak load periods, discharge power in the valley load periods, and charge less power in flat periods, which could smooth the load demand curve. The ESSs could replace the CGT to provide up/down reserve capacity for the WPP and PV by their charging-discharging characteristics.

(4) When both ESSs and IBDR are introduced into the VPP, also PBDR is implemented on the demand side, the grid connection of the WPP and PV power and the VPP operation income reach their maximum, and the abandoned power reaches the minimum. These results indicate that ESSs and DR have a coordinated effect in achieving linkage optimization between the generation side and the demand side, which helps the system to achieve the optimal scheduling scheme.

Nomenclature

abbreviations		$\rho_{i,t}^{R,dr}$	cost of DPR i participating in up demand-side reserve scheduling
VPP	virtual power plant	$\rho_{W,t}$	grid-price of WPP at time t
DR	demand response	$\rho_{PV,t}$	grid-price of PV at time t
PBDR	price-based DR	$\rho_{ESS,t}^{dis}$	discharge price of ESSs at time t
IBDR	incentive-based DR	$\rho_{ESS,t}^{chr}$	charge price of ESSs at time t

WPP	wind power plant	$\rho_{CGT,t}$	grid-price of CGT at time t
PV	photovoltaic generators	ϕ_W	power loss rate of WPP
CGT	convention gas turbine	ϕ_{PV}	power loss rate of PV
ESSs	energy storage systems	ϕ_{CGT}	power loss rate of CGT
DRPs	demand resource providers	v	wind speed
MILP	mixed integer linear programming model	φ, ϑ	shape factor and scale factor
DERs	distributed energy resource	$P(v)$	probability of the wind speed v
Set		v_a, v_b	wind speeds limitation of state v
s, t	index for time	v_{in}	cut-in speed of wind turbine
i	index for DPR	v_{rated}	rated speed of wind turbine
		v_{out}	cut-off speed of wind turbine
j	index for step	v_t	actual speed of wind turbine at time t
k	index for scenario	$\mathcal{G}_R$	rated output of wind turbine
W	index for WPP	α, β	shape parameters of Beta distribution
PV	index for PV	θ_t	solar irradiance at time t
CGT	index for CGT	u, σ	mean value and standard deviation of irradiance
ESS	index for ESSs	θ_c, θ_d	solar irradiance limits of state θ
Variable		η_{PV}	efficiency of PV
π_t^{PB}	cost of DPRs participating in PBDR at time t	S_{PV}	total area of PV
π_t^{IB}	cost of DPRs participating in IBDR at time t	f_1	the objective function of the maximum VPP operation revenue
L_t	load change after PBDR at time t	$R_{W,t}$	operation revenue of WPP at time t
$\Delta L_{i,t}^E$	load reduction of DPR i	$R_{PV,t}$	operation revenue of PV at time t
$\Delta L_{i,t}^{R,dn}$	up demand-side reserve of DPR i at time t	$R_{ESS,t}$	operation revenue of ESSs at time t
$\Delta L_{i,t}^{R,up}$	down demand-side reserve of DPR i at time t	$R_{CGT,t}$	operation revenue of CGT at time t
$\mathcal{G}_{CGT,t}$	power output of CGT at time t	γ_s	the weight of scenario s
$\mathcal{G}_{ESS,t}^{dis}$	discharge power of ESSs at time t	$\pi_{CGT,t}^{pg}$	power generation cost of CGT at time t
$\mathcal{G}_{ESS,t}^{chr}$	charge power of ESSs at time t	$\pi_{CGT,t}^{ss}$	startup-shutdown cost of CGT at time t
$\mathcal{G}_{W,t}$	output of WPP at time t	$a_{CGT}, b_{CGT}, c_{CGT}$	cost coefficient of CGT power generation
$\mathcal{G}_{PV,t}$	output of PV at time t	N_{CGT}^{cold}	cold startup cost of CGT
$\mathcal{G}_{VPP,t}$	output of VPP at time t	N_{CPP}^{hot}	hot startup cost of CGT
$\mathcal{G}_{GC,t}$	power output of system purchasing from generation company	$T_{CPP}^{\min}$	minimum allowable downtime of CGT
$\Delta L_{PB,t}$	load change produced by PBDR at time t	T_{CPP}^{cold}	cold startup time of CGT
Q_t	storage electricity of ESS at time t	$\mathcal{G}_{CGT}^{\max}, \mathcal{G}_{CGT}^{\min}$	upper and lower limitation of CGT
$D_{CGT,t}$	startup-shutdown cost of CGT at time t	$\Delta \mathcal{G}_{CPP}^+, \Delta \mathcal{G}_{CPP}^-$	upper and lower limitation of CGT
$T_{CGT,t}^{\text{off}}$	continuous downtime of CGT at time t	M_{CPP}^{on}	minimum startup time of CGT
$T_{CPP,t-1}^{\text{on}}$	continuous operation time of CGT at time $t-1$	M_{CPP}^{off}	minimum shutdown time of CGT
$T_{CPP,t-1}^{\text{off}}$	continuous shutdown time of CGT	Q_0	initial storage electricity of ESS

	at time $t-1$		
$\Delta L_{IB,t}$	reserve capacity provided by DRPs.	$\rho_{ESS,t}^{dis}$	power loss rate of ESS discharging at time t
$\mathcal{G}_{CGT,t}^*$	revised output of CGT at time t	$\rho_{ESS,t}^{chr}$	power loss rate of ESS charging at time t
$\Delta L_{i,t}^{*E}$	revised IBDR output plan participating in energy market	$\bar{\mathcal{G}}_{EV,t}^{chr}$	maximum discharging power of ESS at time t
$\Delta L_{i,t}^{*R,dn}, \Delta L_{i,t}^{*R,up}$	revised IBDR reserve capacity participating in reserve market	$\bar{\mathcal{G}}_{EV,t}^{dis}$	maximum charging power of ESS at time t
H_t	system net load at time t	$\Delta L_{PB,t}^{\max}$	maximum load change at time t
Parameter		$\Delta \bar{L}_{PB}, \Delta \underline{L}_{PB}$	pickup/drop off rate of load produced by PBDR
e_{st}	demand-price elastic	$\Delta L_{PB}^{\max}$	maximum load change
P_t^0	electricity price before PBDR	$\mathcal{G}_{VPP,t}^{\max}$	maximum output of VPP at time t
L_s^0	load demand before PBDR	$\mathcal{G}_{VPP,t}^{\min}$	minimum output of VPP at time t
ΔL_s	electricity changes of demand after PBDR	r_1, r_2, r_3	up reserve coefficients of load, WPP and PV
ΔP_t	electricity changes of price after PBDR	r_4, r_5	down reserve coefficients of WPP and PV
$D_i^{j,\min}$	minimum acceptable load reduction of DPR i in step j	$\mathcal{G}'_{PV,t}$	actual output of WPP at time t
$D_i^{j,\max}$	sum of all deployed load curtailments of DPR i in step j	$\mathcal{G}'_{W,t}$	actual output of PV at time t
$\Delta L_{i,t}^j$	load reduction of DPR i in step j at time t	$X_{t-1}^{\text{on}}, X_t^{\text{off}}$	startup and shutdown time limitation of load curtailment at time t
$D_{i,t}^j$	deployed load curtailment of DPR i in step j at time t	T_U, T_D	minimum startup and shutdown time of load curtailment at time t
$D_i^{\min}$	minimum load reduction of DPR i	$\rho_{GC,t}$	power price of system purchasing from generation company
$D_i^{\max}$	maximum load reduction of DPR i	$\mathcal{G}_{GC,t}$	power output of system purchasing from generation company
$\rho_{i,t}^E$	cost of DPR i participating in demand-side reserve scheduling	$\rho_{SP,t}$	punish price of power shortage.
$\rho_{i,t}^{R,dn}$	cost of DPR i participating in down demand-side reserve scheduling	$\mathcal{G}_{SP,t}$	electricity of power shortage

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