A multi-energy complementary virtual power plant operation optimization model for distributed energy aggregation is considered

Xiaoyun Qu¹, Xiong Xiong¹, Yu Ji¹, Ying Zhang¹, Chuanzheng Gong² and Hang Liu² *
¹ State Grid Shanghai Energy Interconnection Research Institute, Beijing, China
² School of Economics and Management, North China Electric Power University, Beijing, China

*Corresponding author e-mail: liuh2018@ncepu.edu.cn

Abstract. In this paper, a stochastic scheduling optimization model of virtual power plant (VPP) is established to maximize the net operating income of VPP considering the loss of uncertain risks. Firstly, the model of conventional scheduling optimization of virtual power plant is presented. Then, the risk conditional value (CVaR) theory is introduced to quantify the operational risk level of VPP, and the constraint conditions containing random variables are converted by the confidence method to establish the risk avoidance scheduling optimization model of VPP. Finally, an improved IEEE30 node system is used as a simulation system to verify the validity and applicability of the proposed model.

1. Conventional operation optimization model of virtual power plant
Through advanced information technology, virtual power plant technology can effectively aggregate a large number of distributed power sources, controlled loads and energy storage units installed in different regions, and realize energy interconnection and sharing in a wide range [1]. Therefore, this paper focuses on the construction of its risk avoidance scheduling optimization model, in order to provide decision support for VPP optimization operation.

1.1. Objective Function
In VPP power generation scheduling involving wind power plant (WPP), photovoltaic[2] power generation unit (PV) and small hydropower station (SHS), the optimization goal is to maximize the expected operating income, and the basic mathematical model is constructed. The specific objective function is as follows:

\[ \max N(g_{VPP}) = R(g_{VPP}) - C(g_{VPP}) \]  (1)

Where, \( g_{VPP} \) represents the power output power of VPP, \( N(\cdot) \) represents VPP's net operating income, \( R(\cdot) \) and \( C(\cdot) \) represents VPP's operating income and cost respectively, which are specifically calculated as follows:
Where, $R_{WPP,t}$, $R_{PV,t}$, $R_{SHS,t}$, $R_{CGT,t}$, $R_{ESS,t}$ and $R_{IBDR,t}$ respectively represent the operating income of WPP, PV, SHS, gas turbine (CGT), ESS and incentive demand Response (IBDR) at time $T$. Where, except ESS and IBDR, the operating income of other types of generating sets is equal to The Times value of electricity price and electricity quantity [3]. The return calculation of ESS is shown in Formula (3):

$$R_{ESS,t} = P_{ESS,t}^{dis} * g_{ESS,t}^{dis} - P_{ESS,t}^{ch} * g_{ESS,t}^{ch}$$  (3)

Where, $P_{ESS,t}^{dis}$ and $P_{ESS,t}^{ch}$ respectively represent the charging and discharging prices of ESS at time $T$; $g_{ESS,t}^{dis}$, and $g_{ESS,t}^{ch}$ respectively represent the charge and discharge quantity of ESS at time $T$; Further, the operating costs of VPP are mainly composed of CGT, SHS and ESS, which are specifically calculated as follows:

$$C(g_{VPP}) = \sum_{t=1}^{T} \left( C_{CGT,t} + C_{SHS,t} \right)$$  (4)

Where, $C_{CGT,t}$ and $C_{ESS,t}$ respectively represent the operating costs of CGT and ESS. This paper only considers the water cost in the running stage. Therefore, this paper believes that the operating cost of SHS is equal to the product of water consumption and water price. Furthermore, the power generation cost of CGT is mainly equal to the consumption cost of natural gas [4] and start-stop cost.

### 1.2. Constraints

The specific constraints for VPP to optimize its operation are as follows:

1. **Load supply and demand balance constraint**

$$g_{VPP,t} \left(1 - \psi_{WPP} \right) + g_{PV,t} \left(1 - \psi_{PV} \right) + g_{CGT,t} \left(1 - \psi_{CGT} \right) + u_{IB,t} \Delta L_{IB,t}^{E} + \left( g_{ESS,t}^{dis} - g_{ESS,t}^{ch} \right) \geq L_t^0 - u_{PB,t} \Delta L_{PB,t}$$  (5)

Where: $\Delta L_{IB,t}^{E}$ represents the output power provided by IBDR to the energy market at time $T$; $L_t^0$ Represents end-user load demand; $u_{IB,t}$ and $u_{PB,t}$ respectively represent the state variables of IBDR and PBDR, 0-1 variables; $\Delta L_{PB,t}$ represents the load change generated by PBDR at time $t$.

2. **SHS operation constraint**

Small hydropower is subject to seasonal constraints, there are low water period and high water period [5]. Accordingly, the water demand of the reservoir, the power generation discharge and the water abandonment constraint are as follows:

$$V_{min} \leq V_{t-1} + \int_{t_{t-1}}^{t} (q_t - Q_t - S_t) dt \leq V_{max}$$  (6)

$$Q_{min} \leq Q_t \leq Q_{max}$$  (7)

$$S_{min} \leq S_t \leq S_{max}$$  (8)

Where: $V_{t-1}$ is the water demand of the reservoir adjusted before the start of any power generation period; $V_{max}$ is the minimum allowable reservoir capacity; $V_{min}$ is the maximum amount of water available for the permitted reservoir; $q_t$, $Q_t$ and $S_t$ are respectively the natural inflow, power generation diversion and abandonment flow of SHS at time $T$; $Q_{min}$, $Q_{max}$ are respectively the minimum and maximum of SHS power generation flow; $S_{min}$, $S_{max}$ are respectively the minimum and maximum amount of allowable water abandonment by SHS.
(3) Standby constraint of system rotation

\[ g_{\text{WPP},t}^{\text{max}} - g_{\text{WPP},t}^{\text{min}} + \Delta L_{\text{PB},t}^{\text{up}} + \Delta L_{\text{LR},t}^{\text{up}} \geq r_1 \cdot \Delta L_{\text{IB},t} + r_2 \cdot g_{\text{WPP},t} + r_3 \cdot g_{\text{PV},t} \]  

(9)

\[ g_{\text{WPP},t}^{\text{min}} - g_{\text{WPP},t}^{\text{max}} + \Delta L_{\text{LR},t}^{\text{dn}} \geq r_4 \cdot g_{\text{WPP},t} + r_5 \cdot g_{\text{PV},t} \]  

(10)

Where, \( g_{\text{WPP},t}^{\text{max}} \) and \( g_{\text{WPP},t}^{\text{min}} \) respectively represent the maximum and minimum available output of VPP at time \( t \); \( g_{\text{IB},t} \) represents the generation output of VPP at time \( t \); \( \Delta L_{\text{PB},t}^{\text{up}} \) denotes the output power of output IBDR at time \( t \); \( r_1 \), \( r_2 \), and \( r_3 \) respectively represent the up-rotation reserve coefficients of load, WPP and PV; \( r_4 \) and \( r_5 \) respectively represent the down-rotation reserve coefficients of WPP and PV.

(4) Other constraints

For VPP, also consider the running constraints of CGT, ESS, IBDR, and PBDR.

2. Virtual power plant risk avoidance operation optimization model

2.1. Uncertainty analysis

There are four types of uncertainty factors in VPP, namely \( g_{\text{WPP},t} \), \( g_{\text{PV},t} \), \( g_{\text{SHS},t} \), and \( L_t \). For load demand, load forecasting deviation \( L_t \) can be described by normal distribution \( L_t \sim [\mu, \sigma] \), and then load demand \( L_t \) can be described by normal distribution \( L_t \sim [\mu, \sigma] \) [6]. In this paper, the small hydraulic power generation system with annual regulating reservoir is selected. The output of SHS is adjustable and controllable in the short term. This paper does not consider the impact of load and SHS uncertainty on VPP operation.

2.2. Risk aversion model

In order to consider the risk brought by uncertainty factors to VPP operation, CVaR theory is applied to describe the risk of VPP scheduling operation. \( \mathbf{G} = [g_{\text{WPP},1}, g_{\text{WPP},2}, \ldots, g_{\text{WPP},T}] \) is a decision vector, \( \mathbf{y} = [g_{\text{WPP},t}, g_{\text{PV},t}, L_t] \) is a multivariate random vector, and the operating net income target of VPP is \( \mathcal{N}(G, g) \). VPP operation loss function is defined as \( L(E, y) = -N(E, y) \), then the VPP scheduling CVaR function after considering the uncertainty is represented as follows:

\[
F_\beta(E, \alpha) = \alpha + \frac{1}{1-\beta} \int \left( L(E, y) - \alpha \right) p(y) dy
\]  

(11)

Where: \( \alpha \) represents the threshold value of decision maker’s risk judgment. \( \beta \) represents the confidence with which VPP runs the objective function. When formula (11) reaches the minimum, it is the value of CVaR, and then \( \alpha \) is the value of VaR. \( g_{\text{WPP},t}^{*} \), \( g_{\text{PV},t}^{*} \), \( g_{\text{CGT},t}^{*} \), \( \Delta L_{\text{LR},t}^{\text{up}} \), and \( \Delta L_{\text{LR},t}^{\text{dn}} \) are the analytical expressions of the objective function \( p(y) \) is difficult to be determined, an approximate solution algorithm can be constructed, usually using historical data of \( Y \) or Monte Carlo simulation sample data to estimate the integral term. Let \( y_1, y_2, \ldots, y_N \) be \( Y \)’s sample data, then the estimated value of the function \( F_\beta(G, \alpha) \) is:

\[
F_\beta(G, \alpha) = \alpha + \frac{1}{N(1-\beta)} \sum_{i=1}^{N} L(E, y) - \alpha \right) \end{array}^y
\]  

(12)

Based on robust stochastic optimization theory, the constraints with uncertain variables are transformed into stochastic constraints by introducing robust coefficients[5]. In this paper, the uncertainty factors \( g_{\text{WPP},t} \) and \( g_{\text{PV},t} \), set \( e_{\text{WPP},t} \) and \( e_{\text{PV},t} \) respectively represent WPP and PV forecasting biases, and then \( g_{\text{WPP},t} \) and \( g_{\text{PV},t} \) will fluctuate in \( [1 - e_{\text{WPP},t}] \cdot g_{\text{WPP},t}, (1 + e_{\text{WPP},t}) \cdot g_{\text{WPP},t}] \).
and \[ \left(1-e_{\text{PV}}, \cdot g_{\text{PV}}, (1+e_{\text{PV}}, \cdot g_{\text{PV}}) \right) \]. For convenience of expression, \( e_{\text{RE}} \) is used for substitution \( e_{\text{WPP}}, e_{\text{PV}} \) and \( g_{\text{RE}}, g_{\text{WPP}}, g_{\text{PV}} \). Accordingly, \( g_{\text{RE}} \) will be fluctuations in \[ \left(1-e_{\text{RE}}, \cdot g_{\text{RE}}, (1+e_{\text{RE}}, \cdot g_{\text{RE}}) \right) \].

Setting the net load of the system is \( M_i \), and the specific calculation is as follows:

\[
M_i = g_{\text{CGT},j} \left(1 - \varphi_{\text{CGT}} \right) + u_{\text{IB},j} \Delta \varphi_{\text{IB},j} + g_{\text{UG},j} - \left( L_{i,j} - u_{\text{PB},j} \Delta L_{\text{PB},j} \right)
\]

(13)

Then, rewrite formula (13) as follows:

\[
-\left[ g_{\text{RE},j} \left(1 - \varphi_{\text{RE}} \right) \pm e_{\text{RE},j} \cdot g_{\text{RE},j} \right] \leq M_i
\]

(14)

Finally, the VPP risk avoidance scheduling optimization model is established, as follows:

\[
\min F_{\beta} (G, \alpha) = \alpha + \frac{1}{N \left(1-\beta \right)} \sum_{k=1}^{N} z_k
\]

\[
\begin{align*}
Eq. (6-9) &- Eq. (6-14) \\
Eq. (6-17) &- Eq. (6-18)
\end{align*}
\]

(15)

s.t. \( z_k = L \left( E, y \right) - \alpha \)

\[ z_k \geq 0 \]

other constraints

In a word, CVaR based on robust scheduling can guarantee the safe and stable operation of the system within a certain disturbance range under the condition of incomplete operation information of the system, and realize the scheduled target of scheduling.

### 2.3. Mathematical model solving algorithm

Formula (12) determines the objective function \( V \) of the VPP risk avoidance scheduling model, and the proposed objective function and constraint conditions should be linearized before the model is solved. When the objective function and constraints are linearized, the MINLP model is converted to a mixed integer linear programming (MIP) model [7]. Furthermore, this paper introduces the specific simulation scenario as follows: considering the robustness of CvaR virtual power plant self-dispatching. The scene in the focus on the objective function of WPP and PV, on the basis of uncertainty, uncertainty factors in the further consideration constraints on VPP operation, the effect of structural random constraints by using the robust optimization theory, and discussed under different robust coefficient and the prediction precision VPP scheduling optimization strategy, analysis of CvaR robust method is effective.

### 3. Example analysis

#### 3.1. Basic Data

In this chapter, an independent micro-power grid in an industrial park is selected as an example, which is configured with \( 2 \times 0.25 \text{MW} \) WPP, \( 4 \times 0.1 \text{MW} \) PV, \( 1 \times 1 \text{MW} \) CGT, and \( 1 \times 0.2 \text{MW} \cdot \text{H ESS} \). At the same time, SHS is equipped with a \( 5 \times 50 \text{kW} \) small hydroelectric generating unit with an average annual water flow of \( 40 \text{m}^3/\text{h} \), the maximum storage capacity of the regulating reservoir is \( 9 \times 10^4 \text{m}^3 \), the initial water volume of the reservoir shall be 70% of the maximum reservoir capacity. The CGT mainly selects G3406LE gas turbine with rated output power of 1.025MW and natural gas consumption of 107.7m3/h. The start-up and shutdown time of this gas turbine is 0.1h and 0.2h respectively, and the start-stop cost is about 95 yuan/MW•h, and the cost of power generation and gas is a unary quadratic function. The generation cost function is linearized into two parts, the slope coefficients of the two parts are respectively 105 yuan/MW and 355 yuan/MW, and the generation loss of the unit is about 2.5%. Among them, the charging power of the energy storage system does not exceed 0.04MW, the discharging power does not exceed 0.05MW, and the ESS initial storage power is 0. At the same time, in order to ensure the safe and reliable operation of energy storage, ESS is limited not to charge and discharge.
simultaneously. In this paper, the load demand of typical load days in summer and winter is selected as the input data of the system. The maximum and minimum loads of typical load days in summer and winter are 0.9MW, 0.709MW and 0.879MW and 0.737MW respectively. WPP's cutting, rated and cutting wind speeds were set at 2.8m/s, 12.5m/s and 22.8m/s respectively, as well as shape parameters \( \varphi = 2 \) and scale parameters \( \theta = \frac{2\varphi}{\sqrt{\pi}} \). Set the PV density parameter \( \xi \) and \( \psi \) respectively are 0.3 and 8.54. The prediction error of WPP and PV was set as 5%. When the probability density functions of wind speed, radiation intensity and load demand are obtained, 100 sets of simulation scenarios are generated with the scenario simulation strategy proposed in literature [8], and 10 sets of typical cleaning sets are obtained with the scenario reduction strategy. The average results of each scenario are selected as the input data. Table 1 shows the basic parameters of PBDR and IBDR for typical load days.

| Time division | PBDR | IBDR |
|---------------|------|------|
| **Energy market** | **Secondary market** | **peak** | **valley** | **flat** | **Under** |
| **summer** | | At 10:00-18:00 | At 7:00 | At 19:00-8:00-9:00 | - |
| **winter** | | At 12:00-20:00 | At 7:00 | At about 8:00-11:00 & - 24:00 | - |
| **Electricity price** | 0.69 | 0.33 | 0.55 | 0.5 | 0.2 | 0.6 |

WPP, PV, SHS and CGT set the benchmark electricity prices for Internet access at 0.51¥/kW•h, 0.88¥/kW•h, 0.31¥/kW•h and 0.42¥/kW•h, respectively. At the same time, it is designed to implement PBDR on the user side to motivate the end-user response system for generation scheduling. The electricity price of the user before PBDR is 0.59¥/kW•h. According to literature [9], the price elasticity of power demand is selected, and the price in normal period is set unchanged. The electricity price in peak period is increased by 30%, and that in valley period is reduced by 50%. For IBDR, the energy market offers energy at 0.45¥/kW•h, while the standby market offers up and down rotation at 0.25¥/kW•h and 0.55¥/kW•h. At the same time, in order to avoid excessive load fluctuation and "peak-valley inversion" phenomenon, load variation generated by PBDR was set to be no more than ±0.04mW, and power generation output of IBDR participating VPP was no more than ±0.03MW.

### 3.2. Example results

The initial robustness coefficient \( \Gamma = 0.9 \) was set to calculate the optimal scheduling strategy for VPP. Typical load days of WPP, PV and SHS in summer are 4.797MW•h, 1.760MW•h and 4.407MW•h, and typical load days in winter are 6.984MW•h, 1.455 MW•h and 1.901MW•h. When the uncertain variables in the constraint conditions are considered, the decision makers' sensitivity to risks will be increased. To avoid the operational risks of VPP, the decision makers will reduce the generation output of WPP and PV. Figure 1 shows the VPP power generation output distribution on a typical load day.
According to Figure 1, when the robust stochastic optimization theory is introduced, VPP will further compress the grid-connection space of WPP and PV. Taking a typical load day in summer as an example, WPP and PV outputs were reduced by 0.11MW·h and 0.307MW·h, respectively. However, due to its stable and controllable output, CGT was called more by VPP, increasing by 0.431MW·h and 1.152MW·h, respectively. As the power generation output of WPP and PV decreased, the outlet of ESS and IBDR were also reduced. ESS discharge release energy and IBDR were only called during peak period to reduce the output, and ESS charge storage energy and IBDR were called during valley period to increase the load. Table 2 shows the VPP operation scheduling results under different scenarios.

Table 2. VPP operation scheduling results under different scenarios

| A typical day | Generation output /MW·H | Operating Results /¥ |
|---------------|--------------------------|----------------------|
|               | CGT | PV | WPP | SHS | ESS | IBDR      | earning | VaR | CVaR |
| summer        |     |    |     |     |     |           |         |     |      |
| Case 1        | 7.562 | 2.09 | 5.517 | 4.652 | (0.25, 0.24) | (0.36, 0.39) | 7804.85 | -   | -    |
| Case 2        | 8.49 | 1.870 | 5.104 | 4.41 | (0.40, 0.40) | (0.33, 0.18) | 7645.50 | 1716.77 | 1725.59 |
| Case 3        | 8.921 | 1.760 | 4.797 | 4.407 | (0.30, 0.28) | (0.09, 0.15) | 7440.70 | 1785.48 | 1824.35 |
| winter        |     |    |     |     |     |           |         |     |      |
| Case 2        | 8.190 | 1.550 | 7.912 | 1.97 | (0.45, 0.44) | (0.27, 0.18) | 8137.68 | 1827.29 | 1836.67 |
| Case 3        | 9.342 | 1.455 | 6.984 | 1.901 | (0.30, 0.24) | (0.09, 0.09) | 7793.98 | 1842.36 | 1875.48 |

According to Table 2, the values of revenue, VaR and CVaR under different scenarios were compared. When robustness coefficients are introduced to transform constraints with uncertain variables, the risks brought by WPP and PV to VPP can be better described. Decision-makers will further control the power generation output of WPP and PV, and correspondingly, VPP operating earnings will also decrease, but the VaR and CVaR values under the same confidence degree β will indeed increase, which indicates that the returns and risks are interrelated, and decision-makers need to bear the corresponding risk level while pursuing high economic returns. Conversely, when policymakers want to avoid risk, they will have to sacrifice some of the economic gains.

Acknowledgments
This research is supported by the Science and Technology Program of State Grid Corporation of China (Key technology research and demonstration application of multi agent multi energy virtual power plant in Energy Internet environment).

References
[1] Jizhen Liu, Mingyang Li, Fang Fang, et al. Review on Virtual Power Plants. J. Proceedings of the CSEE, 34(2014), pp. 5103-5111.
[2] Hang Liu, Ming Zeng, Ting Pan, et al. The Green Photovoltaic Industry Installed Capacity Forecast in China: Based on Grey Relation Analysis, Improved Signal Decomposition Method, and Artificial Bee Colony Algorithm. 2020, 2020.
[3] Zhe Wang, Peng Yang, Siyuan Liu, et al. Coordination and Optimization Strategy of VPP Considering Demand Response and Multi-Energy Coordination. J. Electric Power Construction, 38(2017), pp. 60-66.
[4] Ming Zeng, Hang Liu, Shenyuan Wang, et al. Research on Competitive Natural Gas Market Construction and Price Formation Mechanism ——Analysis of Main Experiences and Practices of Natural Gas Market Construction in Typical Countries. J. Price: Theory & Practice, 04(2020), pp. 56-59.
[5] Songli Fan, Qian Ai, Xing He. Risk Analysis on Dispatch of Virtual Power Plant Based on Chance Constrained Programming. J. Proceedings of the CSEE, 35(2015), pp. 4025-4034.
[6] Wenlue Dong, Qun Wang, Li Yang. A Coordinated Dispatching Model for a Distribution Utility and Virtual Power Plants with Wind/Photovoltaic/Hydro Generators. J. Automation of Electric Power Systems, 30(2015), pp. 75-82.
[7] Yuhang Xia, Junyong Liu, Chao Feng, et al. Optimal Scheduling Model of Virtual Power Plant Considering Demand Response, J. Power System Technology, 40(2016), pp. 1666-1674.

[8] Yunyang Zou, Li Yang. Synergetic Dispatch Models of a Wind/PV/Hydro Virtual Power Plant Based on Representative Scenario Set, J. Power System Technology, 39(2015), pp. 1855-1859.

[9] Modassar Chaudry, Nick Jenkins, Goran Strbac. Multi-time period combined gas and electricity network optimisation, 78(2007), pp. 1265-1279.