ISSN 2004-2965 Energy Proceedings, Vol. 20, 2021

International Conference on Applied Energy 2021
Nov. 29 - Dec. 5, 2021, Thailand/Virtual
Paper ID: 619

Cooperative Decision Model of Electric Vehicle Participation in Power System Generation and Reserve Based on Risk Measurement Theory

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ABSTRACT

With the increasingly mature of interaction technology between electric vehicles and the power grid, the participation of electric vehicles in the collaborative decision-making of power generation and reserve in power systems has a broad application prospect. Considering the uncertainties such as electric vehicle failure, generator unit outage, renewable energy power output and power load prediction deviation, the Worst-Case Value-at-Risk (WCVaR) is studied in this paper, and the collaborative risk decision-making model determined by power generation and reserve determining based on the risk measurement theory is constructed. The 22-bus system is taken as an example. The simulation examples of electric vehicles and photovoltaic power stations are given, and the influence of different confidence level combinations on the simulation results is analyzed. The results show that the high-cost operation risk caused by random factors can be effectively solved by the model.

Keywords: electric vehicles, power system reserve, collaborative decision-making, risk measure theory

1. INTRODUCTION

In traditional power systems, the spinning reserve is usually provided by the committed capacity of the generating unit. However, after the deregulation of the power market, the demand-side resources and their aggregators can also participate in the market as virtual power plants and provide a spinning reserve to improve the reliability of the system. At present, some independent system operators such as Pennsylvania, New Jersey, Maryland, New York independent system operator and New England have provided opportunities for demand-side resources to participate in the spinning reserve market [1,2].

With the rapid development of electric vehicle (EV) related industries, the charging load of electric vehicles in the power system is increasing. On the one hand, its random charging behavior will bring great adverse effects to the power system. On the other hand, as a flexible controllable load, cluster electric vehicles have become a demand-side resource that cannot be ignored. The focus is on how to tap the auxiliary service potential of cluster electric vehicles with strong randomness through guiding measures or control methods [3,4].

This paper aims at the generation and reserve decision-making problem of power systems with electric vehicle access. The relevant uncertain factors such as electric vehicle default, power outage, renewable power and load forecasting deviation are comprehensively considered. The risk measurement theory is adopted to model the decision-making risk, and the chance-constrained optimization method is used to deal with the relevant probabilistic constraints.

2. RISK MEASUREMENT THEORY

Value-at-Risk (VaR) is a risk measure used by financial enterprises and other institutions to measure the maximum possible loss value of the portfolio of securities investment or financial assets due to market fluctuations in a certain period [5]. Suppose $f(x, y)$ denotes the loss function of the above portfolio, x is the portfolio of possible decisions, and y is the portfolio of random variables subject to the probability density $p(y)$ of the quantitative value of risk factors. The direct expression of the definition and distribution form of VaR is as follows

$$\begin{cases} \Pr\left\{ f(x,y) \geqslant \mathrm{VaR}_{\alpha} \right\} = \alpha \\ \mathrm{VaR}_{\alpha} = \min\left\{ \beta \in R \middle| \ \psi(x,\beta) = \int_{f(x,y)\leqslant\beta} p(y)\mathrm{d}y \geqslant \alpha \right\} \end{cases} \tag{1}$$

where α is a given confidence level, which shows the probability of portfolio loss exceeding VaR value. It can be seen that VaR is the one-sided critical value of portfolio loss under the given confidence level α. Although the concept of VaR measure shown in (1) is clear and easy to understand, it has some shortcomings, such as difficulty to solve, nonconvex, ignoring the end of distribution. Therefore, based on VaR measurement, another risk measure Conditional VaR (CVaR) has been developed. CVaR is defined as follow.

$$\begin{aligned} \mathrm{CVaR}_{\alpha} &= E\left[f(x,y) \ \middle| \ f(x,y) \geqslant \mathrm{VaR}_{\alpha} \right] \\ &= \frac{1}{1-\alpha} \int_{f(x,y)\geqslant \mathrm{VaR}_{\alpha}} f(x,y) p(y) \mathrm{d}y \end{aligned} \tag{2}$$

In (2), the lower loss value f exceeds the average value at the end of the distribution of VaR at the same confidence level, which makes up for the disadvantage that VaR cannot quantify the loss at the end of the distribution. The discrete CVaR value is easy to be transformed into a linear programming problem. VaR and CVaR values often need to be calculated based on historical data and simulated future data, but it is difficult to fully determine the distribution function of risk factors in actual decision-making, and even the estimation based on historical data will be different from the actual occurrence scenarios in the future. In this regard, a more robust CVaR model theory α-WCVaR is defined as follow.

$$\mathrm{WCVaR}_{\alpha} = \max \quad \frac{1}{1-\alpha} \int_{f(x,y)\geqslant \mathrm{VaR}_{\alpha}} f(x,y) p(y) \mathrm{d}y \tag{3}$$

For a set of discrete random variables, WCVaR can be expressed as

$$\begin{aligned} &\min \quad \varphi \\ &\text{s.t.} \quad \mu = \theta + \frac{1}{1-\alpha} \sum_{j=1}^{J} \left[f\left(x, y_j\right) - \theta \right]^{+} p\left(y_j\right) \leqslant \varphi \\ &\left[f\left(x, y_j\right) - \theta \right]^{+} = \max\left\{ 0, f\left(x, y_j\right) - \theta \right\} \end{aligned} \tag{4}$$

where ϑ and μ are the approximate values of VaR and CVaR corresponding to decision x under random distribution y. The Monte Carlo method is used to generate the set of discrete variables which obey the specified distribution. According to the sample data. According to (4), the optimal solution of φ is the WCVaR value of the corresponding risk decision problem.

3. COLLABORATIVE RISK DECISION MODEL

3.1 Objective function

To establish a collaborative risk decision-making model of power system generation and reserve based on risk measurement theory, this paper combines the WCVaR model construction method under the discrete random variable. Firstly, the multi-scenario method based on the Monte Carlo method and scenario reduction method is used to generate a large number of discrete scenarios formed by the combination of various risk factors. The objective function of risk decision-making based on the expected value model is established. The objective function is divided into three parts, the generation cost of the controllable generation unit, the reserve cost of the controllable generation unit and the electric vehicle aggregator, and the additional power purchase cost caused by the above risk factors. Thus, forming the objective function of the expected value minimization model of the comprehensive cost of generation and reserve (hereinafter referred to as the expected value minimization model). It is shown in (5).

$$\min \sum_{\omega=1}^{N_{\mathrm{s}}} p(\omega) F(\omega) = \sum_{\omega=1}^{N_{\mathrm{s}}} p(\omega) \left(f_{\mathrm{gen}} + f_{\mathrm{res}} + f_{\mathrm{risk}}(\omega) \right) \tag{5}$$

where N_s is the total number of scenes generated by multi-scene method. $p(\omega)$ is the occurrence probability of scene ω. $F(\omega)$ is the total reserve purchase cost under scenario ω. f_{gen} is the generation cost of the generator. f_{res} is the reserve cost. $f_{\mathrm{risk}}(\omega)$ is the default cost of the reserve under scenario ω, which is the risk source of cooperative decision-making of generation reserve.

In the next, referring to the establishment and transformation methods of risk measurement models described in (1)-(4), the objective function of WCVaR minimization model is obtained.

$$\begin{aligned} &\min \quad \varphi \\ &\text{s.t.} \quad \theta + \frac{1}{1-\alpha} \sum_{\omega=1}^{N} \left[f\left(\omega\right) - \theta \right]^{+} p\left(\omega\right) \leqslant \varphi \end{aligned} \tag{6}$$

3.2 Constraints

According to the characteristics of power system, the variables in the following constraint conditions are standard unit variables, and the standard unit value symbol is omitted.

The limit constraint of line power transmission in scenario ω is shown in (7).

$$\left| P_{\mathrm{LINE},t,ij}(\omega) \right| \leqslant P_{\mathrm{LINEmax},ij} \tag{7}$$

where $P_{\mathrm{LINEmax},ij}$ is the power transmission limit of line ij.

For controllable units, the upper and lower limits of power are shown in (8).

$$\begin{cases} s_{\mathrm{G},t,i} P_{\mathrm{Gmin},i} \leqslant P_{\mathrm{G},t,i} \leqslant s_{\mathrm{G},t,i} P_{\mathrm{G\,max},i} \\ \Pr\left\{ s_{\mathrm{G},t,i} \leqslant \delta_{\mathrm{G},t,i}(\omega) \right\} \geqslant \beta, \quad \omega = 1,2,\cdots,N_{\mathrm{s}} \end{cases} \tag{8}$$

where, $P_{\mathrm{Gmin},i}$ and $_{\mathrm{Gmax},i}$ are the minimum and maximum ower of the generator at node i, respectively. $S_{\mathrm{G},t,i}$ is the on-off state of the generator at node i. 1 is the start-up state. $\delta_{\mathrm{G},t,i}$ is the one generated randomly by combining the for index of the generator at node i with the fault repair time, indicating 0-1 variable of fault state, 1 means normal state.

The reserve capacity constraints of controllable units are shown in (9).

$$\begin{cases} P^{\mathrm{G}}_{\mathrm{re1},t,i} \leqslant \min\left\{ R_{\mathrm{G}i} P_{\mathrm{Gmax},i}, P_{\mathrm{Gmax},i} - P_{\mathrm{G},t,i} \right\} \\ P^{\mathrm{G}}_{\mathrm{re2},t,i} \leqslant \min\left\{ R_{\mathrm{G}i} P_{\mathrm{Gmax},i}, P_{\mathrm{G},t,i} - P_{\mathrm{Gmin},i} \right\} \end{cases} \tag{9}$$

where $R_{\mathrm{G}i}$ is the ramp rate of generator at node i.

Based on the probability of default index, combined with the up and down reserve contract of electric vehicle users, the reserve constraint of electric vehicles can be obtained, as shown in (10).

$$\begin{cases} 0 \leqslant P^{\mathrm{EV}}_{\mathrm{re1},t,i} \leqslant s_{\mathrm{EV},t,i} P^{\mathrm{EV}}_{\mathrm{re1},t,i,0} \\ 0 \leqslant P^{\mathrm{EV}}_{\mathrm{re2},t,i} \leqslant s_{\mathrm{EV},t,i} P^{\mathrm{EV}}_{\mathrm{re2},t,i,0} \\ \Pr\left\{ s_{\mathrm{EV},t,i} \leqslant \delta_{\mathrm{EV},t,i}(\omega) \right\} \geqslant \beta, \quad \omega = 1,2,\cdots,N_{\mathrm{s}} \end{cases} \tag{10}$$

where $P^{\mathrm{EV}}_{\mathrm{re1},t,i}$ and $P^{\mathrm{EV}}_{\mathrm{re2},t,i}$ are the up/down power that can be scheduled by EV aggregator charging at node i, respectively. $\delta_{\mathrm{EV},t,i}$ is a variable representing the degree of EV default (as a percentage of the expected reserve supply) at node i, with a value between 0-1.

To meet the operation requirements of the power system, the total power balance constraints of the system are shown in (11)-(12).

$$\begin{aligned} &\sum_{i=1}^{N_G} P_{\mathrm{G},t,i} + \sum_{i=1}^{N_{\mathrm{DG}}} P_{\mathrm{DG},t,i}(\omega) + P_{\mathrm{ubl},t}(\omega) \\ &= \sum_{i=1}^{N_{\mathrm{BUS}}} P_{\mathrm{L},t,i}(\omega) + \sum_{i=1}^{N_{\mathrm{EV}}} P_{\mathrm{EV},t,i} + P_{\mathrm{ub2},t}(\omega) \end{aligned} \tag{11}$$

$$\begin{cases} P_{\mathrm{ubl},t}(\omega) <= z_{\mathrm{ubl},t,i}(\omega) \left(\sum_{i=1}^{N_{\mathrm{BUS}}} P_{\mathrm{L,max},t,i} + \sum_{i=1}^{N_{\mathrm{EV}}} P_{\mathrm{EV,max},t,i} \right) \\ P_{\mathrm{uh2},t}(\omega) <= \left(1 - z_{\mathrm{ubl},t,i}(\omega)\right) \left(\sum_{i=1}^{N_{\mathrm{G}}} P_{\mathrm{Gmax},i} + \sum_{i=1}^{N_{\mathrm{DG}}} P_{\mathrm{DGmax},i} \right) \\ P_{\mathrm{ubl},t}(\omega), P_{\mathrm{uh2},t}(\omega) \geqslant 0 \end{cases} \tag{12}$$

where $P_{\mathrm{ubl},t}(\omega)$ and $P_{\mathrm{uh2},t}(\omega)$ are the uplink and downlink system power vacancies at time t, respectively. $z_{\mathrm{ubl},t,i}$ is the auxiliary 0-1 variable, and the uplink and downlink system power vacancies cannot be positive at the same time through (12).

4. EXAMPLE SETTING

4.1 Calculation model

In order to verify the model proposed in this paper, YALMIP toolbox and Gurobi solver are used to model and solve the mixed integer nonlinear programming model. A 22-node network example is selected as the basis [6]. The example is modified as follows. A micro gas turbine unit is added at node 1. A 0.5 MW roof Photovoltaic Station is added at node 8. Electric vehicles are connected to the grid in the form of two small charging stations at node 5 and node 18. They interact with the power grid as two aggregators, and the user participation of both stations is set at 30%. As shown in Fig. 1. Taking the load of node 2 and generator operation of node 1 as an example, the corresponding risk factor scenario set is generated, as shown in Fig. 2.

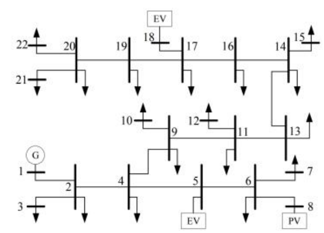

Fig. 1. 22-bus test system

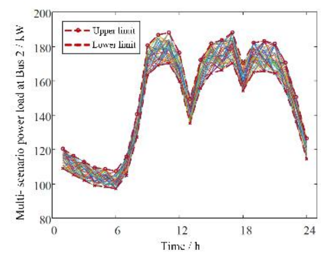

Fig. 2. Power load at bus 2

4.2 Analysis of calculation results

In the analysis, WCVaR confidence level α is 0.9, chance constrained confidence level β is 0.9, the collaborative risk decision results of generation and reserve considering the participation of electric vehicles are shown in Fig. 3. The histogram is the decision result of the reserve power of the cluster electric vehicles with two nodes, and the values refer to the left y-axis. The solid line is the result of generator decision, and the value is referred to the right y-axis.

The total load superimposed is in the low state and it is in a certain downward trend, while photovoltaic has little output, so the output of the generator set gradually decreases with the decrease of load. Meanwhile, due to the low-level of both source and load, the risk factors caused by the prediction error are also small. As can be seen from Fig. 3, according to the comparison of generation cost, standby cost and additional power purchase cost, the results of the spare quantity optimization of cluster electric vehicles and generator sets in this period are all 0, and the power deviation will be balanced by additional power purchase. From 8 a.m., with the increase of load, the photovoltaic output is difficult to meet the power demand of the system, the output of the generator unit increases rapidly, and the randomness caused by the source and load prediction deviation increases. To meet the load power supply and line power flow constraints, the cluster electric vehicles begin to provide backup. In addition, since the generation cost of generating units is lower than the additional power purchase cost in this period, the priority generation and full generation state are maintained, and the standby optimization result of the generator set is 0.

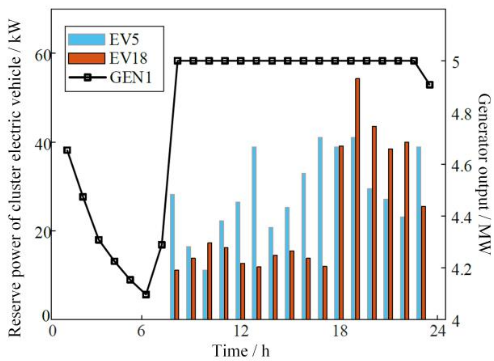

Fig. 3. Decision for power generation and reserve determining

In the following, WCVaR risk confidence level α is increased from 0.84 to 0.99, chance constrained confidence level *β* is varied from 0.8 to 0.95, the expected value *E* minimization (min(*E*)) model and WCVaR minimization (min(WCVaR)) model under each combination are optimized and solved respectively. The comparison of comprehensive cost expectations of the two models under each combination is shown in Fig. 4. WCVaR risk confidence level *α* increasing from 0.84 to 0.99, chance constrained confidence level *β* from 0.8 to 0.95, the expected min(E) model and min(WCVaR) model under each combination are optimized and solved respectively. The comparison of comprehensive cost expectations of the two models under each combination is shown in Fig. 4.

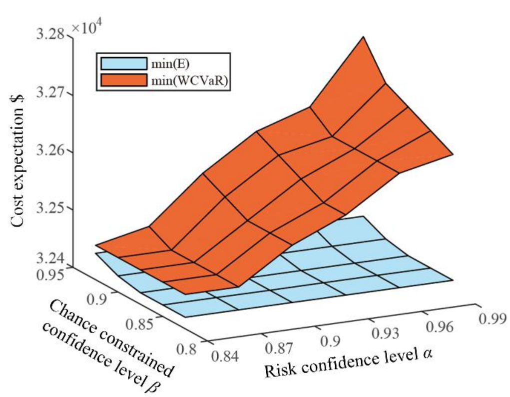

Fig. 4. Comparison of the combined cost expectations

5. CONCLUSION

According to the theory of risk measurement, this paper considers the uncertain factors such as electric vehicle default, power outage, renewable power and load forecasting bias, and constructs the collaborative risk decision model of generation and reserve.

Based on the WCVaR index risk quantification method of risk measurement theory, a collaborative risk decision-making model of generation and reserve of power system considering the participation of electric vehicles is proposed. Combined with multi-scenario method and opportunity constraint, the auxiliary variable is introduced, and the probability form constraint is transformed into the mixed integer programming form, which can effectively deal with the default, power outage, power failure, etc. of electric vehicles Renewable power and load forecasting deviation and other risk factors.

ACKNOWLEDGEMENT

This work was supported by the State Grid Headquarters Science & Technology Project “Research on Power Grid Planning Optimization Method Considering Whole System Cost in Market Environment” under Grand No. B3440821K004.

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