

Evaluation and optimization for virtual power plants under different operational strategies¹

ZEJING QIU², JIE XIANG², QIQI QIAN², CHUNXUE LI², MING ZENG³

Abstract. A Reliability and Operation Model (ROM) and unit commitment model are used for modeling and accessing virtual power plants under self-supply maximization and market profits maximization for two different operational strategies. Furthermore, a numerical example is presented to verify the scientific and validity of the model and provide certain decision support for the operation of virtual power plants.

Key words. Virtual power plant, operational strategies, ROM model.

1. Introduction

Virtual power plants, which are considered as a way of demand response, Virtual power plants which are considered as a way of demand response effectively combine distributed generators, controllable load and a variety of distributed energy storage device together, and by the coordinated regulation technology and communications technology to integrate and module all types of distributed energy [1]. And they have great significance to balance the power supply and demand, ensure the economy and security of the operation of power system, and help alleviate energy shortage problem and environmental deterioration problem.

Current research on virtual power plants has exhibited continuous increase. Zdrilić et al. [2] maximize the profit of the virtual power plant by a mixed-integer linear

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²Nari (Wuhan) Electrical Equipment & Engineering Efficiency Evaluation Center, Wuhan, 430074, China

³School of Economics and Management, North China Electric Power University, Beijing, 102206, China

programming model which incorporates long-term bilateral contracts with weekly forecast hourly market prices. Shabanzadeh et al. [3] introduce an efficient MILP model based on robust optimization approach proposed to enable informed decision making under different levels of uncertainty. To manage a VPP, Ruiz et al. [4] provide an optimization algorithm composed of a large number of customers with thermostatically controlled appliances, and Kiény et al. [5] consider two types of aggregation EU project FENIX: the commercial virtual power plant (CVPP) that tackles the aggregation of small generating units with respect to market integration and technical virtual power plant (TVPP) that tackles aggregation of these units with respect to services that can be offered to the grid. Kuzle et al. [6] and Sučić et al. [7] consider the dispatch of VPP and come up with different programming model to overcome it. Tai-Her et al. [8] present a novel approach based on Weibull distribution to determine the capacity of wind turbine generators using capacity factor, normalized average power and product of CF and Punder different values of tower height and rated wind speed. Kuntschke et al. [9] present a fundamental system architecture and a concept enabling VPPs and DSOs to negotiate their positions to satisfy the needs and requirements of both sides. Robu et al. [10] design a payment mechanism that encourages distributed energy resources to join "cooperative" VPPs with large overall production. In ref. [11] by Caldon et al., an optimization algorithm is proposed to integrate many DG into a VPP, which will be able to generate and sell both thermal and electrical energy. Vale et al. [12] present a multi-level negotiation mechanism for Smart Grids optimal operation and negotiation in the electricity markets, considering the advantages of VPPs' management.

The main structure of this paper is as follows: Section 2 establishes the Reliability and Operation Model (ROM) and unit commitment model to evaluate virtual power plants on the basis of maximizing self-supply and market profits two different strategies. Section 3 selects one Chinese province as a numerical example to verify the scientific and validity of the model established before. Finally, analyzing and summarizing the influence of virtual power plants is performed on the power system under different operating strategies.

2. Model construction

In this paper, we use ROM model to simulate the overall operation of power system. ROM model was proposed at Comillas Pontifical University and is widely used for scheduling optimization in day-ahead power system. Meanwhile it is subject to restrictions related to units' operating conditions, including: unit output's upper and lower limits, units' ramp constraints, availability of intermittent units and regulatory reserve requirements. When some unexpected events happen, for example, the power units become faulty or units are deviated from the preset level, the day ahead optimal scheduling results should be initialized. Meanwhile, the target year for this study is 2020, thus before 2020, the daily operation of power system all need to be solved.

2.1. Unit commitment model

In ROM model, we use a unit commitment model to simulate the daily operation of power system before the target year. The specific objective function has the form

$$\min C_{\text{total}} = \sum_{i,t} (C_i^{\text{fd}} \cdot \phi_{i,t} + C_i^{\text{vrb}} \cdot P_{i,t}^{\text{min}} \cdot \phi_{i,t} + C_i^{\text{vrb}} \cdot P_{i,t}) + \sum_t (C_{\text{ne}} \cdot N_t), \quad (1)$$

where C_{total} are the total variable thermal costs, C_i^{fd} are the fixed costs, C_i^{vrb} are the variable costs, C_i^{st} are the start-up costs, and C_{ne} are the unit costs of non-supplied energy. The variable $\phi_{i,t}$ represents the unit commitment results of thermal power unit i in the period t . Symbol $P_{i,t}^{\text{min}}$ denotes the lower limit of the unit output, $P_{i,t}$ stands for the power output over the smallest output, and finally, N_t stands for non-supplied energy quantity in period t . As for the quantities $\phi_{i,t}$, they are binary variables, and their value is 0 if the thermal power plant i is shut down in period t .

Equation (1) is used to calculate the daily operating costs. Meanwhile, the values of relevant variables in the previous day are used as the initial values to calculate the following day's operating costs. Furthermore, the annual operating costs are cumulative results of daily operating costs.

This paper takes into account a series of technical restrictions when establishing the model, which are shown in the following relations.

$$D_t - D_t^{\text{gen}} - N_t = \sum_i P_{i,t}^{\text{min}} \cdot \phi_{i,t} + P_{i,t}, \quad (2)$$

$$\sum_i (P_{i,t}^{\text{max}} - P_{i,t}^{\text{min}}) \cdot \phi_{i,t} - P_{i,t} \geq I_t^{\text{up}}, \quad (3)$$

$$\sum_i P_{i,t} \geq I_t^{\text{down}}, \quad (4)$$

$$P_{i,t} \leq (P_{i,t}^{\text{max}} - P_{i,t}^{\text{min}}) \cdot \phi_{i,t}, \quad (5)$$

$$P_{i,t} - P_{i,t-1} \leq R_i^{\text{up}}, \quad (6)$$

$$P_{i,t-1} - P_{i,t} \leq R_i^{\text{down}}, \quad (7)$$

$$\phi_{i,t} - \begin{pmatrix} U_i, & p = 1 \\ \phi_{i,t-1} & 1 \end{pmatrix} = \lambda_{i,t} - \mu_{i,t}. \quad (8)$$

Here, D_t is the customers' power demand, D_t^{gen} is the output of the distribution network, N_t is the quantity of non-supplied energy, I_t^{up} and I_t^{down} stand for the upper and lower limits of regulatory reserve requirements, respectively, $P_{i,t}^{\text{max}}$ is the largest output of the single unit i , R_i^{up} and R_i^{down} represent the upper and lower unit

ramp rate, respectively, while U_i stands for the initial state of the units. Finally, $\lambda_{i,t}$ is the parameter for start-up of units in period t , $\mu_{i,t}$ is the decision-making parameter for shut-down of units in period t . Both these parameters are binary variables and their values are either 0 or 1; $\lambda_{i,t} = 0$ if thermal power plant i is shut down in period t , while $\mu_{i,t} = 1$ in the same case, and vice versa.

Equations (3) and (4) show the regulatory reserve requirements, equations (5) and (6) show the power output limits and equation (8) ensures the logical sequence of starting up, unit commitment and shutting down.

2.2. Elasticity demands of virtual power plants

In this paper, we use the demand variable d^t to describe the constraints related to energy conservation, and then consider both the original demand D^t and the demand variable d^t to obtain the final power demand. The demand variable d^t is given as

$$d_t = D_t + v_t^{\text{up}} - v_t^{\text{down}} \quad (9)$$

where v_t^{up} and v_t^{down} stand for the upper and lower limits of demand response, respectively.

In this paper, we use the changes of demand as the only available demand response, so that during system's routine operation the increasing and decreasing amounts of power demand are balanced. This means that the two amounts of power demand during daily operation are equal, and the constraint can be expressed as follows

$$\sum_t v_t^{\text{up}} = \sum_t v_t^{\text{down}}. \quad (10)$$

Logically speaking, for the elasticity of demand some constraints need to be met, and the variable of load must be limited between values ε_{up} and $\varepsilon_{\text{down}}$ denoting certain percentages of the total demand.

$$\sum_t \varepsilon_{\text{up}} \cdot D_t \geq \sum_t v_t^{\text{up}}, \quad (11)$$

$$\sum_t \varepsilon_{\text{down}} \cdot D_t \geq \sum_t v_t^{\text{down}}. \quad (12)$$

2.3. Power supply and demand in virtual power plants

We assume that in virtual power plants, about 10% is the distributed power generation system. Then we need to estimate the power demand in virtual power plants. The specific process is described by equations

$$\min \sum_t (G_t - \alpha D_t). \quad (13)$$

As

$$0 < \alpha < 1, \quad (14)$$

$$\sum_t G_t - \alpha D_t > 0. \quad (15)$$

Here G_t is the generated energy of virtual power plants in period t and α is a scale parameter.

2.4. Operation strategies of virtual power plants

2.4.1. Self-supply strategy. Self-supply strategy is related to virtual power plants' internal supply and demand. With the help of the model stated above, we can simulate virtual power plants' operation process which can be divided into two phases. In phase one, due to virtual power plants having the ability of self-supply to some extent, the possibility of purchase and sale power at this stage does not need to be considered. Based on this, it needs to minimize the power supply costs of local load, including the cost of non-supplied energy in virtual power plants. Meanwhile, in this phase, non-supplied energy in virtual power plants is avoided by a penalty factor, and all the local power generation has the priority to meet the internal power demand of virtual power plants, details is shown in equation (9) to (12). In addition, in this phase, the power demand which is met by self-supply of virtual power plants needs to be estimated, and when the power demand is higher than the corresponding power supply, it is necessary to go for the next phase, and that means meeting the power demand by purchasing power from the market.

Additionally, in phase two, we allow virtual power plants to purchase and sale power in the power market, and by means of equation (1)–(11) to minimize the operating costs of power system. At the same time, we need to ensure that the power purchased from the market in phase two less than the shortage power which cannot be met by self-supply in phase one and then the elasticity of demand used to minimize system costs in virtual power plants can be guaranteed.

2.4.2. Market profits maximization strategy. Virtual power plants mainly maximize the market profits by purchase power in a low price when power is needed and sale power in a high price when power is surplus in virtual power plants. At the same time, the elasticity of power demand in virtual power plants also helps to increase the market profits to some extent.

Similarly to self-supply strategy of virtual power plants, the implementation and simulation of market profits maximization is also divided into two phases, while the market profits of daily operation before the target year are all required to be calculated, and then accumulated to obtain the total market profits. Based on the variable of power demand in virtual power plants, the calculation of daily market profits is divided into two phases: in the first phase, we assume that the market price is known, and virtual power plants are designed to maximize their market profits, and then on the basis of this to calculate the demand variable. The second phase, we must iteratively ensure the consistency between demand variable calculated in the first phase and the market price. When the differences of two successive iterations of the market price fall below a certain threshold, we consider that this iterative

process is converged.

During each iteration, the obtained solutions of virtual power plants' market profits all need to be compared with the solution in the former iteration, and if the solution is lower than the former solution, it is proved that the solution is not the optimal solution, and iteration is needed to obtain the optimal solution; meanwhile, if the solution is not lower than the former solution, then we stop the iterative process and get the optimal solution. If the maximum number of iterations is reached, we also stop iteration and recognize the obtained solution as the final optimal solution. Through the continuous iterations we can progressively approach to the optimal solution, until we finally find the optimal solution. Specific solving process is shown in the equation

$$\max M_j = \sum_t -D_{t,j}^{\text{net}} \cdot [Q_{t,j-1} + \frac{Q_{t,j-1} - Q_{t,j-2}}{D_{t,j-1}^{\text{net}} - D_{t,j-2}^{\text{net}}} \cdot (D_{t,j}^{\text{net}} - D_{t,j-1}^{\text{net}})], \quad (16)$$

here M_j is the market profit, $D_{t,j}^{\text{net}}$ is the net demand in virtual power plants, and $Q_{t,j-1}$ and $Q_{t,j-2}$ are the reference prices in iteration $j-1$ and $j-2$, respectively.

Meanwhile, when the net demand $D_{t,j-1}^{\text{net}}$ and $D_{t,j-2}^{\text{net}}$ in the previous two iterations are the same, the demand variable is set to zero; in equation (16), variable $D_{t,j}^{\text{net}}$ and $Q_{t,j-1}$ are consistent with the market profits of virtual power plants. If power demand is greater than power supply, that is, the net demand $D_{t,j}^{\text{net}}$ is positive, the surplus power will be sold in the power market at price $Q_{t,j-1}$, which represents a cost of virtual power plants. If power supply is greater than the power demand, that is, the net demand $D_{t,j}^{\text{net}}$ is negative, then the market profits of virtual power plants will increase. The other profit part of the equation is intended to reflect possible influence that the changing demand may have on the market price. In addition, when using this equation to obtain the optimal solution, equation (9) and (10) also need to be considered.

3. Case study

The principal data of the study are summarized in Table 1 and Table 2.

Table 1. Supply and demand data of one Chinese province

Annual demand (TWH)	60.8
Peak demand (GW)	10.1
Nuclear power (GW)	1.4
Thermal power (GW)	7.2
Hydropower (GW)	3.1
Wind Power (GW)	3.6
PV (GW)	1.4
Cogeneration (GW)	0.9
Biomass power (GW)	0.5

Table 1 displays the specific power supply and demand data of one specific province in China. From Table 2 it can be seen that the technical parameters are very de-

tailed, including scheduled outage rate, forced outage rate, minimum and maximum power outputs, ramping rate and other related parameters. In addition, there is some data related to costs and emissions. These are all the input parameters of the model we established before. Meanwhile, this paper assumes that from 2020 the distributed power system will account for 10% of virtual power plants.

Table 2. Average technical parameters of thermal plants in one Chinese province

	Thermal power	Closed-cycle gas turbines with one axis	Closed-cycle gas turbines with more axes	Gas turbines	Nuclear power
Scheduled outage rate (%)	0.05	0.015	0.015	0.023	0.08
Forced outage rate (%)	0.05	0.04	0.05	0.09	0.05
Minimum output (MW)	71	59	124	16	500
Variable heat rate (te/MWh)	1280	760	760	1200	1250
Non-load heat rate (te/h)	29,000	140,000	260,000	60,000	
Fuel costs (EURO/te)	0.17	0.34	0.34	0.34	0.019
Maximum output (MW)	176	196	398	153	500
Upper limit of ramping (MW/h)	51	68	139	65	
CO ₂ costs (Euro/t CO ₂)	18	18	18	18	
Emissions (t CO ₂ /MWh)	0.876	0.312	0.312	0.312	
Startup consumption (te/str)	710,000	180,000	390,000	250,000	
Startup time (h)	18	6	6	13	
Number of power plants	15	10	28	6	6

This paper's study of virtual power plants is representative to some extent. So far, the size estimation for the virtual power plant which greatly organizing and utilizing distributed energy barely has been studied except for a European report. This paper demonstrates single virtual power plants, and then expands it to all virtual power plants existing in China's large power system. Therefore, on the basis of virtual power plants' power supply situation, we expand our research based on the above 10% of cases. In addition, we assume that in virtual power plants wind power, photovoltaic power cogeneration account for the same percentage. At the

same time, we assume that the total power consumption of one Chinese province in 2020 is 60.8 Terawatthours. Then we select the demand data in 2011 as the basis, and the average annual growth rate is 2 percent until 2020, so that we can estimate the power consumption in 2020. The final calculation results obtained from the model are shown in Table 3 and Table 4.

Table 3. Solutions under different operation strategies from perspective of virtual power plant

	Self-supply strategy	Profits maximization	Costs minimization
Purchases of power (GW)	313	683	689
Sales of power (GW)	459	752	759
Net sales of power (GW)	146	69	70
Costs (Mio. Euro)	21	41	41
Incomes (Mio. Euro)	25	49	48
Net profits (Mio. Euro)	4	8	7
Demand coverage rate (%)	91.6	83.2	83.9
Variations of demand (GWh)	441	607	671

Table 4. Solutions under different operation strategies from the perspective of power system

	Self-supply strategy	Profits maximization	Costs minimization
Thermal cost (Mio. Euro)	1442	1445	1430
Emissions (Mio. Euro)	7.3	7.5	7.5
Spillage (GWh)	1186	1183	1191

It can be seen from the results that in terms of power demand coverage the self-supply strategy obviously surpasses the market profits maximization strategy, while market profits maximization strategy is relatively beneficial to virtual power plants' profits. And the differences between self-supply strategy and market profits maximization strategy are not obvious in terms of thermal costs, emissions and power spillage.

4. Conclusion

With the development of China's economy, problems of energy shortages and environmental pollution have become increasingly prominent, and this has made the integrated and controllable virtual power plants become more and more important. This paper utilizes the ROM model and unit commitment model for modeling and accessing virtual power plants under self-supply maximization and market profits maximization with two different operational strategies. The illustrative example used for verification of the scientific value, practicality and validity of the model proves that it can be used for modeling and evaluating virtual power plants' operation to promote the healthy and orderly development of China's power system.

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