Incentive-based Demand Response for a Virtual Power Plant

Yingyi Li1, Zhe Luo2*, Lifeng Liu1, Ke Sun1,3, Xuan Yang4 and Tian’en Huang4
1 State Grid Zhejiang Electric Power Co., Ltd., Hangzhou, Zhejiang, 310007, China
2 Tsinghua-Berkeley Shenzhen Institute, Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen, Guangdong, 518000, China
3 Zhejiang Huayun Electric Power Engineering Design & Consulting Co., Ltd., Hangzhou, Zhejiang, 310014, China
4 State Grid Hangzhou Power Supply Company, Hangzhou, Zhejiang, 311100, China
*Corresponding author’s e-mail: luo.zhe@sz.tsinghua.edu.cn

Abstract. With the development of Energy Internet, the virtual power plant (VPP) has been regarded as a creative and attractive form to realize the integration of different energy resources. The VPP could make advantages of demand-side participation and distributed energy resources (DERs) to eliminate the peak loads and thus to maintain the stability of power grid. Here, an incentive-based demand response (DR) scheme is designed to model the energy transactions in the VPP internal market. This scheme considers different attitudes of different kinds of consumers according to their DR bid offers. Especially, we also introduce the dissatisfaction function to model the impact of load reductions on the enthusiasm of consumers. With the objective to minimize VPP operation costs, the proposed scheme is formulated as an optimization problem with guaranteeing the interests of consumers. The experimental results show that the proposed incentive-based DR scheme could encourage consumers to reduce more load demands by offering corresponding incentive prices, which helps to decrease the total operation cost of the VPP and also improve the profits of consumers.

1. Introduction
In decades, there are more and more discussions on the ever-increasing energy demands and severe environment environmental issues with the increasing development of the economy. Especially, the peak load problems have become a prominent one, which might cause the power grid instability and even result in the high electricity prices [1]. Overall, it becomes crucial to reduce the energy demand during the peak-periods, based on which a win-win solution for utility companies and consumers would be achieved [2]. With the development and prevalence of smart grids, it has been proved that the distributed energy resources (DERs) and the demand-side participation show the great potential in eliminating peak loads [3]. In this background, one emerging trade is to integrate all kinds of energy resources, which needs the new technologies to combine the available energy components as a single system and then to optimize its operations [4]. Moreover, the energy utilization efficient also becomes more important than ever.

Considering aforementioned situations, the concept of the Energy Internet is proposed, which provides an architecture to aggregate different kinds of energies and then improves the utilization efficiency of those energy components by integrating several technologies, such as the information technology, advanced power electronic technology, and intelligent control technology [5]. In practice,
the virtual power plant (VPP) has been regarded as one kind of creative and attractive forms which could realize the integration of different energy resources. And from the perspective of the energy internet, DERs could participate into the electricity market through being aggregated in the VPP. Moreover, to smooth the aggregated load, the energy consumers are allowed to participate in the VPP internal market through the demand response (DR) program, which also helps to improve the stability of the grid [6]. The important researches on the VPP include the bidding strategies and optimal scheduling operation. To minimize the total operation cost of the VPP, an imperialist competitive algorithm was proposed in [7] to determine the optimal bidding strategy of the VPP. Considering the uncertainty characteristics of the renewable energy sources, a combined stochastic and robust optimization program was proposed in [8] to solve the self-scheduling problem of the VPP and thus to determine its optimal operations. However, those works focused on the operations of the DER, rather than consider the DR programs which helps consumers to participate into the electricity market.

Generally, there are two types of DR programs including the price-based DR program and the incentive-based DR program. According to the change of dynamic electricity prices, the price-based DR program encourages consumers to re-schedule their energy demands, which helps to improve more economical and reliable operations of power systems [9]. By providing the incentive payments, the incentive-based DR program induces consumers to reduce their load demands directly, which also contributes to promote the stability and feasibility of the power system [10]. There are several researches on the DR applications in the VPP. For example, aiming to minimize the operation cost of the VPP, authors in [3] designed an incentive-based DR scheme on the day-ahead basis, which determined the optimal bidding strategy of consumers and the optimal operations of different kinds of power generators. The authors of [11] proposed a price-based DR model to control a cluster of price-responsive demands. Most researches on VPP are focused on the price-based DR while a few of them investigate the incentive-based DR. However, the data reported by USA reveals that 93% peak load reductions were contributed by applying the incentive-based DRs, but only 7% reductions were from the price-based DR applications [12]. The report indicates that it is important to make a research on the incentive-based DR of the VPP.

Considering the above limitations, this study establishes a bi-level electricity market based on the day-ahead electricity market. On the one hand, the VPP participates into the wholesale electricity market for energy transactions; on the other hand, it administrates its internal market in which the VPP participants are involved. Based on this architecture, an incentive-based DR scheme is proposed in this study for the VPP and thus to encourage the load reduction from consumers by offering them appropriate incentive prices. The main contributions of this work can be revealed in three aspects. First, we are focused on the energy transactions in the VPP internal market and then design an incentive-based DR scheme for it. Second, the dissatisfaction function is introduced in this DR scheme to model the impact of load reductions on the enthusiasm of consumers, which gives a better representation of what's actually going on when consumers attend the incentive-based DR program. And third, the proposed DR scheme considers the characteristics of different consumers and through which the VPP can induce more load reductions from different kinds of consumers and thus to relieve the energy pressure during the peak-periods and contribute to the stability of the power grid.

The organization of the paper is as follows: Section II introduces the mathematic formulation in detail to explain the demand response process of the VPP system; based on which Section III designs the case study to evaluate the performance of the proposed IDR scheme with the result analyses. Section IV contains conclusions and future work.

2. Mathematical formulations

In this study, the VPP consists of a centralized energy management system, consumers, distributed generators (DGs) and energy storage system (ESS). The basic DR process is as follows, before the opening of the electricity market, the VPP operator would obtain the bid offer \( (p^{\text{bid}}, \Delta d^{\text{new}}) \) from consumers, which reveals the willing of consumer to participate into the DR program indicated by two information. It means that if the VPP pays to the consumer more than \( p^{\text{bid}} \), the consumer would like to
curtail his/her energy demand by no more than \( \Delta d_{c}^{\text{cap}} \) during the whole DR program period. With the objective to minimize the operation cost based on a day-ahead electricity market, the VPP operator determines optimal incentive prices for the consumers, the optimal operation strategy of the DG units and that of the IESS facilities. The detailed mathematical formulations are as follows:

\[
\min \sum_{t=1}^{24} \left( \pi_{c}^{\text{cap}} \sum_{j=1}^{N} \Delta d_{c,j} + e^{g} \cdot p_{p}^{g} + \pi_{c}^{b} \cdot p_{b}^{g} - \pi_{c}^{b} \cdot p_{b}^{g} \right)
\]

s.t.
\[
\Delta d_{c,j} = d_{c,j} \cdot (1 - e^{-\alpha_{c,j} \cdot (d_{c,j}^{\text{bid}} - d_{c,j}^{\text{cap}})}) \quad (2a)
\]
\[
\pi_{c}^{\text{bid}} \leq \pi_{c}^{\text{cap}} \leq \pi_{c}^{b} \quad (2b)
\]
\[
0 \leq \sum_{j} \Delta d_{c,j} \leq \Delta d_{c}^{\text{cap}} \quad (2c)
\]
\[
P_{c,j} = \pi_{c}^{\text{bid}} \cdot \Delta d_{c,j} - \varphi_{c,j} / \alpha_{c,j} ; P_{c,j} \geq 0 \quad (3a)
\]
\[
\varphi_{c,j} = \theta_{c} \cdot (\Delta d_{c,j})^{2} + \gamma \cdot \Delta d_{c,j} / \alpha_{c,j} \quad (3b)
\]
\[
\theta_{c} = \pi_{c}^{\text{bid}} / \sum_{c} \pi_{c}^{\text{bid}} \quad (3c)
\]

In the objective function, the first term \( \sum_{t=1}^{24} \pi_{c}^{\text{cap}} \sum_{j=1}^{N} \Delta d_{c,j} \) is the incentive payment for all consumers in time slot \( t \); where \( \pi_{c}^{\text{cap}} \) is the incentive price provided by the VPP to consumers in type \( c \) during the time slot \( t \), and \( \Delta d_{c,j} \) is the corresponding load reduction. The second term is the cost to generate energy by using the DGs; where \( g_{p}^{c} \) is the day-ahead prices and \( p_{b}^{g} \) is the generated power of DG unit during time slot \( t \). The third term is the cost of purchasing energy from the wholesale market; where \( b_{t} \) is the price to sell energy back to the wholesale market during time slot \( t \) and \( b_{p}^{g} \) is the corresponding energy amount.

Equation (2a) shows the relationship among the consumer load curtailment \( \Delta d_{c,j} \), the incentive prices \( \pi_{c}^{\text{cap}} \) and the bid price \( \pi_{c}^{\text{bid}} \) of consumer in type \( c \), which is obtained from [3]. The constraint (2b) and (2c) respectively restricts the boundaries of incentive prices and the total load reductions to protect the interests of both consumers and VPP operators. Especially, equation (2c) restricts that the total load reduction of a consumer cannot exceed its curtailment capacity \( \Delta d_{c,j}^{\text{cap}} \) which is the bid information known before.

Constraints (3) show the restrictions related with consumer profit \( P_{c,j} \). In detail, equation (3a) presents the profit of consumers with considering their dissatisfactions \( \varphi_{c,j} \) caused by the load reductions [13], which should be positive during the whole DR process. Especially, in the dissatisfaction function (3b), the attitudes of consumers to reduce demands are reflected by [14], in
which $\theta$ and $\gamma$ are coefficients. In equation (3c), the consumer attitudes are defined and represented by their bid offers, which is consistent with the definition of bid offer.

Constraints (4) restrict the operations of the DG, such as its generation capacity $p$ and the ramping rate constraints ($r/r'$) in equation (4b); here, the DGs involved in this study are regarded as an integrated DG system.

Moreover, the ESS is used as a backup component to store energy during the low-price periods and then to supply energy during the high-price periods. Constraints (5) restrict the operation of the ESS. In detail, equation (5a) represents the energy storage amount ($S_t$) of the ESS in time slot $t$, which shows a continuous process from time slot $t$ to $t+1$ with considering the charging and discharging process of the ESS. During each time slot, the charging/discharging amount ($ch_t/ dis_t$) should be limited by its capacity value ($ch_{max}/ dis_{max}$). As restricted by equation (5c), if the ESS charges, the charge index $i_{ch} = 1$, otherwise the vice. As shown in equation (5d), if the ESS discharges, the discharge index $i_{dis} = 1$, otherwise the vice. And equation (5e) restricts that during the same time slot, only one operation (charge or discharge) would be occurred.

Finally, the energy balance of the whole system is regulated by constraint (6), which means that the energy generated by DG plus the energy purchased from the power grid minus the extra energy sold back to the power grid should be equal to the load demand of consumers minus their load reduction with considering the charging and discharging process of the ESS.

3. Case study

3.1. Parameters

In this study, we consider three kinds of consumers, namely the residential, commercial and industrial consumers. The load profile of a single consumer in different types is obtained from [15]. And the corresponding bid information is listed in Table 1. Experientially, we set the load elasticity coefficients of different (i.e., residential, commercial, and industrial) consumers as 0.15, 0.1, and 0.05 [18]. $\gamma$ is set as 0.1. And the day-ahead prices were obtained from the PJM website [16] and the prices to sell energy back to the wholesale market is set as the 85% of the day-ahead prices. The parameters of DG units and ESS are listed in Table 2.

| Table 1. Bid information of consumers [15]. |
|---------------------------------------------|
| Type             | Consumer number | Curtailment capacity (MW) | Bid price ($/MWh) |
| Residential      | 331             | 0.6                        | 40.00             |
| Commercial       | 124             | 12                         | 32.61             |
| Industrial       | 62              | 30                         | 30.57             |

| Table 2. DG unit and ESS parameters. |
|---------------------------------------|
| Items                          | Values          |
| Unit price of DG generation      | 70              |
| DG/ESS Capacity (MWh)            | 500/500         |
| Lower/upper limit of ramp constraint | -100/100     |
| Maximum Charge/discharge amount (MWh) | 50             |
| Charge/discharge coefficient     | 0.9             |

3.2. Results

We use the Lingo optimizer [17] to solve the optimization problem. Figure 1 shows optimal incentive prices for consumers in each type; for example, IP1/ IP2/ IP3 mean the incentive prices for consumers of residential/commercial/industrial type respectively. And we can find that the incentive prices for consumers are relatively high during the high-price periods, which helps to induce more consumers to
participate in the DR program. The load curtailments of consumers are illustrated in Figure 2; LR1/ LR2/ LR3 means the load reduction of consumers of residential/commercial/industrial type respectively. The results show that there are more load reductions during the peak-periods. Moreover, we make an analyses on the energy transactions from the perspective of the VPP, which is shown in figure 3. The results show that during the low-price periods, the VPP tends to purchase energy from the market and stores energy using the ESS; while during the high-price periods, the VPP would supply its internal demand by generating energy using the DG, discharging energy and even sell energy back to the electricity market.

Figure 1. Optimal incentive prices for different types of consumers.

Figure 2. Load curtailments of consumers over one day.

Figure 3. Energy transactions of the VPP.

Here, we conduct a benchmark case and make the result comparisons to verify the superiority of the proposed incentive-based DR scheme. In the benchmark case, the VPP provides the same incentive prices for all consumers without considering their different characteristics. Table 3 shows that the proposed scheme has a better performance than that of the benchmark case. In detail, the proposed scheme induces a higher total reduction, provides a higher incentive payment, and reduces the total operation cost of the VPP, and obtains more incomes by selling energy back to the power grid. Moreover, results reveal that the profits of consumers in different types are also improved by applying the proposed incentive-based DR scheme.

| Items               | Total Load reduction (MWh) | Incentive payment ($) | VPP operation cost ($) | Residential consumer profit ($) | Commercial consumer profit ($) | Industrial consumer profit ($) |
|---------------------|-----------------------------|-----------------------|------------------------|---------------------------------|-------------------------------|--------------------------------|
| Benchmark case      | 1967.59                     | 90256.4               | 352146.2               | 2398.86                         | 10051.13                      | 3767.26                        |
| Proposed scheme     | 2787.39                     | 125012.4              | 345570.6               | 2562.16                         | 16831.15                      | 8893.46                        |

4. Conclusions and future work

In this study, we proposed an incentive-based DR scheme for the VPP, based on which the VPP can determine optimal incentive prices for consumers while aiming to minimize the operating cost. In
addition, the proposed incentive-based DR scheme determines the optimal scheduling for the DG unit and ESS, which helps to relieve the peak-load pressure and thus makes contributions for the stability of the power grid. In conclusion, the proposed incentive-based DR could encourage consumers to participate to the electricity market and reduce more load demands, which helps VPP to decrease its costs and also the power grid to relieve its pressure during the peak-periods.

In future, we will extend the proposed IDR model to the real-time market, and the VPP will act as a price-maker to interact with the electricity market in the further study.

References
[1] Saffari, M., de Gracia, A., Fernández, C., Belusko, M., Boer, D., & Cabeza, L. F. (2018) Optimized demand side management (DSM) of peak electricity demand by coupling low temperature thermal energy storage (TES) and solar PV. Applied Energy, 211: p. 604-616.
[2] Wang, Y. and Li, L. (2016) Critical peak electricity pricing for sustainable manufacturing: Modeling and case studies. Applied Energy, 175: p. 40-53.
[3] Mnatsakanyan, A. and Kennedy, S. (2013) Optimal demand response bidding and pricing mechanism: Application for a virtual power plant. in 2013 1st IEEE Conference on Technologies for Sustainability (SusTech). Portland, OR. pp. 167-174,
[4] Zhu, J., Xie, P., Xuan, P., Zou, J. and Yu, P. (2017) Renewable energy consumption technology under energy internet environment. 2017 IEEE Conference on Energy Internet and Energy System Integration (EI2), Beijing. pp. 1-5.
[5] Hu, J., Liu, Y., Yan, Z., Wang, S., Wu, Z. and Hua, Y. (2017) Modeling on Electrical Power Market Clearing with Consideration of the Participation of VPP and MG in View of Energy Internet. IEEE International Conference on Energy Internet (ICEI), Beijing. pp. 171-175.
[6] Yu, M. and Hong, S.H. (2017) Incentive-based demand response considering hierarchical electricity market: A Stackelberg game approach. Applied Energy. 203: p. 267-279.
[7] Kasaei, M.J., Gandomkar, M., and Nikoukar, J. (2017) Optimal management of renewable energy sources by virtual power plant. Renewable Energy. 114: p. 1180-1188.
[8] Baringo, A. and L. Baringo. (2017) A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant. IEEE Transactions on Power Systems. 32(5): p. 3492-3504.
[9] Kazempour, J. and Hobbs, B.F.. (2018) Value of Flexible Resources, Virtual Bidding, and Self-Scheduling in Two-Settlement Electricity Markets with Wind Generation—Part I: Principles and Competitive Model. IEEE Transactions on Power Systems. 33(1): p. 749-759.
[10] Deng, R., Yang, Z., Chow, M. Y., & Chen, J.. (2015) A survey on demand response in smart grids: Mathematical models and approaches. IEEE Transactions on Industrial Informatics. 11(3): p. 570-582.
[11] Rahimiyan, M. and Baringo, L.. (2016) Strategic bidding for a virtual power plant in the day-ahead and real-time markets: A price-taker robust optimization approach. IEEE Transactions on Power Systems. 31(4): p. 2676-2687.
[12] Cappers, P., Goldman, C. and Kathan, D.. (2010) Demand response in US electricity markets: Empirical evidence. Energy. 35(4): p. 1526-1535.
[13] Lu, R., Hong, S.H. and Zhang, X.. (2018) A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach. Applied Energy. 220: p. 220-230.
[14] Yu, M. and Hong, S.H.. (2016) Supply–demand balancing for power management in smart grid: A Stackelberg game approach. Applied energy. 164: p. 702-710.
[15] Luo, Z., Hong, S.H., Ding, Y.M.. (2019) A data mining-driven incentive-based demand response scheme for a virtual power plant[J]. Applied Energy. 239: 549-559.
[16] PJM. “Day-Ahead Energy Price Data” 201705. Available from: http://www.pjm.com.
[17] Lingo optimizer. Available from: https://www.lindo.com.