Optimal Behavior of Demand Response Aggregators in Providing Balancing and Ancillary Services in Renewable-Based Power Systems

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Abstract. Due to the limited predictability and associated uncertainty of renewable energy resources, renewable-based electricity systems are confronted with instability problems. In such power systems, implementation of Demand Response (DR) programs not only can improve the system stability but also enhances market efficiency and system reliability. By implementing cloud-based engineering systems the utilization of DR will be increased and consequently DR will play a more crucial role in the future. Therefore, DR aggregators can efficiently take part in energy, balancing and ancillary services markets. In this paper, a model has been developed to optimize the behavior of a DR aggregator to simultaneously participate in the mentioned markets. To this end, the DR aggregator optimizes its offering/bidding strategies based on the contracts with its customers. In the proposed model, uncertainties of renewable energy resources and the prices of electricity markets are considered. Numerical studies show the effectiveness of the proposed model.

Keywords: DR aggregator · Demand response · Ancillary services markets · Renewable energy resources

1 Introduction

Increase of environmental conservation concerns and decrease of fossil fuel resources have caused penetration of renewable energy resources to be significantly augmented all over the world [1]. Due to the limited predictability and associated uncertainty of these resources, renewable-based electricity systems are confronted with instability problems [2]. In such power systems, implementation of Demand Response Programs (DRPs) not only can improve the system stability but also can enhance market efficiency, decrease peak demand, reduce price instability, and increase the system reliability [3]. The enhancement in market efficiency enables most of market participants, such as transmission system owner, distributors, and retailers to take advantages of implementing DR [4]-[6].

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On the other hand, by implementing Cloud-based Engineering Systems (CES) the utilization of Demand Response (DR) will be increased and consequently DR will play a more crucial role in the future. Development of CES can significantly facilitate the aggregation of DR. Therefore, it can be an effective solution to increase the participation of electricity consumers to electricity markets [3]. To this end, both technology (e.g. CES) and policy (e.g. market rules and regulations) infrastructures are required to support implementation of DRPs in electricity markets [7], [8]. By developing the mentioned infrastructure, DR aggregators can efficiently take part in different electricity markets such as energy, balancing and ancillary services. In such situations, development of CES can definitely support DR aggregators to participate in the mentioned electricity markets as an important linking participant between Independent System Operator (ISO) and end users.

The literature covers many works regarding responsive demands who bid to the electricity markets [7]-[9]. However, DR aggregator performance has not been addressed in the reports. Although the participation of DR providers in the Demand Response eXchange (DRX) market has been presented in [10], the participation in energy and ancillary services markets has not been addressed. In [11], the DR aggregator has been considered as an agent in the electricity market modeled by multi-agent systems. However, the participation of the agent in ancillary services markets has not been modeled. It is noticeable that the simultaneous participation of DR aggregators in the energy, balancing and ancillary services markets has not been reported in the previous works, which is a new contribution this paper provides. In the renewable-based power systems, optimal behavior of these participants is complex due to many uncertainties. The major proportion of the energy is cleared in day-ahead session. Therefore, all market participants have to submit their offers for all hours of the day ahead, several hours in advance. Because of the unpredictable nature of renewable-based power systems in the future smart grid, the offers have a meaningful degree of uncertainty. Thus, employing the balancing markets and ancillary services market is crucial for market operators to supply the spinning reserve requirement. On this basis, the DR aggregators have the opportunity to participate in the mentioned markets and supply a proportion of required spinning reserve and regulation.

In this paper, a model has been developed to optimize the behavior of a DR aggregator to simultaneously participate in energy, balancing and ancillary services markets. To this end, the DR aggregator optimizes its offering/bidding strategies for the mentioned markets based on the contracts with its customers. In the proposed model, uncertainties of renewable energy resources and the prices of electricity markets are considered. Numerical studies show the effectiveness of the proposed model. In addition, Conditional Value at Risk (CVaR) is incorporated into the model to tackle the uncertainties of market prices and the behavior of consumers.

2 Contribution to Cloud-Based Engineering Systems

Due to significant growth of the importance of energy conservation and environmental protections, DR can favorably affect the future smart grid [12]-[13]. In this context, Cloud-based Engineering Systems (CES) certainly have meaningful impacts on the future smart grid by increasing the collaboration between market players from both electricity and information viewpoints.

In this context, since a large number of managing and controlling data in the network imposes market participants to employ new computational methods to mitigate the system operation time, the CES can have the most important application.

The CES strongly influences the developing network impact while it depends on the access to numerous computational resources (i.e. cloud) in order to tackle the environmental restrictions by using the scarce processing and information storage proficiency. On this basis, improvements in CES enable end-users to more efficiently behave in demand side programs. DR aggregators possess the technology to perform DR and they are responsible for the installation of the smart meters at the end-users' components. As a matter of fact, DR aggregators can provide connectivity communication capabilities to end-users' components in order to connect them to the cloud. This can reduce the technical complexity and the required efforts to increase the local computational resources at the level of each end-user's component. On the other hand, CES can improve the security of the mechanisms and consequently increase the robustness of collecting data by the aggregator. Since each aggregator represents a significant amount of total demand in the DR market, it can negotiate on behalf of the end-users with the operator more efficiently. Since these players are the link between customers and electricity markets, they have a critical role in moving towards the future smart grid. In the future smart grid, by developing the CES and consequently increasing the participation of customers in DRPs, the players will have a more important role in the electricity markets.

3 Modeling the Self-scheduling of DR Aggregators

DR aggregator aims to maximize its profit by participating in day-ahead energy, balancing and spinning reserve markets. A schematic of DR aggregator presence in the mentioned markets, including both renewable and thermal Generation Companies (Gencos) in the supply side and retailers and large customers in the demand side, is illustrated in Fig. 1.

3.1 Uncertainty Characterization

In this paper two major types of uncertainty have been considered: the uncertainties related to market prices and the uncertainties associated with the quantity of activated reserve by ISO. The modeling of these uncertainties is explained as follows.

Modeling the Uncertainty of Market Prices. In order to participate in the renewable-based electricity market, the DR aggregator has to forecast market prices. In this paper, three uncertain market prices are considered: day-ahead energy, balancing and spinning reserve. To this end, the Roulette Wheel Mechanism (RWM) technique [14] is applied for scenario generation. In order to develop an accurate and appropriate model, market prices have been characterized by log-normal distribution in each hour [15]. Thus, considering that μ and σ represent the mean value and standard-deviation, respectively, the Probability Distribution Function (PDF) of market prices can be formulated as follows:

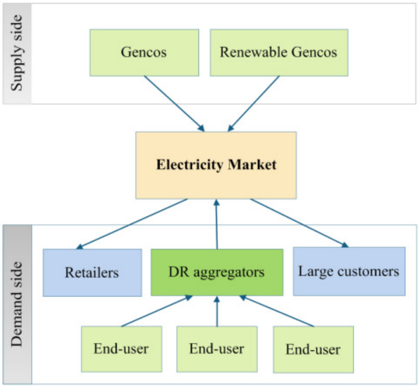

Fig. 1. Electricity market scheme

$$f_{Pr}(Pr,\mu,\sigma)=\frac{1}{Pr\sigma\sqrt{2\pi}}\exp\left[-\frac{(\ln Pr-\mu)^2}{2\sigma^2}\right] \tag{1}$$

Modeling the Uncertainty of Activated Reserve by ISO. In order to model the probability of quantity of activated reserve by ISO, Act_{ts}^{Res}, it is considered to be uniformly distributed between 0 and the offered amount by the DR aggregator. On this basis, the PDF of quantity of reserve activated by the ISO can be formulated as follows:

$$f(x)=1/P_{ts}^{Res} \quad , \quad 0\le x\le P_{ts}^{Res} \tag{2}$$

Considering (2) different outcomes of ISO's behavior for calling the DR aggregator and the activated quantity of reserve are taken into account by the RWM-based scenario generation process [14].

3.2 Incorporating Risk Management

The uncertain behavior of DR aggregator's customers enforces the profit of this participant with a high risk. Based on this, the DR aggregator has to manage the mentioned risk. To this end, Conditional Value-at-Risk (CVaR) as an appropriate technique is employed to incorporate risk management into the problem. The CVaR can be formulated as follows:

$$Max: \quad \xi-\frac{1}{1-\alpha}\sum_{s=1}^{S_N}\rho_s.\eta_s \quad , \quad \eta_s\ge 0 \tag{3}$$

$$-B_s+\xi-\eta_s\le 0 \tag{4}$$

The parameter α is usually assigned within the interval of 0.90 to 0.99, and in this paper it is set to be equal to 0.95. If the profit of scenario s is higher than ξ, the value of η_s is set to 0. Otherwise, η_s is assigned to the difference between ξ and the related profit. The above constraints are employed to unify the risk-metrics CVaR.

3.3 Mathematical Model of the DR Aggregator

The DR aggregator offers a specified quantity in day-ahead energy and spinning reserve markets in order to obtain an accepted level of energy and ancillary services into day-ahead market for each hour. Then, it can submit new energy offers or update the previous ones in the balancing market. Moreover, in the proposed stochastic framework, risk aversion is implemented by restricting deviations of expected profit using the CVaR technique. According to the above mentioned description, the optimal offer of the DR aggregator at each hour can be obtained by solving the self-scheduling problem to maximize its profit. The objective function can be expressed as (5):

$$\text{Max } EP=\sum_{s=1}^{S_N}\rho_s\sum_{t=1}^{T}\begin{bmatrix}\pi_{ts}^{DA}.P_{ts}^{DA}+\pi_{ts}^{Res}.P_{ts}^{Res}+\pi_{ts}^{bal}.P_{ts}^{bal}\\ +Act_{ts}^{Res}.\pi_{ts}^{DA}.\rho_{ts}^{call}.\rho^{Response}\\ -Act_{ts}^{Res}.\pi_{ts}^{bal}.\rho_{ts}^{call}.(1-\rho^{Response})\\ -D_t.\pi_t^{tariff}+\pi_{ts}^{DA}.r_t^{+}.\Delta_{ts}^{+}-\pi_{ts}^{DA}.r_t^{-}.\Delta_{ts}^{-}\end{bmatrix}+\beta\left(\xi-\frac{1}{1-\alpha}\sum_{s=1}^{S_N}\rho_s.\eta_s\right) \tag{5}$$

where, β is the weighting factor to achieve a trade-off between profit and CVaR.

The first term of (5) denotes the income of taking part in the day-ahead energy market. The next two terms represent the income resulting from spinning reserve and balancing markets. The fourth part represents the income resulting from delivering energy while it is called by the ISO. The fifth term denotes the purchase cost of energy from the balancing market that results from not delivering the activated reserve to the grid. The sixth term denotes the cost of responsive demands. The next two terms represent the positive and negative profit resulting from the balancing market and the last term indicates the CVaR multiplied by β.

The objective function is maximized considering the constraints described as follows:

$$P_{ts}^{DA}+Act_{ts}^{Res}+P_{ts}^{bal}\le D_t \tag{6}$$

$$-\sum_{t=1}^{T}\begin{bmatrix}\pi_{ts}^{DA}.P_{ts}^{DA}+\pi_{ts}^{Res}.P_{ts}^{Res}+\pi_{ts}^{bal}.P_{ts}^{bal}+Act_{ts}^{Res}.\pi_{ts}^{DA}.\rho_t^{call}.\rho^{Response}\\ -Act_{ts}^{Res}.\pi_{ts}^{bal}.\rho_t^{call}.(1-\rho^{Response})-D_t.\pi_t^{tariff}+\pi_{ts}^{DA}.r_t^{+}.\Delta_{ts}^{+}-\pi_{ts}^{DA}.r_t^{-}.\Delta_{ts}^{-}\end{bmatrix}+\xi-\eta_s\le 0 \tag{7}$$

$$0\le P_{ts}^{DA}\le P^{\max} \tag{8}$$

$$0\le P_{ts}^{bal}\le P^{\max} \tag{9}$$

$$0\le P_{ts}^{Res}\le P^{\max} \tag{10}$$

$$\Delta_{t\omega}=P_t^{Act}-P_{ts}^{DA} \tag{11}$$

$$\Delta_{t\omega}=\Delta_{t\omega}^{+}-\Delta_{t\omega}^{-} \tag{12}$$

The total capability of the aggregator in all day-ahead, balancing and ancillary services markets are given in (6). Eq. (7) represents the incorporation of risk into the problem. Constraints (8)-(10) are limits on the offer of DR aggregator, based on the contribution in different markets. Equations (11) and (12) are employed to calculate the energy deviation using the actual injected energy.

4 Numerical Study

Some numerical studies are accomplished on the common load curve of a real-world system [16], in order to indicate the usefulness of the proposed model. It is assumed that the peak of the typical load curve is equal to 100MW. Various scenarios have been generated by means of the probability distribution function which is explained in Section 3. On this basis, all uncertainties of market prices and calling by ISO have been divided into the hours of the day. Changes in β have been accomplished to study the impact of being risk taker or risk averse. Considering $\beta=0$ means the DR aggregator takes no risk. The results are expressed in Table 1.

It can be concluded from Table 1 that, as the risk coefficient increases the total expected profit is reduced, but the violation from this profit value is also reduced. In other words, if a risk-averse DR aggregator makes a decision to mitigate the risk of violation of the obtained profit value it pays as a reduction in the expected profit value, while a risk-taker aggregator prefers to have a more expected profit but at the cost of more violation probability from that expected profit value. Moreover, as it can be seen in Table 1, DR aggregator participation in ancillary services and balancing markets increases its expected profit and manages its risk.

Table 1. Effect of different electricity markets on DR aggregator’s profit and CVaR

Risk Level (β)	**Electricity Market**			**Expected Profit ($)**	**CVaR ($)**
	Day-ahead Energy	**Balancing**	**Spinning Reserve**		
0	✓			9421.5	8861.7
	✓	✓		9844.9	9420.5
	✓	✓	✓	11231.1	10783.3
0.5	✓			9278.6	8899.0
	✓	✓		9676.5	9458.7
	✓	✓	✓	11058.1	10897.2
1	✓			9159.4	8989.8
	✓	✓		9501.8	9492.2
	✓	✓	✓	11036.4	10962.0

Table 1 presents the effect of participation in the different markets on the DR aggregator’s expected profit. As it can be seen in Table 1, an increase in DR aggregator’s risk causes a reduction in its expected profits. Moreover, the participation in the balancing and spinning reserve markets can significantly improve the profit.

The hourly offers of a DR aggregator in the mentioned markets are indicated in Fig. 2. As it can be observed, the offers of the DR aggregator to the spinning reserve market are mostly more than the one to day-ahead energy market. In other words, DR aggregator prefers to participate in ancillary services more than energy markets. In addition, the effect of participation in balancing and ancillary services markets on DR aggregator's costs and incomes are presented in Table 2.

It should be mentioned that, in this paper the response probability of DR aggregator is considered to be equal to 0.05. According to Table 2, participation of a DR aggregator in ancillary services increases its expected profit. Moreover, participation in the balancing market can also augment the profit.

Table 2. Terms of costs and incomes of DR aggregator

Case	Participation in all day-ahead energy, balancing and ancillary services markets
Income from day-ahead energy market	5767.3
Income from balancing market	830.2
Income from spinning reserve market	7565.5
Positive imbalance income	243.3
Negative imbalance cost	454.2
Penalty resulted from not responding	295.1
Cost of responsive demands	2425.9
Expected profit ($)	11231.1

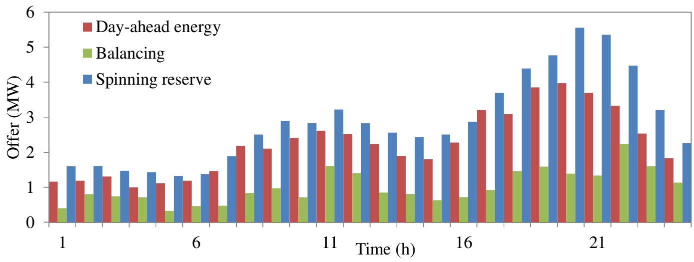

Fig. 2. Offers of the DR aggregator in day-ahead energy, balancing and ancillary markets

5 Conclusion

This paper investigated the impacts of different electricity markets on the optimal behavior of a DR aggregator in a renewable-based power system. In this regard, the DR aggregator can participate in day-ahead energy, balancing and spinning reserve markets in order to maximize its profit. In addition, the uncertain nature of market prices and quantity of activated reserve by ISO were modeled using RWM method. Furthermore, CVaR was applied as a risk measure for the DR aggregator, thus being able to specify the desirable weighting between expected profit and risk due to the uncertainty of customers' behavior. The results showed that the participation in balancing and ancillary services markets can provide a significant opportunity for DR aggregators. These markets not only could increase the expected profit of DR aggregators, but also could reduce their risks.

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