PSC NRI Niroo Research Institute Tavanir Co.
PSC 2015 سی امین کنفرانس بین المللی برق
۱۱ تا ۱۳ آبان ماه ۱۳۹۴ / تهران – ایران

No. E-15-AAA-0000

Stochastic Optimization of Demand Response Aggregators in Wholesale Electricity Markets

Atefeh Zomorodi Moghadam
Electrical Engineering department
Ferdowsi University of Mashhad
Mashhad, Iran
Atefeh.zomorodi@yahoo.com

Javad Saebi
Faculty of Engineering
University of Bojnord
Bojnord, Iran
jsaebi@ub.ac.ir

Hossein Javidi Dasht Bayaz
Electrical Engineering department
Ferdowsi University of Mashhad
Mashhad, Iran
hossein_javidi@yahoo.com

***Abstract*— This paper proposes a stochastic framework for demand response (DR) aggregator to procure DR from customers and sell it to purchasers in the wholesale electricity market. The aggregator assigns fixed DR contracts with customers based on three different load reduction strategies. In the presented problem the uncertainty of market price is considered and the risk of aggregator participation is managed in stochastic optimization problem with CVaR. The feasibility of this problem is studied on a case of Alberta electricity market.**

***Keywords*—DR aggregator; electricity market; risk management; stochastic optimization**

I. Introduction

Demand response (DR) is defined as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time at times of high wholesale market prices or when system reliability is jeopardized [20]. Introducing various demand response programs and their considerable benefits in electricity market in one hand and deployment of advanced metering tools to fill the gap of data on the other hand, cause a rising rate of DR programs penetration in power market [1] [6].The potential benefits of DR participation in the wholesale electricity market are discussed in the literatures [21], [6]. In the deregulated power system, there are two groups of players in market who benefit from DR programs. First group includes the market operator (MO), the Transmission System Operator (TSO), Distributors and Retailers who are the users of DR to improve the reliability of their related business. Second group consists of aggregators and costumers who are suppliers [11].

In recent years, regulatory agencies are trying to remove the obstacles for the integration of DR programs into electricity market. Under recent rules set by the Federal Energy Regulatory Commission (FERC), the FERC order 719 required ISOs in U.S. to accept DR bids comparable to other resources in wholesale markets [22]. It means that load reduction by a DR aggregator can be assumed as a virtual resource which is exchanged in market between users and suppliers [4]. In other words, beside the electricity produced by generating companies as the major source, DR is a minor source for improving reliability of the system [11].

In practice, DR participation in electricity market has been applied for large industrial customers; however, smaller costumers such as, residential sector, has more challenges. The reason is that participating in the whole sale electricity market has some requirements such as minimum reduction level. In this regard DR aggregators register costumers, aggregate their offer, and submit the aggregated offers on electricity market [3]. In other words, aggregators react as decision makers who have to find an optimal DR supply curve for offer. In fact DR aggregators participate in electricity markets as a medium between the ISO and retail customers and cause the integrating of small costumers into market by combining them into one [1].

The growing interest in participation of aggregators into the electricity market arises some new technical and economic challenges. An important challenge is related to the bidding strategy of an aggregator participating in the market. A few recent works have considered the role of aggregator on electricity market. A pool-based DR exchange model is introduced in [11] where all DR capacity is aggregated in a pool managed by DR exchange operator. The purpose of this paper is to maximize total market benefit; nevertheless, a linearly increasing supply curve is assumed for DR aggregator in objective function instead of finding an optimal bidding. The role of aggregator in the future smart grid has been studied in [18] which the interactions among end-users, utility operator and several aggregators have been investigated. An optimal demand bidding is proposed in [5], [15] with the objective function of minimizing the cost of a retailer participation in electricity market. Reference [1] is one of the recent activities that proposed a price-based self-scheduling for DR aggregator participation in the day-ahead electricity market. The goal of this paper is to maximize the agent's profit along with optimizing its bid by considering special DR contracts.

In the aforementioned bidding model for DR aggregator, the market price plays an important role. Moreover because of the uncertain nature of market price and its considerable impact on the optimal solution, the effects of this uncertainty and the associated risk should be taken into account in decision-making problem of aggregators. Moreover, it is not rational to consider just the expected values in bidding problem as in [16]. It is a common situation that the decision maker faces imperfect information about a parameter. In this circumstance, the decision maker has to make optimal decision over a specified horizon with incomplete data [8]. In [7] a stochastic optimization developed for real-time price-based DR to consider real time price uncertainty and the corresponding financial risk by robust optimization. Author in [17] propose a stochastic optimization for DR aggregator trading in market and manages the risk by CVaR approach. In [17] the source of uncertainty is customers' behavior.

In this paper, we propose a stochastic framework for aggregators' decision making problem. In the proposed framework, the uncertainty of market prices has been taken into account as well as aggregators' financial risk. The deterministic objective function of such an aggregator is based on reference [1]. To consider the probabilistic nature of market prices, Monte Carlo simulation is utilized. In order to take into consideration the associated risk, the conditional value at risk (CVaR) is added to the stochastic optimization. To the best of our knowledge, no literature has been incorporated the uncertainty of market price into a DR aggregator self-scheduling optimization problem with consideration of risk. The proposed model is verified by a realistic case study.

The rest of this paper is organized as follow. Section II presents the business framework for DR participation in wholesale electricity market. The self-scheduling model for DR aggregator, in both deterministic and stochastic ones, is described in section III, explaining how risk management can be considered. The simulation results of and discussion are presented in section VI. Finally, conclusion is given in section V.

II. FRAMEWORK

According to various structures for electricity market, DR aggregators could be one of the existing market participants such as, distribution system operator and load-serving entity or act independent of system operator [1], [2]. In the former circumstance, market participants aggregate different DR programs of the costumers as a DR aggregator. In the proposed model of self scheduling DR aggregator problem in [1], DR aggregator is assumed to be an independent financial entity which participates in the market instead of a group of costumers.

DR aggregators take part in the day-ahead electricity market as negative load which offer different kinds of load reductions to the market operator. These entities assign contracts with costumers to prompt their participation into the market with specified price. These assigned prices are assumed as cost for DR aggregators. After utilizing an optimizing function to determine proper load reductions, DR aggregators offer optimal DR program to the day-ahead electricity market in order to maximize their profit.

Costumers are involved typically in one of the four types of load reduction strategies which are, load curtailment (LC), load shifting (LS), on-site generation (OG) and using energy storage devices. In [3], the definition of these load reductions is explained in detail. DR aggregators attempt to find optimal quantities of these different groups of load reduction for maximizing the profits in the subsequent day of market. The ISO receives these load reductions from DR aggregator and incorporate them in market clearing procedure [3].

In this paper, three load reduction types, load curtailment, on-site generation and load shifting are considered for the customer participation in the market. We utilize the self-scheduling model for the optimal participation of aggregators in the day-ahead energy market which proposed in [1]. The point is that the price uncertainty is not considered in the formulation proposed in [1]. Therefore, in this paper we attempt to incorporate this uncertainty into the problem and propose a framework in which the risk of decision can be considered.

Our work in this paper includes four steps to proceed: 1) Introducing participation of DR aggregator into the market in deterministic situation. 2) Characterization the uncertain parameter and develop a stochastic optimization. 3) Controlling the associated risk of decision making. 4) Calculation of the expected value and variance of the profit of DR aggregator.

Details of each step are described in the following. In step 1, the objective function of a DR aggregator is introduced which is extracted from [1]. In this function, it is assumed that the DR aggregator can forecast the market price and is able to consider the effects of other DR aggregators on the market price in its forecasting. Hence this problem is deterministic and market price has a certain value.

In step 2, the impacts of unknown data will be considered. First we should characterize the uncertainty of market price for day-ahead market hence a scenario generation method is used to simulate this uncertainty. Then a stochastic optimization is developed to deal with uncertain market price.

In step 3, we enter a risk measure into the stochastic problem in order to simulate the behavior of DR aggregator in the market as a risk-averse decision maker. The CVaR approach is used for risk management [10].

In step 4, we simulate the proposed stochastic optimization in order to find the optimal value of load reduction for the next day participation in the market. Because of risk control during the optimization, the result of this simulation is more reliable; moreover, we can calculate the variance of the profit and the ratio of variance to expected value in order to examine risk for the next day optimization.

III. MODEL FOR DR AGGREGATOR

A. Deterministic

The objective of this formula is to maximize the gained profit. The revenue of DR aggregator is obtained from selling of the load reduction in the market and its cost is related to the assigned contract with costumers. The objective function is based on what proposed in [1] for three load reduction scenarios i.e. load curtailment, on site generation and load shifting. This objective function is defined below:

$$\sum_{t\in N_t}[\rho_t\left(\mathrm{LR}_t^{LC}+\mathrm{LR}_t^{OG}+\mathrm{LR}_t^{LS}\right)-\left(\mathrm{CLR}_t^{LC}+\mathrm{CLR}_t^{OG}+\mathrm{CLR}_t^{LS}\right)] \quad (1)$$

Where N_t is the time horizon, which in this study is 24 hours of next day, ρ_t is the market price, LR refers to the load reduction by LC, OG and ES and CLR is the cost of load reduction for respectively.

The first term of this function is the obtained revenue of the aggregator in the day-ahead market and the second term refers to the total cost of load reduction. These costs consist of primary price for participation in DR program and initial cost of different load reductions. Each of these load reductions have their own constraints. For example in LC contracts, minimum and maximum load reduction and maximum duration for load reduction should be included. Moreover this load curtailment has an initiation cost which should be considered. The details of these limitations and corresponding formulations for LC and OG and LS programs are explained in [1]. Due to the existence of some binary variables in the constraints, this formulation is a mixed integer linear programming (MILP) which can easily be solved with available tools. What encourages DR aggregators to take part in an electricity market is the difference between market price and the price paid to the costumers.

It is clear that the market price can have a significant effect on the profit and because of the uncertain nature of the market price, this uncertainty should be considered. DR aggregators should utilize one of the forecasting approaches to predict day-ahead electricity market price.

In this paper, different scenarios for market price are generated according to the historical data which is available for DR aggregator and develop a stochastic optimization instead of abovementioned deterministic approach.

B. Stochactic Programming Approach

The DR aggregator problem discussed above is subject to one source of uncertainty i.e. market price. In order to consider this source of uncertainty, we develop a stochastic optimization. Stochastic optimization is a well-known method that has studied and matured during recent years. An overview of stochastic programming is discussed in [23], [24]. As expressed in The Stochastic Programming Community [8] stochastic programming can be defined as “a framework for modeling optimization problems that involve uncertainty.” In this context, a stochastic programming model can be defined as a mathematical programming model with uncertainty about the values of parameters [14].

In stochastic programming, random variables are usually represented by a finite set of realizations or scenarios [8]. There are different scenario generation approaches which are about to represent an uncertain parameter in stochastic optimization. In [14], [25] various scenario tree generation, discrete scenario generation and clustering of scenarios have been studied. In this paper, scenario generation includes four stages. First of all we assume different normal probability distribution functions for every hour of historical market price with predefined values for mean and variance [16]. In the next stage, because of this fact that mathematical solutions are not able to handle continuous distributions, we divide them to discrete parts. Then, in the third stage, a scenario generation approach is used based on Mont Carlo simulation to produce a set of realization for market price of subsequent day. Since an optimization problem, which consists of all possible scenarios for a parameter, is too large and make the problem difficult to compute, in the last stage we utilize a scenario reduction method, named fast forward selection, which is expressed in [13]. By using this method a small number of scenarios, 16 scenarios in this case, with reasonable approximate represent the market price. In this case, instead of a single value for market price, we have 16 different values for the day-ahead market price with specified probability (π_w) and the sum of all probabilities is equal to one.

The stochastic objective function with the consideration of price uncertainty is as follows:

$$\begin{aligned}&\sum_{w\in N_w}\sum_{t\in N_t}\pi_w[\rho_{w,t}\left(\mathrm{LR}_{w,t}^{LC}+\mathrm{LR}_{w,t}^{OG}+\mathrm{LR}_{w,t}^{LS}\right)-\\&\left(\mathrm{CLR}_{w,t}^{LC}+\mathrm{CLR}_{w,t}^{OG}+\mathrm{CLR}_{w,t}^{LS}\right)]\end{aligned} \quad (2)$$

In this formulation N_w is the number of scenarios and all the variables get another dimension which refers to the different scenarios. Moreover, there is a multiplied parameter π_w that specifies the probability of every scenario. The aim of this function is to maximize the sum of profit over all the scenarios according to their probabilities. It should be noted that the introduced constraints in [1] for deterministic approach are still valid here.

C. Risk Control

The abovementioned stochastic programming maximizes the expected value of the profit, ignoring the associated risk to this decision making problem. These problems are called risk-neutral models [8]. When risk is considered, the profit values in the worst scenario take into account as well. It means that the variance of the profit impacts on the optimal value. In this case the agent becomes a risk-averse one [8].

In order to account the risk of the problem, risk measure should incorporate into the stochastic optimization. Value at risk (VaR) is one of the metrics for risk that inserts additional difficulties into the problem because of its need to binary variables for simulation [9]. CVaR is an appropriate technique to consider risk in a stochastic optimization problem. Moreover this method is expressed linearly and can be added to the optimization problem easily. In this paper we take the advantage of CVaR in order to incorporate risk into our problem and our program still remains MILP.

The risk considered formulation of the problem for a DR aggregator is as follow:

$$\sum_{w=1}^{N_w}\left\{\begin{aligned}&\sum_{t=1}^{N_t} n_w[\rho_{w,t}\left(\mathrm{LR}_{w,t}^{\mathrm{LC}}+\mathrm{LR}_{w,t}^{\mathrm{OG}}+\mathrm{LR}_{w,t}^{\mathrm{LS}}\right)-\\&\left(\mathrm{CLR}_{w,t}^{\mathrm{LC}}+\mathrm{CLR}_{w,t}^{\mathrm{OG}}+\mathrm{CLR}_{w,t}^{\mathrm{LS}}\right)]\end{aligned}\right\}+$$
$$\beta(\zeta-\frac{1}{1-\mathrm{a}}(\sum_{w\in N_w}\pi_w*\eta_w)) \tag{3}$$

Subject to constraints defined in [1] plus the following that are for CVaR and make the formulation linear [10]:

$$\sum_{t=1}^{N_t}\pi_w[\rho_{w,t}\left(\mathrm{LR}_{w,t}^{\mathrm{LC}}+\mathrm{LR}_{w,t}^{\mathrm{OG}}+\mathrm{LR}_{w,t}^{\mathrm{LS}}\right)- \left(\mathrm{CLR}_{w,t}^{\mathrm{LC}}+\mathrm{CLR}_{w,t}^{\mathrm{OG}}+\mathrm{CLR}_{w,t}^{\mathrm{LS}}\right)]+\zeta-\eta_w\le 0 \qquad \forall w \tag{4}$$

$$\eta_w \ge 0 \qquad \forall w \tag{5}$$

These constraints make the formula linear. The objective is to maximize the expected value of the profit and the CVaR which is added by a weighting factor, $\beta \in [0, \infty]$. The value of this factor shows how much risk averse the agent is in such a way that the higher the value of β, the more risk- averse the DR aggregator is. The parameter α is the confidence level which is chosen within the interval of 0.90-0.99. If the profit of scenario w is higher than ζ , the value of η_w is set to 0. Otherwise, it is assigned to the difference between ζ and the related profit [9], [10].

What we expect from the result of this optimization is that, DR aggregator attempts to sell load reduction in those hours which market price is significantly more than the price of contracts with aforementioned constraints during the optimization.

In the rest of this paper we assume the data which are essential for participation of DR aggregator to the market i.e. assigned contracts with costumers. Then the proposed method is simulated in order to assess the validation of this formulation.

IV. NUMERICAL RESULTS AND DISCUSSION

This section presents the results of applying the proposed stochastic optimization to a DR aggregator for its participation in electricity market. For simulating the optimization problem, we need to define the data of market price and the contracts of different load reduction by costumers. Then the proposed formulation in section III is solved using MILP solver CPLEX in GAMS which is a modeling system for mathematical programming problems. It is specifically designed for modeling linear, nonlinear and mixed integer optimization problems.

TABLE I. DR CONTRACTS

SC(1)	1	2	3	4	5	6	7	8
μ(2)	0.48	0.98	1.41	1.37	1.11	0.88	0.95	1.38
SD(3)	0.61	1.23	1.76	1.72	1.4	1.1	1.2	1.74

SC	9	10	11	12	13	14	15	16
μ	1.76	2.14	2.27	2.43	2.31	2.3	1.93	1.75
SD	2.21	2.68	2.84	3.05	2.9	2.88	2.42	2.19

SC	17	18	19	20	21	22	23	24
μ	2.03	3.11	3.12	2.99	2.9	2.39	1.74	1.43
SD	2.54	3.9	3.91	3.75	3.64	2.99	2.18	1.79

1. Number of scenarios
2. *Mean of normal distribution*
3. *Standard deviation of normal distribution*

TABLE II. DR CONTRACTS

contract	Price ($)	Initiation cost ($)
LC	10	50
OG	10	50
LS	10	50

A. *Data Prepration*

Scenarios for market price: In order to enhance the validity of the results, the historical market price for scenario generation is based on Alberta’s market price on first day of February in year 2014, which is the month that the highest consumption occurs [19]. Alberta’s electricity market is an energy-only, real-time market with uniform market clearing mechanism. As mentioned in section III we should define two main parameters of normal distribution which are used for scenario generation. These data are represented in table I. The output of this algorithm is the market price for every hour of the day-ahead market with 16 different probabilities.

Data of the assigned contracts: The data of the DR contracts related to the LC, OG and LS load reduction are given in table II. These data are approximately based on defined data in [1] with different contract price and initial cost.

B. *Simulation Results*

The following results show how a DR aggregator can take part in an electricity market with the goal to maximize its profit while considering the uncertain nature of market price. Our simulation consists of two steps. In step 1, we assess the proposed risk neutral formulation in section III and examine the results. In step 2, we simulate the risk control formulation and analyze the results under this circumstance. At the end, we calculate the expected value and variance of profit regard to changing the value of β.

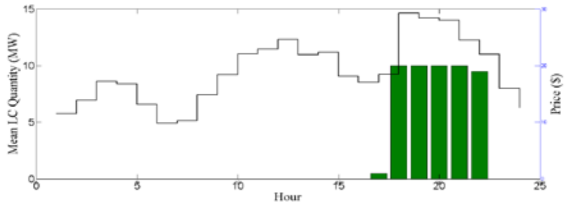

Fig. 1. Optimal average LC scheduling (β=0)

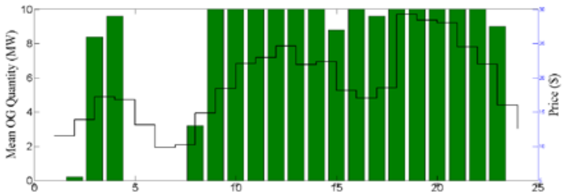

Fig. 2. Optimal average OG scheduling (β=0)

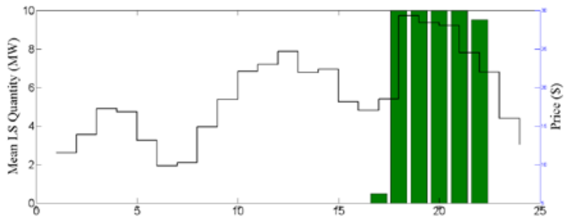

Fig. 3. Optimal average LS scheduling (β=0)

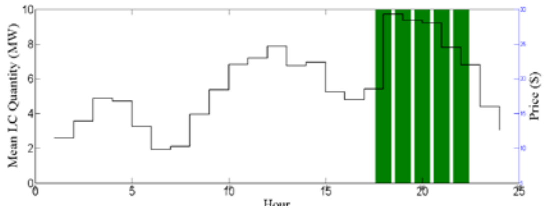

Fig. 4. Optimal average LC scheduling (β=0.5)

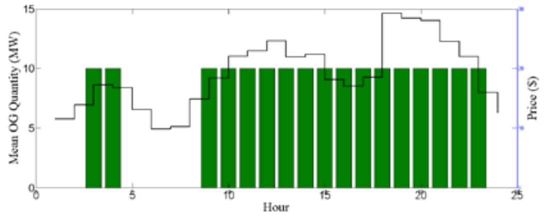

Fig. 5. Optimal average OG scheduling (β=0.5)

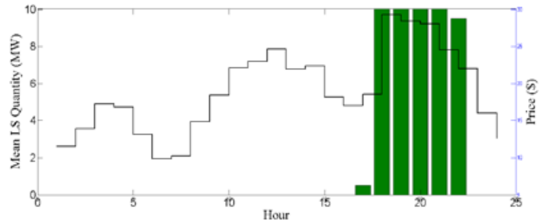

Fig. 6. Optimal average LS scheduling (β=0.5)

The results of step one are based on formula (2). The optimal solution for three defined DR strategies is represented in Figs.1-3 for average of load reduction quantities in all the scenarios in comparison to the average of hourly market price. The expected value of the DR profit for day-ahead market is 2135.5 $. As is shown in Fig.1, we can state that at hours 1-16 and 23-24 no load reductions in terms of LC have been scheduled because the difference between market price and the price of contracts in these hours are lower than others. Moreover, the maximum and minimum duration of load reduction are satisfied in this programming.

In Fig. 2 the optimal quantity for on-site generations has been shown. As is clear, the OG is started up at hour 3 till 4 and 8 till 23 when difference between market price and contract price is larger than other hours. The OG contract is not programmed at hours 5-7 because of the start-up cost for OG. Fig.3 illustrates that LS contract is activated at hour 17 and remains active until hour 22, those hours that consumption should be shifted because of the high market price.

The results of step two are based on managing the risk of next day participation of aggregator in the market. For this aim a single value for β is selected, which is 0.5. The obtained expected value for profit of DR aggregator is calculated as 2127.4$ which is lower than what gained in the risk neutral situation. The average amount of load reduction quantities are shown in Figs.4-6. As Fig.4 depicts, the LC contract is scheduled at hour 18-22, those hours that selling load reduction is profitable for aggregator considering market price and assigned price.

Fig.5 shows that optimal OG contract is not programmed at hours 1-2, 5-8 and hour 24 because of the low market price and the cost of starting up. Moreover, Fig.6 represents that customers shift their consumption from hours 18-22, because of the high market price, to hours that using electricity costs less.

By comparing the results of these two cases we can state that, considering risk causes a decrease in the profit of the aggregator that is because the less quantity of DR contracts is programmed for the next day participation of DR aggregator. Specially, the amount of OG contract is much lower when risk is considered in the optimization. For measuring the risk we need to find the variance of profit. The variance is calculated based on its mathematical definition as below:

$$\mathrm{Var(profit)=E(profit-E(profit))^2} \qquad (6)$$

In case one the variance of profit is 5.0534×10^5 while in case two this value decreases to 5.0273×10^5. This result proves what we expected from risk management which is reducing the profit in condition to less variance.

To make the impact of risk clear, we change the value of β from 0 to 2 in order to compare the expected value and the variance of profit gained by DR aggregator. The result is depicted in Fig.7. As we expected, with the increasing of β there will be a downward trend in the expected value of profit and that of the variance as well. It means, a conservative aggregator prefers to gain less profit but faces less risk in day-ahead market. However, a risky aggregator accepts the risk of the participation in order to gain more profit. Actually, the aim of a DR aggregator is to minimize the ratio of variance to

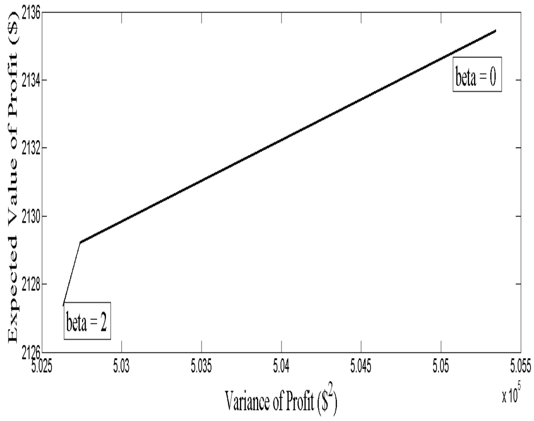

Fig. 7. Impact of risk on expected value and variance of profit

expected value in order to gain more profit with less risk in the market. We should note that the difference between the expected value of profit for different values of β will be more considerable when aggregator 1) assigns more DR contracts with customers, that mean more quantities trade in the market, and 2) is programming for longer horizon of time. For instance, when the DR aggregator is supposed to gain more profit the importance of reducing the associated risk becomes more remarkable.

V. NUMERICAL RESULTS AND DISCUSSION

This paper defines a stochastic framework to facilitate DR aggregator participation into the electricity market. The aggregator assigns three contracts based on three different load reduction strategies with customers and aims to maximize its profit for day-ahead through a stochastic price-based self scheduling problem. The uncertainty of market price is considered in optimization by the introduced scenario generation method and the associated risk is taken into account. The feasibility of the proposed model is examined by considering DR contracts and the following results obtained:

1) DR aggregator can offer the optimal scheduling in order to maximize its profit for day ahead electricity market.

2) Market price plays an important role in optimum scheduling and the aggregator need to forecast market price in a proper way.

3) Incorporating risk control shows that DR aggregator prefers to decrease its profit subject to face lower risk in the market.

4) Minimum and maximum load duration beside the risk control constraints mostly limit the optimum scheduling.

REFERENCES

[1] M. Parvania, M. Fotuhi-Firuzabad, M. Shahidehpour. "Optimal demand response aggregation in wholesale electricity markets." Smart Grid, IEEE Trans. , vol. 4,no. 4, pp. 1957-1965, Dec. 2012.

[2] M. Parvania, M. Fotuhi-Firuzabad, M. Shahidehpour. "Demand response participation in wholesale energy markets." In Proc. IEEE Power Energy Society General Meeting, San Diego, CA, USA Jul. 22-26, 2012.

[3] M. Parvania, M. Fotuhi-Firuzabad. "Integrating load reduction into wholesale energy market with application to wind power integration." IEEE Syst. J., vol. 6, no. 1, pp. 35-45, Mar. 2012.

[4] C. Chen, S. Kishore, Z. Wang, M. Alizadeh, A. Scaglione. "How will demand response aggregators affect electricity markets?—A Cournot game analysis." In *Communications Control and Signal Processing (ISCCSP), 2012 5th International Symposium on*, pp. 1-6. IEEE, 2012.

[5] R. Herranz, A M. S. Roque, J. Villar, and F. A. Campos. "Optimal demand-side bidding strategies in electricity spot markets.", *IEEE Trans. power syst.* , vol. 27, no. 3, pp. 1204-1213, Aug. 2012.

[6] Federal energy regulatory commission, "Assesment of demand response and advanced metering.", Aug. 2006.

[7] Z. Chen, L. Wu, and Y. Fu. "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization." *Smart grid, IEEE trans.* , Vol. 3, no. 4, pp. 1822-1831, Sep. 2012.

[8] M. C. Ruiz-Peinado, "Medium-term decision making for consumers, retailers, and producers in electricity markets via stochastic programming", PhD diss. , Universidad de Castilla La Mancha, 2008.

[9] E. Heydarian-Forushani, M. Parsa Moghaddam, M. Kazem Sheikh-El-Eslami, M. Shafie-khah, and J. P. Catalao."Risk-constrained offering strategy of wind power producers considering intraday demand response exchange." Sustainable Energy, IEEE trans. , vol. 5, no. 4, pp. 1036-1047, June. 2014.

[10] J. M. Morales, A.J. Conejo, and J. Pérez-Ruiz. "Short-term trading for a wind power producer." *Power Syst., IEEE trans. , vol. 25, no. 1, pp. 554-564. Jan. 2010.*

[11] T. D. Nguyen, M. Negnevitsky, and M.D. Groot. "Pool-based demand response exchange—concept and modeling." *Power Syst. , IEEE trans. , vol. 26, no. 3, pp. 1677-1685, Dec. 2010.*

[12] M. Negnevitsky, T. D. Nguyen, and M. D. Groot. "Novel business models for demand response exchange." *Power and Energy Society General Meeting, 2010.*

[13] N. Gröwe-Kuska, H. Heitsch, and W. Römisch. "Scenario reduction and scenario tree construction for power management problems." *Power Tech Conference Proceedings,IEEE, 23-26 June. 2003.*

[14] M. Kaut, and S. W. Wallace. "Evaluation of scenario-generation methods for stochastic programming.", 2003.

[15] Y. Liu, and X. Guan. "Purchase allocation and demand bidding in electric power markets." *Power Syst. , IEEE trans. , vol. 18, no. 1, pp. 106-112, Feb. 2003.*

[16] J. Sadeh, H. R. Mashhadi, and M. A. Latifi. "A risk-based approach for bidding strategy in an electricity pay-as-bid auction." *European trans. on Electrical Power, vol. 19, no. 1, pp. 39-55, Jan. 2009.*

[17] N. Mahmoudi, T. K. Saha, and M. Eghbal. "A new trading framework for demand response aggregators." *PES General Meeting| Conference & Exposition, IEEE, 27-31 July 2014.*

[18] L. Gkatzikis, I. Koutsopoulos, and Th. Salonidis. "The role of aggregators in smart grid demand response markets." *Selected Areas in Communications, IEEE Journal, vol. 31, no. 7, pp. 1247-1257, July 2013.*

[19] Alberta electric system operator (AESO). [online].available: http://www.aeso.ca/.

[20] Available: http://www.naesb.org/

[21] R. N. Boisvert, P. A. Cappers, and B. Neenan. "The benefits of customer participation in wholesale electricity markets." *The Electricity Journal, vol. 15, no. 3, pp. 41-51, Apr.2002.*

[22] Federal energy regulatory commission, "wholesale competion in regions with organized electricity markets", FERC order No. 719.

[23] J. R. Birge and F. Louveaux, " Introduction to stochastic programming", springer-verlag, New York, 1997

[24] P. Kall and S. W. Wallace, "stochastic programming", Wiley, Chichester, 1994.

[25] N. ülpınar, B. Rustem, and R. Settergren, "Simulation and optimization approaches to scenario tree generation.", Journal of economic dynamics and control, vol. 28, no. 7, pp. 1291-1315, Apr. 2004.