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Bidding strategy of demand response aggregators in DRX market

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***Abstract*—In this paper a bi-level model is proposed for participation of demand response aggregator in demand response exchange market. The objective of aggregator, modeled through upper level problem, is to maximize its profit and finding an optimal supply function. The upper level problem is constrained by the procedure of demand response market clearing, which is modeled in lower level problem. Utilizing KKT optimality condition the bi-level problem is converted to a mixed integer single level formulation. The feasibility of this problem is studied on a case study and results are presented.**

***Keywords*—bi-level model; demand response aggregator; demand response exchange market.**

Notation

The notation used throughout this papaer is stated below for quick reference:

A. Indices

t	24 hours of a day
w	Number of scenarios
n	Steps of supply and demand function
k	Number of binary variables for linearization

B. Real variables

$q_{DR}(w,t)$	Offered load reduction to DRX
AO(w,t), AV(w,t)	Incentive in obligatory and voluntary programs
penO(w,t)	Penalty in obligatory programs
qofferO(w,t), qofferV(w,t)	Offered load reduction in obligatory and voluntary programs
$qO_{DR}(w,t)$,$qV_{DR}(w,t)$	Load reduction by customers in obligatory and voluntary programs
prV(w,t), prO(w,t)	Paid incentive to customers in obligatory and voluntary programs
xO(w,t), xV(w,t)	Binary variable, 1 if incentive based programs scheduled
pAgg(w,t)	Price steps in supply function
qAgg(w,t)	quantity steps in supply function
stV(w,t), stO(w,t)	Starting indicator of obligatory and voluntary programs
endV(w,t), endO(w,t)	Stopping indicator of obligatory and voluntary programs
$qAgg_{max}(n,t)$	Maximum offered quantity of each step

C. Constants

$d_0(t)$	Initial demand of customers
ρ_0	Price of electricity for customers
ρ_RTP(t), ρ_TOU(i)	RTP and TOU rate
$qD_{max}(n,t)$, $pD_{max}(n,t)$	Steps of demand function in DRX
Pen agg(t)	Penalty of aggregator
$q_{max}(t)$	Maximum offered quantity at each hour
E	Elasticity coefficient
LRD_{min}, LRD_{max}	Minimum and maximum duration of load reduction
LRN_{max}	maximum number of load reduction

II. Introduction

Since 1990, power systems have been deregulated in order to bring competition in generation and retailing level and enhance the efficiency of electricity system. As a result of restructuring, the conventional approach to supply demand whenever it occurred has changed [1]. In the deregulated power system, customers become an active part in the market and change their demand pattern according to operator needs or when system reliability is in jeopardy. This new philosophy of operating power system is defined as demand response (DR).

DR programs bring lots of advantages in the electricity market such as reducing price volatility, improving reliability, avoiding the need of upgrading distribution , and transmission infrastructure, etc. [2], [15], [16]. Market participants who benefit from DR programs are categorized in two different groups. Players in the first group, including market operator (MO), transmission system operator (TSO), distributers, and retailers need DR to improve their reliability, decrease their financial risks and improve profit [3]. Players in the second group are the ones who provide DR and negotiate it for participants in the first group. In order to find a comprehensive approach to divide DR benefits across all players, the concept of demand response exchange (DRX) has been introduced [3].

In the pool based DRX model, the aggregated supply and demand function are cleared in a virtual pool handled by DRX operator [4]. Aggregators and large customers are the sellers of DR which apply their bidding to the DRX operator while TSO, retailers, and distributers are the buyers of DR in this market. Therefore DR becomes a tradable commodity that can be traded in a virtual framework separated from energy market [4].

On the sellers' side of DR trade, large customers satisfy the requirements of bidding into the DRX market such as minimum load reduction; however, each small industrial and residential customer does not have the minimum required capacity. Aggregators are independent entities which combine two or more customers and negotiate the DR capacity with buyers on behalf of their customers. Moreover, aggregators are responsible for implementing DR programs for their customers. Hence, these agents act as medium between customers and buyers of DR [4]. One of the main issues of aggregators is how to bid DR capacity to the DRX market in an optimal and profitable way.

Since DRX is a new concept in the power system, there is a growing interest in developing approaches for aggregators bidding into the DRX market. The model of a pool based DRX market and its clearing procedure was defined in [4] with predefined linearly increasing and decreasing function for buyers and sellers, respectively. In [5] an optimization framework for participation of aggregated DR in day ahead energy market was proposed. The aim of this paper is to find the optimal load reduction quantity that should be offered to the energy market according to different DR contracts with customers. An optimizing biding strategy for offering DR to wholesale market is developed in [6]. This paper concluded that if DR resources are unable to set locational marginal price (LMP) and do not compete with generators, the total revenue is more than when they are able to reduce LMP. The DRX market has been considered in [7] as an independent market from energy. The objective of this paper is to develop a dynamic bidding strategy for both buyers and sellers in this market while considering customers' tendency for participation in DR programs.

In the previous studies, constant curves were defined as supply function in DRX. This paper focuses on supply side of the DRX market; so, we propose a framework for participation DR aggregators in DRX market to achieve DR supply curves. In the proposed approach, aggregator offers different DR programs to its customers and utilizes the customers' DR capacity to develop a supply function for day-ahead DRX market. This procedure relies on a bi-level formulation. The upper level problem represents the objective of the aggregator, i.e. maximizing aggregator's profit with the aim of finding optimal supply function for each hour of the day ahead market. The lower level problem is the DR market clearing procedure with the objective function of maximizing social welfare. The upper level problem is restricted with the lower level one. The proposed bi-level formulation allows considering the effects of DR market clearing and demand for DR in aggregator bidding, simultaneously. Because of the presence of uncertain variable, demand curve in DRX, the formulation is modeled as a probabilistic one.

The rest of this paper is organized as follows. Section III represents the proposed bi-level framework, the corresponding nonlinear program, the equivalent linear form and the procedure of transforming formulation to single level program. In section IV, the input data of model and the result of simulation are described. Section V provides the conclusion for proposed optimization framework.

III. PROPOSED FRAMEWORK

A. *Model overveiw*

This model comprises a local DRX market where DR programs are supplied by one local aggregator as seller. The aggregator negotiates for selling DR capacity in this local market on behalf of its customers. The buyers' side of this market includes retailer, TSO and distributer who need DR.

In the proposed model, aggregator offers different kind of DR programs to their customers, which could be residential or small industrial customers. These programs include incentive based and price based programs. In incentive based programs, participating customers receive financial rewards in order to decrease or shift their load according to operator needs. Incentive based programs are divided to obligatory and voluntary programs [2]. In the former one, customers will be penalized if they do not perform the predetermined amount of load reduction. In price based programs, the electricity rates fluctuate based on the real time cost of electricity. In this paper, one type of price based programs, real time pricing (RTP), is utilized. The details of different kind of DR programs are discussed in [8], [9].

Price based programs directly rely on customers' behavior which make it difficult for aggregator to schedule the response of these programs for offering to the market. As a result, aggregator utilizes incentive based programs to compensate price based programs. After suggesting different DR programs, aggregator offers aggregated response of customers to the DRX operator as its optimal supply function.

It should be noted that in this paper, only load reduction is offered to the market as the aggregator's supply function.

Hence, shifted demand is not considered in aggregator's bidding to the DRX market.

B. Bilevel model

The decision making problem is related to a DR aggregator that jointly responsible for performing DR at customers' side and maximizing its own profit by offering DR commodity to the DRX market. Because the aggregator's bidding directly depend on the buyers' demand for DR and the system condition, the abovementioned problem is formulated as a bi-level programming model. The target of upper level program is to obtain supply function of aggregator, while the lower level program represents a market clearing procedure of DRX. The upper level program is constrained by the lower level one. The concept of the bi-level program and the connection between these two levels is shown in Fig.1. As it is shown in Fig.1, the upper level program develops the aggregator's optimal supply function with regarding the market clearing point. Data of market clearing, including price and quantity, is the output of lower level problem. The market clearing procedure in lower level problem, is performed with the supply function of aggregator as input.

Because of the uncertainty of aggregated demand curve for the DR aggregator, different scenarios are considered for this parameter instead of an exact one. This prompts to a probabilistic bi-level programming which is defined as follows:

$$Max \sum_{t,w} prob(w).\left\{ \begin{array}{l} q_{DR}(w,t)\times DR\ price(w,t) \\ -prO(w,t)-prV(w,t)+penalty(w,t) \\ -agg\ penalty(w,t) \end{array} \right\} \quad (1)$$

$$agg\ penalty(w,t) = price(t)\times \left[\begin{array}{l} q_{DR}(w,t)-qred(w,t)- \\ qV_{DR}(w,t)-qO_{DR}(w,t) \end{array} \right] \quad (2)$$

$$q\ offerO(w,t)+q\ offerV(w,t) = q_{DR}(w,t)-qred(t) \quad (3)$$

$$qred(w,t)=qRTP(w,t) \quad (4)$$

$$qRTP(t)=d_0(t)-d_0(t).\left(1+\sum_{l=1}^{24} E(t,l)\times\frac{\rho RTP(l)-\rho_0}{\rho_0}\right) \quad (5)$$

$$qV_{DR}(w,t)=d_0(t).\left(1+\sum_{t=1}^{24} E(t,l)\times\frac{AV(w,t)}{\rho_0}\right) \quad (6)$$

$$prV(W,t)=AV(W,t)\times qV_{DR}(W,t) \quad (7)$$

$$qO_{DR}(w,t)=d_0(t).\left(\begin{array}{l} 1+ \\ \sum_{t=1}^{24} E(t,l)\times\frac{AO(w,t)+penO(w,t)}{\rho_0}\end{array}\right) \quad (8)$$

$$prO(W,t)=AO(W,t)\times qO_{DR}(W,t) \quad (9)$$

$$penalty(w,t)=penO(w,t)\times\left[q\ offerO(w,t)-qO_{DR}(w,t)\right] \quad (10)$$

$$pAgg(n,t)\le pAgg(n+1,t) \quad (11)$$

$$qAgg(n,t)=q\max(t)/n \quad (12)$$

Where:

$$DR\ price(w,t),\ q\ offer(w,t)\in$$
$$\arg\left\{ \max \sum_{t,w,n} prob(w).\left[\begin{array}{l} pD(w,n,t)\times qD(w,n,t) \\ -pAgg(w,n,t)\times qAgg(w,n,t)\end{array}\right]\right\} \quad (13)$$

$$\sum_n qD(w,n,t)=\sum_n qAgg(w,n,t)\ :\ price\ DR(w,t) \quad (14)$$

$$0\le qAgg(w,n,t)\le qAgg_{\max}(n,t):\mu_1,\mu_2(w,n,t) \quad (15)$$

$$0\le qD(w,n,t)\le qD\max(n,t):\mu_3,\mu_4(w,n,t) \quad (16)$$

Model (1)-(13) comprises upper level problem. Its objective function is to maximize the mean of profit over all scenarios, which is modeled in (1). In this formula, q_{DR}(w,t) and DR price(w,t) are the quantity and price at market clearing point at hour t and scenario w. The aggregator's penalty to the market operator is defined in (2). This penalty will be imposed to aggregator, if there is different between q_{DR} and performed load reduction. As stated in (3), the difference between offered quantity to DRX and load curtailment by price based programs (q_{red}) is offered to the customers by incentive based programs. The response of customers to the voluntary and obligatory incentive based programs is defined in (6)-(10) [16].

Constraints (11) and (12) express the price and quantity steps of aggregator's supply function, respectively. Constraint (12) explains the increasing trend of price steps. Moreover, the quantity steps of supply function are considered equal to each other in constraint (12). It should be noted that the decision variables, pAgg and qAgg, are independent of scenarios; because, the supply function of aggregator should be optimal in all possible scenarios.

Lower level problem is defined in (13)-(16) which attempts to find the market clearing point by maximizing social welfare. Social welfare is defined as difference between amounts of money that buyers pay with what is paid to sellers in DRX market.

In order to considering customer's welfare in incentive based DR programs, the following constraints are added to the bi-level formulation for both voluntary and obligatory programs. These constraints determine the maximum number of possible load reduction during a day and maximum and minimum duration of load reduction each time [5].

$$\sum_{t'=t}^{t+LRD_{\min}-1} xO(w,k,t')\ge LRD_{\min}\times stO(t) \quad (17)$$

$$\sum_{t'=t}^{t+LRD_{\max}-1} endV(t')\ge stV(t) \quad (18)$$

$$\sum_t stO(t) \le LRN_{max} \quad (19)$$

$$stO(t) - endO(t) \le xO(w,k,t) - xO(w,k,t-1) \quad (20)$$

$$stO(t) - endO(t) \le 1 \quad (21)$$

The proposed model in (1)-(16) is nonlinear because of products of two variables in (1), (7) and (9), (10). In this paper, the binary expansion scheme in [10] is used to make the model linear and is applied to all mentioned statements.

$$AV(w,t) = AV_{min}(t) + \frac{\Delta AV(t)}{2^k} \sum_{k=0}^{K} 2^k . xV_{lin}(w,k,t) \quad (22)$$

$$prV(w,t) = AV_{min}(t).qV_{DR}(w,t) + \frac{\Delta AV(t)}{2^k} \sum_{k=0}^{K} 2^k . yV(w,k,t) \quad (23)$$

$$0 \le qV_{DR}(w,t) - yV(w,k,t) \le G(1 - xV_{lin}(w,k,t)) \quad (24)$$

$$0 \le yV(k,t) \le G.xV_{lin}(k,t) \quad (25)$$

The basic idea is to approximate the continuous decision variable by a set of discrete values. The detail of this method is described in [10]. By means of abovementioned approach, the products of variables transform to mixed integer linear expressions.

C. Single level model

In order to solve the proposed model with existing commercial software, the bi-level formulation should be transformed into an equivalent one-level mixed integer problem by means of KKT optimality conditions [11].

The KKT condition corresponding to lower level problem is represented in (26)-(31).

$$-pD(w,n,t) + price\ DR(w,t) - \mu_3(w,n,t) - \mu_4(w,n,t) = 0 \quad (26)$$

$$-pagg(n,t) - price\ DR(w,t) - \mu_1(w,n,t) + \mu_2(w,n,t) = 0 \quad (27)$$

$$0 \le qAgg(w,n,t) \perp \mu_1(w,n,t) \ge 0 \quad (28)$$

$$0 \le (qAgg_{max}(w,n,t) - qAgg(w,n,t)) \perp \mu_2(w,n,t) \ge 0 \quad (29)$$

$$0 \le qD(w,n,t) \perp \mu_3(w,n,t) \ge 0 \quad (30)$$

$$0 \le (qD_{max}(w,n,t) - qD(w,n,t)) \perp \mu_4(w,n,t) \ge 0 \quad (31)$$

The statements (28)-(31) make the single level model a nonlinear mixed integer problem which is converted to a mixed integer linear program as follows:

$$0 \le qAgg(w,n,t) \le M.u_1(w,n,t) \quad (32)$$

$$0 \le u_1(w,n,t) \le M.(1 - u_1(w,n,t)) \quad (33)$$

D. Scenario generation method

In this section, the scenario generation method, which is used to define different scenarios for demand curves in DRX market, is introduced. In this paper, we assume that aggregator is able to forecast aggregated demand curves with errors. The error of forecasting is expressed as normal probability distribution function with specified mean values. Then different values around the mean choose as scenarios; so that, the sum of the probabilities over of all scenarios become 1.

IV. NUMERICAL RESULT

This section presents the results of applying the proposed stochastic optimization problem to a DR aggregator for its participation into the DRX market. For simulating the optimization problem, we need to define the data of buyers' offer for DR and the initial demand of customers. 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.

A. Data prepration

The data which is used to produce the scenarios of demand curve is based on [4] and changed to adjust the condition of model. The buyer's demand is a monotonously decreasing curve which becomes step-wise in order to avoid nonlinearity. As an example, the mean value of the step-wise buyers' offer at hour 8, is illustrated in Fig.2.10 scenarios are defined to model the uncertainty of this parameter.

Data of Alberta electricity market [12] on 15th December is used for initial demand of customers. In this market, 50% of demand is pertaining to residential and small industrial customers. We assume that 20% of total residential consumers are in the aforementioned local DRX market. This demand is depicted in Fig.3.

The constraints for incentive based programs are defined as below: maximum number of load reduction in one day is 3 and 0 hours, respectively.

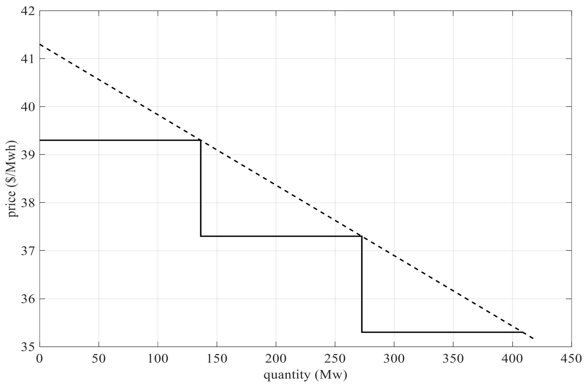

Fig. 1. Demand curve

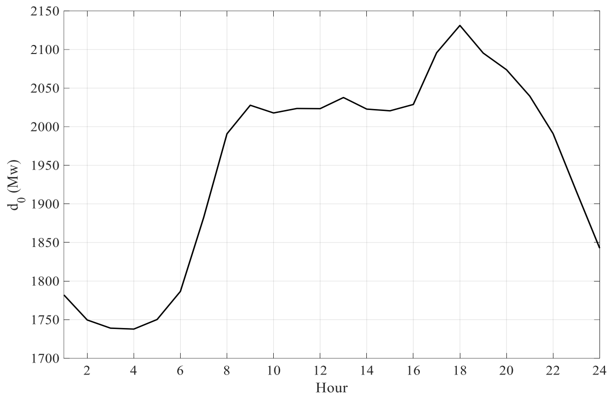

Fig. 2. Alberta electricity demand at 15th December 2015

For modeling the response of customers to price based programs, the rate of RTP should be defined. In the power system, retailers are responsible for setting these rates. These rates are specified RTP programs in Fig.4 [13]. The regular price of electricity for customers is assumed 7.5 cent/KWh.

B. Results

The following results show how a DR aggregator can take part in DRX market with the goal to maximize its profit while considering the DR market clearing procedure. The results of simulation are evaluated the scheduling of incentive based programs and the supply function of aggregator in different hours.

Fig.5 shows the load reduction of customers based on RTP programs. As is clear in Fig.5, at peak and off-peak periods, customers reduce their demand. The profit of aggregator of participation in DRX market is $ 48291. The scheduling of incentive based programs with the amount of incentive and penalty is depicted in Fig.6 and 7. It shows that, these programs are offered at peak and off-peak hours which are profitable for aggregator

The amount of load reduction offered to customers is shown in Fig.8. As can be seen, aggregator prefers to gain more amount of load reduction through obligatory programs. The reason is that, customers try to decrease their demand in obligatory programs in order to not become penalized. It is clear that in scheduling these programs, the constraints (17)-

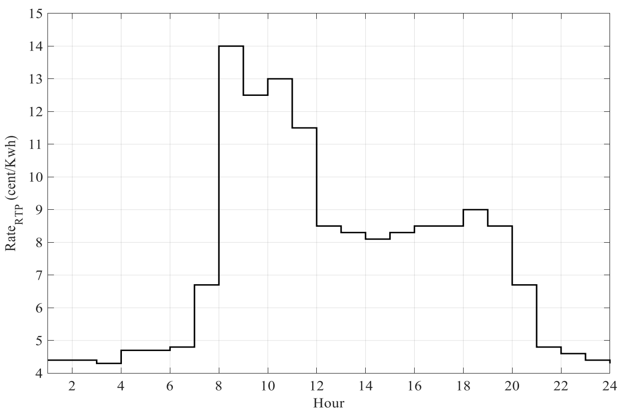

Fig. 3. RTP rates for customers

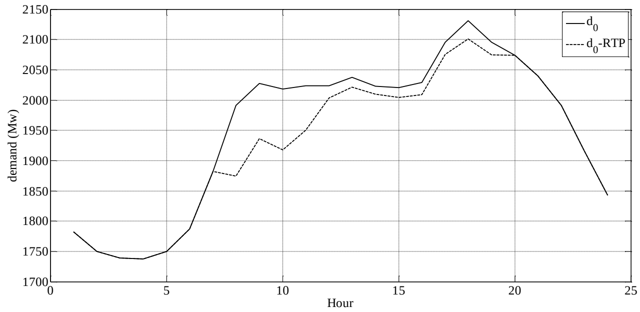

Fig. 4. Load reduction by RTP program

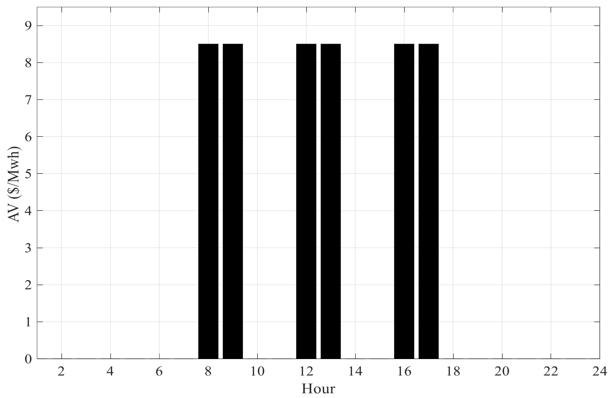

Fig. 5. Incentive for voluntary programs

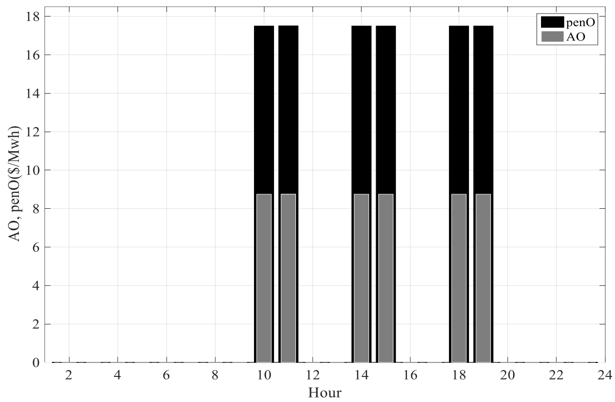

Fig. 6. Incentive and penalty for obligatory peograms

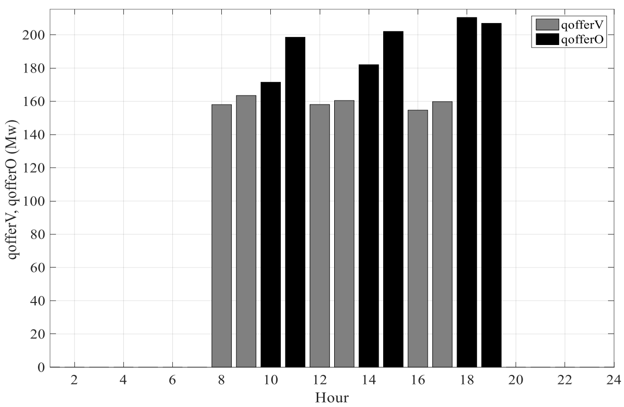

Fig. 7. Load reduction in obligatory and voluntary programs

(21) are satisfied and the customers' welfare is taken into account.

The mean of DR clearing price over all scenarios in comparison to mean offered DR, is depicted in Fig.9. At hours 8-11 and 18-19, the price of DR is more than rest of the day. That is because these hours are peak hours in which the demand for DR is high. In off-peak period, hours 12-17, DR clearing price is lower than peak hours; therefore, less amount of DR is offered by aggregator compare to peak hours. At the beginning and end of the day, no DR quantity is traded in DRX market because the demand for it is very low.

The optimized supply function of aggregator with the mean accepted value of DR is depicted in Figs. 10-12. The number of supply function steps is assumed 4 steps at most. Fig.10 shows aggregator offer at hour 8, which is one of the peak hours. At this hour, both incentive based and RTP programs are performed and price steps of supply function cover the aggregator's cost in incentive based program. The aggregator offers its capacity through 3 steps in an optimal way for all scenarios.

The supply function of hours 12 and 17 is shown in Figs.11 and 12, respectively. In these off-peak hours, demand for DR is lower than peak period. Hence, aggregator offers its supply function in lower step price. Supply function consists of 4 steps in these hours.

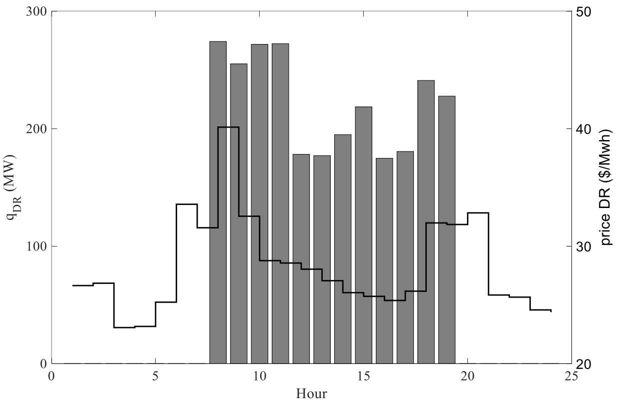

Fig. 8. Market clearing price and offerd quantity

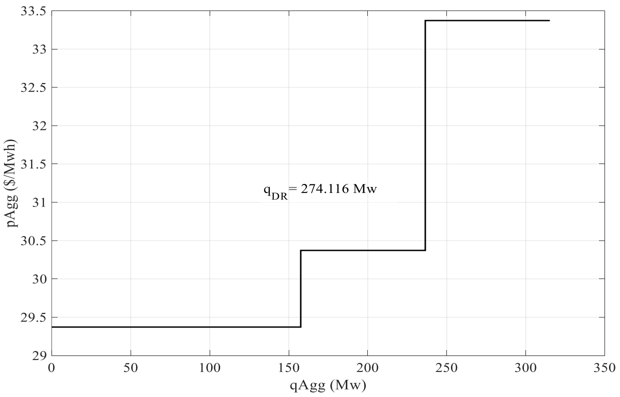

Fig. 9. Supply function at hour 8

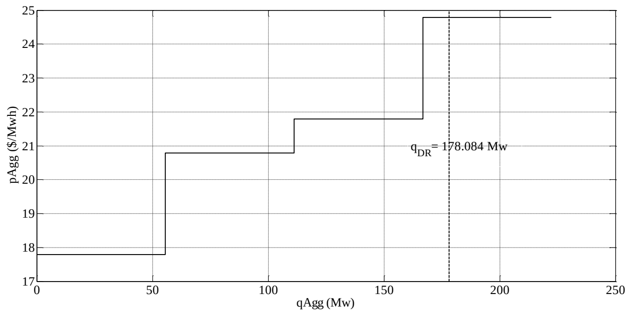

Fig. 10. Supply function at hour 12

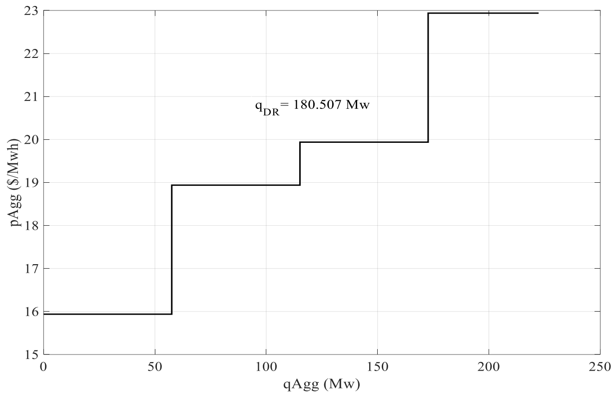

Fig. 11. Supply function at hour 17

In Fig.13, the DRX market clearing procedure at hour 12 and scenario 4 is studied to check its accuracy. The intersection between demand and supply function occurs at price \$ 24.43 and quantity 166.7 MW. This is exactly the clearing point which is obtained during the optimization and clearing procedure.

V. DISCUSSION

This paper proposes a stochastic framework for DR aggregator participation into the DRX market. The aggregator suggests different kinds of DR programs, including price based and incentive based, to its customers. The DR capacity of aggregator is obtained from customer responses to these programs. Then, aggregator offers its capacity to DRX market

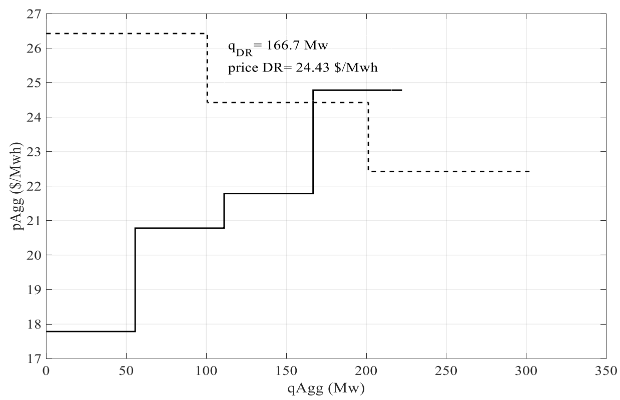

Fig. 12. Market clearing procedure

within an optimal supply function with the aim of maximizing its profit. This results in a bi-level optimization problem in which upper level is related to decision making problem of aggregator and lower level models the DRX clearing procedure. The feasibility of proposed model is examined and the results approve the efficiency of the model by being profitable for aggregator. Moreover it was shown that price based programs can be significant part of load reduction capacity.

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