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Optimal Modelling for Decision Making of Electricity Retailer in Power Market Contracts by Considering Demand Side Management Programs

Kourosh Apornak, Soodabeh Soleymani*, Faramarz Faghihi, Babak Mozafari
Faculty of Mechanic, Power and Computer Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran,
S.Soleymani@srbiau.ac.ir

Abstract

The growth and expansion of economic concepts in the power system is increasing in last years. Energy economists have considered the optimal decision-making of electricity market retailers in recent years. In this paper, a demand response program based model is pro-posed in order to make the optimal decision of the retailer in the electricity market, taking into account the different conditions that the retailer may face. The optimal model presented by modeling the behavior of retailers and consumers, while maximizing the profit of retailers, also leads to the optimal purchase of retailers from conventional contracts in the electricity market. The formulation of the proposed model is based on the presence of the retailer in the bilateral con-tracts as well as the pool market contracts in such a way that the optimization problem is solved in the form of nonlinear programming with SNOPT solver in GAMS software. The results indicate the effectiveness of the proposed model based on the fact that while increasing the retailer profit, the retailer purchase is also managed in the bilateral contract and the pool market.

Keywords: Power Market, Retailer's Profit Optimization, Electricity Retailer, Consumer, Demand Side Management, Decision- Making Model
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1. Introduction

The reforming and reregulation of the power system bring about substantial competitive, technical and regulatory modifications. Individual power producer and agents have added a new and vital aspect to the duty of securing a reliable electric system. Restructuring of the power system and deregulation causes comprehensive technological advances, which have helped to reform the methods for helping the utility companies to manage their business.

In our study, Electric restructuring is the procedure of replacing laws and rules that manage the power system to give consumers the selection of electrical suppliers who are either retailers or traders by permitting competitions. Restructuring in the power system develops the efficiency of energy economics in the power system for electrical production. Because of competition in the power system, the prices of electricity are likely to decrease which profits the customers.

- The principal objectives of the deregulated power market:
- To supply electricity for all reasonable demands.
- To encourage competition in the generation and supply of the electrical power system.
- To develop the continuity of supply and the quality of electricity.

[1] Provides a model from a retailer perspective to encourage those consumers who participated in the time of use pricing program and want to transfer their consumption from the peak hour to off-peak hours by shifting demand. In the model presented in this reference, the amount of risk is measured by the CVaR criterion. The most important goal in this reference is to provide an

efficient and rational way for retailers who agree upon with the consumer during the pool market and bilateral contracts and intend to persuade the consumer to move their demands. Also, in this model, price-based demand response programs are used as an incentive factor for the consumer. In [2], the benefits of real-time pricing programs for all electricity market customers and retail market customers are shown by presenting a statistical model based on Demand response. The basis of this proposed model is based on consumer demand elasticity. The proposed model presented in this reference also examines the economic benefits of demand response for consumers in the retail market. Besides, this demand elasticity statistical model has been tested for a variety of customers, including commercial, industrial, and household customers. In [3], short-term programming and a bidding algorithm are suggested to create a purchase offer curve for consumers entering the day-ahead energy market. An uncertainty, improbable interval information decision theory models uncertainty in the day-ahead market prices. The proposed algorithm presented in this reference depends on the presence and effectiveness of demand response programs definable. In [4], a plan has been provided for the proper performance of response programs so that the participants in the electricity market, including the owners of the lines, the distribution company, and the retailers, can enjoy the benefits of the response programs. This reference also addresses the formation of a market for the secure exchange of demand response with the DRX concept. The focus of this study is on encouragement-based demand response programs. The optimization algorithm is also presented in order for maximizing profit of the players who participated in the demand response programs. [5] Simulates the electricity market using demand response based on agent-based modeling and simulation (ABMS) commercial buildings. The main focus of this reference is on the consumption behavior of commercial buildings at different levels of demand response in different structures of the electricity market. It also examines the effects of commercial buildings consumption that react to tariff changes in the electricity market and the results of these changes in the retail electricity market. Other notable cases in this reference include changes in electricity prices and changes in demand profiles in the existence or absence of demand response. [6] Examined the risk of price volatility in the retail market. In this reference, the role of retailers and their management during price changes is discussed by highlighting the presence of demand response programs. The model presented in this reference also examines the electricity tariffs of the retail market in the existence of the Energy Storage System (EES) and distributed generation. [7] examined all the details and important points on how to enter the retail market, i.e., consumer behavior in the retail market is taken into account, and some information on competition between retailers is provided. This reference has studied the performance of the retail market in the long and edium-term.[8] Presents a stochastic multi-layered participatory model to study the behavior of electricity market players. In this multi-layered environment, the first layer is made up of renewable producers in the wholesale market. In this study, the goal of market players and participants is to optimize the strategy of purchasing (selling) energy. The next layers in this study consist of plug-in electric vehicle owners and customers participating in demand response programs. Interactions and behavior of actors in the day-ahead market and the real-time market are based on the Game Theory algorithm. [9]Investigates the impact of surveying consumers who have flexibility in their consumption and participating in demand response programs. This study has been conducted primarily in the real-time market and the regulation market. This reference investigates barriers and problems that may arise for flexible consumers in their consumption and disrupting their presence in the electricity market.[10] Presented the optimal strategy for proposing the purchase of energy in a microgrid, including distributed generation resources, consumers participated in the demand response programs. In this microgrid, the main goals is to reduce operating costs. In this regard, the logical relationship between energy production and consumption in this microgrid and energy exchange by the real-time market and the day-ahead market will be important. To this end, a robust, hybrid optimal stochastic programming has been performed based on demand changes and power market issues to reduce some costs, including expected net costs. [11], the goal is to maximize retailer profits by offering to buy energy from the day-ahead market. In this reference, consumers have an active presence in response programs under the supervision of the said retailer. This article also provides a solution for estimating and forecasting demands through dynamic tariffs and creates an energy purchase offer curve with these tariffs. [12] Discusses the optimal proposed strategies based on the presence of a plug-in electric vehicle (PEV) and responsive demands. In this paper, an uncertainty-based purchasing strategy model is proposed by examining the types of costs incurred by a plug-in electric vehicle for charging. The optimization problem is solved in several steps, and the optimization is solved based on MILP. [13] Addresses only electricity market interactions. This paper presented an optimal method for trading in the electricity market based on pool and bilateral contracts in terms of demand response. Retail activity is also divided into medium and short-term perspectives. In the medium-term perspective, the optimal amount of energy purchase is calculated during the power pool and bilateral contracts based on Monte Carlo simulations for uncertainties. [14] uses a robust, optimal approach for retailers' decision making inorder to consider uncertainties. Also, in their study, an optimal energy proposal strategy is presented as a set of optimal resilient strategies taking into account all the logistics costs in the demand response programs that the retailer has to pay. In modeling this issue, the upper and lower bounds of the pool market prices have also been considered. [15] Investigates retailer risk management issues; for example, retailer risk has been analyzed in several contracts in the electricity market based on VaR. In [16], methods for determining the customer compensation function are also reviewed, and the reliability and reliability value indicators were evaluated in addition to defining tariffs. [17] Addresses the relationship between customers and retailers with a proprietary perspective. This reference also investigates the effect of ownership structure on prices and tariffs. Besides, it discusses whether the criterion for electricity prices in the retail market is the average cost of fuel or the situation in the wholesale market. In [18], a stochastic programming method is proposed to determine the optimal strategy of retailers in a one-week time horizon in order to maximize profits and, at the same time, minimize the risk of the retail company, and performing the real-time, time of use and fixed pricing besides combination pricing optimally. [19]Provides a stochastic programming framework for determining the optimal retail strategy in which the company minimizes the maximum risk by etermining how to provide power and how to price it. The reference also modeled intermittent demands and how customers react to price changes. In [20] and in the context of the real-time market in which fixed tariffs cover most residential and small commercial consumers, retailers are exposed to price risk and quantities resulting from market price fluctuations and their unpredictable nature. In [21], demands often depend on factors such as time, weather, and type of consumers, which can be predicted with high accuracy using statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and specialized systems that are important to retailers in reducing risk. [22] Provides a framework based on the stochastic programming market in the medium-term, according to which the selling price of energy to customers is determined based on time of use tariffs. Besides, in this reference, the retailer uses various sources to secure his demand in order to be safe from the inherent risks of the electricity market. [23] Examines how energy is supplied from various sources, such as the option, ahead, and distributed generation contracts to maximize retailer profits. [24] Presents a framework for determining how to purchase energy using the following contracts in order to reduce the cost of Local Distribution Company (LDC) energy supply while taking into account price constraints. This reference answers the questions "What should be bought" and "How to buy?" using a hypothetical LDC in the city of Florida. In [25], approaches and policies of manufacturers and energy buyers in the power market are presented, in this reference investigation of the household consumers' performance in the electricity market is illustrated. In [26], an appropriate and associated model for exact analysis of the electricity retailer, the relation between programs based on demand response price, equipment overview, standards and new policies for smart measurement are presented, and methods for maintaining customers' knowledge in the competitive type of the retailer are established. In [27] an ideal bidding policy of retailers that buys its electrical energy in the electricity market, participating in the pool and a bilateral contract is suggested. [28] for the first time presents a theoretical and quantitative analysis of the beneficial effect of demand shifting (DS) in decreasing market power by the generation side. Quantitative analysis is presented by a multi-period equilibrium programming model of the imperfect electricity market, accounting for the time-coupling operational constraints of DS as well as system constraints. [29] Is the first piece of research that includes the DS flexibility in an imperfect electricity market model through also considering the cross-price elasticity of the demand side, but no theoretical or measurable analysis of the specific impacts of demand shifting on strategic producers' market power is offered. Also, the Incentive-based demand response program could be developed by price curves as described in [30] and [31]. In [32] a model for making bidding curves for the day-ahead market proposed.

This paper presents a model based on interval optimization in order to make optimal retailer decisions in bilateral contracts in the electricity market and the pool market. The proposed model is considering the price uncertainty in the pool market. Based on the proposed model and considering the demand-side management programs, the retailer maximizes its profit by creating participation in consumers. The proposed approach determines the most appropriate and optimal retail decisions based on the criteria of average profit, profit deviation and optimal pareto approaches.

Different sections of the paper include the following:

Introducing the retailer entity in the electricity market, demand side management, demand response in the electricity market and flowchart of the proposed model, input parameters of the problem, formulation of the proposed model and fuzzy approach to determine pareto points, result and discussion and finally paper conclusion.

2. Demand Side Management

Retailers are profit-based entities which purchase electricity from wholesale market with variable price and sell it to the end-use consumers with fixed tariff. The main aim of retailers is to make more profit in the electricity market reducing the financial risk of participation in the wholesale market .

Demand-side management (DSM) programs consist of the planning, implementing, and monitoring activities of electric utilities which are designed to encourage consumers to modify their level and pattern of electricity usage. In this regard demand response programs are defined: “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is put in danger. In other words, Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. Demand response programs are being used by some electric system planners and operators as resource options for balancing supply and demand. Such programs can lower the cost of electricity in wholesale markets, and in turn, lead to lower retail rates. Methods of engaging customers in demand response efforts include offering time-based rates such as time-of-use pricing, critical peak pricing, variable peak pricing, real time pricing, and critical peak rebates. It also includes direct load control programs which provide the ability for power companies to cycle air conditioners and water heaters on and off during periods of peak demand in exchange for a financial incentive and lower electric bills.

In this paper demand side management and demand response programs are applied by retailer to encourage customers to use their electricity in off-peak hours. The flowchart of the following problem is shown in figure (1).

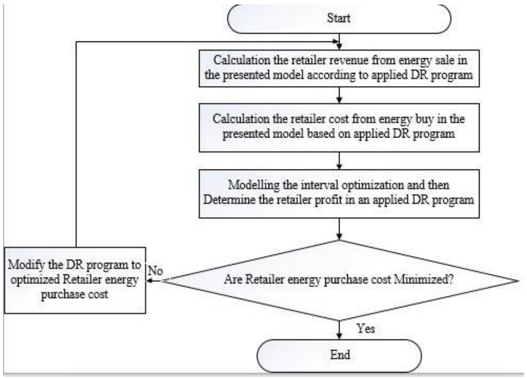

Fig. 1. Suggested flowchart of the presented model

3. Input Data

We count a retailer working in a power market and a time limit of 1 month for 6 bilateral contracts. Peak, medium and off peak hours besides bilateral contracts specifications are depicted respectively in table (1) and (2). Hourly pool prices are collected in 6 periods based on the Iberian electricity market [33].

The retailer sells energy to a group of 100 customers separated into three groups with related features about a) selling prices, b)consumption patterns, and c) reaction to the price suggested by the retailer. The three kinds of customers are residential (84 customers), commercial (12 customers) and industrial (4 customers). Power consumption for peak and off-peak periods is about 3.6 kW and 2.9 kW for residential customers, about 60 kW and 49 kW for commercial customers, and about 3.3 MW and 2 MW for industrial customers.

Table.1.
Levels of load

Levels of load	*Hours of a day*
Peak	1-6
Medium	6-17
Off-peak	18-24

Table.2.
Bilateral contracts specifications

Number of bilateral contracts	*Price($/kWh)*
1	0.054
2	0.051
3	0.059
4	0.065
5	0.041
6	0.048

4. Formulation

An optimization model for deterministic optimization problem can offered. It must be observed that the optimization model with both equal and unequal constraints in the occurrence of a ρ that is uncertain parameter in standard form structure is presented as shown below.

$$Min\ f(V,U,\rho), s.t. \tag{1}$$

$$g(V,U,\rho) = 0 \tag{2}$$

$$h(V,U,\rho) \leq 0 \tag{3}$$

In the presented optimization that is interval, the upper and the lower limit of the mentioned parameter were used as an alternative for $\rho \epsilon U = [U^{Min}, U^{Max}]$ that is the expected values. In other words, the parameter which is uncertain is described in form of parameter that is interval. So, the up and low bounds are obtained for the objective function instead of being considered for the desired quantity, since the ρ is assumed in place of input data in the uncertainty parameter $(f(v) \in [f^{-}(V), f^{+}(V)])$. Equations 4 and 5 are the up and low limits for the main objective function and are calculated as follows:

$$f^{+}(V) = \max_{\rho \subseteq U} f(V) \tag{4}$$

$$f^{-}(V) = \min_{\rho \subseteq U} f(V) \tag{5}$$

It should be noted that the objective function of the interval is formulated due to the existence of an interval parameter with uncertainty. So, the final objective function that is in form of uncertainty and interval must minimalized. At end, the final objective function that is in form of uncertainty and interval could be changed in form of a multi objective. In the proposed model changing the profit are minimized until the retailer is resistant to uncertainties of market price. The proposed multi-objective model is expressed through equations (6)-(8), based on the interval optimization method.

$$Min\ f(V) = \min(-f^{M}(V), f^{W}(V)) \tag{6}$$

$$f^{M}(V) = \frac{f^{+}(V) + f^{-}(V)}{2} \tag{7}$$

$$f^{W}(V) = \frac{f^{+}(V) - f^{-}(V)}{2} \tag{8}$$

It should be noted that $f^{W}(V)$ and $f^{M}(V)$ are the average profit and changes in the profit of the electricity retailer, respectively.

The presented multi-objective modelling of the problem based on multi-objective and interval structure could solved by means of the ε-constraint method [34] - [35] or weighted sum method [36] - [37] or using pareto solution method. The weighted sum method in this paper is used to solve the presented model. Lastly, fuzzy method is operated to choose a suitable result among all Pareto solutions.

Several weight coefficients are applied based on the significance of all objective function in method of weighted sum. So, the final objective function for optimization of multi-objective model with weighting sum way can be described as shown below:

$$\begin{aligned} &MinOF = w_1 \times f^{M}(V)_{pu} + w_2 \times f^{W}(V)_{pu} \\ &s.t. \\ &\begin{cases} w_1 + w_2 = 1 \\ All\ equal\ \&inequal\ \ constraints \end{cases} \end{aligned} \tag{9}$$

It must be mentioned both $f^{W}(V)_{pu}$ $besides$ $f^{M}(V)_{pu}$ are the value of average profit and profit changes in the normalized form. These values in normalized form are calculated according to the fuzzy method are shown below:

$$f^{M}(V)_{pu} = \frac{f^{M}(V) - f^{M}_{min}(V)}{f^{M}_{max}(V) - f^{M}_{min}(V)} \tag{10}$$

$$f^{W}(V)_{pu} = \frac{f^{W}_{max}(V) - f^{W}(V)}{f^{W}_{max}(V) - f^{W}_{min}(V)} \tag{11}$$

In the weighted sum method, the maximum and minimum average profits and profit changes are calculated $(f^{W}_{min}, f^{W}_{max}, f^{M}_{min}, f^{M}_{max})$. Then the normalized function of the average profit besides the profit deviations multiplied by various weight coefficients are add with each other in form of the separate objective function. Lastly, Pareto solutions of the proposed function minimization (9) are obtained by changing w_1 and w_2 between zero and one so that $w_1 + w_2 = 1$.

Values in the normalized form for average profit and profit changes per iteration are then computed based on Equations (10) & (11). Next, the lowest value among the normalize value in per iteration is chosen according to Equation (12). Lastly, the maximum value chosen between the minimum values is fixed on the appropriate solution for the multi-objective of the proposed problem. According to Equation (13).

$$\begin{aligned} &f^{n} = \text{minimum}(f^{n}_{1}, \dots, f^{n}_{N}); \\ &\forall\, n = 1, \dots, N_p \end{aligned} \tag{12}$$

$$f^{max} = \text{maximum}(f^{1}, \dots, f^{N_p}) \tag{13}$$

In smart network, retailer's profit in electricity market must subtracted from equation (14).

Retailer's profit is equal to income minus the cost. Revenue is derived from the supply of consumer demand that is defined by the selling price that is variable multiplied by customer demand. Costs of purchasing power from electricity market, besides to bilateral contracts which added to total purchase cost. It must mentioned in this paper, the selling price that is variable is defined by three tariffs including fixe pricing, TOU pricing and also real-time pricing.

$$Maxf(x) + \sum_{t=1}^{T} \lambda_t P_t^P = \sum_{t=1}^{T} \sum_{l=1}^{L} SP(l,t)D(l,t) - \sum_{b}^{B} \sum_{t=1}^{T} \lambda_{b,t} P_{b,t} \quad (14)$$

Profit function of the retailer (14) must maximized in the existence of the balancing power constraints indicated by (15).

$$\sum_{j=1}^{J} P_t^P = \sum_{l=1}^{L} D(l,t) - \sum_{b=1}^{B} P_{b,t} \quad (15)$$

Equation (16) shows the income of collection l consumers in time period t, which is obtained gained because of meeting consumer demand by selling energy to customers.

$$P_R(l,t) = SP(l,t)D(l,t) \quad (16)$$

Equation (17) shows cost for purchasing the energy from electricity pool market. Cost for purchasing energy from the bilateral contracts is also shown in Equation (18).

$$C_P = \sum_{t=1}^{T} \lambda_t \times P_t \quad (17)$$

$$C_B = \sum_{b}^{B} \sum_{t=1}^{T} \lambda_{b,t} P_{b,t} \quad (18)$$

Equation (19) shows permissible bounds besides the purchased power from bilateral contract.

$$P_b^{min} S_b < P_{b,t} < P_b^{max} S_b \quad (19)$$

According to Equations (20-23), the retailer determines the supplied demand and real-time pricing for the consumer group. It should be noted that the supplied demand is a function of the selling price proposed by the consumer group and is determined by the retailer.

$$D(l,t) = \sum_{z=1}^{Z} D^{offer}(l,z,t) A(l,z,t) \quad (20)$$

$$SP(l,t) = \sum_{z=1}^{Z} SP(l,z,t) \quad (21)$$

$$SP^{offer}(l,t)A(l,z,t) \leq SP(l,z,t) \leq SP^{offer}(l,z-1)A(l,z,t) \quad (22)$$

$$\sum_{z=1}^{Z} A(l,z,t) = 1 \quad (23)$$

It must be mentioned that the demand response and demand side management program could be operated in the coming years for the peak period management according to former research to maximize the retailer's desired profit. In the presented model, the price of selling is decided by retailer for per hour that is similar to the real-time pricing according to constraints (24). Similarly, the price of selling can be defined in fixed pricing under constraint (25). Lastly, the price of selling can be defined for average peak besides low-demand time periods by retailer using time of use pricing in constraint (26).

$$SP(l,t) \leq SP^{RTP}(l,t) \quad (24)$$

$$SP(l,t) \leq SP^{Fixed}(l,t) \quad (25)$$

$$SP(l,t) = \begin{cases} SP_L^{TOU}(l) & for \quad t \in low\ load\ level \\ SP_M^{TOU}(l) & for \quad t \in medium\ load\ level \\ SP_P^{TOU}(l) & for \quad t \in peak\ load\ level \end{cases} \quad (26)$$

The multi-objective optimization model of the proposed interval is modeled using the MIP model based on the interval optimization method for the problem of defining the price of selling by retailer in presence of PEV and ESSs. This problem is solved using the SNOPT solver [38] under the GAMS optimization package [39].

5. Result and discussion:

Figure(2) depicts the purchasing costs from the pool market in RTP, TOU and fixed pricing. As it can be seen, the minimum cost is for the RTP and maximum cost is for the fixed pricing. The retailer is managing all pool contracts that has uncertainty in energy prices in a best way based on RTP compared to TOU and fixed pricing. This managing will cause the minimum cost in RTP pricing.

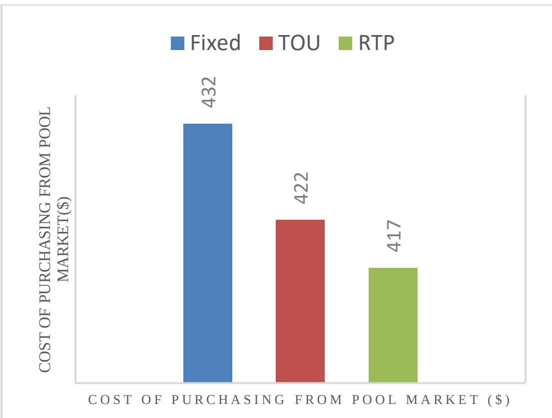

Fig. 2. Purchasing cost from pool market

Figure (3) shows the cost of purchasing energy from a bilateral contract. Due to the stability in the energy price of the bilateral contract, the retailer is interested in having a greater presence in this type of electricity market contract. Also, due to more customer participation in demand-side management (DSM) programs, the cost of buying energy by retail in real-time pricing is lower than the other two methods.

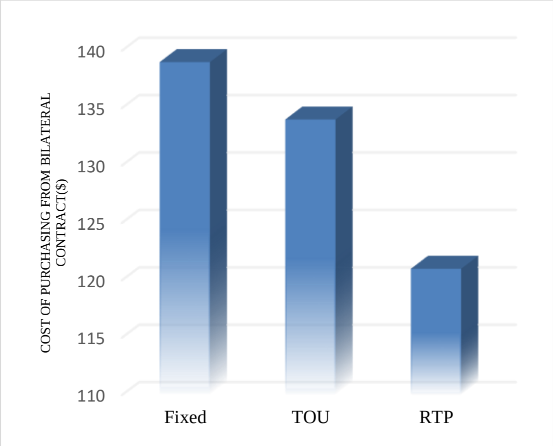

Fig. 3. Purchasing cost from bilateral contract

Figure (4) shows average profit of the proposed model in fixed, TOU and RTP for some selected scenarios. In this figure and Based on the equations (6)-(11), due to participation of customer in demand side management program, RTP reflects better situation of power market. Also by applying interval optimization in the proposed model, the retailer has more interaction with customer and can manage the market contracts with maximum revenue and minimum cost.

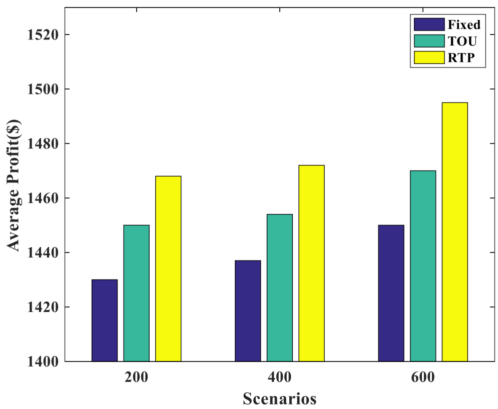

Fig. 4. Retailer's average profit in RTP, TOU and Fix Pricing

Also, by executing the fuzzy model optimal Pareto solution are defined according to Figure (5).

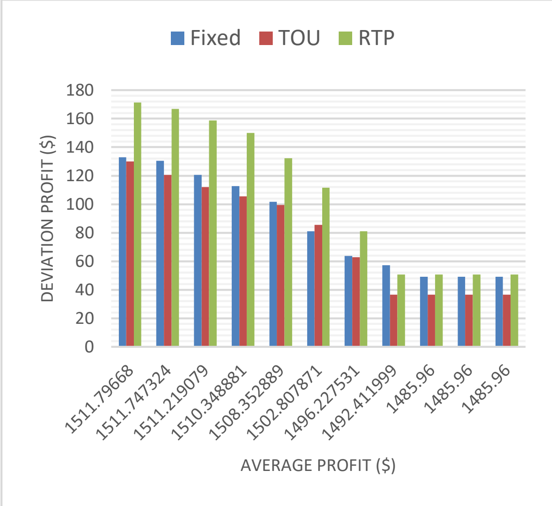

Fig. 5. The Pareto based on multi-objective interval approach

Following Pareto solutions and the selected appropriate solution shown in Figure (5), average of retailer profit for the fixed pricing is $1492/4119 while the retail profit changes is $57.1577. Also, based on time of use pricing, average of retailer profit is $1535.65, while the profit change is $ 62.86. It indicates that because of positive impacts of the time of use pricing, average of retailer profit has increased, compared to the fixed pricing. Also, utilizing the real-time pricing, average of retailer profit is $1559.1, however profit changes are $81,081. It means that average of the retailer profit in real-time has increased compared to the real-time pricing and fixed pricing. lastly, by evaluating the appropriate solutions gotten in the fixed pricing besides the time of use pricing and real-time pricing, it can be investigated that the average retail profit increased by more than 4.30% compared to fixed pricing and 1.54% compared to time of use pricing. It denotes that because of modeling the uncertainty in interval optimization method compared to the algebraic method, the retailer's resistance is higher than the electricity market price.

Figures (6) depicts the retailer's profit in TOU, RTP and fixed pricing method in sample scenarios. Besides to inspiring consumers for participation in the demand side management program, electricity retailer will increase profit by suggesting and utilizing more proper program like real time pricing. TOU pricing shows sectional reality of the power market. Based on figure (6), average of the retailer's profits in RTP method has increases approximately 12 to 16 % in comparison with TOU pricing method. Generally, because the real time pricing method depicts the real situations in power market, it is predictable that retailer's profit will increase more than other pricing method.

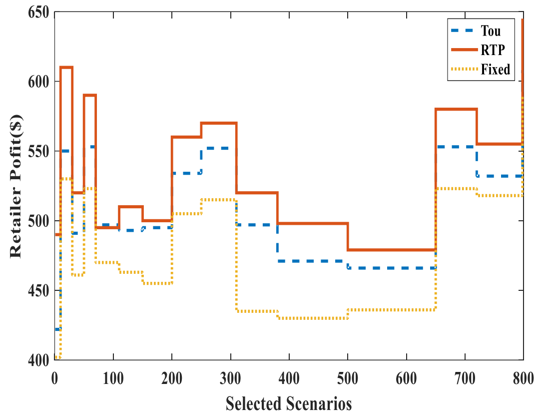

Fig. 6. Comparison of retailer profit between TOU, RTP and fixed pricing in the proposed model

Figure (7) depicts comparison between energy purchase in simple model and proposed model for the bilateral contract. As can be depicted in figure(7), according to the proposed model, because of stability the price settled with the consumer, the electricity retailer increases energy purchase from bilateral contract in comparison to the state in which the presented model for bilateral electricity contract was not considered. Lastly, the electricity retailer supply more customer demand via bilateral contract.

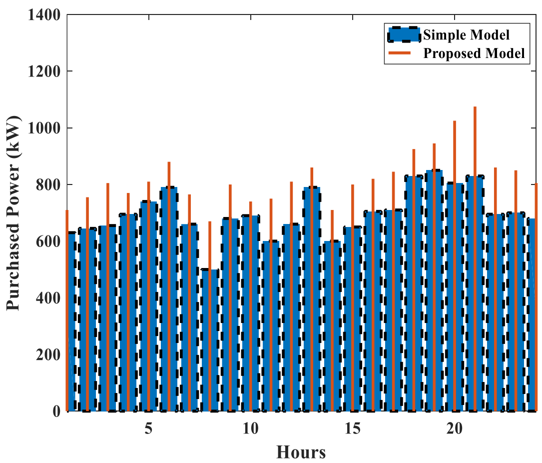

Fig. 7. Impact of the proposed model on purchase from bilateral contract

Figure (8) shows the retailer's revenue on bilateral contracts at selected time of a day. Due to the price stability in the bilateral contract as well as the real reflection of market conditions in real time pricing compared to the other two methods, the retailer's income in this pricing is higher than the other two methods. Accordingly, the retailer enters into a bilateral contract based on the proposed interval optimization model.

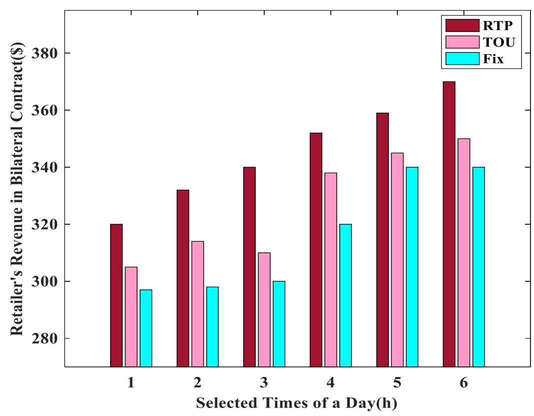

Fig. 8. Retailer’s revenue in bilateral contract

Figure (9) shows a comparison of retailer's revenue in two state; not considering the proposed model and considering the proposed model in the electricity pool market contracts. Accordingly, the retailer has increased its revenue based on using interval optimization and encouraging customer to articipate in demand-side management programs. In other words, the retailer has maximized its revenue by selling more energy and managing uncertainties in the pool market based on proposed optimization model.

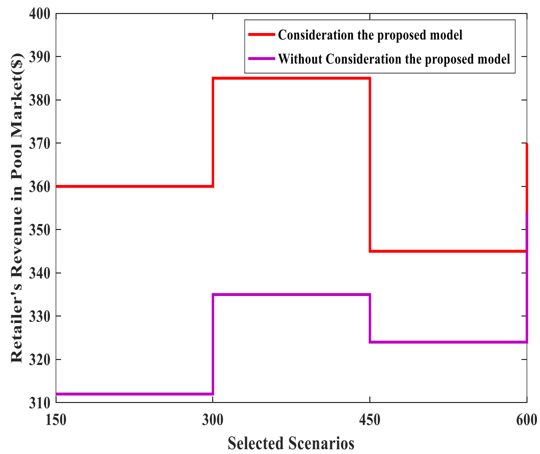

Fig. 9. Retailer’s revenue in pool market contract

Figure 10 shows the retail profit based on the penetration percentage of demand-side management programs. As it is known, with the increase of the influence of demand side management programs in the proposed model, the amount of retailer's profit in the two pricing programs, the time of use and the real time pricing has increased. Also, due to the lack of price change in fixed pricing, the retailer's profit is equal in all three percent penetration. Therefore, in the proposed model, by using demand-side management programs, the maximum amount of retailer profit will be achieved.

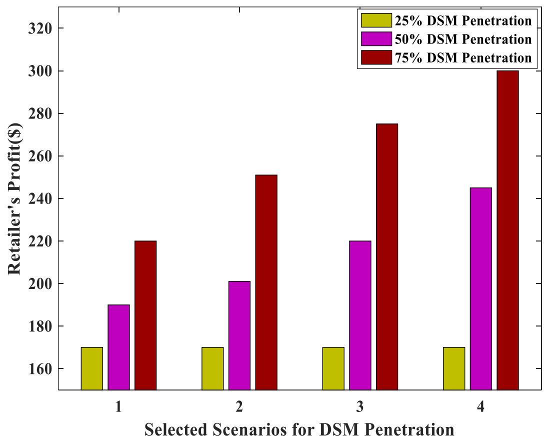

Fig. 10. Penetration of DSM programs on Retailer's Profit

6. Conclusion

Increasing economic activity in the power system has led to the growth and expansion of new institutions in the electricity market. Electricity retailers are one of the most influential institutions in the electricity market. In this paper, a new model based on interval optimization for optimal retailer decision making was presented. The proposed modeling is done by considering the demand side management programs. This proposed model led to the optimal decision of the retailer in the electricity market contracts, so that in addition to minimizing the retail cost in bilateral contracts and the pool market, the retailer's revenue from these two types of contracts was also maximized. Finally, based on the optimization, the most effective demand-side management program was identified in the proposed model of real time pricing method.

Nomenclature:

λ_t	*Price of pool electricity market*
P_t^P	*Amount of power which purchased from pool electricity market*
$SP(l,t)$	*Price of energy selling*
$D(l,t)$	*Customer's energy demand supplied by retailer*
$\lambda_{b,t}$	*Price of bilateral contracts*
$P_{b,t}$	*Amount of power which purchased from each bilateral contract*
P_{BC}^t	*All power which purchased from bilateral contracts*
B	*Index for bilateral contracts*
L	*Customer's demand level*
T	*Index for time*
$P_R(l,t)$	*Revenue for retailer from customer*
C_P	*Cost of purchasing power from pool electricity market*
C_B	*Cost of purchasing power from bilateral contracts*
P_b^{min}	*Minimum of power in bilateral contracts*
P_b^{max}	*Maximum of power in bilateral contracts*
S_b	*Variable in binary form for selecting bilateral contracts*
$A(l,z,t)$	*Variable in binary form for determining the selling price to customers*
$D^{offer}(l,z,t)$	*Customer's demand offered to retailer*
$SP(l,z,t)$	*Interval Selling price of retailer for customer*
$SP^{offer}(l,t)$	*Selling price of retailer offered to customer*
$SP^{RTP}(l,t)$	*Selling price of retailer offered to customer in real-time tariff*
$SP^{Fixed}(l,t)$	*Selling price of retailer offered to customer in fixed tariff*
$SP_L^{TOU}(l)$	*Selling price of retailer offered to customer in time of use tariff*

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