INTERNATIONAL JOURNAL of SMART GRID
F. Zishan et al., Vol.9, No.2, 2025

A New Strategic Bidding Model for the Retail Market for Maximum Profit by Demand Response Programs

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Received: 20.05.2025 Accepted:25.06.2025

Abstract- This research aims to plan the retailer's profit and the amount of electricity exchanged in the presence of both batteries and demand response programs(DRP) for load-serving entities via a mixed-integer linear programming (MILP) model. For power system operators, various DRPs have been proposed as potential resources for balancing supply and demand, reducing peak load hours, and increasing generation efficiency. The two main sources of uncertainty are the issue of power pool prices and customer demand. The uncertainty of these parameters affects the amount of electricity exchanged, the retailer's profit, and decision-making variables. A retail store that only uses batteries or a DRP maximizes its profit by reducing the cost of purchasing energy from the market. Thus, if DRP is used, by encouraging customers to reduce demand, it is not necessary to buy more from the spot market, and, if batteries are used, by buying during non-peak hours while charging the battery for later use, the income increases during peak time. In this capacity planning with 200 MW and expected profit considering DR and without DR, the value of the local limit price is determined. In the expected profit of the retailer's market in different uncertainty states, the trading power of the retailer's planning considering the coupon-based DRP and battery allocation (taking into account the uncertainty of the customer's behavior). The goal of the electricity retailer is to manage futures contracts and determine the selling price offered to its consumers. In purchasing electrical energy and selling to consumers, the retailer faces two important tasks. First, in purchasing electrical energy, it must deal with market price uncertainty and conclude futures contracts at higher prices. Second, in selling electricity, it must consider consumers' uncertainty and take into account the fact that consumers may choose another retailer if the selling price is not competitive enough. Therefore, in this paper, the financial risk associated with market price uncertainty is modeled using the expected probability, which is used explicitly as a constraint in a stochastic optimization problem with MILP.

Keywords: Electricity exchanged, retailer market, demand response programs, mixed integer linear programming.

1. Introduction

In traditional power systems, energy consumption management programs have been used in order to overcome issues [1]. Among them, DRP were also used as the main tool [2]. However, after the restructuring undergone by power systems, these programs were no longer compatible with market policies, and they gradually became obsolete. Sometime later, due to problems such as price inconsistency, energy consumption management programs were used again [3]. These programs underwent changes upon the basis of being aligned with the management structure of the restructured system. It is noteworthy that, after the restructuring of the electricity industry, DRP now play a major role in energy consumption management programs, as they inherently have the ability to adapt to the new management structure of power systems. Currently, these programs are being proposed as a desirable solution to solve some problems in restructured power systems [4-5]. A retailer must choose the best strategy to maximize profits within their planning horizon. This strategy must be able to minimize the cost of buying energy from the wholesale market and determine the optimal selling price offered to customers. It is clear that, if the selling price is too high, customers will choose another retailer, and, if this price is too low, the retailer will lose profit [6]. One of the issues that complicates a retailer's decision and affects their profits is parameter uncertainty. In the planning carried out by the retailer, DRP and batteries are simultaneously involved [7]. It can be claimed that the profits of the retailer will be much higher than those obtained when these two are used separately [8]. In the aforementioned method, on the one hand, by using DRP and applying incentives and fines to consumers, the retailer forces them to balance their consumption; on the other hand, the battery system is charged during off-peak hours. If the retailer faces an increase in consumer demand in the market during the next day, they compensate all or part of this increase using the power stored in the battery system, which was purchased at the price of off-peak hours. If, on the other hand, the retailer does not face an increase in consumer demand, or if this increase is less than the capacity of the installed battery, they can sell the excess power in the spot market and increase their income and profit accordingly. Under this pricing policy, the daily prices of the wholesale market are variable. This, in contrast to other price-oriented programs in which the price of electricity is determined in advance [9]. The work done in this regard during the last few years is outlined below:

In [10], a contingency planning method limited to risk is proposed for determining future contracts and the price of selling electricity to consumers, with the aim of maximizing the expected profit of the retailer at an acceptable risk level. According to [11], the electricity retailer faces the risk of supplying the load, as well as the risk of the spot price in buying from the market. In this vein, this article proposes a multi-stage random optimization method that considers price and load uncertainty. As per [12], the goal of an electricity retailer is to manage future contracts and determine the selling price offered to the consumers, in [13] a new framework is presented that uses DR for a retail energy source. In this method, an incentive-based response program is proposed for bridges as real-time resources for electricity retailers. The work by [14] solves the medium-term planning problem via the contingency planning method for electricity retailers. In [15], an electricity retailer uses two strategies to track momentary load changes. According to the study by [16], an electricity retailer uses a DRP as a source of virtual power generation, in addition to the common sources of the electricity market and bilateral contracts. The research carried out by [17] studies the short-term planning of electricity retailers without considering uncertainties in the electricity market. The authors of [18] present a buyer-electricity technical-economic model for the restructured electricity market. This model results in an optimization problem regarding the calculation of the optimal electricity sales prices, with the aim to maximize the economic profits obtained by the electricity retailer. In [19], the short-term decision-making problem for electricity retailers in the electricity market is formulated as a multi-objective optimization model, where retailers with certain existing assets in the distribution network are considered. The work by [20] presents a two-level planning model for a retailer with distributed generation to supply electricity to price-sensitive consumers. In this regard, it is important to remember that uncertainties in consumer demand and market prices create major problems for retailers. Finally, it is worth mentioning that the authors of [21-23] have investigated-load serving entities in the electricity market. The studies reviewed in the last few months, which are among the most up-to-date researches, are: new participation in electricity market ancillary services, demand management and peer-to-peer energy trading is in the future [24]. This problem studies the price-driven demand response in the non-regulated retail electricity market with the aim of coordinating end-users' energy consumption behavior under dynamic retail prices [25]. The model illustrates the complex interactions between the electricity and natural gas grids and the complexities arising from uncertainties and changes in renewable energy sources and demand profiles by integrating DRP [26]. It is a new decentralized energy market consisting of retailers, consumers and DRP. A reliable multi-objective optimization method for the retailer is evaluated based on the uncertainty and integration of different DRPs, considering the costs and benefits of the retailers to adapt [27].

From the reviewed works, it can be concluded that, in a fully competitive electricity market, retailers play an important role to complete the gap between all customers and wholesale market operators, connecting them to an optimal exploitation structure. As a profit-seeking organization, the objective of the retail market is to maximize the expected payoff, given the uncertainty of both the wholesale market and all customers. Most customers pay a flat rate electricity bill, whereas the retail market buys electricity from the wholesale market at a time-varying rate. Moreover, retailers are naturally motivated to satisfy the inherent pull of all customers by offering loyalty programs.

The short-term decision-making problem of the electricity retailer in the electricity market is formulated as a multi-objective optimization model. Retailers are considered with existing assets such as generation and storage units in the distribution network. With the establishment of smart grid infrastructures, electricity retailers will be able to manage more collective DR plans in addition to their existing assets to manage market prices and load variations. In this model, the DR plan planning is done simultaneously with the generation and storage unit planning. The ultimate goal is to find the optimal financial hourly incentives offered to the end-user-supplier. The proposed model considers the offers downloaded by the network operator to the retailer. The retailer seeks to maximize its profit. It also seeks to minimize the overcapacity to avoid high capacity costs in the form of network tariffs or heavy penalties. The multi-objective function proposed in this paper is multi-objective by an intelligent algorithm.

The need for this research is explained by the fact that, until now, the impact of the simultaneous presence of battery systems and DRP on retailers' profit has been underestimated. Thus, the main contributions of this paper are the following.

- Improving and promoting retailers' medium-term planning (finding a more optimal solution than those of existing plans) via mixed-integer linear programming.
- Presenting a new retailer model for the simultaneous use of batteries and DRP
- Increasing retailers' expected profit regardless of the response time.
- Analyzing the increase in the expected profits of the retailer market in different states of uncertainty while using a robust model.

The structure of this article is summarized as follows: in the second section, materials and methods is explained; the third section presents the simulation results; and, finally, the conclusions of this work are presented in the fourth section.

2. Materials and Methods

When In this section it is presented: energy consumption management; the need to implement DRP; the existing markets and the formulation of the problem.

2.1. Energy Consumption Management

Electricity consumption management includes a series of interconnected activities between the electricity industry and its subscribers which aim to adjust the shared consumption load, so that the same utility can be achieved in the field of consumption with more efficiency and less cost [28]. In this way, both the supplier and the consumer of electricity obtain more profits. The benefits of energy consumption management for members of the electricity industry are described in Table 1

Table 1. Benefits of energy consumption management

For the electricity company	For the community	Energy-related benefits
Lower service cost	Reduced environmental waste	Providing electricity
Improved operating efficiency	Conservation of resources	Reduced and stable electricity prices
Reduced need for investment	Global environmental protection	Improved service level
Improved customer service	Maximized social welfare	Improved life conditions and productivity

2.2. On the Need to Implement DRP

Electric energy cannot be widely stored at the level of power systems, so the capacity available for production at all times must be equal to or greater than the total load of the system's consumers. At some times during a year, the power consumption of the system increases drastically. In this situation, regardless of DRP, there is an increase in the production capacity required to provide power and storage for these hours. It is known that installing more power plant units to respond to the increase in demand is a time-consuming matter and implies high costs [29]. Another obstacle to using DR resources is the long expected response times. The characteristics of most interruptible loads include the fact that they cannot be interrupted indefinitely, i.e., the response time is limited. For example, loads such as domestic water heaters and air conditioning and water pumping systems can be interrupted intermittently but for shorts period of time. According to the conditions specified by some guardians of network security such as the north american electric reliability corporation (NAERC) [30] for the resources intended to participate in the market, a high penetration of DR resources poses several problems. For example, the conditions determined by the NAERC for the presence of interruptible loads in the reserve market are such that the resources responsible for the reserve capacity must be able to respond quickly and enter the entire committed capacity within 10 minutes at most. Moreover, they must maintain their response for up to 2 hours, which is a long response time and constitutes a serious obstacle for the wide implementation interruptible loads as reserve capacity.

In general, DRP can be divided into two main categories [9]:

- DRP based on electricity price
- DRP based on encouragement

Incentive DRP are divided into two categories: classic and market-based. In classic methods that include direct load control and interruptible loads, consumers receive an incentive fee in the form of electricity consumption credit or a discount for participating in the program. This is while in market-based methods, market participants receive an amount according to their performance and the amount of consumption reduction.

2.3. A Glance at the Existing Markets

Generators Electricity markets are usually a combination of several sub-markets that are related to each other in a complex way. These submarkets are classified based on different criteria. One of the most important classification criteria is the type of market production, which is mentioned in this section. The general division of the markets is as follows:

Bilateral market: In bilateral markets [31], sellers and buyers can enter into a bilateral contract to send and receive electricity based on pre-negotiated prices. This exchange may be done directly or through some electricity market brokers. Bilateral markets are highly decentralized, and the role of the system operator in these markets is limited to verifying the availability of sufficient transmission capacity to carry out exchanges.

Pool market: Pool markets [32] are short-term energy exchange markets. These types of markets are divided into the following three models, which are different from the point of view of monopoly limits:

- Single-buyer model.
- Competitive model at the wholesale level.
- Competitive model at the retail level.

The transaction of goods in each market is based on the seller's offer and the consumer's demand. Therefore, in the pool market, the offers by energy sellers and the demand of consumers are first received by the market players. Then, the received offers and demand, along with their physical and technical limitations, are entered into the optimized load distribution software, and the amount of production and its price are determined for each seller.

Energy market: This one is a trading market for primary energy production [33]. In the energy market, the settlement price is determined based on the offer sent by sellers and buyers.

Transmission market: In this market, the right to transmit electricity to the distribution sector is auctioned by the system operator [34-35]. The exclusive right for electricity transmission corresponds to the ability to extract or inject power through the transmission network.

Ancillary services market: In this example of the market, ancillary services are produced by the system operator. This market has different structures for reserve capacity. In addition to the aforementioned cases, there are several other forms for electricity markets, *e.g.*, the dealer market, brokerage markets, and exchange markets.

Spot submarket: In a spot submarket, electricity producers immediately deliver the desired service immediately and the consumer pays the price in the same way. The grocery market is a very good example of a momentary submarket. In this market, the buyer chooses the desired product and announces it to the seller, the vendor then delivers the goods to the buyer, and the buyer instantly pays the amount specified by the seller. Slow down, and the exchange ends.

Daily market: The daily market involves the exchange and auction of energy for a future time [36]. On the day before delivery, the auction ends at a certain hour, and calculations are performed by the independent system operator in order to determine the market settlement price and the production and consumption plan of the participants, which is then announced. The program is usually announced in the afternoon of the previous day, and, from 00:00 on the delivery day, the participants must receive or deliver energy from the network according to the program. The settlement of these markets is usually established on a daily or weekly basis.

Long-term market: One of the long-term markets is the capacity market, which is implemented in order to ensure the electricity network's sufficiency of resources in the future [37].

Reserve market: In a restructured environment, ancillary services are purchased through the market. In this regard, reserve is one of the types of ancillary services that bears considerable importance. Rotating reserve is purchased in order to provide the system with ability to deal with events such as line or generator outages [38].

In time-of-use pricing, electricity tariffs are determined as different prices for different time periods throughout the day, taking into account the average cost of electricity generation and transmission in each time period. In this type of policies, tariffs can be changed by changing time periods. Therefore, it is determined for several months or years in advance. In this pricing method, three modes of high load, medium load and low load are calculated and received based on different energy prices.

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In these programs, electric companies benefit due to maintaining the reliability of the system and reducing the peak load, and as a result, preventing expensive units from being turned on or being ready for system storage, and consumers also benefit from these programs. For the ability to change and reduce consumption, they receive money or credit for electricity consumption from the operating company, and as a result, they make a profit.

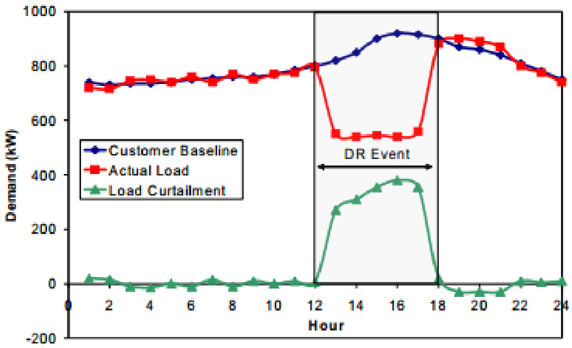

Fig. 1. The effect of the load reduction program on the consumption curve of customers

3. Formulation of the Problem

Figure 2 shows the effect of price demand response (P-DR) on both the electricity supply curve and the elastic demand curve. Here, (D_1,π_1) denotes the intersection between the expected supply curve and the original demand curve (D_2,π_4) represents the intersection between the expected supply curve and the new demand curve, along with the incentive tariffs' locational marginal prices (LMP), π_1 is greater than the flat rate price η at the system demand level D_1. If the production capacity is higher than the predicted value, the LMP will be higher by π_3. At the same time, if the generating capacity produces more power than the predicted value, the LMP will decrease by π_2. Below the demand level D_1, the expected net return to the retailer's market $(\eta,\pi_1)D_1$ is negative [8]. When an incentive is provided, the elastic demand curve shifts from $D_1(P)$ to $D_2(P)$. With the new demand curve, the corresponding LMP is π_4, which is less than the flat rate η. Consequently, as long as the net return $(\eta-\pi_4)D_2-r(D_1-D_2)$ is greater than$(\eta-\pi_1)D_1$, the retailer market will be motivated to offer the incentive price r to customers in P-DR. Therefore, the P-DR program with appropriate coupon prices can help the retail market to increase their profit by discounting price fluctuations due to price uncertainty in the wholesale market.

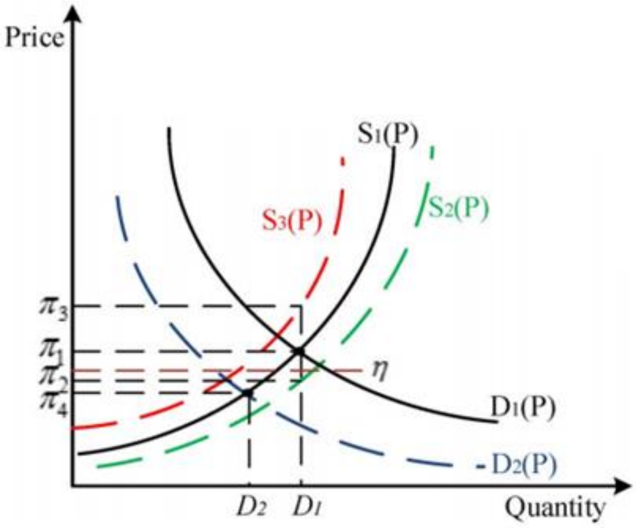

Fig. 2. Effect of P-DR and price on production and demand curves.

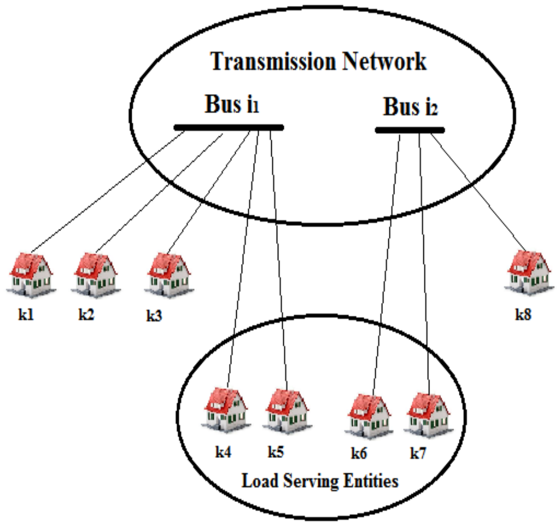

Fig. 3. Market structure regarding retailers and consumers.

The retailer's market receives a gross return from each customer $k(k\in B_i)$ in bus $i(i\in A)$, as shown in k_4 to k_7 of retailer A's market in Figure 3.

$$R_n=\sum_{i\epsilon A}\sum_{k\epsilon B_i}[(\eta_{i,k}-\pi_i)\times D_{i,k}-r_{i,k}\times(D^0_{i,k}-D_{i,k})] \tag{1}$$

The partial price $\eta_{i,k}$ and the electricity consumption $D_{i,k}$ are calculated (spot price $\pi_i$and power consumption $D_{i,k}$). The financial incentives paid by the retail market to customers must also be reduced, which is the result of the coupon price $r_{i,k}$ and the deviation between the actual electricity demand and the base electricity consumption [8]. The proposed surface strategic model is presented with the Equation (2).

$$\begin{cases}\max\sum_{i\epsilon A}\left(\sum_{k\epsilon B_i}(\eta_{i,k}\times D_{i,k}-r_{i,k}\times(D^0_{i,k}-D_{i,k})-\pi_i\times D_i)\right)\\ s.t.\ D^{min}_{i,k}\le D_{i,k}\le D^{max}_{i,k}\ ,\forall i\ \epsilon\ A,k\ \epsilon\ B_i\end{cases} \tag{2}$$

According to the strong duality theory, the objective of the original problem is equal to the objective of the corresponding dual problem. For the problem of spreading the economic load, the relationship between the objectives of the dual and primary problems can be expressed for Equation (3) and Equation (4).

$$\lambda \times \sum_{i=1}^{N} D_i + \sum_{l=1}^{M} \mu_l^{max} \times \left(-Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) + \sum_{l=1}^{M} \mu_l^{min} \times \left(-Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) + \sum_{i=1}^{N} \omega_i^{max} \times (-G_i^{max}) + \sum_{i=1}^{N} \omega_i^{min} \times \left(G_i^{min}\right) = \sum_{i=1}^{N} c_i \times G_i \tag{3}$$

Where:

$$\left\{\begin{array}{c}
\min \sum_{i=1}^{N} c_i \times G_i \\
s.t. \sum_{i=1}^{N} G_i = \sum_{i=1}^{N} D_i \ : \ \lambda \\
D_i = \sum_{k \epsilon B_i} D_{i,k}\,, \quad \forall i \ \epsilon \ A \\
-Limit_l \leq \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \leq Limit_l \ : \ \mu_l^{min}\,, \mu_l^{max}\,, \forall l = 1,2,\ldots,M \\
G_i^{min} \leq G_i \leq G_i^{max} \ : \ \omega_i^{min}\,, \omega_i^{max}\,, \forall i = 1,2,\ldots,N \\
\pi_i = \lambda + \sum_{l=1}^{M} GSF_{l-i} \left(\mu_l^{min} - \mu_l^{max}\right) \\
c_i = \lambda + \sum_{l=1}^{M} GSF_{l-i} \times \left(\mu_l^{min} - \mu_l^{max}\right) + \omega_i^{min} - \omega_i^{max} \\
0 \leq \mu_l^{min} \perp Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \geq 0 \\
0 \leq \mu_l^{min} \perp Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \geq 0 \\
0 \leq \mu_l^{max} \perp Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \geq 0 \\
0 \leq \omega_i^{min} \perp G_i - G_i^{min} \geq 0 \\
0 \leq \omega_i^{max} \perp G_i^{max} - G_i \geq 0
\end{array}\right. \tag{4}$$

From the LMP expression in $\pi_i = \lambda + \sum_{l=1}^{M} GSF_{l-i} \left(\mu_l^{min} - \mu_l^{max}\right)$, the resulting term $\pi_i D_{i,k}$ can be converted into Equation (5). Note that Equation (3) states that $D_i (i \in A)$ is related to the demand at the bus in the retail market bidding, while Equation (5) has to do with the wholesale market. By inserting Equation (5) into Equation (3), the Equation (6) is obtained. The MILP problem formulation is obtained via Equation (7).

$$\sum_{i \epsilon A} \pi_i \times D_i = \lambda \times \sum_{i \epsilon A} D_i + \sum_{l=1}^{M} \sum_{i \epsilon A} GSF_{l-i} \left(\mu_l^{min} - \mu_l^{max}\right) \times D_i \tag{5}$$

$$\lambda \times \sum_{i=1}^{N} D_i + \sum_{l=1}^{M} \mu_l^{max} \times \left(-Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) + \sum_{l=1}^{M} \mu_l^{min} \times \left(-Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) + \sum_{i=1}^{N} \omega_i^{max} \times (-G_i^{max}) + \sum_{i=1}^{N} \omega_i^{min} \times \left(G_i^{min}\right) = \sum_{i=1}^{N} c_i \times G_i \tag{6}$$

$$\max \sum_{i\epsilon A}\sum_{k\epsilon B_i}\left(\eta_{i,k}\times D_{i,k}-r_{i,k}\times\left(D_{i,k}^{0}-D_{i,k}\right)\right)-\sum_{i=1}^{N}c_i\times G_i+\lambda\times\sum_{i\notin 1}^{N}D_i+\sum_{l=1}^{M}\mu_l^{max}\times\left(-Limit_l-\sum_{i\notin A}GSF_{l-i}\times D_i\right)$$
$$+\sum_{l=1}^{M}\mu_l^{min}\times\left(-Limit_l+\sum_{i\notin A}GSF_{l-i}\times D_i\right)-\sum_{i=1}^{N}\omega_i^{max}\times\left(-G_i^{max}\right)-\sum_{i=1}^{N}\omega_i^{min}\times\left(G_i^{min}\right) \tag{7}$$

The retail market still needs to find the optimal incentive price. Based on the probabilistic model of demand reduction presented, customers will have different behavioral patterns related to different incentive prices in the DR program. The expected net revenue (ENR) is determined as an indicator for the retailer's market bid to determine the most profitable coupon price. ENR under incentive price is defined according to the equation:

$$ENR_j=\sum_{d=1}^{N^d}p_{j,d}\times R_{n,j,d} \tag{8}$$

where $R_{n,j,d}$ the LSE's net yield is in the block of decreasing demand under the j coupon price. When all ENRs are obtained under different incentive prices, the retail market can choose the optimal incentive price with the maximum ENR and the corresponding demand distribution. It should be noted that although demand uncertainty under a specific incentive price can be modeled in the optimization model using similar approaches to price uncertainty, however, the model that will be created in this way will be more complex in terms of dimension. The electricity retailer uses two strategies to follow the instantaneous changes in load: 1) purchasing electricity from the pool market and 2) entering into bilateral contracts with electricity generators. Since the electricity market price is variable, the electricity retailer enters into contracts with electricity generators to reduce the risk of electricity market prices. Ideally, the electricity retailer would like to match the energy it sells to consumers with the energy purchased from bilateral contracts. However, unpredictable changes in the load of consumers force the retailer to buy or sell energy from the electricity market. Therefore, this paper proposes a model for adjusting the price changes from the perspective of the retailer, where consumers are encouraged to shift their load by considering the time-of-use tariff. This redistribution of load will generate energy reserves for the retailer, thus reducing the energy purchased from the electricity market during times of high prices. On the other hand, consumers redistribute their load to reduce their costs based on the new prices. In addition, the uncertainty of electricity market prices and consumer elasticity are included in the calculations by contingency planning and scenario methods. The risk involved is also modeled by the MILP method.

4. Discuss the Results

The main software used in this research to analyze the data and the results was MATLAB software. In the planning carried out by the retailer, the presence of DRP and batteries are simultaneously considered. It can be claimed that the profit of the retailer's sales will be much higher than that obtained when employing these alternatives separately. In Figure 4, the coupon price changes from zero to 10 $ per MWh. This shows that, the higher the offered coupon price, the customers are more willing are to reduce the load. Figure 5 shows the load considered for five different modes. The value of the local limit price without considering DR, the expected profit with DR, and the new local price value considering the DR and the coupon price value are shown in Figures 6 to 9. According to the figures, it is clear that the amount of system load is in the lowest state, the amount of profit of the retailer's market is negative. When the system load is low, the value of the local threshold price is low and the price offer to reduce the load is not economical, and as a result, when the price offer is presented to reduce the load, the expected profit will be negative. The local marginal price is in the lower limit, and as a result, the optimal coupon price is zero, which means that the retailer market does not want to offer a price offer to its customers. Due to the increase of the local limit price, offering the price offer to the subscribers has an economic justification for the retailer market and it causes the optimal price of the coupon offer to increase. In general, in any case, the value of the local limit price in the desired bus is higher, the retail market has more incentive to offer the price to its subscribers. It can also be seen that in cases three and four, the amount of expected profit of the retail market increases uniformly with the increase in the coupon price, but in cases two and five, it first increases and then decreases. The reason for this can be explained in the following way: in cases two and five, since the amount of expected profit is primarily dependent on the payment amount of the retailer's market, as a result, when the working point is set to the amount As long as the critical load is larger than the critical load, any reduction in demand will not have much effect on prices. But in cases three and four, any decrease in demand will lead to a large decrease in the local marginal price and will have a double effect on the expected profit of the retailer market.Now, the presence of bilateral contracts and the cash market is examined on the functioning of the retail market. First, the influence of the production capacity on the local marginal price and the amount of expected profit of the retailer market is investigated. In general, since the cost of production is considered zero, their entry into the system will reduce the marginal prices. Considering the total capacity of 200 MW, the simulation is done.

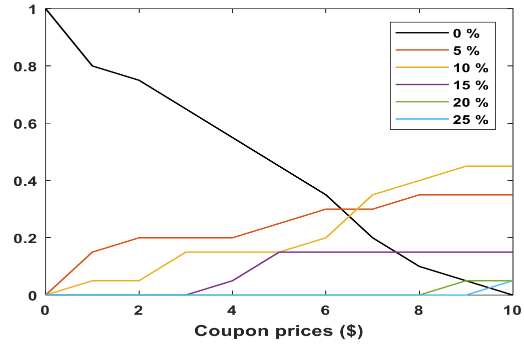

Fig. 4. Coupon prices provided by the retailer market.

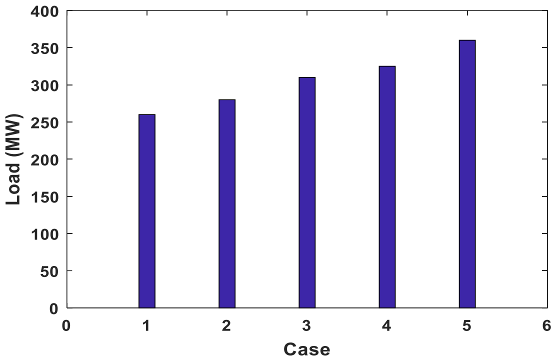

Fig. 5. Load considered for five different modes.

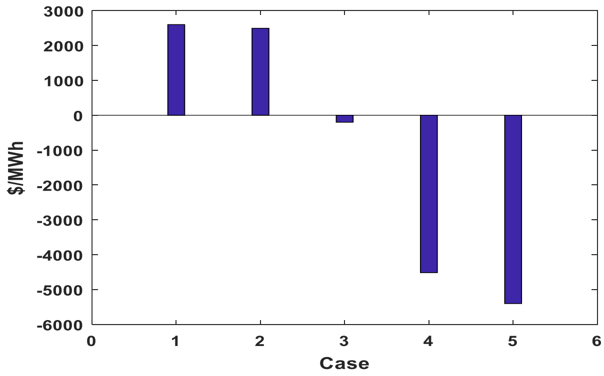

Fig. 6. Local limit price without considering DR.

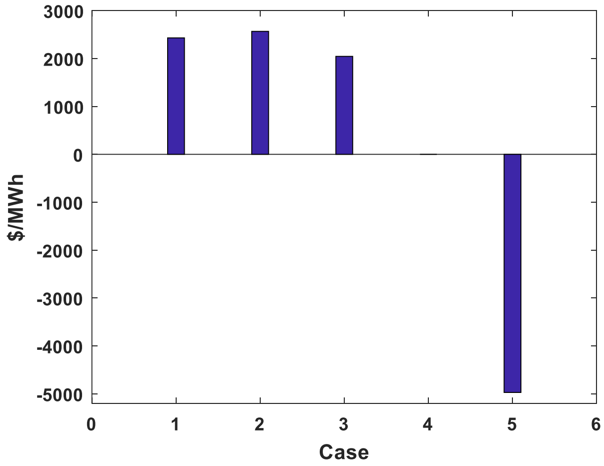

Fig. 7. Expected profit considering DR.

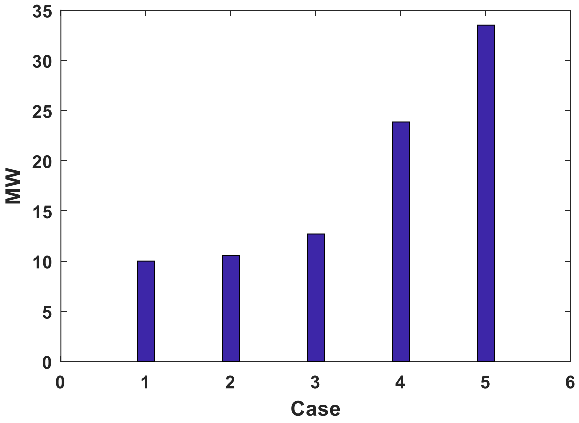

Fig. 8. Local limit price considering DR.

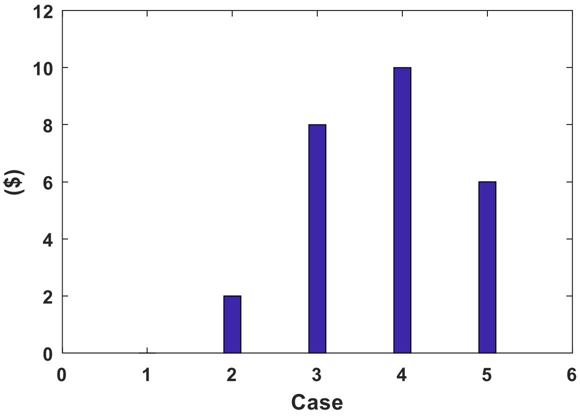

Fig. 9. Coupon price.

The expected profit margin of the retailer market for the five studied cases is shown in Figures 10 and 11. The effect of batteries on the profit for 24 hours is as follows (Figure 12).

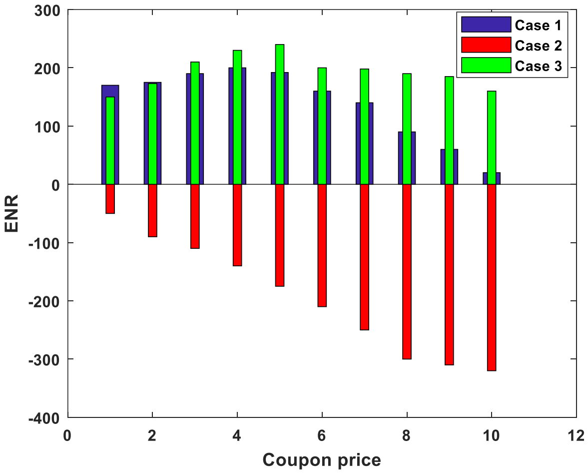

Fig. 10. Expected profit margin for the retailer's market (cases 1, 2, and 3).

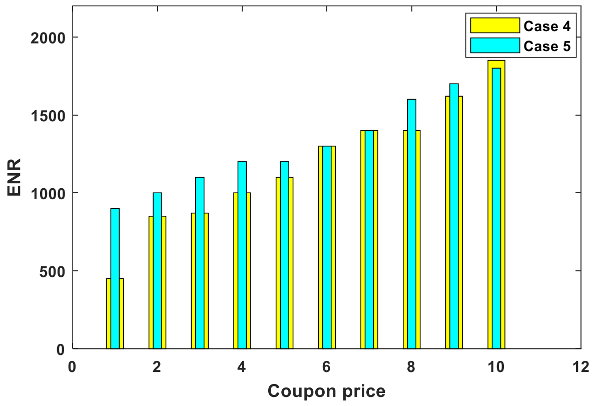

Fig. 11. Expected profit margin for the retailer's market (cases 4 and 5).

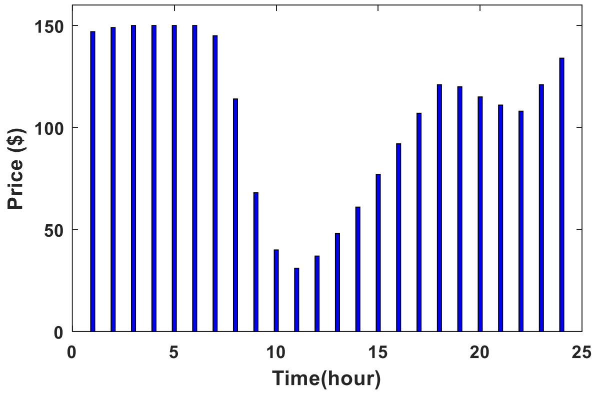

Fig. 12. Effect of batteries on profits.

With the values related to the mean and variance of a random variable, scenarios can be generated to model its uncertainty. The larger the variance, the greater the uncertainty in predicting power production, in order to observe the effect of uncertainty on the production capacity, different values are selected for the variance, and, based on that, scenarios are produced for the output power. Table 2 shows the increase in the income of the retailer market for different values of variance.

Table 2. Increase in the expected profit of the retailer market, considering different states of uncertainty

Variance	Case 1	Case 2	Case 3	Case 4	Case 5
0	151	169	4106	2109	98
0.05	147	173	3869	223	114
0.1	136	180	2877	2455	117
0.15	132	181	2510	2108	165
0.2	131	189	2396	2226	181
0.25	135	196	2300	2175	201
0.3	132	201	2012	2235	208
0.35	133	208	1988	1996	220
0.4	134	216	1677	2158	211
0.45	136	222	1240	1988	217
0.5	136	228	1100	1821	205

The amount of power exchanged in 24 hours is shown in Figure 13, which considers the coupon-based DRP and the allocation of batteries (taking the uncertainty of customers' behavior into account). In this case, the retailer's market profit with market participation is equal to $4182. Moreover, Figure 14 shows the amount of power exchanged within the retailer's planning, considering the coupon-based DRP and the allocation of batteries (according to the resistant model). In this case, the retailer's market profit with market participation is equal to $4651.

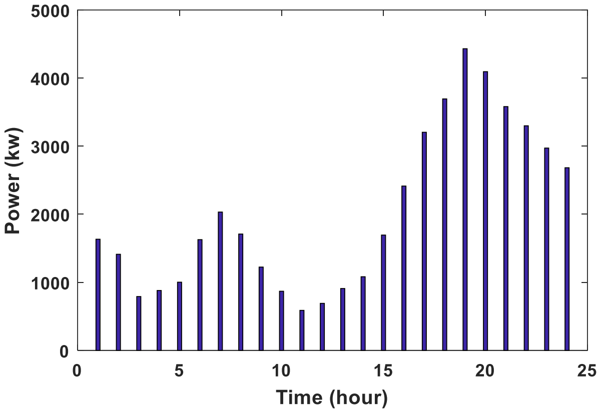

Fig. 13. Power exchanged (considering the uncertainty of customers' behavior).

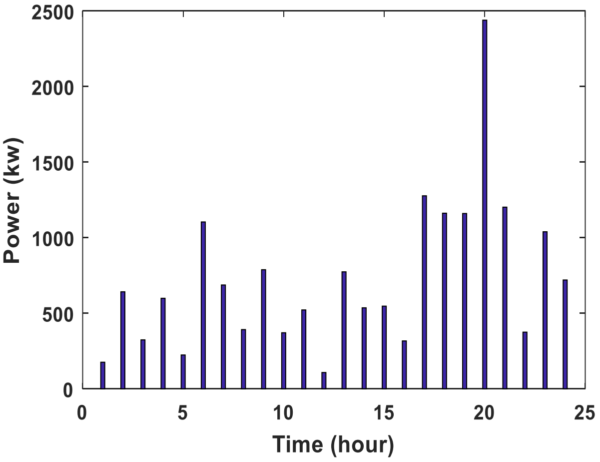

Fig. 14. Power exchanged (considering the resistant model).

5. Conclusion

Retail is one of the roles involved in restructuring in the field of buying and selling electrical goods, which, according to the rules of each market, can perform various tasks. Among these, the most important one is buying electricity from the wholesale market and selling it. Therefore, the profit of a retailer is obtained by reducing the purchasing costs and increasing the income from sales. This article addressed the capacity and profit planning of a retailer with DRP. The problem was modeled as a short-term plan for 24 hours in several different study steps, in the form of a correct mixed planning, thus obtaining the amount of exchanged power and the resulting profit by comparing the two modes of retailer market participation, considering battery systems and the response of the coupon-based load in the two modes (uncertainty and resistant model). It was concluded that profits from the market increase by employing the resistant model.

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