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Electricity retail market and accountability-based strategic bidding model with short-term energy storage considering the uncertainty of consumer demand response

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ABSTRACT

Electricity retailers participate in electricity markets as intermediaries between wholesale and retail markets. They acquire energy on the wholesale side by participating in next-day markets and the pool of power. On the retail side, they make contracts with consumers in order to meet their energy demand at a fixed price for a set period of time –generally a year. To maximize profit in planning, a retailer must choose the best strategy, which should be able to reduce the cost of purchasing energy in the wholesale market while simultaneously determining the best selling price for consumers. Customers may choose a different retailer if the selling price is too high, and the retailer may take a loss if the price is too low. One of the issues that complicate retailers' decision is the uncertain demand response parameters that affect profit. This paper contributes with a strategic bidding model for planning with short-term energy storage while considering the uncertainty of consumer demand response and load response programs simultaneously. GAMS and MATLAB are implemented in this research to analyze the data and review the results, which indicate that an increase in profit is expected to be greater than when the retailer uses only a load response program or a short-term energy storage system. As uncertainty grows, so does local price sensitivity, and, as a result, so does the predicted rate of profit. Profits from participatory reservation, energy, and regulation markets increase in the robust model, while profits from the common participatory market decrease, *i.e.,* according to this study, which looked at both probabilistic and robust models of retail market participation. When a robust model is used, the overall profit is higher than that obtained from a probabilistic model.

1. Introduction

Electricity companies have to switch from integrated vertical mechanisms to open market systems for a variety of reasons. The concept of operating systems has changed as a result of the reorganization and deregulation of the electrical sector [1]. The traditional approach was to meet the entire power demand at any given time [2,3], but the new philosophy suggests that a system performs best if load fluctuations are kept to a minimum [4,5]. Hence, in the new philosophy, independent operators, transmission line operators, and retailers were added to the market. Electricity retailers participate in the electricity market as intermediaries between wholesale and retail markets. On the wholesale side, they buy energy by participating in the markets of the next day and the pool of power. On the retail side, they sign contracts with consumers to meet their energy demands at a fixed price for a specified period of time, which is usually a year [6,7]. One of the issues that complicate a retailer's the decision corresponds to the uncertain parameters that affect its profit. In this regard, the two main sources of

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uncertainty are power pool prices and customer demand, affects the retailers' profit as well as decision variables. There are several ways to plan a retailer in order to maximize profits. In previous methods, retailers used load response programs or energy storage systems alone. Retailers, who used a short-term energy storage battery bank with a charge response program, maximized their profit by reducing the cost of purchasing energy from the market. Therefore, if they used load response programs, they would not have to buy more from the market by encouraging customers to reduce demand. This could improve revenue by means of acquiring a battery bank during off-peak times, charging the battery, and then employing the battery during peak periods. This research intends to simultaneously include the presence of load and battery response programs in retailer planning. It could be argued that retailer profit would be much greater than that obtained by using these options separately.

The authors of [8] studied cost-effective energy demand response management system [9]. presents a multi-objective schedule for the daily operation of an intelligent network by considering the maximization of the minimum number of available reservations and minimizing the operation costs while considering the reliability requirements of critical and vulnerable loads. In Ref. [10], demand and electrical responses for an electrical distribution network were studied. In Ref. [11] presents a closed loop model aimed at minimizing the cost of operating commercial buildings in the wholesale electricity market. Regardless of demand-side management, the increasing number of electric vehicles overloads distribution feeders [12]. presents a centralized framework that searches the solution space with the aim of minimizing consumer operating costs in response to time-varying prices. In addition, the proposed framework provides incentive costs that reduce the potential for overload. The authors of [13] analyzed battery energy storage system investment, and retail electricity markets were studied in Refs. [14, 15]; P [16]. [17]. focuses on the impact of the load response mechanism on micro-grid reliability. The degree of coordination between micro-grids' loads and new energies can affect their reliability. Economic dispatch due to the increase in price uncertainty and cost-sensitive demand faces many challenges in today's leading markets. Despite the challenges of load handling, independent system operators have adapted to manipulating node costs and loads subject to different conditions. It is known that strong referral mechanisms can be developed through demand-side management. This is our motivation for proposing a new Optimal Resist Active Dispatching model, as per (X [18]. In the presented robust optimization model, the effects of load cost response are determined for all conditions while considering dynamic optimization [19]. presents a simulation method for wind energy that considers the external environment. This simulation is based on the Brownian theory of motion.

Price-based and incentive-based load response programs have been implemented to create load response models [20]. provides an expanded bidding structure that provides more realistic specifications and demand behaviors for flexible bids. Nowadays, demand varies over time in the form of bidding between independent system operators and energy markets. This article describes different types of bids that can be adjusted for different loads and can accurately express their value and extract load response programs with direct market participation. The authors of [21] described the components of a smart power network and analyzed how consumers participate in load response programs and intelligent systems. In this reference, the challenges and opportunities of implementing load response programs in an intelligent network are examined while considering technical, informational, and economic aspects.

The authors of [22] used an economic load model to analyze the effect of load response programs and some power grid parameters. This reference focuses on incentives such as capacity market programs and load reduction and cutting programs. In addition, the profits and losses of consumers after the implementation of incentive-based load response programs are examined [23,24]. conducted sensitivity analyses and employed an economic load model to establish a load response program. Appropriate loads were selected to participate in the load response plan. In addition, rotating system storage was determined using stochastic indices in the presence of load response programs.

[25] scheduled the implementation of the load response plan in the form of a planning problem related to unit participation security by using the random combination integer programming method. Additionally, this reference examines the impact of load response programs on the provision of operational reserves [26]. offers a flexible function for customer profit and flexibility of demand, simulates sensitive loads, and examines the flexibility of load response programs before and after their implementation in a competitive electricity market [27]. combines a demand function to model electrical energy consumption segments for use in a comprehensive load response program based on dynamic elasticity.

The main objective of this research is to achieve mid-term retailer planning (while considering the uncertainty of consumer behavior, probabilistic, and robust models), the short-term energy storage (battery bank) and load response programs simultaneously. The novelty of this paper is the strategic bidding model for a retail market in which the main goal is to maximize the profit of the retail market by providing an optimal incentive-oriented response. Regarding the impact, with this method, the retailer be able use load response programs and impose incentives and penalties on consumers in order to force them to balance consumption while charging its battery system during non-peak hours. A retailer using only a battery, or a charge response program could maximize profits by reducing the cost of purchasing its energy from the market.

2. Mathematical methods and modeling approach

2.1. Load liability

A comprehensive definition of load liability involves the participation of small consumers in electricity markets, their exposure to current market prices, and their reaction to them [28,29]. Currently, only a few consumers are aware of the real price of electricity. As a result of the approach under study, consumers will have no worries about their participation in the market and will adapt their consumption to generation direction, grid conditions, and electricity prices.

2.2. Load response programs

In general, load response programs can be divided into two main categories [7]:

- Electricity price-based load response programs: Time of use, Real-time pricing, Critical peak pricing;
- Incentive-based load response programs [30]: Direct control, Interruptible or curtail-able programs, Demand bidding, Emergency demand response, Capacity market, Ancillary service market.

Essentially, the price of energy should be straightforward and agreeable to consumers, utilities, and the general public. Electricity companies are required to supply electricity to their customers through long-term contracts, the use of distributed generation resources, and the purchase of electricity from existing markets. Due to the fact that the price of electricity varies according to time and place, providing electricity at a fixed rate from customers constitutes a high risk for electricity companies that are faced with fluctuating electricity prices in the wholesale market.

The Time Response Program (TRP) is the most common time-varying program. This method encourages customers to improve their consumption patterns during off-peak hours and reduce consumption during peak hours by changing the price of electricity at different times. It has been previously stated that informing consumers about the true

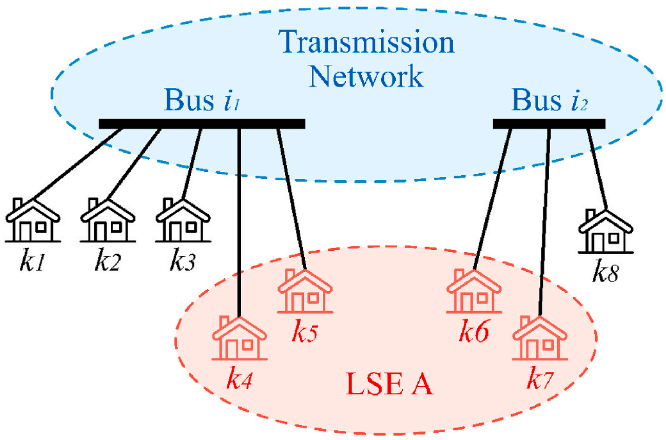

Fig. 1. Structure of a retail market and its consumers.

price of power and paying this fee in return for the electricity consumed was the best approach to persuading them to minimize usage. Considering the instantaneous change in the market price of electricity, announcing this price to consumers will likely confuse them, as most customers do not have the time and equipment to respond to instantaneous changes. The best solution to this problem is to use several different time intervals during the day in order to apply different electricity prices to consumers [31].

$$\psi = \left(\sum_{i=1}^{N} c_i \times G_i\right) - \lambda\left(\sum_{i=1}^{N} G_i - \sum_{i=1}^{N} D_i\right) - \sum_{l=1}^{M} \mu_l^{min}\left(\sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) + Limit_l\right) - \sum_{l=1}^{M} \mu_l^{max}\left(Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i)\right)$$
$$- \sum_{i=1}^{N} \omega_l^{min}\left(G_i - G_i^{min}\right) - \sum_{i=1}^{N} \omega_l^{max}\left(G_i^{max} - G_i\right) \tag{7}$$

2.3. Retail market net returns

The retail market [14,15]; P [16]. receives gross returns from each customer $k(k \in B_i)$ at the bus $i(i \in A)$, as shown in Fig. 1 for the A retail market. This return is calculated as a function of the retail price $\eta_{i,k}$ and electricity consumption $D_{i,k}$. Then, the payment (*e.g.*, the point price π_i and the electricity consumption $D_{i,k}$) is reduced, as the retail market buys electricity from ISOs in wholesale markets at light-knot prices. Finally, the financial incentives that the retail market pays to customers are reduced, which is the result of coupon prices $r_{i,k}$ and the deviation between real electricity demand and basic electricity consumption. Therefore, the net retail market return should be expressed as Equation (1).

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

2.4. ISO economic load distribution

Economic load distribution is performed by ISOs [32,33], in order to clear the market, identify LMPs and distribute production. Since the P-DR program is between the retail market and customers, the demands in an ISO's economic load distribution model do not retain any flexibility. Here, a fixed transmission network with a linear DC model is assumed, and perfectly competitive and reasonably priced products are evaluated at their final cost. This is compatible with various optimal DC load distribution models used by many ISOs. Moreover, when evaluating DRs for price uncertainty modeling, other sources of uncertainty can be added as needed. Therefore, the approach regarding different DC optimal load distribution models has been used to model the electricity market and predict LMPs [34]. While real models are very complex in practice due to the need for robust computation and productivity, economic load distribution based on different DC optimal load distribution models is used to illustrate the main point of the proposed study. Different DC optimal load distribution models are basically a linear programming problem given by equations (2)–(6).

$$\min \sum_{i=1}^{N} c_i \times G_i \tag{2}$$

$$s.t. \sum_{i=1}^{N} G_i = \sum_{i=1}^{N} D_i \ : \ \lambda \tag{3}$$

$$D_i = \sum_{k \epsilon B_i} D_{i,k} \ , \forall i \ \epsilon \ A \tag{4}$$

$$-Limit_l \leq \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \leq Limit_l \ : \ \mu_l^{min}, \mu_l^{max}, \forall l = 1, 2, \ldots, M \tag{5}$$

$$G_i^{min} \leq G_i \leq G_i^{max} \ : \ \omega_l^{min}, \omega_l^{max}, \forall i = 1, 2, \ldots, N \tag{6}$$

After obtaining the optimum economic load distribution solution, the LMP can be calculated with the Lagrangianfunction. This function and the LMP can be written describe through equations (7) and (8).

$$\pi_i = \frac{\partial \psi}{\partial D_i} = \lambda + \sum_{l=1}^{M} GSF_{l-i}\left(\mu_l^{min} - \mu_l^{max}\right) \tag{8}$$

2.5. Two-tier strategic bidding model

In the bidding process [35,36], the decision variables are the incentive prices $(r_{i,k})$ and the corresponding demand spreads $(D_{i,k})$. Since LMPs depend on the ISO's distribution of economic loads from (3-2) to (3-6), the issue of strategic bidding is formulated as a two-stage issue. The two-tier strategic bidding model is given by equations (9)–(11).

$$\max \sum_{i \epsilon A} \left(\sum_{k \epsilon B_i} \left(\eta_{i,k} \times D_{i,k} - r_{i,k} \times \left(D_{i,k}^0 - D_{i,k}\right) - \pi_i \times D_i\right)\right) \tag{9}$$

$$s.t. \ D_{i,k}^{min} \leq D_{i,k} \leq D_{i,k}^{max} \ , \forall i \ \epsilon \ A, k \ \epsilon \ B_i \tag{10}$$

In the above relations,

$$\pi_i \ , \forall i \ \epsilon \ \arg\{((2-3)) - ((6-3)), ((8-3))\} \tag{11}$$

In Equation (10), $D_{i,k}^{min}$ and $D_{i,k}^{max}$ are the minimum and maximum demand values from demand k and bass i, respectively. B_i is the set of customers on the i-bus that have P-DR with this retail market. The economic load distribution LMP depends on the $D_{i,k}$demand. as well as bid prices/generator quantities. Note that both retail prices and retail market demand are decision variables in the bidding process and are a

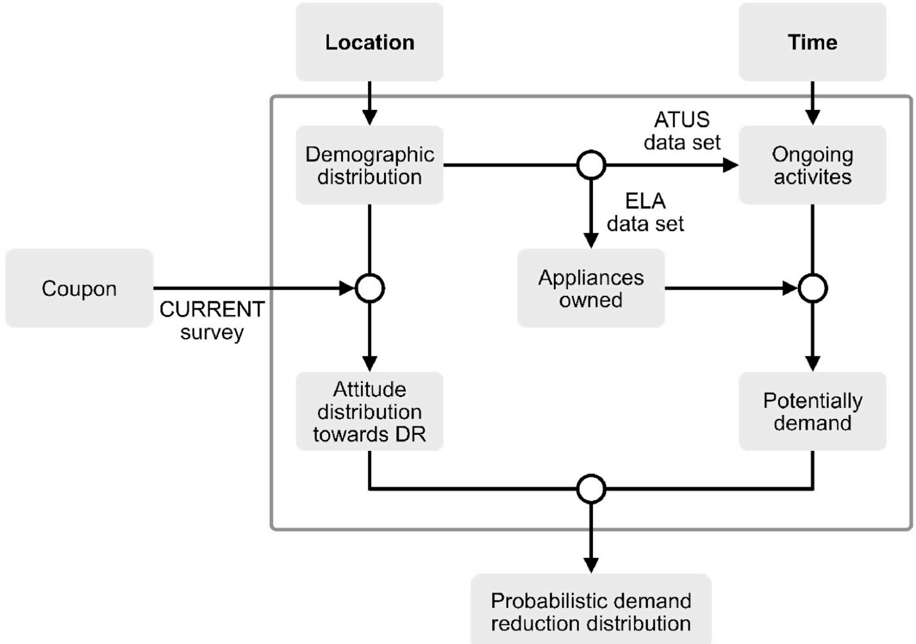

Fig. 2. Information processing diagram for the demand reduction model.

Table 1
Discrete probability function of percentage reduction of load in exchange for coupon prices offered by the retail market.

Coupon price $))	0	5%	10%	15%	20%	25%
0	1	0	0	0	0	0
1	0.8	0.15	0.05	0	0	0
2	0.75	0.2	0.05	0	0	0
3	0.65	0.2	0.15	0	0	0
4	0.55	0.2	0.15	0.05	0	0
5	0.45	0.25	0.15	0.15	0	0
6	0.35	0.3	0.2	0.15	0	0
7	0.2	0.3	0.35	0.15	0	0
8	0.1	0.35	0.4	0.15	0	0
9	0.05	0.35	0.45	0.15	0.05	0
10	0	0.35	0.45	0.15	0.05	0.05

nonlinear target function. In order to solve the strategic model (9)–(11), it is first necessary to discuss the demand model. Since $r_{i,k} \times (D^0_{i,k} - D_{i,k})$ is linear with a given encouraged price, $D_{i,k}$ in (9) to (11) can be determined for a particular $r_{i,k}$ via the algorithm described in the next section. These are solved with different wind scenarios.

2.6. Potential demand reduction model

As discussed earlier, the uncertainty of declining consumer demand is typically modeled in P-DR based on strategic bidding:

- The retailer offers its customers a coupon price.
- Customers provide the relevant demand reduction spectrum for the retail market.
- The retail market calculates the expected net income with a tender. This demand is revised in the ISO electricity market.
- By repeating steps 1 to 3 with different coupon prices, the optimal coupon price that provides the maximum net return to the retail market can be found.

However, there are potential challenges to this process:

- Customer demand reduction information is rarely kept up to date.

Thereupon, this paper presents a possible practical demand reduction model with different incentive prices. The schematic of said model is shown in Fig. 2, where the incentive price model inputs are the

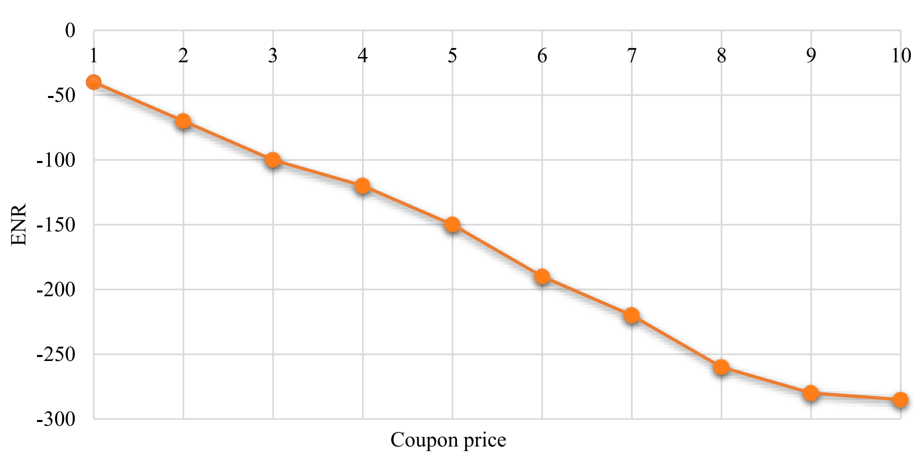

Fig. 3. Expected profit margin of the retail market in the first load scenario.

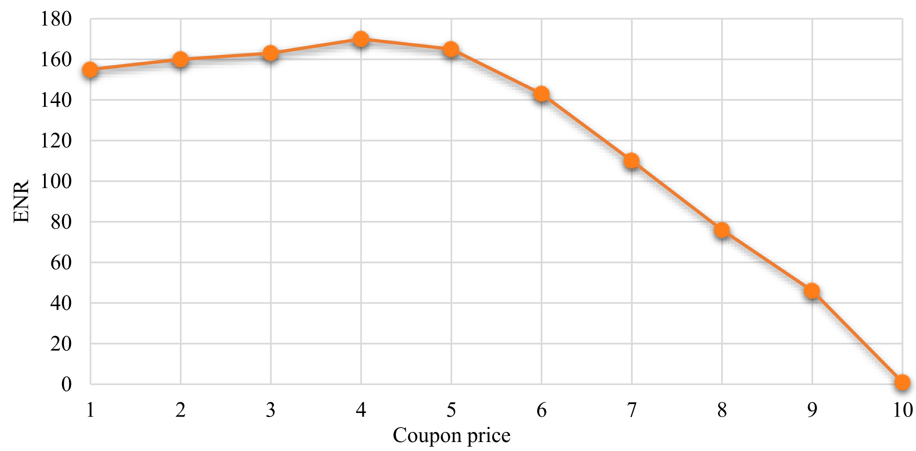

Fig. 4. Expected profit margin of the retail market in the second load scenario.

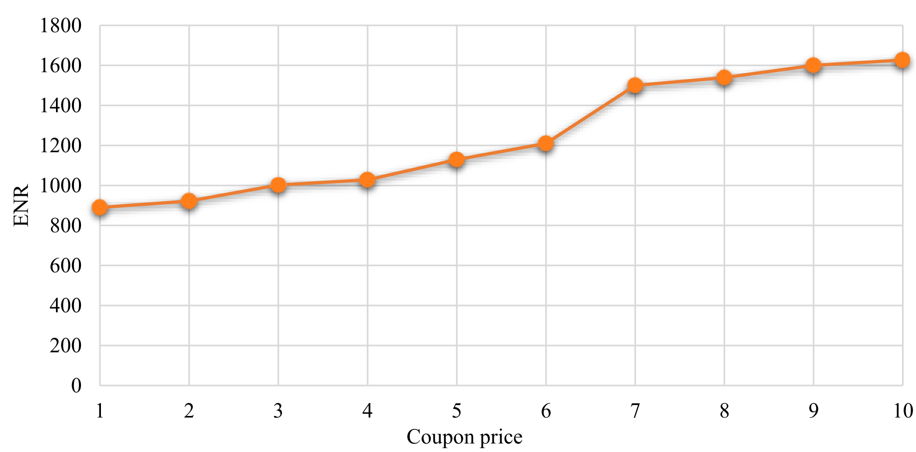

Fig. 5. Expected profit margin of the retail market in the third load scenario.

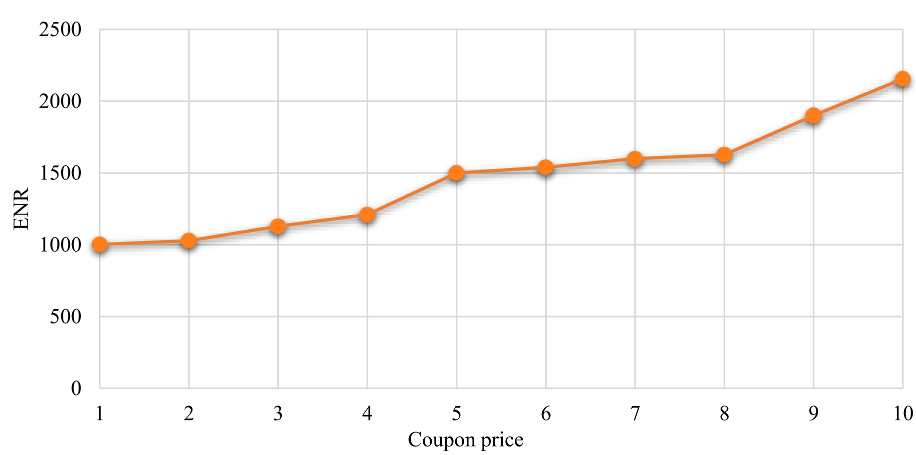

Fig. 6. Expected profit margin of the retail market in the fourth load scenario.

location and duration of the P-DR. This figure shows that the output of the corresponding probability distribution is due to a decrease in demand.

The method for producing this model can be summarized as follows:

Step 1: By reviewing location data, residents are classified into several groups $(G_1, G_2, \ldots, G_N)$ based on their demographic information. For each group of residents, steps 2 to 5 will be applied.

Step 2: For group G_i, the types and ratings of appliances can be obtained by analyzing residential energy consumption estimates issued by the Energy Information Administration.

Step 3: For Group G_i, the time-use survey made by the department of labor can shed light into the current activities of residents.

Step 4: Potential demand reduction can be achieved by integrating information on the equipment used and the activities performed by residents.

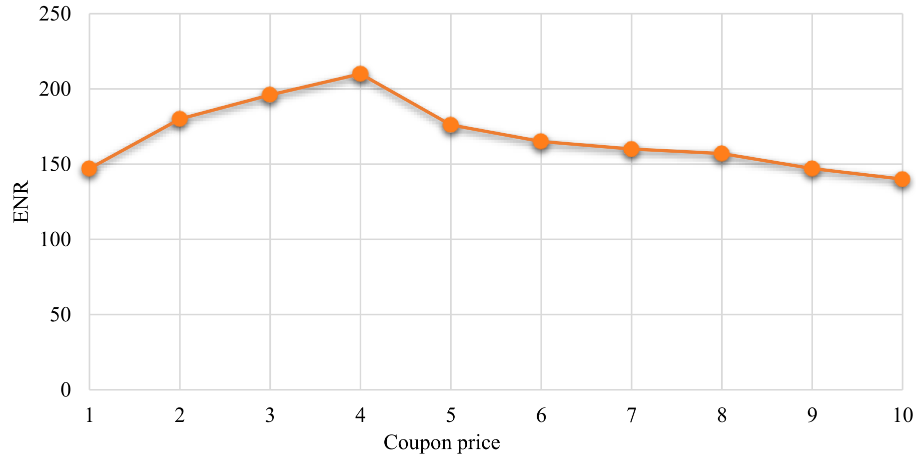

Fig. 7. Expected profit margin of the retail market in the fifth load scenario.

Table 2
Retail market outputs considering coupon axis load sensitivity.

Load	Coupon price amount	Amount of local price limits taking into account load responsiveness	Expected profit considering load accountability	Local price limit value regardless of the load response	Expected profits regardless of load accountability	Load amount	Case
260	0	10	2431	10	2600	260	1
276.39	2	10.56	2567	11.287	2494.492	286	2
281.65	8	12.791	2045	20.654	−199.47	305	3
295.183	10	23.816	−2214.871	33.765	−4514.92	328	4
321.791	6	33.51	−497.61	35	−5400	360	5

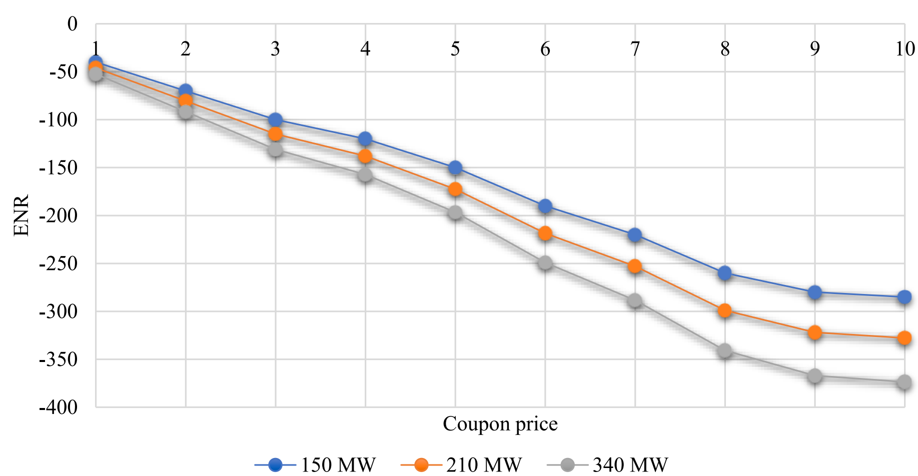

Fig. 8. Expected profit margin of the retail market for different production capacities and the first load scenario.

Step 5: Depending on the residents' attitude towards different incentives, potential demand reduction activities can be modeled. As long as the distribution of these attitudes and the potential demand reduction of all groups are known, it is easy to obtain a distribution that is likely to reduce demand.

2.7. Proposed mathematical solution

The issue of strategic bidding in Equations 9–11 is a two-stage optimization problem. These two optimization problems are interrelated due to the existence of dependent variables at each level. In this paper, DCOPF is implemented to clean up the ISO market. Due to the linearity of DCOPF, its optimal solution must be unique and satisfy the Karush – Kuhn – Tucher (KKT) optimization conditions. As a result, the two-level optimization problem is formulated as a mathematical program with equilibrium constraints (MPEC) by integrating the low-level problem into a high-level one using its KKT terms as additional definition constraints. According to the strong duality theory, the MPEC model can be converted into a MILP one that can be solved with existing software.

2.8. Formulating the problem as an MPEC

Given that low-level economic burden distribution is an LP problem, the two-tier strategic bidding model can be converted into an MPEC one by redesigning the low-level problem as the KKT optimization condition (equation (12)) and then adding it to the higher-level problem as a set of additional definition constraints (equations (13)–(19)).

$$\max ((9)) \tag{12}$$

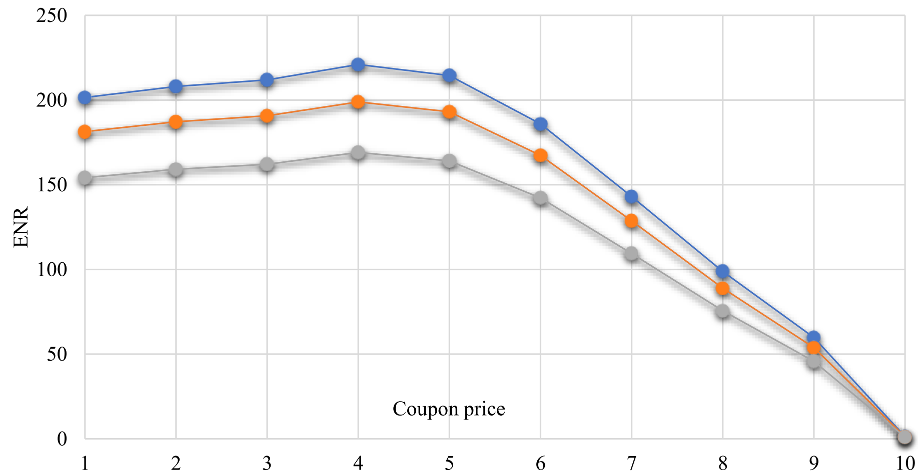

Fig. 9. Expected profit margin of the retail market for different production capacities and the second load scenario.

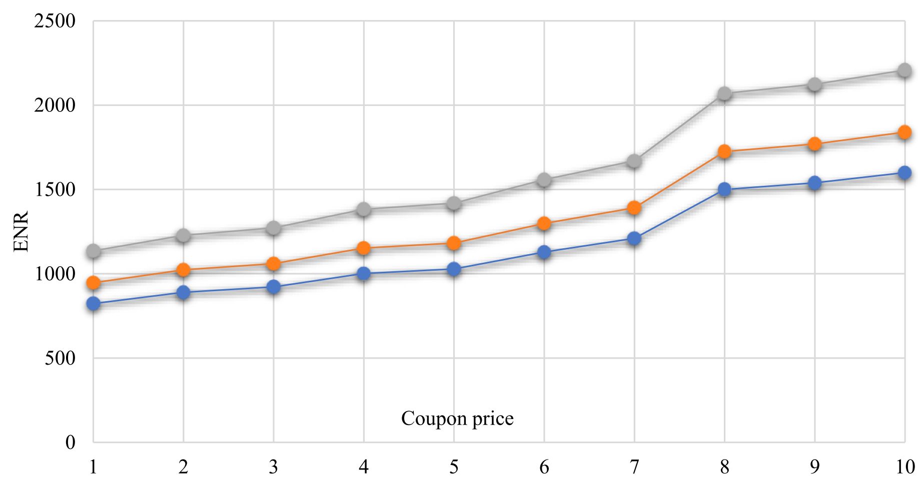

Fig. 10. Expected profit margin of the retail market for different production capacities and the third load scenario.

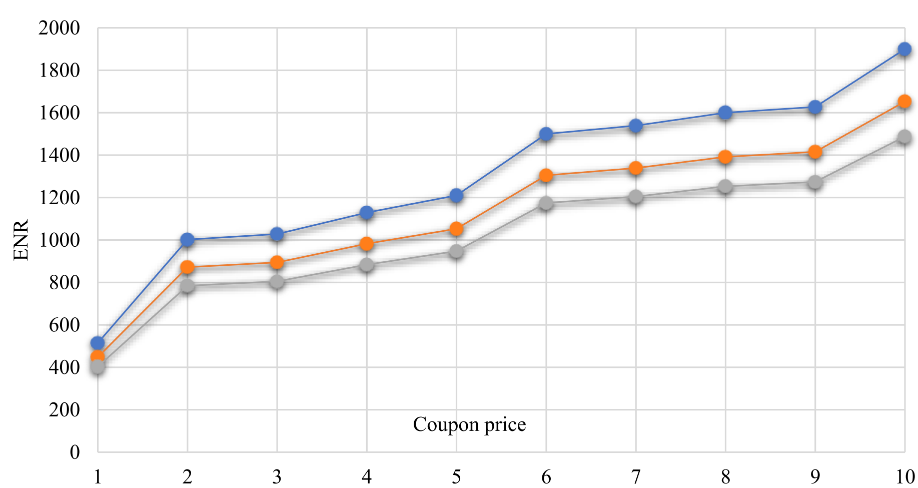

Fig. 11. Expected profit margin of the retail market for different production capacities and the fourth load scenario.

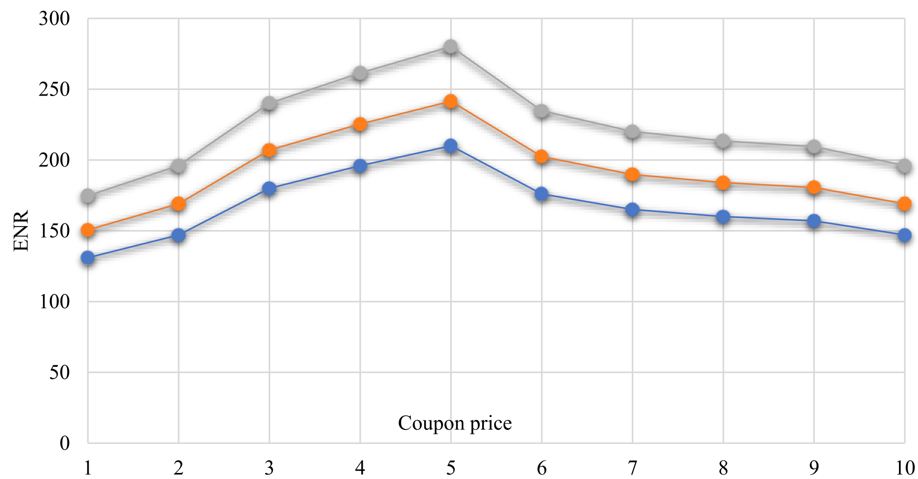

Fig. 12. Expected profit margin of the retail market for different production capacities and the fifth load scenario.

Table 3
Rate of increase in the expected profit of the retail market in different situations of uncertainty.

Variance	Case1	Case2	Case3	Case4	Case5
0	152	171	4100	2101	101
0.05	149	175	3871	2238	116
0.1	137	180	2871	2451	117
0.15	130	183	2502	2101	167
0.2	131	190	2398	2222	181
0.25	137	196	2300	2173	201
0.3	132	203	2010	2234	209
0.35	134	210	1982	1999	220
0.4	134	218	1678	2156	210
0.45	134	222	1239	1989	217
0.5	134	230	1102	1821	204

$$\text{s.t. Constraint in } ((3)), ((4)), ((8)) \text{ and } ((10)) \tag{13}$$

$$c_i = \lambda + \sum_{l=1}^{M} GSF_{l-i} \times \left(\mu_l^{min} - \mu_l^{max}\right) + \omega_l^{min} - \omega_l^{max} \tag{14}$$

$$0 \le \mu_l^{min} \perp Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \ge 0 \tag{15}$$

$$0 \le \mu_l^{min} \perp Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \ge 0 \tag{16}$$

$$0 \le \mu_l^{max} \perp Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \ge 0 \tag{17}$$

$$0 \le \omega_i^{min} \perp G_i - G_i^{min} \ge 0 \tag{18}$$

$$0 \le \omega_i^{max} \perp G_i^{max} - G_i \ge 0 \tag{19}$$

3. Results and discussion

In previous methods, retailers have only used load response programs with energy storage systems. A retailer using only a battery, or a charge response program could maximize profits by reducing the cost of purchasing its energy from the market. If it used load response programs, it would not need to buy more energy from the current market by encouraging customers to reduce demand. Using batteries, it could increase its income by purchasing it during off-peak times and charging the battery and using it during peak times. In this article, load and battery response programs are simultaneously included in retail planning. It can be argued that the retailer's profit will be far greater than that gained by using these options separately. With this method, the retailer can use load response programs and impose incentives and penalties on consumers in order to force them to balance consumption while charging its battery system during non-peak hours. Now, if there is an increase in consumer demand in the market on the next day, it compensates all or part of this increase from the power stored in the short-term energy storage battery system, thus reducing the cost of

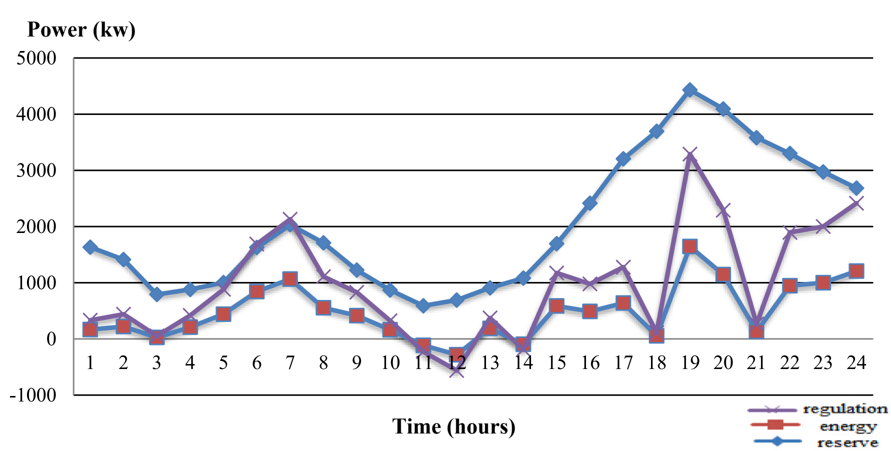

Fig. 13. Amount of power exchanged in the presence of participatory and retail markets, considering the random behavior of customers.

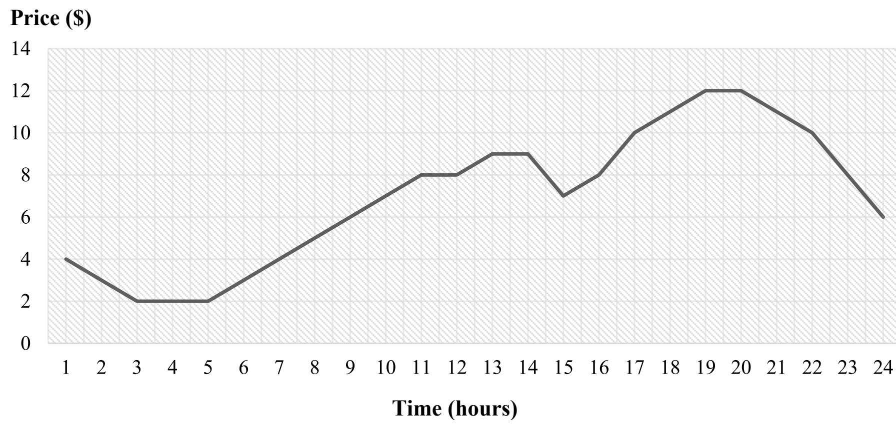

Fig. 14. Relative profit considering the random behavior of customers from a risk management perspective, in the presence of a participatory energy market and a retail one.

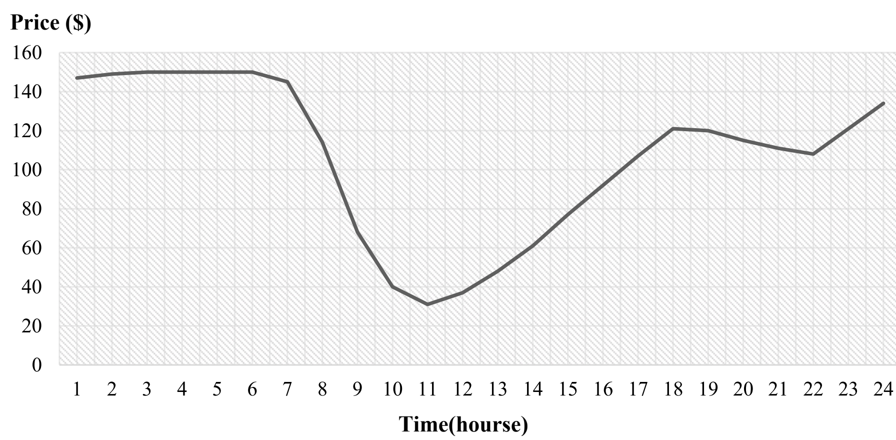

Fig. 15. Profit from the presence of batteries for 24 h.

Table 4
Retail market profits with common market participation, regulation, reservation, and energy.

Type of market participation	Profit in USD
Common	7161
Reserve	7091.2
Energy	2316.63
Regulation	4182.2

Table 5
Retail market profits with common market participation, regulation, reservation, and energy (probabilistic model).

Type of market participation	Profit in USD
Common	*7343.1*
Reserve	*2445.2*
Energy	*1894.2*
Regulation	*4304.9*

purchasing energy from the current market.

The scenarios studied in this article are the following:

(a) Retail planning while considering the coupon-based load response program
(b) Retail planning while considering the coupon-based load response program and battery allocation (considering the uncertainty of customer behavior)
(c) Retail planning while considering the coupon-based load response program and battery allocation (considering the possible model)
(d) Retail planning while considering the coupon-based load response program and battery allocation (considering the robust model)

3.1. Scenario (a): retail planning while considering the coupon-based load response program

Table 1 shows the expected percentage for the prices of the loads participating in the load response program.

Table 1 shows that, if the price of the offered coupon is higher, customers will be more inclined to reducing the load. In fact, after extracting the model related to the retail market, which is done by considering the objective function of the independent operator of the system, by changing the load bidding price from 0 to $10, the load reduction percentage distribution function can be discretely modeled discretely according to the aforementioned Table 1. In the obtained model, after subtracting the load reduction percentage distribution model for different prices, the problem is solved for each coupon price and each of the possible blocks in order to extract the optimal amount for the offered price. Different modes are considered to perform the

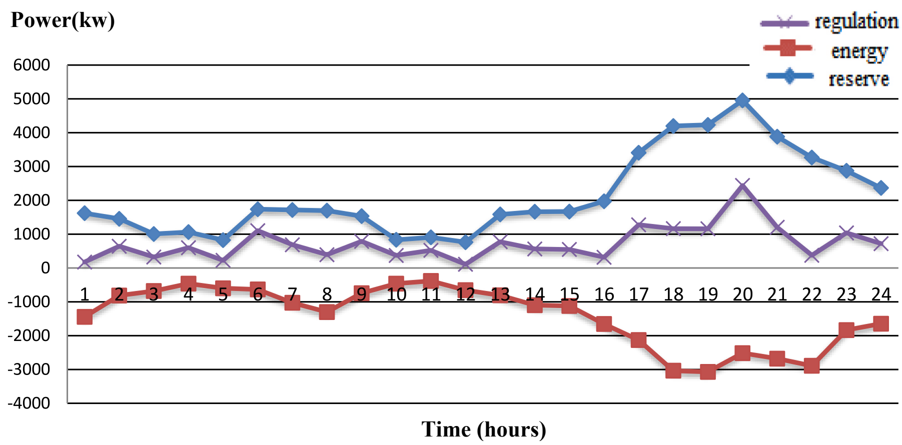

Fig. 16. Amount of power exchanged in the presence of participatory and retail markets, considering the probabilistic model.

Table 6
Retail market profits with common market participation, regulation, reservation, and energy (robust model).

Type of market participation	Profit in USD
Common	*6765.6*
Reserve	*4956*
Energy	*2316.3*
Regulation	*4653.6*

simulation. First, uncertainty is ignored and, according to the system load level, five modes are considered. From 1 to 5, the system load increases. The retail price is $20 per MWh. Moreover, the price of the offered coupon is usually no more than 50% of the retail price and ranges from 0 to $10 per MWh. Figs. 3–7 show the expected retail market profit for different coupon prices in the five cases considered. Table 2 also shows the values of the load, the amount of the local limit price, the optimal amount of the coupon price, and the reduced load in the five different load level modes.

In this scenario, the results imply that, in the first case, where the amount of system load is at its lowest, the retail market profit is a negative amount. When the system load is low, the local price value is low, and the price offer to reduce the load is not economical. As a result, the expected profit is negative when offering a price to reduce the load. Furthermore, the first line of the Table (2) shows that the local limit price is at a low level, so the optimal coupon price is 0, meaning that the retail market is reluctant to a price offer for its subscribers. In the next four cases, due to the increase in the local limit value, offering a price to subscribers has an economic justification for the retail market and increases the optimal price of the coupon offer. In general, in any case where the local limit value is higher at the desired bus, the retail market has more incentive to offer prices to its subscribers. Moreover, in the third and fourth cases, it is seen that the expected profit of the retail market increases at the same rate as the coupon price does, but, in states two and five, it first increases and then decreases. This can be explained by the fact that, in the second and fifth cases, the expected amount of profit primarily depends on the amount of retail market payments. As a result, when the operating point is significantly larger than the critical load, any reduction in demand does not have a significant effect on prices. However, in cases three and four, any decrease in demand leads to a large reduction in the local limit price, which has a double effect on the expected profit of the retail market.

The cash market was examined for the existence of bilateral contracts and the way in which the retail market works, which first involves the effect of production capacity on the local limit price and the expected profit of the retail market. In general, since the cost of production is 0, their entry into the system reduces the marginal prices. In this case, simulations were performed while considering total capacities of 150, 210, and 340 MW. Figs. 8–12 show the expected retail market profit for the different coupon prices and three capacity scenarios. Based on these figures, the amount of production capacity does not affect the expected profit change pattern.

As shown in Figs. 8–12, the pattern of expected profit changes is not altered by coupon prices. It is the load level in the system that plays a decisive role in this case. It is important to note that the amount of production is uncertain. In other words, the amount of production is like

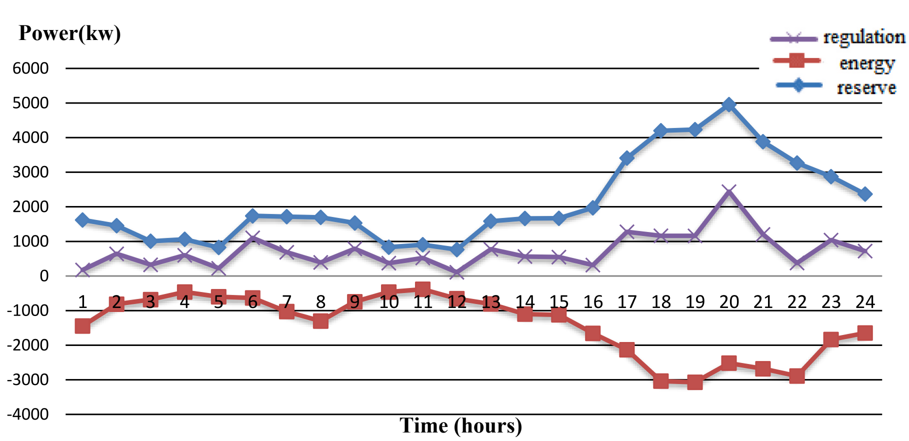

Fig. 17. Amount of power exchanged in the presence of participatory and retail markets, considering the robust model.

a random variable. Various models have been proposed to consider this uncertainty, which can have a significant impact on problem solving. In this article, a simple model of random number production is used, assuming the mean and variance of the random variable related to the output power. By having the values of the mean and variance of a random variable, scenarios can be constructed in order to model the uncertainty of said random variable. The greater the variance, the greater the uncertainty in estimating power generation. In order to observe the effect of production uncertainty on production capacity, different variance values are selected, and scenarios are created accordingly for output power. Table 3 shows the increase in retail market revenue for different variances.

It is observed that, in cases 3 and 4, as the variance increases, the uncertainty increases, the local margin price sensitivity decreases, and the expected profit decreases. In contrast, in cases 2 and 5, as uncertainty increases, the local price sensitivity increases, which results in a higher expected rate of profit. In general, as the total uncertainty in the system increases, it becomes more likely for a retail market to increase revenue.

3.2. Scenario (b): retail planning while considering the coupon-based load response program and battery allocation (considering the uncertainty of customer behavior)

The main innovation of this article is demonstrated in this scenario. In other words, in this scenario, the optimal planning of batteries in the retail market is carried out by considering the random behavior of customers. Retail market profits with the participation of common markets, regulation, reservation, and energy are shown in Table (4).

The amount of power exchanged for 24 h in the participatory markets of reservation, energy, and regulation in the retail market is depicted in Fig. 13.

The relative profitability of risk management for the participatory energy market in the presence of the retail market and batteries is shown in Fig. 14.

In addition, the effect of batteries on profit for 24 h is the one shown in Fig. 15.

According to Table 4 and considering the four participatory markets in the retail market, the profit from the common market is the highest and the profit from the energy market is the lowest. It is noteworthy that these markets are participatory and exchange with the retail market. According to the profits from the participatory markets, it can be said that the lowest level of risk is related to the common market and that the highest risk corresponds to the energy market. Fig. 13 examines the exchange rate of participatory markets in the presence of a retail market. Based on this figure, it is obvious that, in many hours of a 24-h horizon, the power exchange related to the regulating market is the highest and the energy market power exchange is the lowest. By comparing the battery allocation mode and combining it with the load response mechanism, it can be seen that the possible profit also increases. Thus, it can be said that adding batteries to the retail market process increases the overall profit.

3.3. Scenario (c): retail planning while considering the coupon-based load response program and battery allocation (considering the possible model)

In this section, the problem is solved by considering the probabilistic model. The results are compared with the robust model given in the next section. Retail market profits with the participation of common markets, regulation, reservation, and energy are given in Table 5.

The amount power exchanged in 24 h for the participatory markets of reservation, energy, and regulation in the retail market is shown in Fig. 16.

3.4. Scenario (d): retail planning while considering the coupon-based load response program and battery allocation (considering the robust model)

In this section, the problem is solved by considering a robust model. Retail market profits with the participation of common markets, regulation, reservation, and energy are given in Table 6.

The amount of power exchanged in 24 h for the participatory markets of reservation, energy, and regulation in the retail market is shown in Fig. 17.

By comparing the two retail market modes while considering battery and coupon-based load response in both probabilistic and robust modes, it is concluded that the profit from the reservation, energy, and regulation participatory markets increases in the case of the robust model, whereas the profit from the common participatory market decreases. In general, it can be said that the use of a robust model increases the overall profit in comparison with probabilistic models.

4. Conclusions

For power system operators, various load response programs have been expanded as potential resources to balance supply and demand, reduce peak load times, and increase production efficiency. In a fully competitive electricity market, the retail market plays an important role in filling the gap between all customers and wholesale market operators in order to connect them to an optimal operating structure. In competitive wholesale markets, there are two ways to implement the incentive-oriented load response: managed by the retail market to maximize profits and managed by an independent system operator to maximize social welfare. The purpose of this paper was to present a new strategic bidding model for a retail market in which the main goal is to maximize the profit of the retail market by providing an optimal incentive-oriented response. The following conclusive remarks are obtained by simulating the proposed model:

(a) Because the predicted amount of profit is based entirely on the amount paid by the retailer market, any decrease in demand will have little influence on pricing when the operating point is substantially higher than the critical load. As uncertainty increases, local price sensitivity increases, and, as a result, the expected rate of profit increases.
(b) In general, as the total level of uncertainty in the system rises, a retail market will have a higher chance of increasing revenue.
(c) Adding a strategy of short-term energy storage battery banks to the retail market process has increased overall profits.
(d) Profits from participatory reservation, energy, and regulation markets grew in the robust model, but profits from the common participatory market declined, i.e., according to our study, which looked at both probabilistic and robust models of retail market participation.
(e) When a robust model is used, the overall profit is higher compared to that obtained from a probabilistic model.

Authorship statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the Results in Engineering.

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

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Category 3: Approval of the version of the manuscript to be published (the names of all authors must be listed): F. Zishan, E. Akbari, O.D. Montoya, D.A. Giral-Ramírez, A.M. Nivia-Vargas.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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