Risk-based Offering strategy for a retailer in a wholesale and local electricity market considering demand response

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Abstract

Uncertainties in wholesale market prices and consumer demand pose risks to electricity retailers. Distributed energy resources (DER) and responsive demand exchange energy in the local market. Local markets provide a good opportunity for retailers to improve their economic situation by influencing market prices through demand response (DR). Thus, the issue that needs to be addressed is how the interaction of retailers in the local market can affect its strategy. This paper proposes a new framework to assist electricity retailers in optimizing the offering strategy in both wholesale and local electricity markets under uncertainty. The proposed framework is based on a stochastic bi-level optimization model. At the upper level, with the aim of maximizing profit of retailers, optimal decisions are made on the power purchased from wholesale and local markets. At the lower level, the local market is considered, with the aim of minimizing the operating cost. Wholesale market price uncertainties and the production of renewable resources are modeled using a set of scenarios. The model is turned into a single-level problem by substituting the lower-level with its KKT conditions. Simulation results showed that using the proposed method, the average retailer's profit has increased approximately 12% to 16% comparing conventional methods.

Keywords: Demand response, Retail Electricity Providers, optimization model, local market clearing, Local Markets.

1. Introduction

1.1 Motivation

The electricity industry has recently changed significantly in many countries because of its reorganization process. A major goal of this process in the electricity industry is the replacement of the formerly incorporated electricity corporations with competitive marketplaces. The newly created setting has led to various emerging institutes with a variety of activities. An example of such institutes is electricity retailers acting as mediators between electricity-producing corporations and consumers. In such corporations, electricity is purchased from wholesalers and it is sold to consumers, hence, setting indentures is needed on both the supply and demand parties. Buying energy at inconstant prices from wholesalers and selling it at stable prices at the retail level is challenging for retail traders. To keep pace with traders, it requires seeking proper solutions economically thus

1.2 Literature review

In the last decade, numerous researches related to the topics of retail, demand response and electricity market have been conducted [1]. Simultaneously the profit and risk has been considered for a retailer involving futures contracts and the wholesale market. In 2, a model for determining the strategy of a light-asset retailer is presented in the electricity market. In [3], the approaches and plans of energy-producing corporations and buyers are examined in the electricity market. The behaviors of home subscribers for participating in the electricity market are also examined. The whole issues probably encountered by a retail, from the electricity market worldwide, are outlined in [4]. In [5] a model is presented to provide more accurately consideration the retail market, the introduction of new equipment, standards and strategies related to smart metering and solutions to keep customer information. Competitive retail is addressed to optimize the retailer's revenue, considering that the prices are invariable. A simple execution of Demand Response (DR) programs according to shifts in demands. DR decreases outages, improves customer participation, increasing market capability. In the majority of DR models, economic and technical factors are incorporated as objective functions, such as quality of service, peak demand, utility linked to energy usage, and discomfiture accompanied by usage behaviors [7-10]. For instance, an agent-based model encompassing both balancing and spot power market is presented in [11]. A stochastic multi-objective unit commitment real-time DR model with resilient optimization is presented in [12]. In [13], the possible use of price-response dynamics for limiting power usage is demonstrated with a one-way price signal. In a bi-level optimization model offered in [14], the grid efficiency is improved via setting time-differentiated power rates by a provider and reducing electricity consumption. For maximizing revenue and multiple followers (customers), [15] presented a model with a single leader (retailer). In [16], a multi-leader-multi-follower game model is proposed for load shifting caused by time-of-use pricing for interplays among utilities, local agents, aggregators, and consumers. It was assumed that the whole but one electrical supplier's decision variables are clear and maximizes the rest of the provider's decisions as a single-leader-multi-follower game. In [17] an exclusive price-based model is presented for a DR aggregator. A stochastic programming method was presented in [18] to calculate the superior retailing plan in a timetable of one week for maximizing revenue and the business corporation's risk is limited at the same time; the ideal optimization is then achieved for real time, fixed price, and combination pricing [19]. It is presented a stochastic programming framework for identifying the best retailer's strategy. Retailers are vulnerable to pricing risks and volume fluctuations caused by market price variations and unpredictability in [20] and the real-time market, where fixed tariffs cover the bulk of private and small commercial customers.

According to [21], the demand depends on some factors, including weather conditions, time, and the kind of customer. Highly accurate prediction of these issues is possible by applying statistical methods or artificial intelligence algorithms such as regression, fuzzy logic, neural networks, and specialized systems, which can critically decrease risk for retail traders. Price curves could also be used to construct an incentive-based demand response strategy as described in [22, 23]. A mechanism for creating bid curves for the day-ahead market is proposed in reference [24].

Current approaches for optimum operation of integrated energy systems that take unknown elements into account include stochastic optimization, resilient optimization, interval optimization, possibility method, information gap decision theory (IGDT), and the hybrid optimization method. The optimization goals might be categorized as either economics, environmental protection, dependability, or flexibility, or a combination thereof [25-27]. To deal with system uncertainty, stochastic optimization employs various probability strategies, including the scene method, Monte Carlo simulation, point estimation method, chance constrained programming. The PDFs of random variables are used to characterize the uncertainty of the system [25-27]. According to [28] the real-time selling price of retailers for consumers, namely industrial, commercial, and residential were determined. A down-side risk constraint method has been used to analyze the results. The objective function is to maximize the retailers' expected profit in the presence of several dispatch- able/non-dispatch-able resources. In [29] a short-term two-stage decision-making scheme is presented for electricity retailers with self-generation renewable resources. DA and RT markets, as well as DR have been included. The optimal selling price of retailers in the presence of DR programs has been investigated in [31]. At the upper level, the retailer decides about its participation in the DA and RT markets and its price bids to minimize its procurement costs. At the lower-level, these producers respond to the retailer's price bids in order to maximize their revenues. In [32] electricity optimal strategy of retailers is investigated by considering shifts of the demands. At the upper-level, the retailer's required energy from available options as well as shiftable loads' incentive prices are determined. At the lower-level, customers' loads are shifted based on the retailer's offered incentive prices. A transaction mechanism is proposed in [33] based on the interaction among electricity retailers and customers with considering DR. Results show that,the revenue of retailers has increased, and consumers' payment has reduced. The multi-leader multi-follower Stackelberg game has been exploited to model the interaction between market players. A two-stage bi-level model has been presented in to simultaneously clearing wholesale and retail electricity markets relying on:

(i) A fully-decentralized algorithm able to run by all system operators, preserving privacy aspects of all market players and data security over the whole system,

(ii) Considering inherent uncertainty of electricity generation of renewable units and power consumption of customers using a stochastic programming approach,

(iii) Modeling and analyzing financial risk of the uncertain parameters and their effects on all parts of the system.

Authors in [36] proposed a bi-level optimization model to study the strategic retail pricing and demand bidding problems, where considers DR. In [37] a three-level game intelligent structure was presented to evaluate individual and collaborative strategies of electricity manufacturers, considering network and physical constraints. At the first level, aiming at maximizing the profits, the particle swarm optimization (PSO) algorithm is implemented to determine the optimum power of distributed energy resources (DERs). Further, the fuzzy logic algorithm is applied to model the intermittent nature of the renewable sources and implement load demand in the power grid. At the second level, DERs are classified into two different fuzzy logic groups to secure the fairness between every participant. Finally, at the third level, the DERs in each group are combined by cooperative game algorithms to increase the coalition profits. In [38], an optimal scheduling of plug-in electric vehicles (PEVs) as mobile power sources was presented for enhancing the resilience of multi-agent systems (MAS) with networked multi-energy microgrids (MEMGs). In each MEMG, suppliers, storage, and consumers of energy carriers of power, heat, and hydrogen are taken into account under the uncertainties of intermittent nature of renewable units, power/heat demands, and parking time of PEVs [39].The optimization of distributed generation technologies and storage systems are essential for a reliable, cost-effective, and secure system due to the uncertainties of Renewable Energy Sources (RESs) and load demand [40].

Authors in [41] presented a model for planning and utilizing a district heating system. The model is applied to a province in Turkey to fulfill environmental, technical, and economic goals. In the first step, indices have been used, including demographics, efficiency of the buildings and the number of households, to predict the required heating load by support vector regression (SVR) as a supervised machine learning method until 2030. Researchers in [42] deployed harmonized natural gas and fuel cell CHP technologies alongside RES and battery energy storage systems (BESS) to facilitate EVs' G2V and vehicle-to-grid (V2G) operations. While the BESS supports V2G operations and stores excess power from the CHP and RES, the CHP's by-product heat could be employed in heating homes and industrial facilities. In order to compare reviewed articles, a brief summary of them is shown in Table 1.

The review of the articles shows:

- The simultaneous use of local market, wholesale market and bilateral contracts by the retailer to reduce the economic risk was not investigated;
- Considering that the local market is formed at the distribution level with the presence of renewable sources, the issue of hosting capacity is not considered in the literature;
- The majority of the study has concentrated on supplying consumers with wholesale market energy purchase techniques and approaches, as well as sales tactics, and as far as we know, retailer earnings in the local market have not been analyzed and maximized.

Hence, this paper attempts to fill all mentioned gaps and flaws by proposing a novel Bi-Level programming approach for the short-term scheduling of electricity retailers in the presence of the Smart DR.

1.3 Contributions

As mentioned above, most of the research in the last few years has focused on presenting an optimal method of providing the required energy for a retailer. The use of the capacities of the resources such as decentralized generation, demand response programs, renewable energy resources as well as the pool market and bilateral contracts were emphasized for this purpose. With the development of renewable resources and demand management in the distribution network, the structure of the wholesale market was not suitable for accessing these resources. Therefore, local markets are presented in response to these resources in order to be active in the market. In addition to providing energy through other resources and the wholesale market, electricity retailers can get the energy they need from the local market. It should be noted that despite their role in the wholesale market, retailers are price makers in the local market. Hence, the way in which energy is purchased from other resources and the wholesale market influence the demand in the local market. Therefore, the local market price taking this into account and assuming predetermined tariffs for end customers. This article presents a comprehensive two-step model for determining the strategy of energy purchasing by the retailer through the wholesale market, decentralized generation resources and demand-response programs, and aims to achieve profit for the retailer to maximize under the associated uncertainties. The contributions of this paper are highlighted as follows.

- ✓ Introducing bi-level model for optimal determination of retailer portfolio considering the retailer interactions with wholesale and local markets.
- ✓ Optimizing hosting capacity leads to optimizing retailer profits in the local market. In this case, the number of energy storage resources, including the number of solar cells and the number of wind turbines in the distribution network, is optimized so that the retailer's profit in the local market is optimized.
- ✓ In this proposed local market structure, a smart responsive load program in addition to network hosting capacity constraints has been considered to achieve minimum retailer's risk in cooperation with the market.

1.4 Paper organization

The rest of the article is organized as follows: in section 2, the proposed framework is presented, in section 3the model formulation is presented. Section 4 describes hosting capacity formulation. Section 5 is dedicated to smart DR model. Section 6 explains how to resolve a two-level problem, and the numerical results are presented in the section 7. Finally, it is summarized in section 8 of the article.

2. The proposed framework

Our working framework in this article is presented according to Figure (1), which is the input of this framework network information and purchase rate from the upstream market, as well as information on bilateral contracts. And the output is the optimal retail buying strategy from local market wholesale market sources and bilateral contracts and local market settlement prices. The body of the framework is modeled on two levels. The upper-level objective function is the maximization of the retailer's expected profit according to the sources of purchase and taking into account the uncertainties, the optimal purchased energy from forward contracts ,wholesale market and local market. In the lower-level's objective function is minimizing the cost of providing energy to consumers through the two-stage programming. The first-stage is based on the number of solar and wind resources. Hosting capacity is done with the aim of observing the local market indicators and in the second- stage, the local market is settled, in which the retailer participates through the load response program and makes the optimal purchased energy from the local market and optimal traded energy in the RT market, and Curtailed DR.

3. Model formulation

3.1Upper-level problem

Due to the two-level nature of the issue, upper-level retailers seek to maximize their profits. Relationships (1) include the sale of energy to unmet and responsive demand. In relation $\sum_t \lambda_P(t).P_t^p(t)$, $\sum_t \lambda_{local}(t).P_t^{plocal}(t)$, $\sum_b^B \sum_{t=1}^T \lambda_{b,t} P_{b,t}$, respectively, the costs related to the purchase of energy from responsive demands, upstream market, local market and bilateral contract .Equation $\sum_{dr,t,k}^{\Sigma} DR_{max}$ shows the retail revenue generated by energy sales of responsive demand by offering price curves to local markets.

$$Max = \begin{bmatrix} \sum_t D_y(t).Tarrif(t) + \sum_{dr,t} DR\_Consume(dr,t).Tarrif(t) \\ -\sum_{dr,t} DR\_\mathrm{Re}duce(dr,t).Tarrif\_DR(t) \\ +\sum_{dr,t} DR\_Consume(dr,t).Tarrif(t) \\ -\sum_{dr,t} DR\_\mathrm{Re}duce(dr,t).Tarrif\_DR(t) \\ +\sum_{dr,t,k}^{\Sigma} DR_{max} - \sum_t \lambda_P(t).P_t^p(t) - \sum_t \lambda_{local}(t).P_t^{plocal}(t) \\ -\sum_b^B \sum_{t=1}^T \lambda_{b,t} P_{b,t} \end{bmatrix} \quad (1)$$

According to Equations (2-5), the provided demand and real-time pricing are determined for the customer group by the retail trader. In this case, the retail trader determines the supply-demand and is a function of the sale price presented by the customer group.

$$D\left(l,t\right)=\sum_{z=1}^{Z} D^{offer}\left(l,z,t\right)A\left(l,zt\right) \quad (2)$$

$$SP\left(l,t\right)=\sum_{z=1}^{Z}SP\left(l,z,t\right) \quad (3)$$

$$SP^{offer}\left(l,t\right)A\left(l,z,t\right)\leq SP\left(l,z,t\right)\leq SP^{offer}\left(l,z,t\right)A\left(l,z,t\right) \quad (4)$$

$$\sum_{z=1}^{Z}\left(l,z,t\right)=1 \quad (5)$$

Subject to :

$$P_t^{\min}\leq P_t^{p}\leq P_t^{\max} \quad (6)$$

$$P_b^{\min}s_b\prec P_{b,t}\prec P_b^{\max}s_b \quad (7)$$

$$\sum_{j=1}^{J}P_t^{p}=\sum_{l=1}^{L}D\left(l,t\right)-\sum_{b=1}^{B}p_{b,t}-\sum_{t}\lambda_{local}\left(t\right).P_t^{plocal}\left(t\right) \quad (8)$$

The retail trader's revenue function (1) necessarily occurs when the power limitations of power are present (8).
According to the literature, the peak period can be managed by implementing the demand-response program and demand-side management for maximizing the retail trader's desirable revenue. The retail trader sets the selling price per hour in the introduced model, which resembles real-time pricing because of limitations (9). Likewise, the selling price is definable in stable pricing under the limitation (10). Lastly, the retail trader can define the selling price for the mean peak beside the low demand periods utilizing time-of-use pricing in limitation (11).

$$SP\left(l,t\right)\leq SP^{RTP}\left(l,t\right)$$

(9)

$$SP\left(l,t\right)\leq SP^{Fixed}\left(l,t\right)$$

(10)

$$SP\left(l,t\right)=\begin{cases}SP_L^{TOU}\left(l\right) fort\in lowloadlevel\\ SP_L^{TOU}\left(l\right) fort\in mediumloadlevel\\ SP_P^{TOU}\left(l\right) fort\in peakloadlevel\end{cases}$$

(11)

3.2 Modeling of risk

A systematic model is used to model retail sales risk.

Systematic risk is used to model retailer profit risk. The systematic risk factor is presented according to Equation (12). [1,17]:

$$\frac{dM\left(t\right)}{M\left(t\right)}=\mu_M dt+\sigma_M dW\left(t\right) \tag{12}$$

So that μ_M is late, σ_M is the retailer's profit fluctuation and W (t) is the standard Brownian motion under size P whose high dynamics indicate uncertainty due to systematic risk. The base profit values of $S_i(t)$ under size P follow the following process [1,17]:

$$\frac{dS_i\left(t\right)}{S_i\left(t\right)}=\mu_i dt+\beta_i\sigma_M dW\left(t\right)+\sigma_i dB_i\left(t\right). \quad i=1.2 \tag{13}$$

So that μi is the expected instantaneous return; Si (t) and σi^2 is the instantaneous variance of the retailer's return or profit; B1(t), B2(t) and W(t) are independent standard Brownian motions, which $\beta_i \ .i=1,2$ indicates the uncertainty caused by the non-systematic risk of assets; Si(t) and W(t) indicates the source of risk of systematic risk affecting the total profit of the retailer.

β_i which indicates the sensitivity to systematic risk, is calculated by the following equation:

$$\frac{\mathrm{Cov}(\ln M\left(t\right).\ln S_i\left(t\right))}{\mathrm{Var}(\ln M\left(t\right))}=\frac{\mathrm{Cov}(\sigma_M \mathrm{W(t)},\beta_i\sigma_M \mathrm{W(t)}+\sigma_i \mathrm{B(t)}).}{\mathrm{Var}(\sigma_M \mathrm{W(t)})}=\beta_i \quad i=1,2 \tag{14}$$

3.3 Smart demand response program model

To represent the sensitivity of the demand to price changes, they use a subject called elasticity, which is as follows:

$$E=\frac{\rho_0}{d_0}\frac{\partial d}{\partial p} \tag{15}$$

Where ρ is electricity price, d demand consumption and zero indices represent the initial value. Price elasticity in period i (hour) relative to period j) The sensitivity of the demand in period i to the price of period j is as follows:

$$E\left(i,j\right)=\frac{\rho_0\left(j\right)\partial_{d(i)}}{d_0\left(i\right)\partial_{\rho(j)}} \qquad \begin{cases}E\left(i,j\right)\le 0 & if\ i=j\\ E\left(i,j\right)\ge 0 & if\ i\ne j\end{cases} \tag{16}$$

If prices change in different periods, Load can respond to these changes in two ways:

- If the demand cannot be shifted to other hours, it is called with a single periodic sensitivity and its own elasticity, which is always negative.

- If the demand can be shifted to other hours, it has a multi-period sensitivity to which the reciprocal elasticity is always positive.

3.4 Lower-level problem and solving approach

Equation (17) represents the lower-level objective function of downstream network, which is maximizing social welfare or equivalent to minimizing the cost of providing energy to consumers. The cost of supplying energy to the sources of production, the cost of purchasing energy from the upstream grid, and the cost of selling energy to the retailer are shown in Equation (17).

$$X = \min = \sum_{i,t} a + bP_G + \sum M_P(t) P_W(t) + \sum DR\_ReduceTarrif\_DR(dr,t) \tag{17}$$

In relation, $\sum_{i,t} a + bP_G$, $\sum M_P(t) P_W(t)$, $\sum DR\_ReduceTarrif\_DR(dr,t)$, respectively, the costs related to the purchase of energy from local market, upstream market and the cost of selling energy to the retailer .

3.4.1 Modeling of wind and solar power

Wind power generation capacity is a function of wind speed and wind turbine specifications, which is unique to each wind turbine, is expressed as follows:

$$P_G^W(s_W, W, t) = \begin{cases} 0 & 0 \le WS(s_W, W, t) < WS_{ci}(W) \\ P_{WN}(W).\left(A(W).WS^3(s_W, W, t) - B(W)\right) & WS_{ci}(W) \le WS(s_W, W, t) < WS_n(W) \\ P_{WN}(W) & WS_n(W) \le WS(s_W, W, t) < WS_{co}(W) \\ 0 & WS_{co}(W) \le WS(s_W, W, t) \end{cases}$$

(18)

In equation (18), p_{WN} is the nominal power of the wind farm, WS wind speed, WSci is the minimum wind speed at which the wind turbine, if it is below this value, it does not produce any electricity (cut-off speed). In addition, WSn is the rated speed and WSco is the speed at which the turbine blades are blocked due to protection problems of the wind turbine when the wind speed is higher than this value and therefore do not generate any electricity. Finally, A (W) and B (W), which are parameters for wind turbines, are obtained from the following equations:

$$A(W) = \frac{1}{WS_n^3(W) - WS_{ci}^3(W)} \tag{19}$$

$$B(W) = \frac{WS_{ci}^3(W)}{WS_n^3(W) - WS_{ci}^3(W)} \tag{20}$$

Equations (21-25), respectively, are the limitations of the battery of the photovoltaic unit in the charge and discharge mode, the switching charges of the charge and discharge, the initial and final energy of the battery of this unit, the amount of energy stored in the battery, the production capacity of the photovoltaic unit and its battery:

$$0 \le P_{BATT}^{charge}\left(PV, s_{PV}, t\right) \le P_{BATT}^{max,charge}\left(PV\right) Z_{charge}\left(PV, s_{PV}, t\right) \tag{21}$$

$$0 \le P_{BATT}^{discharge}\left(PV, s_{PV}, t\right) \le P_{BATT}^{max,discharge}\left(PV\right) Z_{discharge}\left(PV, s_{PV}, t\right)$$

(22)

$$0 \le Z_{charge}\left(PV, t\right) + Z_{discharge}\left(PV, t\right) \le 1$$

(23)

$$ENR\left(PV, t=1\right) = ENR_{ini}\left(PV\right) \quad , \quad ENR\left(PV, t=24\right) \ge ENR_{end}$$

(24)

$$P_{sale}^{PV}\left(s_{PV}, PV, t\right) = P_{G}^{PV}\left(s_{PV}, PV, t\right) + P_{SR}^{PV}\left(s_{PV}, PV, t\right) + P_{BATT}^{charge}\left(s_{PV}, PV, t\right) + \delta P_{BATT}^{discharge}\left(s_{PV}, PV, t\right) \tag{25}$$

In the above relations, P_{BATT}^{charge} is the power that charges the battery of the photovoltaic unit and $P_{BATT}^{max,charge}$ (max, charge) is its maximum allowable value. $P_{BATT}^{discharge}$ is the power discharged by the batteries of this unit and $P_{BATT}^{max,discharge}$ is the maximum allowable value. According to Equation (23), when the battery is in the charging state, Z_{charge} is one, $Z_{discharge}$ is zero, and when the battery is in the discharge state, Z_{charge} is zero and $Z_{discharge}$ is one. ENRini is the primary energy in the battery, P_{sale}^{PV} is the power that this unit sells, δ is the battery discharge efficiency of this unit, P_{SR}^{PV} is the power that this unit participates in the rotating energy storage market.

4. Hosting capacity formulation

In this section, in order to optimize the number of photovoltaic units and wind turbines, we must obtain the restrictions related to these products in order to optimize the retailer's profit. The objective function of the problem is stated below, which is the income minus the cost in which the objective of the problem is to maximize the objective function in order to achieve maximum profit.

$$MAX\ ER_{T} = \sum_{t=1}^{T} \left[\sum_{s \in S}^{\rho_{S}} \begin{array}{l} \left(P_{sale}(s,t) \times E_{p}\left(s_{p}, t\right) + P_{sale}^{SR}(s,t) \times\right) SR_{p}\left(s_{p}, t\right) + P_{sale}^{NR}(s,t) \times NR_{p}\left(s_{p}, t\right) \\ -P_{buy}(s,t) \times E_{p}\left(s_{p}, t\right) - C_{T}\left(s, W, PV, TST, FC, CHP, K, B, t\right) \end{array} \right] \tag{26}$$

The following two relationships are the probabilities and indicators of each scenario tree, respectively.

$$\rho_{s} = \rho_{P} \times \rho_{W} \times \rho_{TSS} \times \rho_{PV} \times \rho_{PL} \times \rho_{HL} \tag{27}$$

$$s = s_{P}, s_{W}, s_{TSS}, s_{PV}, s_{PL}, s_{HL} \tag{28}$$

The following equation indicates the cost of producing the units that the terms in (29) are given in Equations (30) to (31):

$$C_T\left(s,W,PV,TST,FC,CHP,B,t\right)=\sum_{W=1}^{W_N}A_W\left(W\right)+\left(A_{PV}+BATT_{COST}\left(PV,t\right)\right)\times M\left(PV,t\right)$$
$$+\left(A_{FC}+B_{FC}P_G^{FC}\left(s,t\right)\right)\times M\left(FC,t\right)+A_{TST}\times M\left(TST,t\right) \quad (29)$$

$$C_{CHP}\left(P,H\right)=A_{CHP}+B_{CHP}P_{G,CHP}\left(t\right)+C_{CHP}P_{G,CHP}^2\left(t\right)+D_{CHP}H_{G,CHP}^2\left(t\right)$$
$$+E_{CHP}H_{G,CHP}\left(t\right)+F_{CHP}H\left(t\right)P\left(t\right) \quad (30)$$

In equatiom (30), CHP (P, H) is the cost of electricity and thermal energy production of CHP power plant in which A_CHP, B_CHP, C_CHP, D_CHP, E_CHP and F_CHP cost function coefficients, P_ (G, CHP) (t) Electric power generated and H_ (G, CHP) (t) are the thermal power generated by this uint.

$$BATT_{COST}\left(K,t\right)=\left[a^{CH}\left(K\right)Z_{BATT}^{CH}\left(K,t\right)+b^{CH}\left(K\right)P_{BATT}^{CH}\left(s,K,t\right)\right]+CC\left(K\right) \quad (31)$$

In equation (31), $\mathrm{a^{CH}}\left(K\right)$ and $\left(K\right)$ function coefficients electric energy storage cost at charge, $\mathrm{a^{DCH}}\left(K\right)$ and $\mathrm{b^{DCH}}\left(K\right)$ function coefficients The cost of storing electrical energy during discharge, CC (K) is the fixed cost of this equipment and also when this storage element is being charged $\mathrm{Z_{BATT}^{CH}}\left(K,\mathrm{t}\right)$ is equal to one and $\mathrm{Z_{BATT}^{DCH}}\left(K,\mathrm{t}\right)$ is equal to zero and when this element is being discharged $\mathrm{Z_{BATT}^{CH}}\left(K,\mathrm{t}\right)$ is equal to zero and $\mathrm{Z_{BATT}^{DCH}}\left(K,\mathrm{t}\right)$ is equal to one. Obviously, $\mathrm{Z_{BATT}^{CH}}\left(K,\mathrm{t}\right)$ and $\mathrm{Z_{BATT}^{DCH}}\left(K,\mathrm{t}\right)$ cannot take one value at a time. Also, $\mathrm{P_{BATT}^{CH}}$ is a power stored in this element at any time interval, and $\mathrm{P_{BATT}^{DCH}}$ is a power that is discharged by this device at any time interval. Cost of batteries in the photovoltaic unit is as follows:

$$BATT_{COST}\left(PV,t\right)=\left[a^{CH}\left(PV\right)Z_{BATT}^{CH}\left(PV,t\right)+b^{CH}\left(PV\right)P_{BATT}^{CH}\left(s_{pv},PV,t\right)\right]+$$
$$\left[a^{DCH}\left(PV\right)Z_{BATT}^{DCH}\left(PV,t\right)+b^{DCH}\left(PV\right)P_{BATT}^{DCH}\left(s_{pv},PV,t\right)\right]+CC\left(PV\right)$$

(32)

In equation to (32), $a^{CH}\left(PV\right)$ and $\mathrm{b^{CH}}\left(PV\right)$ coefficients of the cost function of the photovoltaic unit batteries while charging, $a^{DCH}\left(PV\right)$ and $b^{DCH}\left(PV\right)$ coefficients of the battery cost function photovoltaic units at discharge, CC (PV) is the fixed cost of this equipment and also when this storage element is being charged $Z_{BATT}^{CH}\left(PV,t\right)$ equal to one and $Z_{BATT}^{DCH}\left(PV,t\right)$ equal to Z is zero and when this element is being discharged $Z_{BATT}^{CH}\left(PV,t\right)$ is zero and $Z_{BATT}^{DCH}\left(PV,t\right)$ is one. Obviously, $Z_{BATT}^{CH}\left(PV,t\right)$ and $Z_{BATT}^{DCH}\left(PV,t\right)$ cannot take one value at a time. Also, P_{BATT}^{CH} is a power stored in this element at any time interval, and P_{BATT}^{DCH} is a power that is discharged by this device at any time interval.

5. The smart DR model

The first stage uses hosting capacity optimization to optimize the merchant's profit. This means that the number and type of renewable energies will be optimized to maximize retail profits. For this, the number of PV and wind power plants is optimized. This article also presents a needs-based model of the demand-response program for optimal retailer decision making, considering different retail framework conditions
The proposed model maximizes retailer profits by changing the behavior of retailers and consumers.
Moreover, it optimizes retail traders' purchases from customary agreements in the electricity marketplace. In the introduced model, it is assumed that retail traders are present in two-sided covenants. Besides an increase in retail traders' revenues, the introduced model also assumes that retail traders' purchase is managed in a two-sided covenant. The smart DR model is depicted in Figure 2.
Smart demand response program constraints also affect hosting capacity. The purpose of the demand response program is to transfer local market demand from high hours when energy prices are high to low hours when energy prices are low. It should be noted that demand transfer planning can only change part or a percentage of the demand from one hour to another. These restrictions are:

$$L(s,t) = \left(1 - DR(s,t)\right) \times L_0(s,t) + L_{shift}(s,t) \tag{33}$$

Equation (33) shows the final demand after applying the demand response program, where L_0 (s, t) and L (s, t) indicate the amount of demand before and after applying the response program, respectively Also, DR (s, t) indicates the percentage of demand transferred from hour t and the phrase L_shift (s, t) indicates the amount of demand transferred from other hours to time t. On the other hand, only a certain amount of demand can be transferred to other hours. Therefore, another constraint that limits the distribution network planning is the maximum demand transfer rate, which is stated in equation (34):

$$DR(s,t) \le DR_{max} \tag{34}$$

Another constraint that must be considered is the maximum amount of demand increase in each of the time intervals that prevents the extra amount of demand shift in different time intervals, this constraint is stated below:

$$0 \le L_{increased}(s,t) \le \varepsilon_{increased}(s,t) \times L_0(s,t) \tag{35}$$

Where ε_increased (s, t) indicates the amount of demand increased per hour t (demand coefficient limit compared to the initial demand). In Equation (36), L_increased (s, t) is obtained from the following equation:

$$L_{increased}(s,t) = L_{shift}(s,t) - \left(DR(s,t) \times L_0(s,t)\right) \tag{36}$$

Now another limitation is the amount of ε_increased (s, t) which must meet the following condition:

$$\varepsilon_{increased}(s,t) \le \varepsilon_{max} \tag{37}$$

What should be noted is that the total daily consumption of electricity before and after the demand response program is the same and the local market operator, only by using the demand response program with how to manage its consumption at different times of the day, increases the profit from local market planning will be. This condition is stated in relation (38):

$$\sum_{t=1}^{T} L_{shift}(s,t) = \sum_{t=1}^{T} \left(DR(s,t) \times L_0(s,t) \right) \tag{38}$$

Demand for delivery on the demand side is expressed in Equations 38 and 39. Production resource constraints are based on equations 40and 41. Reactive power limits of production sources are also introduced in accordance with Equations 41 and 42.

6. Solving the bi-level problem

Normally, one of the most accurate and also prevailing methods to solve the Bi-Level problems is the Karush-Kuhn-Tucker (KKT) formulation. In this approach, the lower-level, follower, is replaced with its KKT conditions. Nonetheless, it should be noted that when the lower-level is convex and linear, it could be substituted with its KKT conditions [34]. On the other hand, the KKT conditions convert the non-linear Bi-Level problem into a non-linear Single-Level problem. The existence of complementary constraints leads to the non-linearity of this method. Consequently, in this work, in order to linearize these types of limitations, the Big-M technique is employed.

The general mathematical formulation of the considered scheme is explained in more details in [35].

Based on the above descriptions, the final linear Single-Level model of the proposed Bi-Level problem can be formulated as follows:

Delivery capacity constraints on the demand side are expressed in [34] and [35]. Production resource constraints are applied based on equations (41) and (42). Reactive power limits in production sources are also introduced in accordance with equations (43) and (44).

$$P_{wm} \geq -P_{\max}^{TieLine} \tag{39}$$

$$P_{wm} \leq P_{\max}^{TieLine} \tag{40}$$

$$P_g \geq P_g^{\min} \tag{41}$$

$$P_g \leq P_g^{\max} \tag{42}$$

$$Q_g \geq Q_g^{\min} \tag{43}$$

$$Q_g(t) \leq P_g(t).t_g(\cos^{-1}(0.9)) \tag{44}$$

Equation (45) represents the transmission power in line L + 1 and the active power balance constraint in each bus.

$$P^{Line}(L+1,t) = \sum_{L} P^{Line}(L,t) + P^{Gen}(b,t) - P^{D}(b,t) \tag{45}$$

The reactive power balance constraints per bus are expressed in Equations 52to 55.

$$Q^{Line}(L+1,t) = \sum_{L} Q^{Line}(L,t) + Q^{Gen}(b,t) - Q^{D}(b,t) \tag{46}$$

$$V^{bus}(b+1,t) = V^{bus}(b,t) - (R_L P^{Line}(L,t) + X_L Q^{Line}(L,t)) \tag{47}$$

$$V^{bus}(b,t) \geq 0.95$$
$$V^{bus}(b,t) \leq 1.05 \tag{48}$$

$$P^{Line} \leq P^{Line}_{\max} \tag{49}$$

The KKT terms of the objective function are shown in relations 50to 63.

$$\frac{\partial l}{\partial P_G(i,t)} = 0 \longrightarrow b_i - \lambda_p(b,t) - \sum \eta_P^{\min}(i,t) + \sum \eta_P^{\max}(i,t) = 0 \tag{50}$$

$$\frac{\partial l}{\partial P_V(t)} = 0 \longrightarrow M_P(t) + \mu_{wm}^{\min}(t) + \mu_{wm}^{\max}(t) = 0 \tag{51}$$

$$\frac{\partial 2}{\partial P^{Line}} = 0 \longrightarrow -\lambda_p(b,t) + R_L \lambda_V(b,t) + \sum_L \gamma^{\max}(L,t) = 0 \tag{52}$$

$$\frac{\partial l}{\partial Q_y(i,t)} = 0 \longrightarrow -\lambda_Q(b,t) - \sum \eta_Q^{\min}(i,t) + \sum \eta_Q^{\max}(i,t) = 0 \tag{53}$$

$$\frac{\partial L}{\partial Q^{Line}} = 0 \longrightarrow -\lambda_Q(b,t) + X_L \lambda_V(b,t) = 0 \tag{54}$$

$$(P_{wm}(t) - P^{Tieline}_{\max} \geq 0 \perp \mu_{wm}^{\min} \geq 0) \Rightarrow \begin{cases} P_{wm}(t) - P^{Tieline} \geq 0 \\ \mu \geq 0 \\ P_{tib} \leq u_m, \mu^{\min} \leq (1-u)\mu \end{cases} \tag{55}$$

$$(P^{Tieline}_{\max} - P_{wm}(t) \geq 0 \perp \mu_{wm}^{\max} \geq 0) \tag{56}$$

$$(P_y - P_y^{\min} \geq 0 \perp \eta_P^{\min} \geq 0) \tag{57}$$

$$(P_y^{\max} - P_y \geq 0 \perp \eta_P^{\max} \geq 0) \tag{58}$$

$$(Q_g - Q_g^{\min} \geq 0 \perp \eta_Q^{\min} \geq 0) \tag{59}$$

$$(Q_g^{\max} - Q_g \geq 0 \perp \eta_Q^{\max} \geq 0) \tag{60}$$

$$(1.05 - V^{bus}(b,t) \geq 0 \perp \eta_V^{\max}(b,t) \geq 0) \tag{61}$$

$$(V^{bus}(b,t) - 0.95 \geq 0 \perp \eta^{\min}(b,t) \geq 0) \tag{62}$$

$$(P^{Line}_{\max} - P^{Line}(L,t) \geq 0 \perp \gamma^{\max}(L,t)) \tag{63}$$

The relations below the Lagrange Equation represent the downstream objective function

$$
\begin{aligned}
l = X &+ \lambda_P(b,t).(P^D(b,t) - P^{Gen}(b,t) - \sum_l P^{Line}(l,t) - P^{Line}(l+1,t)) \\
&+ \lambda_Q(b,t).(Q^D(b,t) - Q^{Gen}(b,t) - \sum_l Q^{Line}(l,t) - Q^{Line}(l+1,t)) \\
&+ \lambda_V(b,t).(R_L P^{Line}(l,t) + X_l Q^{Line}(l,t) - V^{bus}(b,t) - V^{bus}(b+1,t)) \\
&+ \mu_{wm}^{\min}(P_{\max}^{Tieline} - P_{wm}(t)) + \mu_{wm}^{\max}(P_{wm}(t) - P_{\max}^{Tieline}) \\
&+ \sum_{i,t} \eta_p^{\min}(i,t)(P_g^{\min} - P_g(i,t)) + \sum_{i,t} \eta_p^{\max}(i,t)(P_g(i,t) - P_g^{\max}) \\
&+ \sum_{i,t} \eta_Q^{\min}(i,t)(Q_g^{\min} - Q_g(i,t)) + \sum_{i,t} \eta_Q^{\max}(i,t)(Q_g(i,t) - Q_g^{\max}) \\
&+ \sum_{b,t} \eta_v^{\min}(b,t)(0.95 - V^{bus}(b,t)) + \sum_{b,t} \eta_v^{\max}(b,t)(V^{bus}(b,t) - 1.05) \\
&+ \sum_{l,t} \gamma^{\max}(l,t)(P^{Line}(l,t) - P_{\max}^{Line})
\end{aligned} \tag{64}
$$

Given all of these models and the constraints presented in this paper, according to the proposed flowchart in Figure 2, the retailer's revenue is first calculated based on the proposed SDR model. In the next step, the number of renewables is calculated based on the hourly demand on the part of the retailer. The calculation of the retailer cost from the energy side is done in the presence of the proposed SDR and the risk model in the next step. The model is developed to optimize the retailer's profit in an SDR program and optimize the hosting capacity and include the risk. If the retailer's profit is maximized, the optimization process will be completed. Otherwise, the SDR parameters, hosting capacity and risk model are modified.

7. Numerical study

The results of simulation of the proposed model is demonstrated on real sample network. According to Figure (3), the network under investigation is a 182-bus network with a voltage of 20 kV and a load of about 6.3 MW [28].The retailer offers energy to 100 consumers who are divided into three groups based on a) selling prices, b) consumption habits, and c) reaction to the merchant's proposed pricing.Residential (84 consumers), business (12 customers), and industrial (12 customers) are the three types of clients (4 customers). Residential users use roughly 3.6 kW and 2.9 kW during peak and off-peak hours, business customer's use about 60 kW and 49 kW, and industrial customers use about 3.3 MW and 2 MW.

The present research considers a retail trader with a 1-month time limit and six two-sided covenants. Tables (2) and (3) respectively represent peak, mean, and non-peak hours along with the conditions of two-sided covenants. According to the Iberian electricity marketplace, local hourly prices are gathered in six periods. Tables (4) ,(5)and (6) respectively represent Characteristics of PV,WT,MT

Figure (4) shows the buying costs from the local market for the method and set pricing that has been proposed so far (FP). Because it is more cost effective, the suggested solution is the most cost effective, while set pricing is more expensive to implement. Based on the proposed smart DR (SDR) against fixed pricing, the retailer is managing all local contracts with unpredictability in energy prices in the most efficient manner feasible. It is anticipated that this approach will result in the lowest RTP pricing cost. For the purpose of comparison, the recommended SDR method is compared with one that does not include SDR.

The cost of purchasing electricity under a bilateral agreement is shown in Figure 5. In this sort of electrical market contract, the retailer is interested in extending its position since the energy price in the bilateral contract is stable, which encourages the retailer to do so. Furthermore, because of increased consumer participation in demand-side pricing, the cost of purchasing energy via retail in real-time pricing is less expensive than the cost of purchasing energy through the other two techniques.

The average profit of the recommended approach is shown in Figure 6 for a variety of different scenarios. Because of increased customer participation on the demand side, the recommended SDR displays a more favorable power market situation in this figure, which is based on equations (17)-(18). (21). the retailer also has a stronger level of involvement with consumers, and by using interval optimization in the proposed model, he or she may be able to manage market contracts with the highest possible revenue and the lowest possible cost.

The retailer's downtown is $1,420 for fixed pricing. Also, based on TOU pricing the average retailer's profit is $1,480 while the profit variation is $62. This shows that due to the positive effect of time-of-use pricing, the retailer's profit margin has increased compared to fixed pricing. Also, using SDR, the retailer's profit is $1,670. This means that the average retail profit in SDR has increased compared to TOU and fixed pricing. Finally, by evaluating the appropriate solutions obtained in fixed pricing in addition to TOU and SDR pricing, it can be verified that the retail profit is more than 13% higher than fixed pricing and 12% higher than TOU pricing. This shows that the proposed model increases the retailer's income.

Figure (7) shows the retailer's profit in TOU mode With SDR, FP, Without SDR in sample scenarios. By encouraging consumers to participate in the demand side management program, the electricity retailer will increase profits by offering and using more suitable programs such as SDR. TOU pricing reflects the cross-sectional reality of the electricity market. According to Figure (7), the average profit of the retailer in the SDR method has increased by approximately 12-16% compared to the without SDR pricing method. In general, since the real-time pricing method captures the actual situations in the electricity market, it can be expected that the retailer's profit will increase more than other pricing methods.

Figure (8) shows the comparison of the retailer's income in two cases of not paying attention to the proposed model and considering the proposed model in local market contracts. Accordingly, the retailer has increased revenue based on the use of time slot optimization and encouraging subscribers to participate in demand side management programs. In other words, the retailer has maximized his income by selling more energy and managing uncertainties in the local market based on the proposed optimization model.

The PAR diagram is seen in Figure 9. In reality, PAR is the ratio of highest demand to average demand, and it is roughly equivalent to the peak demand created during a single day of operation. This metric is important for major corporations because it helps them maintain energy supply and demand. If the PAR is high, the facility will need more production units in order to meet the highest level of demand, and these production units will only be available for use during peak hours. Because of this, the company's operational costs grow. Low PAR contributes to the reduction of the facility's operating expenses. When comparing various scheduling approaches, it can be noted that PAR is roughly the same, but is much lower when compared to the non-scheduling mode. As a result, these hosting capacities, along with intelligent demand response, assist huge corporations in lowering their operational costs. Figure 8 depicts the retailer's profit chart in a 24-hour cycle for two operating modes: one with and one without consideration of the proposed risk model, in order to demonstrate the impact of incorporating the suggested risk model on the retailer's profit. As can be seen, taking risk into consideration may result in a large boost in store earnings.Figure 10 shows the effect of SDR on retailer profit. It can be seen that the proposed smart demand response program has a strong impact on retailer profits and also leads to a significant increase in retailer profits compared to conventional demand response.The effect of hosting capacity on retailer’s profit is seen in Figure 11. The diagram clearly shows that optimizing hosting capacity has resulted in a large rise in retailer earnings. The hosting capacity also increases the retailer's profit during the lower hours, and the amount remains the maximum amount for a longer period of time. This is due to the fact that the number of renewable resources is optimized based on the amount of consumption per hour and upstream, resulting in an increase in store profits.

8. Conclusion

In this work, a model is developed based on the demand response program to help retailers adopt the best possible decisions on the energy market, considering many opportunities that may be encountered. While maximizing retailer profit, the optimal model offered by modeling retailer and customer behavior also leads to the optimal purchase of retailer from traditional contracts in the energy market. The suggested approach is based on the participation of the retailer in bilateral contracts as well as local market contracts in order to maximize the retailer's profit. The local market is at the level of the distribution network. The main purpose of this article is to influence the retailer in the local market. Therefore, in the lower level, first, optimization regarding the number of solar and wind cells and demand responsiveness for retailers to participate in the local market through retailers can be considered as one of the operating constraints of the local market. It showed that using proposed smart DR the retailer's profit can increase noticeably and by using risk mode, the profit of retailers in local market can increase significantly. Simulation results show that:

- It was shown that the proposed option is the most cost efficient, whereas fixed pricing is more costly to perform. To maximize efficiency, the retailer manages all local contracts with unpredictability in energy costs based on the proposed smart DR (SDR). This strategy has resulted in the lowest RTP price cost. The proposed SDR approach is in contrast to one that does not use SDR. The proposed SDR reflects a more favorable power market environment as a result of increased consumer demand.
- Using interval optimization in the proposed model, the retailer may be able to manage market contracts in a way that generates the most money and incurs the fewest expenses.
- As shown, taking risk into account may greatly boost retailer profitability.
- It is also shown that, the proposed smart demand response program significantly increases retailer profitability compared to traditional demand response.
- Finally, the results showed that optimizing hosting capacity has resulted in a large rise in retailer profits. This was due to the fact that the number of renewable resources is optimized based on the amount of consumption per hour and upstream.

As a future work, the problem of power outage in the power distribution network can be investigated.

Nomenclature

$sp(l,t)$	Energy selling Price	$\sum_t D_y(t).Tarrif(t)$	Revenue for retailer from customer
$D(l,t)$	Customer's energy demand supplied by retailer	$\sum_{dr,t} DR\_Consume(dr,t).Tarrif(t)$	Cost of purchasing power from DR
$\lambda_{b,t}$	Bilateral trade Price	$\sum_{i,t} a+bP_G$	Cost of purchasing power from Local Generator
$p_{b,t}$	The amount of power purchased from any bilateral contract	$\sum_{dr,t,k}^{\Sigma} DR_{max}$	retail revenue generated by energy sales by offering price to local markets.
$\lambda_P(t)$	Price of pool electricity market	$\sum_t \lambda_{local}(t).P_t^{plocal}(t)$	purchase of energy from local market
$\lambda_{local}(t)$	Price of local market	$\sum_t \lambda_P(t).P_t^{p}(t)$	purchase of energy from upstream market

P_t^P	Amount of power which purchased from upstream market	$\sum_b^B \sum_{t=1}^T \lambda_{b,t} P_{b,t}$	purchase of energy from bilateral contract
P_t^{Plocal}	Amount of power which purchased from local electricity market	$L(s,t)$	amount of demand before applying the response plan
S_b	Binary variable for selecting bilateral contracts	$L_{shift}(s,t)$	amount of demand transferred from other hours to time t
$SP^{RTP}(l,t)$	tariff Selling price real-time of retailer offered to customer	$L_0(s,t)$	amount of demand after applying the response plan
$A(l,z,t)$	Variable in binary form for determining the selling price to customers	$DR(s,t)$	percentage of demand transferred from clock t and the phrase
$D^{offer}(l,z,t)$	Customer's demand offered to retailer	$\varepsilon_{increased}(s,t)$	amount of demand increased per hour t
$SP(l,z,t)$	Interval Selling price of retailer for customer	$P_t^{\min}, P_t^{\max}$	Maximumand Minimum of power in pool
$SP^{Fixed}(l,t)$	Selling price of retailer offered to customer in fixed tariff	$P_b^{\min}, P_b^{\max}$	Maximumand Minimum of power in bilateral contracts
$SP_L^{TOU}(l,t)$	Selling price of retailer offered to customer in time of use tariff	T,l	Index for time, Customer's demand level
DER	Distributed energy resource	SDR	Smart demand response
MCP	Market clearing price	WT	Wind turbine
ζ	Electrical efficiency of non-frame control sources (%) A	MT	Micro turbine
π_t^f	Fuel price offer at the moment t (£/kWh)	PV	Photovoltaic
RLD	Responsive load demand	HC	Hosting capacity
DR	demand response	FP	Fix Price
$P^{+A} P^{-A}$	Min/Max output power A (kW)	PAR	Ratio of highest demand to average demand

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Table 1. Differences between the current paper and previous studies.

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ref	Publication year	Bi-level method	Dr program	Bilateral contracts	Local market	Hosting capacity
[7]	2020	✓	✓	×	×	×
[9]	2020	✓	✓	×	×	×
[10]	2020	✓	✓	×	×	×
[11]	2020	✓	×	×	×	×
[21]	2021	×	✓	×	✓	×
[28]	2020	×	×	×	×	×
[29]	2019	×	✓	×	×	×
[30]	2020	✓	×	×	×	×
[33]	2020	✓	✓	×	×	×
[34]	2016	✓	✓	✓	×	×
[35]	2019	✓	×	×	✓	×
[36]	2022	✓	✓	×	✓	×
[37]	2023	✓	×	×	×	✓
This paper		✓	✓	✓	✓	✓

Table 2. Demand levels

Demand levels	**Hours of day**
Peak	1-6
Medium	6-17
Off-peak	18-24

Table 3. Characteristics of bilateral contracts

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

Table 4. Characteristics of (PV)

6	$\boldsymbol{P^{+PV}}$
0	(kW)P^{-PV}

Table 5. Characteristics of WT

8	**(kW)** $\boldsymbol{P^{+WT}}$
0.45	(kW)P^{-WT}

Table 6. Characteristics of MT

12	**(kW)** $\boldsymbol{P^{+MT}}$
3.6	(kW)P^{-MT}
0.65	ξ
0.012076	π_t^f

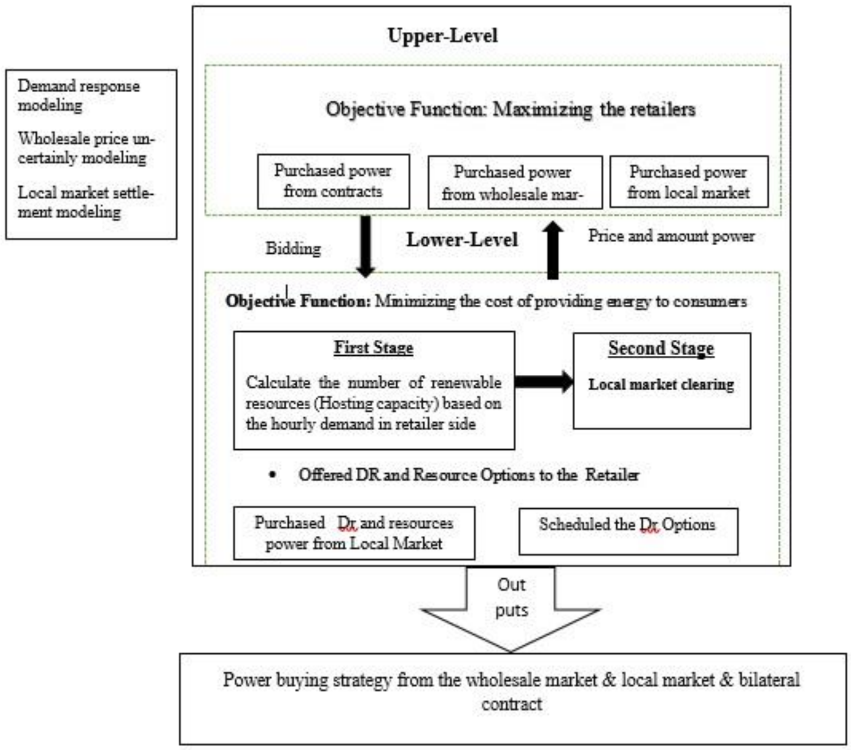

Figure 1. The proposed framework

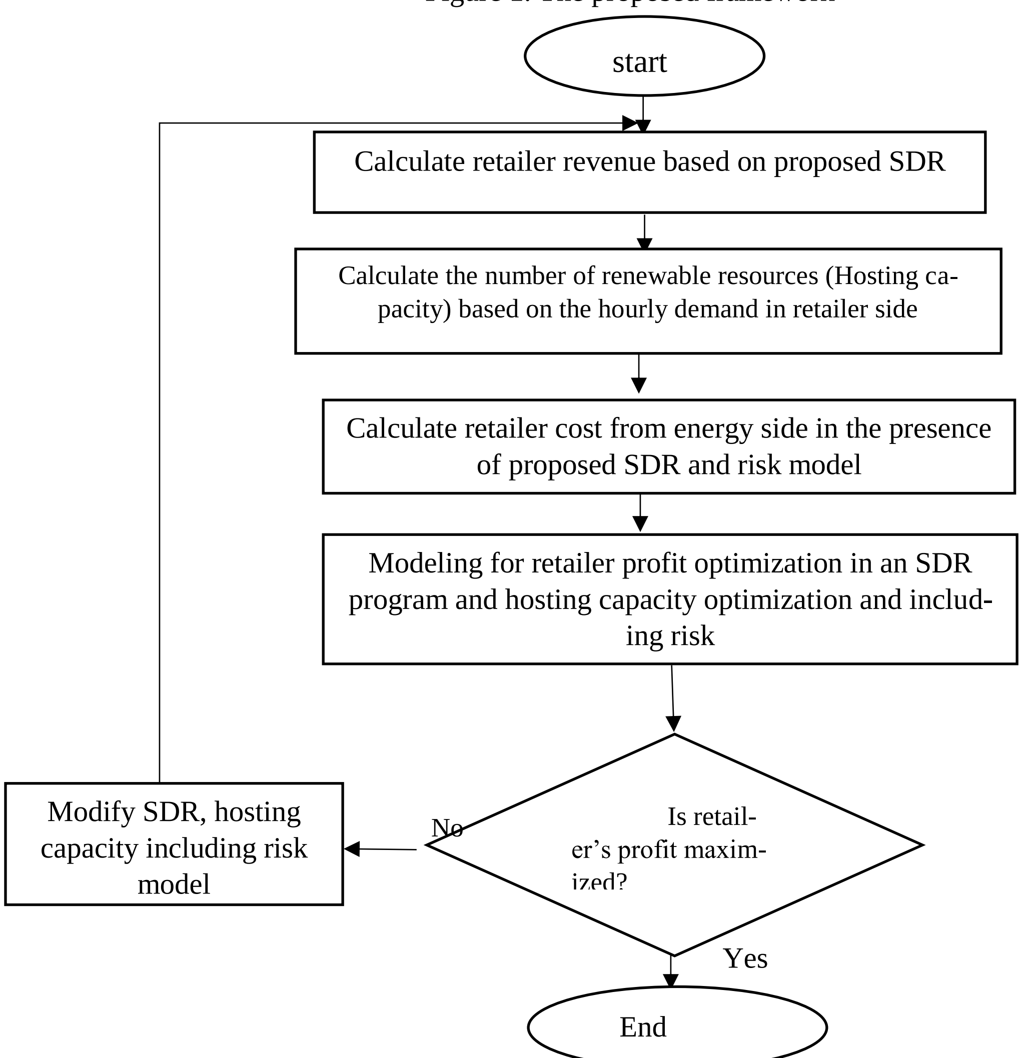

Figure 2. The smart DR model.

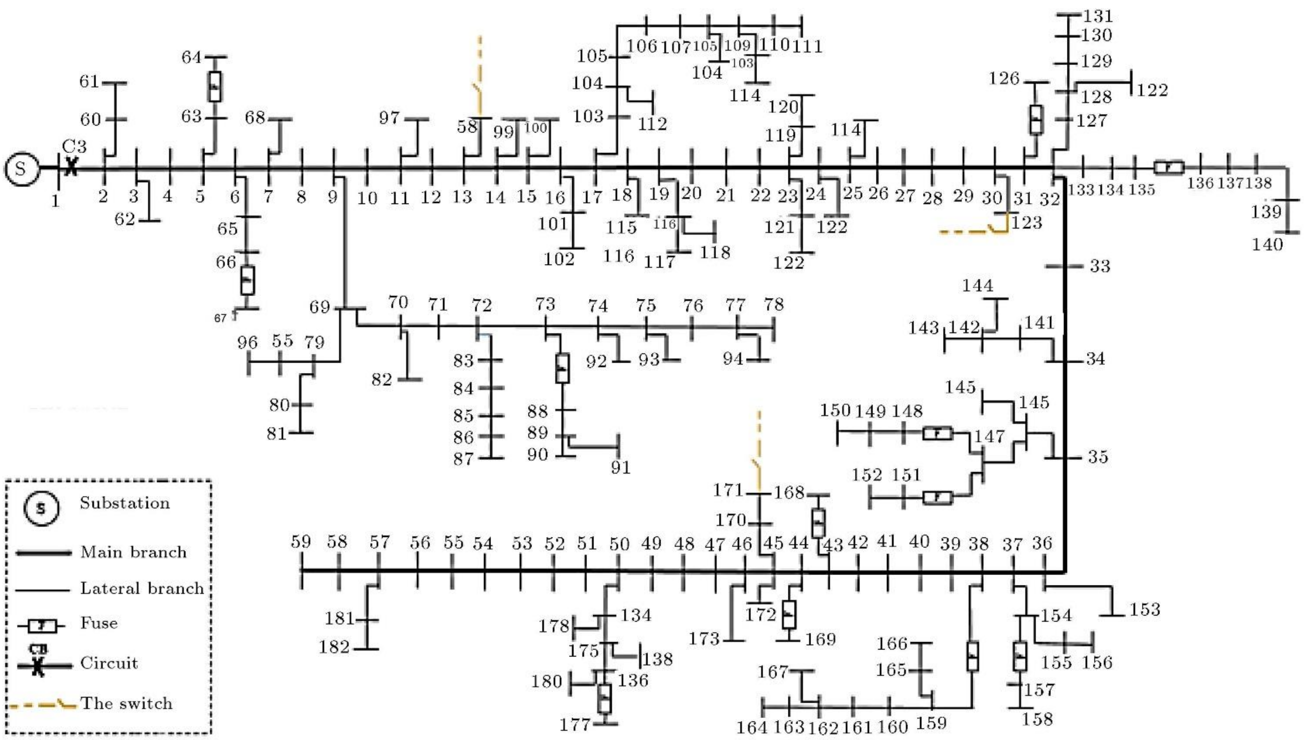

Figure 3. The system under consideration

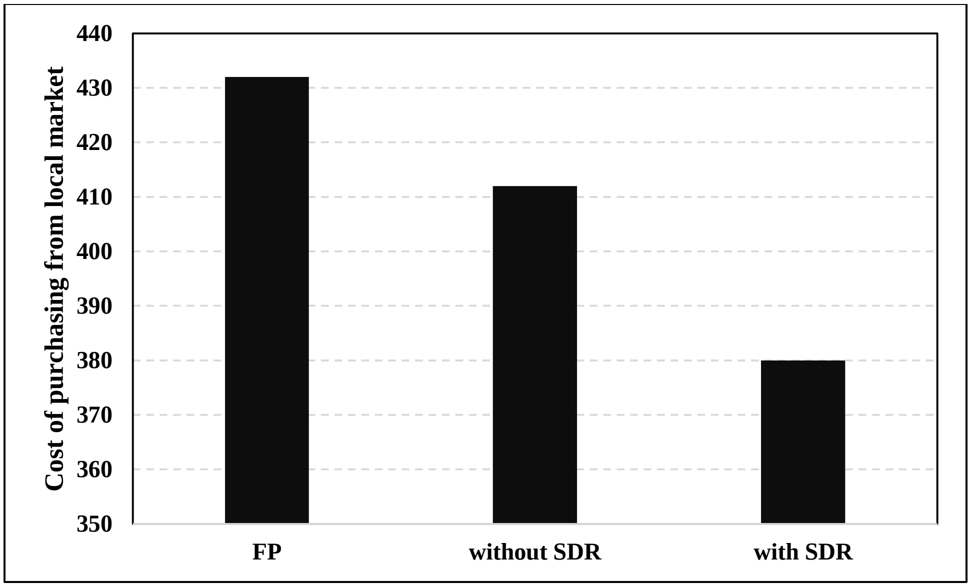

Figure 4. Purchase cost of local market

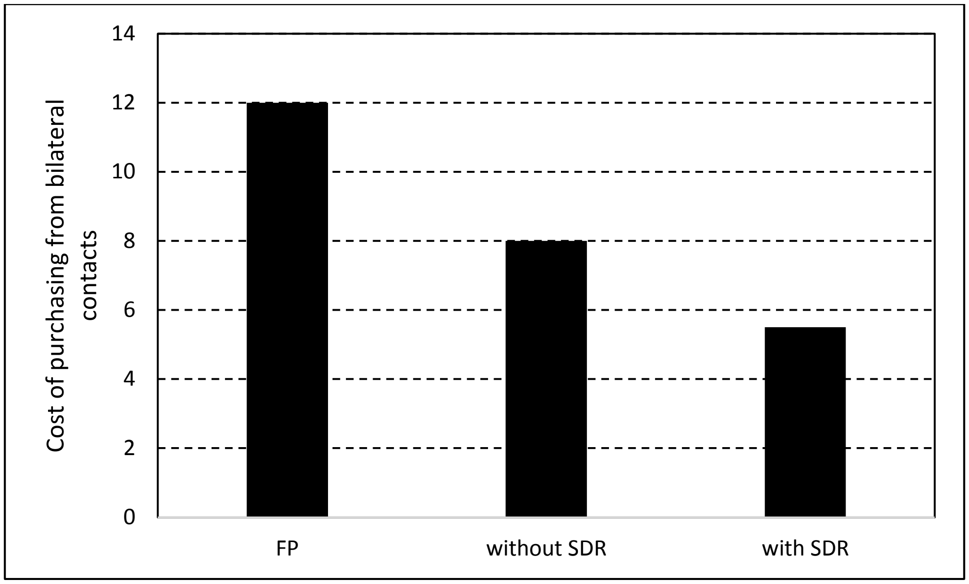

Figure 5. Purchase cost of bilateral contracts

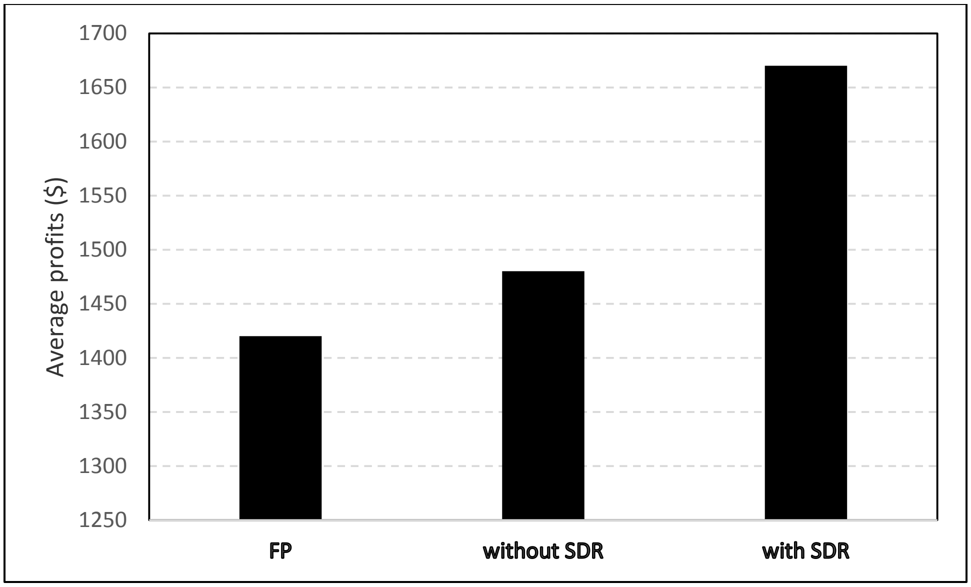

Figure 6. Retailer's average profits

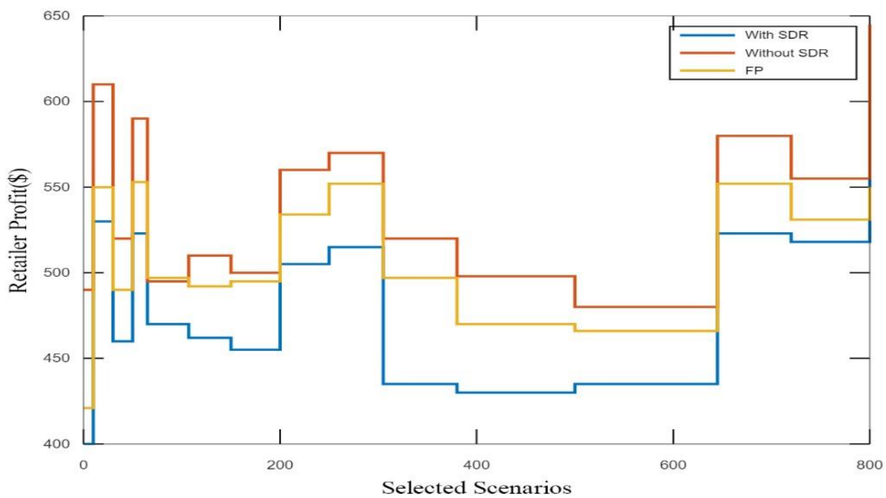

Fig. 7. Comparison of retailer profit between TOU, RTP and fixed pricing in the proposed model

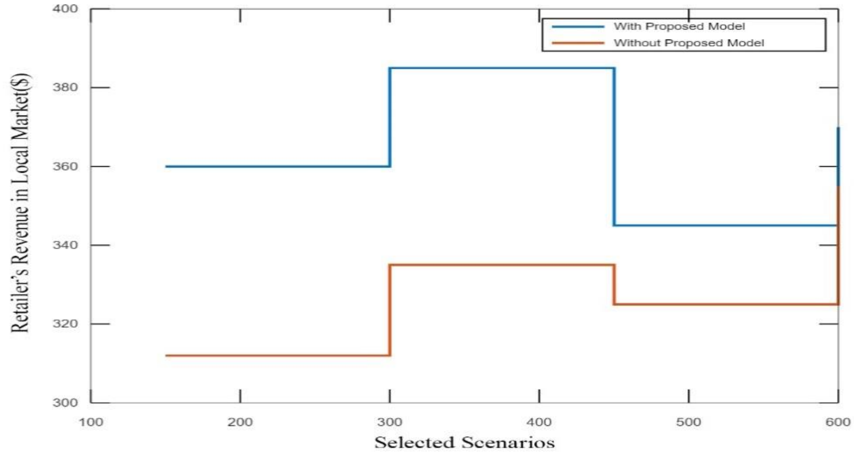

Fig. 8. Retailer’s revenue in Local Market contract

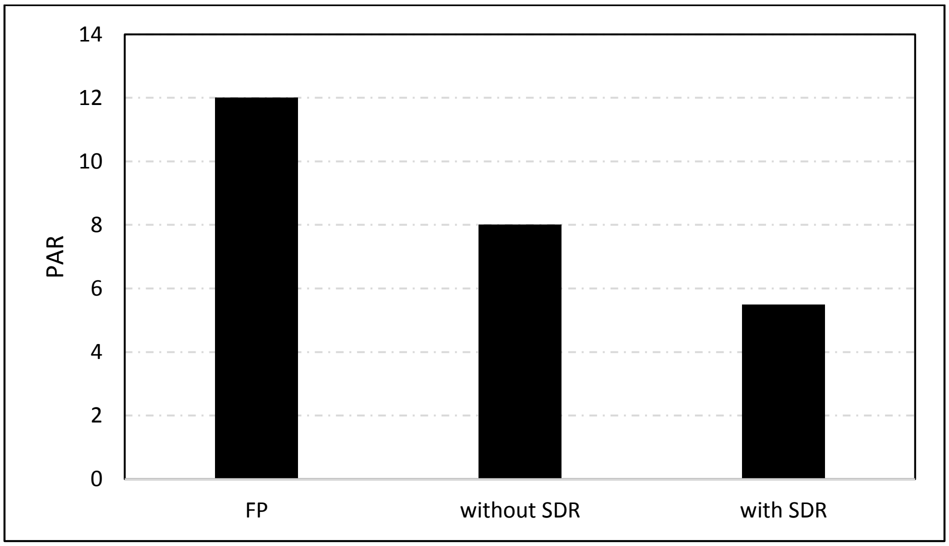

Figure 9. PAR diagram

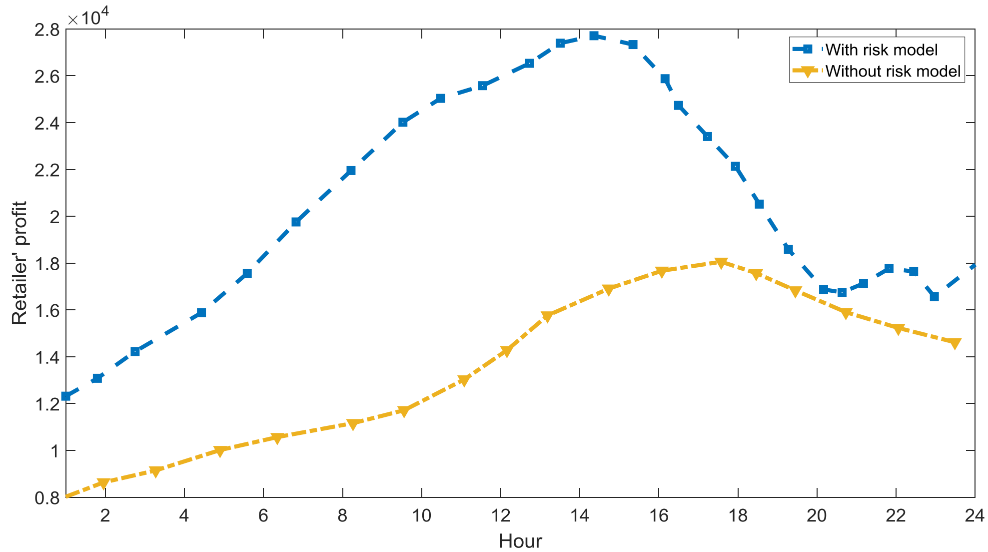

Figure 10. Retailer's profit with and without risk model

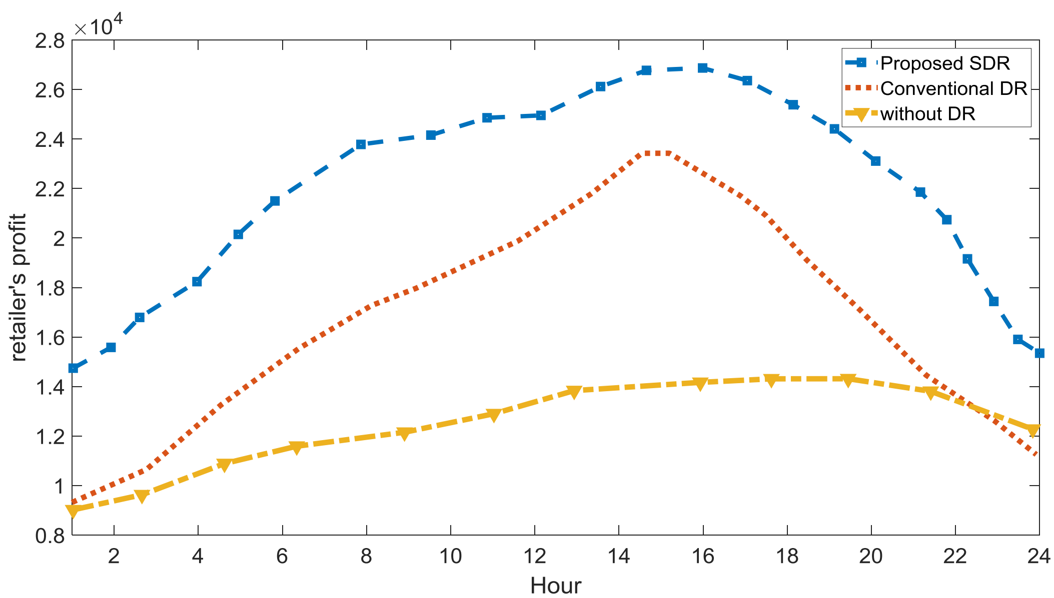

Figure 10. Comparison of retailer's profit with and without SDR model

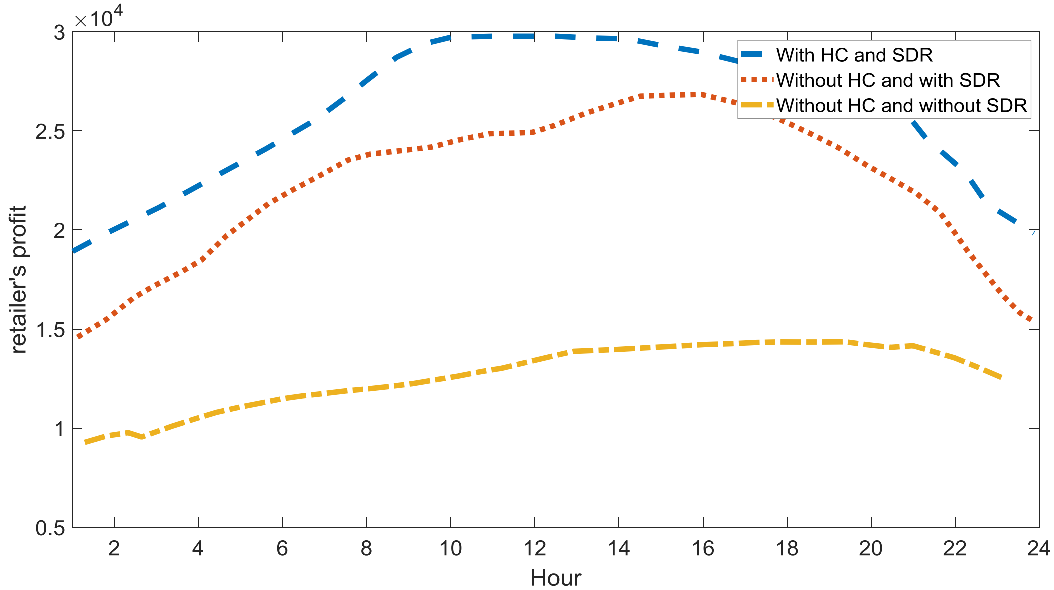

Figure 11. The effect of hosting capacity on retailer's profit