Risk-Based Optimal Decision-Making by the Retailer in A Mixed Local and Wholesale Market Environment Considering Demand Response Solution

Faramarz Separi

Ph.D student, electrical engineering, Faculty of electrical and computer engineering, Babol Nooshirvani university of technology, Babol, Iran
fa_separi@yahoo.com

Abdolreza Sheikholeslami*

Associate Professor, electrical engineering, Faculty of electrical and computer engineering, Babol Nooshirvani university of technology, Babol, Iran
asheikh@nit.ac.ir
Tel: +989123092368
*Corresponding author

Taghi Barforoshi

Assistant Professor, electrical engineering, Faculty of electrical and computer engineering, Babol Nooshirvani university of technology, Babol, Iran
barforoshi@nit.ac.ir

Abstract

This paper proposes a comprehensive model to determine the retailer strategy for purchasing electrical power from the wholesale and/or local market in an active distribution network. The uncertainties associated with the load and distributed generation resources in the active distribution network, the wholesale market price and the behavior of the local market players, are all considered in the presented model. A retailer in the demand response program is employed as retailers' ability to govern the risks. A risk-based decision-making scheme is provided in this paper which takes into account every instrument that is accessible for retailers along with their associated uncertainties. The major target of this paper is to maximize the retailer benefit concerning a tolerable risk. In order to model risks, the scenario theories are exploited and for solving the optimization problem, particle swarm optimization (PSO) has been utilized. The proposed scheme has been simulated on an actual network and the obtained results confirm the effectiveness and computability of this method.

Keywords: Active Distribution Network, Retail Electricity Providers, Locational Marginal Prices, Decision-Making, Local Markets.

1. Introduction

In recent decades, the power industry has been reorganized by transforming into a competitive field, whereas new organizations are established in the new arrangement. In this new frame, the electricity retailers have appeared as the intermediary between the producer companies and the customers [1]. The electricity retailer plays the role of an electricity intermediate between the wholesale market and the end-users. Within the rearranged electricity markets, retailers buy the required demand of consumers from various energy sources including self-producing plans, mutual contracts, and pool market [2].

The retailers need to handle and govern the procured power in order to maximize their predicted benefit. At the same time, retailers' gain will be reduced due to a low vending price. However, when the vending price is high, it causes the clients not to buy from this retailer and results in a decline in retailer's benefit.

Retailer participation in wholesale market

There are certain authentic and well-established articles which define retailer' presence in the wholesale market, especially in the field of retailers' electrical energy purchasing. A new and unique approach that is rested on the Information Gap Decision Theory (IGDT) has been suggested in [2] to assess the risk levels under unstructured pool price uncertainty. An optimum approach for retailers is illustrated in [3] where they afford the energy via the pool market and forward contracts taking into account medium-run and long-run decisions. A mathematical technique has been suggested in this paper which is rested on mixed-integer random programming in order to determine the retailer's optimum contract price with users and his electricity policy provision for a specific time. Ref. [4] proposes a random linear planning to determine the curve of the buying offers of the wholesale market. A load profile clustering method has been suggested for an optimum price to be offered to clients in order to maximize a retailer's benefit. In [5], a scheme has been provided for regulating price spikes which motivate clients to move their loads regarding time-of-use tariffs. [6] Proposes a game theoretical model accounting for the Stackelberg relationship between retailers and consumers in a dynamic price environment. Both players in the game solve an economic optimization problem subject to stochasticity in prices, weather-related variables and must-serve load.

in [7] A strong optimization strategy is proposed for identifying the optimum purchasing model which helps retailer to employ it in the pool market. A random structure is also proposed for an electricity retailer to satisfy the targets such as predicted benefit and predicted downward risk which assist the retailer to decide optimum level of engagement in forward contracting and the pool and place optimum vending prices for customers.

In [8] a robust optimization approach (ROA) is proposed to obtain optimal bidding and offering strategies for the retailer. Authors in [9] proposed a real-time pricing (RTP) framework considering uncertainties of various input parameters such as electricity demand, output power of renewable energy resource, and pool market price.

Most of the reviewed researches which have been shown in Table (1) have been focused on presenting strategies and approaches for purchasing energy from the wholesale market and selling strategies to the customers.

The emergence of the retail market

By moving toward smart networks, various tools have been raised in the distribution network, including the local market, energy-producing resources (like renewable energy resources), and demand response. The strategy of electricity retailers is affected by the emergence of these tools, which will affect the manner of their electricity buy and sell. In such conditions, the retailer can buy electricity from the wholesale market, distributed generation units, forward contracts, and demand response programs. A comprehensive model of a retailer activity in an active distribution network is presented in [10]. In the proposed method, it is assumed that several retailers are active in the distribution network and can provide the energy for their customers through different resources such as distributed generations, storage resources, retailers, and demand response. Ref. [11] presents a combinatorial model to find a way of providing the energy for the retailer through different options such as self-sufficient generators, mutual contracts, and the wholesale market. An optimization method for integrated portfolio management in wholesale and retail power markets is proposed in [12]. The proposed model results quantify the risk facing electric utilities participating in both wholesale and retail markets under several market conditions and with some schemes on the generation side, as well as with different representation shares on the demand side. A short-term decision-making model for a price-maker distribution company in wholesale and retail electricity markets considering demand response and real-time pricing is presented in [13] to develop the sell and purchase strategies for a strategic distribution company in the energy and retail markets. A Risk-Based Purchasing Energy for Electricity Consumers by Retailer Using Information Gap Decision Theory Considering Demand Response Exchange is provided in [14]. Furthermore, based on opportunity and robustness functions, an optimal bidding strategy of electricity retailer is obtained using IGDT technique. A two-stage stochastic framework for an electricity retailer considering demand response and uncertainties using a hybrid clustering technique are proposed in [15] to maximize the expected value of the retailer's profit, whereas the exposure risk is confined to a pre-specified level.

In [16] a new method is proposed for retailer's decision-making considering day-ahead and real-time markets as well as liberalized distributed renewable energy (DRE) market in which the retailer competes with other load serving entities (LSEs) for procuring DRE is proposed. Authors in [17] presented a bi-level hybrid framework to support a retail electric provider (REP) to make the best day-ahead dynamic pricing decisions in a realistic scenario with the aim of maximizing the profit achieved by the REP While some of the customers have installed smart meters with an embedded home energy management system (HEMS). In [18] for the first time the interactions among electricity retailers and local energy markets are modelled and a method is proposed for pricing decisions of a strategic retailer.

Paper contribution

As mentioned above, in recent years, most of the researches have been focused on presenting an optimal method for providing the required energy for a retailer. The usage of the capacities of the resources such as distributed generations, demand response programs, renewable energy resources, alongside the pool market and bilateral contracts have been emphasized to reach this purpose. With the development of the renewable resources and demand response in the distribution network, the structure of the wholesale market has not been suitable for the entrance of these resources. Therefore, local markets are presented as a response to these resources to be active in the market [18-21]. In addition to providing energy through other resources and wholesale market, the electricity retailers can obtain their required energy from the local market. It should be noted that despite the role of retailers in the wholesale market, they are price makers in the local market. Therefore, the manner of purchasing the energy from other resources and the wholesale market affects the amount of demand from the local market, and; thus, the local market price. With the consideration of this fact and assumption of specified tariffs for the final customers, a comprehensive two-stage model is presented in this article for the determination of the strategy of purchasing energy by the retailer through the wholesale market, distributed generations resources, and demand response programs, and it aims to maximize the profit for the retailer under the related uncertainties. The contributions of this paper are highlighted as follows.

- Introducing a comprehensive two-stage model for optimal determination of retailer portfolio considering the retailer interactions with wholesale and local markets.
- Considering the effect of uncertain variables on decision making process using a risk-based model and determining optimal risk-taking and risk-averse decisions.
- Assessing the role of DR program as an effective solution in the hands of retailer for price making in local market.
- Considering losses reduction as the result of using DR program by the retailer

The rest of the paper is organized as follows: Section 2 describes the decision factors related to the electricity retailer and provide the proposed framework. Determination of the value of DR programs from the retailer perspective is presented in Section 3. The proposed structure for the local market is presented in section 4. The comprehensive decision-making formulation is presented in section 5. In order to validate the proposed method, simulation results are described in Section 6, and finally concluding remarks are presented in Section 7.

2. Decision factors related to the electricity retailer and the proposed framework

A retailer can purchase electricity from various resources and sell it to the customers. In addition to the tasks of electricity trading, the retailers have the responsibility of presenting service to the customers and measurement and billing. The retailers can provide energy for their customers through the wholesale market, distributed generations, and local market. Energy sellers in wholesale and local market are power plant and virtual power plant respectively. According to definition, a virtual power plant is a cluster of dispersed generator units, controllable loads and storages systems, aggregated in order to operate as a unique power plant. Also, the retailer can use the potential of demand response programs. The DR programs consist of a variety of programs, and, in this article, it is assumed that the retailer uses the demand reduction program as one of the DR programs. On the customer side, the retailer provides electricity with predefined tariffs for the customers [22]. The overall structure of providing and selling the electricity by the retailer is presented as the Figure 1.

In interactions with the distribution company, the retailer has the responsibility of presenting services to the customers. Generally, the manner of interactions between the Distribution Company and retailer can be done under different models. In one of these models, the retailer is responsible for providing the electricity for all of the customers of one feeder. In this model, which is being implemented in Iran, the issue of non-technical losses is also more important to the retailer. In fact, the distribution company determines a level for technical losses according to the network coordinates and takes responsibility for it. The remaining losses of the feeder are considered as non-technical losses and are under the responsibility of the retailer.

It is also assumed that the retailer is equipped with storage. Retail decision-making variables include the amount of purchases from the wholesale market, the amount of purchases from the local market, the amount of purchases from dispersed sources, the amount of load response programs used, and how to charge and discharge storage. Both the local market and the wholesale market are assumed to be of the day ahead market type. However, the retailer is a price taker in the wholesale market and is a price maker in the local market.

Retail decision-making variables include the amount of purchases from the wholesale market, the amount of purchases from the local market, the amount of purchases from dispersed generation units, the amount of load response programs used, and the charge/discharge pattern of storage. Both the local market and the wholesale market are assumed to be of the day ahead market type, assuming that the retailer is a price taker in the wholesale market and is a price maker in the local market.

The market price is uncertain in a day-ahead market. Therefore, “scenario theory” will be used to model wholesale market uncertainty. Since the retailer is a price maker in the local market, it is necessary to consider the local market clearing model in the main decision-making function. Therefore, a two-stage programming model is used to solve

the problem. The behavior of other actors will be modeled by scenario theory, in the local market function.
Modeling of distributed generation and storage will also be based on the corresponding cost functions. The uncertainties related to load and production of distributed generation resources are also considered as scenarios. For the load response program, it is assumed that the load reduction program is used. Accordingly, a contract is concluded with some subscribers, under which the subscriber must reduce its load to a specified amount at the specified time. The retailer will reward the customer for reducing the load. Since load reduction also affects network losses, the cost of the load reduction program will be determined in advance of the losses and the average price on the main bus. This price varies across different network buses. The overall structure proposed to solve the problem is as shown in Fig. 2:

3. Determination of the value of DR programs from the retailer perspective

As mentioned in the previous section, in this paper, it is assumed that the retailer acts on a specified feeder. To provide the load for the customers and manage the electricity purchase, the retailer can use the potential of the DR program alongside other energy-providing resources. The DR programs consist of a variety of programs, and, in this article, it is assumed that the retailer uses the demand reduction program as one of the DR programs. This program is known as Direct Load Control (DLC) in literature. In this program, the retailer pays a sum as a reward to the customer in exchange for the demand reduction in a specified bus. It should be noted that the effects of these programs on the feeder loss reduction vary depending on which bus customers participate in the DR programs.

Considering the feeder depicted in Fig.3, the higher the final feeder load, the higher the losses of the network. Therefore, given it is assumed that the retailer is responsible for the losses of the feeder, the more demand reduction by the customers of the feeder, the more it will affect the network losses. Assuming that the price of the demand reduction program from the retailer standpoint and regardless of the network losses is$\lambda_{DR,}$ this value can be different depending on the location of the customers that participate in the demand reduction programs, according to the network losses. In reference [23], loss value for a certain amount of power injection to the ith bus is calculated as follows:

$$\lambda_{DGi}^{loss,h} = \frac{1}{2}\left(\lambda_{DGi}^{0,h} + \lambda_{DGi}^{p,h}\right) \tag{1}$$

$$\lambda_{DGi}^{0,h} = \lambda_n^h \left.\frac{\partial Ploss}{\partial P_{DGi}}\right|_{\left\{P_{DGj}=0 \middle| j=1,2,..,N\right\}} \tag{2}$$

$$\lambda_{DGi}^{p,h} = \lambda_n^h \left.\frac{\partial Ploss}{\partial P_{DGi}}\right|_{\left\{P_{DGj}=P_J \middle| j=1,2,..,N\right\}} \tag{3}$$

where λ_n is the energy price in the main bus of the network, and P is the amount of power injected to the various buses of the network. Therefore, any amount of power injected into the network is equivalent to the reduction of the same amount of demand on that bus. Hence, the value of the demand response program for a specified amount in the ith bus of the network for the retailer is as the below Equation.

$$\lambda_{DR}^{loss} = \lambda_{DR} + \frac{1}{2}\lambda_n^h \left(\left. \frac{\partial Ploss}{\partial P_{lr,i}} \right|_{\left\{ P_{lr,j}=0 \middle| j=1,2,..,N \right\}} + \left. \frac{\partial Ploss}{\partial P_{lr,i}} \right|_{\left\{ P_{lr,j}=P_J \middle| j=1,2,..,N \right\}} \right) \tag{4}$$

Where $P_{lr,i}$ is the amount of consumption reduction in the ith bus.

It should be noted that in the above Equation, it is assumed that the retailer transfers all of the benefits of reducing the losses caused by implementing the demand reduction program to the customer. If the retailer transfers α percent of the benefits to the customer, the price of the demand reduction program for customer participation is as follows:

$$\lambda_{DR}^{loss} = \lambda_{DR} + \frac{1}{2}\alpha\lambda_n^h \left(\left. \frac{\partial Ploss}{\partial P_{lr,i}} \right|_{\left\{ P_{lr,j}=0 \middle| j=1,2,..,N \right\}} + \left. \frac{\partial Ploss}{\partial P_{lr,i}} \right|_{\left\{ P_{lr,j}=P_J \middle| j=1,2,..,N \right\}} \right) \tag{5}$$

4. The proposed structure for the local market

The infrastructure in the electricity markets is designed such that the power plants with large capacities are capable of selling electricity in it. Due to the development policies of the distributed generation resources such as renewable and storage resources, it is necessary to provide a business field for these resources in the distribution sector. Therefore, the local markets can obtain the opportunity of trading the generations locally with customers [24].

Since it is not possible to predict the production of distributed resources in the long run, the trade period should be close to the real operation time in these markets.

The schematic diagram of a local market is shown in the Figure 4 below. The market operator is the entity that manages the local market. The optimal price of the local market is determined by the market operator based on the information received from the sellers and buyers. As shown in the related Figure, several retailers can participate in the local market separately. Also, it is assumed that the sellers are participating in the local market as virtual power plants and a set of distributed generation resources and can work in the market in the form of energy trading or even ancillary services. The local market will be managed and cleared such that the benefits of all of the participants are provided. Since there is an interaction and competition between different retailers, Therefore, non-cooperative game theory is used for the settlement of the market. In this game, each player has its target function, and the players with different targets seek to achieve their interests.

The overall structure of the problem-solving consists of the stages named below:

1- Producing the scenarios of virtual power plants: in this stage, since various actors of the retail market are known in the local market, and with the consideration of various parameters effective in the amount of power presented in the market, different scenarios will be produced for the virtual power plants.
2- Producing the scenario of retailer demands: since the actors of the local market are known in the virtual power plants, the number of demands for the retailers will be predicted based on effective parameters in the form of different scenarios.
3- Predicting the price proposed by the producers and retailers: the price proposed by the producers and retailers will be predicted in different scenarios.
4- Determining the market settlement price: in this stage, since different scenarios and the retailer demands are known, we will calculate the market settlement price by the NIRA algorithm through the game theory to find the Nash equilibrium point.

4.1. Formulation of the local market problem

As mentioned in the previous section, we will use the NIRA game theory method to solve the market problem. For this purpose, it is assumed that the intended local market consists of n participants in a non-cooperative game. The target function of each player is presented in the following to be utilized in the local market settlement mechanism.

Target function of producers:

The profit of the generator i at the time t and the scenario ω is $g^{i}_{t,\omega}$, which is as follows:

$$\max g^{i}_{t,\omega} = R^{i}_{t,\omega} - C^{i}_{t,\omega}, t \in \{1,2,,....,24\}, i \in t \in \{1,2,,....,n\} \tag{6}$$

$$R^{i}_{t,\omega} = \pi^{j}_{t} \times \left[P^{DGU,j}_{t,\omega} + P^{NDU,j}_{t,\omega} \right] \tag{7}$$

$$\begin{aligned} C^{i}_{t} &= C^{DGU,j}_{t} \\ C^{DGU,j}_{t} &= a^{j}.(P^{DGU,j}_{t,\omega})^{2} + b^{j}.P^{DGU,j}_{t,\omega} + c^{j} \end{aligned} \tag{8}$$

In these equations, R and C are the revenue and the cost of power generation. Also a, b and c are power generation cost coefficients.

The objective function of the retailer:

The cost function of the retailer at the time t in the market will be as follows:

$$\min C_{t,\omega}^{r,k} = \pi_t^{r,k} \times P_{t,\omega}^{r,k} t \in \{1,2,,....,24\}, k \in \{1,2,,....,n'\} \tag{9}$$

General constraints:

$$\sum_{j=1}^{n} P_{t,\omega}^{DGU,j} + P_{t,\omega}^{NDU,j} = \sum_{k=1}^{n'} P_{t,\omega}^{r,k} \tag{10}$$

$$\min P_{t,\omega}^{DGU,j} \le P_{t,\omega}^{DGU,j} \le \max P_{t,\omega}^{DGU,j} \tag{11}$$

$$0 \le P_t^{NDU,j} \le EV_t^{NDU,j} \tag{12}$$

$$0 \le P_t^{r,k} \le EV_t^{r,k} \tag{13}$$

In this article, the local market price will be calculated based on the Nash equilibrium calculations and according to the information received from players and also the above target functions [12].

5. The comprehensive decision-making formulation

In the previous section, the usage of the demand response program as one of the available options for the retailer and also the usage of local market capacity for providing the energy with the least costs possible were mentioned.

Furthermore, in this article, it is assumed that the retailer can provide energy through the wholesale market, the distributed generations, and storage resources. In the wholesale market, the retailer is the receiver of the price. Furthermore, in terms of time, the wholesale market is performed before the local market. The prices of the local market and wholesale market have uncertainties among the parameters of the problem.

In this paper, the risk-averse two-stage stochastic programming framework is considered

similar to those of [7]. The general form of the retailer plan problem is formulated as:

$$(1-\beta) Z + \beta \chi \tag{14}$$

In which Z is the retailer predicted expenditure and X characterizes risk associated with the retailer schedule. The factor β ∈ [0,1] has been exploited to develop the risk aversion of the retailer in the objective function. The zero value of β shows that the retailer is risk-neutral, and the one represents the retailer is risk-averse. The predicted expenditure of the two-stage random retailer problem has been formulated as:

$$Z = f\left(X_c\right) + \sum_{\omega=1}^{N_\Omega} \pi_\omega q\left(\omega\right) \tag{15}$$

In which f (X_c) and q (ω) are the objective functions of the first-stage problem for a decision vector X_c and the second-stage problem relating to the realization of the scenario ω, respectively. The predicted cost and risk related to it are described below.

A. Expected profit (Z)

The cost in scenario ω is mathematically expressed as:

$$Z = Rev_c - C_{DG} - C_{ESS} - C_{DR} - \sum_{\omega=1}^{N_\Omega} \pi_\omega \sum_{t=1}^{N_T} \left\{ C_{LM}\left(Y_{t\omega}\right) + C_{WM}\left(Y_{t\omega}\right) \right\} \tag{16}$$

Where Rev_C is the income from the customer billings, C_P is the costs of purchasing the power from the upstream network, C_{DG} is the costs of providing energy through the distributed generations, C_{ESS} is the costs of providing power for the customers through the storage resources, and C_{DR} is the costs of encouraging the customers to carry out the demand response programs. The following shows how to calculate each cost mentioned above.

Equation (17) shows the amount of income for the retailer from receiving the costs of electricity consumed by customers.

$$Rev_c = \sum_{t=1}^{T} \sum_{c=1}^{N_c} R_c^t \left(L_c^t - \Delta L_c^t \right) \tag{17}$$

Where R_c^t is the cost for the consumption of each kWh of energy in hour t by the customer c, $L_c^t$is the amount of demand for the customer c in the hour t, and ΔL_c^t is the amount of demand reduction for the customer c in the hour t caused by participation in the demand response program.

The equation (18) shows the costs of purchasing power from the upstream network.

$$C_{WM}\left(Y_{t\omega}\right) = \lambda_{t\omega} P_{t\omega} \tag{18}$$

Where $\lambda_{t\omega}$ is the price for purchasing each kWh of energy from the upstream network in the main bus, hour t, and scenario ω, and $P_{t\omega}$ is the amount of power received from the upstream network in the hour t and scenario ω. Also, the costs of proving energy from the local market are as below.

$$C_{LM}\left(Y_{t\omega}\right) = \lambda_{t\omega}^L P_{t\omega}^L \tag{19}$$

The critical point is that the price scenarios of $\lambda_{t\omega}^{L}$ are obtained during the problem-solving process and through solving the problem of the local market, whereas the scenario of the wholesale market price is obtained based on the price prediction.

Equation (20) is the target function for Equation (6) for providing power through the distributed generations.

$$C_{DG}=\sum_{t=1}^{T}\sum_{g=1}^{N_{DG}}(\alpha_g u_g^t+\beta_g P_g^t+\gamma_g\left(P_g^t\right)^2+c_g^{start}v_g^t) \tag{20}$$

Where α_g, β_g, and γ_g are the coefficients of the cost function for the power production of the distributed generation resource of g, c_g^{start} is the cost of setting up the distributed generations resource of g, and v_g^t is the binary variable that indicates the setup of the distributed generation resource of g at the time t.

Also, the costs considered for providing energy for the storage resource is as Equation

$$C_{ESS}=\sum_{t=1}^{T}\Sigma\sum_{ES=1}^{N_{ES}}\Sigma_{ES}^{out,t}c_{ES}^{deg} \tag{21}$$

where c_{ES}^{deg} is the depreciation cost for the ES storage resource for each kW of power, and $P_{ES}^{out,t}$ is the amount of power produced by the ES storage resource in hour t.

Eventually, the final phrase is the first target function for the costs of encouraging the customers to reduce their consumption (demand response) and is shown as Equation (22).

$$C_{DR}=\sum_{t=1}^{T}\sum_{c=1}^{N_c}\lambda_{DR_c}^{t}\times\Delta L_c^t \tag{22}$$

Where FI_c^t is the sum paid to the customer c (the amount of encouragement) for reducing each kW of power in hour t, and ΔL_c^t is the amount of the power reduction of the customer c in hour t and is calculable by Equation (23).

$$\Delta L_c^t=a_{2,c}\times FI_c^t+a_{1,c}\times FI_c^t+a_{0,c} \tag{23}$$

where $a_{2,c}$, $a_{1,c}$, and $a_{0,c}$are the coefficients of behavior modeling for the customer c when facing the encouragement offering from the retailer.

Target functions of (16) are optimized by considering the constraints stated in Equations (24) to (27).

$$P_g^{min}\le P_g^t\le P_g^{max} \tag{24}$$

$$P_{ES}^{in,\,min}\le P_{ES}^{in,t}\le P_{ES}^{in,max} \tag{25}$$

$$P_{ES}^{out,\,min}\le P_{ES}^{out,t}\le P_{ES}^{out,max} \tag{26}$$

$$SOC_{ES}^{min} \le SOC_{ES}^{t} \le SOC_{ES}^{max} \qquad (27)$$

The (24) to (27) constraints represent the allowed limits of output power for the distributed generation resources, the allowed limits of charge power for the storage resources, the allowed limits of discharge power for the storage resources, the allowed limits for the amount of charge in the storage resources, and the allowed limits of encouragement for the customers by the retailer, respectively.

Risk measure (χ)

Value at Risk (VaR) is a commonly used risk measure used to estimate exposure to risk [25]. In the profit maximization context, VaR_{α} is the α-quantile of the distribution of the profit, and it provides a lower bound that is exceeded only by a small probability of $(1-\alpha)$ which is formulated as follows [7]:

$$P\left[Z_P \le VaR_{\alpha}\right] = \alpha \qquad (28)$$

No information is offered by VaR on the worst possible expenditure outside the confidence level. Hence, in this paper, the conditional value-at-risk (CVaR) has been exploited, that is specified as the predicted cost of the (1-α) × 100% scenarios with the largest expenditure [26,27]. The CVaR of model is described by:

$$CVaR_P = E[Z_P \,|\, Z_P \le VaR_{\alpha}] = \frac{\int_{-\infty}^{VaR_{\alpha}} Z_p f\left(Z_p\right) dZ_p}{P[Z_p < VaR_{\alpha}]} \qquad (29)$$

Given the expression of the profit in scenario ω, (29), the $\alpha - CVaR$ is computed as:

$$\alpha - CVaR = max_{\zeta,\eta_{\omega}} \qquad \zeta - \frac{1}{1-\alpha}\sum_{\omega=1}^{N_{\omega}} \pi_{\omega}\eta_{\omega} \qquad (30)$$

Subject to

$$\varsigma - \sum_{C=1}^{N_C} \nu_c \{C_L(X_c) + C_S\left(X_c\right)\} + \sum_{t=1}^{N_T} \{C_L\left(Y_{t\omega}\right) + C_S\left(Y_{t\omega}\right) + CDF\left(Y_{t\omega}\right)\} \le \eta_{\omega} \forall \omega \qquad (31)$$

$$\eta_{\omega} \ge 0, \forall \omega \qquad (32)$$

5.1. General formulation:

Based on the material discussed in the previous sections as well as the overall risk-based model, the general formulation of the problem will be consistent with the following equation.

$$Z = (1-\beta)\left(Rev_c - C_{DG} - C_{ESS} - C_{DR} - \sum_{\omega=1}^{N_\Omega} \pi_\omega \sum_{t=1}^{N_T} \{ C_{LM}(Y_{t\omega}) + C_{WM}(Y_{t\omega}) \} \right) + \beta \left(\zeta - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_\omega} \pi_\omega \eta_\omega \right) \tag{33}$$

We use the particle swarm optimizing algorithm to find the optimal answer with the highest profit [28]. Assuming that the number of decision-making variables for the retailer is N, each chromosome will be an array of $1 \times N$genes. These genes can take different numbers, and each one of these numbers represents the amount of purchasing or usage of different resources by the retailer [29, 30]. The initial population of chromosomes will be produced randomly, such that the limitations of the problem are observed [31]. If an answer does not observe the constraints of the problem, it will be eliminated from the algorithm. Otherwise, the costs for this answer will be calculated for each chromosome for the establishment of the convergence condition. The Figure below shows the algorithm used for finding the optimal answer.

Algorithm
1- Adjusting the parameters and β
2- Producing the scenarios
3- Producing the initial population
4- Solving the problem to reach the convergence
5- Producing the function of the profit probability distribution for each chromosome
6- Calculating the expected profit and risk for each chromosome
7- Calculating the value function for each chromosome
8- Updating the population
9- The end

6. The simulation results

In this section, the results of simulating the proposed model on a real sample network will be presented. According to Figure (5), the network under study is a 182-bus network at a voltage level of 20 kV and supplies a load of approximately 6.3 MW. The information about loads and lines of this network are not presented in this paper and the interested parties can request the data by email. We applied corrections to this network to fit the problem in this article. A 156 kW diesel distributed generation resource, whose properties are mentioned in Table (2), is placed at the bus number 32, and an energy storage resource device, whose properties are mentioned in Table (3), is placed at the bus number 69. Also, the loads in buses 26, 68, and 49 are considered as responsive loads. We simulated the proposed method using the MATLAB software and through a computer with 3.4 GHz CPU and 16 GB RAM, and the run time was 2 hours. We used the PSO algorithm to find the answer, and its parameters are shown in Table (4).

In this article, it is assumed that the retailer has to decide on three different periods. Due to the uncertainty of the wholesale market price, the scenario method is used for modeling this uncertainty. The scenarios of the wholesale market are assumed as shown in Table (5).

Furthermore, since the retailer also participates in the local market, the behavior of the other actors of the local market has uncertainty for the retailer. With the assumption of the presence of another retailer and two virtual power plants in the local market, the offerings of these actors are assumed as shown in Tables (6) to (8). Also, it is assumed that these actors have the same behavior in three different periods.

Given the information above, the problem of decision-making for the retailer is solved in the active distribution network with different βs from 0.2 to 1. The expected profit and value of CVaR for the best answer for each β are shown in Table (9). As can be seen in this Table, different expected profit and CVaR values are obtained for different βs. The small values of β represent the fact that the retailer is more risk-seeking, and; therefore, its expected profit is higher, and the CVaR value is low. For β=1, the retailer is entirely risk-averse, and; therefore, its expected profit is the least value, and the CVaR value is the highest possible amount.

For β=0.2, the results of the retailer decision-making are shown in Table (10). As can be seen, the items such as the amount of energy for the customers and manner of providing this energy by the retailer through purchasing from the wholesale market, local market, performing the demand response program, the distributed generation resources, and the energy storage are mentioned in this table for each one of the three periods. Also, the local market settlement price is specified in this Table for each one of the three periods.

The results indicate that, in the first period, due to the low wholesale price, all of the energy required by the retailer to respond to the customer consumptions is provided through this market. The power purchased from the wholesale market is around 16.2 MWh, which is higher than the amount of customer consumption in the first period, which is around 15.7 MWh. It is because the retailer has decided to charge the storage resource for usage in the second and third periods. It should be noted that utilizing the demand response program was not affordable, and, based on this, the amount of DR in the first period is obtained zero. Also, the usage of the power of the distributed generation resource is relatively limited in this period. In the second and third periods, due to the higher price of the wholesale market, the local market participation rate for providing the energy required by the retailer increases. Also, we implemented the demand response program in these two periods to decrease the required energy. 1880 kWh and 425 kWh demand reduction were reached in these two periods, respectively, by the demand reduction of responsive customers. On the other hand, the storage resource was in the discharge mode in these periods and provided a part of energy by injecting power into the network. Also, the energy produced by the DG in bus number 32 has increased by 1248 kWh and 880 kWh in the second and third periods, respectively, compared to the first period. In other words, in the second and third periods, the retailer decides to provide a more significant share of energy through the available resources and local market to increase the profit. It has led to an increase in the power purchased from the local market and; as a result, an increase in the local market settlement price.

As said before, considering the small size of the local market, the retailer acts as a price maker player and can affect the local market price through the amount of power purchased. Fig. 6 shows the effect of the risk management strategy of the retailer on the local market clearing-price.

As shown in Fig.6, the local market-clearing price decreases with an increase in β. In other words, toward the risk-aversion approach (increase in β), the local market clearing price decreases. In order to justify this, we should pay attention to risk sources (uncertainty sources). Considering that there are more sources of uncertainty in providing power from the local market, the retailer tends to provide the required power from the wholesale market in the risk-aversion approach. Therefore, the amount of power that is provided from the local market as well as the local market-clearing price decreases.

6.1. DR Program Role

In this section, the role of DR program as an effective solution in the hands of retailer to manage local market and increase expected profit is investigated through sensitivity analysis. For this purpose, the main results compared to each other in two case of implementing and ignoring DR program by retailer. Fig.7 shows the value of local market price in these two cases and three periods of study in a specified risk management strategy (β=0.2). As can be seen, the values increase in all three periods in the case of ignoring DR program by retailer. That’s because retailer can reduce the local market energy demand through implementing DR program and so on affect the local market price. It should be noted that the effectiveness of DR program is more prominent in period 2 compared to period 2 and period 3. In other words, the positive role of DR program becomes more obvious in the peak period.

7. Conclusion

With the expansion of distributed energy resources including distributed generation and demand response programs, as well as the development of local markets, retailers have more option to provide energy for their customers. With the consideration of this fact, in this paper a comprehensive two-stage model was proposed for the determination of the strategy of purchasing energy by the retailer through the wholesale market, local market, distributed generations, storages and demand response programs to maximize the profit of the retailer under the related uncertainties. The results of this research show that according to the risk-based decision making, retailers can provide the required energy of their customers through the optimal way. On the other hand, the results indicated that the retailer acts as a price maker player and thus can affect the local market price. Also, demand response programs provide the retailer with the ability to control local market price and covering the associated risk.

References

[1] Ahmadi A., Charwand M., and Aghaei J., "Risk-constrained optimal strategy for retailer forward contract portfolio," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 704-713, 2013.

[2] Charwand M. and Moshavash Z., "Midterm decision-making framework for an electricity retailer based on information gap decision theory," *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 185-195, 2014.

[3] Hatami A., Seifi H., and Sheikh-El-Eslami M., "Optimal selling price and energy procurement strategies for a retailer in an electricity market," *Electric Power Systems Research,* vol. 79, no. 1, pp. 246-254, 2009.

[4] Mahmoudi-Kohan N., Moghaddam M.P., Sheikh-El-Eslami M., et al., "A three-stage strategy for optimal price offering by a retailer based on clustering techniques," *International Journal of Electrical Power & Energy Systems,* vol. 32, no. 10, pp. 1135-1142, 2010.

[5] García-Bertrand R., "Sale prices setting tool for retailers," *IEEE Transactions on Smart Grid,* vol. 4, no. 4, pp. 2028-2035, 2013.

[6] Zugno M., Morales J. M., Pinson P., et al., "A bilevel model for electricity retailers' participation in a demand response market environment," *Energy Economics,* vol. 36, pp. 182-197, 2013.

[7] Charwand M., Ahmadi A., Siano P., et al., "Exploring the trade-off between competing objectives for electricity energy retailers through a novel multi-objective framework." *Energy Conversion and Management* 91 (2015): 12-18.

[8] Nojavan S. K., and Mohammadi-Ivatloo B., "Robust bidding and offering strategies of electricity retailer under multi-tariff pricing." *Energy Economics* 68 (2017): 359-372.

[9] Tingting D., Yan W., Nojavan S., et al., "Risk evaluation and retail electricity pricing using downside risk constraints method." Energy 192 (2020): 116672.

[10] Kettunen J., Salo A., and Bunn D. W., "Optimization of electricity retailer's contract portfolio subject to risk preferences," IEEE Transactions on Power Systems, vol. 25, no. 1, pp. 117-128, 2009.

[11] Herranz R., San Roque A. M., Villar, J. et al., "Optimal demand-side bidding strategies in electricity spot markets," IEEE Transactions on power systems, vol. 27, no. 3, pp. 1204-1213, 2012.

[12] Koltsaklis N.E., and Dagoumas A.S., "An optimization model for integrated portfolio management in wholesale and retail power markets" Journal of Cleaner Production, vol. 248, p.119198, 2020.
[13] Moghimi F.H.,. and Barforoushi T., "A short-term decision-making model for a price-maker distribution company in wholesale and retail electricity markets considering demand response and real-time pricing" International Journal of Electrical Power & Energy Systems, 117, p.105701, 2020.
[14] Nourollahi R., Nojavan S., Zare K., "Risk-Based Purchasing Energy for Electricity Consumers by Retailer Using Information Gap Decision Theory Considering Demand Response Exchange" Electricity Markets. Springer, 2020.
[15] Gilvaei M. N., and Baghramian A., "A Two-Stage Stochastic Framework for an Electricity Retailer Considering Demand Response and Uncertainties Using a Hybrid Clustering Technique" Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 43(1), pp.541-558, 2019.
[16] Do Prado J., and Qiao W., "A Stochastic Bilevel Model for an Electricity Retailer in a Liberalized Distributed Renewable Energy Market." *IEEE Transactions on Sustainable Energy* 11.4 (2020): 2803-2812.
[17] Taherian H., Aghaebrahimi M. R., Baringo L., et al. "Optimal dynamic pricing for an electricity retailer in the price-responsive environment of smart grid." *International Journal of Electrical Power & Energy Systems* 130 (2021): 107004.
[18] Qiu D. and Papadaskalopoulos D., "Exploring the effects of local energy markets on electricity retailers and customers." *Electric Power Systems Research* 189 (2020): 106761
[19] Nojavan S., Mohammadi-Ivatloo B., and Zare K., "Robust optimization based price-taker retailer bidding strategy under pool market price uncertainty," International Journal of Electrical Power & Energy Systems, vol. 73, pp. 955-963, 2015.
[20] Nojavan S., Zare K., and Mohammadi-Ivatloo B., "Optimal stochastic energy management of retailer based on selling price determination under smart grid environment in the presence of demand response program," Applied energy, vol. 187, pp. 449-464, 2017.
[21] Del Granado P. C., Pang Z., and Wallace S. W., "Synergy of smart grids and hybrid distributed generation on the value of energy storage," Applied energy, vol. 170, pp. 476-488, 2016.
[22] Mazidi M., Monsef H., and Siano P., "Robust day-ahead scheduling of smart distribution networks considering demand response programs," Applied energy, vol. 178, pp.2016 ,929-942 .
[23] Gabriel S. A., Conejo A. J., Plazas M. A., et al., "Optimal price and quantity determination for retail electric power contracts," IEEE Transactions on power systems, vol. 21, no. 1, pp. 180-187, 2006.
[24] Marzband M., Javadi M., Pourmousavi S. A., et al., "An advanced retail electricity market for active distribution systems and home microgrid interoperability based on game theory," Electric Power Systems Research, vol. 157, pp. 187-199, 2018.

[25] X. Feng, S. Lu, G. Lin, et al., " Research on the Medium term Market Decision of Electricity Retailer Considering Risk", International Conference on Power System Technology (POWERCON), 2018.

[26] M. Shafie-khah, D. Z. Fitiwi, J. P. S. Catalão, et al., " Simultaneous participation of Demand Response aggregators in ancillary services and Demand Response eXchange markets", IEEE/PES Transmission and Distribution Conference and Exposition (T&D), 2016.

[27] Jianbin Li; Minghui Xu, "The optimal strategies in a two-echelon supply chain with risk-aversion and customers rebates ", IEEE Conrferance ICSSSM11, 2011.

[28] M. Gutierrez,L.E. Mancilla Espinoza, M.R. Baltazar Flores, et al., "Applying Adapted PSO Approach to Minimize Costs in the Beer Distribution Game Using Three Dynamic Demand Patterns ", IEEE Ninth Electronics, Robotics and Automotive Mechanics Conference, 2012.

[29] Hatami A., Seifi H., and Sheikh-El-Eslami M. K., "A stochastic-based decision-making framework for an electricity retailer: Time-of-use pricing and electricity portfolio optimization," IEEE Transactions on Power Systems, vol. 26, no. 4, pp. 1808-1816, 2011.

[30] Conejo A. J., Carrión M., and Morales J. M., Decision making under uncertainty in electricity markets. Springer, 2010.

[31] Larimi S. M. M., Haghifam M. R., Zangiabadi M., et al., "Value based pricing of distribution generations active power in distribution networks," IET Generation, Transmission & Distribution, vol. 9, no. 15, pp. 2117-2125, 2015.

Faramarz Separi received B.Eng. and M. Eng. degrees in Electrical Engineering from Shahid Abbaspoor University, Tehran and Tehran Azad University, Tehran South branch in 2001 and 2007, respectively. He is currently a Ph.D. candidate in Electrical Engineering with the faculty of Electrical Engineering, Babol Nooshirvani University of Technology, Babol, Iran. He has worked as the Advisior of CEO at Great Tehran Electric Power Distribution Co., Tehran, Iran. His areas of interest are the optimization of electrical systems, energy management and efficiency, smart girds and renewable energies.

Abdolreza Sheikholeslami is an Associate Prof. of Electrical Engineering at Babol Noshirvani University of Technology (NIT), Babol, Iran. He got his MSc. and PhD degrees from Strathclyde, UK. His research interests are power electronics, power quality and harmonics. He published more than 100 research papers in international journals and conferences.
ORCID: 0000-0002-0910-7854

Taghi Barforoushi received the B.Sc. degree in electrical engineering from Iran University of Science and Technology, Tehran, Iran, in 1994 and the M.Sc. and Ph.D. degrees from Tarbiat Modares University, Tehran, in 1999 and 2008, respectively. He is currently an associate professor at Babol Noshirvani University of Technology. His research interests include power system operation and planning, electricity markets.

Table 1. Reviewed papers

Ref	Publication year	Considered market	objective	Optimization method
[2]	2014	Wholesale market	assess the risk levels under unstructured pool price uncertainty	approximation/Equality-Relaxation (OA/ER) algorithm

[3]	2009	Wholesale market	determine the retailer's optimum contract price	branch and cut algorithm
[4]	2010	Wholesale market	optimal price offering to customers for maximizing the profit of a retailer	-
[5]	2013	Wholesale market	set price changes which encourage customers to shift their loads considering time-of-use tariffs	generalized reduced-gradient (GRG) algorithm
[6]	2013	Demand response market	maximum retailer profit,	commercial off-the-shelf optimisation
[7]	2015	Wholesale market	maximum retailer profit,	e-constraint method
[8]	2017	Wholesale market	obtain optimal bidding and offering strategies	mixed-integer linear programming
[9]	2020	Wholesale market	Retailer's real-time pricing	-

Table 2. Technical and Cost Characteristics of DG Unit

Capacity (kW)	Minimum generation (kW)	Initial commitment status	a ($)	b ($/kWh)	c ($/(kWh)^2)	Startup cost ($)	Bus
156	18	0	14.628	0.1023	0.00003526	16.25	32

Table 3. Technical and Cost Characteristics of ESS

Charging efficiency	Discharging efficiency	Maximum energy level (kWh)	Minimum energy level (kWh)	Charging rate (kW/h)	Discharging rate (kW/h)	Initial energy (kWh)	Degradation cost ($/kWh)	Bus
0.95	0.8	1245	316	254	186	426	0.0394	69

Table 4. The Input Value of PSO's Parameters

Parameter	Value
Particle size	5
Population size	500
Number of iterations	1000

Table5. Wholesale market data ($/MWh)

Scenario#	Period#		
	1	2	3
1	30.94	42.5	36.7
2	29.5	43.8	34.2
3	31.4	41.2	36.7
4	35.7	41	40.1

Table 6. Retailer#2 buying curve data

Scenario#	Price ($/MWh)		demand (MW)	
	Block#		Block#	
	1	2	1	2
1	38.4	50.5	4	3.5
2	37.4	52.4	4.2	3.4

3	39.2	49.4	4.1	3.7

Table7. VPP#1 offering curve data

Scenario#	Price ($/MWh)		power (MW)	
	Block#		Block#	
	1	2	1	2
1	39.4	51.4	1.5	2.5
2	38.4	52.4	1.8	2.9
3	37.2	51.2	1.3	2.3

Table 8. VPP#2 offering curve data

Scenario#	Price ($/MWh)		power (MW)	
	Block#		Block#	
	1	2	1	2
1	34.2	48.2	1.8	2.3
2	33.2	49.4	1.7	2.4
3	35.3	50.4	1.9	2.6

Table 9. Profit and CVaR

β	Expected profit ($)	CVaR0.05 ($)
0	1150.224	352.345
0.2	1094.862	499.324
0.4	942.033	565.29
0.6	824.423	626.942
0.8	764.821	795.423
1	642.423	824.32

Table 10. Optimal Retailer Decisions for three periods

β=0.2	Period 1	Period 2	Period 3
Energy Demand (kWh)	15720	43799	26624
Upstream Network (kWh)	16249	31292	20453
Local Market (kWh)	0	8665	4651

DR (kWh)	0	1880	425
DG (kWh)	400	1248	880
ESS (kWh)	-929	+714	+215
Local Market Price ($/kWh)	0.030	0.039	0.037

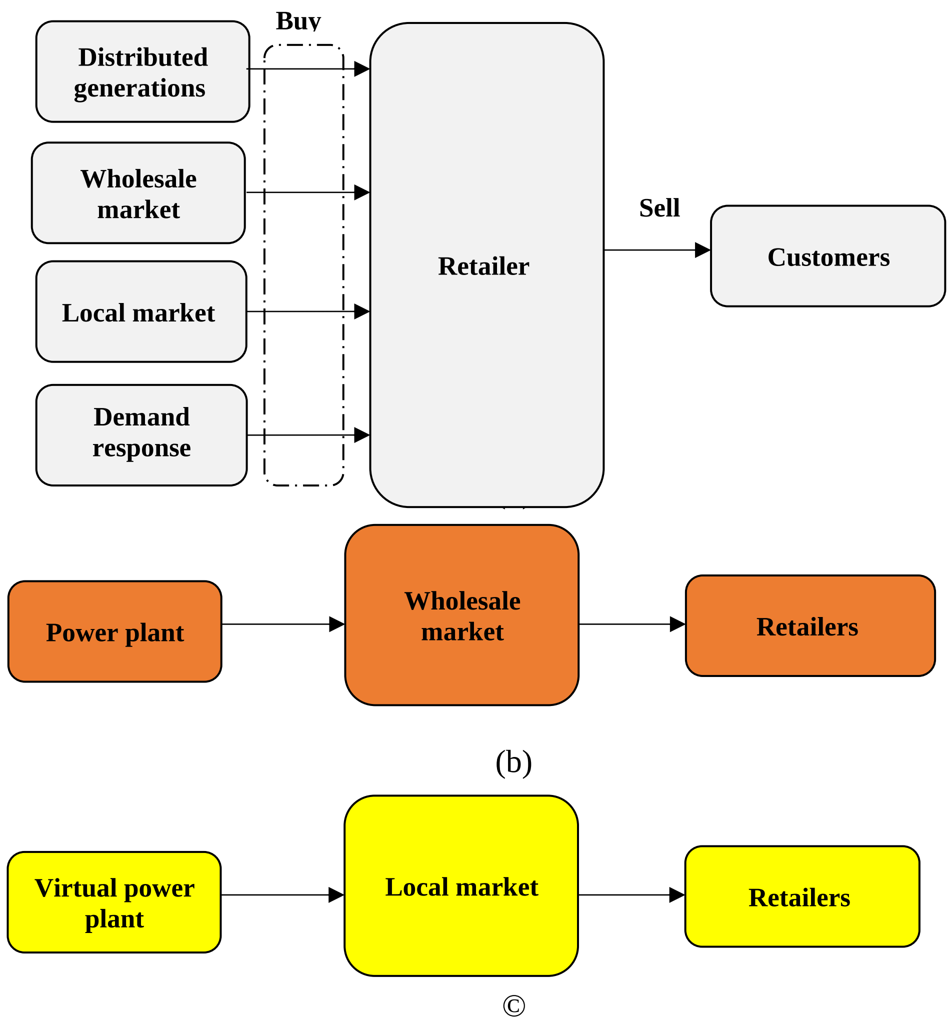

Fig. 1. The overall structure of buying and selling the electricity by the retailer

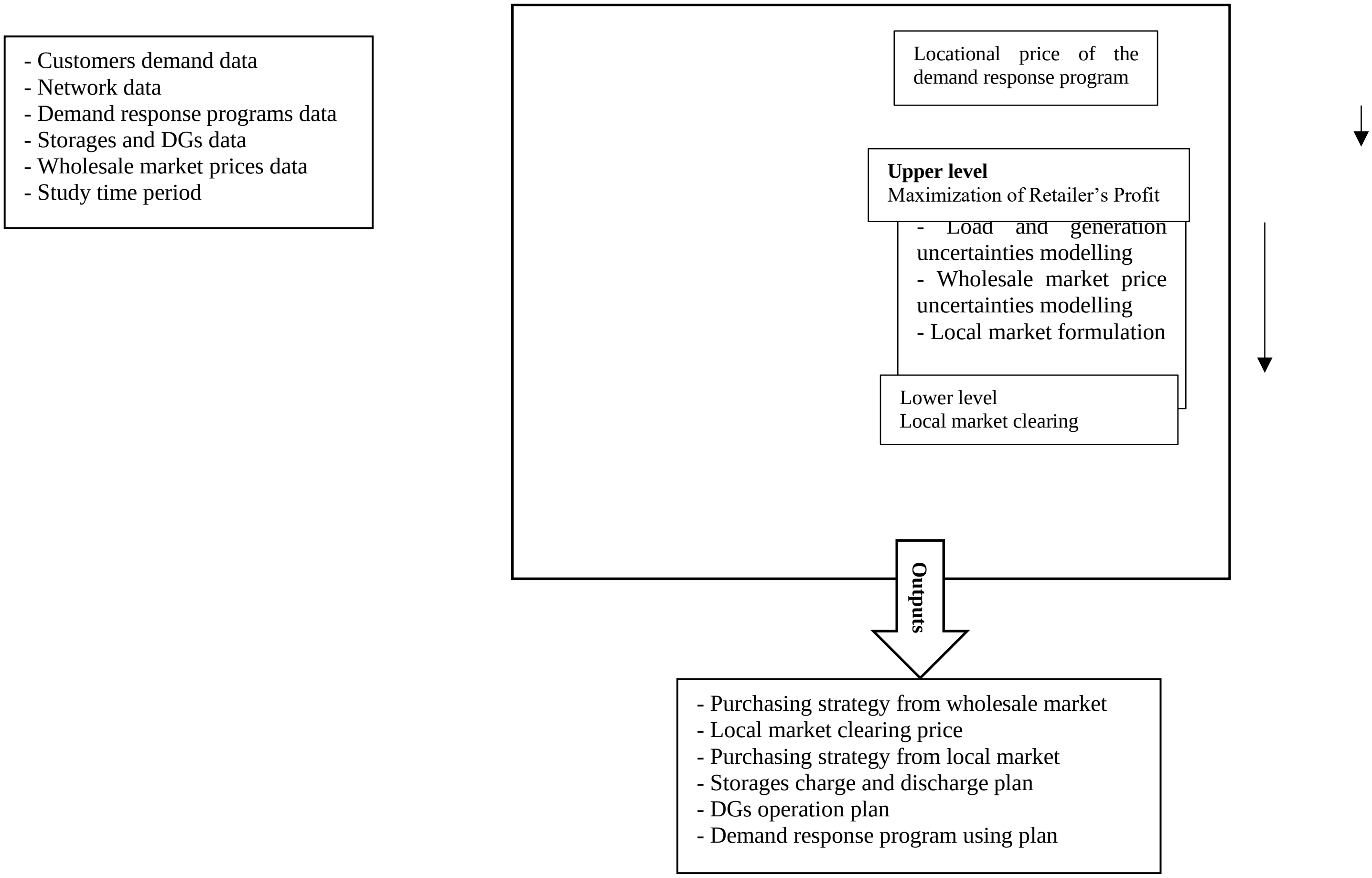

Fig. 2. The overall structure proposed to solve the problem

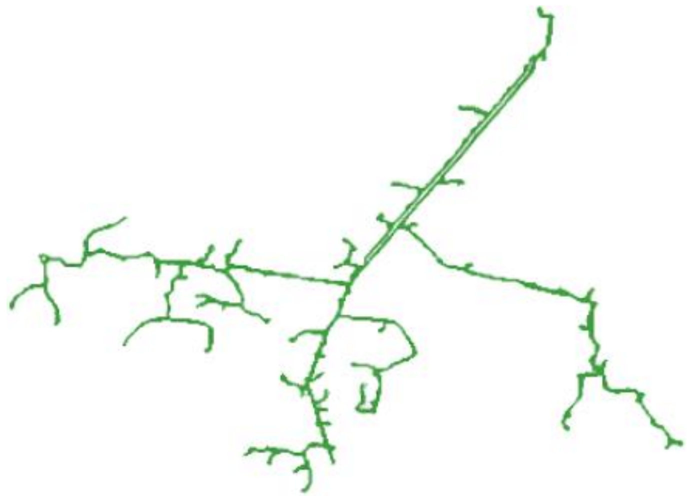

Figure3. Sample Feeder

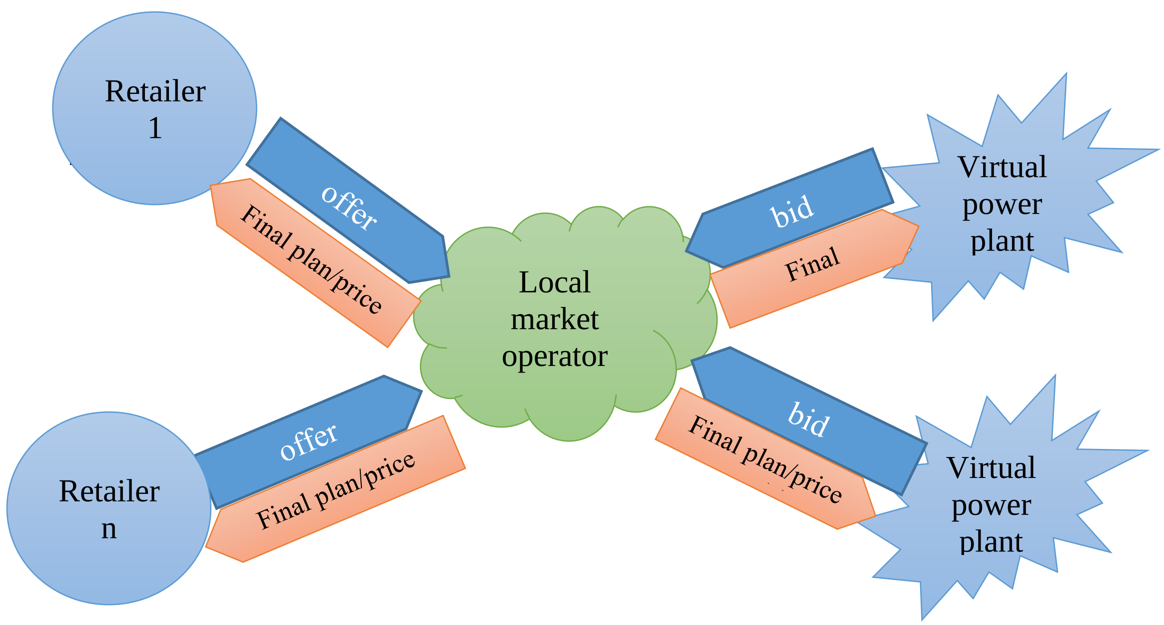

Fig. 4. Retail interactions and actors in the local market

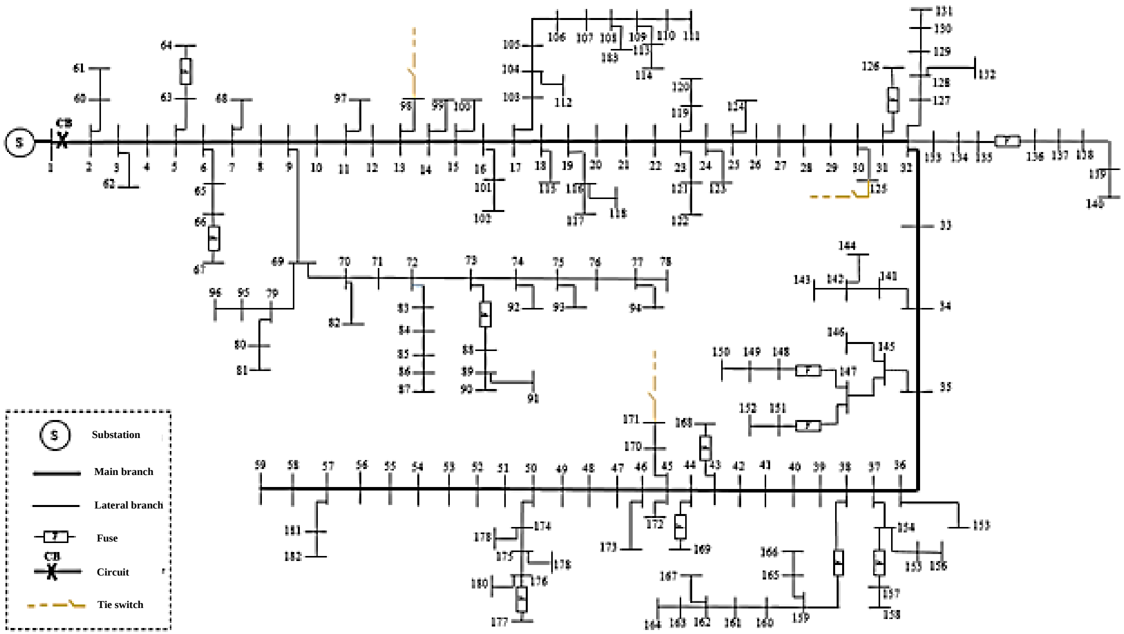

Figure 5. Under Study Distribution System

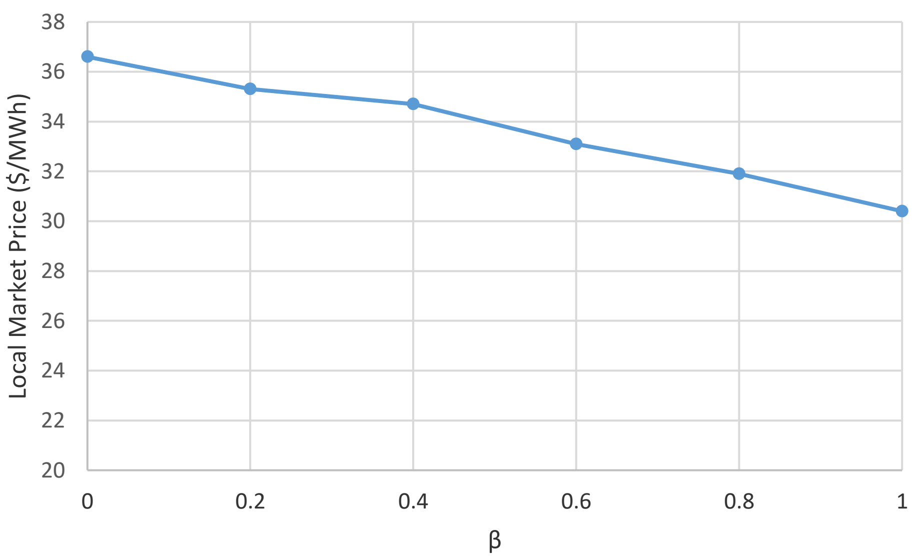

Figure6. Effect of β on Local Market Price

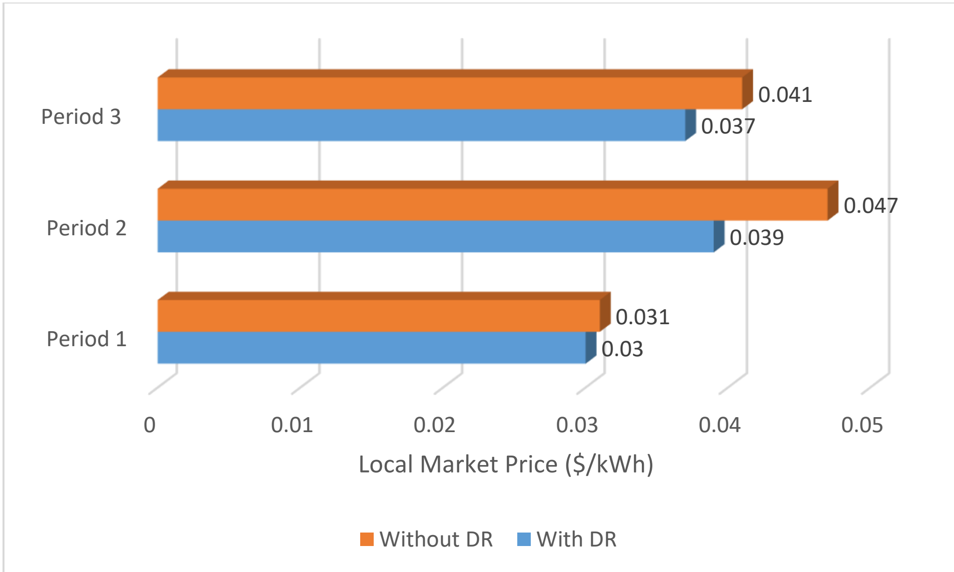

Figure7. Local Market Price Sensitivity to DR Program (β=0.2)