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Risk-based optimal decision-making by the retailer in a mixed local and wholesale market environment considering demand response solution

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Abstract. The present research 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, wholesale market price, and behavior of the local market players were all incorporated into the presented model. The demand response program benefits the retailers in governing the risks. A risk-based decision-making scheme was established in this paper that considered every instrument accessible to retailers and the uncertainties involved. The major objective of this paper is to maximize the retailer benefit concerning a tolerable risk. In order to model risks, scenario theories were exploited and Particle Swarm Optimization (PSO) was employed to solve the optimization problem. The proposed scheme was simulated in an actual network, and the obtained results confirmed the effectiveness and computability of this method.

1. Introduction

In recent decades, the power industry has gone through restructuring following its transformation into a competitive field with new organizations emerging in a new arrangement. In this new frame, electricity retailers appear as intermediaries between the producer companies and customers [1]. An electricity retailer plays the role of an electricity intermediary between the wholesale market and end users. Within the rearranged electricity markets, retailers buy the required demand of consumers from a variety of 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, their gain will be reduced due to the low vending price. However, when the vending price is high, customers will be discouraged to buy from this retailer, hence a decline in the retailer's benefit.

1.1. Retailer participation in the wholesale market

There are certain authentic and well-established studies in the literature that define the retailer's presence in the wholesale market, especially in the field of retailers' electrical energy purchasing. A new and unique approach that rests on the Information Gap Decision Theory (IGDT) was suggested in [2] to assess the risk levels under unstructured pool price uncertainty. An optimum approach for retailers was also presented

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in [3] where they afforded energy costs via the pool market and forward contracts, taking into account medium- and long-run decisions. More importantly, this study suggested a mathematical technique that rested on mixed-integer random programming in order to determine the retailer's optimum contract price with users and the corresponding electricity policy provision for a specific time. The authors in [4] proposed random linear planning to determine the curve of the buying offers of the wholesale market. A load profile clustering method for an optimum price was also proposed for offering to the clients in order to maximize the retailer's benefits. In [5], a scheme was introduced to regulate price spikes that motivate the clients to move their loads regarding time-of-use tariffs. In [6], a game theoretic model accounting for the Stackelberg relationship between retailers and consumers in a dynamic price environment was proposed. 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 was proposed for identifying the optimum purchasing model that helped retailers to use it practically in the pool market. A random structure was also offered to electricity retailers to satisfy the targets such as predicted benefit and predicted downward risk, which could help them determine the optimum level of engagement in forward contracting and pool and place the optimum vending prices for customers.

In [8], a Robust Optimization Approach (ROA) was proposed to obtain optimal bidding and offering strategies for the retailer. In [9], a Real-Time Pricing (RTP) framework was introduced, considering the uncertainties of various input parameters such as electricity demand, output power of renewable energy resource, and pool market price.

Most of the reviewed studies, introduced in Table 1, focused on presenting proper strategies and approaches to facilitate purchasing energy from the wholesale market and selling strategies for the customers.

1.2. The emergence of the retail market

As a result of the inclination toward smart networks, different tools have emerged 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, in turn, will affect the manner of their electricity buy and sell. Under such conditions, the retailer can buy electricity from

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

Ref.	Publication year	Considered market	Objective	Optimization method
[2]	2014	Wholesale market	Assessing the risk levels under unstructured pool price uncertainty	Approximation/Equality-Relaxation (OA/ER) algorithm
[3]	2009	Wholesale market	Determining the retailer's optimum contract price	Branch and cut algorithm
[4]	2010	Wholesale market	Offering optimal price to customers for maximizing the profit of a retailer	–
[5]	2013	Wholesale market	Setting 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	Obtaining optimal bidding and offering strategies	Mixed-integer linear programming
[9]	2020	Wholesale market	Retailer's real-time pricing	—

the wholesale market, distributed generation units, forward contracts, and demand response programs. A comprehensive model of a retailer activity in an active distribution network was presented in [10]. In the proposed method, it is assumed that several retailers are active in the distribution network who can provide the required energy for their customers from different resources such as distributed generations, storage resources, retailers, and Demand Response (DR). The authors in [11] presented a combinatorial model to find a way of providing energy for the retailer via different options such as self-sufficient generators, mutual contracts, and wholesale market. An optimization method for integrated portfolio management in the wholesale and retail power markets was also proposed in [12]. The results from the proposed model quantify the risk threatening the electric utilities 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 both wholesale and retail electricity markets was presented in [13], considering the demand response and RTP, 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 IGDT considering the DR exchange was provided in [14]. Further, based on the opportunity and robustness functions, an optimal bidding strategy of electricity retailer can be obtained using IGDT technique. A two-stage stochastic framework for an electricity retailer was proposed in [15], considering the DR and uncertainties based on a hybrid clustering technique, to maximize the expected value of the retailer's profit while the exposure risk was confined to a pre-specified level.

In [16], a new method was proposed for retailer's decision-making considering day-ahead and real-time markets as well as liberalized Distributed Renewable Energy (DRE) market where the retailer competes with other Load Serving Entities (LSEs) for procuring DRE. A bi-level hybrid framework was given in [17] to support Retail Electric Providers (REPs) and 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 already installed smart meters with an embedded Home Energy Management System (HEMS). For the first time, the interactions between electricity retailers and local energy markets were modeled in [18], and a method was proposed for pricing decisions of a strategic retailer.

1.3. Paper contribution

As mentioned above, most of the studies in recent years have focused on presenting an optimal method for providing the required energy for a retailer. For this purpose, we highlighted efficient use of the capacities of the resources such as distributed generations, DR programs, and renewable energy resources alongside the pool market and bilateral contracts. With the development of the renewable resources and DR in the distribution network, the structure of the wholesale market was not found suitable to incorporate 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 energy procurement from other resources as well as the wholesale market determines the demand from the local market and, consequently, the local market price. Given this fact and assumption of specified tariffs for the final customers, this study proposed a comprehensive two-stage model to determine the strategy of energy procurement by the retailer through the wholesale market, distributed generations resources, and DR programs with the main objective of maximizing the retailer's profit under the related uncertainties. The main contributions of this paper are highlighted in the following:

- Introducing a comprehensive two-stage model for optimal determination of the retailer portfolio considering the retailer's interactions with the wholesale and local markets;
- Considering the impact of uncertain variables on the decision-making process using a risk-based model and determining the optimal risk-taking and risk-averse decisions;
- Assessing the role of DR program as an effective solution in the hands of retailer(s) for price making in the local market;
- Reducing losses through the application of the 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 illustrates the proposed framework. Section 3 determines the value of the DR programs from the retailer's perspective. Section 4 presents the proposed structure for the local market. Section 5 provides a comprehensive decision-making formulation. Section 6 presents simulation results to validate the proposed method and finally, Section 7 gives the concluding remarks.

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

A retailer can purchase electricity from different resources and sell it to customers. In addition to their electricity trading role, the retailers are responsible for offering services to the customers as well as taking measurements and billing. The retailers can provide energy for their customers through the wholesale market, distributed generations, and local market. Energy suppliers in the wholesale and local markets are power plant and virtual power plant, respectively. According to the given definition, a virtual power plant is a cluster of dispersed generator units, controllable loads, and storages systems that were aggregated in order to operate as a unique power plant. In addition, the retailer can benefit from the potentials of DR programs. The DR programs comprise a variety of programs and in this study, 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 the predefined tariffs for the customers [22]. The overall structure of providing and selling the electricity by the retailer is presented in Figure 1.

In interactions with the distribution company, the retailer is responsible for offering services to the customers. Generally, the manner of interactions between the distribution company and retailer can be elaborated in different models. In one of these models, the retailer is responsible for supplying electricity for all customers of one feeder. In this model, which is currently implemented in Iran, the issue of non-technical losses is of high significance 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 that are under the responsibility of the retailer.

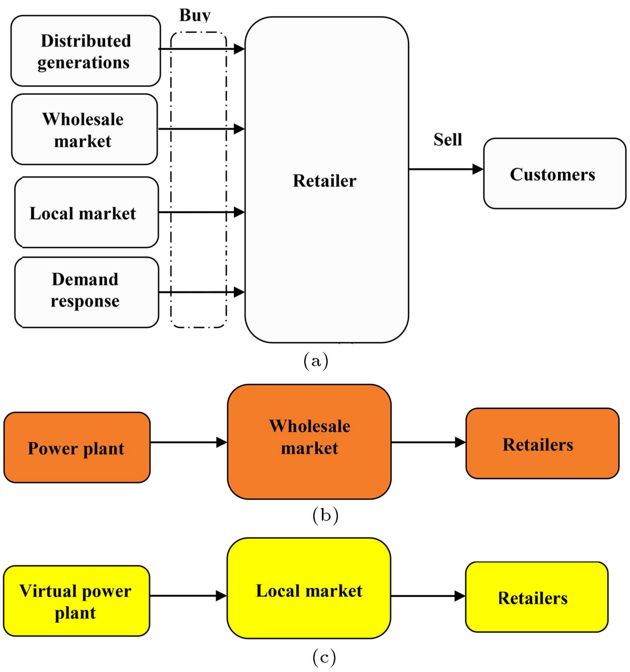

Figure 1. The overall structure of buying and selling the electricity by the retailer.

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

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

The market price is uncertain in a day-ahead market. For this reason, "scenario theory" was used to model the wholesale market uncertainty. Since the retailer is the price maker in the local market, it is essential that the local market clearing model is considered in the main decision-making function. Therefore, a two-stage programming model is used to solve the problem. The behavior of other actors is further modeled based on the scenario theory in the local market function.

The distributed generation and storage are then modeled based on the corresponding cost functions. The uncertainties related to the load and production of the distributed generation resources are also considered as scenarios. In the case of 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 within a specified time. The retailer then rewards 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 average price on the main bus. This price varies across different network buses. The overall structure proposed to solve the problem is shown in Figure 2.

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

As stated in the previous section, it is assumed that the

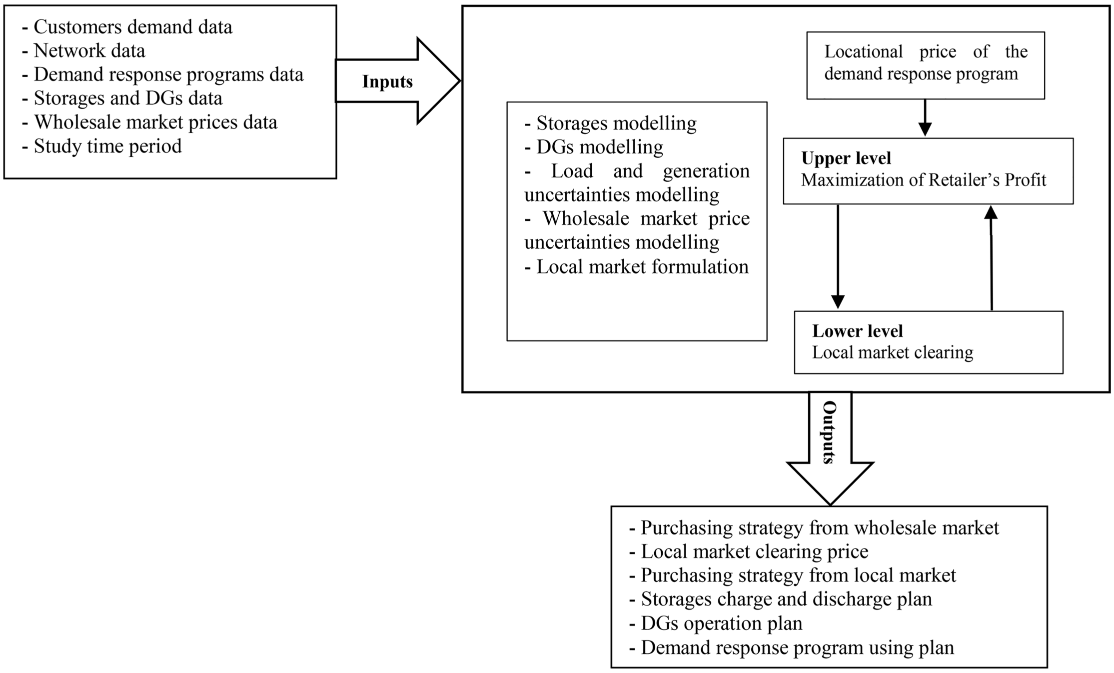

Figure 2. The overall structure proposed to solve the problem.

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. In this study, 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 the 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 presented in Figure 3, the higher the final feeder load, the higher the network losses. Since 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 regardless of the network losses is λ_{DR}, we can conclude that this value may differ depending on the customers' locations, which play a role in the demand reduction programs according to the network losses. In [23], the loss value for a certain amount of power injection into the ith bus was calculated as follows:

Figure 3. Single line sample feeder based on GIS.

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

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

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

where λ_n is the energy price in the main bus of the network, and P the amount of power injected into different buses within 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 DR program for a specified amount in the ith bus of the network for the retailer is obtained as follows:

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

$$+\left.\frac{\partial Ploss}{\partial P_{lr,i}}\right|_{\{P_{lr,j}=P_J|j=1,2,..,N\}}\Bigg), \quad (4)$$

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 gained from loss reductions resulting from implementation of the demand reduction program to the customer. In case the retailer transfers α percent of the benefits to the customer, the price of the demand reduction program for customer participation is as follows:

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

$$+\left.\frac{\partial Ploss}{\partial P_{lr,i}}\right|_{\{P_{lr,j}=P_J|j=1,2,..,N\}}\Bigg). \quad (5)$$

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 supplying electricity within it. Owing 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 will have the opportunity to locally trade the generations with customers [24].

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

The schematic diagram of a local market is shown in Figure 4. 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 this figure, several retailers can separately participate in a local market. In addition, it is assumed that the suppliers participate in the local market as the virtual power plants as a set of distributed generation resources and they can work in the market involving energy trading or even ancillary services. The local market will be managed and cleared such that the benefits of all participants are provided. Given the interaction of and competition between different retailers, non-cooperative game theory was used for the market settlement. In this game, each player has its target function, and the players with different targets seek to achieve their interests.

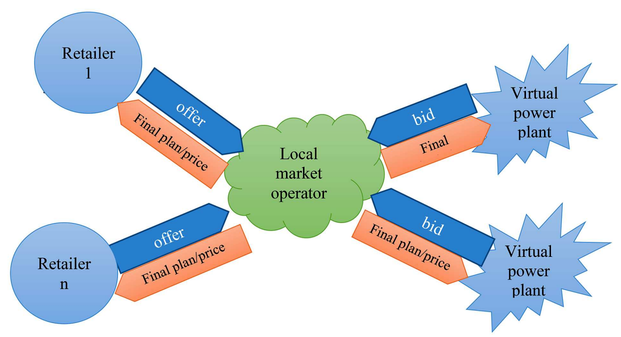

Figure 4. Retail interactions and actors in the local market.

The overall structure of the problem-solving model can be summarized in the following stages:

1. Producing the scenarios of the virtual power plants: Since different actors of the retail market are known in the local market and there are several parameters that affect the amount of power presented in the market, different scenarios will be produced for the virtual power plants;
2. Producing the scenario of the retailer's demands: Since the actors in the local market are known in the virtual power plants, the number of demands for the retailers will be predicted based on the 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: Given that different scenarios and retailer demands are known, the market settlement price can be calculated using 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, the NIRA game theory was employed 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 implemented in the local market settlement mechanism.

Target function of producers: The profit of the generator i at time t and scenario ω is $g^i_{t,\omega}$, which can be calculated as follows:

$$\max g^i_{t,\omega} = R^i_{t,\omega} - C^i_{t,\omega}, \quad t \in \{1,2,,....,24\},$$

$$i \in t \in \{1,2,,....,n\}, \quad (6)$$

$$R^i_{t,\omega} = \pi^j_t \times \left[P^{DGU,j}_{t,\omega} + P^{NDU,j}_{t,\omega}\right], \quad (7)$$

$$C^i_t = C^{DGU,j}_t$$

$$C^{DGU,j}_t = a^j.(P^{DGU,j}_{t,\omega})^2 + b^j.P^{DGU,j}_{t,\omega} + c^j, \quad (8)$$

where R and C are the revenue and cost of the power generation, respectively. In addition, a, b, and c are the power generation cost coefficients.

4.1.1. The objective function of the retailer

The cost function of the retailer at time t in the market can be obtained through the following equation:

$$\min C_{t,\omega}^{r,k} = \pi_t^{r,k} \times P_{t,\omega}^{r,k} t \in \{1, 2, , ..., 24\},$$

$$k \in \{1, 2, , ..., n'\}. \tag{9}$$

General constraints:

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

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

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

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

In this research, the local market price will be calculated based on the Nash equilibrium calculations, information received from the players, and aforementioned target functions [12].

5. The comprehensive decision-making formulation

In the previous section, the application of the DR program as one of the available options for the retailer and how to benefit from the local market capacity to provide the required energy with the least costs possible were discussed.

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

This research also took into consideration the risk-averse two-stage stochastic programming framework similar to those of [7]. The general form of the retailer plan problem is formulated as follows:

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

where Z is the retailer's predicted expenditure, and χ the risk associated with the retailer's schedule. The factor $\beta \in [0, 1]$ was considered to develop the risk aversion of the retailer in the objective function. While the zero value of β denotes that the retailer is risk-neutral, the value one indicates that the retailer is risk-averse. The predicted expenditure of the two-stage random retailer problem can be formulated as:

$$Z = f(X_c) + \sum\nolimits_{\omega=1}^{N_\Omega} \pi_\omega q(\omega), \tag{15}$$

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

- *Expected profit (Z):* The cost in scenario ω is mathematically expressed as:

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

where Rev_c is the income from the customer billings, $C_{WM}(Y_{t\omega})$ the cost of purchasing power from the upstream network, C_{DG} the cost of providing energy through the distributed generations, C_{ESS} the cost of providing power for the customers through the storage resources, and C_{DR} the cost of encouraging the customers to run the DR programs. The following formula shows how to calculate each cost.

Eq. (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 at hour t by the customer c, L_c^t the amount of demand for the customer c at hour t, and ΔL_c^t the amount of demand reduction for the customer c at hour t caused by participation in the DR program.

Eq. (18) shows the costs of purchasing power from the upstream network:

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

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 at hour t and scenario ω. Of note, the costs of providing energy from the local market can be calculated as follows:

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

The critical point here is that the price scenarios of $\lambda_{t\omega}^L$ were obtained during the problem-solving process by solving the local market problem. On the contrary, the scenario of the wholesale market price was obtained based on the price prediction.

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

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

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} the cost of setting up distributed generations resource of g, and v_g^t the binary variable that indicates the setup of the distributed generation resource of g at time t.

The costs of providing energy for the storage resource can be calculated through the following equation:

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

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

The final phase is the first target function of the costs required for encouraging the customers to reduce their consumption (DR):

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

where C_{DR} is the sum of money paid to the customer c (the amount of encouragement) for reducing each kW of power at hour t, and ΔL_c^t the amount of the power reduction of the customer c at hour t calculated by Eq. (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 offered by the retailer.

Target functions of Eq. (16) were optimized, considering the constraints stated in Eqs. (24) to (27):

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

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

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

$$SOC_{ES}^{\min} \le SOC_{ES}^{t} \le SOC_{ES}^{\max}. \tag{27}$$

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

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

$$P\left[Z_P \le VaR_\alpha\right] = \alpha. \tag{28}$$

No information is offered by VaR on the worst possible expenditure beyond the confidence level. The current research employed Conditional Value-at-Risk (CVaR), i.e., the predicted cost of the $(1-\alpha)\times 100\%$ scenarios with the largest expenditure [26,27]. The CVaR of model is described by:

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

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

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

Subject to:

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

$$\eta_\omega \ge 0, \forall\omega. \tag{32}$$

5.1. General formulation

Based on the material used in the previous sections as well as the overall risk-based model, the general formulation of the problem is consistent with the following equation:

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

The particle swarm optimizing algorithm was used to find the optimal answer with the highest profit [28].

Given 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 randomly produced to determine the limitations of the problem under study [31]. If an answer does not determine the constraints of the problem, it will be eliminated from the algorithm. Otherwise, the costs for this answer will be calculated for each chromosome to establish convergence. The following algorithm is 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 in a real sample network are presented. According to Figure 5, the network under study is a 182-bus network at a voltage level of 20 kV that supplies a load of approximately 6.3 MW. The information about the loads and lines of this network was neglected in this study; however, the interested parties can request the data through email. Of note, some corrections to this network were made to fit the problem in this article. A 156-kW diesel distributed generation resource, the properties of which are listed in Table 2, was placed at the bus number 32, and an energy storage resource device, the properties of which are mentioned

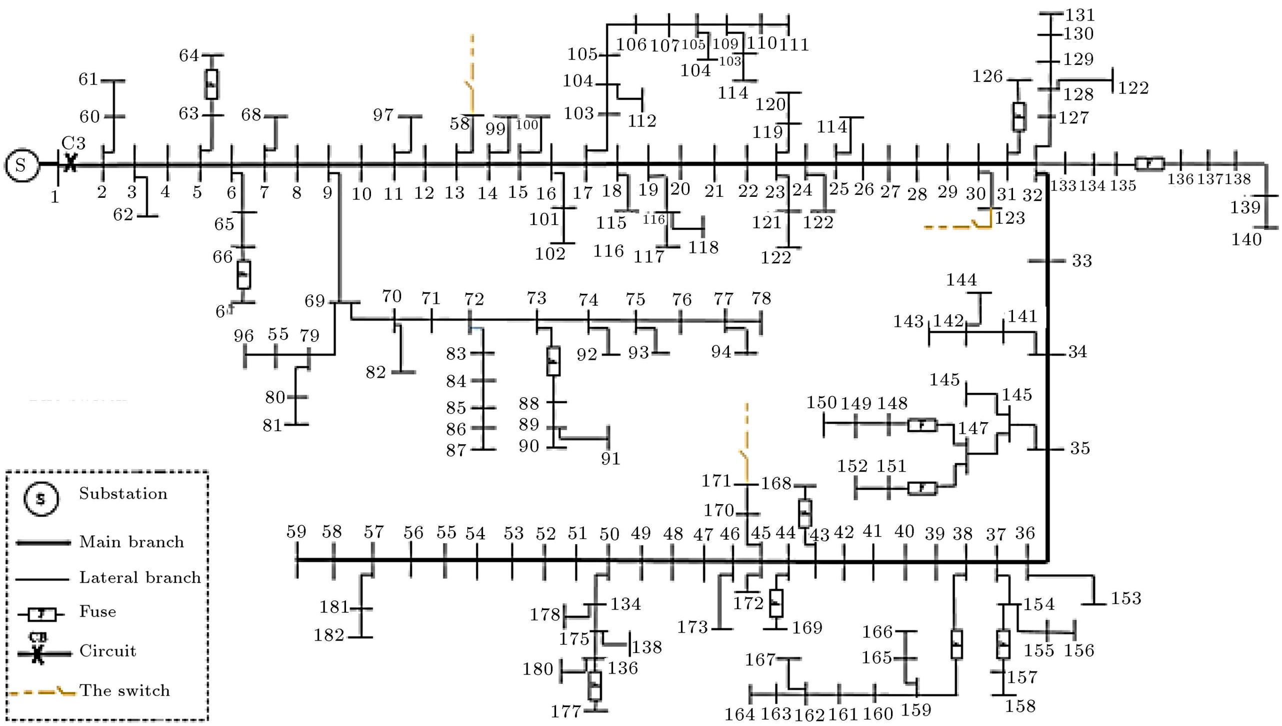

Figure 5. Distribution system under study.

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

Table 5. 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#	Block			
	Price ($/MWh)		Demand (MW)	
	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

Table 7. VPP#1 offering curve data.

Scenario#	Block			
	Price ($/MWh)		Power (MW)	
	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#	Block			
	Price ($/MWh)		Power (MW)	
	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 ($)	CVaR 0.05 ($)
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

in Table 3, was placed at the bus number 69. The loads at buses 26, 68, and 49 are regarded as the responsive loads. The proposed method was simulated using the MATLAB software on a PC with 3.4 GHz CPU and 16 GB RAM. The run time was set as two hours. Further, the Particle Swarm Optimization (PSO) algorithm was employed to find the answer, the parameters of which are shown in Table 4.

According to the assumptions in this study, the retailer should determine three different periods. Due to the uncertainty in the wholesale market price, the scenario method was used for modeling this uncertainty. The scenarios of the wholesale market are assumed and shown in Table 5.

Given that the retailer also participates in the local market, the behavior of other actors in the local market is subject to a certain degree of uncertainty concerning the retailer. Given the presence of another retailer and two virtual power plants in the local market, the offerings of these actors are determined as shown in Tables 6 to 8. It is also assumed that these actors exhibit the same behavior in three different periods.

Based on the above-mentioned discussions, it can be concluded that the retailer's decision-making problem can be solved in an active distribution network with different βs ranging from 0.2 to 1. Table 9 offers the expected profit and value of the CVaR for the best answer to each β. As observed in this table, different expected profit and CVaR values are obtained for different βs. The small values of β confirm that the retailer is more risk-seeking and consequently, the expected profit is higher than that of others, while the CVaR value is low. At $\beta = 1$, the retailer is entirely risk-averse. Hence, its expected profit is minimum, while the CVaR value is maximum.

Table 10 presents the results of the retailer's decision-making for $\beta = 0.2$. To be specific, several items are allocated to each one of the three periods, namely the amount of the customers' demand for energy and the way the retailer provides this energy by purchasing from the wholesale and local markets, run-

Table 10. Optimal retailer decisions for three periods.

$\beta = 0.2$	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

ning the DR program, distributed generation resources, and energy storage. In addition, this table suggests the local market settlement price for each one of the three periods.

The results indicate that due to the low wholesale price in the first period, the whole energy required by the retailer to respond to the customer consumptions is provided within this market. The amount of power purchased from the wholesale market is around 16.2 MWh, which is higher than that of customer consumption in the first period, i.e., approximately 15.7 MWh, mainly because the retailer is supposed to decide to charge the storage resource for usage in the second and third periods. Of note, the application of the DR program is not affordable and for this reason, the amount of DR in the first period is obtained as 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 DR program in these two periods to decrease the required energy. 1880 kWh and 425 kWh demand reductions were reached in these two periods, respectively, through the demand reduction of responsive customers. On the other hand, the storage resource was in the discharge mode in these periods and provided part of the energy by injecting power into the network. Furthermore, the energy produced by the DG in bus number 32 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. This led to an increase in the power purchased from the local market, hence a rise in the local market settlement price.

As mentioned earlier, considering the small size of the local market, the retailer acts as a price-making player that can influence the local market price through the amount of power purchased. Figure 6 shows the

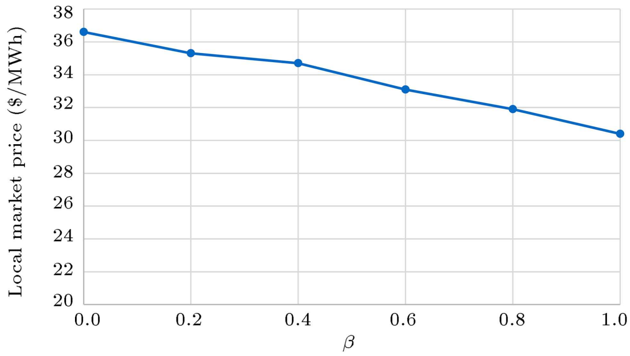

Figure 6. Effect of β on local market price.

effect of the risk management strategy for the retailer on the local market clearing price.

As shown in Figure 6, the local market-clearing price decreases with an increase in β. In other words, in the process of achieving the risk-aversion approach (increase in β), the local market clearing price decreases. In order to justify this, risk sources (uncertainty sources) should be considered closely. 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 provided from the local market as well as the local market-clearing price are reduced.

6.1. DR program role

This section discusses the role of the DR program as an effective solution employed by the retailer to manage the local market and increase the expected profit based on the sensitivity analysis. For this purpose, the main results were compared with each other in two cases of implementing and ignoring the DR program by the retailer. Figure 7 shows the values of local market price in these two cases and three periods of study in a specified risk management strategy ($\beta = 0.2$). As observed, in case the retailer ignored the DR program, the given values increased in all three periods mainly due to the ability of the retailer to reduce the local market energy demand by implementing DR program

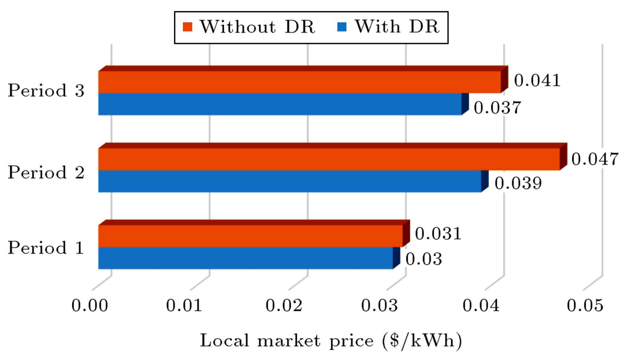

Figure 7. Local market price sensitivity to DR program ($\beta = 0.2$).

and, consequently, affect the local market price. It should be noted that the effectiveness of the DR program is more prominent in Period 2 than Period 3. In other words, the positive role of the DR program becomes more obvious in the peak period.

7. Conclusion

With the expansion of the distributed energy resources including the distributed generation and demand response programs as well as the development of local markets, retailers are given more options to provide energy for their customers. With this said, the current research proposed a comprehensive two-stage model to determine the best strategy for energy procurement by the retailer through the wholesale market, local market, distributed generations, storages and demand response programs to maximize the retailer's profit under the related uncertainties. The obtained results indicated that according to the risk-based decision-making strategy, retailers could optimally provide the required energy of their customers. However, it should be noted that the retailer acts as a price-determining player, thereby affecting the local market price. In addition, the implementation of demand response programs was found successful in providing the retailer with the ability to control the local market price and deal with the associated risks.

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