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Bi-level Programming of Retailer and Prosumers' Aggregator to Clear the Energy of the Day Ahead Using the Combined Method of Mixed Integer Linear Programming and Mayfly Optimization in Smart Grid

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Abstract— In the restructured electricity industry, the electricity retailer, as a profit-oriented company, buys electricity from wholesale electricity markets and sells it to end customers. On the other hand, with the move of the electricity networks towards smart grids, small customers who, in addition to receiving energy from the distribution network, can generate power on a small scale, have emerged as prosumers in the electricity market environment. Therefore, the prosumers' aggregator is defined to maximize the profit of a set of prosumers in this environment. In this paper, the energy exchange between the retailer and the aggregator has been modeled as a bi-level game. At a higher level, the retailer, as a leader to maximize its profit or minimize its expenses, offers a price to buy or sell energy to the prosumers' aggregator. The aggregator also decides on the amount of exchange energy to buy or sell, to minimize the energy supply costs required of its consumers according to the retailer's bid price. In this paper, a combined method based on MILP (Mixed Integer Linear Programming) and MO (Mayfly Optimization) has been used to find the optimal point of this modeled game. To evaluate the efficiency of the proposed method, the three pricing methods FP (Fixed Pricing), TOU (Time Of Using), and RTP (Real Time Pricing) as price-based demand response programs have been compared using the proposed algorithm. The simulation results show that among the three pricing methods for customers, the RTP pricing method has the highest profit for the retailer and the lowest cost for the aggregator.

Keywords— Retailer; Smart grid; Renewable energy resources; Prosumers' aggregator; Energy procurement.

NOMENCLATURE

Variables

$\alpha(t)$	Binary variable for the sales mode of retailer to the prosumers' aggregator at time t
$\beta(t)$	Binary variable for the purchasing mode of retailer from prosumers' aggregator at time t
$A(q,z,t)$	Binary variable to determine the retail price for selling to customers by the retailer from the offered price-power curve
$C_{DG_j}(t)$	Purchased cost from the j^{th} DG unit at time t
$D(q,t)$	Demand supplied of the q^{th} customers group at time t
fl	A random walk coefficient
$Gbest$	The best social experience of mayflies
$P_l^{charge}(t)$	Power charged of the l^{th} energy storage system from the retailer at time t
$P_{j,h}^{DG}(t)$	The power of the h^{th} block corresponding to the j^{th} DG in the linear cost function of the DG at time t
$P_l^{disc}(t)$	Power discharged of the l^{th} energy storage system at time t
$P_{buy,pro}(t)$	Power purchased by the retailer from prosumers' aggregator at time t
$P_{PM}(t)$	Power purchased by retailer from the pool market at time t
$P_{sell,pro}(t)$	Power sold by the retailer to prosumers' aggregator at time
$Pbest$	The best flight experience of each mayfly
R	A random number
r	A random number
r_g	Distance between X_u and $gbest$
r_p	Distance between X_u and $pbest_u$
r_{mf}	Distance between male and female mayflies
$SP(q,z,t)$	Price of the z^{th} interval of the price-power curve for the q^{th} customers group from the retailer at time t
$U_l^{charge}(t)$	Binary variable for the charging mode of the l^{th} energy storage system at time t
$U_l^{disc}(t)$	Binary variable for the discharging mode of the l^{th} energy storage system at time t
v	Mayfly's velocity
x	Mayfly's male position
$X_l^b(t)$	Energy stored by the l^{th} energy storage system at time t
y	Mayfly's female position
$SP^{Fixed}(q)$	Fixed selling price offered to the q^{th} customers group by the retailer
$SP^{RTP}(q,t)$	Real-time selling price offered to the q^{th} customers group by the retailer at time t
$SP_l^{TOU}(q)$	Time-of- use selling price offered to the q^{th} customers group by the retailer in low load level
$SP_M^{TOU}(q)$	Time-of- use selling price offered to the q^{th} customers group by the retailer in medium load level
$SP_p^{TOU}(q)$	Time-of- use selling price offered to the q^{th} customers group by the retailer in peak load level

Indices and Sets

H	Number of production blocks of DG units

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h	Index for generation block in linear modeling of DG units
J	Number of DG units
j	DG unit index
K	Number of wind power producer units
k	Wind power producer unit index
L	Number of energy storage system units
l	Energy storage system unit index
Q	Number of consumers groups of the retailer
T	Number of time periods
t	Time period index
t^{MO}	Time step in mayfly optimization algorithm
q	Customer group index

Constants

χ	Charging efficiency of energy storage system
η	Discharging efficiency of energy storage system
d	The coefficient of nuptial dance
$D^{offer}(q,z,t)$	Offered demand of the q^{th}customers group of the z^{th}step in time t
P_k^r	Rated power of the k^{th} wind power unit
$P_l^{charge,max}$	Maximum chargeable power of the l^{th} energy storage system
$P_l^{disc,max}$	Maximum dischargeable power of the l^{th} energy storage system
$P_{buy,pro}^{max}$	Maximum power that can be bought by the retailer from prosumers' aggregator
P_{PM}^{max}	Maximum power that can be bought by the retailer from pool market
$P_{sell,pro}^{max}$	Maximum power that can be sold by the retailer to prosumers' aggregator
$P_k^{wind}(t)$	Wind power produced by the k^{th} wind power unit at time t
v_k^r	Rated wind speed of the k^{th} wind power unit
v_k^{ci}	Cut-in wind speed of the k^{th} wind power unit
v_k^{co}	Cut-out wind speed of the k^{th} wind power unit
$v_k^{wind}(t)$	Wind speed related to the k^{th} wind turbine area at time t
X_0^l	Primary energy stored in the l^{th}energy storage system
$price_{buy}^{max}$	Maximum price of buying that can be bid by the retailer to prosumers' aggregator
$price_{sell}^{max}$	Maximum price of the selling that can be bid by the retailer to prosumers' aggregator
$price_{pm}(t)$	Pool market price of power at time t

1. Introduction

In the last few years, the use of renewable energy resources, distributed production sources, as well as energy storage systems in smart grids has increased intending to increase system efficiency [1]. Also, the smart grid has provided the possibility of communication between the participants at the level of production and consumption. Therefore, consumers can participate in the process of modifying the load curve through demand response programs [2].

The structure of the smart grid refers prosumers to as those customers who play the role of both generating and consuming power in the electricity networks. Given that prosumers have small energy resources, it seems necessary to use an aggregator to make the most of the benefits of being in a smart grid environment and exchanging information and power with other players in the electricity market [3]. Electricity retailers, on the other hand, as profit-oriented companies, buy electrical energy from wholesale electricity markets and sell it to end consumers [4]. Therefore, how information and power exchange between retailers and consumers is one of the important issues in the structure of the smart grid. Accordingly, this paper provides a structure for modeling the relationship between retailers and types of consumers.

1.1. Related research

Reference [5] has presented an energy management system for residential prosumer based on fuzzy logic. In this paper, the information related to the energy price has been obtained from the main network in the form of fixed parameters. The authors in reference [6] have used prosumers to adjust the voltage and reduce line congestion. Therefore, the details of prosumers' local energy management are omitted in this article. The article [7] has discussed the planning of electric vehicles and energy storage systems belonging to prosumers using Mixed Integer Linear Programming (MILP). In this paper, the authors have considered an aggregator for consumers. In this reference, the incentive-based pricing method is considered, so other pricing methods such as Time of Use (TOU) and Real Time Pricing (RTP) are not considered. The paper [8] has divided prosumers into superior and inferior. According to this classification, the superiors, as leaders, are responsible for being present in the energy market and determining the scheduling strategy for the day ahead. Inferiors, meanwhile, were responsible for generating renewable power and responding to the price signals of leaders. One of the positive features of this article is the consideration of day-ahead and real-time markets. In this paper, the different pricing methods for prosumers are not compared with each other. In reference [9], the authors have presented a two-level multi-leader and multi-follower game to model the behavior of prosumers and end users. Not needing a central operator in the presented method is one of the innovations of the article. However, not considering price-based demand response programs and not comparing pricing methods to consumers can be negative points of this article. Ref. [10] deals with a two-step planning for prosumer's aggregator and determining TOU pricing tariffs for consumers in the medium term. This article is different from our article due to its focus on medium-term planning. In paper [11], the authors have used the Particle Swarm Optimization (PSO) algorithm and the ability of smart loads to provide a way to manage the power of the day-ahead as well as the real-time of prosumers. Reference [12] has presented a structure for energy sharing between prosumers with renewable resources and energy storage systems. The purpose of this article is to minimize the lack of power in the community intended for prosumers. Therefore, the economic interests of each prosumer have not been emphasized. The paper [13] by presenting the concept of an Energy Storage (ES)-equipped Energy Sharing Provider (ESP), which proposed sharing or exchanging energy between neighboring PV prosumers. The proposed model has provided a stochastic programming method for scheduling the day-ahead and uses the Stackelberg game model to use real-time demand response. Paper [14] has presented a distributed method for energy exchange between independent prosumers to maximize their level of social welfare. Unlike this article, which did not use a central controller, reference [15] has modeled a collaborative game between the energy hub manager and prosumers equipped with a photovoltaic system. Morstyn et al. in ref. [16] has provided a unique platform for the energy market to model the energy exchange between prosumers with different priorities. In this platform, different classifications have been done based on different items such as the type of production technology, the location of prosumers in the network, and the reputation of the owners. The paper [17] has modeled prosumer planning into two stages. In the first stage, the resources of each prosumer are determined the day ahead, and in the second stage, they decided to participate in intraday markets, such as peer-to-peer and flexible markets, according to the shortage or excess power predicted. The contribution of this article is to consider several markets. However, references [14–17] have not discussed the effect of different pricing methods on the profits of prosumers. The authors in [18] have presented a model for peer-to-peer energy exchange between prosumers and consumers based on RTP. Paper [19] has proposed a decentralized model based on peer-to-peer energy exchange for energy exchange between prosumers. One of the features of this article is considering a retail market to compensate for the lack of local products when necessary. By dividing prosumers into two categories of buyers and sellers, the ref. [20] has provided a mechanism to determine the price between these two categories. According to the review of papers [5–20], none of the articles has a comprehensive review of the impact of different pricing methods on the profit earned by prosumers and also the cost of consumers.

On the other hand, references [21–30] have investigated the presence of retailers in the smart grid environment. In the article [21], the retailer has settled the power in the presented model by using the possibility of concluding a contract with the wind power producer as well as its presence in the wholesale market. In ref. [22], to reduce the risk of the retail market, the contract of interruptible loads has been used in the form of an optional contract. One of the positive features of this article is a detailed review of the impact of DR contracts on the retailer's profit. The retailer's energy clearance strategy presented in the paper [23] consists of two steps. Decisions about day-ahead and real-time market presence are made by the retailer in the first and second stages, respectively. The retailer in this paper has the possibility of arbitrage between the day-ahead market and the real-time market. In ref. [24], the authors have proposed a bi-level stochastic planning model for the presence of retailers in the distributed renewable energy market. At a higher level, the retailer decided on the level of the presence in the day-ahead and real-time markets, as well as the price offered to renewable sources. At the second level, renewable energy producers maximized their profits. Not considering demand response programs is one of the weaknesses of two articles [23] and [24]. In reference [25], the authors have presented a model based on a data-driven decision-making strategy to increase retailers' profits and reduce consumers' costs. This method has based on received information instead of relying on the model. Reference [26], by presenting a new method based on the supervised learning method, has investigated the two issues of energy settlement and retailer pricing simultaneously. Nojavan et al. in [27] have used a robust method of retailer energy procurement in the presence of a variety of demand response contracts. The paper [28] considered a bi-level game between retailers at a higher level and consumers at a lower level. The goal of the higher level of the game was to maximize the retailer's profit by using pricing tools for wholesale markets and using demand response programs. The goal of the lower level of the game was to minimize the cost of purchasing energy and also to maintain the level of welfare of consumers. It should be noted that at the lower level of the game, consumers and independent system operators were presented. The model presented in [29] to determine the strategy of operation of energy storage systems by retailers has used the real-time pricing method as a tool to use demand response programs. Authors in the reference [30] provided a hybrid model for estimating retailers' profits with responsive consumers in the electricity market. In the proposed model, the MILP problem has been used to simulate the electricity market, and an economic model has been used to estimate the amount of revenue and price fluctuations of electricity demand. Based on our studies, few papers on the decision-making process model between retailers and prosumers have focused more on how prosumers use the resources available. Ref. [31], using a bi-level model, has modeled the exchanges between retailers and prosumers over the medium term. The comparison period considered for this article is one year. Meanwhile, in this article, we have discussed the day ahead planning. Also, in the papers reviewed in a short term, the impact of different pricing methods on end users and prosumers has not been investigated in detail, so this issue has been investigated in the paper presented by us. On the other hand, the smart grid environment has made it possible to establish telecommunications between different participants in the competitive electricity market. Therefore, this telecommunication structure has made it possible to exchange information between retailers and all types of customers. Thus, in such an environment, it is possible to use a variety of demand response programs to improve the profits of various participants. FP, TOU, and RTP pricing methods are price-based demand response programs. TOU and RTP pricing methods provide more flexibility for energy settlement of retailers and prosumers than the FP method. So, it is expected that retailers and prosumers will benefit more in TOU and RTP pricing methods. Therefore, in this article, the effect of this pricing method on consumers is compared in the proposed structure. In Table 1, a comparison has been made between some of the latest relevant studies and the model presented in this paper.

1.2. Features and innovations of the paper

Given the above, a bi-level structure for energy exchange between higher-level retailers and prosumers in the form of a lower-level aggregator is presented in this paper. Therefore, to find the optimal point instead of using mathematical models to convert a bi-level to a single-level problem, an innovative model is presented that combines the Mayfly optimization (MO) algorithm with the MILP. Therefore, the features and innovations of this paper can be summarized in the following sections:

1) A bi-level structure for scheduling the day-ahead power of retailers and prosumers' aggregators is presented. In this structure, the retailer, as the leader, determines the price of power exchange between itself and prosumers, and the aggregator, as a follower, determines the amount of power exchange.
2) In the proposed structure, the retailer has no ownership over renewable generation resources and DGs, but prosumers have renewable generation resources including wind turbines, photovoltaics, and DGs.
3) To solve a bi-level problem, unlike many papers in this field, instead of using complex mathematical formulations, a combined MILP model and Mayfly optimization algorithm have been used.
4) To check the efficiency of the proposed method, the presented structure has been compared with a centralized power management model.
5) To evaluate the proposed method in the presence of demand response programs, three methods of pricing as price-based demand response programs have simulated and their results have compared.

1.3. paper structure

In the continuation of this article, in Section 2, the proposed structure of information exchange and power exchange between retailers and prosumers' aggregator has been described. Also, in Section 2, the proposed algorithm for solving the bi-level problem has presented in general. Section 3 has showed the formulation of the problem. In Section 4, the simulations have been performed on a sample network and the efficiency of the proposed method has been investigated. Finally, Section 5 has concluded the paper.

2. PROBLEM DESCRIPTION

The structure presented in this paper has shown in Fig. 1. The retailer in this structure buys electricity from the wholesale market and resells it to consumers. There are two categories of customers in this paper. The first group is prosumers whose collection is intended as an aggregator. Other customers are also considered as price-sensitive consumers. In this paper, it is assumed that the price-power curve of consumer consumption was informed to the retailer the day before of operation. The aggregator of prosumers has facilities such as wind products, photovoltaics, energy storage system, and DG, and also there is a certain amount of load for these prosumers. This paper hypothesizes that the aggregator of prosumers can be considered a buyer or seller of power. Therefore, according to Fig. 1, the power exchange between the retailer

Table 1. Literature comparing

Reference	Power management of prosumers	Power management of retailer	Bi-level programming	Pricing method to consumers
[7]	Yes	No	NO	Incentive based
[8]	Yes	No	YES	Parameter (market price)
[10]	Yes	No	NO	TOU
[13]	Yes	No	NO	RTP
[14]	Yes	No	NO	parameter(market price)
[21]	No	YES	NO	Parameter
[24]	No	Yes	YES	RTP
[27]	No	YES	NO	Parameter (DR programs)
[28]	No	YES	YES	RTP
[30]	No	YES	NO	FP
This paper	Yes	YES	YES	FP,TOU and RTP

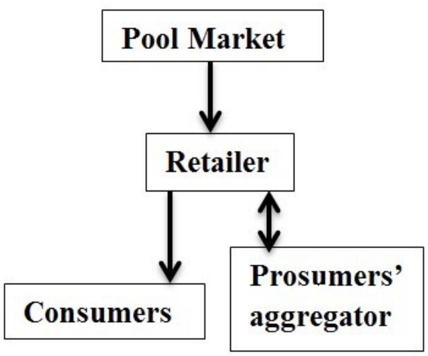

Fig. 1. Schematic of the proposed structure

and the aggregator of prosumers is considered bidirectional. In this paper, a bi-level structure is considered to power settle the retailer and prosumers' aggregator on the day before the operation. The decision-making process in the proposed structure is by the following steps.

1) The retailer randomly generates prices for the purchase and sale of power in the next 24 hours of the next day to the prosumers' aggregator and announces them.
2) The prosumers' aggregator according to the offered purchase and sale price received from the retailer and according to its available resources and its consumption demands, determines the amount of its ability to buy or sell to the retailer at any hour of the day ahead and announces it to the retailer. It also specifies the amount of its cost.
3) The retailer, considering the constant amount of exchange power with the aggregator and its bid price, manages the power to settle the energy of other consumers as well as determine the amount of purchase from the wholesale market. The retailer calculates its cost according to new information.
4) The retailer uses the MO algorithm to maximize its profit, update the bid prices to the prosumers, and announce them to the prosumers' aggregator.
5) Steps 2 to 4 continue until the stop condition is reached. The maximum stop condition is the number of iterations of the MO (mayfly optimization) algorithm.

2.1. Mayfly Optimization (MO)

Zervoudakis and Tsafarakis introduced the MO algorithm in 2020[32]. The MO algorithm used a mathematical model of the flight and mating process of mayflies. The MO algorithm initially produces two random populations, the male set, and the female set, respectively. Each position of the mayflies is a potential solution to the optimization problem. Vectors of position and velocity in d^{th}imension search-space are as $X = (x_1, x_2, \ldots, x_d)$ and $V = (v_1, v_2, \ldots, v_d)$ respectively. To determine the direction of flight of each mayfly, it uses the best flight experience of each mayfly ($pbest$) and also the best social experience of mayflies ($gbest$). Equation 1 is modelled the velocity of movement of a male mayfly [32]:

$$\begin{aligned} v_{uw}^{t^{MO}+1} &= v_{uw}^{t^{MO}} + a_1 * e^{-\beta r_p^2} * \left(pbest_{uw} - x_{uw}^{t^{MO}}\right) \\ &+ a_2 * e^{-\beta r_g^2} * \left(gbest_w - x_{uw}^{t^{MO}}\right) \end{aligned} \tag{1}$$

In Eq. (1) $v_{uw}^{t^{MO}}$ indicates the velocity of the male mayfly, $x_{uw}^{t^{MO}}$ shows the position, t^{MO} denotes the time step, u is the mayfly number, $w = 1, \ldots, n$ is the space dimension. While a_1 and a_2 as constant values represent the effect of cognitive and social components, respectively. Also," β denotes a visibility coefficient. Finally, r_p , r_g represent the distance between X_u and $pbest_u$and $gbest$, respectively. The new position of each male mayfly changes using Eq. (2) as follows [32]:

$$x_u^{t^{MO}+1} = x_u^{t^{MO}} + v_u^{t^{MO}+1} \tag{2}$$

Where $v_u^{t^{MO}+1}$ is calculated as follows for the best mayflies [32]:

$$v_u^{t^{MO}+1} = v_u^{t^{MO}} + d * r.. \tag{3}$$

Here, d is the coefficient of nuptial dance. While r is selected randomly from [-1,1] interval.

Equation (4) models the speed of movement of a female mayfly using a simulation of the attraction process between male and female mayflies [32]:

$$v_{uw}^{t^{MO}+1} = \begin{cases} v_{uw}^{t^{MO}} + a_3 * e^{-\beta r_{mf}^2} * \left(x_{uw}^{t^{MO}} - y_{uw}^{t^{MO}}\right) & s.t: \quad f(y_u) > f(x_u) \\ v_{uw}^{t^{MO}} + fl * r & s.t: \quad f(y_u) \leq f(x_u) \end{cases} \tag{4}$$

In Eq. (4) $v_{uw}^{t^{MO}}$ indicates the velocity of the female mayfly, $y_{uw}^{t^{MO}}$ shows the position, t^{MO} denotes the time step," u is the mayfly number, $w = 1, \ldots, n$ is the space dimension. Besides," a_3 is a constant applied to scale the contribution of the social and cognitive components. Also, β denotes a visibility coefficient. While r_{mf} represents the distance between male and female mayflies. Finally, d is the random walk coefficient and r is a random number with a [-1, 1] range. Therefore, the new position of the female mayfly is calculated as follows [32]:

$$y_u^{t^{MO}+1} = y_u^{t^{MO}} + v_u^{t^{MO}+1} \tag{5}$$

The mating process for mayflies is formulated by two Eqs. (6 and 7). The fitness value is used to pick out the parents for a mating that results in offspring, which are generated as follows [32]:

$$offspring^1 = R * male + (1 - R) * female \tag{6}$$

$$offspring^2 = R * female + (1 - R) * male \tag{7}$$

Where male indicates the male parent, female denotes the female parent and R is a random number within a predefined range. The initial velocities $offspring^1$ and $offspring^2$ are assumed to be zero. According to ref. [32], the Mayfly optimization algorithm has the following steps:

1) Determine random values for the position and speed of male and female mayflies.
2) Calculate the objective function based on the given initial values.
3) Find global best ($gbest$).
4) Update velocities and position of male and female mayflies.
5) Calculate the objective function based on new values.
6) Rank male and female mayflies.
7) Mate the mayflies.
8) Calculate the offspring.
9) Divide offspring into two groups randomly.
10) Replace the worst solutions with the best new ones.
11) Update $pbest$ and $gbest$
12) If the stop condition is reached, go to the next step, otherwise return to step 4.
13) Display results and end of simulation.

3. Problem formulation

the proposed model in this paper, a bi-level structure is considered, in which at the higher level is the retailer and at the lower level is the prosumers' aggregator.

3.1. Higher level problem: energy procurement from the retailer's point of view

The retailer in the structure proposed in this paper buys energy from the pool market and seeks to meet the needs of its consumers and prosumers. The goal of every retailer is to gain maximum profit from participating in the power market environment. Equation (8) has shown the objective function of the retailer.

$$\begin{aligned} min\ C_{Re} &= \sum_{t=1}^{T}\Big\{price_{PM}(t)*P_{PM}(t) \\ &+ price_{buy,pro}(t)*P_{buy,pro}(t) \\ &- price_{sell,pro}(t)*P_{sell,pro}(t)) \\ &- \sum_{q=1}^{Q} SP(q,t)*D(q,t)\Big\} \end{aligned} \tag{8}$$

The retailer's purchase from the pool market is limited by equation (9):

$$0 \le P_{PM}(t) \le P_{PM}{}^{max} \tag{9}$$

Equations (10-12) have introduced the sale and purchase restrictions from the prosumers aggregator and the impossibility of simultaneous buying and selling from the prosumers aggregator in the model, respectively.

$$0 \le P_{sell,pro}(t) \le \alpha(t) * P_{sell,pro}^{max}(t) \tag{10}$$

$$0 \le P_{buy,pro}(t) \le \beta(t) * P_{buy,pro}^{max}(t) \tag{11}$$

$$0 \le \alpha(t) + \beta(t) \le 1 \tag{12}$$

Equations (13-14) show the limit of the retailer's bid price for sale and purchase to/from the aggregator, respectively.

$$0 \le \text{price}_{sell,pro}(t) \le \text{price}_{sell}^{max} \tag{13}$$

$$0 \le \text{price}_{buy,pro}(t) \le \text{price}_{buy}^{max} \tag{14}$$

The equations for the demand of each group of consumers are entered in the model according to Fig. 2 [33]. The equations for the amount and price of selling power to price-sensitive consumers are as follows [33]:

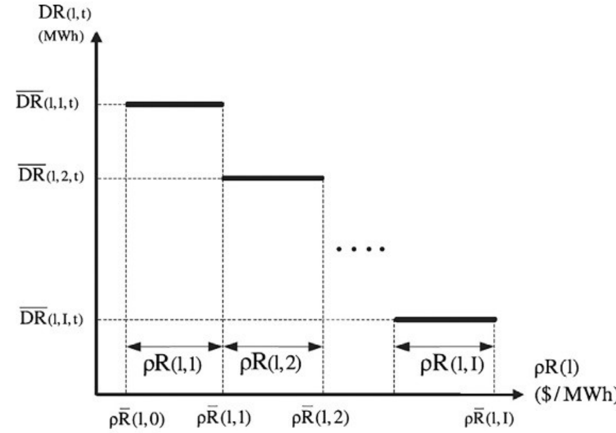

Fig. 2. Price-load curve of the demand supplied by the retailer [33]

$$D(q,t) = \sum_{z=1}^{Z} D^{offer}(q,z,t) * A(q,z,t) \tag{15}$$

$$SP(q,t) = \sum_{z=1}^{Z} SP(q,z,t) \tag{16}$$

$$\begin{aligned} SP^{offer}(q,z-1,t)*A(q,z,t) \le SP(q,z,t) \\ \le SP^{offer}(q,z,t)*A(q,z,t) \end{aligned} \tag{17}$$

$$\sum_{z=1}^{Z} A(q,z,t) = 1 \tag{18}$$

Also, according to the seller's pricing method, equations (19) to (21) are entered in the model for FP, TOU, and RTP pricing modes, respectively [33].

$$SP(q,t) = SP^{Fixed}(q) \tag{19}$$

$$SP(q,t) = \begin{cases} SP_L^{TOU}(q) & , \quad t \in \text{low load level} \\ SP_M^{TOU}(q) & , \quad t \in \text{ medium load level} \\ SP_P^{TOU}(q) & , \quad t \in \text{peak load level} \end{cases} \tag{20}$$

$$SP(q,t) = SP^{RTP}(q,t) \tag{21}$$

Constraint (22) shows the balance of power associated with the retailer.

$$P_{PM}(t) + P_{buy,pro}(t) - P_{sell,pro}(t) = \sum_{q=1}^{Q} D(q,t) \tag{22}$$

3.2. lower level problem: energy procurement from the prosumers' aggregator point of view

At the lower level of the proposed structure in this paper, there is an aggregator of prosumers whose goal is to obtain the highest profit (lowest cost) to provide the required load demand from available resources. Therefore, the objective function (23) has defined for the prosumers' aggregator.

$$minC_{pro} = \sum_{t=1}^{T}\Big\{\sum_{j=1}^{J}(C_{DG_j}(t) - price_{buy,pro}(t)*P_{buy,pro}(t) + price_{sell,pro}(t)*P_{sell,pro}(t)\Big\} \tag{23}$$

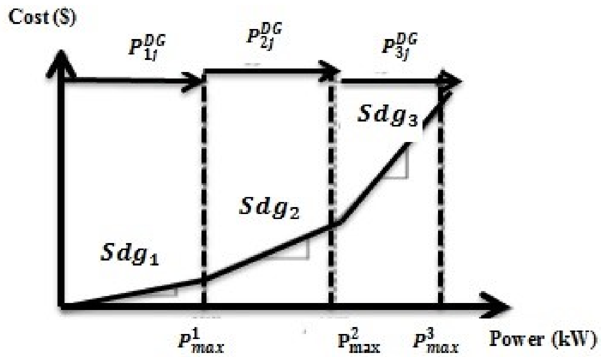

Fig. 3. Linear operation cost model of DG units [33].

Equations (24-26) have included the sales and purchasing limit of the retailer to/from the prosumers' aggregator and the impossibility of simultaneous buying and selling from the prosumers' aggregator in the model, respectively:

$$0 \le P_{sell,pro}(t) \le \alpha(t) * P_{sell,pro}^{max}(t) \tag{24}$$

$$0 \le P_{buy,pro}(t) \le \beta(t) * P_{buy,pro}^{max}(t) \tag{25}$$

$$0 \le \alpha(t) + \beta(t) \le 1 \tag{26}$$

Equations (27-28) show the limit of the seller's bid price for sale and purchase to the aggregator, respectively:

$$0 \le price_{sell,pro}(t) \le price_{sell}^{max} \tag{27}$$

$$0 \le price_{buy,pro}(t) \le price_{buy}^{max} \tag{28}$$

Conditions (29-31) related to DGs owned by prosumers' aggregator are [33]:

$$C_{DG_j}(t) = \sum_{h=1}^{N} S_{j,h}^{DG} * P_{j,h}^{DG}(t) \tag{29}$$

$$0 \le P_{j,h}^{DG}(t) \le P_{j,h}^{MAX} - P_{j,h-1}^{MAX} \quad , \ h = 2, \ldots, N \tag{30}$$

$$0 \le P_{j,1}^{DG}(t) \le P_{j,1}^{MAX} \tag{31}$$

Fig. 3 provides a better understanding of equations (29-31). Equation (32) has shown the amount of production capacity of wind power generation sources belonging to the aggregator of prosumers [33]:

$$P_k^{wind}(t) = \begin{cases} 0 & s.t: \ v^W(t) \le V_k^{ci} \\ P_k^r \left(\frac{v^W(t) - V_k^{ci}}{V_k^r - V_k^{ci}} \right) & s.t: \ V_k^{ci} \le v^W(t) \le V_k^r \\ P_k^r & s.t: \ V_k^r \le v^W(t) \le V_k^{co} \\ 0 & s.t: \ v^W(t) \ge V_k^{co} \end{cases} \tag{32}$$

Equation (33) has shown the amount of generating power of solar power generation sources (photovoltaic system) belonging to the prosumers' aggregator [34]:

$$P_g^{PV}(t) = \eta_g^{PV} * S_g^{PV} * \emptyset(t) * \left(1 - 0.005 \left(Te^{PV} - 25\right)\right) \tag{33}$$

Equations (34-39) for energy storage systems belong to aggregator [33]:

$$X_l(t_0) = X_0^l \tag{34}$$

$$P_l^{charge}(t) \le P_l^{charge,max} * U_l^{charge}(t) \tag{35}$$

$$P_l^{disc}(t) \le P_l^{disc,max} * U_l^{disc}(t) \tag{36}$$

$$X_l^{min} \le X_l(t) \le X_l^{max} \tag{37}$$

$$U_l^{charge}(t) + U_l^{disc}(t) \le 1 \tag{38}$$

$$X_l(t) = X_l(t-1) + \chi * P_l^{charge}(t) - \frac{P_l^{disc}(t)}{\eta} \tag{39}$$

The power balance constraint for the aggregator of prosumers has given in Equation (40):

$$\begin{aligned} &\sum_{j=1}^{J} \sum_{h=1}^{N} P_{j,h}^{DG}(t) + P_{sell,pro}(t) - P_{buy,pro}(t) \\ &+ \sum_{k=1}^{K} P_k^{wind}(t) + \sum_{g=1}^{G} P_g^{PV}(t) + \sum_{l=1}^{L} P_l^{disc}(t) \\ &- \sum_{l=1}^{L} P_l^{charge}(t) = P^{demand,pro} \end{aligned} \tag{40}$$

3.3. Simulation process

The algorithm of the proposed method is shown in Fig. 4. The proposed method to solve the problem has the following steps:

i. Initialization: Start the process with $iteration = 1$. Allocate the random values to $price_{buy,\ pro}(t)$, and $price_{sell,pro}(t)$ at the beginning of the process subject to constraints of Eqs. (13) and (14). Here, $price_{sell}^{max}$ and $price_{buy}^{max}$ are assumed to be 0.1 $/kWh.
ii. By solving the objective function (23) and according to the constraints (24) to (40), each prosumers' aggregator announces to the retailer the amount of power that can be sold or the amount of power that can be purchased from the retailer. At this stage, the prices received from the retailer are assumed to be fixed.
iii. The retailer according to the information received from the prosumers' aggregator and assuming the amount of power sold and purchased to/from the aggregator is constant, solving the objective function (8) according to the constraints (9) to (22) performs power management. After performing power management and considering the exchange of power with the prosumers' aggregator, it calculates its cost.
iv. The retailer uses the MO optimization algorithm to update the sale and purchase prices of power and inform the prosumers' aggregator to make a decision, with the aim of function (8) and according to the costs calculated in the previous step.
v. Updating of iteration number: At this step, if the maximum number of iterations is reached, stop. Else, go to Step ii.

4. Case Studies

In In this section, the proposed model is implemented on a sample network. The network includes a retailer, procumers aggregator, and three groups of price-sensitive consumers. The retailer buys power from the wholesale market to meet the consumption demand of its consumers and prosumers. The results of applying the proposed method using three pricing methods FP, TOU, and RTP have given below. Also, these results have been compared with the results of the centralized power management method. Also, to investigate the effectiveness of using the MO optimization algorithm in the proposed method, the results of using the MO algorithm have been compared with two optimization methods, PSO and HHO.

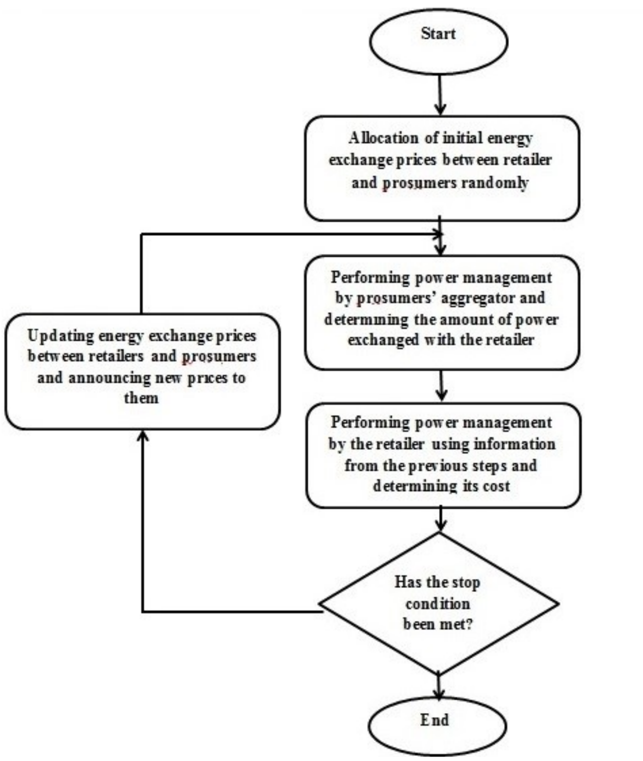

Fig. 4. The flowchart of the proposed algorithm

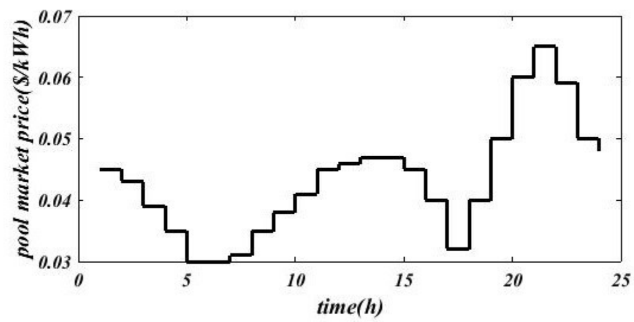

Fig. 5. Pool market price

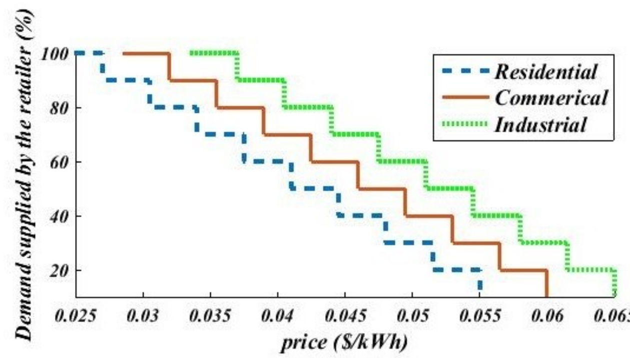

Fig. 6. Demand-price curve

4.1. Data

Fig. 5 showed the wholesale market prices. In this network, three groups of residential, industrial, and commercial consumers are considered. The consumer's load sensitivity to price is considered in a graph consisting of ten steps. Fig. 6 has shown the percentage of loads demanded by these consumers based on price. The prosumers' aggregator has used various sources in addition to exchanging energy with retailers to supply the consumption demand of its consumers. Fig. 7 showed the basic load of consumption of the three groups of consumers as well as the amount of a load of prosumers' aggregator. Information on DGs owned by prosumers has shown in Table 2. It also has shown information on wind generation sources, photovoltaic systems, and energy storage systems in Tables 3, 4, and 5, respectively. Meteorological information has shown in Table 6. Information on daily load classification at three levels of consumption for use in TOU pricing has shown in Table 7.

4.2. numerical results

In this section, the efficiency of the proposed algorithm has compared to a power management algorithm described in case 1. Based on our studies, in none of the previous studies, a structure similar to the structure presented in this article has not been used for short-term planning of retailers and prosumers aggregators. However, in references [30], and [33–35], a centralized power management structure is used to minimize retailer costs. Therefore, in this article for comparison, a centralized power management method is used from the point of view of the retailer as a central operator. Also, to find the best pricing method and evaluate price-based demand response programs, three pricing methods FP, TOU, and RTP have been used in the proposed algorithm.

Case 1. First, using the centralized power management method from the perspective of the retailer as a central operator to minimize the cost of the entire system, production and demand planning for the day ahead 24 hours are done. In this method, it is assumed that pricing to price-sensitive consumers is done in the form of FP. Also, the central operator is allowed to plan production resources and demand related to prosumers. Therefore, the difference between production and demand related to prosumers' aggregator is settled based on the prices of the pool market shown in Fig. 5. Accordingly, the amount of profit and loss of retailers and prosumers' aggregators is determined in this method.

Case 2a. FP pricing method has been used to determine to price for consumers and prosumers aggregator in the proposed algorithm.

Case 2b. TOU pricing method has been used to determine to price for consumers and prosumers aggregator in the proposed algorithm.

Case 2c. RTP pricing method has been used to determine to price for consumers and prosumers aggregator in the proposed algorithm.

The results of applying case 1, case 2a, case 2b, and case 2c on retailer and prosumer aggregator costs have shown in Table 8. The maximum number of iterations of the proposed algorithm has assumed to be 50. As it is clear from the results of the table, applying the proposed method using three pricing methods FP, TOU and RTP have caused the retailer to get out of the loss

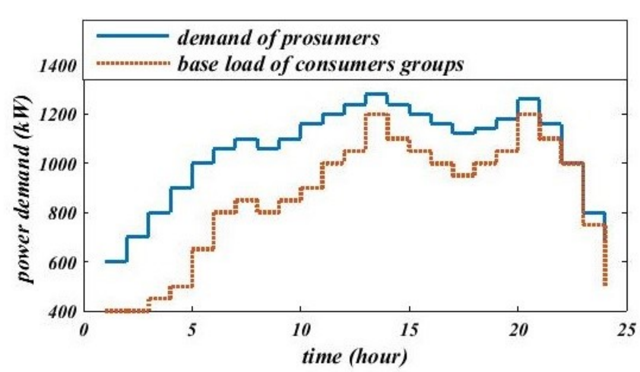

Fig. 7. Base load profile for retailer's consumers group and demand profile of the prosumers' aggregator

Table 2. The parameters data of the Distributed Generations (DGs)

Parameters	First DG	Second DG	Third DG	Furth DG	Units
Maximum power output	150	180	200	200	KW
Minimum power output	0	0	0	0	KW
S_1^{DG}	0.030	0.037	0.040	0.033	\$/KWh
S_2^{DG}	0.036	0.040	0.043	0.038	\$/KWh
S_3^{DG}	0.039	0.045	0.045	0.043	\$/KWh
P_1^{max}	60	80	100	100	KW
P_2^{max}	110	120	150	150	KW
P_3^{max}	150	180	200	200	KW

Table 3. The parameters data of the wind power producer

Parameters	Values	Units
Rated power	400	KW
Cut-in wind speed	3.5	m/s
Rated wind speed	10.5	m/s
Cut-out wind speed	20	m/s

situation in case 1. Therefore, in case 2a, case 2b, and case 2c, the retailer has earned \$193.36, \$206.78, and \$225.72, respectively. In the comparison between case 1 and our proposed method in this paper, the pricing ability of the retailer to the prosumer aggregator can be seen as the main reason for the difference in the much lower costs created for the retailer in the proposed method. Also, in the proposed method using RTP, a 3.8% lower cost is created for the prosumers' aggregator than the other two pricing methods. According to the results of the table, it is clear that the lowest cost or the highest profit for the retailer is obtained for the RTP, TOU, and FP respectively. To further explore the strategies adopted by the retailer and prosumers' aggregator, the final prices offered by the retailer to its consumers as well as how the energy is settled by the retailer and prosumers' aggregator are given below. Table 9 has shown the price offered by the retailer to three groups of consumers in case 1. Fig. 8 has shown the energy procurement strategy of retailers and prosumers' aggregators in the centralized power management method. According to the information in Table 9, the highest price has been offered to the group of industrial customers. Based on Fig. 6, it is clear that the group of industrial consumers has requested more load than the other two groups at the same price, so it is reasonable for the retailer to offer a higher price to this group. Therefore, it can be seen in Fig. 9 that the most power sold to consumers is related to industrial, commercial, and residential groups, respectively. It can also be seen from Fig. 9 that when the total amount of production from DG, PV, and wind power sources is at its lowest, the amount of purchase from the pool market is higher. Also, the discharge

Table 4. The parameters data of the PV system

Parameters	Values	Units
Capacity(KW)	550	KW
η^{PV}	15.7	%
S^{PV}	3500	m^2

Table 5. The energy storage system parameters data

Parameters	Values	Units
$X^{b,max}$	300	KW
$X^{b,min}$	30	KW
$P^{charge,max}$	180	KW
$P^{disc,max}$	180	KW
χ	90	%
η	90	%

Table 6. Forecasted daily wind speed, temperature and irradiation for a sample day

Time (h)	Wind speed (m/s)	Temperature (°C)	Irradiation (W/m^2)
1	10.5	24.7	0
2	13.5	24.5	0
3	14.9	24.3	0
4	15.6	24.4	0
5	19.5	24.5	93.5
6	20.6	26.5	219
7	14.4	27.5	467.5
8	14.1	28	637.5
9	11.3	28.5	780
10	9.7	28.8	916
11	7	29	1100
12	5.9	29.7	1033
13	8.9	29.8	850
14	9.5	30	680
15	10.4	29.8	595
16	8.8	29.5	255
17	7.1	29	212.5
18	8.3	27.7	153
19	9.9	26.5	63
20	7.5	24.8	0
21	8.8	25	0
22	9.8	24.8	0
23	9.2	24.6	0
24	8.4	24.8	0

Table 7. Classification of daily load levels

Level	Hours of the day
Low (L)	1, 2, 3, 4, 5, 6, 7, 8
Medium (M)	9, 10, 11, 12, 13, 14, 15, 16
Peak (P)	17, 18, 19, 20, 21, 22, 23, 24

of the energy storage system has occurred during hours with high energy prices in the pool market.

Table 10 shows the retailer pricing to prosumers' aggregator and the three groups of consumers using the FP method. Fig. 9 and. 10 have shown the retailer and prosumers aggregator energy procurement strategy in the FP method using the proposed algorithm, respectively. As can be seen from the figures, the prosumers' aggregator prefers to buy energy from the retailer during peak hours of the night, in the hours when the aggregator is short of power, based on the retailer's bid price to sell energy to prosumers' aggregator. This is also due to the high price offered by the retailer. Also, considering the retailer's offer price to buy power from the prosumers' aggregator, the aggregator prefers to choose the power sold to the retailer during off-peak hours, which is more economical for him. Also, the amount of power sold to residential, commercial, and industrial groups is selected from the lowest to the highest, respectively. This case can also be justified according to the price offered to the three groups of consumers by the retailer as well as the price-sensitivity figure of these consumer three groups. Fig. 10 also has shown how the prosumers' aggregator uses the available resources to supply the energy required

by their customer. One of the things that can be deduced from this figure is that the simultaneous use of wind and solar energy during the day under study has to some extent been able to complement each other to provide the power required by customers. Also, charging energy during off-peak hours and discharging it during higher price hours can have a positive effect on reducing the costs of prosumers.

Table 11 has shown the pricing of the retailer to its customers in the TOU pricing method. Fig. 11 and. 12 also show the energy procurement strategy of the retailer and prosumers' aggregator in the TOU pricing method, respectively.

Table 8. Cost of the retailer and prosumers' aggregator

Case	Retailer's cost ($)	Aggregator's cost ($)
Case 1	239.80	69.78
Case 2a (FP)	-193.36	542.38
Case 2b (TOU)	-206.78	542.38
Case 2c (RTP)	-225.72	521.53

Table 9. Retailer's pricing to the customers in the case1

Unit	Price of the energy selling to residential consumers	Price of the energy selling to commercial consumers	Price of the energy selling to industrial consumers
($/Kwh)	0.0515	0.0530	0.0545

As can be seen from the figures, power exchange is based on the retailer's bid prices at 6, 20, and 21 hours from the retailer to the aggregator. The aggregator also prefers to sell energy to the retailer only at 1 o'clock, based on the retailer's bid prices. Also, in most hours, according to the consumption- price figures of the three groups of consumers, the amount of power provided by the retailer between residential, commercial, and industrial consumers is from the lowest to the highest amount, respectively. Comparing Fig. 10 and. 12, it can be seen that the aggregator strategy is about the buying and purchasing capacity as well as the charging and discharging of the energy storage system and DG resources in two pricing modes FP and TOU vary in hours. However, the results in Table 8 show that this change in strategy did not change the aggregator costs in either case. However, the change in the retailer's pricing strategy and the consequent change in the customers' energy procurement strategy has increased the retailer's profit.

Table 12 has shown the retailer pricing to its customers in the RTP method using the algorithm proposed in this paper. Fig. 13 and 14 are related to the energy settlement strategy of the retailer and the prosumers' aggregator, respectively. Comparing Fig. 13 with Fig. 9 and. 11, it is clear that the possibility of more flexible retail pricing in the RTP method than the other two pricing methods, FP and TOU, has led to greater energy exchange between the retailer and the aggregator. Also, the change in pricing method has caused a change in the amount of purchases from the pool market. Also, the supply of power to three groups of consumers by retailers has increased. Also, the change in the use of energy storage systems and distributed generation resources by the prosumers' aggregator in the three pricing methods in Fig. 10,. 12, and. 14 is evident.

What can be said from the results of the tables and figures presented in this section, is that in general, the use of the RTP method using the proposed algorithm has generated the most profit for retailers and aggregators. This is due to the variation in prices offered to customers, which has led the prosumers' aggregator to use their available resources to better meet the demand of consumers.

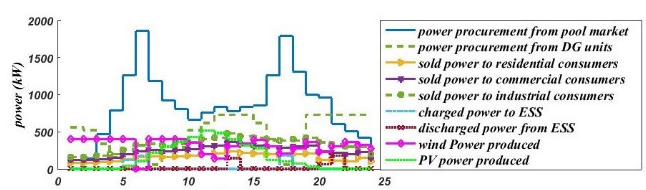

Fig. 8. The power procurement of retailer and prosumers' aggregator in case 1

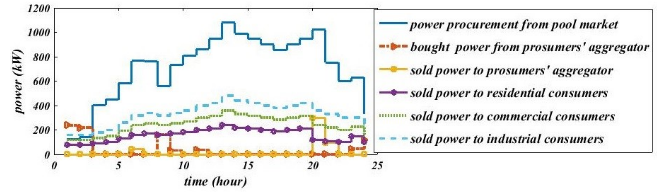

Fig. 9. The power procurement of the retailer in FP method (case 2a)

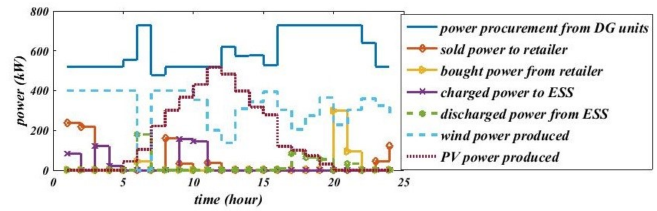

Fig. 10. The power procurement of the prosumers' aggregator in FP method (case 2a)

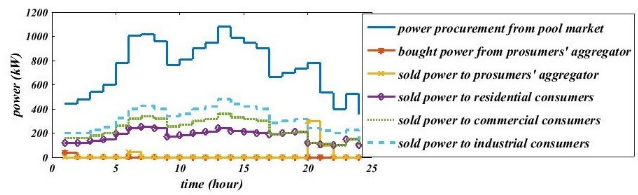

Fig. 11. The power procurement of the retailer in TOU method (case 2b)

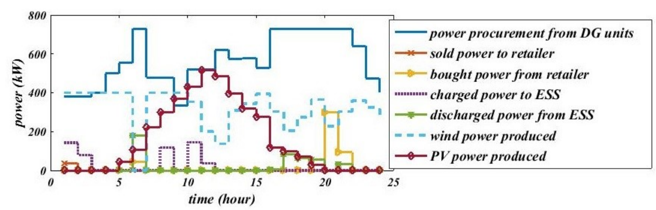

Fig. 12. The power procurement of the prosumers' aggregator in TOU method (case 2b)

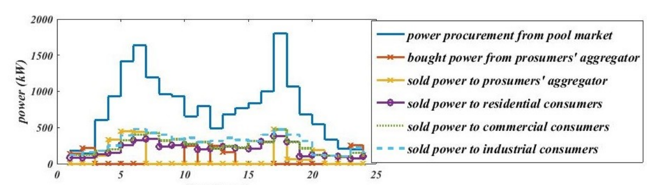

Fig. 13. The power procurement of the retailer in RTP (case 2c)

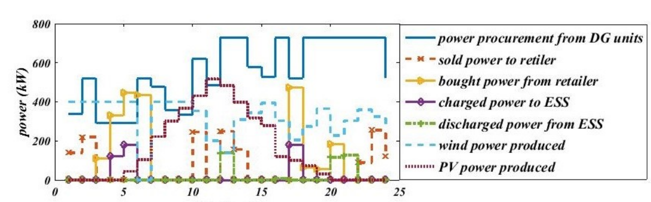

Fig. 14. The power procurement of the prosumers' aggregator in RTP method (case 2c)

Table 10. Retailer's pricing to the customers in the FP method (case 2a)

Unit	Price of the energy selling to aggregator	Price of the energy buying from aggregator	Price of the energy selling to residential consumers	Price of the energy selling to commercial consumers	Price of the energy selling to industrial consumers
($/Kwh)	0.1	0.0414	0.0515	0.0530	0.0545

Table 11. Retailer's pricing to the customers in TOU method (case 2b)

Daily load level	Price of energy selling to aggregator ($/Kwh)	Price of energy buying from aggregator ($/Kwh)	Price of energy selling to residential consumers ($/kwh)	Price of energy selling to commercial consumers ($/Kwh)	Price of Energy selling to industrial consumers ($/Kwh)
Low	0.0533	0.0314	0.0480	0.0495	0.0510

Table 12. Retailer's pricing to the customers in RTP method (case 2c)

Time (hour)	Price of energy selling to aggregator ($/Kwh)	Price of energy buying from aggregator ($/Kwh)	Price of energy selling to residential consumers ($/Kwh)	Price of energy selling to commercial consumers ($/Kwh)	Price of energy selling to industrial consumers ($/Kwh)
1	0.0461	0.0388	0.0515	0.0530	0.0580
2	0.0583	0.0411	0.0515	0.0530	0.0545
3	0.0366	0.0374	0.0480	0.0495	0.0545
4	0.0368	0.0403	0.0480	0.0495	0.0510
5	0.0372	0.0255	0.0445	0.0460	0.0475
6	0.0434	0.0668	0.0445	0.0460	0.0475
7	0.1	0.0405	0.0445	0.0460	0.0510
8	0.0422	0	0.0480	0.0495	0.0510
9	0.0442	0.0195	0.0480	0.0495	0.0545
10	0.0854	0.0435	0.0480	0.0530	0.0545
11	0.0525	0.0272	0.0515	0.0530	0.0580
12	0.0804	0.0521	0.0515	0.0565	0.0580
13	0.0634	0.0457	0.0515	0.0565	0.0580
14	0.0545	0.0429	0.0515	0.0565	0.0580
15	0.0618	0.0356	0.0515	0.0530	0.0580
16	0.0824	0.0265	0.0480	0.0530	0.0545
17	0.0417	0.0561	0.0445	0.0460	0.0510
18	0.0487	0.0569	0.0480	0.0530	0.0545
19	0.0539	0.0434	0.0550	0.0565	0.0580
20	0.0946	0.0245	0.0550	0.0600	0.0650
21	0.0958	0.0885	0.0550	0.0600	0.0650
22	0.0514	0.0470	0.0550	0.0600	0.0650
23	0.0790	0.0456	0.0550	0.0565	0.0580
24	0.0855	0.0405	0.0515	0.0565	0.0580

4.3. Comparing the results of using MO and other meta-heuristic algorithms in the proposed method

Given the advantages of MO compared to other meta-heuristic techniques [32], this paper emphasizes the use of MO in the proposed method. Nevertheless, the profit acquired by retailers using MO and other meta-heuristic algorithms in the proposed method for the 2a, 2b, and 2c cases are compared in Table 13. For comparison, in this section, Particle Swarm Optimization [36] and Harris Hawks Optimization (HHO) [37] have been used. The maximum number of iterations of these optimization algorithms is assumed to be 50. The results of this table show that, via employing MO as the optimization method of the proposed strategy, retailers earned higher total profits in FP and RTP pricing methods. However, the use of all three optimization algorithms in the TOU pricing method has given equal benefits to the retailer. In the FP pricing method, the use of the MO optimization algorithm in the proposed method has given retailers 0.3 and 0.8 percent more profit than the PSO and HHO algorithms, respectively. Also, in the RTP pricing method, the use of the MO optimization algorithm in the proposed method has provided retailers with 2.4 and 16.67 percent more profit than PSO and HHO algorithms, respectively.

Table 13. Comparing the profit of retailer using different optimization algorithms in the proposed method

Pricing methods	Using MO($)	Using PSO ($)	Using HHO($)
FP (case 2a)	193.36	192.59	191.64
TOU (case 2b)	206.78	206.78	206.78
RTP (case 2c)	225.72	220.42	193.46

4.4. Discussion

According to the review of the papers written by the researchers in the field of the day ahead planning of retailers and prosumers, there is a gap that can examine both the planning of retailers and prosumers aggregator in a short term. Therefore, in this paper, a bi-level structure is presented for the day ahead planning of these two participants in the smart grid environment. To compare the efficiency of the proposed method, a central power management model has been used to minimize the grid cost. Also, to compare FP, TOU, and RTP pricing methods, these three pricing methods to consumers and prosumers have been used in the proposed model. The results of the simulations have proven the effectiveness of the proposed method from the point of view of the retailer. This issue is because, in the proposed method, the possibility of pricing to consumers as well as prosumers is considered. Also, in the proposed method at a higher level, the profit of the retailer is considered as the target. Also, out of the three pricing methods, RTP, TOU, and FP have given the most profit to the retailer, respectively. This is also due to the RTP pricing method being more flexible than the other two methods. Also, to compare the efficiency of the MO optimization algorithm, the results of using this algorithm have been compared with the PSO and HHO algorithms. This comparison has also shown the effectiveness of the MO optimization algorithm.

5. Conclusions

This paper presents a bi-level structure for energy exchange between retailers and aggregators of prosumers, as well as energy procurement of these two participants of the electricity market for the day ahead. To solve the bi-level structure presented in this paper, the combined method of MILP and MO algorithm is proposed. In this paper, renewable energy sources, distributed generation resources, and energy storage systems are used to provide energy for the prosumers aggregator. To compare the effectiveness of the proposed method, a central power management method has been used as a benchmark. To use the telecommunication infrastructure of the smart grid to take advantage of the potential of price-based demand response programs, three pricing methods FP, TOU, and RTP have been used to offer the retail price to its consumers in the proposed model and their results have been compared with each other. The simulation results show that the retailer and aggregator of prosumers, if the RTP pricing method is used in the proposed model, will have more profit than the other two pricing methods, from the presence in a smart network environment. Since in this paper the uncertainties related to the production of renewable energy and the common market prices of power are not considered for the day ahead, the effects of these uncertainties can be considered in future studies. Also, in future studies, the planning of retailers and prosumers can be considered in the context of the electricity distribution network, so the effect of line restrictions can be analyzed in the obtained results. Also, due to the use of demand response programs in the planning of retailers and prosumers, the presence of these participants in the real-time and intra-day markets can be investigated.

REFERENCES

[1] H. Shayeghi, M. Alilou, "Multi-Objective Demand Side Management to Improve Economic and Environmental Issues of a Smart Microgrid," *J. Oper. Autom. Power Eng.* ,vol. 9, no. 3, pp.182-192, 2021.

[2] Y. Babaei Shahmars, J.Salehi, N. Taghizadegan Kalantari, "Bi-Level Unit Commitment Considering Virtual Power Plants and Demand Response Programs Using Information Gap Decision Theory," *J. Oper. Autom. Power Eng.*, vol. 9, no. 2, pp. 88-102, 2021.

[3] A. Gh. Azar, H. Nazaripouya, B. Khaki, C. Chu, R. Gadh, R. H. Jacobsen, "A Non-Cooperative Framework for Coordinating a Neighborhood of Distributed Prosumers," *IEEE Trans. Indus. Informatics*, vol. 15, pp. 2523-2534, 2019.

[4] H. Taherian, M. R. Aghaebrahimi, L. Baringo, S. R. Goldani, "Optimal dynamic pricing for an electricity retailer in the price-responsive environment of smart grid," *Int. J. Electr. Power Energy Syst.*, vol. 130, 2021.

[5] P. Dimitroulis, M. Alamaniotis, "A fuzzy logic energy management system of on-grid electrical system for residential prosumers," *Electr. Power Syst. Res.*, vol. 202, 2022.

[6] I. Wasiak, M. Szypowski, P. Kelm, R. Mieński, A. Wędzik, R. Pawełek, M. Małaczek, P. Urbanek, "Innovative energy management system for low-voltage networks with distributed generation based on prosumers' active participation," *Appl. Energy*, vol. 312,2022.

[7] E. Srilakshmi, S. P. Singh, "Energy regulation of EV using MILP for optimal operation of incentive based prosumer microgrid with uncertainty modelling," *Int. J. Electr. Power Energy Syst.*, vol. 134, 2022.

[8] S. Yin, Q. Ai, Z. Li, Y. Zhang, T. Lu, "Energy management for aggregate prosumers in a virtual power plant: A robust Stackelberg game approach," *Int. J. Electr. Power Energy Syst.*, vol. 117, 2020.

[9] Y. Xiao, X. Wang, P. Pinson, X. Wang, Transactive Energy Based Aggregation of Prosumers as a Retailer, *IEEE Trans. Smart Grid*, vol. 11, pp. 3302-3312, 2020.

[10] M. Ferrara, A. Violi, P. Beraldi, G. Carrozzino, T. Ciano, "An integrated decision approach for energy procurement and tariff definition for prosumers aggregations," *Energy Econ.*, vol. 97, 2021.

[11] G. Ma, J. Lyu, Y. Wang, J. Zhang and J. Xu, "The Prosumer Energy Management Method Based on Smart Load, *IEEE Access*, vol. 8, pp. 117086-117095, 2020.

[12] U. Mussadiq, S. Ahmed, N. Gul, J. Kim and S. M. Kim, "Priority-Based Energy Sharing and Management Among Prosumers in Smart Grids," *IEEE Access*, vol. 10, pp. 12179-12190, 2022.

[13] N. Liu, M. Cheng, X. Yu, J. Zhong , J. Lei, "Energy-Sharing Provider for PV Prosumer Clusters: A Hybrid Approach Using Stochastic Programming and Stackelberg Game," *IEEE Trans. Ind. Electron.*, vol. 65, pp. 6740-6750, 2018.

[14] G. Li, Q. Li, W. Song, L. Wang, "Incentivizing distributed energy trading among prosumers: A general Nash bargaining approach," *Int. J. Electr. Power Energy Syst.*, vol. 131, 2021.

[15] L. Ma, N. Liu, J. Zhang, L. Wang, "Real-Time Rolling Horizon Energy Management for the Energy-Hub-Coordinated Prosumer Community From a Cooperative Perspective," *IEEE Trans. Power Syst.*, vol. 34, pp. 1227-1242, 2019.

[16] T. Morstyn, M. D. McCulloch, "Multiclass Energy Management for Peer-to-Peer Energy Trading Driven by Prosumer Preferences," *IEEE Trans. Power Syst.*, vol. 34, pp. 4005-4014, 2019.

[17] M. Khorasany, A. Najafi-Ghalelou, R. Razzaghi, "A Framework for Joint Scheduling and Power Trading of Prosumers in Transactive Markets," *IEEE Trans. Sustainable Energy*, vol. 12, pp. 955-965, 2021.

[18] D. Kanakadhurga, N. Prabaharan, "Demand response-based peer-to-peer energy trading among the prosumers and consumers," *Energy Reports*, vol. 7, pp. 7825-7834, 2021.

[19] M. Mehdinejad, H. A. Shayanfar, B. Mohammadi-Ivatloo and H. Nafisi, "Designing a Robust Decentralized Energy Transactions Framework for Active Prosumers in Peer-to-Peer Local Electricity Markets," *IEEE Access*, vol. 10, pp. 26743-26755, 2022.

[20] B. Mao, D. Han, Y. Wang, X. Dong and Z. Yan, "Pricing mechanism for community prosumers in decentralized electricity market," *CSEE J. Power Energy Syst.*, 2015.

[21] S. M. Mousavi, T. Barforoushi, F. H. Moghimi, "A decision-making model for a retailer considering a new short-term contract and flexible demands," *Electr. Power Syst. Res.*, vol. 192, 2021.

[22] K. Wang , Z. Zhu, Z. Guo, "Optimal Day-Ahead Decision-Making Scheduling of Multiple Interruptible Load Schemes for Retailer With Price Uncertainties, *IEEE Access*, vol. 9, pp. 102251-102263, 2021.

[23] J. C. Do Prado, U. Chikezie, "A Decision Model for an Electricity Retailer With Energy Storage and Virtual Bidding Under Daily and Hourly CVaR Assessment," *IEEE Access*, Vol. 9, pp. 106181-106191, 2021.

[24] J. C. do Prado, W. Qiao, "A Stochastic Bilevel Model for an Electricity Retailer in a Liberalized Distributed Renewable Energy Market," *IEEE Trans. Sustainable Energy*, vol. 11, pp. 2803-2812, 2020.

[25] Y. Liu, D. Zhang and H. B. Gooi, "Data-driven decision-making strategies for electricity retailers: A deep reinforcement learning approach," *CSEE J. Power Energy Syst.*, vol. 7, no. 2, pp. 358-367, 2021.

[26] H. Xu, J. Wen, Q. Hu, J. Shu, J. Lu and Z. Yang, "Energy procurement and retail pricing of electricity retailers via deep reinforcement learning with long short-term memory," *CSEE J. Power Energy Syst.*, 2022.

[27] S. Nojavan, R. Nourollahi, H. Pashaei-Didani, K. Zare, "Uncertainty-based electricity procurement by retailer using robust optimization approach in the presence of demand response exchange," *Int. J. Electr. Power Energy Syst.*, vol. 105, pp. 237-248, 2019.

[28] R. Sharifi, A. Anvari-Moghaddam, S. Hamid Fathi, V. Vahidinasab, "A bi-level model for strategic bidding of a price-maker retailer with flexible demands in day-ahead

electricity market," *Int. J. Electr. Power Energy Syst.*, vol. 121, 2020.

[29] W. Sun, J. Zhang, P. Zeng, W. Liu, "Energy storage configuration and day-ahead pricing strategy for electricity retailers considering demand response profit," *Int. J. Electr. Power Energy Syst.*, vol. 136, 2022.

[30] A. S. Dagoumas, M. L. Polemis, "An integrated model for assessing electricity retailer's profitability with demand response," *Appl. Energy*, vol. 198, pp. 49-64, 2017.

[31] V. Grimm, G. Orlinskaya, L. Schewe, M. Schmidt, G. Zöttl, Optimal design of retailer-prosumer electricity tariffs using bilevel optimization," *Omega*, vol. 102, 2021.

[32] K. Zervoudakis, S. Tsafarakis, "A mayfly optimization algorithm," *Comput. Ind. Eng.*, vol. 145, 2020.

[33] S. Nojavan, K. Zare, "Interval optimization based performance of photovoltaic/wind/FC/electrolyzer/electric vehicles in energy price determination for customers by electricity retailer," *Solar Energy*, vol. 171, pp. 580-592, 2018.

[34] S. Zeynali, N. Rostami, A. Ahmadian, A. Elkamel, "Stochastic energy management of an electricity retailer with a novel plug-in electric vehicle-based demand response program and energy storage system: A linearized battery degradation cost model," *Sustainable Cities Soc.*, vol. 74, 2021.

[35] S. Nojavan, K. Zare, "Optimal energy pricing for consumers by electricity retailer," *Int. J. Electr. Power Energy Syst.*,vol. 102, pp. 401-412,2018.

[36] J. Kennedy and R. Eberhart, "Particle swarm optimization," *Proce. ICNN'95 - Int. Conf. Neural Net.*, vol.4, pp. 1942-1948, 1995.

[37] A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, H. Chen, "Harris hawks optimization: Algorithm and applications," *Future Generation Computer Systems*, Vol. 97, 2019,pp. 849-872, 2019.