Optimal Day-Ahead of Decision-Making Model for an Electricity Retailer Considering the Uncertainty in the Presence of Renewable Energy Sources

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ABSTRACT

The issue of the retailer's selling price based on three time-of-use (TOU) tariffs, fixed pricing (FP), and real-time pricing (RTP) in a microgrid with the presence of wind turbines, photovoltaics, distributed generation (DG), a hydrogen storage system (HSS), fuel cells, and plug-in electric vehicles (PEV), taking demand response program reviews into consideration, is discussed in this paper. The profit function is modeled based on the retailer's uncertainty using two models: deterministic (algebraic) optimization and multi-objective periodic optimization. This paper presents a Mixed Integer Linear Programming (MILP) planning model for periodic multi-objective optimization that can be addressed using the Pareto approach or weighted summation. To choose a suitable outcome from Pareto solutions, the fuzzy method is used. The CPLEX solver from the GAMS optimization package was used for this. The game theory technique is used to compare the outcomes of two deterministic and interval portions of a Mixed Integer Non-Linear Programming (MINLP) model that combines CPLEX and DICOPT solvers in the GAMS package to solve the model.

1. INTRODUCTION

Referencing [1] from the retailer's viewpoint, the strategy encourages customers to shift their purchases from busy periods to less busy times. This model's main objective is to offer a framework for merchants that, by participating in the pool market and bilateral agreements, win the happiness of customers and cause them to alter their desires. The most crucial objective is to offer a template for merchants that concur with the buyer throughout the pool market and bilateral contracts and want to modify their wishes. Researchers [2] have examined three different basic infrastructures that can be used to charge electric vehicles. The remaining two infrastructures were more expensive and more powerful. In addition, three specific intelligent charging approaches as well as the impact of these approaches on the realization cost and load index of the power system are examined separately. A stochastic programming method has been proposed by another group of researchers [3] for optimal programming of connected MG and RES with connected electric vehicles (PEV). They have utilized a variety of sources, including battery storage systems, microturbines, wind turbines, fuel cells, and solar photovoltaic systems. The MG was regarded as being powered by an upstream system when it was linked to the grid. The suggested stochastic optimization issue was resolved using an appropriate optimization technique, such as the modified harmonic search algorithm (MHS). In Ref. [4], The economic advantages of various charging techniques have been assessed by academics in light of various subsidy programs. They examine the pattern of shifting subsidy policies in the first stage and provide an overview of these policies for EVCI (Electric Vehicle Charging Infrastructure). Then, two various EVCI fabrication business models are assessed. Lastly, a case study comparing the advantages of three distinct charging methods based on cost-benefit analysis and EVCI subsidy schemes was conducted. Researchers looked at hybrid-electric cars connected to supply and demand schemes related to the grid in Ref. [5]. The charge was then scheduled and optimized using the ICA (Imperial Competitive Algorithm) and PSO (Particle Swarm Optimization) algorithms. In Ref. [6], it is said that this will both lower the cost of charging EVs and stop the distribution transformer from operating normally. Researchers have proposed an optimal charging strategy that is consistent with the Dynamic Spike Pricing (DSP) policy. In the first stage, they created electric car load models in four different types. Second, they created a new DSP strategy for transmitting high loads during rush hour based on the TOU approach. They have developed the best charging model to safeguard EV owners from different financial losses and avoid transformer overload in order to lower the cost of electric car charging. The model was solved using a genetic algorithm (GA) in the last stage. In summary, this study

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proposes an ideal charging approach and shows how it affects the correction peak and lowers charging costs. In Ref. [7], an island microgrid powered by EVs is suggested as a means of facilitating energy storage and supporting voltage management. In addition, they have proposed a control method for power distribution between each EV, and this procedure is simulated on a microgrid. The proposed controller can improve the stability along with the reliability of the microgrid. In reference [8], a model for studying the behavior of power market players is presented in a multilayered manner.

Reference [9] looks at how demand-side response systems are used and how consumer surveys affect consumers' ability to be flexible with their purchases. The majority of this study is conducted on the market and is done in real-time.

The distribution of ideal energy procurement plans from dispersed microgrid production sources and customer involvement in demand-side response initiatives to cut operational costs are provided in reference [10]. According to reference [11], the logical connection connecting energy production and consumption in the microgrid and energy exchange via the real-time market and the day-ahead market is crucial for optimizing retailer profitability.

The proposed strategy is based on consumer participation in retailer-monitored demand response programs and the availability of connected electric vehicles [11-12]. In reference [13], interactions in the energy market are discussed, and a best practice for selling in the marketplace using a pool and bilateral agreements to meet requirements is provided. Uses a robust and optimal approach to retailers' decisions in order to take into account uncertainties [14]. Examines retailer risk management issues in [15]. In reference [16], customer compensation methods and in reference [17] value and reliability indicators are examined by defining tariffs and the relationship between customers and retailers. A stochastic programming technique is employed in reference [18] to identify the best retail strategy, apply it in real-time, and maximize profit while lowering the risk to the retail organization. To ascertain the retailer's ideal approach using a stochastic reference planning framework in which the retailer minimizes risk by setting prices and offering power, see reference (19). Demand is influenced by a number of variables, including the time of day, the kind of consumers, and the weather, all of which may be forecasted utilizing actuarial methods or artificial intelligence algorithms like neural networks, fuzzy logic, and regression [21]. In accordance with the structure presented in the reference [22], the purchase cost of electricity for subscribers is determined using consumption-time charges. This framework is based on the medium-term random planning market. In the reference [22], retailers employ a variety of sources to satisfy their demand while being protected from the inherent hazards of the electrical marketplace. The reference [23] looks at how energy is obtained from various sources to increase retailer profitability. Reference [24] provides a structure for selecting how to obtain power using the subsequent agreements, with the aim of reducing the expense of supply to the local distribution company (LDC) by considering price limits: A fictitious LDC in the city of Florida is used in this reference. In the proposed model of this paper, which is solved as the MIP model in GAMS software, the electricity retailer's profit function, which is uncertain, is formulated based on a definite two-objective structure in addition to the average profit and its changes. According to this study, real-time pricing (RTP) provides higher average profits than constant prices and TOU (Time of Use Pricing). The decision for buying energy from POOL market, bilateral contract, renewable units, as well as the amount of customer demand met by the retailer and other related issues affecting the retailer's profit based on three types of RTP, TOU, and fixed are discussed in this study.

The Innovations of the paper are as follows:

1) It is suggested to use the interval optimization approach to simulate price uncertainty in the power market.

2) The function of profit based on the custom of uncertainty of sellers with the model of the target medium with the average profit and its changes They become a contradictory objective function.

The following suggestions that can be used to improve the article and to have more research in this field are as follows.

Use of other sources of new energy and other technologies of energy storage systems by retailers

Sell electricity to increase retailer profits

- Use of energy storage systems by electricity retailers to increase retailer profits
- Use other time-based burden response programs or incentives to increase retail profit Sale
- Use of other smart grid technologies to increase the profit of electricity retailers

Multi-level problem modeling with other market players in mind

Considering common interests as a constraint on the proposed optimization problem

2. INPUT DATA OF THE PROBLEM

The interval market price includes the highest price, the desired price, and the lowest price, which are shown in Figure (1). Figure (2) also shows the basic demand profile of the consumer. Lastly, the correlation between consumer demand and selling price is depicted in Figure (3). Retail price besides the demand supplied via retailer are determined according to this curve. In this curve, 100 stages are considered as step-price curve for all consumer.

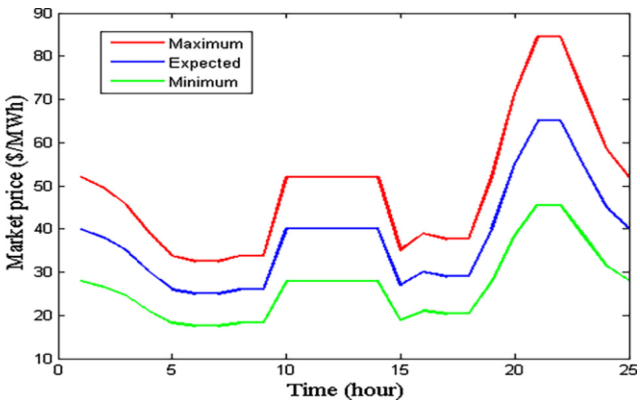


Fig. 1. Upper limit, lower limit, and projected price.

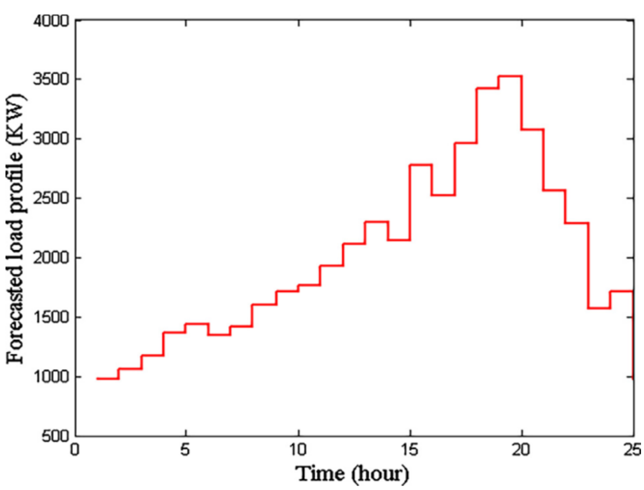


Fig. 2. Consumer predicted demand curve.

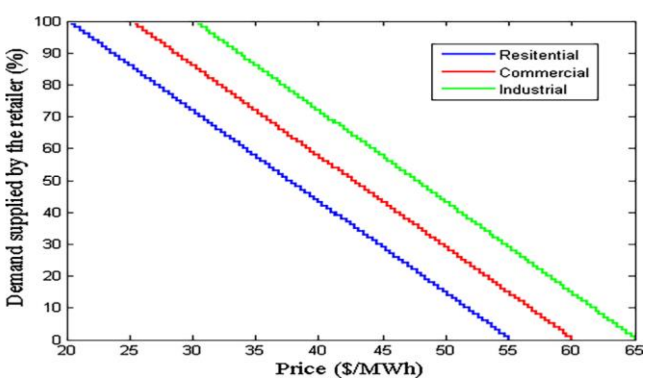


Fig. 3. Price-power curve.

Besides, Table 1 provides three levels of demand, including peak, medium besides low demand for demand of one day. Table 2 proposes data of bilateral contract. In Table 3 data of DG units shown. the predicted of radiation for one day and temperature like the daily wind speed. the parameters of the wind turbine and photovoltaic (PV) system depicted in table (5). Lastly, HSS and parameters of PEV shown in table (6) and (7) respectively.

Table 1. Grouping daily demand based on hours of day

Load Level	Hours
low load (L)	1،2،3،4،5،6،7،8
medium load (M)	9،10،11،12،13،14،15،16
peak load (P)	17،18،19،20،21،22،23،24

Table 2. Parameters of bilateral contract

Contract No.	Level of load	Maximum (kilowatt)	Minimum (kilowatt)	Price (dollar/kilowatt-hour)
One	low, medium and peak	50	15	0.04
Two	low, medium and peak	40	10	0.043
Three	low, medium and peak	50	15	0.05
Four	low, medium and peak	40	10	0.048
Five	low, medium and peak	70	25	0.032
Six	low, medium and peak	60	20	0.041
Seven	low, medium and peak	70	25	0.051
eighth	low, medium and peak	60	20	0.048
9	low, medium and peak	70	25	0.043
10	low, medium and peak	60	20	0.058
11	low, medium and peak	70	25	0.052
12	low, medium and peak	60	20	0.057

Table 3. Data for distributed generation

DG parameters	First DG	Second DG	Third DG	Units
Max for output power	150	180	200	kilowatt
Min for output power	0	0	0	kilowatt
S_1^{DG}	0.03	0.037	0.044	$/ kilowatt
S_2^{DG}	0.036	0.04	0.049	$/ kilowatt
S_3^{DG}	0.039	0.045	0.054	$/ kilowatt
P_1^{MAX}	60	80	100	kilowatt
P_2^{MAX}	110	120	150	kilowatt
P_3^{MAX}	150	180	200	kilowatt
MUT_j	2	2	2	hour
MDT_j	2	2	2	hour
R_j^{up}	80	90	100	kilowatt /h
R_j^{down}	80	90	100	kilowatt /h

Table 4. Predicted daily wind speed, temperature, and intensity of daily radiation for a day

Time (h)	Wind speed (m/s)	Temperature (℃)	Radiation intensity (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 5. Parameters of Wind turbine and PV system

Parameters of Wind turbine			Parameters of PV system		
Parameters of each one	Amount	Parameters Units	Parameters of each one	Amount	Parameters Units
P_r	1200	kW	$P^M_{Max,0}$	700	kW
V_{ci}	2	m/s	G_{a0}	1000	W/m^2
V_r	14	m/s	$T_{M,O}$	25	℃
V_{co}	25	m/s	NOCT	44	℃

Table 6. Hydrogen storage system parameters

Parameters	Amount	Units
P^{H2}_{max}‹P^{H2}_{min}	2 ‹13.8	Bar
$P^{H2}_{initial}$‹P^{H2}_{t0}	10 ‹10	Bar
P^{EL}_{max}‹P^{EL}_{min}	1.5 ‹6.2	kW
$N^{EL}_{H2,max}$	1.05	Nm^3/h
η^{EL}	55	%
N^{EL}	300	No.
LHV_{H2}	240	MJ/kmol
P^{FC}_{max}‹P^{FC}_{min}	0.5 ‹6	kW
$N^{FC}_{H2,max}$	3.9	Nm^3/h
η^{FC}	45	%
N^{FC}	300	No.
$\mathfrak{R}$	8.314	J/kmol
T_{H2}	313	K
V_{H2}	4	m^3

Table 7. Parameters of plug-in electric vehicles

Parameters	Amount	Units	Parameters	Amount	Units
Pc_v^{Min}	0	kW	η_v^c	90	%
Pc_v^{Max}	25	kW	η_v^d	90	%
Pd_v^{Min}	0	kW	SoC_v^{Min}	50	kWh
Pd_v^{Max}	25	kW	SoC_v^{Max}	1	kWh
Ω_v	0.1667	kW/km	N_v	30	No.

3. PROBLEM FORMULATION

For the definite optimization issue, an example of an optimization model may be given. It is crucial to remember that the optimization model is stated using the following formulae with equal and unequal restrictions on the appearance of an ambiguous parameter in the standard form structure:

$$Min\ f(Z,U,\rho) \tag{1}$$

$s.t.$

$$g(Z,U,\rho) = 0 \tag{2}$$

$$h(Z,U,\rho) \leq 0 \tag{3}$$

The interval optimization of the upper and lower bounds using the formula $\rho\epsilon U = [U^{Min}, U^{Max}$. In other terms, the ambiguous parameter ρ is referred to as a distance. With this approach, the goal function's upper and lower limits are determined because ρ is taken into account as $(f(z) \in [f^-(Z), f^+(Z)])$ rather than the uncertainty parameter. The primary goal function's upper and lower limits are computed using equations 4 and 5, respectively.

$$f^+(Z) = \max_{\rho\subseteq U} f(Z) \tag{4}$$

$$f^-(Z) = \min_{\rho\subseteq U} f(Z) \tag{5}$$

The interval parameter, which shifts into the form of a deterministic multi-objective model with an average amount of profit, causes the final objective function to have uncertainty and distance. It takes the shape of the opposite objective function of the average profit, whose change in profit should be minimized and whose maximum value should be sought. The model being suggested Equations 6–

8, which depend on the interval optimization strategy, state that the profit change is decreased till the store is resilient to the unpredictability of the market price.

$$Min\, f(z) = \min\,(-f^{M}(Z), f^{W}(Z)) \tag{6}$$

$$f^{M}(Z) = \frac{f^{+}(Z) + f^{-}(Z)}{2} \tag{7}$$

$$f^{W}(Z) = \frac{f^{+}(Z) - f^{-}(Z)}{2} \tag{8}$$

It should be noted that $(Z)f^{W}$ and $(Z)f^{M}$ are the average profit and changes in the profit of the electricity retailer, respectively.

3.1 Fuzzy method and weighted sum

The Pareto solution approach, the weighted method, the constraint method, or the multi-objective and distance-based objective function can all be used to solve it. The weighted sum approach is employed to resolve the suggested model. Finally, a suitable outcome is chosen from all Pareto solutions using the fuzzy technique. The calculated total technique employs a number of weighting coefficients depending on the significance of each objective function. As a consequence, the ultimate goal function for optimizing the multi-objective model using the calculated total method may be stated as follows:

$$MinOF = w_1 \times f^{M}(Z)_{pu} + w_2 \times f^{W}(Z)_{pu} \tag{9}$$

$$s.t.$$

$$\begin{cases} w_1 + w_2 = 1 \\ All\ equal\ \&inequal\ \ constraints \end{cases}$$

The two expressions$f^{W}(Z)_{pu} besides\ f^{M}(Z)_{pu}$show the average value of profit and the changes of profit in normalized form which are calculated based on the fuzzy method.

$$f^{M}(Z)_{pu} = \frac{f^{M}(Z) - f^{M}_{min}(Z)}{f^{M}_{max}(Z) - f^{M}_{min}(Z)} \tag{10}$$

$$f^{W}(Z)_{pu} = \frac{f^{W}_{max}(Z) - f^{W}(Z)}{f^{W}_{max}(Z) - f^{W}_{min}(Z)} \tag{11}$$

The minimum and maximum average profit and profit changes are first determined using the fuzzy logic weighted summation approach. The profit deviations and the normalized function of the average profit are then multiplied by various weighted factors, and the result is added as a distinct objective function. The next step is to change w1 and w2 between zero and one so that w1 + w2 = 1 to achieve Pareto solutions of the proposed function reduction (9).

The average profit amounts and profit variations for each repetition are computed and normalized in equations (10) and (11). In equation (12), the lowest normalized value is chosen in each iteration, and then, in accordance with equation (13), the highest value chosen between the minimal values is placed on the right answer for a number of goals of the proposed issue.

$$f^{n} = \text{minimum}(f^{n}_{1}, \dots, f^{n}_{N})\,;\ \forall\, n = 1, \dots, N_p \tag{12}$$

$$f^{max} = \text{maximum}(f^{1}, \dots, f^{N_p}) \tag{13}$$

The income less the cost, which must be taken out of equation (14) in the power market, is what makes up the retailer's gain in the smart network. The gain from the supply is the same as the customer demand times the selling price. Three tariffs—fixed pricing, TOU pricing, and real-time pricing—determine the sales price.

$$\begin{aligned} Maxf(x) = \sum_{t=1}^{T}\sum_{l=1}^{L} SP(l,t)D(l,t) \\ - \sum_{t=1}^{T} \lambda_t P^{P}_{t} \\ - \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{h=1}^{H} S^{DG}_{j,h} P^{DG}_{j,h,t} \\ - \sum_{b}^{B}\sum_{t=1}^{T} \lambda_{b,t} P_{b,t} \end{aligned} \tag{14}$$

The equilibrium power limits suggested by (15) should not prevent the retail profit function from being maximized.

$$\begin{aligned} \sum_{b=1}^{B} P_{b,t} + \sum_{j=1}^{J}\sum_{h=1}^{H} P^{DG}_{j,h,t} + P^{P}_{t} + P^{wind}_{t} + P^{PV}_{t} \\ + P^{FC}_{t} + \sum_{v=1}^{V} Pd_{t,v} \\ = \sum_{l=1}^{L} D(l,t) + P^{EL}_{t} \\ + \sum_{v=1}^{V} Pc_{t,v} \end{aligned} \tag{15}$$

Equation (16) displays the set 1 consumer revenue for period t, which was attained by satisfying consumer demand by selling energy to clients.

$$P_R(l,t) = SP(l,t)D(l,t) \tag{16}$$

Equations (17) and (18) illustrate, respectively, the prices associated with buying energy from the power market and through bilateral agreements.

$$C_P = \sum_{t=1}^{T} \lambda_t \times P_t \tag{17}$$

$$C_B = \sum_{b}^{B}\sum_{t=1}^{T}\lambda_{b,t}P_{b,t} \tag{18}$$

In addition to Equation (20), Equation (19) shows the allowable limits along with the power purchased from bilateral contracts.

$$P_b^{min}S_b < P_{b,t} < P_b^{max}S_b \tag{19}$$

$$P_t^{BC} = \sum_{b=1}^{B}P_{b,t} \tag{20}$$

It must be mentioned that method of linear piecewise modeling for distributed generation units should also be considered [29]. The function models the operating cost of DG units in Equation (21) using technical constraints (22-29).

$$C_{DG} = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{h=1}^{H}S_{j,h}^{DG}P_{j,h,t}^{DG} \tag{21}$$

$$0 \le P_{j,h,t,s}^{DG} \le P_{j,h}^{MAX} - P_{j,h-1}^{MAX} \tag{22}$$

$$0 \le P_{j,1,t}^{DG} \le P_{j,1}^{MAX} \tag{23}$$

$$\sum_{h=1}^{H}P_{j,h,t}^{DG} - \sum_{h=1}^{H}P_{j,h,t-1}^{DG} \le R_j^{up} \times U_{j,t}^{DG} \tag{24}$$

$$\sum_{h=1}^{H}P_{j,h,t-1}^{DG} - \sum_{h=1}^{H}P_{j,h,t}^{DG} \le R_j^{down} \times U_{j,t-1}^{DG} \tag{25}$$

$$U_{j,t}^{DG} - U_{j,t-1}^{DG} \le U_{j,t+Up_{j,i}}^{DG} \tag{26}$$

$$U_{j,t-1}^{DG} - U_{j,t}^{DG} \le 1 - U_{j,t+Dn_{j,i}}^{DG} \tag{27}$$

$$Up_{j,i} = \begin{Bmatrix} i & i \le MUT_j \\ 0 & i > MUT_j \end{Bmatrix} \tag{28}$$

$$Dn_{j,i} = \begin{Bmatrix} i & i \le MDT_j \\ 0 & i > MDT_j \end{Bmatrix} \tag{29}$$

Equations (22) and (23) in above constraint bound the purchasing power from distributed generation units. Constraints (24) besides (25) also show the increasing or decreasing production limit. Besides, the minimum increase/decrease time frames are explained by (26) and (27). Finally, approximate parameters are defined using constraints (28) and (29) to provide a linear model of the minimum DG increase/decrease time frames.

Power purchases from wind turbines [30] and photovoltaic systems [31] are calculated with constraints (30) and (31).

$$P_t^{wind} = \begin{cases} 0 & V_t^w < V_{ci} \\ P_r \times (\dfrac{V_t^w - V_{ci}}{V_r - V_{ci}}) & V_{ci} < V_t^w < V_{cr} \\ P_r & V_r < V_t^w < V_{c0} \\ 0 & V_t^w > V_{c0} \end{cases} \tag{30}$$

$$P_t^{PV} = \frac{G_t^a}{G_{a0}} \times \Big\{P_{Max,0}^{M} + \mu_{Pmax} \times (T_t^a + G_t^a \times \frac{NOCT - 20}{800} - T_{M,0}\Big\} \tag{31}$$

In addition to plug-in electric vehicles, retailers may manage energy utilizing clever charging and discharging devices that use hydrogen as a fuel.

Equations of 32-38 give technical scope for plug-in electric vehicles [32], and Equation (32) shows the SOC of PEV at beginning time (SOC initial time). Equation (33) provides SOC of PEV that is used for any plug-in electric vehicle at any desired time. Inequality constraint in (34) shows the up and low bounds for SOC of PEV. Equation (35) depicts energy needed to move a plug-in electric vehicle. The charge besides discharge power ranges for PEV given in inequality constraints (36) & (37). Lastly, constraint (38) limits the modes of charging and discharging of PEV in binary form which cannot operate at the same time.

$$SOC_{t0,v} = E_v^0 \tag{32}$$

$$SOC_{t,v} = SOC_{t-1,v} + \eta_v^c \times Pc_{t,v} - \frac{Pd_{t,v}}{\eta_v^d} - Ptr_{t,v} \tag{33}$$

$$SOC_v^{Min} \le SOC_{t,v} \le SOC_v^{Max} \tag{34}$$

$$Ptr_{t,v} = \Delta D_{t,v} \times \Omega v \tag{35}$$

$$Pc_v^{Min} \times Uc_{t,v} \le Pc_{t,v} \le Pc_v^{Max} \times Uc_{t,v} \tag{36}$$

$$Pd_v^{Min} \times Uc_{t,v} \le Pd_{t,v} \le Pd_v^{Max} \times Uc_{t,v} \tag{37}$$

$$Uc_{t,v} + Ud_{t,v} \le 1 \tag{38}$$

The energy storage system has been studied in [32]. It must be mentioned the electrolyzer system, the hydrogen tanks besides fuel cells are the key elements of HSS. equations (39-51) give technical scope of HSS [32].

Electrolyzers utilise electric electricity during off-peak hours to create hydrogen molecules that are then stored in hydrogen tank systems. Equations (39) besides (40) are constraints showing min and max power consumed by electrolyzer system. Equation (41) limits producing the Molar of hydrogen. lastly, Equation (42) presents relationship among molar of hydrogen produced besides power consumed by electrolyzer system [32].

$$P_t^{EL} \leq P_{max}^{EL} \times U_t^{EL} \tag{39}$$

$$P_t^{EL} \geq P_{min}^{EL} \times U_t^{EL} \tag{40}$$

$$N_{H2,t}^{EL} \leq N_{H2,max}^{EL} \times U_t^{EL} \tag{41}$$

$$N_{H2,max}^{EL} = \frac{\eta^{EL} P_t^{EL}}{LHV_{H2}} \tag{42}$$

Also, the initial pressure equations (43-45) are related to constraints for max and min of the hydrogen tanks system. [32]

$$P_{t0}^{H2} = P_{initial}^{H2} \tag{43}$$

$$P_t^{H2} \leq P_{max}^{H2} \tag{44}$$

$$P_t^{H2} \geq P_{min}^{H2} \tag{45}$$

Moreover, fuel cell during peak period produces power required when hydrogen that is stored in tank of hydrogen is used. Constraint (46) gives maximum amount hydrogen in molar unit which is consumed in a fuel cell. Similarly, relationship among molar hydrogen consumption and production capacity in fuel cell is depicted in (47) [32]. Equations (48) and (49), which are related, represent the highest value and lowest consumption of electricity in fuel cells.

$$N_{H2,t}^{FC} \leq N_{H2,max}^{FC} \times U_t^{FC} \tag{46}$$

$$N_{H2,t}^{FC} = \frac{P_t^{FC}}{\eta^{FC} LHV_{H2}} \tag{47}$$

$$P_t^{FC} \leq P_{max}^{FC} \times U_t^{FC} \tag{48}$$

$$P_t^{FC} \geq P_{min}^{FC} \times U_t^{FC} \tag{49}$$

It should be noted that fuel cells and electrolyzers in HSS must not work sat the same time for producing power consumption (in charge or discharge state). So, the constraint (50) bounds charging and discharging of binary mode, which cannot work at the same time. Lastly, the constraint (51) shows HSS pressure in the form of dynamic model.

$$U_t^{EL} + U_t^{FC} \leq 1 \tag{50}$$

$$P_t^{H2} = P_{t-1}^{H2} + \frac{\Re T_{H2}}{V_{H2}} (N_{H2,t}^{EL} - N_{H2,t}^{FC}) \tag{51}$$

Consumers are flexible about the actual selling price by the seller. Therefore, consumers use more energy at lower prices and conversely. As a result, a price and power curve across the time frame for the retailer to purchase the demand (D (l, t)) is shown in Figure (2). The store then modifies the quantity of consumer demand in accordance with the price-power curve and chooses the appropriate price, exactly like in real-time pricing.

Equations (52)-(55) are used by the retailer to determine supply and demand, which are functions of the selling price and the existing price for the consumer group.

$$D(l,t) = \sum_{z=1}^{Z} D^{offer}(l,z,t) A(l,z,t) \tag{52}$$

$$SP(l,t) = \sum_{z=1}^{Z} SP(l,z,t) \tag{53}$$

$$\begin{aligned} SP^{offer}(l,t)A(l,z,t) \leq SP(l,z,t) \\ \leq SP^{offer}(l,z \\ -1)A(l,z,t) \end{aligned} \tag{54}$$

$$\sum_{z=1}^{Z} A(l,z,t) = 1 \tag{55}$$

Due to limitations, the selling price in the proposed model is determined by the retailer on an hourly basis, which is similar to real-time pricing (56); similarly, the selling price can be defined in a set price under restrictions (57); and finally, the selling price can be applied to both average peak and low demand periods. Demand response programs and demand-side consumption management can be implemented to increase the retailer's desired profit and courier management.

$$SP(l,t) \leq SP^{RTP}(l,t) \tag{56}$$

$$SP(l,t) \leq SP^{Fixed}(l,t) \tag{57}$$

$$\begin{aligned} SP(l,t) \\ = \begin{Bmatrix} SP_L^{TOU}(l) & for & t \in low\ load\ level \\ SP_M^{TOU}(l) & for & t \in medium\ load\ level \\ SP_P^{TOU}(l) & for & t \in peak\ load\ level \end{Bmatrix} \end{aligned} \tag{58}$$

The interval multi-objective optimization model, which is a MIP model, has been used to simulate the issue of pricing definition by the retailer in the presence of PEV and ESS. The CPLEX solver [33] inside the optimization program GAMS [34] resolves this issue.

4. 4. SIMULATION AND ANALYSIS OF RESULTS

4.1 Deterministic and fuzzy model results

Real-time pricing is based on equation (14) (the goal function) and restrictions (15)–(58) of outcomes, as stated in Table (8). This is done by constructing a deterministic model for the study network in three fixed pricing modes. According to this data, a retailer's average profit under a fixed-price tariff is $1511.79. Similarly, because time-of-use pricing was more in line with reality than fixed pricing, the average retail profit in this mode was $1560.149, which is 3.19% higher profit than the predetermined cost. Finally, real-time pricing made greater sense than constant or time-of-use pricing given the circumstances. In real-time pricing, the mean retail profit was therefore $1589.822, or 5.16% higher than the preset cost.

Table 8. Results for deterministic model

Parameters	Fixed	TOU	RTP
Cost of purchasing from Pool Market ($)	432.1069	429.7096	569.377
Cost of Purchasing from Bilateral Contracts ($)	139.77	117.2662	78.90057
Cost of Purchasing from DG Units ($)	146.1255	150.5467	126.899
Total Purchased Cost ($)	718.0024	697.5225	775.1766
Total Revenue ($)	2231.268	2259.028	2366.878
Deviation profit ($)	132.9599	131.5935	174.2948
Average Profit ($)	1511.79	1560.149	1589.822
Total profit increment (%)	0	3.198819	5.161596

Also, by executing the fuzzy model and the resulting beam-like loop and the table of results in each step are as Figure (4) and table (9) (bold points represent the optimal point selected based on the beam curve and the information of the above points is specified shown in bold in the table).

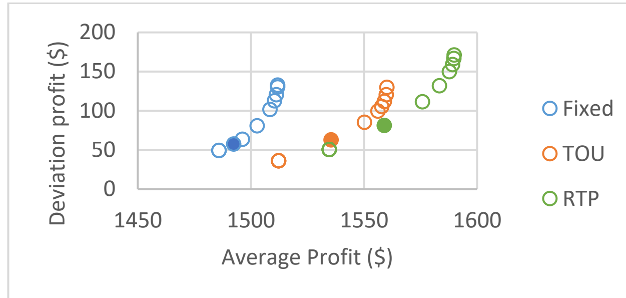


Fig. 4. The beam responses are obtained according to multi-objective interval approach.

The average retailer's profit for fixed pricing based on Pareto solutions and choosing the right solution is $1492/4119, while the change in retailer's profit is $57.1577, which is shown in Figure (4) and Table (9). The average retailer's profit is reduced by 1.36% compared to the deterministic fixed pricing approach, while the profit variation is reduced by more than 56.82%. Average retailer profit based on time-of-use pricing was $1,535.65, while profit variation was $62.86. In comparison to time-of-use pricing's actual performance, the average retailer's profit is down 1.21%, and the profit change is down more than 52.67%. The average merchant now makes more money than they did with fixed pricing because of the advantages of time-of-use pricing.

Table 9. Beam responses according to the interval optimization method

		Fixed pricing				TOU pricing				RTP pricing			
W1	**W2**	**F_M**	**F_W**	**F_M_PU**	**F_W_PU**	**F_M**	**F_W**	**F_M_ PU**	**F_W_ PU**	**F_M**	**F_W**	**F_M_ PU**	**F_W_ PU**
1	0	1511.796 6	132.9599 0	1.000258 6	1.08607E -	1560.1	129.98	1.0000	0.0169	1589.8	171.35	0.9999	0.0237
0.9	0.1	1511.747 3	130.5425 2	0.998347 8	0.028859 2	1559.8	120.57	0.9934	0.1157	1589.7	166.84	0.9971	0.0602
0.8	0.2	1511.219 0	120.6355 6	0.977896 9	0.147125 8	1558.9	111.98	0.9745	0.2060	1589.0	158.86	0.9856	0.1247
0.7	0.3	1510.348 8	112.6891 2	0.944207 5	0.241988 3	1557.8	105.60	0.9520	0.2731	1587.7	150.08	0.9617	0.1958
0.6	0.4	1508.352 8	101.7430 5	0.866933 3	0.372659 5	1556.1	99.536	0.9170	0.3369	1583.3	132.17	0.8824	0.3405
0.5	0.5	1502.807 8	80.98231 0	0.652259 8	0.620495 7	1550.2	85.544	0.7935	0.4840	1575.8	111.51	0.7459	0.5077
0.4	0.6	1496.227 5	63.69097 5	0.397504 0	0.826915 1	**1535.5**	**62.863**	**0.4874**	**0.7224**	**1559.1**	**81.081**	**0.4428**	**0.7538**
0.3	0.7	**1492.411 9**	**57.15770 0**	**0.249787 0**	**0.904907 5**	1512.1	36.454	0	0.9999	1534.6	50.632	0.0002	1.0000
0.2	0.8	1485.96	49.19230 3	0	0.999996 3	1512.1	36.454	0	0.9999	1534.6	50.628	0	1.0001
0.1	0.9	1485.96	49.19230 3	0	0.999996 3	1512.1	36.454	0	0.9999	1534.6	50.628	0	1.0001
0	1	1485.96	49.19230	0	0.999996	1512.1	36.454	0	0.9999	1534.6	50.622	0	1.0001

			3		3								

The average retailer's profit, when using real-time pricing, is $1559.1, although the profit changed by $81,081. Real-time pricing results in a profit reduction for the average retailer of 1.07% compared to the deterministic method and a profit variation reduction of more than 53.45%. Comparing real-time pricing to immediate pricing and fixed pricing, the retailer's average profit has improved. The average profit of the retailer may be assessed to see if it exceeds the industry average by comparing the suitable solutions acquired in time-of-use pricing and instant pricing. It is now higher than fixed pricing by 4.30% and time-of-use pricing by 1.54%. In general, it means that the retailer's resistance is greater than the power market price since the interval optimization approach models the uncertainty better than the algebraic method does.

It is evident that 8 points are optimal for the fixed model iteration (i.e., weight 0.3 for the mean value and 0.7 for the deviation value), and 7 points are optimal for TOU and RTP iteration (i.e., weight 0.4 for the mean value and 0.6 for the deviation value).

4.2 Results from fixed pricing, time of use pricing and real-time pricing

In order to compare the outcomes of the interval optimization approach based on the suggested uncertainty with the deterministic method based on fixed, time of use, and real-time pricing, Figures (5) through (15) are provided. Figure (5) illustrates how the demand of the client is fulfilled using the sub-method in the deterministic approach as well as the interval optimization technique in accordance with fixed pricing, prices at the time of use pricing, and real-time pricing. This graph shows which demand profiles are more suited to real-time than fixed and time-of-use pricing since there is less demand provided at peak periods, which is advantageous for retailers in bilateral contracts. Therefore, the average profit from real-time pricing is larger than that from fixed and time-of-use pricing, which is also suitable for retailers. Finally, it can be shown that the interval optimization approach's ability to meet demand has been shown to be less effective than the deterministic method, leading to an increase in selling price. Additionally, comparative outcomes for buying energy from the electrical market using bilateral contracts, distributed generation units, an interval-based optimization strategy, a deterministic method based on fixed time-of-use, and real-time pricing are shown in Figures (6) through (8). Real-time energy sales to the upstream grid outpace both fixed pricing and time-of-use pricing in terms of the amount of energy sold. As shown in Figures (7) and (8), the power purchased through bilateral agreements and distributed generation units in the interval optimization method has increased compared to the deterministic method, while the energy purchased from the electricity market in the interval optimization method has decreased compared to the deterministic approach due to the management of market price uncertainty. Additionally, Figures (9) and (10) compare the outcomes of fixed pricing, time-of-use pricing, and real-time pricing using the interval optimization approach that has been described in addition to a deterministic method for industrial and residential users. It can be seen from Figures (9) through (10) that real-time pricing, which is ideal for both consumers and retailers, is significantly more accurate than the time of use and set pricing. In comparison to the time of use and set pricing, the real-time pricing strategy has generally boosted the retailer's profit. Additionally, it may be shown that the interval optimization strategy has a somewhat higher real-time, time-of-use, and fixed price than the deterministic method for modeling the market's uncertainty by retailers. Last but not least, compared to the deterministic technique, the average merchant profit has marginally dropped in interval optimization. Retailers have intensified their resistance to the unpredictable market pricing environment despite the substantial fall in profit changes. Figures (11), which examine the outcomes of PEVs' charging and discharging capacities and SOC for interval optimization and deterministic methods based on fixed pricing, time of use pricing, and real-time pricing, respectively.

- Demands supplied by the retailer:

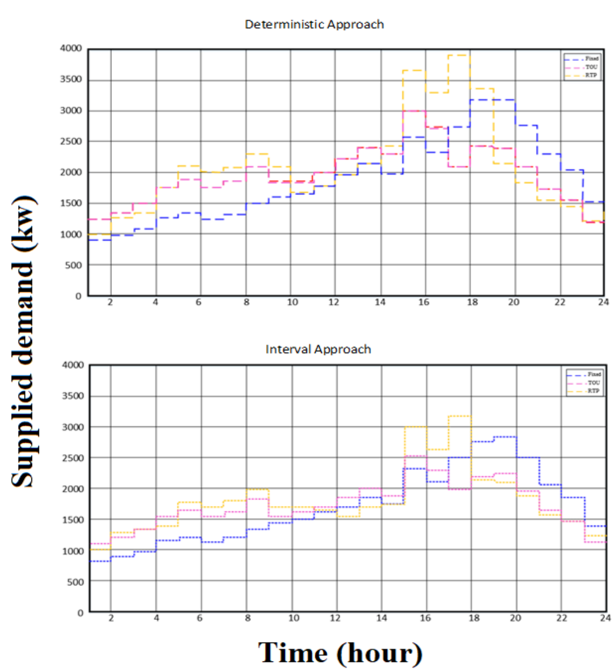


Fig. 5. The amount of demand supplied by the retailer.

- Power purchased from the market:

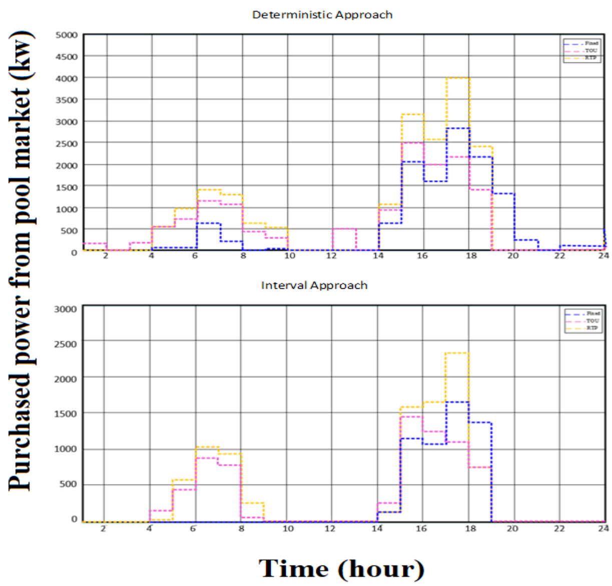


Fig. 6. Energy purchased from the market.

- Purchased power according to bilateral contracts:

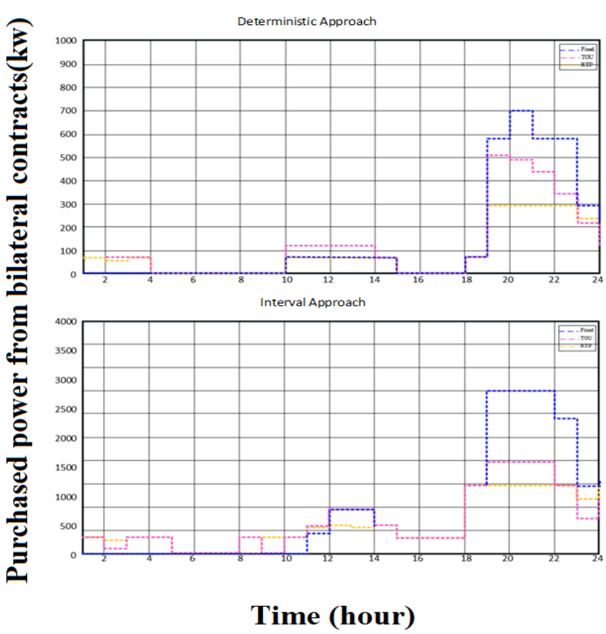


Fig. 7. Energy purchased under a bilateral agreement.

- Power purchased from power plants:

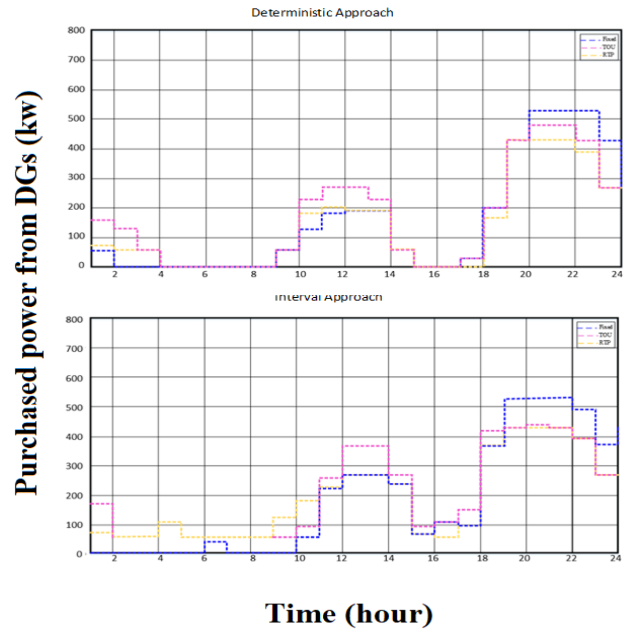
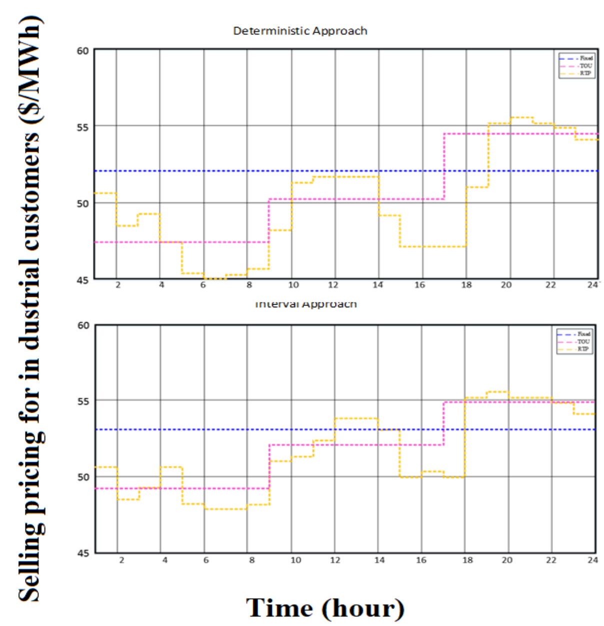


Fig. 8. Energy purchased from distributed generation units.

- The Electricity sale price for industrial use:



Fig, 9. Energy selling price for industrial subscribers.

- The electricity sale price for household use:

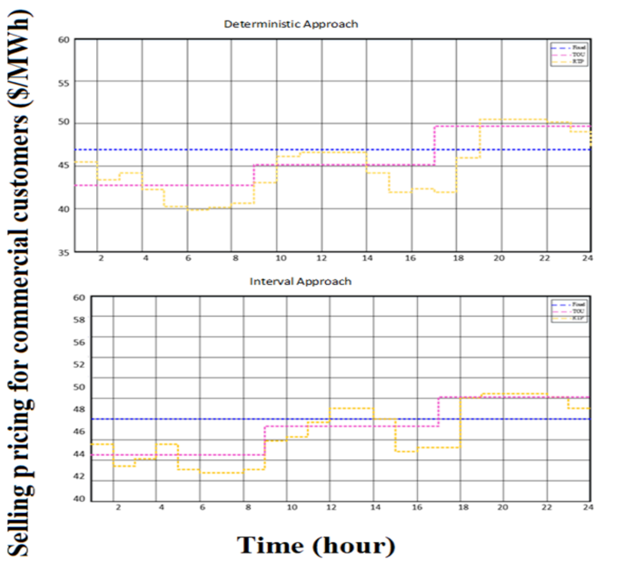


Fig. 10. Energy selling price for home subscribers.

- Charging and discharging rate of plug-in electric vehicles:

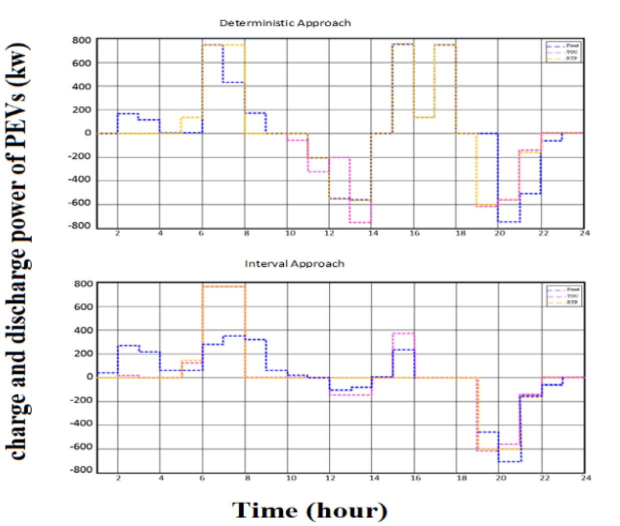


Fig. 11. Charge and discharge rates for plug-in electric vehicles.

4.3 Game Theory Method

In this part of the article, the game theory algorithm is shown for comparison with the results of the previous section (deterministic and interval methods). The steps in this section are shown in Figure (12). In step (1) of this part, the formulation of each of the objective functions is determined based on game theory, which includes two deviations and mean functions. Each function has a linear objective function with several equal and unequal constraints whose general form is displayed. In order to equalize the value of different functions, in step (2), maximum and minimum values of each function have specified and normalized using the definition of normalization. In step (3), each of the functions determines its profit-making programming separately. Then, in step (4), the maximum value obtained in the profit game for each function is determined according to the solution for the other function. In the step (5), the most pessimistic value of each function is determined. In step (6), the maximum multiplication of the deviation of each function relative to the pessimistic value is attempted by determining the most pessimistic value of each function. The best value of each function and related programming is determined in step (7) by solving the above problem.

Flowchart of multi-objective problem-solving steps based on game theory method

Step 1: A multi-objective MIP of the form:

$$\min\left\{f_1(x),\ldots,f_p(x)\middle|f(x)=c^T X, AX\le b, EX=d\right\}$$

Step 2: Normalize the objective functions:

$$f_i(x)\in\left[f_i^{\min},f_i^{\max}\right]$$

$$f_i(x)\xrightarrow{normalize}F_i(x)$$

Step 3: **For** $i=1,\ldots,p$ **do**:

$$\min\left\{F_i(x)\middle|AX\le b, EX=d\right\}$$

To get solution x_i^*

Step 4: **For** $i=1,\ldots,p$ **do**:

$$F_i^w=\max_{1\le j\le p}F_i\left(x_j^*\right)$$

Step 5: Set $S=\prod_{i=1}^{p}\left[F_i^w-F_i\left(x\right)\right]$

Step 6: Maximize S by solving following problem:

$$\max\left\{S\middle|AX\le b, EX=d\right\}$$

Step 7: Return efficient solution

The following model shows that, in contrast to the basic functions, which are Mixed Integer Linear Programming (MILP), the ultimate model of game theory is mixed integer non-linear programming (MINLP). In the simulation, CPLEX and DICOPT solvers are employed, respectively, to solve each issue.

4.3.1 Programming Constraints

Various programming constraints include network security constraints and restrictions on the operation of various equipment. Among the above constraints, one of the most critical constraints is how the retailer offers the price and the suggestion of purchasing/selling. In order to use the linear model, the linear piecewise model has been used to model the sensitivity between price and energy. Figure 12. shows the general structure of the method:

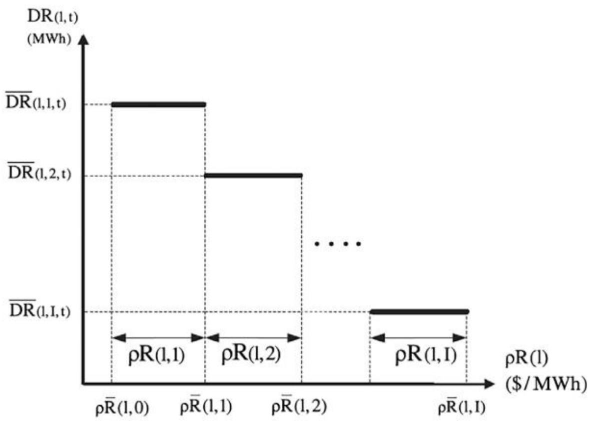


Fig. 12. Price offer curve by retailer.

The nonlinear price curve was used in the model used and to simulate the number of 100 steps for modeling.

4.3.2 Game theory simulation result

In this part, results for the simulation are presented in two multi-objective modes using weight sum method and game theory and finally, the results of the operation of the equipment are shown using the game theory method. The examined modes are shown in Table (10).

Table 10. Reviewed modes

Mode number	Pricing type	Multi-purpose solving method
1	Fix	Min-Max Fuzzy
2	TOU	Min-Max Fuzzy
3	RTP	Min-Max Fuzzy
4	Fix	Game Theory
5	TOU	Game Theory
6	RTP	Game Theory

4.3.3 Fixed pricing mode

In this case, the beam bound table obtained in the fuzzy state is formed based on consecutive iterations in the table, and the optimal point is determined based on the fuzzy satisfaction condition. Also, in the case of using the game theory model, in case the model is solved only once, the answer obtained is shown in Table (11). The values of the two mean and deviation objective functions are 1492.412 and 57.158, respectively, in mode 1 and are equal to 1462.801 and 31.622 for mode 4. It is clear that in the game theory mode, with a decrease of 1.98% in the average profit, the deviation from the answer has decreased to 44.67%. As a result, the game theory model has achieved lower profits with less risk.

Table 11. Results of the first and fourth modes

	Average function amount	Deviation function amount	Total profit of the retailer ($)
Mode 1	1492.412	57.158	1493.024
Mode 4	1462.801	31.622	1463.12

4.3.4 Time of use pricing

The results obtained in this mode are shown in Table (12). The values of the two mean and deviation objective functions are 1535.565 and 62.863, respectively, in mode 2 and are 1454.282 and 0 for mode 5. In this mode, the profit earned relative to fixed pricing in both has increased with increasing risk. However, in the face of rising price volatility in this mode, the game theory method has decided to eliminate risk.

Table 12. Results of the second and fifth modes

	Average function amount	Deviation function amount	Total profit of the retailer ($)
Mode 2	1535.565	62.863	1536.216
Mode 5	1454.282	0	1454.282

4.3.5 Real-time pricing mode

The results obtained in this mode are shown in Table (13). The values of the two objective and deviation objective functions are 1559.102 and 81.082, respectively, in mode 3 and 1461.249 and 0 for mode 6. In this mode, it is observed that the average profit has increased in both models, but the increase in profit in the game theory model is risk-free and deterministic.

Table 13. Results of the third and sixth modes

	Average function amount	Deviation function amount	Total profit of the retailer ($)
Mode 3	1559.102	81.082	1559.793
Mode 6	1461.249	0	1461.249

4.3.6. Results for fixed, time of use and real-time pricing in game theory approach

According to the obtained results, it is clear that in game theory, programming has been conducted cautiously, and by changing the price model, the priority is to keep the risk at a lower level compared to the fuzzy method programming. In the following, how to operate the equipment in the three programming modes of 4, 5, and 6 is shown comparatively in Figures (13) - (20).

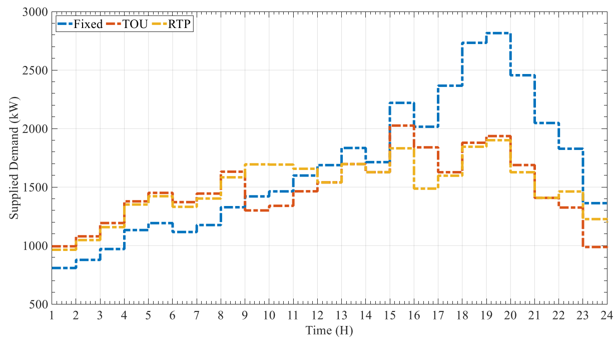


Fig. 13. Demands supplied in different modes.

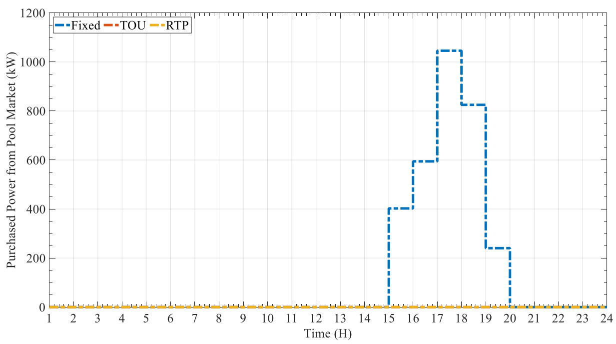


Fig. 14. The amount of energy purchased from the upstream grid.

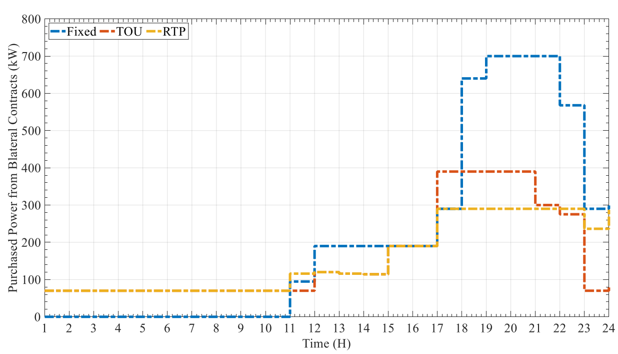


Fig. 15. The rate of use of bilateral contracts in each case.

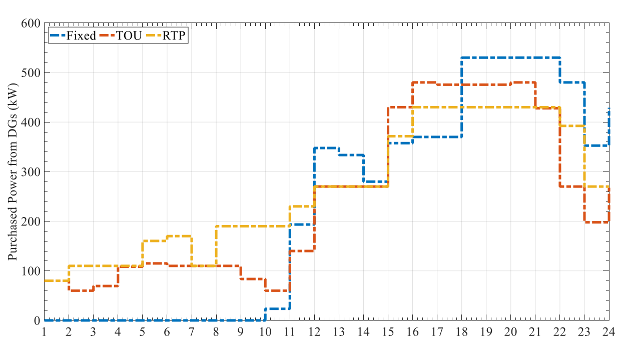


Fig. 16. The amount of power produced by distributed sources.

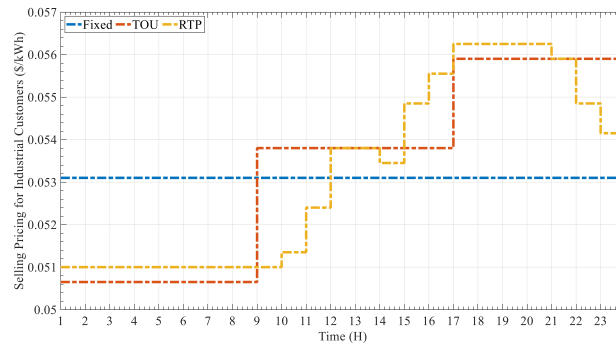


Fig. 17. The selling price of power for industrial consumers.

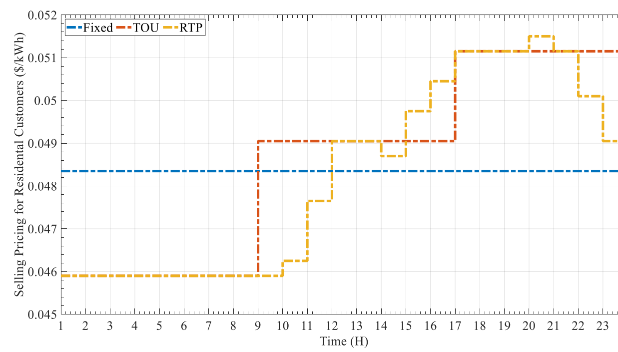


Fig. 18. Power selling price for household consumers

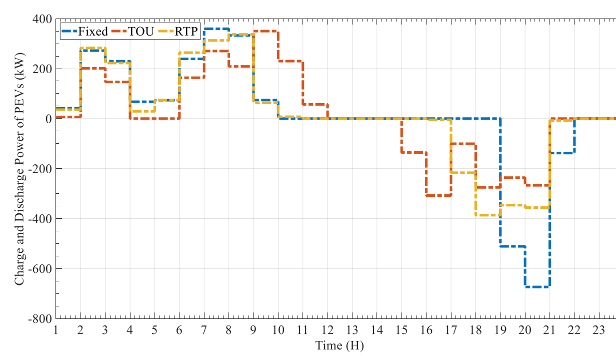


Fig. 19. Charged and discharged rate for plug-in electric vehicle batteries.

5. DISCUSSION

Real-time selling prices were closer to the real situation than fixed pricing and usage time. Thus, in real-time pricing, compared to fixed pricing, it shows an increase of 5.16%. Compared to the firm approach to fixed pricing, the average retail profit fell 1.36% while earnings changes fell more than 56.82%. According to utilization-time pricing, the average retail profit is also $1535.65, while the decrease in profit is $62.86. The typical retail profit decreased by 1.21 percent, while profit changes decreased by more than 52.67 percent from the time of decisive strategy to pricing. This demonstrates that the average profit of the merchant has grown in comparison to fixed pricing due to the favorable impact of pricing at the moment of usage. The average retail profit decreased by 1.07 percent vs. the real-time pricing strategy that was decided upon, while profit changes decreased by more than 53.45%. This indicates that compared to the current price and fixed pricing, the average retail profit is larger in real-time. Finally, compared to fixed pricing and 1.54% compared to time-of-use pricing, the average retail profit grew by more than 4.30%. Due to the flexibility of battery storage systems, plug-in electric cars, and hydrogen storage systems, merchants' predicted profits have improved as a result of setting the price of selling in accordance with real-time pricing by energy providers. It has produced a win-win approach for both customers and retailers. Therefore, real-time pricing has a larger average profit than fixed and time-of-use pricing, which is also suitable for retailers. Lastly, it can be shown that the interval optimization approach's ability to meet demand has been shown to be less effective than the deterministic method, leading to an increase in selling price. Real-time energy sales to the upstream network outnumber use-time pricing and fixed sales of energy. In addition, the interval optimization method uses less energy than the definitive strategy does in the power market. The real-time approach is better for both consumers and retailers since it is far more realistic than the time of usage and a set price. Finally, the average retail profit in the interval optimization method is slightly lower than the definitive method. While profit changes have declined sharply, retailers have increased resistance to market price uncertainty. In game theory mode, less profit is achieved with less risk. In the time-of-use pricing mode, profits relative to fixed pricing in both increased with increasing risk. However, in the face of rising price volatility in this case, the game theory approach has decided to eliminate risk. In real-time pricing mode, it is observed that the average profit in both models has increased, but the profit increase in the game theory model is risk-free and definite.

6. CONCLUSION

The problem of determining the price of selling electricity to residential, commercial, and industrial consumers in three different types of fixed pricing, time of use pricing, and real-time pricing by electricity retailers in the smart grid environment has been considered in this article, given the uncertainties. A benchmark of smart grid technologies has also been provided in this article for the demand response program for controlling network demand peaks and intelligent charging and discharging management for various storage systems. Due to the flexibility of battery storage systems, plug-in electric cars, and hydrogen storage systems, merchants' predicted profits have improved as a result of setting the price of selling in accordance with real-time pricing by energy providers. A demand response program has also been suggested as a way to control peak demand, flatten the demand curve, lower the selling price of power to customers, and boost the profit of the electricity retailer. It has resulted in a strategy that benefits both customers and retailers.

LIST OF SYMBOLS

Indexes

b : Index for bilateral contracts

h : Index for production of blocks of linear piecewise model of distributed generation units

i : Index for Constraint demonstrating of minimum on time and off time for distributed generation units

j : Distributed generation unit index

v : Electric car index

s : Scenario index

t : Time of study index

z : Index of price-consumer curve stairs based on sales price

Sets

B : Number of bilateral contracts

H : Number of generation blocks of linear piecewise curves of distributed generation units

I : The maximum amount of on and off values of distributed generation units

J : Number of distributed generation units

V : plug-in electric vehicles number

S : Scenarios number

T : All time considered

Z : Number of steps of consumer price-power curve

Parameters

$Dn_{j,i}$: Auxiliary variable for linear modeling stipulates the minimum shutdown time of distributed generation units

$D^{offer}(l,z,t,s)$: Power offered by the consumer group in curve of price-power expressed in kW

DRP^{max} : The maximum percentage for demand which can participate in demand response program

$G^{a}_{t,s}$: Sunlight at any time and in any scenario expressed in w/m^2

G_{a_0} : Sunlight in standard conditions expressed in w/m^2

$NOCT$: The normal operating temperature of photovoltaic systems expressed in °C

ρ_s : Probability of any scenario

P^{max}_{b} : The maximum limit on bilateral contracts per kilowatts (kW)

P^{min}_{b} : The minimum limit on bilateral contracts per kilowatts (kW)

$P^{MAX}_{j,h}$: Nominal power of blocks of distributed generation units in modeling operating costs in piecewise linear functions, per kilowatts

$P^{PV}_{t,s}$: The available power of the photovoltaic system expressed in kW

$P_{Max,0}^{M}$: Maximum power of the photovoltaic system in standard conditions expressed in kW

$P_{t,s}^{wind}$: Available wind turbine power per kilowatts

p_r : Nominal power of wind turbine per kilowatts

P_{charge}^{max} : Maximum battery charge limit per kilowatts

P_{disc}^{max} : Minimum battery charge limit expressed in kW

R_j^{up} : The rate of power increase between two consecutive hours of distributed generation units expressed in kWh

R_j^{down} : The rate of power reduction between two consecutive hours of distributed generation units expressed in kWh

$Sdg_{j,h}$: Cost related to blocks of distributed generation units in the piecewise linear model of operating costs expressed in dollars per kWh

$SP^{offer}(l,z,t)$: Consumer price in the price-power curve in dollars per kWh

$T_{t,s}^{a}$: The ambient temperature at any time and in any scenario

$T_{m,0}$: Photovoltaic system module temperature in standard conditions in degrees Celsius

$Up_{j,i}$: Auxiliary variable for linear modeling stipulates minimum unit on time

$V_{t,s}^{w}$: Wind speed at any moment and time in meters per second

V_r, V_{ci}, V_{c0} : Rated, minimum and maximum speeds in the power-speed curve of the designed wind turbine

X_b^{max} : Maximum limit on the amount of energy stored in the battery storage system expressed in kW

X_b^{min} : Minimum limit on the amount of energy stored in the battery storage system expressed in kW

χ : Charging efficiency for storage system battery

η : Discharging efficiency for the battery storage system

$\lambda_{b,t}$: Energy price of bilateral contracts in dollars per kWh

$\lambda_{t,s}$: Electricity market price in dollars expressed in kWh

Pc_v^{Min} : Minimum power limit for plug-in electric vehicles

Pc_v^{Max} : Maximum power limitation of plug-in electric vehicles

Pd_v^{Min} : Maximum discharge power limit for plug-in electric vehicles

Pd_v^{Max} : Maximum discharge power limit of plug-in electric vehicles

$Ptr_{t,v}$: Travels required for plug-in electric vehicles

η_v^c : Electric car charging efficiency

η_v^d : Plug-in electric vehicle discharge efficiency

SOC_v^{Min} : Minimum of battery power for plug-in electric vehicle

SOC_v^{Max} : Maximum of battery power of plug-in electric vehicle

P_{min}^{EL} : Minimum power consumption limit in the electrolyzer

P_{max}^{EL} : Maximum power consumption limit in the electrolyzer

$N_{H2,\max}^{EL}$: Maximum limit of hydrogen molecules produced in the electrolyzer

η^{EL} : Electrolyzer efficiency

LHV_{H2} : The minimum amount of hydrogen heat

P_{t0}^{H2} : The pressure of hydrogen tanks at start time

$P_{initial}^{H2}$: The initial pressure of hydrogen tanks

P_{max}^{H2} : Maximum pressure limit for hydrogen tanks

P_{min}^{H2} : Minimum pressure limit for hydrogen tanks

$N_{H2,max}^{FC}$: Maximum limit of hydrogen molecules used in the fuel cell

η^{FC} : Fuel cell efficiency

$P_{\max}^{FC}$: Minimum of power limit produced in fuel cell

$P_{\min}^{FC}$: Maximum of power limit produced in fuel cell

$\Re$: Gases constant

T_{H2} : The average temperature inside the chamber

V_{H2} : The total volume of hydrogen storage tanks

$\lambda_t^{\max}$: Upper limit of electricity market prices

$\lambda_t^{\min}$: The lower limit of electricity market prices

$\hat{\lambda}_t$: The predicted price of the electricity market

F_R, F_O : Target critical profits for functions and opportunities

Variables

$A(l,z,t)$: Binary variable for selecting the selling price offered by the retailer to consumer groups from the price-power curve {0 and 1}

C_B : Cost of purchasing energy from bilateral contracts (dollars)

C_P : Cost of purchasing energy from the electricity market (dollars)

C_{DG} : Utilization cost for distributed generation units (dollars)

$D(l,t,s)$: The demand fed by the consumer group by electricity retailer considering the demand response program expressed in kilowatts

$DRP(l,t,s)$: The real variable for implementing a demand response program expressed in kW (it is positive when increasing the demand and negative when reducing demand)

$D^{DRP}(l,t,s)$: New demand fed by the consumer group by the electricity retailer considering the Demand response program expressed in kW

$P_{b,t}$: Power purchasing from bilateral contracts expressed in kW

P_t^{BC} : Total power purchased by bilateral contracts expressed in kW

$P_{t,s}^{charge}$: Charged power of battery storage system expressed in kW

$P_{t,s}^{disc}$: The discharging capacity for battery storage system expressed in kW

$P_{t,s}^{P}$: Purchasing power from electricity market expressed in kW

$P_{j,h,t,s}^{DG}$: Power utilized by distributed generation units

$R_R(l,t)$: Revenue obtained from each of the distributed generation units

S_b : Binary variable for selecting or not selecting bilateral contracts {0 and 1}

$SP(l,z,t)$: Price of power-price curve intervals for groups of consumers in dollars per kWh

$SP^{RTP}(l,t)$: Pricing of real-time sales by electricity retailers for consumer groups in dollars per kWh

$SP_L^{TOU}(l)$: Time of use pricing for sales at low-demand time by electricity retailers for the consumer group in dollars per kWh

$SP_M^{TOU}(l)$: Time of use pricing for sales at medium-demand time by electricity retailers for the consumer group in dollars per kWh

$SP_P^{TOU}(l)$: Time of use pricing for sales at peak-demand time by electricity retailers for the consumer group in dollars per kWh

$U_{t,s}^{charge}$: The Binary variable for determining the charging status of the battery storage system {0 and 1}

$U_{t,s}^{disc}$: The Binary variable for determining the discharging status of the battery storage system {0 and 1}

$U_{j,t}^{DG}$: Binary variable for utilization status of distributed production units {0 and 1}

$X_{t,s}^{b}$: amount of the energy stored in battery storage system expressed in kWh

$SOC_{t,v,s}$: amount of the energy stored in battery of plug-in electric vehicles

$Uc_{t,v,s}$: Binary variable for plug-in electric vehicles charging mode

$Ud_{t,v,s}$: Binary variable for electric vehicle discharge mode

$Pc_{t,v,s}$: Charged power of plug-in electric vehicles

$Pd_{t,v,s}$: Discharged power of plug-in electric vehicles

$N_{H2,ts}^{FC}$: Hydrogen moles consumed by the fuel cell

$N_{H2,ts}^{EL}$: Hydrogen moles produced by the electrolyzer

$P_{t,s}^{H2}$: The pressure of hydrogen tanks

$P_{t,s}^{EL}$: Power consumed by the electrolyzer

$P_{t,s}^{FC}$: The power generated by the fuel cell

$U_{t,s}^{EL}$: Binary variable for electrolyzer working status

$U_{t,s}^{FC}$: Binary variable for fuel cell working status

Functions

$F(p,\lambda)$: Electricity retailer profit function

$\hat{\alpha}(F_R)$: Resistance function in information gap decision theory

$\hat{\beta}(F_O)$: Opportunity function in information gap decision theory

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