Journal of Cleaner Production 363 (2022) 132403

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Smart peer-to-peer and transactive energy sharing architecture considering incentive-based demand response programming under joint uncertainty and line outage contingency

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A R T I C L E I N F O

Handling Editor: Baoshan Huang

Keywords:
Transactive energy sharing
Peer to peer energy trading
Smart incentive-based demand response programming
Uncertainty relaxation through forecasting (RBNN)
Bi-objective profitability
Grid centricity

A B S T R A C T

Due to the widespread deployment of distributed energy resources, renewable energies and battery energy storage, the peer to peer (P2P) energy trading schematic has gained the staple attention for improving the energy efficiency and energy flexibility of power grids. This is while, smart demand response programming (DRP) is considered as the bridge between these two indicators of smart grid. Moreover, the subtle point of proliferating P2P schematics is the regulation towards the maximization of social welfare leading to economic profitability of customers and owner's of microgrid and, eventually, reduction of pollutant emission of fossil fuels. Also, uncertainty, aroused by electrical consumption and renewable energy resources, is the core of every considerations, which has to be dealt with intelligent algorithms for strengthening the stability of transactions. On the other hand, compatibility with upper grid's regulations, i.e. power loss and voltage deviation, along with determining fair price of energy trading are the subjects of P2P-based tactics. Therefore, this paper proposes a P2P-based transactive energy sharing architecture, as two stage mixed integer non-linear programming, using smart DRP integrated with machine learning approach, i.e. radial basis neural network. Firstly, the uncertainty of electrical demand and renewable energies are relaxed through short term forecasting. Doing so, the day-ahead transactions of peers are obtained based on their energy management objective, targeting the energy reliability of customers, which energy not supplied criterion has to be equal to zero. Then, participation of customers in DRP, cost of customers, revenue of microgrid's owner and transactions of real time programming are optimally acquired based on Pareto front technique. Also, the simulations are conducted on IEEE 85 bus test system to realize the considerations. The results convey that the profitability of customers and owners is tied with the implementation of smart DRP and accurate forecasting of uncertain variables. In addition, the maximum improvements towards maximizing the revenue of owners and minimizing the cost of customers take place at hours which the electrical consumption is shifted from peaks to off-peaks and mid-peaks, certifying the performance of proposed methodology.

1. Introduction

Nowadays, peer to peer (P2P) energy trading has been appeared due to the integration of distributed energy resources (DER), e.g., renewable energies, distributed diesel generators (DG) and battery energy storage, and smart meters along with communication assets into the topology of low voltage distribution network. Hence, proactive consumers, such as prosumers (Azim et al., 2020; Ganjeh Ganjehlou et al., 2020), could effectively participate to increase their benefits. Therefore, the studies are targeted in four major areas. The first step of establishing the transactive energy sharing (TES) is to design the energy trading

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https://doi.org/10.1016/j.jclepro.2022.132403
Received 1 October 2021; Received in revised form 7 May 2022; Accepted 23 May 2022
Available online 31 May 2022

Nomenclature

Abbreviations

PV, W, DG	photovoltaic/wind/diesel generator
ch, dch	charging/discharging
AEL, SA	aggregated electric load/signal aggregator
UG,ISO	upstream grid/independent system operator
GEN	renewable and non-renewable generations
P2P	peer to peer
DRP	incentive based-demand response programming
TES	transactive energy sharing
LOC	line outage contingency
SP	stochastic programming
DA	day ahead
AMI	advanced meter infrastructure
PF	Pareto front
MINLP	mixed integer non-linear programming
OP	off-peak
MP	mid-peak
P	peak

Indices

s, g	sellers in P2P
b, o	buying/selling from/ to the UG
t, q	time
α	index of price bound in reward-based DRP
β	index of price bound in penalty-based DRP
i	index of power corresponded to scenario of participation in I-DRP
π	probability of participation in I-DRP

Variables

a_s, b_s, c_s	coefficients of DGs
a_g, b_g	coefficients of the UG
$\underline{R}_s$, $\overline{R}_s$	min/max ramp of DG of seller s (kW)
$\underline{P}_s^{\mathrm{DG}}$, $\overline{P}_s^{\mathrm{DG}}$	min/max power of DG of seller s (kW)
$\underline{P}^{\mathrm{ch}}$, $\overline{P}^{\mathrm{ch}}$	min/max charging power of battery (kW)
$\underline{P}^{\mathrm{dch}}$, $\overline{P}^{\mathrm{dch}}$	min/max discharging power of battery (%)
η^{ch}, η^{dch}	efficiency of charging/discharging (%)
$\underline{\mathrm{SOC}}_t$, $\overline{\mathrm{SOC}}_t$	min/max state of charge at time t (%)
$P_{s,t}^{\mathrm{AEL}}$	relaxed power of demands by seller s at time t (kW)
$\bar{A}_{s,t,\alpha}^{\mathrm{DR,r}}$	upper limit of reward-based DRP in seller s at time t
$\bar{B}_{s,t,\beta}^{\mathrm{DR,in}}$	upper limit of penalty-based DRP in seller s at time t
$P_{s,t,i}^{\mathrm{DR,r}}$	reduced demand of seller s at time t participated in ith scenario
$P_{s,t,i}^{\mathrm{DR,in}}$	increased demand of seller s at time t participated in ith scenario
$\lambda_{s,t}^{\mathrm{P2P,DA}}$	price of seller s in P2P-DA forecast-based energy market at time t
P_t^{total}	total demand of UG considering loss at time t (kW)

Parameters

$\lambda_t^{\mathrm{b,RT}}$	selling price published by ISO at time t ($/kWh)
$\lambda_t^{\mathrm{o,RT}}$	selling price of energy to UG at time t ($/kWh)

Decision-making Variables

$P_{s,t}^{\mathrm{b,RT}}$	purchased power from the UG by seller s at time t (kW)
$P_{s,t}^{\mathrm{P2P,DA}}$, $P_{g,t}^{\mathrm{P2P,DA}}$	net sold power of s/g at time t (kW)
$P_{s,t}^{\mathrm{DG}}$	power of DG of seller s at time t (kW)
$P_{s,t}^{\mathrm{o,RT}}$	sold power to UG by seller s at time t (kW)
$P_{s,t}^{\mathrm{PV}}$, $P_{s,t}^{\mathrm{w}}$	relaxed power of PV/wind by seller s at time t (kW)
$P_{s,t}^{\mathrm{ch}}$, $P_{s,t}^{\mathrm{dch}}$	charged/discharged power of battery by seller s at time t (kW)
$A_{s,t}^{\mathrm{DR,r}}$	reward rate of reduced demand of seller s at time t
$B_{s,t}^{\mathrm{DR,in}}$	penalty rate of reduced demand of seller s at time t
$Y_{s,t,i}$	1 for participating in reward-based DRP
$\Phi_{s,t,i}$	1 for participating in penalty-based DRP
$P_{s,g,t}^{\mathrm{P2P,DA}}$, $P_{g,s,t}^{\mathrm{P2P,DA}}$	sold power of s/g at time t (kW)
$\lambda_{s,t}^{\mathrm{P2P,DA}}$, $\lambda_{g,t}^{\mathrm{P2P,DA}}$	fair prices of sellers at time t ($/kWh)
$\lambda_{s,t}^{\mathrm{DG}}$	sold price of DG of seller s at time t ($/kWh)
$\mathrm{SOC}_{s,t}$	state of charge of seller s at time t (%)
$x_{s,t}^{\mathrm{ch}}$, $x_{s,t}^{\mathrm{dch}}$	1 for charging/discharging of battery of seller s at time t
$x_{s,g,t}^{\mathrm{P2P}}$	1 for selling energy from s to g at time t

Functions

$P_{s,t}^{\mathrm{int}}$	internal non-flexible demand of seller S at time t ($/kWh)
UF	utility function of owner ($)
$\mathbb{C}^{\mathrm{owner}}$	cost of owners for purchasing power to satisfy customers ($)
$\mathbb{C}_{s,t}^{\mathrm{DG}}$	cost of DG of seller s at time t ($)
$\mathbb{C}^{\mathrm{customer}}$	cost of customers for purchasing power from P2P-TES ($)
SW	social welfare function ($)

policies with monetary regulations, costs and revenues. Accordingly, the leading topics could be defined as P2P pricing (Luo et al., 2019; Morstyn et al., 2020; Fernandez et al., 2021; An et al., 2021), optimal deployment of strategies for responsive controllable loads (Liang et al., 2019; do Prado and Qiao, 2019; da Silva et al., 2020; Yang et al., 2020) and making the trade off between utility function (UF) of microgrid's owners and cost of customers (Tushar et al., 2020; Anoh et al., 2020; Maharjan et al., 2016; Niromandfam et al., 2020). The second category follows the limitations of the grid (Paudel et al., 2021; Zhang et al., 2020b; Naik et al., 2021). Therefore, authors, in Paudel et al. (2021), have investigated the voltage regulation in a P2P market maximize the social welfare of prosumers. This approach conducts a pricing mechanism, related to the cost of local generation of each prosumer. After forming an optimization problem, the Lagrangian multiplier has been launched to determine the trading price, based on the objectives of producers and consumers. Then, transacted power has been utilized to justify the voltage of nodes iteratively, considering the mutual resistance of transactive nodes. Other studies have evaluated, line congestion, voltage regulation and transferred loss optimization according to interactive P2P trading (Zhang et al., 2020b), which was controlled by independent system operator (ISO). Moreover, the utility grid casts preventive costs for the violation of prosumers from grid limitations to improve the functionality of ancillary service. In addition, alternating direction method of multipliers (ADMM) has been adopted as the solution study to settle the considerations of Nash equilibrium. Moreover, adaptive energy management strategy has been proposed to confront the voltage stresses forced by uncertainty obstacle of DER along with electrical demand, slow ramp rate of hydro power generation and operational limitation of battery energy storage (Naik et al., 2021). In Naik et al. (2021), the energy management algorithm is based on the scenarios of uncertainty accompanied by the functionality of maximum power point tracking tactic for harvesting optimum energy efficiency of solar energy, hydro power generation and battery energy storage. The third factor deals with the consumer centricity attributes, which leads to encourage the participation of microgrid's owners and small-scale prosumers in P2P paradigm. With respect to the motivational psychology (Tushar et al., 2019, 2020). TES has to include a logical basis leading to pervasive involvement of consumer side parties (Xiao et al., 2020; Yang et al., 2020; Gong et al., 2020),(An et al., 2021). Based on this concept, authors in Xiao et al. (2020) have proposed an iterative upper–lower bounded P2P template, which communizes prosumers to form an aggregation strategy. This method initiates multi-agent decision-making procedure to peruse an unified goal in the first place. Hence, the power load and the price have obtained by day ahead (DA) market offers. Subsequently, the consumers regulate their consumption profile according to the results of the upper level and usage type to achieve optimal outcomes. This mutually beneficial interactive negotiation has been pursued by updated information with the maximum privacy. In literature (Yang et al., 2020), an online P2P structure to cover both thermal and electrical expectations of nested microgrid has solved by average-based ADMM. Besides, validating the transaction is the final goal to be achieved in practical. This view figures out the application of cryptocurrency-based testbeds for certifying transacted negotiations, considering developments of communication assets. Hence, Blockchain is the most renowned secure financing instance of P2P energy trading (Luo et al., 2019). Moreover, the challenges of those noted targets are addressed by scholars to accelerate the process of deploying P2P trading. However, optimality of solutions are still in debate, because of each solutions are unable to handle the challenges uniformly. These challenges could be highlighted as follows.

1.1. Effective implementation of demand response

In this regard, price is the decision-making variable of trading, achieved by the UG's price availability. In fact, the buying and selling prices have been set in a P2P schematic by multi-agent system, in which each agent of prosumers has the responsibility to collect the historical set of generations along with demands. The reason is to determine the amount of purchased/sold power based on forecasting results of the historical datasets and to conduct a consensus-based contract considering neighboring participants, respectively (Luo et al., 2019). However, the impact of interactive pricing of peers on the optimal decisions has been neglected. On the other hand, DA retail price has been estimated by the point estimate method (PEM) to obtain P2P price (Morstyn et al., 2020; Nasiri et al., 2022; Baherifard et al., 2022; Ahmadi et al., 2022). Further, the preferences of peers have added to strengthen the voltage regulation obligation, when increasing the social functions of peers. It should be noticed that PEM is able to capture only the mean and standard deviation of individual unrelaxed variables. In addition, the joint impact of uncertainty, including renewables and retail price have not been investigated. Nevertheless, demand response programming (DRP) is a common practice for bringing economic interests into P2P based structures. Response of demands are always activated by subsidizing or penalizing prosumers. This structure considers incentive-based DRP (I-DRP). Further, I-DRP has a self-positivity attribute to mitigate uncertainty of renewable energies and manage loads in both single-energy and multi-energy systems. Thereby, I-DRP could introduce as an effective strategy to manipulate the consumption and gain economic revenues in P2P-based energy market. However, the uncertainty of the electrical demand and renewable generations are the main obligations to implement I-DRP in real time programming. Hence, conservative consideration, i.e., load growth rate, could be assumed as real time programming. Nonetheless, this action could harm the performance of I-DRP by deviating from optimal decisions and leading to non-profitable economic objectives. Hence, if the noted uncertainty of real time programming could predict accurately, the real time performance of I-DRP is possible. In other words, accurate prediction leads to semi-optimal results. In da Silva et al. (2020), the participation of owners has been captured by the involvement of DRP in renewable energy-based architecture equipped with battery energy storage, aiming to minimize the cost of electricity consumption, curtailment cost of consumption and pollution. Besides, DRP has been activated by the interference of consumption in their energy management using advanced meter infrastructure (AMI). Authors, in Yang et al. (2020), have established three stage-based formulation to minimize purchased power from the retailer and to maximize the self generation–consumption capacity of renewable units through integrating DRP with internal constraints of battery energy storage. Also, the power uncertainty of renewable energies have been modeled by stochastic programming. Furthermore, economic revenue of owners has been modeled via integrating incentive-based DRP with utility function to participate in day ahead energy trading market (Niromandfam et al., 2020). In addition, the uncertainties of wind energy along with electrical demand have been presented by probability scenario-based modeling, representing the risk of participation. Based on the results, deployment of DRP increases the profit of customers via increasing the incentives of reducing electricity usage.

1.2. Bi-objective profitability

This challenge delays the practicality of TES, which causes economic-dependent conflict among consumer side parties, i.e., microgrid's owner and small-scale prosumers, and upper distribution grid operators, i.e., ISO. However, current energy policies are faced with technical deficiencies in the realization of P2P frameworks. For instance, the equilibrium point of game theory-based strategies are obtained by unilateral decision-making action of leader, whether for peak shaving or TES (Tushar et al., 2020; Anoh et al., 2020). However, these solutions cannot handle the scalability issue (Guerrero et al., 2019). On the other hand, Blockchain facilitates fair revenue allocation among peers through publicly announcing energy transaction's order and fulfilling validation duty, These are by consensus-based crypto-decoded mechanisms, leading to consciously optimal actions (Luo et al., 2019). However, this solution cannot tolerate cyber-security obstacles, and harms the security of transactions. The last approach is optimization-based programming. Therefore, mixed integer linear programming (MILP) and mixed integer non-linear programming (MINLP) are accepted as reliable sources for triggering DR, P2P practicality and collaborative modeling of opposing goals (Nguyen et al., 2018). Hence, gathering actors of each objectives, which have an analogy, to uniformly overcome a problem for leveraging the process of optimal decision-making is more realistic than mentioned algorithms. The main reason is the developments of analyzing techniques, e.g., Pareto front technique (PF), to identify optimality based on preferences. In Fernandez et al. (2021), two-stage energy management method has been proposed to target the maximization of revenue and utility function in P2P-oriented energy trading market. In addition, after optimizing the revenue of prosumer, maximum utility function of consumer has been obtained considering game theory approach which fair willingness of participation is achieved via availability of real time price of upstream grid (UG). Therefore, response of consumer to the behavior of UG's price has been inserted into the methodology as the willingness factor (Nasiri et al., 2021; Gholinejad et al., 2021; Faridpak et al., 2021). In other work (An et al., 2021), P2P potential of renewable energy-based market has been examined taking into account of economic feasibility of decisions.

Based on the results, authors have stated that conducting demand reduction techniques increases the profit of participants. Distributed energy management approach has been proposed, in Gong et al. (2020), to create a profitable negotiations between agents of energy hub and smart grid. In this regard, each agent solves the interior energy management problem based on SP. Then, the optimal decisions are cleared in a distributed fashion taking into account of maximum profits obtained in primal–dual formulation.

1.3. Absorbing uncertainty

It arises from a deficiency of current uncertainty modeling algorithms that cannot realize the relaxation process of uncertainty in terms of optimality. The first one is conservative deterministic based methods, which could apply effortless and weak to depend on. However, SP, including two-stages (Paudel et al., 2021), robust (Zhang et al., 2020a) and chance constraints (Liang et al., 2019; do Prado and Qiao, 2019), gain semi-optimal solutions. However, it could result to complex problems regarding scenario generation-reduction obstacles and handling interdependencies of unrelaxed variables. Another solution is to apply the pattern identification based forecasting algorithms, which aim to neutralize destructive characteristic of uncertainty by relaxing its stationary nature. Hence, artificial neural network (ANN) has gained attention due to its ability of learning process to relaxing nonlinear behavior in uncertainty through prediction (Masoumi et al., 2020a). In this regard, support vector machine (SVM) (Li et al., 2020; Pan et al., 2020; Liu et al., 2020), radial basis neural network (RBNN) (Taki et al., 2018; Zhang et al., 2016; Amiri et al., 2021), Gaussian process regression (GPR) (Zeng et al., 2020; Xue et al., 2020; Zhou et al., 2021), and long-short term memory (LSTM) (Wang et al., 2020; Hossain et al., 2021; Jung et al., 2020), have been vastly used by scholars as regression learner algorithms. Nevertheless, the accuracy of regression and compatible error of training and testing are valid qualifications, verifying the performance of the prediction. This is because the outcome of prediction has a direct impact on the optimization of economic objective functions.

1.4. Line outage contingency

Line outage contingency (LOC) is the most critical incident of this challenge, which could deprive consumer side parties from the benefits of P2P energy trading along with jeopardizing transactions. Therefore, consideration of LOC is crucial for proving the generality of P2P-based approaches.

1.5. Contribution direction and paper organization

There are various research gaps and disadvantages in the literature that has been attempted to resolve in this paper. Applying disparate DRP methods with different intentions and constraints is one of the main parts of topic "P2P-TES in microgrids and smart grids". DRP is implemented in the distribution systems as a controlling tool to manage power demand with a specific objective. In the literature, this technique is mostly used to optimize owner's revenue, reducing demand peak and consumer's total cost. Most studies implement DRP to optimize a set of these objectives. For example, in da Silva et al. (2020) the aim of DRP implementation is to reduce consumption cost, consumer's inconvenience and environmental factors. This papers neglects considering owner side revenue. Also, a price based DRP is utilized in a real time manner without optimizing any effective factor in DRP. The aim of implementing DRP in Yang et al. (2020) is to decrease the cost of retailers and maximizing the usage of clean energy. In contrast with (da Silva et al., 2020), the consumer side is neglected in Yang et al. (2020). Other research gap in the literature related to DRP implementation is considering elasticity multipliers as the deterministic values. This paper has been solved this drawback by presenting a smart incentive-penalty based DRP by considering stochastic behavior of participants and their variant elasticities. In this strategy, the marginal prices in P2P-TES platform are optimally calculated in a day-ahead manner by assuming different uncertainties in system. In the real time stage, the presented DRP is utilized these optimally calculated marginal price values to determine incentives and penalties, and the share of participants in DRP as well. As a result, a smart technique is applied to perform DRP in the system. The aim of presented DRP method is to increase owner's revenue and decrease consumers total costs, simultaneously. The consequence of this strategy is also seen in the upper grid's power quality. In addition, the proposed DRP model takes into account the uncertainty in consumer's elasticity. Uncertainty in demand, renewable energy resources and elasticity of participants in DRP is another noteworthy issue in P2P energy trading problems. Several studies have attempted to handle this issue subjected by implementing various machine learning-based techniques. In Li et al. (2020), Pan et al. (2020), Liu et al. (2020), the uncertainties have been modeled by SVM, while (Amiri et al., 2021; Zeng et al., 2020; Xue et al., 2020; Zhou et al., 2021) and Wang et al. (2020), Hossain et al. (2021), Jung et al. (2020) implement GPR and LSTM to model uncertainty. Most of these methodologies have not strong architecture, so their results are nearly unreliable or inaccurate. This paper utilizes RBNN technique to model uncertainties in the problem alongside with applying some preprocessing and fitting models to enhance the performance of stochastic modeling approach. In this regard, the Augmented dickey fuller test (ADF) tactic is used to determine the state of being stationary in dataset. In the second step, partial autocorrelation function (PACF) and autocorrelation function (ACF) methods are implemented to obtain auto regressive lags and moving average lags of time series. Finally, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are utilized to model evaluation based on lags impact on the residuals. These preprocessing approaches helps the RBNN to predict uncertainties in a more accurate way. This claim is proven in the paper by comparing the results of RBNN-based uncertainty modeling method with above-mentioned machine-learning-based algorithms. Comprehensive mathematical formulation and modeling a general objective function that considers all aspects of the problem is another significant challenge in energy trading problems. By thorough investigating in the literature, it can be observed that most of studies only consider some objectives of the system in mathematical formulation and total objective function. In An et al. (2021), Liang et al. (2019), the cost of consumption and revenue of owner have been considered as the objective function of problem. These papers have not included other aspects like energy trading cost between microgrids, DRP cost and reliability aspects of system. The revenue and costs of microgrid's owner have been selected as the objective function in Gong et al. (2020). This study completely omits the cost related to energy trading with upper grid and the costs of customers. Also, the peak-shaving is the only target of optimal energy trading strategy in Tushar et al. (2020). Transmission and environmental costs have been selected as the objective functions in Anoh et al. (2020). Therefore, a comprehensive mathematical model for P2P energy trading problem is needed that considers all aspects of the system from the owner and consumers point of view. To handle this drawback, this study models a comprehensive objective function and mathematical formulation by considering all aspects in owner and consumer side, like generation cost, DRP cost, energy trading cost between multi-microgrids, consumption cost, energy selling revenue, costs and revenues related to energy trading with upstream network and reliability aspect. In addition, the effect of proposed methodology in reducing power loss and voltage deviation index in the upper network has been investigated. This paper considers a multi-owner platform as a test bed to investigate the effect of existing multiple owners in P2P energy trading problem. This assumption has been completely neglected in literature. The other contribution of this research is applying "Pareto front technique" to find optimal value for significance factor of consumers' cost in the social welfare function. Most studies utilize

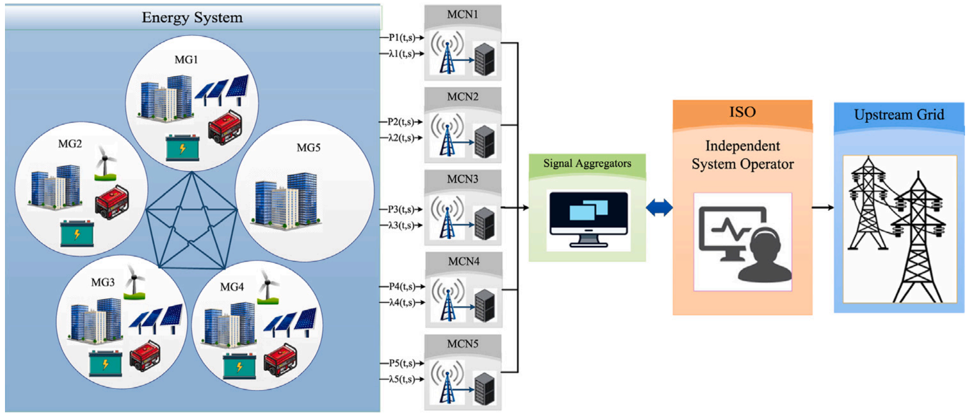


Fig. 1. The schematic of the studied energy system including five microgrids fully interconnected.

day-ahead or real time approaches to solve peer-to-peer energy trading problem (Ahmadi et al., 2022; Sun et al., 2022). This paper presents a novel two-stage stochastic programming approach that exploits the advantages of both real time and day-ahead strategies. To sum up, this paper provides a comprehensive methodology along with the integration of renewable energy resources, targeting cost of customers, energy reliability of customers, revenue of owners and uppers grid's marginal limitations, i.e. active power loss and average voltage. Clearly, integration of renewable energy resources is the main driving force of this paper. However, all challenge are originated from uncertainty of renewable energies and energy demand of customers. Hence, a machine learning technique is applied to predict the time series of uncertain variables. The results showcase that accurate forecasting of renewables minimizes the cost of customers and maximizes the revenue of owners in P2P schematic. Also, accurate forecasting increases the share of renewable energy resources, in line with the deterministic programming, and decreases the share of upper grid for providing the energy demand of customers. Hence, the minimization of customers' cost is beforehanded. Presupposedly, the reduction of pollutant emission is in the nature of results. This is a strong incentive for increasing the integration of renewable energy resources, as cleaner production, into the body of microgrid. Table 12 is drawn, in the appendix section, to depict the compared contribution of current work with conducted studies.

Therefore, the aim is to evaluate the mentioned challenges implemented by a strategy called smart P2P based TES. The contributions could be highlighted as follows:

1. Predicting electrical demand, solar irradiance and wind speed algorithm based on uncertainty relaxation algorithm operated by RBNN
2. Proposing an exquisite smart DRP based on forecasting results of RBNN
3. Designing P2P-TES strategy for obtaining bi-objective profitability and damping the destructive impact of LOC

Moreover, Section 2 describes the model of energy system, problem formulation, the proposed architecture, decision making strategy and evaluations. Followed by the scenarios and case studies which define in Section 3 and the results are discussed in Section 4. Ultimately, Section 5 concludes the contributions of this paper.

2. Model description

The studied system includes five on-grid microgrids (MG) fully interconnected in terms of the physical layer, i.e., lines, and virtual layer, i.e., a mutual communication network. MGs are owned by private utilities which equipped the consumption section with AMI. Furthermore, the utilities and the UG are responsible for providing the expectations of loads. In addition, the utilities send signals to establish P2P, e.g., power and price, to be aggregated by a signal aggregator (SA), which is a consumer side non-profit agent as illustrated in Fig. 1. Moreover, optimal trades are regulated by cooperation of SA with ISO. Transactions are functioned without the third party, i.e., retailer. Hence, the realization of P2P-TES is considered. The economic objectives are revenues of owners and costs of customers. On the other hand, this schematic has faced with those challenges. Therefore, this study proposes a smart P2P-TES architecture, incentive-based DRP, and the relaxation view of ANN, to mitigate challenges uniformly without harming optimality in term of bi-objective MINLP optimization.

2.1. I-DRP

After the P2P market clearing prices are determined with marginal cost of non-renewable energies, i.e. DGs, and day ahead price for all hours and each owner, owners send selling prices and prediction values through AMI. Then, I-DRP is implemented based on the interactions of owners and customers which reshaping the consumption considering flexible loads of customers.

$$P^{\mathrm{fl}}_{s,t} = P^{\mathrm{AEL}}_{s,t} - P^{\mathrm{int}}_{s,t} \tag{1}$$

In other words, the change in demand of each hour is impacted by prices, reward and penalty rates of other hours (Aalami et al., 2010). The decision making variables are the reward and penalty rates, as the prices of P2P energy trading are fixed by ISO. In fact, reward and penalty rates are factors which reduce or increase the consumption at each hour. Practically, customers demonstrate stochastic response for each reward-based and penalty-based DRPs due to their seasonal specifications. By analyzing electrical demand, it is possible to categorize these diverse responses into three scenarios of participation such as low, medium and high with the probability of 0.25, 0.4 and 0.35, respectively. In fact, I-DRP conveys binary functionality at each hour. Hence, customers demonstrate different behaviors for changing their consumption of each hour correspond to the change of reward and penalty rates of other hours. In this study, the response are based on increasing of reward or penalty rates. Thereafter, customers submit offers to be considered in the optimal decisions of owners via price-quota formulation (Conejo et al., 2010b). In particular, I-DRP represents bi-objective profitability by making collaboration between customers and the microgrid's owners to determine optimal reward or penalty rates, which leads to shifting peaks and satisfying objectives of owners and customers, uniformly. Therefore, optimal rewards and penalty rates are obtained based on offers which are P2P-cleared prices multiplied by constant values as follows:

$$\bar{A}^{\mathrm{DR,r}}_{s,t,\alpha} = \vartheta_{s,t,\alpha}\lambda^{\mathrm{P2P,DA}}_{s,t} \tag{2}$$

$$\bar{B}^{\mathrm{DR,in}}_{s,t,\beta} = \theta_{s,t,\beta}\lambda^{\mathrm{P2P,DA}}_{s,t} \tag{3}$$

Table 1
Participation matrices of customers in reward-based DRP for Decreasing their consumption in response to increasing the rewards of other hours.

Scenarios of participation	$i = 1$	$i = 2$	$i = 3$
$E_i(t, q)$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.1 & 0.15 \\ 0.1 & 0 & 0.05 \\ 0.15 & 0.05 & 0 \end{pmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.12 & 0.16 \\ 0.12 & 0 & 0.08 \\ 0.16 & 0.08 & 0 \end{pmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.2 & 0.24 \\ 0.2 & 0 & 0.16 \\ 0.24 & 0.16 & 0 \end{pmatrix} \end{array}$

Table 2
Participation matrices of customers in penalty-based DRP for increasing their consumption in response to increasing the penalty of other hours.

Scenarios of participation	$i = 1$	$i = 2$	$i = 3$
$\tilde{E}_i(t, q)$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.2 & 0.24 \\ 0.2 & 0 & 0.16 \\ 0.24 & 0.16 & 0 \end{pmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.12 & 0.16 \\ 0.12 & 0 & 0.08 \\ 0.16 & 0.08 & 0 \end{pmatrix} \end{array}$	$\begin{array}{cc} & \begin{array}{ccc} \mathrm{OP} & \mathrm{MP} & \mathrm{P} \end{array} \\ \begin{array}{c} \mathrm{OP} \\ \mathrm{MP} \\ \mathrm{P} \end{array} & \begin{pmatrix} 0 & 0.1 & 0.15 \\ 0.1 & 0 & 0.05 \\ 0.15 & 0.05 & 0 \end{pmatrix} \end{array}$

Thereupon, customers submit $[\bar{A}^{DR,in}_{s,t,\alpha}, \bar{A}^{DR,in}_{s,t,\alpha+1}]$ and $[\bar{B}^{DR,in}_{s,t,\beta}, \bar{B}^{DR,in}_{s,t,\beta+1}]$ as steps of offers corresponded to the blocks of power, for reducing or increasing the consumption, respectively. Moreover, the constant of reward-based and penalty-based DRPs are considered to be identical for all customers at each hour, i.e., $\vartheta_{s,t,\alpha} = \theta_{s,t,\beta} = [0.2, 0.4, 0.6, 0.8]$

$$P^{\mathrm{DR,r}}_{s,t,i} = P^{\mathrm{f1}}_{s,t}\left(\sum_{\substack{q=1 \\ q\neq t}}^{24} E_{s,i}(t,q)\frac{A^{\mathrm{DR,r}}_{s,t}}{\lambda^{\mathrm{P2P,DA}}_{s,t}}\right) \tag{4}$$

$$P^{\mathrm{DR,in}}_{s,t,i} = P^{\mathrm{f1}}_{s,t}\left(\sum_{\substack{q=1 \\ q\neq t}}^{24} \tilde{E}_{s,i}(t,q)\frac{B^{\mathrm{DR,in}}_{s,t}}{\lambda^{\mathrm{P2P,DA}}_{s,t}}\right) \tag{5}$$

These specific participation matrices, i.e., $E_{s,i}(t,q)$ and $\tilde{E}_{s,i}(t,q)$ are predetermined for each step of participation in reward-based and penalty-based programmings, respectively. According to the equations, three scenarios of participation are considered for reward-based and penalty-based programmings to test the I-DRP contribution. Notably, the value of participation is categorized by off-peak (OP), mid-peak (MP) and peak (P) hours of UG, i.e., 1–8, 8–18 and 18–24, in each program and each scenario of participation to realize the calculations. As all the offers of customers are submitted at each hour, owners decide reward and penalty rates, accordingly. It is noted that, this trend is extended to all owners and corresponded customers to simplify the calculations in an identical configuration, i.e., $E_{s,i}(t,q) = E_i(t,q)$ and $\tilde{E}_{s,i}(t,q) = \tilde{E}_i(t,q)$, $\forall s$, as in Tables 1 and 2:

2.2. Absorbing uncertainty through prediction

In this section, a methodology has proposed to model the uncertainty of historical time series, i.e., electrical demand, solar irradiance and wind speed. After the modeling process, the one step ahead forecasting is utilized to predict 24 h (Hyndman and Athanasopoulos, 2018). The process is described as follows:

2.2.1. Preprocessing and fitting model

Time series could be modeled by the historical values. In fact, the past values of time series along with past errors of predictions affect the states of present. However, the challenge is about their relationship lies within the configuration of series. Therefore, *"stationary"* is the most essential property which initiates the process of modeling. Statistically, the stationary implies the consistency of mean, variance and co-variance all throughout the time series. Thereby, statistic tests are considered to evaluate stationary time series, i.e., ADF, Kwiatkowski–Phillips–Schmidt–Shin (KPSS), etc (Box et al., 2015). In this paper, ADF test is conducted to determine the state of stationary. Furthermore, if the outcome of test turns to non-stationary, mathematical transforming or differencing operators have performed to make time series become stationary, i.e., removing *"seasonality"* and *"trend"*. It is worth mentioning that, relationship between historical values and past errors of prediction with present values of time series are addressed as the autoregressive orders and moving average orders, respectively. Comprehensively, regression of stationary time series is represented by fixed statistical parameters, specifically constant mean value, and white noises. The next challenge is to determine the orders or so-called *"lags"* of time series. To obtain the autoregressive lags and moving average lags of stationary time series, PACF and ACF are drawn to indicate lags (Hyndman and Athanasopoulos, 2018), i.e., Figs. 2 and 3. PACF demonstrates the relation of each lag, starting from the first component of time series, with the present values. Moreover, ACF plot provides lags of historical errors of prediction, effective for the modeling. Furthermore, the validation of lags is another issue. With this regard, after creating models, AIC and BIC evaluates the model based on the lag's impact on the residuals. Clearly, the model with the least values of AIC and BIC is chosen as the ultimate model. Thereby, stationary time series are modeled by the combination of autoregressive and moving average orders as follows:

$$y_t = F(y_{t-p1}, y_{t-p2}, \dots, y_{t-pn}, \varepsilon_{t-q1}, \varepsilon_{t-q2}, \dots, \varepsilon_{t-qn'}) + \varepsilon_t \tag{6}$$

In particular, the present values, i.e., y_t are function, i.e., F, of autoregressive and moving average lags, i.e., $p_1, p_2, \dots, p_n$ and $q_1, q_2, \dots, q_{n'}$, and white noise of modeling, i.e., ε_t. Clearly, the autoregressive orders, i.e., $y_{t-p1}, y_{t-p2}, \dots, y_{t-pn}$ are determined based on Fig. 2. On the contrary, moving average orders are obtained considering statistical concept of modeling which is the consistency of the mean.

$$y_t \simeq \mu + \varepsilon_t \tag{7}$$

The above formula states that present value is semi-equal to the sum of the mean, i.e., μ, and present error of prediction. Hence, ε_t could be estimated by shifting the mean value to the left hand-side of the formulation. According to the statistical descriptions, white noise includes mean zero and variance 1. Thereby, the left hand-side is divided by variance of present values. While the moving average orders could be determined, accordingly.

$$y_t - \mu \simeq \varepsilon_t \tag{8}$$

$$\frac{y_{t-q_{n'}} - \mu}{\delta_{y_{t-qn'}}} = \varepsilon_{t-qn'} \tag{9}$$

2.2.2. ANN architecture and forecasting

The analysis of the historical dataset clarifies the behavior of every intermittent-based time series. In fact, the uncertainty of every renewable-based energy system is aroused from the output power of renewables and electrical demand. The ANN is a fast responding computational unit deployed by scholars for pattern recognition, classification and analyzing the stationary time-series. Moreover, forecasting

Table 3
Architecture of proposed RBNN for uncertainty modeling time series.

Time series	Inputs	Outputs	NHN[1]	LR0[2] (η_0)	Iteration (u)	LM[3]	RBF
Electrical demand	y_{t-pn}, $\varepsilon_{t-qn'}$	y_t	5(107)	0.01	1000	BP	Gaussian
Solar irradiance	y_{t-pn}, $\varepsilon_{t-qn'}$	y_t	3(33)	0.01	1000	BP	Gaussian
Wind speed	y_{t-pn}, $\varepsilon_{t-qn'}$	y_t	3(31)	0.01	1000	BP	Gaussian

[1] Number of hidden layers (neurons).
[2] Initial learning rate.
[3] Learning method.

the next possible state of such series overcome the barriers of optimization by optimal decision strategies. ANN has three layers as input, hidden and output. The stationary time series are modeled by inserting lags into the input layers. Comprehensively, the output of ANN is the present value of time series. Hence, the remaining layer, hidden, is responsible for creating a relationship between inputs and output.Specifically, the present value begins after the maximum lags till through the long run. It is essential to observe the plot of stationary time series to properly function the model, i.e., Fig. 4. According to Fig. 4, the curves show sigmoid form with local intensity at edges. This is an important hint for modeling based on radial bases function (RBF). As noted, the observed periodicity of time series can be modeled by RBFs better than GPR and SVM for two reasons. On one hand, GPR applied only Gaussian distribution on the elements of time series. Hence, the modeling is prone to over fitting problem, in which the present values are considered to be out of sight, assumed as the outliers of GPR. In other words, GPR itself faces with the deficiency of covering outliers effectively. This incident, directly, has a negative impact on the accuracy of regression. On the other hand, the high volume of hyper-parameters of SVM is another barrier which blocks the accuracy of modeling. With this respect, the penalty factor of SVM is a regulating term which aims to bond the support vectors to cover all the data set. It has to be noted that, in the case of pure classification problem, adjusting hyper-parameters along with the minimization of penalty term can be reach through synchronizing the coefficient of penalty term with concentric semi-circle vectors. However, the periodicity of time series enforces SVM to conduct a interval optimization for adjusting the support vectors based on the occurrence of time series. Understandingly, this process harms the generalization of modeling in regression problem. Besides, LSTM as a subcategory of recurrent NNs, can perform the regression of time series. However, the inter-dependency of sequence precipitates the performance of LSTM with the obstacle of accumulated error. To solve this problem, LSTM applies forget layers which must be tuned in an iterative fashion. The subtle point is that, the dynamic response of LSTM for updating its weights has a high sensitivity to the volume of data set. In other word, response of LSTM to outliers is incompatible with the high periodicity the time series. Thereupon, RBNN is a unique structure of NN which RBF is utilized as the mann transfer function of hidden layers. In this regard, autoregressive and moving average lags demonstrates the periodicity, based on the seasonality attributes of time series. In this work, the Gaussian function is applied to all hidden layers of three stationary time series, i.e., electrical demand, solar irradiance and wind speed, as RBFs to speed up the computations. Hence, RBNN, i.e., Fig. 5, is selected for modeling in which pure linear is the activation function of output layer. The architecture of RBNN is presented as in Table 3:

$$\mathrm{RBF}(x) = \exp(-\frac{1}{2}(\frac{x}{\delta})^2) \tag{10}$$

$$\text{Pure linear } (x) = x \tag{11}$$

where δ is predetermined constant. According to Fig. 5, the layers are connected via weights and biases. The relationship is presented as follows:

$$y_t = \sum_{1}^{m} \exp\left(-\frac{1}{2}\left(\frac{\left(\| \sum_1^n y_{t-pn} + \sum_1^{n'} \varepsilon_{t-qn'} - c_m \|^2 \times w_m + b_m\right)}{\delta_m}\right)^2\right) \times w'_m + B_m \tag{12}$$

where, w_m, b_m, w'_m, B_m, n and n' are weights and biases of hidden layer and weights and biases of output layer, number of autoregressive lags and number of moving average lags, respectively. c_m is the center of each RBF. Furthermore, the evaluation criteria is based on route mean square error (RMSE). The tuning parameters, i.e., weight and bias of hidden layer and output layer, are trained by dynamic training algorithm based on the previous work (Masoumi et al., 2020b). Hence, the dynamic training algorithm is conducted to update tuning parameters by back propagation theorem.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{f=1}^{N}(A_{tf} - y_{tf})^2} \tag{13}$$

$$\Delta w_m^u = -\eta(u)\frac{\partial \mathrm{RMSE}}{\partial w_m^u} \tag{14}$$

$$\Delta b_m^u = -\eta(u)\frac{\partial \mathrm{RMSE}}{\partial b_m^u} \tag{15}$$

$$\Delta w_m'^u = -\eta(u)\frac{\partial \mathrm{RMSE}}{\partial w_m'^u} \tag{16}$$

$$\Delta B_m^u = -\eta(u)\frac{\partial \mathrm{RMSE}}{\partial B_m^u} \tag{17}$$

$$\eta(u) = \eta_0 \exp(-\frac{u}{1000}) \tag{18}$$

$$w_m^{u+1} = w_m^u + \Delta w_m \tag{19}$$

$$b_m^{u+1} = b_m^u + \Delta b_m \tag{20}$$

$$w'^{u+1}_m = w'^u_m + \Delta w'_m \tag{21}$$

$$B_m^{u+1} = B_m^u + \Delta B_m \tag{22}$$

where, η, m, A_{t_f} and y_{t_f} are learning rate, number of RBF neurons, output of RBNN and actual present values of time series, respectively. Hence, the parameters of hidden layer and output layer are updated, until they obtain the termination condition as follows.

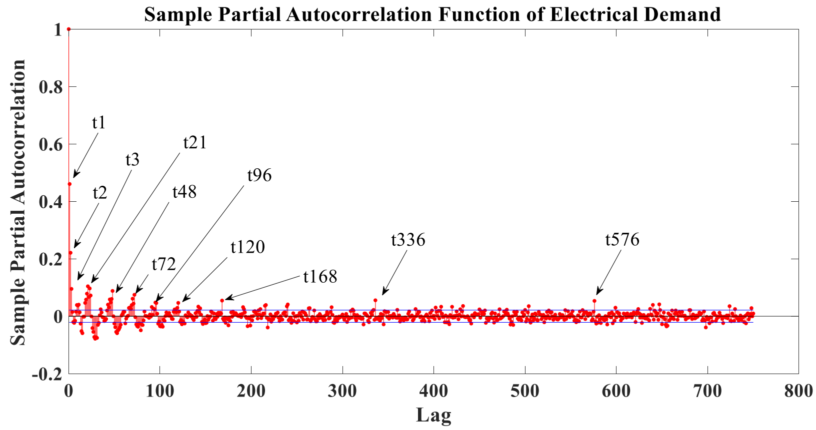
$$|w_m^{u+1} - w_m^u| < \varsigma_m \tag{23}$$

$$|b_m^{u+1} - b_m^u| < \psi_m \tag{24}$$

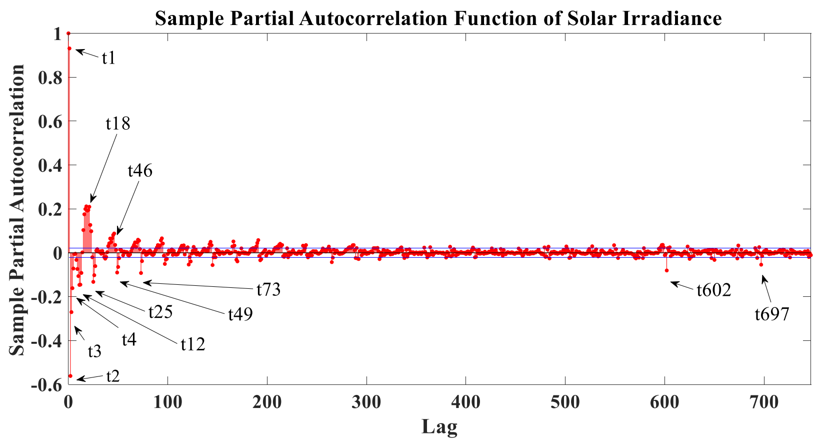
$$|w'^{u+1}_m - w'^u_m| < \varsigma'_m \tag{25}$$

$$|B_m^{u+1} - B_m^u| < \psi'_m \tag{26}$$

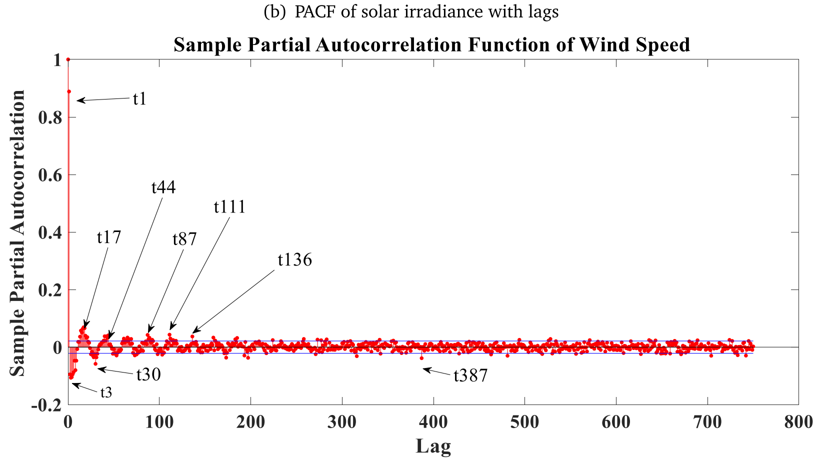
To simplify the calculations, ς_m, ψ_m, ς'_m and ψ'_m are all assumed to be 0.0001. Here, the input and output are divided into two sets, i.e., 95% and 5%, as training set and testing set, respectively. However, the challenging part is the determination of centers and number of RBFs. In particular, centers of RBFs are the features which should be determined for the fitting. Hence, a feature extraction-selection algorithm is conducted as follows.



(a) PACF of electrical demand with lags



(b) PACF of solar irradiance with lags



(c) PACF of wind speed with lags

Fig. 2. PACF curves.

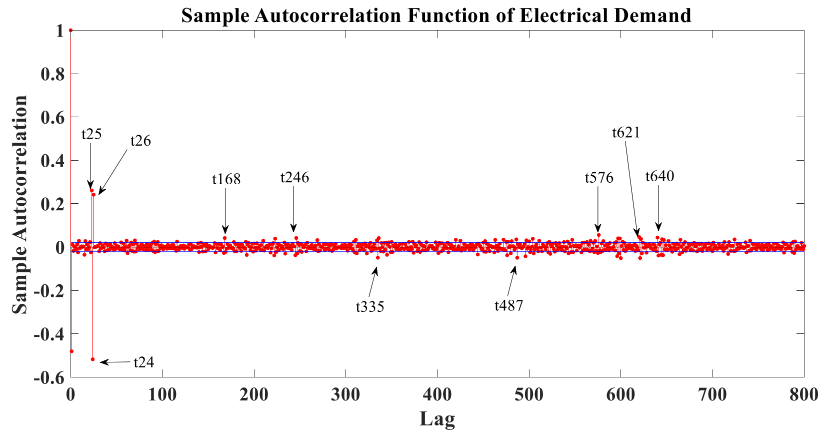
2.2.3. *Feature-extraction-selection*

According to Fig. 5, the present values are sum of RBFs. Therefore, the maximum number of RBFs or centers are obtained by present values of three time series. However, the remaining problem is to determine the values of centers. Most notably, the center has the minimum sum of distance with RBF. This is similar to finding the centers of k-means clustering problem solved by the Lloyd's algorithm (Hamerly and Drake, 2015). This algorithm finds center with minimum distance with members of cluster as follows.

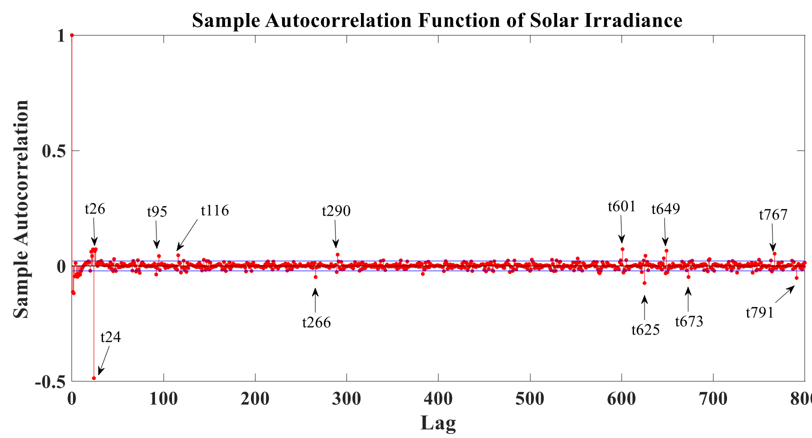
$$\underset{S}{\arg\min} \sum_1^m \sum_{y_{t_N} \in S} \| y_{t_N} - c_m \|^2 \tag{27}$$

where y_{t_N}, S and c_m are present values, cluster and mean value of members in cluster S_m. This step is known as feature extraction of modeling. The input and output of feature extraction step are $y_t = \{y_{t_1}, \ldots, y_{t_N}\}$ and $c = \{c_1, \ldots, c_m\}$, where $m \leqslant N$. Firstly, centers are assigned randomly all over the present values. Then, these values, i.e., y_{t_n}, are grouped into clusters, i.e., S_m, considering minimum distance with center of cluster. Thereupon, centers of clusters are determined in an iterative fashion as follows.

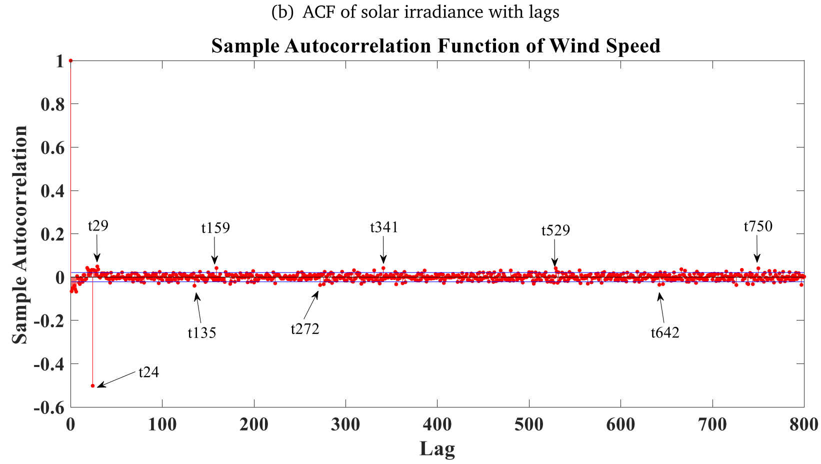
$$\frac{1}{N} \sum_{e=1}^{m} \sum_{f=1}^{N} \min \quad \| y_{t_f} - c_e \|^2 \tag{28}$$



(a) ACF of electrical demand with lags



(b) ACF of solar irradiance with lags



(c) ACF of wind speed with lags

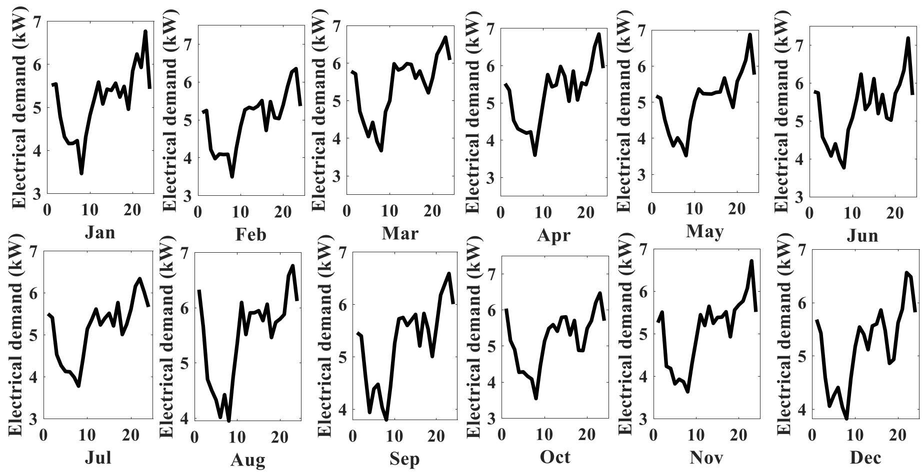
Fig. 3. ACF curves.

$$S_m^u = \{y_{t_N} : \|y_{t_N} - c_m^u\|^2 \leqslant \|y_{t_N} - c_J^u\|^2, \forall J, 1 \leqslant J \leqslant m\} \tag{29}$$

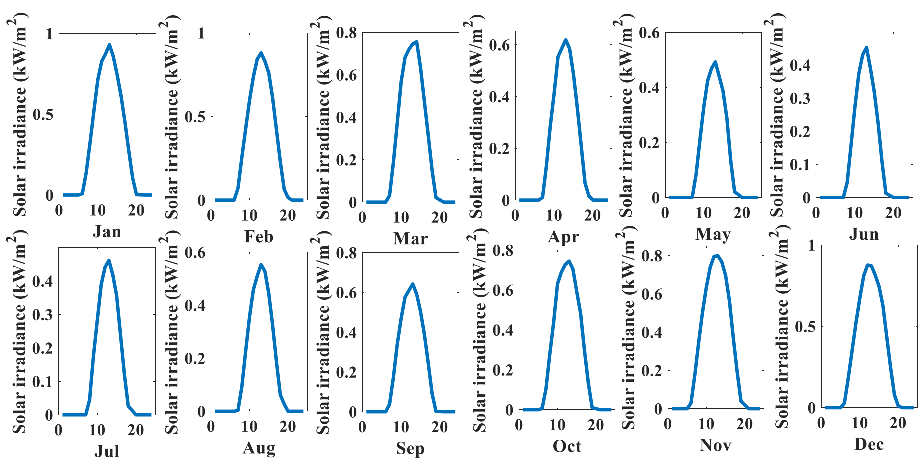
$$c_m^{u+1} = \frac{1}{|S_m^u|} \sum_{y_{t_N} \in S_m^u} y_{t_N} \tag{30}$$

$$|c_m^{u+1} - c_m^u| \leqslant \varpi_m \tag{31}$$

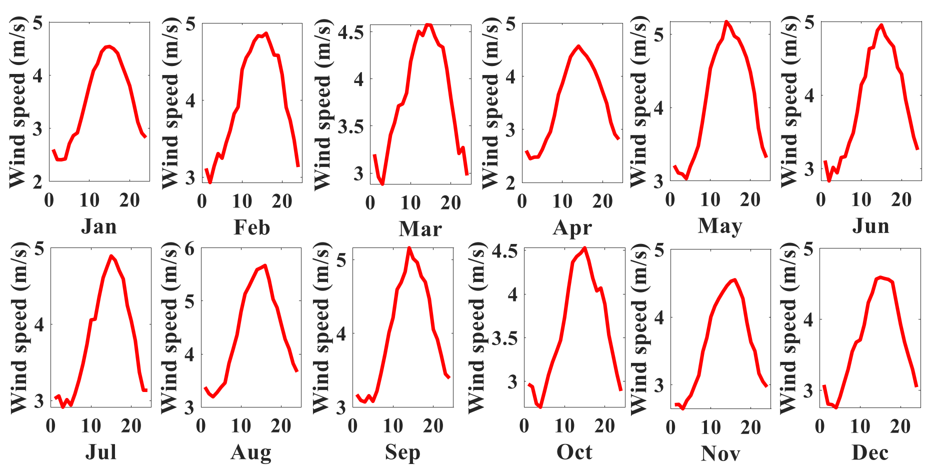
where, $|S_m^u|$ and ϖ_m are number of members in cluster S_m at iteration u and user-defined convergence constant. In fact, 1023, 336 and 348 are determined as maximum number of centers in RBF neurons for modeling electrical demand, solar irradiance and wind speed, respectively. According to Fig. 4, centers of time series are similar in each month. Hence, the optimal RBFs or centers are obtained using feature selection technique regarded as maximum relevancy minimum redundancy (MRMR) (Unler et al., 2011). MRMR is a powerful tool which selects the relevant and effective features, i.e., centers, by their mutual information (Homayoun et al., 2019) (MI). In this regard, MRMR technique filters out one of every two features with same impact on



(a) The monthly mean of electrical demand



(b) The monthly mean of solar irradiance



(c) The monthly mean of wind speed

Fig. 4. Data profiles.

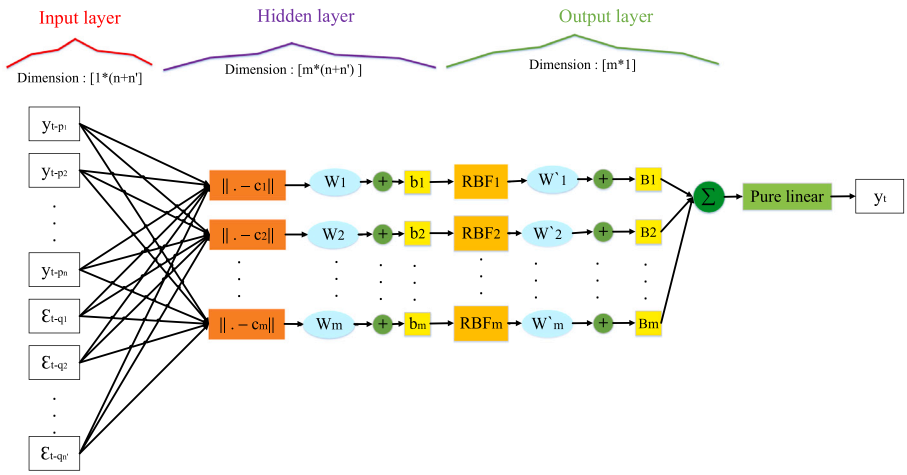


Fig. 5. The schematic of RBNN.

problems such as fitting, classification, etc. Hence, relevancy of features to the present values is expressed as the mean of MI as follows.

$$\text{Relevancy}(c, y_t) = \frac{1}{m}\sum_{e=1}^{m}\text{MI}(c_e, y_t) \tag{32}$$

$$\text{MI}(c_e, y_t) = \sum_{f=1}^{N} p(c_e, y_{t_f}) log(\frac{p(c_e, y_{t_f})}{p(c_e)p(y_{t_f})}) \tag{33}$$

where, $p(c_e, y_{t_f})$, $p(c_e)$ and $p(y_{t_f})$ are joint probability distribution function of c_e and y_{t_f}, probability distribution of c_e and probability distribution of y_{t_f}, respectively. Further, MI is calculated for each pair of features to model their mutual relationship as redundancy indicator.

$$\text{Redundancy}(c_e, c_z) = \frac{1}{m^2}\sum_{e,z=1}^{m}\text{MI}(c_e, c_z) \tag{34}$$

$$\text{MI}(c_e, c_z) = p(c_e, c_z) log(\frac{p(c_e, c_z)}{p(c_e)p(c_z)}) \tag{35}$$

$$1 \leqslant e \leqslant m, 1 \leqslant z \leqslant m \tag{36}$$

where, $p(c_e, c_z)$, $p(c_e)$ and $p(c_z)$ are joint probability distribution function of $p(c_e)$ and $p(c_z)$, probability distribution function of $p(c_e)$ and probability distribution function of $p(c_z)$, respectively. As presents, the feature selection step divide into two stage optimization problem. In the fist stage, relevancy of features to present values are calculated, i.e., (32) and (33). Then, values of relevancy are sorted from the highest to the lowest order. Moreover, the second stage begins with calculating relevancy of this sorted features to each other such as redundancy stage. Thereafter, orders of features are updated from the lowest to the highest value, i.e., (34)–(36), accordingly. Comprehensively, feature with MRMR is selected as the final feature of modeling. Hence, 107, 33 and 31 features are determined as the optimal centers of RBFs for modeling electrical demand, solar irradiance and wind speed, respectively.

2.3. Description of integrated P2P day ahead (P2P-DA) forecast-based energy market

This section synthesizes the nature of two stage multiobjective problem in detail. The schematic of problem is drawn in Fig. 6. According to Fig. 6. SA makes short terms, i.e., hourly, P2P-DA decisions considering predicted values and cleared DA energy market prices. The decisions are processed based on inflexible demand which is 30% of AEL. Therefore, P2P-DA offers are submitted and taken into account of transactions during the operation of next day at the same hour. Specifically, that renewable and non-renewable generations, i.e., DGs, of owners affect the trading volume of P2P-DA programming, directly. Furthermore, SA acts as price taker and sets the upper bound of all P2P-DA energy market prices to cleared DA price of energy market of UG. In addition, the lower bounds are set to DA marginal cost of DGs. Therefore, volume of transactions in P2P-DA energy market along with corresponding prices are optimally determined before every hour of real time programming to maximize the revenues of owners. Then, optimal P2P-DA energy market prices are reported to customers via mutual communication network. Moreover, each customer reveals its willingness to participate in short term, i.e., hourly, I-DRP of next day by sending step-wise reward-based and penalty-based offers, i.e., price-quota illustrations. In this regard, SA clears all offers of hourly I-DRPs, i.e., $A^{\text{DR,r}}_{s,t}$ and $B^{\text{DR,in}}_{s,t}$, to be considered in real time programming. In the second stage, SA clears both real time energy market and hourly DA offers I-DRPs to minimize the cost of customers.

2.4. Objectives and specifications

In this section, two stage multiobjective optimization problem is mathematically modeled as MINLP.

$$\text{Max} \;\; UF = \sum_{s=1}^{5}\sum_{t=1}^{24}\sum_{i=1}^{3}\pi_i\lambda_{s,t,i}\ln(P^{\text{P2P,DA}}_{s,t} + P^{\text{P2P,DA}}_{g,t} + P^{\text{b,RT}}_{s,t} + P^{\text{o,RT}}_{s,t}) \tag{37}$$

$$\lambda_{s,t,i} = E_{s,i}(t,q)Y_{s,t,i} + \tilde{E}_{s,i}(t,q)\Phi_{s,t,i} \tag{38}$$

$$\begin{aligned}\text{Min} \;\; \mathbb{C}^{\text{owner}} = \sum_{s=1}^{5}\sum_{t=1}^{24}(&P^{\text{b,RT}}_{s,t}\lambda^{\text{b,RT}}_{s,t} + \mathbb{C}^{\text{DG}}_{s,t} \\ &+\text{UC}_t - P^{\text{o,RT}}_{s,t}\lambda^{\text{o,RT}}_{s,t} - P^{\text{P2P,DA}}_{s,t}\lambda^{\text{P2P,DA}}_{s,t} \\ &+P^{\text{P2P,DA}}_{g,t}\lambda^{\text{P2P,DA}}_{g,t} - \lambda^{\text{P2P,DA}}_{s,t}\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}Y_{s,t,i} \\ &-\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}A^{\text{DR,r}}_{s,t}Y_{s,t,i} + \sum_{i=1}^{3}\pi_i P^{\text{DR,in}}_{s,t,i}B^{\text{DR,in}}_{s,t}\Phi_{s,t,i})\end{aligned} \tag{39}$$

$$\mathbb{C}^{\text{DG}}_{s,t} = a_s(P^{DG}_{s,t})^2 + b_s(P^{DG}_{s,t}) + c_s \tag{40}$$

$$\lambda^{\text{b,RT}}_{s,t} = 2a_g(P^{\text{total}}_t) + b_g \tag{41}$$

$$\text{Max} \;\; \text{OF}_1 = UF - \mathbb{C}^{\text{owner}} \tag{42}$$

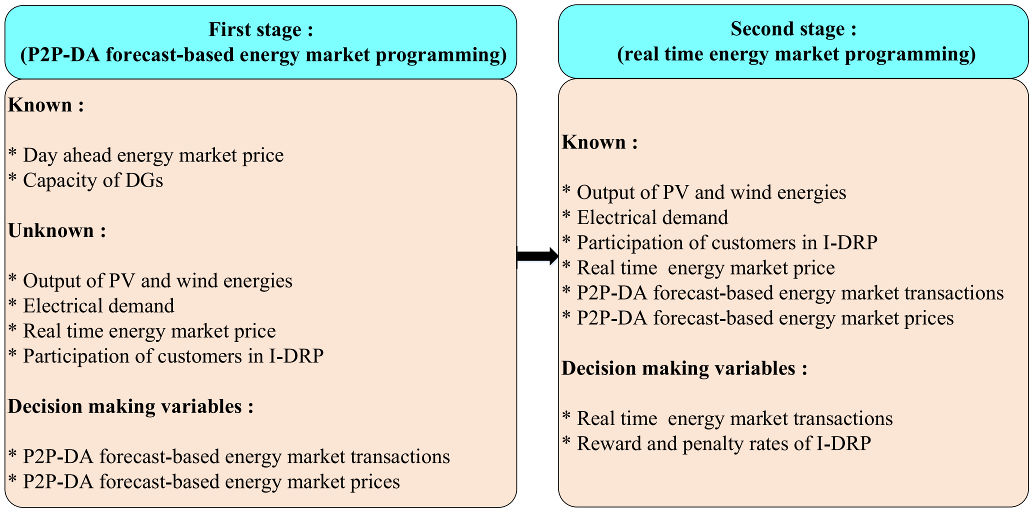


Fig. 6. The schematic of two stage multiobjective optimization.

$$\begin{aligned}&\text{Min}\ \ \mathrm{OF}_2=\mathbb{C}^{\text{customer}}=\sum_{s=1}^{5}\sum_{t=1}^{24}\big(P^{\text{AEL}}_{s,t}\lambda^{\text{P2P,DA}}_{s,t}\\&-\lambda^{\text{P2P,DA}}_{s,t}\textstyle\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}Y_{s,t,i}-\displaystyle\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}A^{\text{DR,r}}_{s,t}Y_{s,t,i}+\\&\sum_{i=1}^{3}\pi_i P^{\text{DR,in}}_{s,t,i}B^{\text{DR,in}}_{s,t}\Phi_{s,t,i}\big)\end{aligned}\tag{43}$$

$$P^{\text{GEN}}_{s,t}=P^{\text{PV}}_{s,t}+P^{W}_{s,t}+P^{\text{DG}}_{s,t}\tag{44}$$

$$\lambda^{\text{DG}}_{s,t}=2a_s(P^{\text{DG}}_t)+b_s\tag{45}$$

$$P^{\text{int}}_{s,t}=P^{g}_{s,t}-P^{\text{P2P,DA}}_{s,t}\tag{46}$$

$$\begin{aligned}&P^{b,\text{RT}}_{s,t}+P^{\text{GEN}}_{s,t}+P^{\text{P2P,DA}}_{s,t}+P^{\text{dch}}_{s,t}=P^{\text{AEL}}_{s,t}+P^{\text{ch}}_{s,t}\\&+P^{\text{P2P,DA}}_{g,t}+P^{o,\text{RT}}_{s,t}-\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}Y_{s,t,i}+\textstyle\sum_{i=1}^{3}\pi_i P^{\text{DR,in}}_{s,t,i}\Phi_{s,t,i}\end{aligned}\tag{47}$$

$$P^{\text{DG}}_{s,t}-P^{\text{DG}}_{s,t-1}\leqslant \underline{R}_s\tag{48}$$

$$P^{\text{DG}}_{s,t-1}-P^{\text{DG}}_{s,t}\leqslant \overline{R}_s\tag{49}$$

$$\underline{P}^{\text{DG}}_{s}\leqslant P^{\text{DG}}_{s,t}\leqslant \overline{P}^{\text{DG}}_{s}\tag{50}$$

$$\underline{P}^{\text{ch}}_{s}\leqslant P^{\text{ch}}_{s,t}\leqslant \overline{P}^{\text{ch}}_{s}\tag{51}$$

$$\underline{P}^{\text{dch}}_{s}\leqslant P^{\text{dch}}_{s,t}\leqslant \overline{P}^{\text{dch}}_{s}\tag{52}$$

$$\text{SOC}_{s,t}=\text{SOC}_{s,t-1}+x^{\text{ch}}_{s,t}P^{\text{ch}}_{s,t}\eta^{\text{ch}}-x^{\text{dch}}_{s,t}\frac{P^{\text{dch}}_{s,t}}{\eta^{\text{dch}}}\tag{53}$$

$$\underline{\text{SOC}}_t\leqslant \text{SOC}_{s,t}\leqslant \overline{\text{SOC}}_t\tag{54}$$

$$0\leqslant\sum_{\substack{g=1\\g\neq s}}^{5}P^{\text{P2P,DA}}_{s,g,t}\leqslant P^{\text{GEN}}_{s,t}x_{s,g,t}\tag{55}$$

$$0\leqslant\sum_{\substack{g=1\\g\neq s}}^{5}P^{\text{P2P,DA}}_{g,s,t}\leqslant P^{\text{GEN}}_{g,t}(1-x_{s,g,t})\tag{56}$$

$$P^{\text{P2P,DA}}_{s,t}=\sum_{\substack{g=1\\g\neq s}}^{5}P^{\text{P2P,DA}}_{s,g,t}\tag{57}$$

$$P^{\text{P2P,DA}}_{g,t}=\sum_{\substack{g=1\\g\neq s}}^{5}P^{\text{P2P,DA}}_{g,s,t}\tag{58}$$

$$\lambda^{\text{DG}}_{s,t}\leqslant\lambda^{\text{P2P,DA}}_{s,t}\leqslant\lambda^{\text{b,DA}}_{s,t}\tag{59}$$

$$\lambda^{\text{DG}}_{g,t}\leqslant\lambda^{\text{P2P,DA}}_{g,t}\leqslant\lambda^{\text{b,DA}}_{s,t}\tag{60}$$

$$\begin{aligned}&P^{b,\text{RT}}_{s,t}\leqslant\Big[\Big(P^{\text{AEL}}_{s,t}+P^{\text{P2P,DA}}_{s,t}+\sum_{i=1}^{3}\pi_i P^{\text{DR,in}}_{s,t,i}\Big)-\\&\Big(P^{\text{P2P,DA}}_{g,t}+P^{\text{GEN}}_{s,t}+\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}\Big)\Big]x_{s,b,t}\end{aligned}\tag{61}$$

$$\begin{aligned}&P^{o,\text{RT}}_{s,t}\leqslant\Big[\Big(P^{\text{P2P,DA}}_{g,t}+P^{\text{GEN}}_{s,t}+\sum_{i=1}^{3}\pi_i P^{\text{DR,r}}_{s,t,i}\Big)-\\&\Big(P^{\text{AEL}}_{s,t}+P^{\text{P2P,DA}}_{s,t}+\sum_{i=1}^{3}\pi_i P^{\text{DR,in}}_{s,t,i}\Big)\Big](1-x_{s,b,t})\end{aligned}\tag{62}$$

$$P^{b,\text{RT}}_{s,t}\geq 0\tag{63}$$

$$P^{o,\text{RT}}_{s,t}\geq 0\tag{64}$$

$$\lambda^{\text{P2P,DA}}_{s,t}\vartheta_{s,t,\alpha}Y_{s,t,i}\leqslant A^{\text{DR,r}}_{s,t}\leqslant\lambda^{\text{P2P,DA}}_{s,t}\vartheta_{s,t,\alpha+1}Y_{s,t,i}\tag{65}$$

$$\lambda^{\text{P2P,DA}}_{s,t}\theta_{s,t,\beta}\Phi_{s,t,i}\leqslant B^{\text{DR,in}}_{s,t}\leqslant\lambda^{\text{P2P,DA}}_{s,t}\theta_{s,t,\beta+1}\Phi_{s,t,i}\tag{66}$$

$$\sum_{i=1}^{3}Y_{s,t,i}+\sum_{i=1}^{3}\Phi_{s,t,i}\leqslant 1\tag{67}$$

$$x^{\text{ch}}_{s,t}+x^{\text{dch}}_{s,t}\leqslant 1\tag{68}$$

$$\begin{aligned}&Y_{s,t,i}\in\{0,1\}\ \Phi_{s,t,i}\in\{0,1\}\ x_{s,b,t}\in\{0,1\}\\&x_{s,g,t}\in\{0,1\}\ x^{\text{ch}}_{s,t}\in\{0,1\}\ x^{\text{dch}}_{s,t}\in\{0,1\}\end{aligned}\tag{69}$$

$$\text{Max}\ \ OF1-k\text{OF2}\ \ s.t\ \ \text{Eqs. (1)–(69)}\tag{70}$$

$$\text{SW}=\ OF1-OF2=Total\ OF\tag{71}$$

The main concern of this paper could be categorized in to two main parts: (1) maximizing the objective function of owners affected by P2P-DA forecast-based market, real time market and I-DRP, i.e., (37)–(42). In this regard, $\lambda_{s,t,i}$ (Fan, 2011) and UC_t are customer willingness to participate in only hourly DA I-DRP and the usage cost of UG,

Table 4
Structure of DER.

	MG1	MG2	MG3	MG4	MG5
Power of PV (kW)	6.1806	0	4.1204	5.1505	0
Power of wind (kW)	0	6.93	4.62	6.93	0
$\underline{P}_s^{\mathrm{DG}}$, $\overline{P}_s^{\mathrm{DG}}$, $\underline{R}_s$, $\overline{R}_s$ (kW)	0,20,7,7	0,15,7.5,7.5	0,12,5,5	0,20,7,7	0,0,0,0
Capacity of battery (kWh)	10	10	10	10	0

respectively; (2) minimizing the cost of customers electrical demand consumption. In (43) captures the participation capacity of customers in I-DRPs. Moreover, the advantages of I-DRP could be categorized in to two factors. The first is the benefit from not purchasing reduced demand at P2P-DA forecast-based price and participating in reward-based programming in which prosumer centricity duty is fulfilled by reducing the cost of customers. The second is to increase the consumption gradually before reach to peak hours at price lower than P2P-DA forecast-based price in which grid centricity obligation is satisfied by increasing the power quality of UG, i.e., reduction of total loss and improve the voltage deviation index (VDI). Constraints (44)–(46) are the total generation of microgrids, marginal cost of DGs (Jafari et al., 2020) and inflexible forecasted demand, respectively. Moreover, constraint (47) guarantees the power balance of two stage multi objective approach. These purchased power from real time market, total generation of microgrids, purchased power from P2P-DA forecast-based market and discharged power of batteries (Khalili et al., 2019) are aligned with AEL, charged power of batteries, sold power in P2P-DA forecast-based market, sold power in real time market and participating in I-DRPs. Further, constraints (48)–(50), describe the regulations of DGs, while constraints (51)–(54), explain the regulations of batteries. Constraints (55)–(58) indicate the functionality of purchased/sold power from/in P2P-DA forecast-based market to total generation of microgrids. Hence, prosumers could only sell or buy power in P2P-DA forecast-based market at time t. Constraints (59)–(60) describe the P2P-DA forecast-based market prices in which $\lambda_{s,t}^{\mathrm{P2P,DA}}$ and $\lambda_{g,t}^{\mathrm{P2P,DA}}$ are the selling/buying prices of prosumer s to/from prosumer g at time t. Therefore, these prices are cleared in the first stage of optimization before the operation of next day at same hour. Constraints (61)–(64) are the representation of purchased/sold power in real time market, whereas prosumers could only buy/sell power from/to UG at time t. Function (65) and (66) are the reward and penalty rates of blocks for participating in I-DRP, which one I-DRP could be initiated at time t. Also, (67)–(69) are considered as the binary regulations of I-DRP, real time programming and batteries, respectively. Finally, (70)–(71) is presented as the compact representation of this paper which showcases the accumulation of opposing objectives, i.e. revenue of owners and cost of customers, to maximize the social welfare (SW) of P2P-TES schematic. In addition, the details of the IEEE 85 bus test system (Jafari et al., 2020), i.e., hourly price, power flow of each feeder, VDI and total power loss of test system, are taken into account based on Distflow formulation (Zhang et al., 2020b). Table 4 is presented the DER applied to each MG. Hence, the proposed objectives are to maximize the revenues of owners and minimize the cost of customers in a P2P-TES framework.

The proposed architecture is a smart hierarchy algorithm in which I-DRP and prediction values play a crucial role in realizing the P2P-TES. Furthermore, ISO and SA are in compatible harmony due to the concise connection of both sides. That is because each side has an accessibility to the mutual purchased/sold orders. Hence, the proposed method has equipped with the privacy-preserving. The usage cost, i.e. UC_t, is considered as 0.03 of selling price of the UG published by ISO.

2.5. Decision-making strategy, reliability criterion and grid centricity indexes

As mentioned before, bi-objective profitability could be considered as a prime consideration. Hence, SW function is formed to direct the decisions into optimality. In fact, the P2P-TES has to satisfy the grid centricity regulations. Due to the importance of energy providing role of the owners, the weight values of owners have set to 1. Hence, the weight value of the customer, i.e., K, has to be allocated optimally. With this respect, PF technique is utilized as a powerful tool to direct the calculations towards optimality.

Besides, energy not supplied (ENS) is considered as the reliability criterion. In this paper, VDI and total loss allocation are used to imply compatibility of the proposed method with grid centricity matters (Uniyal and Kumar, 2018). To improve those noted indexes, the excess energy sell to the UG after providing energy to other peers. In particular, the selling price to the UG, $\lambda_t^{o,\mathrm{RT}}$, is fix to be 0.9 of selling price published by ISO, $\lambda_t^{b,\mathrm{RT}}$, to encourage the UG.

3. Simulation discussion and case study (CS) description

In this paper, all are equipped with DERs to realize the calculations except MG5. Furthermore, the interconnected MGs are coupled with the IEEE 85 bus test system. However, efficient implementation of P2P energy trading challenge to disrupting TES. To initiate the handling process of challenges, first, fitted models of electrical demand, solar irradiance and wind speed are obtained based on AIC and BIC, considering the fitted models with the least value of AIC and BIC are the ultimate fitted models of time series. Notably, that number of models correspond to lags are equal to $2^n - 1$ which n is the number of autoregressive lags. Hence, 11, 12 and 9 are lags of electrical demand, solar irradiance and wind speed, forming 2047, 4095 and 511 models, respectively. With respect to AIC and BIC, the optimal fitted models of electrical demand, solar irradiance and wind speed are obtained as in Table 5. Thereafter, one step ahead forecasting is conducted on fitted models to predict 24 h as in Table 6. Here the scenarios are described in term of bi-objective MINLP. In accordance with Fig. 7, these scenarios facilitate four cases, i.e., A-D, categorized by the application of P2P-TES among owners to cover the challenges and demonstrate the contribution of the proposed P2P-TES. Hence, eight case studies are gathered under three scenarios accordingly. The first scenario is the deterministic mode in which the real time information of consumption, solar irradiance and wind speed are available to conduct the optimization. In the second scenario, 20% load growth rate is assumed without considering the uncertainties of solar irradiance and wind speed. Specifically, solar irradiance and wind speed are considered based on the DA information. Therefore, the second scenario could be introduced as the conservative mode of this paper. Moreover, the third scenario involves the uncertainty obstacle relaxed by RBNN-based prediction method (Masoumi et al., 2020a). Further, each P2P-TES strategy is solved with/without consideration of I-DRP. In addition, the LOC analysis is modeled at the peak time of the community microgrid as the major fault of this paper, particularly at 23. Nevertheless, SP (Conejo et al., 2010a) is considered as scenario-based techniques directed by Monte Carlo simulation to operate the relaxation strategy, i.e., RBNN-based model. Moreover, the large number of scenarios are reduced to 20 by SCENRED (Anon, 2018). Afterward, the assessments and illustrations are presented for the normal energy system condition, ***CS7***, to reduce the complexity. The simulations are gathered from MATLAB and CONOPT optimizer of GAMS to relax the uncertainty and perform the optimization, respectively (system: Intel Core i7-6700HQ CPU at 3.5 GHz, 12G RAM).

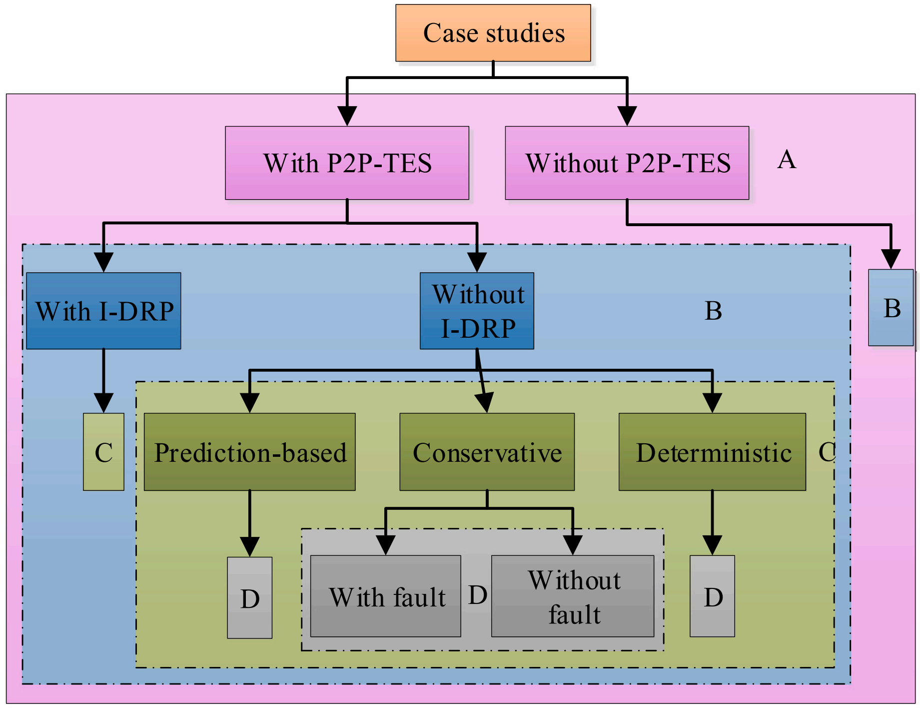


Fig. 7. Description of case studies.

Table 5
Selected autoregressive Lags for Modelings based on AIC and BIC.

Time series	Autoregressive lags	AIC	BIC
Electrical demand	t1-t2-t3-t4-t21-t72-t96-t120-t336	2345.6	2641.3
Solar irradiance	t1-t2-t3-t4-t12-t18-t25-t49-t73	1672.1	1876.9
Wind speed	t1-t3-t17-t30-t44-t136-t387	1548.6	1606.3

Table 6
The training results.

Unrelaxed variables	RMSE			
	SVM	GPR	LSTM	Proposed RBNN
Electrical demand	0.7600	1.0200	0.8200	**0.352**
Wind speed	0.9810	1.6300	1.0700	**0.5295**
Solar irradiance	0.0901	0.3000	0.1170	**0.06597**

Table 7
The testing results.

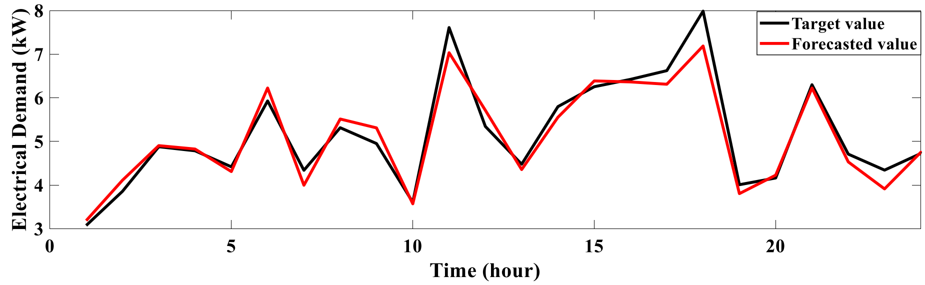
Unrelaxed variables	RMSE			
	SVM	GPR	LSTM	Proposed RBNN
Electrical demand	0.8	1.019	0.804	**0.359**
Wind speed	0.99	1.51	1.062	**0.5211**
Solar irradiance	0.102	0.251	0.107	**0.063**

Table 8
The regression of forecast values for 24 h.

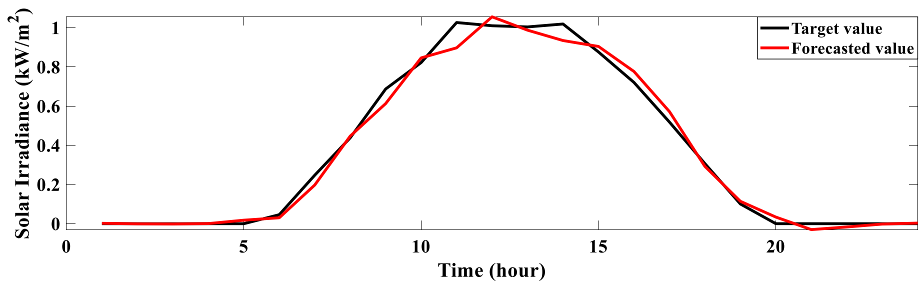
Unrelaxed variables	Regression			
	SVM	GPR	LSTM	Proposed RBNN
Electrical demand	0.542	0.44	0.5	**0.972**
Wind speed	0.491	0.411	0.478	**0.88**
Solar irradiance	0.767	0.528	0.705	**0.984**

4. Obtained results and discussions

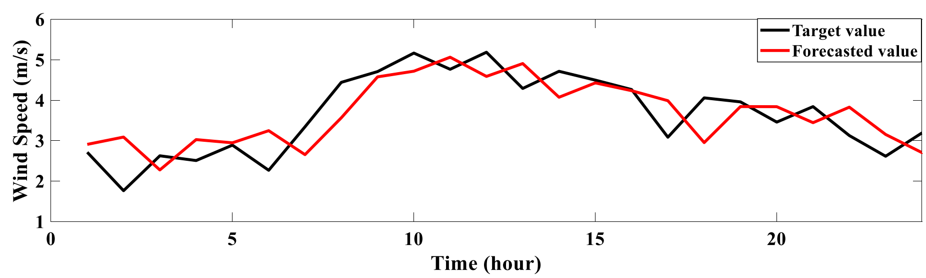
Firstly, the results of proposed RBNN is compared with two machine learning-based and one deep learning-based regression algorithms, i.e., SVM, GPR and LSTM, to illuminate the adequacy of modeling, as illustrated in Tables 6 and 7. According to those tables, proposed RBNN outperforms the results of mentioned regression algorithms by the means of the least RMSE obtained in both training and testing sets. Further, regression results of proposed RBNN is presented in Table 8 to illustrate the accuracy of linear regression. Hence, the forecast results are presented in Fig. 8. Therefore, SA shares predictions and $\lambda_{s,t}^{P2P,DA}$ with consumers to modify their consumption and the optimization is obtained by the smart P2P-TES tactic. According to Table 9, case-studies 2 and 4 violate the reliability criterion and unable to satisfy the expectations of consumers. Thereby, these cases could be identified as the infeasible because MG5 are not able to satisfy its consumers without P2P-TES. Besides, the owner's revenues have been increased while the costs of customers have decreased in all cases. Hence, it is clear that the proposed tactic has gained practicality in all feasible cases. Further, I-DRP has contributed equally to the objectives considering the LOC in all P2P-based case studies (**CS7** and **CS8**). Therefore, the exquisite role of I-DRP is proven for optimal management in all scenarios. In (**CS5** and **CS7**), the revenue of owners has increased by 10.6%, and the cost of customers reduced by 9.86%, which are the instances representing adequacy of I-DRP and integration of renewable energy resources into the body of microgrid. In fact, the major portion of the cost is compensated by utilizing P2P-TES (**CS1**, **CS3**, **CS5** and **CS7**). Therefore, the practicality of smart I-DRP is proven. It is also important to consider the revenue and cost improvements of owners and customers, compared to cases without P2P-TES, where the revenues are increased to 23.32% in **CS3** and **CS7**. However, the costs of customers have increased to 8.48% comparing with the deterministic (**CS3** and **CS7**), due to the optimal economic weight obtained for customers. On the contrary, TotalOF is improved significantly by 63.83%. This trend can be seen in the comparison of **CS1** and **CS5**. During LOC, revenue of owners are and cost of customers are improved by 29.62% and 1.51% considering deterministic case studies, i.e., **CS6** and **CS8**. The reason behind is



(a) Electrical demand



(b) Solar irradiance



(c) Wind speed

Fig. 8. Forecasted values during 24 h.

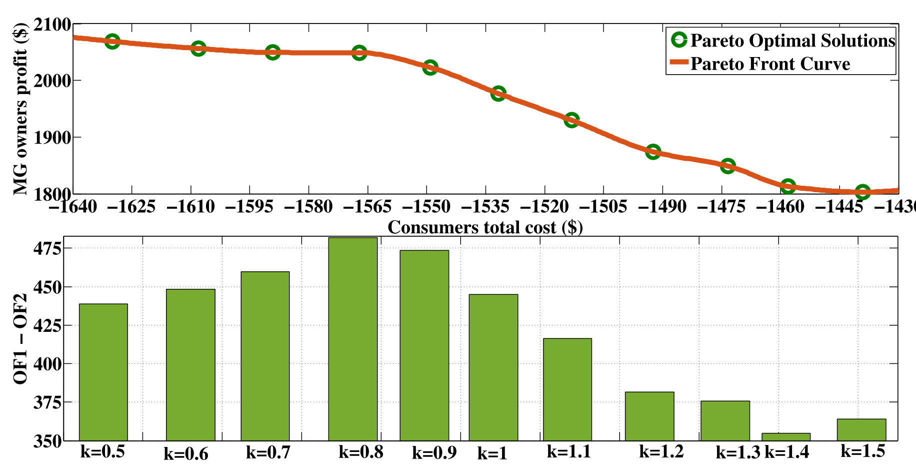


Fig. 9. Decision-making strategy applied by PF technique.

the accurate forecasting results of RBNN, directing P2P regulations to benefit from the integration of renewable energy resources. Hence, the proposed algorithm relays the attribute of being environmentally friendly in its basis. Comparing all case studies of **CS6** and **CS8** with **CS2** and **CS4**, the proposed strategy absorbs the negative impact of LOC by utilizing I-DRP. Therefore, the smart P2P-TES algorithm contributes to indicate the novelty of the proposed architecture for handling the joint uncertainty and LOC thoroughly. On the other hand, the decision-making role of the PF technique is taken into account to prove the accuracy of calculations. Specifically, PF determines the optimal values of this methodology, while considering the SW function which satisfies both objectives uniformly, as in Fig. 9. Note that cost of customers are presented by negative sign as the indication of purchased cost of buying energy. On the contrary, revenue of owners are expressed by positive

Table 9
The Results of Problem Using Smart P2P-TES Algorithm (K=0.8).

CS	Without P2P-TES								With P2P-TES							
	Without I-DRP				With I-DRP				Without I-DRP				With I-DRP			
	Without fault (CS1)		With fault (CS2)		Without fault (CS3)		With fault (CS4)		Without fault (CS5)		With fault (CS6)		Without fault (CS7)		With fault (CS8)	
	OF1	OF2	OF1	OF2	OF1	OF2	OF1	OF2	OF1	OF2	OF1	OF2	OF1	OF2	OF1	OF2
Deterministic	**1095**	**1562**	–	–	**1582**	**1449**	–	–	**1764**	**1744**	**1482**	**1588**	**1951**	**1572**	**1921**	**1564**
Conservative	968	1944	–	–	1334	1710	–	–	1644	2082	1285	1928	1749	1848	1713	1831
Prediction-based	1145	1541	–	–	1527	1417	–	–	1840	1743	1631	1691	2049	1567	1929	1561

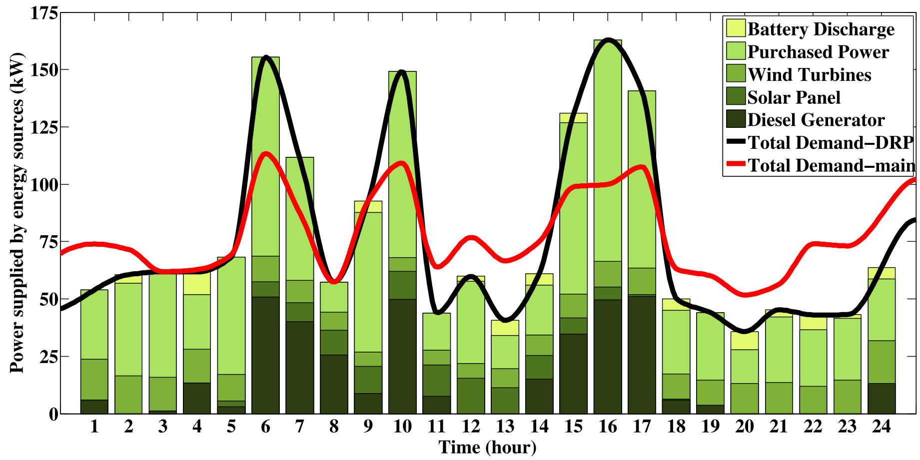


Fig. 10. The energy management results of the CS7.

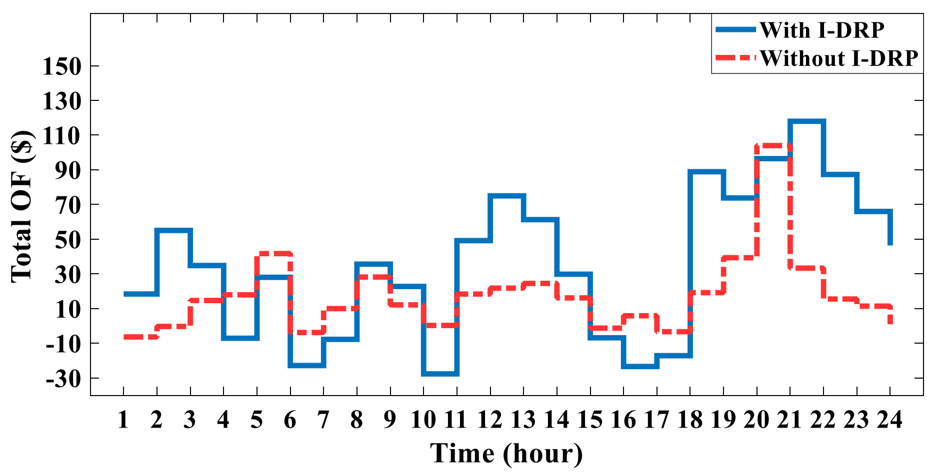


Fig. 11. The Total OF in CS7.

sign as the representation of profit of selling power to customers. According to Fig. 9, by altering from 0.5 to 1.5, the solutions are non-dominated based on objectives. Hence, K is fixed to 0.8 to satisfy the SW. Further, Table 10 illustrates the optimality of the proposed method. Table 10 is presented the improvement in the trend of solutions, with the smart P2P-TES algorithm. The proposed method has taken the advantage of optimality in all the case studies, considering the proximity of solution in deterministic one which is gathered based on the perfect information of uncertainties.

Moreover, the performance of I-DRPs is discussed through Figures 10–16. According to Fig. 10, I-DRP has reduced the electrical demand at 1–3, 11–14 and 18–24 and the major portion of reduction is performed at peak times, i.e., 18–24. With respect to Fig. 11, by applying I-DRP, the optimal value of total objective function, i.e., Total OF, is increased in fifteen hours of the day and decreased in remaining nine hours. Further, the increasing ratio is higher compared to decreasing ratio. Fig. 11 indicates that the maximum improvement of Total OF is functioned at 1–3, 11–14 and 18–24. Comparing with Fig. 10, it could be concluded that the rise of Total OF occurs at consumption times which electrical demand of MGs are reduced by applying I-DRP. Similar to Fig. 11, Fig. 12 implies that the optimal value of OF1 is significantly increased at hours of load reduction. In addition, the optimal value of OF1 is decreased in six hours of the day. On the contrary, the increasing rate is notably higher than the decreasing rate in the remaining eighteen hours, which demonstrates the optimal performance of I-DRP to rise the revenue of owners. According to Fig. 13, OF2 is decreased during major hours of the day, i.e., fifteen hour. Furthermore, the optimal value of OF2, in fifteen hours, is higher than remaining nine hours. Similar to Fig. 11 and Fig. 12, the maximum improvement of OF2 is operated at hours where the consumption is

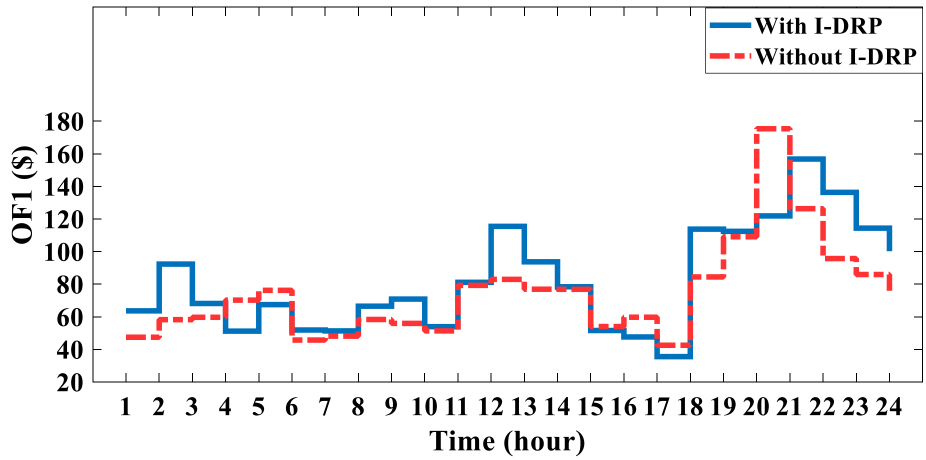


Fig. 12. The revenue of owners in CS7.

Table 10
The Results of PF Technique for Obtaining Bi-Objective Profitability (K=0.8).

CS	Without P2P-TES				With P2P-TES			
	Without I-DRP		With I-DRP		Without I-DRP		With I-DRP	
	Without fault (CS1) Total OF	With fault (CS2) Total OF	Without fault (CS3) Total OF	With fault (CS4) Total OF	Without fault (CS5) Total OF	With fault (CS6) Total OF	Without fault (CS7) Total OF	With fault (CS8) Total OF
Deterministic	−155	–	**423**	–	369	212	**693**	**670**
Conservative	−587	–	−34	–	−22	−257	271	248
Prediction-based	−88	–	393	–	446	278	**795**	**680**

reduced by I-DRP. According to Fig. 14, the shifting hours of consumption funcionalized by the prices of real time programming. Particularly, the optimal performance of I-DRP is in harmony with hourly prices of real time programming. With this respect, I-DRP cuts off electrical demand which is consumed at hours with prices higher than selling prices of P2P-DA forecast-based energy market. Comprehensively, the excess purchased power from UG is completely consumed at off-peaks, i.e., 6 and 10, and mid-peaks, i.e., 15–17, and unable to sell to UG, simultaneously, to maintain the stability of transactions, i.e., Fig. 15. Hence, the generated power of renewable energies are stored in battery at off-peak hours. Therefore, the reduced consumption of peak hours are gained by the portion of battery energy storage and released capacity of DGs, i.e., Fig. 16. This is because, the maximization of revenue could be realized only at peak hours, due to the high price of power. Therefore, Figs. 10–16 convey the bi-objective profitability of I-DRP for increasing the revenue of owners and cost of customers, uniformly. Besides, the SP analyses the application of the relaxation process. According to Table 11, the absolute error indicates the distance of the obtained solution from the optimal solution. Hence, it is clear that the proposed method by the relaxation algorithm is performed effectively.

Furthermore, P2P-TES has to abide by the grid centricity obligations: the total power loss and the total voltage deviation as shown in Figs. 17 and 18. According to Fig. 17, the total power loss of grid-connected mode is less than island model, i.e., 6.98%: 1.58589 (MW) and 1.70506 (MW), respectively. Moreover, grid-connected mode improves VDI of the grid, i.e., 2.19%, 1.228 p.u., to 1.201 p.u. as in Fig. 18. In addition, the VDI of UG has been enhanced by the proposed method . Fig. 15 shows that the smart P2P-TES strategy provides almost 0.03% of UG's demand at peak times. Therefore, total power loss and the VDI in UG are improved at peak times, while removing the grid centric obligations and facilitating to apply the proposed method generally.

Table 11
Comparison of the proposed method with SP.

CS	CS7	CS8	CS7	CS8
	Total OF	Total OF	Total OF	Total OF
Deterministic	**693**	**670**	Absolute Value	
SP	**801**	**722**	**108**	**52**
Smart P2P-TES	**795**	**680**	**102**	**10**

5. Conclusion

In this paper, a smart method is proposed to handle the challenges of P2P trading system named smart P2P-TES. In this regard, the proposed strategy applies an intelligent-based technique, i.e., RBNN, to predict electrical demand, solar irradiance and wind speed of real time programming. Based on the results of forecasting, I-DRPs are initiated to reshape the consumption of customers for gaining economic interests. To do so, the P2P-DA forecast-based energy market is, firstly, cleared by SA, determining optimal volume of transactions and prices for maximizing the revenue of owners. Then, SA determines optimal offers submitted in I-DRPs to minimize the cost of customers. Hence, real time energy market transaction are cleared and reported by ISO to UG. Besides, two case studies, i.e., deterministic and conservative, are described to validate the performance of RBNN. The results convey that using smart P2P-TES and I-DRP leads to decreasing the cost of customers and increasing the revenue of owners via integrating with prediction results of RBNN. Considering the application of I-DRPs, the revenue of owners has increased by 10.6%, and the cost of customers reduced by 9.86%. Moreover, TotalOF, is significantly, increased by 63.83% considering the cooperation of P2P-TES and I-DRP . On the other hand, compared results of the proposed method with SP and conservative one excel in term of proximity with the deterministic case which information of the next day are determined. Also, results show the adequacy of the proposed method against load curtailment at peak time, guaranteeing ENS of customers be equal to zero. On the

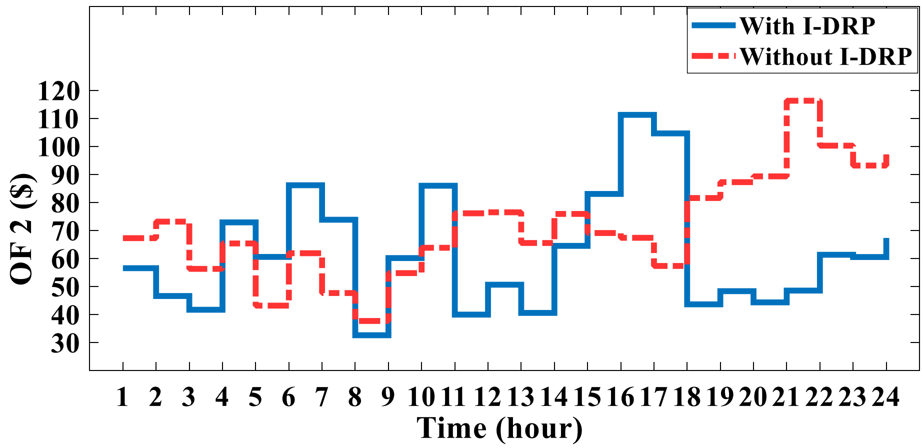


Fig. 13. The cost of customers in CS7.

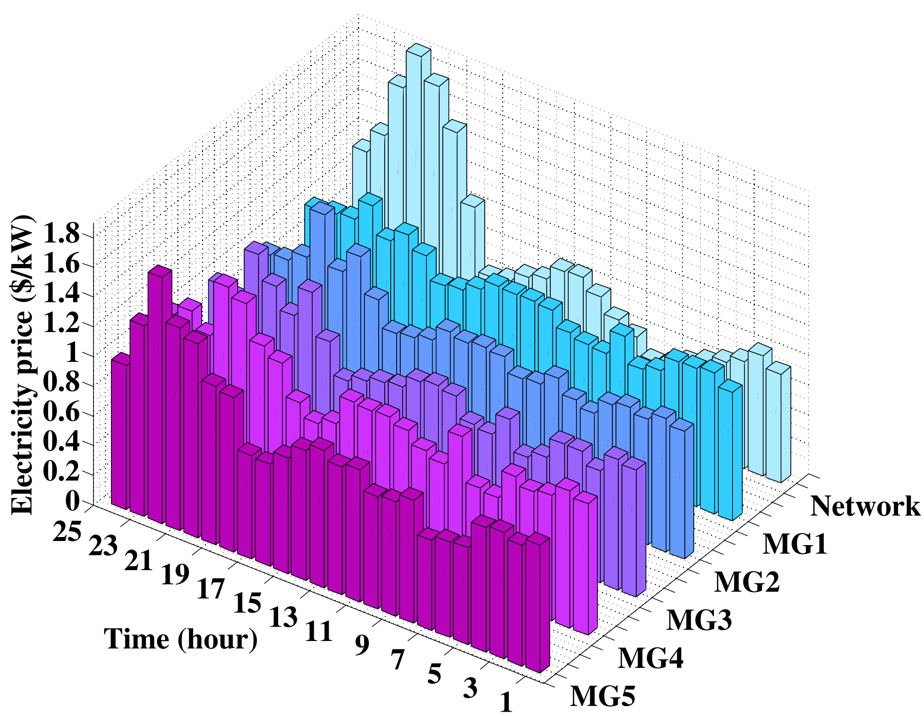


Fig. 14. Selling price for each MGs in CS7.

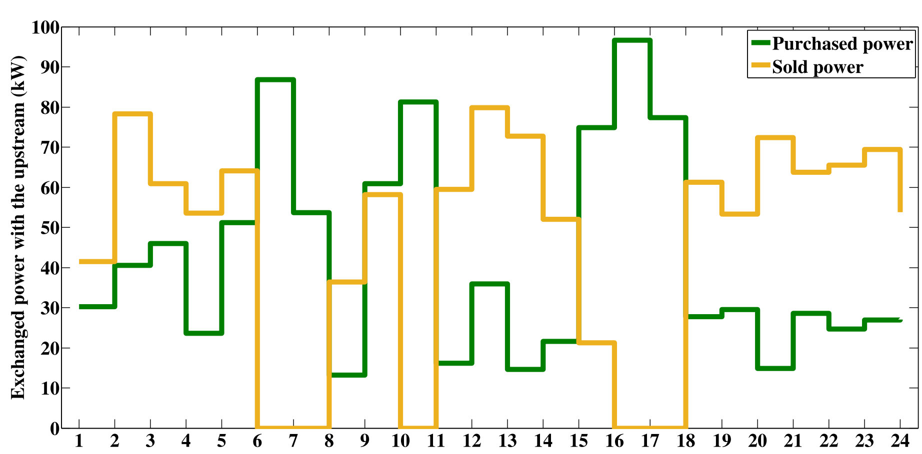


Fig. 15. Interactions of P2P-TES with UG as purchased and sold powers for CS7.

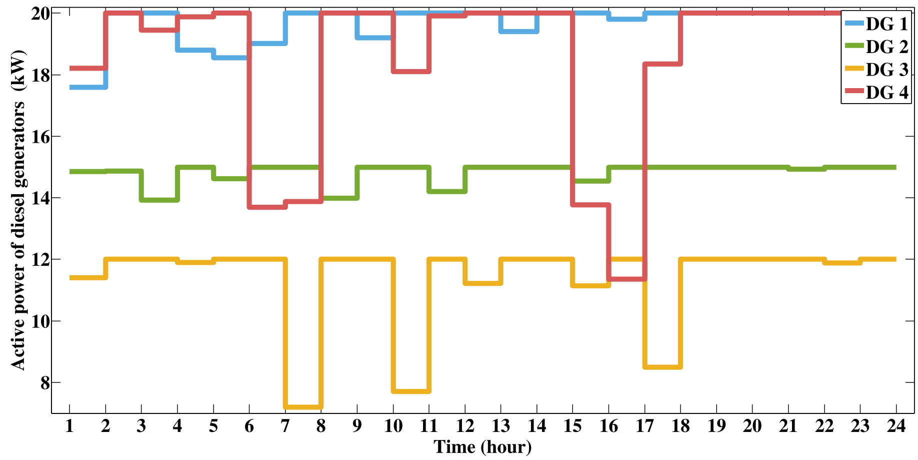


Fig. 16. Generated power of DGs for CS7.

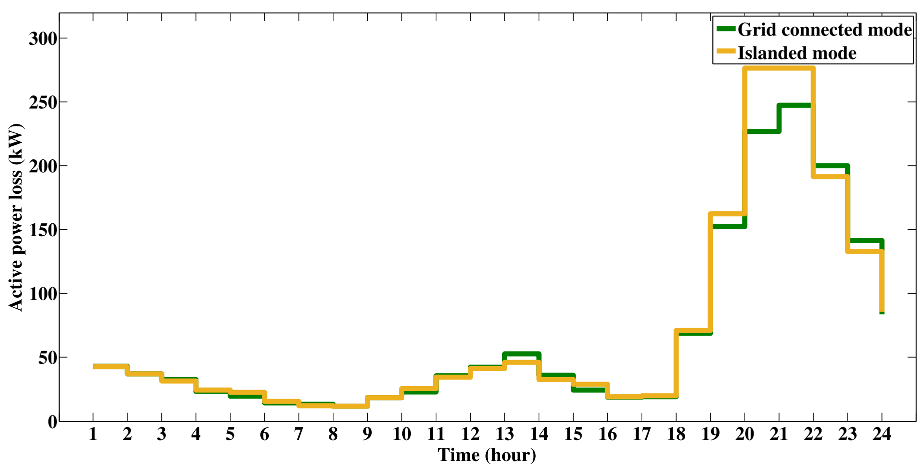


Fig. 17. Total power loss with and without MGs for CS7.

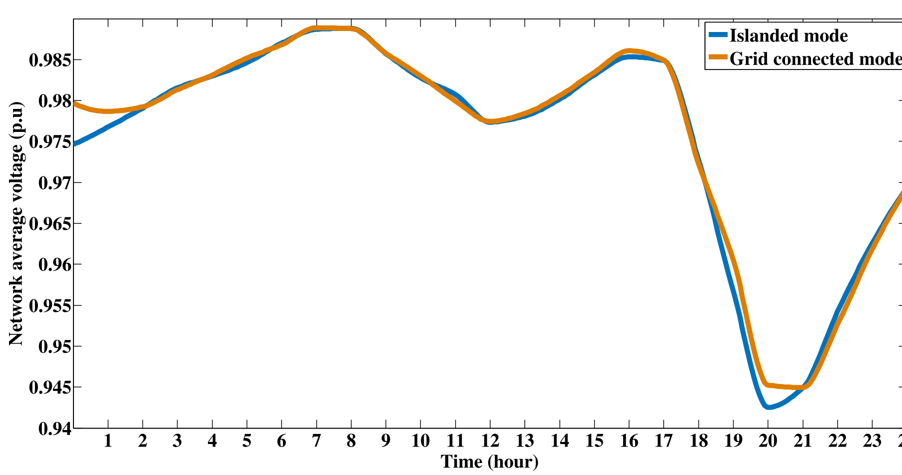


Fig. 18. Total deviation of voltages obtained with and without MGs for CS7.

Table 12
The comparison of contribution of this work with references.

References	Mathematical formulation				Energy market			Uncertainty modeling	Stochastic elasticity	DRP	Optimization method
	Consumer side	Owner side	UG	Reliability	DA	RT	DA&RT				
Azim et al. (2020)	Yes	No	Yes	No	No	Yes	No	No	No	No	NLP
Ganjeh Ganjehlou et al. (2020)	Yes	No	Yes	Yes	Yes	No	No	SP	No	Yes	LP
Luo et al. (2019)	Yes	Yes	No	No	No	Yes	No	No	No	No	LP
Morstyn et al. (2020)	Yes	Yes	No	No	No	No	Yes	PEM	No	No	MINLP
Fernandez et al. (2021)	Yes	Yes	No	No	Yes	No	No	No	No	No	Bi-level/Game theory
An et al. (2021)	Yes	Yes	No	No	Yes	No	No	RETScreen	No	Yes	MINLP
Liang et al. (2019)	Yes	No	Yes	Yes	No	No	Yes	SP	No	Yes	Risk constraint/Two-stage
do Prado and Qiao (2019)	No	Yes	No	No	Yes	Yes	No	SP	Yes	Yes	MILP
da Silva et al. (2020)	Yes	No	No	Yes	No	Yes	No	SP	No	Yes	MINLP
Yang et al. (2020)	No	Yes	No	Yes	Yes	No	No	SP	Yes	Yes	Chance constraint
Tushar et al. (2020)	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	Game theory
Anoh et al. (2020)	Yes	Yes	Yes	No	No	Yes	No	No	No	Yes	Game theory
Maharjan et al. (2016)	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Game theory
Niromandfam et al. (2020)	Yes	Yes	No	Yes	Yes	No	No	SP	No	Yes	Two-stage
Paudel et al. (2021)	Yes	Yes	Yes	No	No	Yes	No	SP	No	No	Two-stage
Zhang et al. (2020b)	No	Yes	Yes	No	No	Yes	No	No	No	No	ADMM
Tushar et al. (2019)	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Game theory
Tushar et al. (2020)	Yes	Yes	No	No	No	Yes	No	No	No	Yes	Game theory
Xiao et al. (2020)	Yes	Yes	No	No	No	Yes	No	No	No	No	Game theory
Yang et al. (2020)	Yes	Yes	No	No	No	Yes	No	SP	No	Yes	ADMM
Guerrero et al. (2019)	No	Yes	Yes	No	No	Yes	No	No	No	No	NLP
Nguyen et al. (2018)	Yes	Yes	No	No	Yes	No	No	No	No	No	MILP
This work	Yes	Yes	Yes	Yes	No	No	Yes	RBNN	Yes	Yes	MINLP

other hand, bi-objective profitability is obtained as electrical demand is decreased from peak hours. Further, power loss and VDI of UG are reduced by 6.98% and 2.19%, respectively. Hence, the results convey the grid centricity attribution of proposed smart P2P-TES.

CRediT authorship contribution statement

Hadi Niaei: Methodology, Software, Writing – original draft, Formal analysis. **Amin Masoumi:** Methodology, Investigation, Formal analysis, Writing – review & editing. **Amir Reza Jafari:** Methodology, Investigation, Formal analysis, Writing – review & editing. **Mousa Marzband:** Supervision, Investigation, Formal analysis, Writing – review & editing. **Seyed Hossein Hosseini:** Supervision, Investigation, Formal analysis, Writing – review & editing. **Amin Mahmoudi:** Supervision, Investigation, Formal analysis, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table 12.

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