Optimal Risk-Constrained Peer-to-Peer Energy Trading Strategy for a Smart Microgrid

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Nowadays, encouraging consumers to use renewable resources and generate electricity locally in a microgrid is very important that has attracted much attention. In this paper, an optimal strategy is proposed to model energy trading among the photovoltaic (PV) prosumers in a smart microgrid. A prosumer is considered to be able to exchange energy with other prosumers through a peer-to-peer (P2P) energy trading mechanism. Moreover, they could have contracts with the utility grid to purchase or sell electricity as well. For this purpose, first, a new energy pricing model based on the production and consumption of each prosumer is presented that shows how consumers interact with the utility grid as well as other consumers. The price-based demand response (DR) programs is used to increase the profitability of each consumer and reduce the microgrid dependency to the utility grid. The uncertainty of PV systems generation is taken into account through forecasting by deep learning method. For this purpose, the long short-term memory (LSTM) model based on time series information is used. Moreover, the risk associated with the generation uncertainties is modeled by downside risk constraint (DRC). The classical optimization method is employed to minimize the total incurred costs. Simulation analysis and results show that not only the costs of energy trading will be decreased using the proposed model, but also the willingness of the prosumers to participate in the P2P energy trading will be increased significantly.

keywords: *Smart microgrid, peer-to-peer energy trading, demand response, downside risk constraint, deep learning.*

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NOMENCLATURE

B_n Upper bound of PV energy feed in the utility grid

$\mathbf{T}$ Total number of time slots during operation time

$\mathbf{n}$ Total number of prosumers

P_{CT_i} Power consumption of PV prosumer i with an energy storage system during operation time$t$

$\mathbf{P}^t_{C_i}$ Power consumption of PV prosumer i without storage system in time slot

$\mathbf{E}^t_{dcharge_i}$ The amount of discharge of the prosumer i storage system in time slot t

$\mathbf{E}^t_{charge_i}$ The amount of charge of the prosumer i storage system in time slot t

$\mathbf{E}^t_{charge_{i,s}}$ The amount of charge of the prosumer storage system i in time slot$t$ and scenario s

$\mathbf{P}_{GT_i}$ Produced PV power of prosumer i with storage system during operation time

$\mathbf{P}^t_{G_i}$ Produced PV power of prosumer i without storage system in time slot t

$\mathbf{P}^t_{G_{i,s}}$ Produced PV power of prosumer i without storage system in time slot t and scenario s

$\mathbf{NP}^t_i$ Energy of net power/energy of PV prosumer in the time slot

$\mathbf{NP}^t_{i,\omega,s}$ Energy of net power/energy of PV prosumer in the time slot t and scenario ω and s

$\mathbf{TES}^t$ Total energy sold in time slot t

$\mathbf{TES}^t_{\omega,s}$ Total energy sold in time slot and scenario ω and s

$\mathbf{pr}^t$ Internal price in time slot t

$\mathbf{pr}^t_{\omega,s}$ Internal price in time slot t and scenario ω and s

$\mathbf{R}$ Revenue of the ESP in an operation day

$\mathbf{TEB}^t$ Total energy bought in time slot t

$\mathbf{PCR}^t_{\omega,s}$ PCR of the energy trading area in time slot t and scenario ω and s

$\mathbf{pr}_b$ Internal buying price of the energy trading area

$\mathbf{pr}_s$ Internal selling price of the energy trading area

$\mathbf{X}^t_i$ Adjusted power consumption of PV prosumer i without DR uncertainty in time slot i

$\mathbf{P}^t_{adj_i}$ Adjusted power consumption of PV prosumer i with DR uncertainty in time slot i

$\mathbf{inc}_i$ Cost of inconvenience of PV prosumer i

$\mathbf{C}^t_i(.)$ Cost function of PV prosumer i in time slot t

$\mathbf{C}^t_{i,\omega,s}(.)$ Cost function of PV prosumer i in time slot t and scenario ω and s

α_i Sensitivity coefficient of PV prosumer i

γ Percentage of service fee by traded energy

λ_b Unit price of buying energy from utility grid

λ_s Unit price of selling energy to the utility grid

$\mathbf{e}^t_{i,\omega,s}$ Related error (%) of forecasted value of PV prosumer$i$ in time slot$t$ and scenario ω and s

$\mathbf{PCR}^t$ PCR of energy trading area in time slot t

1. INTRODUCTION

In recent years, the use of PV systems has increased because of economic and environmental benefits. In this regard, the policy aims to encourage consumers to use PV systems considering self-consumption, which decreases their energy costs that may reduce their dependence on the utility grid [1]. Hence, the consumer's desire to become a prosumer may increase accordingly [2]. A microgrid contains a set of distributed energy resources such as wind turbines, fuel cells, PV systems, energy storage systems and loads that acts as a controllable unit according to grid conditions and supply electricity [3]. There are various ways to use or trade the power generation of distributed energy resources, including self-consumption, P2P energy trading and trading with the utility grid [4]. In P2P trading, participants trade without intermediaries, transactions are made directly between a local producer and consumer that may improve the costs of each participant [5]. In [6], it is shown that P2P energy trading is more economically profitable than trading only with the utility grid, while a local electricity market is offered for the P2P energy trading. Residential prosumers determine their generating power or consumption power in order to minimize the electricity bills and dependence on the grid. In literature, two types of competition in P2P trading are discussed. The first is the competition to determine the suitable price between the sellers and the second is the competition between the buyers to choose a suitable seller [7]. In the P2P trading, prosumers first use their surplus power to supply the power of the neighbor prosumers. They use the remaining power to charge their batteries, and if they have a power shortage, first they buy from the neighbor prosumers and then, if needed, buy from the utility grid. The presence of prosumers in a microgrid reduces the costs of the utility grid significantly [8]. A P2P energy trading market model has been expressed using a dynamic programming optimization algorithm for greater profitability [9]. In [10], a P2P energy trading model based on multi-classes energy management has been proposed to coordinate trading between prosumers and wholesale electricity market according to their priorities with the aim of minimizing the total costs, considering both power losses as well as battery lifetime. One of the most important issues in energy trading is energy pricing especially in smart grids that may affect consumers' behaviors [11]. Encouraging prosumers to P2P trading and using its benefits much depends on the financial transactions between the buyers and sellers as prosumers. Therefore, energy pricing models have many applications, where it is not possible to model the DR programs without pricing [12]. In [13], an algorithm is presented for real-time pricing considering the DR to achieve optimal load control, and a Stackelberg game has been formulated for the electricity market. For the coordination of the smart houses, an energy sharing model with dynamic pricing has been proposed such that the smart houses are modeled as a multi-agent system [14]. A real-time multi-agent theory-based platform is presented for a microgrid market operation in [15], while an aggregator performs a dynamic pricing mechanism considering DR programs for energy trading [16]. End-users with electric and thermal loads choose the best strategy using cloud information that may improve trading performance. Based on the minimum and maximum electricity trading prices, P2P energy trading is provided that guarantees the profitability of consumers as well as producers [17]. In [18] to increase energy sharing, the DR program and prosumers determine their load behavior based on internal prices. Its purpose is to increase the operating profit that may improve the network power profile. A cooperative game for energy trading among prosumers with an energy storage system to is presented to minimize the total costs and fair distribution of energy considering DR program [19]. In [20], a two-stage energy sharing model has been proposed with regard to DR and market prices and renewable energy uncertainties. Uncertainties are modeled through a scenario-based stochastic approach, considering the DR program, while the risk-taking of renewable resources is modeled using downside risk constraints [21]. In [22], a demand-side management and pricing model coordinated with P2P energy trading among the smart homes is assumed, and fair distribution is also considered. In [23], peer-to-peer energy trading model is presented considering a price-based demand response program for energy management and increasing welfare. The decentralized alternating direction method of multipliers (ADMM) is used to solve the proposed problem. Deep Learning is one of the machine learning methods that has been highly regarded by researchers in many issues such as forecasting the energy production and demand. For instance, in [24], a robust model based on Deep Learning has been used to forecast solar irradiation. The quantile regression forecasting model is applied for interval analysis. A deep network with LSTM model for time-series prediction improvement has been used to forecast wind generation in [25]. A deep belief network has been applied for day-ahead generation forecasting of a solar power plant in [26]. A summary comparison of some recent studies with the current paper are presented in Table 1.

A. Contribution

To bridge these research gaps, a peer-to-peer energy trading model considering the uncertainty of PV systems as well as DR programs is presented that investigate the impact of risk on the costs of each prosumer. Since the prosumers in this type of microgrid can act as a buyer or seller of energy per hour and have a direct effect on retail pricing, a pricing method has been proposed for the energy trading regionally. In summary, the main contributions of this paper are as follows:

- An energy-trading model is defined with a virtual organization called energy sharing provider to facilitate energy trading between prosumers.
- The generation of PV systems is forecasted by Deep Learning method and the risk associated with the PV systems generation is considered.
- A dynamic internal pricing approach with regards to feed-in tariffs based on the production and consumption ratios of prosumers is proposed for energy trading in the region, while the prosumers participate in a DR program based on internal prices and their load profiles.
- The uncertainty arising from participating in a DR program is formulated using the fuzzy-Markov method.

Fig. 1 shows the flow diagram of different parts of energy sharing provider (ESP). The rest of this paper is structured as follows: The model has been formulated in section 2, and the implementation of the model is presented in section 3. Case studies and simulation analysis are provided in section 4, while concluding remarks is presented in section 5.

2. PROBLEM FORMULATION

In the following the problem is formulated consistently in different parts.

A. Energy trading structure

The structure of energy trading is shown in Fig. 2. To facilitate energy trading, a new organization called Energy Sharing Provider (ESP) has been introduced to handle energy trading and ensure power balance and payments. As shown in Fig. 2, the energy trading area includes PV prosumers, user energy management systems (U-EMS), ESP and smart meters. Two-way communication between the ESP and prosumers is required to trade energy. ESP is an independent entity that acts as an intermediary for energy trading that is, if PV power generation exceeds the power consumption, it will sell the extra power to the utility grid or other prosumers, and if the PV power generation is less than the power consumption it buys, they need power from the utility grid or other prosumers. All prosumers will cover the costs of ESP for service required. Each PV prosumer consists of a PV system, load, U-EMS, smart meters, etc. and they trade their additional PV power in the microgrid. The applications of U-EMS include collecting PV systems power generation data, awareness of prices and optimal scheduling of shiftable/ curtailable loads to participate in DR programs. As shown in Fig. 3, the performance of the U-EMS is demonstrated.

B. Formulation of energy trading

The production and consumption pattern of each prosumer may be different. For participating in energy trading, the power consumption of each prosumer during the 24 hours of operation is as follows:

$$\begin{aligned} &P_{CT_i} = [P_{C_i}^1, P_{C_i}^2, ..., P_{C_i}^T] - \\ &\left[E^1_{dch\,\arg e_i}, E^2_{dch\,\arg e_i}, ..., E^T_{dch\,\arg e_i}\right] \\ &i = [1, 2, ..., n], T = [1, 2, 3, ..., 24] \end{aligned} \tag{1}$$

where is the total number of prosumers and is the number of operation time slots. The PV output of each prosumer during the operation is as follows:

$$\begin{aligned} &P_{GT_i} = [P_{G_i}^1, P_{G_i}^2, ..., P_{G_i}^T] - \\ &\left[E^1_{dch\,\arg e_i}, E^2_{dch\,\arg e_i}, ..., E^T_{dch\,\arg e_i}\right] \end{aligned} \tag{2}$$

The net power of each prosumer in time interval is defined as follows:

$$NP_i^t = P_{CT_i}^t - P_{GT_i}^t, t \in [1, 2, ..T] \tag{3}$$

Prosumers act as buyers or sellers per hour based on their net power. Accordingly, the total energy sold (TES) and the total energy bought (TEB) at each time interval are calculated as:

$$TES^t = -\sum_{i=1}^{n} NP_i^t \tag{4}$$

$$TEB^t = \sum_{i=1}^{n} NP_i^t \tag{5}$$

C. Formulation of pricing model

Pricing is one of the most important principles for the energy trading. Among the pricing principles this paper assumes that: the range of prices should be between the feed-in tariff and the price of the electricity utility grid, prices are inversely proportional to the ratio of production and consumption, the economic equilibrium and the equitable distribution must be in the energy trading zone. Pricing is determined by the amount of production consumption ratio (PCR) of each prosumer that is defined as follows:

$$PCR^t = \frac{TES^t}{TEB^t} \tag{6}$$

The output of PV systems and loads may vary from hour to hour the value of PCR can be varied. For energy trading, ESP buys power at the price of λ_b from the utility grid and at the price of Pr_b from other prosumers, and also sells power at the price of λ_s to the utility grid and at the price of Pr_s to other prosumers. According to the principles of economics, in general, the relationship between price and PCR is inversely proportional [27]. The higher the PCR, the lower the price and vice versa. Therefore, due to the limitations, energy buying and selling prices in the energy trading area are presented as follows:

$$\begin{aligned} &{pr_s}^t = f(PCR^t) \\ &= \left\{ \frac{\lambda_s.\lambda_b}{(\lambda_b - \lambda_s).PCR^t + \lambda_s} \right. , 0 \le PCR^t \le 1 \\ &\lambda_s, PCR^t \ge 1 \end{aligned} \tag{7}$$

$$\begin{aligned} &{pr_b}^t = f(PCR^t) \\ &= \{ {pr_s}^t.\ PCR^t + \lambda_b(1 - PCR^t), 0 \le PCR^t \le 1 \\ &\lambda_s, PCR^t \ge 1 \end{aligned} \tag{8}$$

If PCR=0, it means that no prosumers sell electric power in the energy trading area. If PCR1, it indicates that there is an extra PV power in the energy trading area that can be sold to the utility grid. Since the amount of PV production cannot be predicted, PCR may change with the amount of power consumption, having an inverse relationship that may decrease the ratio with increasing power consumption and increases with reducing power consumption. Therefore, it is assumed that each prosumer has a certain number of shiftable/ curtailable loads that can participate in DR programs and affect the PCR as well as internal prices in the energy trading area.

Table 1. A summary comparison of some recent studies with the current paper

Ref.	P2P trading	Energy pricing	Storage system	Demand response	Inconvenience cost	U-EMS	Uncertainties	risk	Deep Learning
[6]	✓	✓	✓	✓	-	-	-	-	-
[7]	✓	-	✓	✓	-	-	-	-	-
[9]	✓	✓	✓	-	-	-	-	-	-
[14]	✓	-	✓	✓	-	-	-	-	-
[16]	-	✓	✓	✓	-	-	✓	✓	-
[18]	-	-	✓	✓	✓	-	✓	-	- ✓
[19]	-		-	-	-	-			
[20]	✓	✓	✓	✓	-	-	-	-	-
[25]	-	-	-	-	-	-	✓	-	✓
Current study	✓	✓	✓	✓	✓	✓	✓	✓	✓

D. PV prosumers costs model

A PV prosumer refers to a consumer who can use its own PV system production to play both the roles of power consumer and power producer in a microgrid. Different type of prosumer is as commercial, home, office buildings [28]. It is assumed that each prosumer with shift able/curtailable load may participate in DR programs, and, according to the set of prices, adjusts its power consumption profiles [29]. Sometimes for any reason such as insufficient PV production and/or inappropriate price, prosumers may not be able to provide the its commitment in DR programs. Therefore, the uncertainty should be considered for prosumers' level of participation in DR program [30]. In this paper, such uncertainty is modeled based-upon fuzzy Markov [31] that may affect the real-time market conditions. In fact, since power consumption may vary in some hours, which is called adjusted power. The power is adjusted by considering the uncertainty and without considering the uncertainty as follows:

$$P_{adj_i} = [P^1_{adj_i}, P^2_{adj_i}, ..., P^T_{adj_i}] \tag{9}$$

$$X_i = [X^1_i, X^2_i, ..., X^T_i] \tag{10}$$

where P_{adj_i} is the adjusted power considering uncertainty for the i-th PV prosumer at time interval t, and is the adjusted power for each prosumer at time interval t for the day-ahead market. So the net power at day-ahead as well as real-time markets is expressed as follows:

$$\mathrm{NP}^t_{i,s} = P^t_{adj_i} - (P^t_{G_{i,s}} - E^t_{ch\arg e_{i,s}}), t = [1, 2, ..., T] \tag{11}$$

$$NP^t_{i,s} = X^t_i - P^t_{GT_i}, t = [1, 2, ..., T] \tag{12}$$

Consumers' willingness and sensitivity to participate in DR programs may also vary. If they decide to participate in DR program and transfer their shiftable loads from the current point to another time, which may affect their comfort. Therefore, the costs of inconvenience caused by participating in DR is as follows:

$$inc_i = \alpha_i \sum_{t=1}^{T} (X^t_i - P^t_{GT_i}) \tag{13}$$

where inc_i is inconvenience costs for any prosumer, α_i is a sensitivity factor that indicates the tendency of prosumers to adjust the shiftable load and participate in DR. The larger it is, the more sensitive the prosumer is to changing its load, and it's less inclined to shift loads. Therefore, the objective function of the optimal operating costs of each prosumer can be stated as follows:

$$C^t_i(X^t_i) = pr^t_i(X^t_i - P^t_{GT_i}) + \alpha_i(X^t_i - P^t_{CT_i})^2 \tag{14}$$

$$C_i = \sum_{t=1}^{T} C^t_i(X^t_i) \tag{15}$$

$$\sum_{t=1}^{T} X^t_i = \sum_{t=1}^{T} P^t_{CT_i} \tag{16}$$

$$\min(P_{GT_i}) \leq X^t_i \leq \max(P_{GT_i}) \tag{17}$$

$$P^t_{CT_i} - X^t_i \leq B_n \tag{18}$$

where $C^t_i(X^t_i)$ includes the total costs and the willingness of users, so that the $pr^t_i(X^t_i - P^t_{GT_i})$ costs or revenue of using electricity and $\alpha_i(X^t_i - P^t_{CT_i})^2$ is the costs of inconvenience. The prices of the energy trading area are also defined as follows:

$$pr^t_i = f(NP^t_i) = \left\{ \begin{array}{c} pr^t_s, NP^t_i < 0 \\ pr^t_b, NP^t_i \geq 0 \end{array} \right\} \tag{19}$$

Prices include both purchase and sale price. If the net power is positive, the prosumer needs to buy power from the seller's prosumers, and if the net power is negative, the prosumer sells the excess power to the buyer's prosumers. Eq. (16) means that the shiftable load can be transferred to another time interval, but it is assumed that the total power consumption kept constant. In Eq. (17), the adjusted power is considered the main power consumption and Eq. (18) shows that for the sake of grid security, power production is limited.

E. Downside Risk Constraints

In this section, the constraints related to risk-in-cost are stated. In this way, the prosumer tries to reduce the expected operation cost in each scenario from the predetermined target cost ($T_{\cos t}$) so that the risk caused by the uncertainty of the production of PV

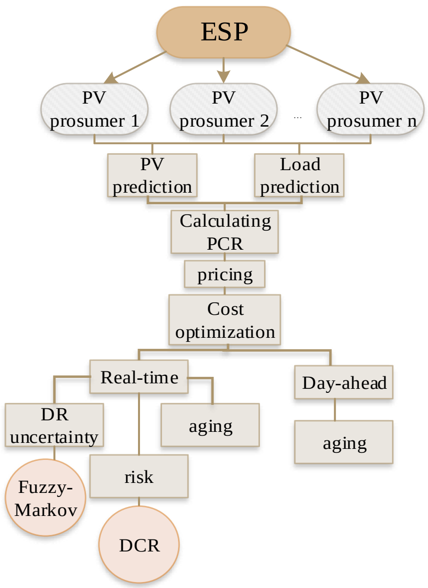

Fig. 1. Diagram of the proposed P2P energy trading model

systems to be zero [21]. Therefore, the DRC for each prosumer is as follows:

$$\begin{cases} if C_{s,i} > T_{\cos t} \quad then: Risk_{s,i} = C_{s,i} - T_{\cos t} \\ otherwise: \quad Risk_{s,i} = 0 \end{cases} \tag{20}$$

where $Risk_{s,i}$ is the risk cost and $C_{s,i}$ is the operation cost. Equation (20) can be reformulated as (21) and (22):

$$\begin{aligned} & 0 \leq C_{s,i} - Risk_{s,i} \leq M \times (1 - U_{s,i}) \\ & 0 \leq Risk_{s,i} \leq M \times U_{s,i} \end{aligned} \tag{21}$$

$$\begin{cases} if C_{s,i} > T_{\cos t} \quad then: \ U_{s,i} = 1 \\ otherwise: \quad U_{s,i} = 0 \end{cases} \tag{22}$$

where M is a positive and large number. So, the expected downside risk (EDR) for the operation cost function for each prosumer is as follows:

$$\sum_{S=1}^{N_s} \rho_s \times Risk_{s,i} \leq \lambda \times EDR_i \tag{23}$$

$$EDR_i = \sum_{S=1}^{N_s} \rho_s \times (C_{s,i}^{No\ risk} - T_{cost}) \tag{24}$$

where $C_{s,i}^{No\ risk}$ is the operation cost amount in each scenario for each prosumer without considering downside risk constraints. λ is the number between 0 and 1 that represents the balance between risk and expected operation cost.

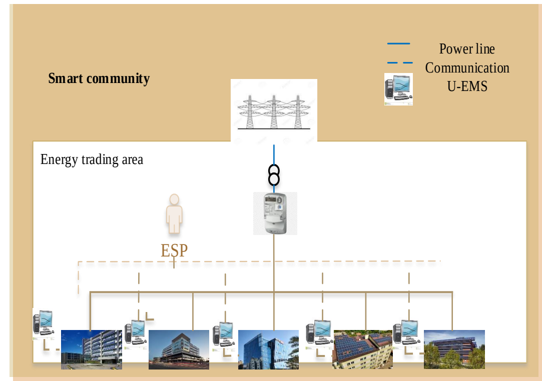

Fig. 2. Energy trading structure in a microgrid

F. The business model of ESP

ESP acts as a third party and intermediary between prosumer and the utility grid, which has no personal gain and income and spends its revenue that charged from prosumers on energy trading area services. The ESP could charge the service fee from the participating prosumers in energy sharing, which is directly proportional to the amount of shared PV energy. The ESP earns a percentage of the minimum between energy sales and purchases shared among prosumers in the P2P energy trading as the business from prosumers' service fees. The ESP business from prosumers' service fees in one day of operation can be formulated as follows:

$$S = \gamma \sum_{t=1}^{T} \min(TES^t, TEB^t) \tag{25}$$

Prosumers should pay for the service fees according to their contributions of shared energy. The service fee model for prosumers can be formulated as:

$$S_i^t = \frac{\gamma.\left|NP_i^t\right|.\min(TES^t, TEB^t)}{TES^t + TEB^t} \tag{26}$$

where γ is the percentage of a service fee by energy trading

G. Fairness index

Ensuring a fair exchange of energy is one of the most important principles in energy trading. For this purpose, an indicator called the fairness index (k) is defined in [32], which is a variance of the benefit-to-cost ratio for the shiftable loads of each prosumer

$$k = \frac{1}{n} \sum i^n \left(\frac{EB_i}{sh_i} - \frac{1}{n} \sum_{i=1}^{n} \frac{EB_i}{sh_i} \right)^2 \tag{27}$$

$$[EB_i = C_i^e - C_i^{e'} \tag{28}$$

$$sh_i = \frac{\sum_{t=1}^{T} \left| P_{CT_i}^t - X_i^t \right|}{2} \tag{29}$$

where EB_i is the economic benefit of the prosumer i , C_i^e and $C_i^{e'}$ are the cost of prosumer before and after participating in both P2P energy trading and DR program, respectively. sh_i is the total energy of load shifting of the prosumer in operation time. If k is too large, it indicates that some prosumers have contributed more or less than the specified share, and this indicator could be effective in the prosumers' willingness to trade energy.

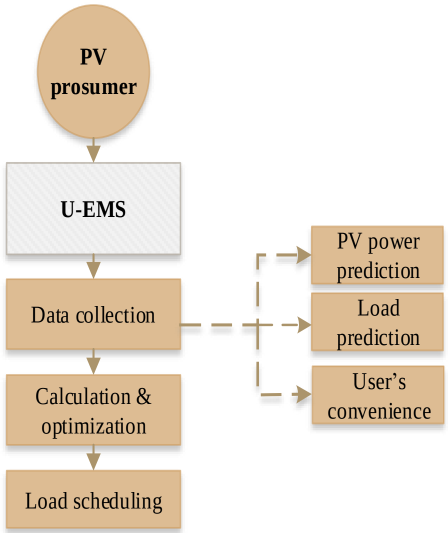

Fig. 3. Performance of U-EMS

H. Long short-term memory (LSTM)

The LSTM has been a developed structure of conventional recurrent neural network to done short-term forecasting for a data with long-term dependency [24]. LSTM unit keeps the effective information for a long time. Therefore, the LSTM recognizes long-term dependency better than conventional recurrent neural network. A deep LSTM network consists of several LSTM models in different layers. In this paper, the LSTM has been used in a Deep Learning method based on model presented in [24] to forecast a short-term output from a long-term data.

3. PROBLEM IMPLEMENTATION

In this study, a two-level optimization model was used to optimize energy trading. At a higher level, first, according to Eq. (14), internal prices are determined for the energy trading area. Then at a lower level, the minimum cost of each prosumer is calculated as follows:

$$\begin{cases} \min_x C_i(x_i, pr_i) \\ = \sum_{t=1}^{T} \begin{pmatrix} pr_i^t(x_i^t - P_{GT_i}^t \\ +\alpha_i(x_i^t - P_{C_i}^t)^2 \end{pmatrix} \\ s.t. \sum_{t=1}^{T} x_i^t = \sum_{t=1}^{T} P_{CT_i}^t \\ \min(P_{CT_i}) \leq x_i^t \leq \max(P_{CT_i}) \\ P_{GT_i}^t - x_i^t \leq B_n \end{cases} \tag{30}$$

At a higher level, the goal is to set a fixed pricing model for each prosumer in the period , and at a lower level, the goal is to minimize the costs of prosumers. Considering the forecasting error of PV, the error percentage of the forecasted value of prosumer ' PV generation in the scenario is as follows:

$$e_{i,s} = [e_{i,s}^1, e_{i,s}^2, ..., e_{i,s}^T] \tag{31}$$

So the real-time market cost function is as follows:

$$\begin{aligned} \min_{P_{adj}} C_i(P_{adji}, pr_{i,\omega,s}) &= C_i^h(P_{adj_i}^h) \\ &+ \frac{1}{M}\sum_{m=1}^{M}\sum_{t=1}^{T} \begin{pmatrix} pr_{i,\omega,s}^t.(P_{adj_i}^t \\ -P_{GT_{i,s}}^t(1+e_{i,\omega_m,s}^t)) \\ +\alpha_i.(P_{adj_i}^t - P_{CT_i}^t)^2) \end{pmatrix} \end{aligned} \tag{32}$$

where t is the current time, the first part of the cost function is the minimum cost of each prosumer obtained in the lower level and the second part of the cost function is the expected cost of each prosumer in all scenarios, which is obtained using the approximated average sampling method [33, 34].

4. SIMULATION RESULT AND RESULT ANALYSIS

A case study of a microgrid that includes residential buildings (RB), commercial buildings (CB) and office buildings (OB) is shown in Fig. 4. The parameters for each of them are given in Table 2 that the values of the second and third columns are taken from [35]. Here, a storage system is provided for some prosumers. In this paper, the values of λ_b , λ_s , α , $\beta$and M are considered as 0.15 $(/kWh)$, 0.06(/kWh), 0.01, 0.12 and 30, respectively. Fig. 5 shows the PV systems generation forecasted

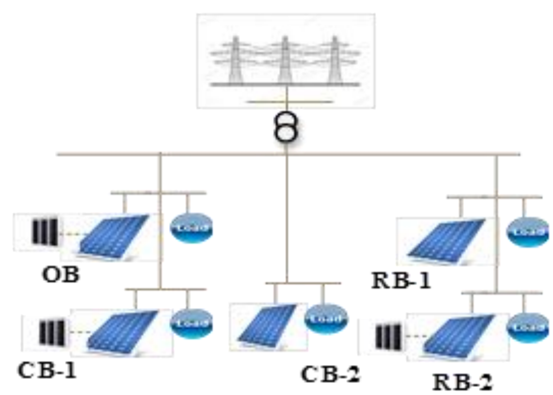

Fig. 4. Study case network of the microgrid

by Deep Learning taking into account the uncertainty. The forecasted PV systems generation of all prosumers for 24 hours of a day is shown in Fig. 6

The LSTM for time-series prediction improvement has been used to forecast PV systems generation based on the model presented in [24]. The value of root mean square error (RMSE) and mean absolute percentage error (MAPE) for the forecasted output of the production of PV system of the prosumer RB2 are 0.0663 p.u and 2.96%, respectively. The daily load of each prosumer is shown in Fig. 7, the net energy of each prosumer in a typical day is shown in Fig. 8, and the total net energy as well as total load of the energy trading area are shown in Fig. 9.

The values of charging and discharging of storage systems are given in Fig. 10, while battery efficiency is 0.95 and the initial state-of-charge is zero

Table 2. Parameters of PV prosumers in the microgrid

Name of PV prosumer	Capacity of PV (kW)	The maximum loadin the typical day (kW)	Capacity of storage system (kW)
OB	250	319.5	100
CB-1	250	256.8	200
CB-2	150	392.4	-
RB-1	100	116.15	-
RB-2	400	236.8	200

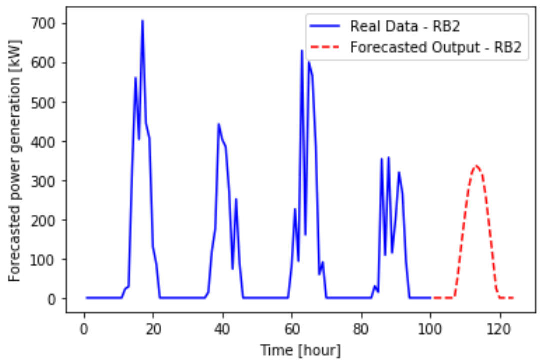

Fig. 5. Real data and forecasted output of solar irradiance by Deep

A. Numerical results

In this section, the simulation results are presented. The results for the internal energy trading prices in the microgrid are shown in Fig. 11. As shown, PV power is traded between the hours 7 and 17 according to the internal prices set among the prosumers and internal prices change according to PCR. The results of the cost of the prosumers and the business of ESP are given in Table 3. The results show that the cost of prosumers in P2P trading decreases either as a buyer or as a seller compared to direct trading with the utility grid using feed-in-tariff. Also, the ESP income in P2P trading increases with the increase in the number of prosumers and more costs are spent on services. In addition, the results show that real-time costs are higher than the day-ahead costs due to the error in predicting PV systems outputs.

Table 3. The cost of prosumers and ESPs' business

Name of PV prosumer	Trading cost using Feed-in-tariff ($)	Day-ahead cost ($)	Real-time cost ($)
OB	283.1	251.3	262.1
CB-1	634.2	296.5	303.5
CB-2	612.9	530.4	546.4
RB-1	206.5	200.0	205.4
RB-2	346.9	298.5	305.8
ESP	0	9.71	9.75

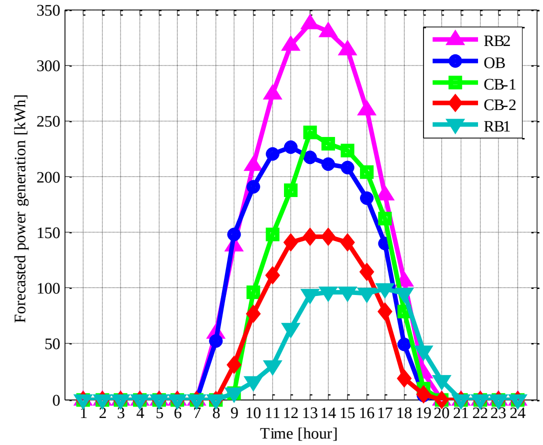

Fig. 6. Forecastd PV systems generation by Deep Learning method for all prosumers

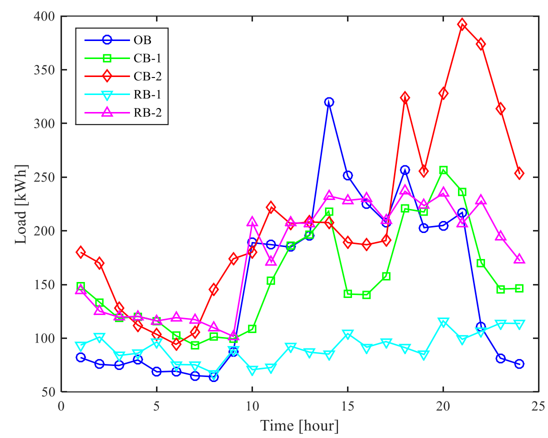

Fig. 7. Prosumers' load [35]

The effect of DR uncertainty on real-time operation cost of the prosumers is considered.

The DRC results for each prosumer are shown in Fig. 12. The expected cost and risk-in-cost of each prosumer are calculated. The risk-in-cost is calculated as the difference between the cost of operation and the expected cost of each prosumer. If the operating cost is lower than the expected cost, the risk-in-cost is zero. As shown in Fig. 12, the amount of risk and the expected cost is calculated for different values of λ . The higher the expected cost, has the lower risk-in-cost. The value of λ varies from 0 to 1 with a step of 0.1. For $\lambda = 1$, the expected cost is the maximum amount and the risk-in-cost is zero. The results of the fairness index (K) for each prosumer are shown in Fig. 13. The more prosumer' willingness to participate in the DR program and P2P energy trading, the higher the fairness index value. According to this index, it can be concluded that although prosumers can affect internal prices by shifting their load, their costs and revenues are affected by the amount of PV power and their willingness to participate in the DR program and P2P energy trading.

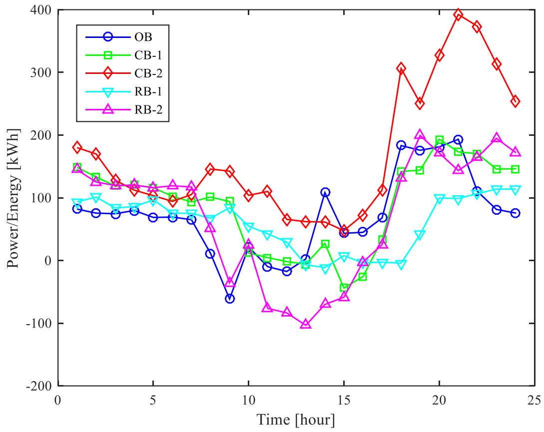

Fig. 8. Prosumers' net power/energy

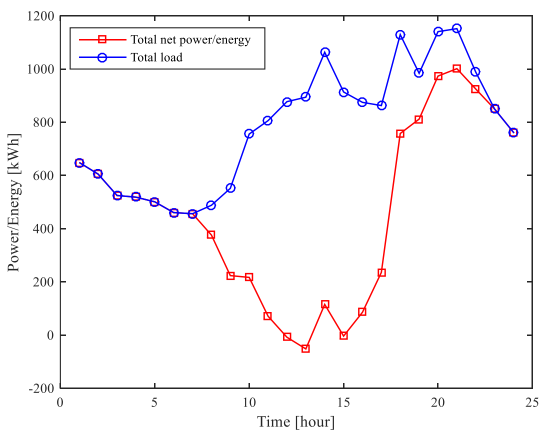

Fig. 9. Total net power/energy and total load of energy trading area

5. CONCLUSION

In this study, an energy trading model for prosumers in a microgrid is presented considering the DR program and its associated uncertainty. The DRC method is employed to model the uncertainty of the PVs production in order to control and manage risk. This energy trading can be in the form of trading with the utility grid or P2P trading with others. One of the most important principles in energy trading is pricing. In this paper, a pricing model is expressed according to the amount of production and consumption of prosumers and their role in energy trading. The time horizon of the energy pricing model is day-ahead and real time market. Prosumers due to their Shiftable loads can participate in demand response programs, the cost of their inconvenience and uncertainty of participation in demand response program were also considered. Fuzzy-Markov model has been used to model the uncertainty of prosumers participation in demand response programs. The uncertainty of PV systems generation is taken into account through forecasting by deep learning method. The LSTM model based on time series information is used. Moreover, the risk associated with the generation uncertainties is modeled by downside risk constraint (DRC). Using this model, prosumers by using the electric energy storage system and P2P trading compared to direct trade with the utility grid, considering the solar energy tariff, can save on their costs and generating electricity in place increase. The results show that the proposed model could provide economic advantages, improve the performance of energy trading, encourage prosumers to P2P trading, improve energy pricing mechanism, and reducing peak load and reserve requirements.

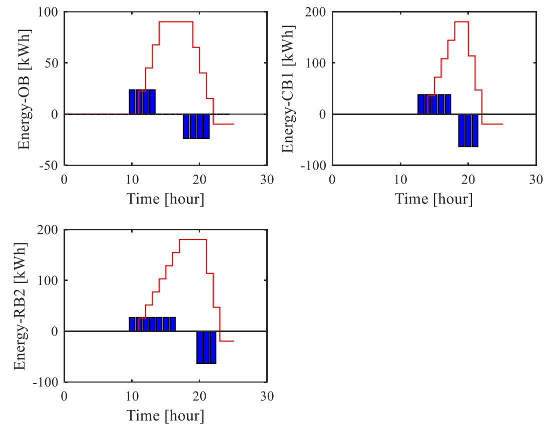

Fig. 10. Optimal charging, discharging and state-of-charge of energy storage systems

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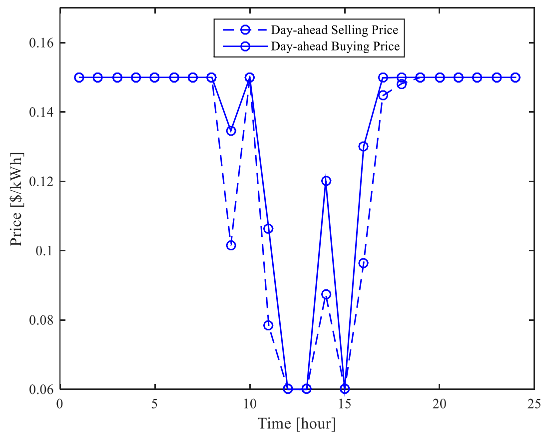
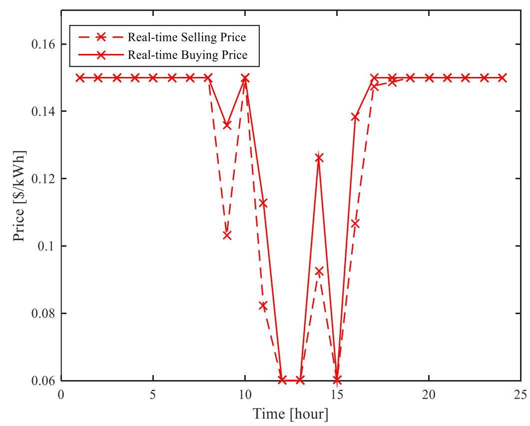


(a). Internal prices in the Day-ahead market



(b). Internal prices in the Real-time market

Fig. 11. operational Internal prices

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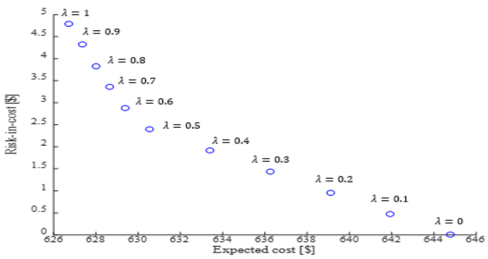
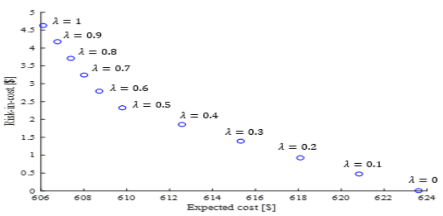
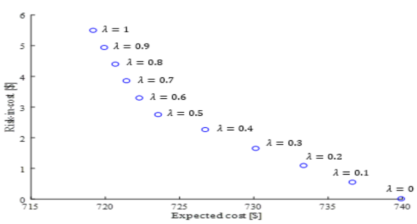


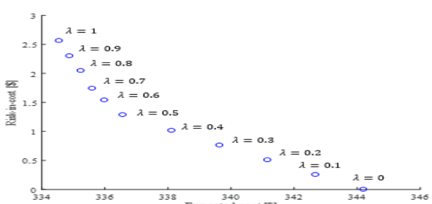
(a). Pareto front between expected operation cost and risk-in-cost of OB



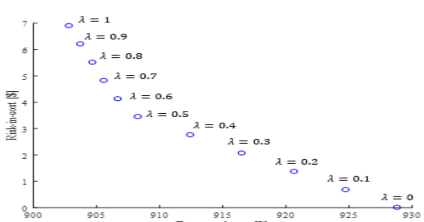
(b). Pareto front between expected operation cost and risk-in-cost of CB-1



(c). Pareto front between expected operation cost and risk-in-cost of CB-2



(d). Pareto front between expected operation cost and risk-in-cost of RB-1



(e). Pareto front between expected operation cost and risk-in-cost of RB-2

Fig. 12. Pareto front between expected cost and risk-in-cost

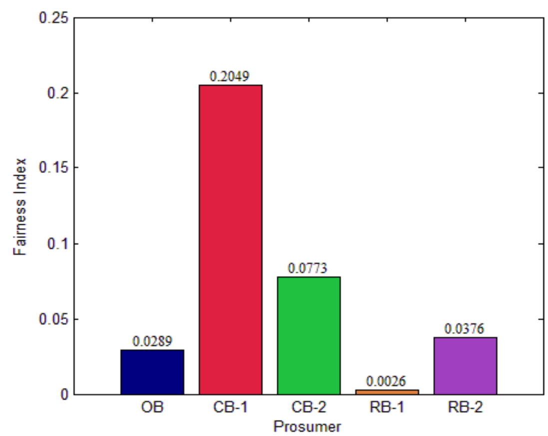


Fig. 13. The fairness index value for each prosumer