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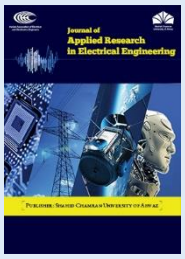

Research Article

A New Peer-to-Peer Energy Trading Model in an Isolated Multi-agent Microgrid

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Abstract: Microgrids, which have newly been included in power systems, have facilitated the management of distributed generations. In this context, the privatization of power systems, as well as flexible sources like electrical vehicles and storage systems, has been enhanced significantly by the advent of microgrids. In a microgrid structure, the microgrid's operator coordinates the agents and ensures the reliability of the network, while the agents manage their local resources independently. Nonetheless, new management methods should be implemented into the multi-agent-structured microgrids to meet their distributed nature. This paper proposes a new peer-to-peer energy market to optimize the operation of a multi-agent microgrid run in the isolated mode. The designed framework facilitates power trading between the system agents and addresses the privacy issues of the network consumers or producers. The proposed scheme is finally simulated on a 15-bus multi-agent-structured microgrid to study its effect on microgrid management in the isolated mode.

Keywords: Multi-agent system, microgrid, distributed energy resources, peet-to-peer transaction, flexibility.

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1. INTRODUCTION

Integration of distributed energy resources, as well as the benefits of reducing dependency on the upstream network, has contributed to prospering microgrids at a notable pace. Microgrids are small-scale systems that could operate several distributed generation units, flexible resources, and load demands. The development of microgrids has many positive effects on power systems, such as decreasing power transmission losses, increasing system reliability, and facilitating the high-rate integration of renewables to the grid [1]. Furthermore, the distributed energy resources installed in a microgrid can be operated by independent agents. In this regard, a new energy management framework is required to ensure the supply-demand balance during the real-time operation of a system.

Energy management in microgrids can be complicated by the large number of distributed resources and information required for the operational scheduling of the resources. So, researchers have employed various methods to handle this complexity, which can be divided into two general categories of centralized and decentralized management. In the centralized management, the microgrid control unit (MCU) will do the overall optimization of the local generations considering society welfare while, in the decentralized management, every consumer/producer will optimize its own objective function. Although the centralized way gives the exact optimum answers, the decentralized way is preferable mainly because it conserves the privacy of the consumer/producer in novel microgrids with multi-agent structures [2, 3].

Recently, several decentralized concepts have been introduced to address the operational scheduling of multi-agent systems (MASs) [4]. In an MAS, the energy system is assumed to consist of several independent entities (i.e. agents) that manage their own local generations independently and can produce/consume energy and participate in various power markets [5]. The capability of buying/selling any amount of power from/to a favorite agent in an MAS is an expedient capability that a peer-to-peer (P2P) market framework enables in distributed systems. This is the reason why the P2P concept has recently been taken into account in operating distributed energy systems.

Reference [6] aims to cluster different loads of buildings and extract their related utility functions. Moreover, this paper focuses on designing two-stage management for facilitating energy sharing in the system. In the first stage, it minimizes the whole energy cost of society to extract the optimum power exchanges for all agents. In the second stage, a non-cooperative game is conducted among the agents, in which the agents' profits are considered to be maximized. This reference, however, has not considered various distributed generations for agents. A new model for P2P trading between agents is proposed in [7] based on the game theory. According to this reference, sellers compete in the price within a non-cooperative game, while buyers compete to select the sellers to purchase energy within an evolutionary game. Finally, the sellers and buyers play a Stackelberg game to interact with each other and determine the optimum power exchange between system agents although they do not predict the prices of next time intervals for the sake of better decision makings in this paper.

Authors in [8] run a market between microgrids in which sellers independently select their respective selling energy with respect to the revenue of selling and the utility of storing the energy. Buyers, on the other side, bid prices to the sellers independently. In this regard, energy is allocated to the buyers based on their announced prices. An auction-based P2P market framework is proposed in [9] to enable the distributed energy resources to trade energy in a distributed system. This paper employs the knapsack approximation algorithm to develop the P2P process, but it considers neither the electrical vehicles (EVs) of the system nor the utility function of agents, which takes the flexibility of loads into account.

Two methods for designing the P2P market are discussed in [10], i.e., auction-based P2P mechanism and bilateral contract-based P2P mechanism. Their capability in the management of electricity markets is then investigated in a distribution system. In [11], authors propose a double auction-based decentralized P2P market, in which agents determine their supply and demand data using the distributed model of management, maximize their benefits, and finally attend in the abovementioned double auction market. A hierarchical P2P framework is designed in [12] for future distribution systems. In this work, the P2P trading market is considered in three levels; i.e., P2P between nano-grids in a microgrid, P2P between microgrids in a multi-microgrid, and P2P between the multi-microgrids.

In [13], authors define a willingness function for every buyer and seller in the P2P energy market. This function consists of various functions, such as historical records, the time pressure owing to market closure, and the supply and demand amounts. In the proposed market of this paper, the first bids of the sellers are equal to the maximum limit of the price, and those of the buyers are equal to its minimum limit. In the next steps of the market's algorithm, the sellers decrease their price bids and buyers increase their price bids. A pair of a buyer and a seller are matched for trading when the price bid of the seller is less than the buyer's bid. In the market proposed in [14], the sellers/buyers first announce their desired sell/buy amount of energy, and the energy price is declared based on the bids. Then, a probability distribution is considered for distributed generations and a Bayesian game is implemented in the market model, in which the players' strategies are the buy/sell amount of energy.

In [15], a non-cooperative game is devised between sellers, in which energy demand and price are known, but the sell amounts of sellers are unknown. After the determination of the seller's supplies in the mentioned game, a double auction is run in which the sellers announce their desired amounts for sale and their minimum prices on one hand, and the buyers announce their desired amounts to buy and the maximum price that they can accept on the other hand. In this auction, the energy price is supposed to be determined having the sell amounts of sellers and the buyers' demand. In this paper, the result of the non-cooperative game is used in the auction, and the result of the auction is used in the game iteratively. It is noteworthy to mention that in [10-15], the model predictive control (MPC) method, which enables the agents to make better decisions about their local resources, is entirely dismissed.

This paper's contribution is designing a new P2P market scheme for energy management in an isolated microgrid with a multi-agent structure, in which the MPC method could be implemented. In the proposed framework, a vast variety of distributed generations are also considered for the agents' resources, which can be demonstrated as $D=\{PV, WT, FC, MT, CHP, DG\}$ representing photo-voltaic, wind turbine, fuel cell, microturbine, combined heat and power, and diesel generator, respectively. In this model, every agent could have any favorite subset generations of *D*, in addition to the energy storage system (ESS) and EV.

The proposed framework facilitates the P2P energy management among the system's agents that can use the MPC method to consider the next time intervals' predicted data in their decisions. Note that, besides the market perspectives, considering different kinds of flexible resources (i.e., distributed generation units, ESSs, and EVs) will improve the flexibility of the agents, which finally results in improving microgrid flexibility [16-18].

In this paper, the multi-agent structure of islanded microgrids is discussed in Section 2.1, Sections 2.2 and 2.3 study how to model the cost function of distributed generation units and the overall cost of each agent. The proposed P2P market framework is discussed in Section 2.4. Finally, Section 3 reports the results of implementing the proposed framework on an islanded microgrid composed of various agents, followed by the concluding points in Section 4.

2. METHODOLOGY

2.1. System Modeling

The system considered in this work is an MAS structured microgrid that is operated in the islanded mode. A simplified structure of the islanded microgrid with a multi-agent structure is shown in Fig. 1. In such a system, the agents will tend to participate in markets, which enable them to sell their extra energy or buy their energy shortage at a lower price. Therefore, this paper aims to address a new and efficient decentralized P2P market framework for the islanded microgrid. In this framework, there is an MCU to monitor the operation of the P2P market among the agents. In this context, for the sake of simplicity, the sets $N=\{1,2,\ldots,n\}$ and $T=\{1,2,\ldots,t\}$ are defined for agents and time intervals, respectively. The notation *n* represents the number of the

agent, and *t* shows the number of the time interval throughout the paper.

2.2. Modeling Cost Functions of Distributed Generations

2.2.1. Cost functions of PV and WT units

Since PVs and WTs have only the maintenance and operation costs, their cost functions will be obtained as follows.

$$C_n^{pv}(P_{n,t}^{pv}) = \alpha_n^{pv} \cdot P_{n,t}^{pv} \quad (1)$$

$$C_n^{wt}(P_{n,t}^{wt}) = \alpha_n^{wt} \cdot P_{n,t}^{wt} \quad (2)$$

$$P_{n,t}^{pv} \le P_n^{pv,\max}, P_{n,t}^{wt} \le P_n^{wt,\max} \quad (3)$$

where C_n^{pv}, $P_{n,t}^{pv}$, α_n^{pv}, and $P_n^{wt,\max}$ are the total cost of utilizing PV, the PV's generated power amount, the maintenance and operation cost per unit of $P_{n,t}^{pv}$, and the maximum generation limit of the PV, respectively. Note that C_n^{wt}, $P_{n,t}^{wt}$, α_n^{wt}, and $P_n^{wt,\max}$ are similarly total cost, power generation, operating cost per unit, and maximum power generation associated with wind power units at node *n*.

2.2.2. The cost function of FC

Since FCs utilize fuel for the generation of electricity, their cost functions are mainly dependent on the fuel price, which is obtained as follows.

$$C_n^{fc}(P_{n,t}^{fc}) = \left(\frac{\pi^{fc}}{L^{fc}\eta_n^{fc}} + \alpha_n^{fc}\right)P_{n,t}^{fc} \quad (4)$$

$$P_n^{fc,\min} \le P_{n,t}^{fc} \le P_n^{fc,\max} \quad (5)$$

where C_n^{fc}, $P_{n,t}^{fc}$, π^{fc}, L^{fc}, η_n^{fc}, and α_n^{fc} present the cost of the FC, the amount of power generation of the FC unit, the FC's fuel cost per m^3, the FC's generation amount per m^3 of fuel, efficiency, and maintenance and operation cost per unit of $P_{n,t}^{fc}$, respectively. Note that $P_n^{fc,\min}$ and $P_n^{fc,\max}$ demonstrate the minimum and maximum generation capability of the FC unit, respectively [19].

2.2.3. The cost function of MT

Similar to the FCs, MTs' cost functions are highly dependent on their fuel prices. Therefore, their cost could be calculated as follows:

$$C_n^{mt}(P_{n,t}^{mt}) = \left(\frac{\pi^{mt}}{L^{mt}\eta_n^{mt}} + \alpha_n^{mt}\right)P_{n,t}^{mt} \quad (6)$$

$$P_n^{mt,\min} \le P_{n,t}^{mt} \le P_n^{mt,\max} \quad (7)$$

where C_n^{mt}, $P_{n,t}^{mt}$, π^{mt}, L^{mt}, η_n^{mt}, α_n^{mt}, $P_n^{mt,\min}$, and $P_n^{mt,\max}$ are the cost of the MT, power generation amount of the MT unit, the MT's fuel cost per m^3, generation amount of the MT per m^3 of fuel, MT efficiency, maintenance and operation cost per unit of $P_{n,t}^{mt}$, the minimum generation capability of the MT unit, and its maximum capability, respectively [19].

2.2.4. The cost function of CHP

As both the generated heat and the electric power are used in CHP units, the cost function of a CHP unit is like the MT units, but with higher efficiency. In this respect, the related cost function could be extracted as below:

$$C_n^{chp}(P_{n,t}^{chp}) = \left[\frac{\pi^{mt}}{L^{mt}\eta_n^{mt}}\left(1 - \frac{\xi_n^{rec}(\eta_n^{chp} - \eta_n^{e})}{\eta_n^{b}}\right) + \alpha_n^{chp}\right]P_{n,t}^{chp} \quad (8)$$

$$P_n^{chp,\min} \le P_{n,t}^{chp} \le P_n^{chp,\max} \quad (9)$$

where C_n^{chp}, $P_{n,t}^{chp}$, α_n^{chp}, $P_n^{chp,\min}$, and $P_n^{chp,\max}$ represent the cost of the CHP, the amount of power generation of the CHP unit, the maintenance and operation cost per unit of $P_{n,t}^{chp}$, the minimum generation capability of the CHP unit, and its maximum capability, respectively. Furthermore, π^{mt}, L^{mt}, and η_n^{mt} show the MT's parameters that are utilized inside the CHP system, ξ_n^{rec} is the factor of heat recovery, and η_n^{chp}, η_n^{e}, and η_n^{b} denote the efficiencies of the CHP, MT, and boiler, respectively [19].

2.2.5. The cost function of DG

DGs consume diesel fuel to produce energy, and their costs are modeled by a quadratic function as follows [20].

$$C_n^{dg}(P_{n,t}^{dg}) = a_n(P_{n,t}^{dg})^2 + (b_n + \alpha_n^{dg})P_{n,t}^{dg} + c_n \quad (10)$$

$$P_n^{dg,\min} \le P_{n,t}^{dg} \le P_n^{dg,\max} \quad (11)$$

where C_n^{dg}, $P_{n,t}^{dg}$, α_n^{dg}, $P_n^{dg,\min}$, and $P_n^{dg,\max}$ are the cost of the DG, the power generation amount of the DG unit, the maintenance and operation cost per unit of $P_{n,t}^{dg}$, the minimum generation capability of the DG unit, and its maximum capability, respectively. Moreover, a_n, b_n, and c_n are the fixed constants modeling the cost function of the DG unit. It is noteworthy that in the case of existing multiple DGs, they can be mathematically modeled as an equivalent DG according to [21].

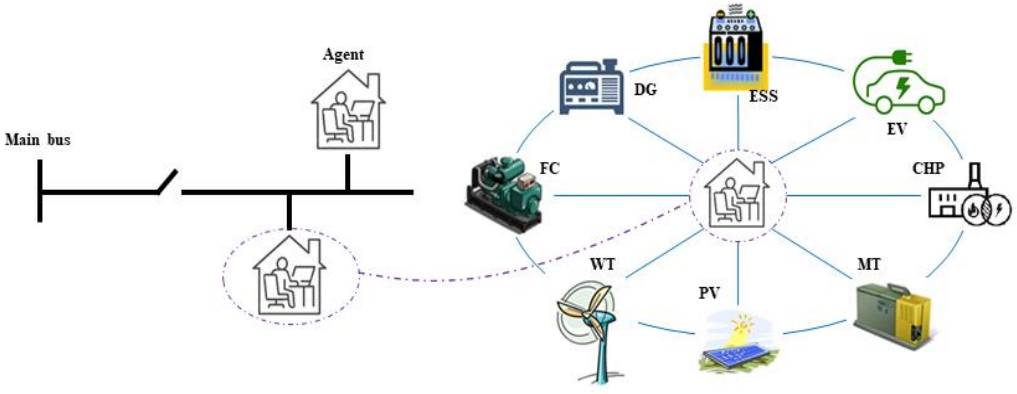

Fig. 1: A simplified model of a multi-agent structured microgrid.

2.3. Modeling Overall Cost Function of Agents

In the proposed P2P model, agents should make some decisions about the amount of power they want to buy/sell. Therefore, they need to extract their overall cost function to utilize it in their respective optimization problem. In this regard, this section develops the overall cost function associated with each agent based upon their different kinds of resources.

2.3.1. The cost function of distributed generations

As was already explained, the agents can have six types of generation units. In this regard, the total cost of the generation units in each agent is modeled as follows:

$$C_{n,t}^{gen} = \sum_{d \in D} G_{nd} \cdot C_n^d (P_{n,t}^d) \quad (12)$$

where $C_{n,t}^{gen}$ is the overall generation cost and G_{nd} is a binary parameter that determines whether or not agent *n* has the generation type *d*.

2.3.2. The cost function of ESS

Agents can also enjoy the ESS to increase their flexibility against the price spikes. In this context, the ESS's cost can be modeled as follows:

$$C_{n,t}^{ess} = \mu_n^{ess,c} P_{n,t}^{ess,c} \Delta t + \mu_n^{ess,d} P_{n,t}^{ess,d} \Delta t \quad (13)$$

$$0 \le P_{n,t}^{ess,c} \le P_{n,\max}^{ess,c}, 0 \le P_{n,t}^{ess,d} \le P_{n,\max}^{ess,d} \quad (14)$$

$$E_{n,t}^{ess} = E_{n,t-1}^{ess} + \eta_n^{ess,c} P_{n,t}^{ess,c} \Delta t - \eta_n^{ess,d} P_{n,t}^{ess,d} \Delta t \quad (15)$$

$$EL_{n,\min}^{ess} E_{n,cap}^{ess} \le E_{n,t}^{ess} \le EL_{n,\max}^{ess} E_{n,cap}^{ess} \quad (16)$$

where $C_{n,t}^{ess}$, $P_{n,t}^{ess,c}$, $P_{n,t}^{ess,d}$, $\mu_n^{ess,c}$, and $\mu_n^{ess,d}$ are the ESS's total cost, charging/discharging power, and the amortized costs of charging/discharging, respectively. Moreover, $P_{n,\max}^{ess,c}$, $P_{n,\max}^{ess,d}$, $E_{n,t}^{ess}$, $\eta_n^{ess,c}$, and $\eta_n^{ess,d}$ demonstrate the maximum limit of charging/discharging, the energy level of the ESS, and the charging/discharging efficiency, respectively. Finally, $EL_{n,\min}^{ess}$, $EL_{n,\max}^{ess}$, and $E_{n,cap}^{ess}$ indicate the ESS's minimum and maximum percent of energy level that ensures ESS's lifetime and models the capacity of ESS [6]. It should be noted that in (15), $\eta_n^{ess,c} \le 1$ while $\eta_n^{ess,d} \ge 1$.

2.3.3. The cost function of EV

Similar to ESSs, the cost function of EVs can be modeled as follows:

$$C_{n,t}^{ev} = \mu_n^{ev,c} P_{n,t}^{ev,c} \Delta t + \mu_n^{ev,d} P_{n,t}^{ev,d} \Delta t \quad (17)$$

$$0 \le P_{n,t}^{ev,c} \le P_{n,\max}^{ev,c}, 0 \le P_{n,t}^{ev,d} \le P_{n,\max}^{ev,d} \quad (18)$$

$$E_{n,t}^{ev} = E_{n,t-1}^{ev} + \eta_n^{ev,c} P_{n,t}^{ev,c} \Delta t - \eta_n^{ev,d} P_{n,t}^{ev,d} \Delta t \quad (19)$$

$$EL_{n,\min}^{ev} E_{n,cap}^{ev} \le E_{n,t}^{ev} \le EL_{n,\max}^{ev} E_{n,cap}^{ev} \quad (20)$$

where $C_{n,t}^{ev}$, $P_{n,t}^{ev,c}$, $P_{n,t}^{ev,d}$, $\mu_n^{ev,c}$, and $\mu_n^{ev,d}$ are the EV's total cost, charging/discharging power, and the amortized costs of charging/discharging, respectively. Additionally, $P_{n,\max}^{ev,c}$, $P_{n,\max}^{ev,d}$, $E_{n,t}^{ev}$, $\eta_n^{ev,c} \le 1$, and $\eta_n^{ev,d} \ge 1$ represent the maximum limit of charging/discharging, the energy level of the EV, and the charging/discharging efficiency, respectively. Finally, $EL_{n,\min}^{ev}$, $EL_{n,\max}^{ev}$, and $E_{n,cap}^{ev}$ indicate the EV's minimum and maximum percent of energy level that ensures the EV's lifetime and the capacity of EV. It is worth noting that $P_{n,t}^{ev,c}$ and $P_{n,t}^{ev,d}$ are the charging/discharging amount of EV only when it is available, while the availability of an EV is defined as the connectivity of the EV to the grid. An EV unit can be operated as vehicle-to-grid (V2G), grid-to-vehicle (G2V) while connecting to the grid. Without loss of generality, it is assumed that the EV unit can merely be connected to the grid when it is at home. In this regard, when an EV arrives at home at t_{arrive}, its energy level is considered to be $EL_{n,arrive}^{ev}$. Moreover, when the unit wants to exit from the home at the time interval t_{exit}, its energy level is assumed to be shown by $EL_{n,exit}^{ev}$. These constraints are mathematically modeled as:

$$E_{n,t_{arrive}}^{ev} = EL_{n,arrive}^{ev} \quad (21)$$

$$E_{n,t_{exit}}^{ev} \ge EL_{n,exit}^{ev} \quad (22)$$

2.3.4. Utility function of agents

In this scheme, the cost of the loads in each agent is modeled using a utility function defined as follows:

$$U_{n,t} = \begin{cases} \beta_{n,t} P_{n,t}^{load} - \frac{\gamma_n}{2} (P_{n,t}^{load})^2 & 0 \le P_{n,t}^{load} \le \frac{\beta_{n,t}}{\gamma_n} \\ \frac{1}{2} \frac{(\beta_{n,t})^2}{\gamma_n} & \frac{\beta_{n,t}}{\gamma_n} \le P_{n,t}^{load} \end{cases} \quad (23)$$

$$P_n^{load,\min} \le P_{n,t}^{load} \le P_n^{load,\max} \quad (24)$$

where $U_{n,t}$ is the utility earned by agent *n* and $\beta_{n,t} > 0$ and $\gamma_n > 0$ are the parameters of consumption. Moreover, $P_{n,t}^{load}$ is the amount of power consumption, which should be greater than the minimum need of the agent (i.e. $P_n^{load,\min}$) and less than the maximum consumption of agent (i.e. $P_n^{load,\max}$) [7, 22].

2.3.5. Trading cost function

In the proposed P2P framework, every agent can trade a favorite amount of power with other agents. Therefore, each agent will earn profits if it sells energy, while the agent will pay the cost of the energy if it buys energy. In this respect, the cost function of each agent can be formulated as follows.

$$C_{n,t}^{trad} = \left(\sum_{i \in N} \pi_{i,t} P_{in,t}^{buy} \right) - \pi_{n,t} P_{n,t}^{\sup} \quad (25)$$

where $C_{n,t}^{trad}$, $\pi_{n,t}$, $P_{in,t}^{buy}$, and $P_{n,t}^{\sup}$ are the trading costs, price of power, power amount that agent *n* wants to buy from agent *i*, and the power amount that agent *n* wants to sell. There are also some constraints for this cost function as follows:

$$P_{in,t}^{buy} \ge 0, P_{n,t}^{\sup} \ge 0 \quad (26)$$

$$P_{nn,t}^{buy} = 0 \quad (27)$$

$$P_{n,t}^{buy} \cdot P_{n,t}^{\sup} = 0 \quad (28)$$

These constraints demonstrate that all amount of power purchased or sold should be positive (26), nobody trades with itself (26), and an agent cannot be a buyer and a seller simultaneously (28). It is noteworthy that the constraint (28) can also be written as (29) which causes the running time of

the optimization stage in the simulation to be decreased significantly.

$$P_{n,t}^{buy} + P_{n,t}^{\sup} = \left| P_{n,t}^{buy} - P_{n,t}^{\sup} \right| \quad (29)$$

2.3.6. Total cost function in the current time interval

To derive an overall cost function for the agent *n* in the current time interval (i.e., *t*), all of the previously discussed cost functions are simply added up as follows. It is noteworthy that here it is hypothesized that *t* is the current time interval that the P2P market is conducted for real-time operation of the microgrid.

$$C_{n,t}^{now} = C_{n,t}^{gen} + C_{n,t}^{ess} + C_{n,t}^{ev} - U_{n,t} + C_{n,t}^{trad} \quad (30)$$

2.3.7. MPC method

In the designed P2P market, agents need to decide about the operation of their ESSs and EVs, as well as their generation units. In this regard, to determine the optimum charging/discharging of ESSs/EVs, the operational information of the current time interval is not sufficient. So, the agent estimates its PV/WT power generation, power consumption, purchasing/selling power, and power prices of next upcoming time intervals to realize the optimum charging/discharging amounts at the considered time intervals [23]. The concept that employs operational scheduling of the agent in future time intervals while participating in the P2P market at the current time interval is called the MPC method. In this work, it is assumed that all the agents anticipate the next H time intervals. In this context, it is necessary to consider a cost function for future time intervals [24] as follows:

$$C_{n,h}^{fut} = C_{n,h}^{gen} + C_{n,h}^{ess} + C_{n,h}^{ev} - U_{n,h} + \pi_h^{fut} P_{n,h}^{fut,buy} \quad (31)$$

where $C_{n,h}^{fut}$, π_h^{fut}, and $P_{n,h}^{fut,buy}$ are the total cost, the predicted average power price, and the amount of power that the agent wants to buy at the future time interval *h*. Note that, in this model, $P_{n,h}^{f,buy}$ is considered to be either negative or positive; negative amounts imply the selling power, and positives imply the purchasing power.

2.4. P2P Market Structure

The corresponding flowchart of the proposed P2P market is shown in Fig. 2. According to this flowchart, the first step is the initialization of prices, which means that all the agents should announce their initial price. Agents can select their respective initial prices based on their prediction of the agents' behavior. Note that as the scheme proceeds, the agents may reconsider their positions as sellers, which means that they will not benefit from power selling. In other words, as the framework proceeds, the buyers will automatically be separated from the sellers. On the other hand, in the model, an agent cannot be both seller and buyer simultaneously.

After the price initializations, the agents run an optimization problem to decide about their power exchanges with the other agents in the market. In the next step, the agents update the prices, and then a termination criterion is checked. If the criterion is satisfied, the market will be cleared and the exchanges will be fixed; otherwise, the same process will be conducted until the criterion is satisfied. These steps are explained in the next subsections as follows.

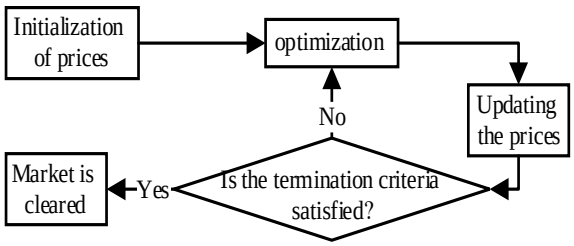

Fig. 2: The flowchart of the proposed P2P market in an islanded multi-agent microgrid.

2.4.1. Optimization problem of Agents

The optimization problem of agent *n* aimed to minimize its prices is described as follows.

$$Min\left\{ C_{n,t}^{now} + \sum_{h=t+1}^{t+H} C_{n,h}^{fut} \right\} \quad (34)$$

which is subject to the predefined constraints of (3), (5), (7), (9), (11), (14), (16), (18), (20) to (22), (24), (26), (27), and (29). Moreover, the power balance constraint for the current time interval and the future time intervals can be modeled as follows:

$$\sum_{d \in D} G_{nd} P_{n,t}^{d} = P_{n,t}^{load} - P_{n,t}^{buy} + P_{n,t}^{\sup} + P_{n,t}^{ess,c} - P_{n,t}^{ess,d} + P_{n,t}^{ev,c} - P_{n,t}^{ev,d} \quad (35)$$

$$\sum_{d \in D} G_{nd} P_{n,t}^{d} = P_{n,t}^{load} - P_{n,t}^{fut,buy} + P_{n,t}^{ess,c} - P_{n,t}^{ess,d} + P_{n,t}^{ev,c} - P_{n,t}^{ev,d} \quad (36)$$

2.4.2. Updating the prices

After conducting agents' optimizations, the power demand of agent *n*, or the requested amount from him/her (i.e., $P_{n,t}^{dem}$), as well as the total power amount that he/she wants to sell (i.e., $P_{n,t}^{\sup}$), will be determined. Having the demand and supply amounts, the agents update their prices according to the following equation:

$$\pi_{n,t}(j+1) = \pi_{n,t}(j) + \varphi\left[P_{n,t}^{dem}(j) - P_{n,t}^{\sup}(j) \right] \quad (37)$$

where *j* is the iteration index, $\pi_{n,t}$ is the price of agent *n*, and φ is the factor of progression pace.

It is noteworthy to mention that the power demand of agent *n* would be calculated easily by summing up all the buy amounts requested from agent *n* in each iteration as the following equation shows.

$$P_{n,t}^{dem}(j) = \sum_{m \in N} P_{nm,t}^{buy}(j) \quad (38)$$

2.4.3. The termination criterion

To ensure the convergence of the proposed iterative P2P market framework, a suitable criterion should be defined. In this regard, if the prices of the agents do not change in every iteration, it means that nobody wants to alter his/her buy/sell amount, and all of the agents are satisfied by the power exchanges. This optimum point will also address the criteria associated with the Nash equilibrium concept. Consequently, the termination criterion is defined as follows:

$$\left| \pi_{n,t}(j+1) - \pi_{n,t}(j) \right| < \varepsilon \quad (39)$$

where ε is a small number that the price variation under this value is negligible.

3. Case Study

The proposed structure has been simulated on a small 15-bus microgrid (MG) demonstrated in Fig. 3. It is assumed that the MG is operated in an islanded mode and each node of the system is considered to be managed by one agent. Moreover, the time intervals in the operational management of the system are considered to be equal to one hour. Fig. 3 also indicates the resources operated by each agent in the P2P market framework. The simulation has been conducted for 24 hours a day considering $H=8$, which means that the agents take into account the next 8 hours in their optimization for the current time interval.

The optimal purchased/sold power by agents 4, 5, 10, and 12, as a sample of agents, over 24 hours are shown in Fig. 4 in which there are both buyers and sellers in every hour of the day. In this figure, agent 4 is a seller, and agent 10 is a buyer all over the 24 hours, but agents 5 and 12 are buyers in some hours and sellers in others. In Fig. 5, the total power exchange amounts between agents over 24 hours are depicted as a Chord diagram. It should be mentioned that for the sake of simplicity, only the total exchanges that are greater than 20 kW are shown in this figure.

In the 24-hour simulation, agent 5 has been selected as an example to investigate its scheduling results over the 24 hours. In this regard, Fig. 6 shows the power generation amounts for each type of distributed generation unit that agent 5 possesses in 24 hours. Moreover, Fig. 7 demonstrates the load consumption amounts of agent 5, and Fig. 8 depicts the average price of seller agents in 24 hours of the day. Note that the MG is operated in the islanded mode, so the energy prices are significantly high in some hours due to generation shortage according to Fig. 8.

Figs. 9 and 10 show the power charging/discharging amounts of agent 5's ESS and EV at each hour of the day, respectively. It is noteworthy that in Fig. 9, the charging/discharging amounts of the EV are shown only when it is available or connected to the grid. Therefore, as the availability hours of this EV are assumed to be in the range of [1,6] and [22,24] in this simulation, the discharge amounts in the other hours are not shown in the figure.

In order to justify the behavior of agent 5 about the charging/discharging amounts of his ESS/EV, it is important to represent Fig. 11, which shows the predicted prices by the agent in 36 hours (one and a half days), noting that he/she always anticipates the prices of next 8 hours. As an example, when the current hour is the 12th hour, he/she uses real-time determined prices from the market as this hour's prices and predicts the average prices of the next 8 hours (i.e., from 13th hour to 20th), which are presented in Fig. 11, as the future hours' prices. Thus, according to this figure, the behavior of agent 5 in Fig. 9 and 10 can be grasped. For instance, when the current time interval is equal to one, he/she does not charge his/her ESS because the current prices' average is nearly 25 and he/she predicts that in hours 4 to 6, the prices will be less than 25. Note that he/she does not discharge his/her ESS because it is assumed that the ESS's initial charge amount and also $E^{ess}_{5,\min}$ are equal to 20%. The ESS in the 2nd hour has a similar scenario, but in the 3rd hour, since the current prices' average is much less than his/her next-8-hour prediction amounts, he/she charges his/her ESS with the maximum charge rate which is postulated to be 6 kW per hour. The ESS charge/discharge behavior of the agent in the

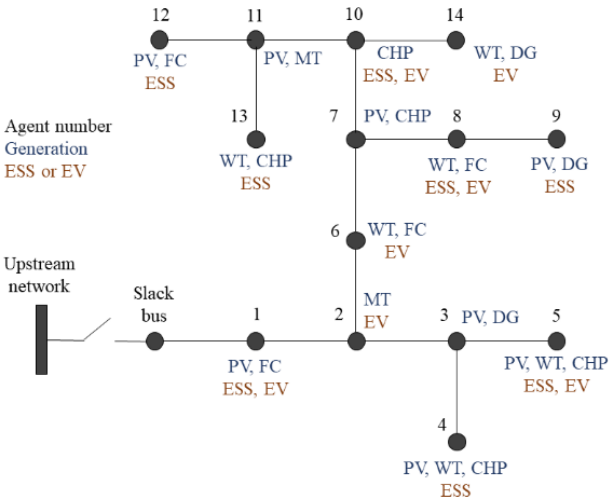

Fig. 3: The islanded microgrid with multi-agent structure considered as a test system.

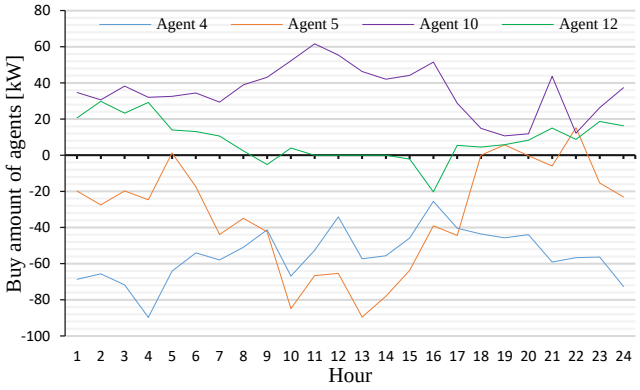

Fig. 4: Purchased/sold power by a sample of agents in 24 hours.

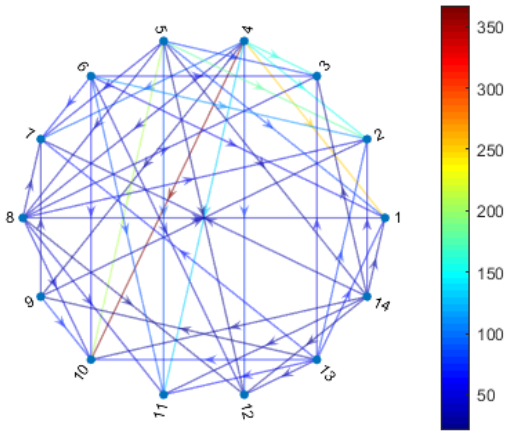

Fig. 5: Chord diagram of the total power exchanges between the agents in kW.

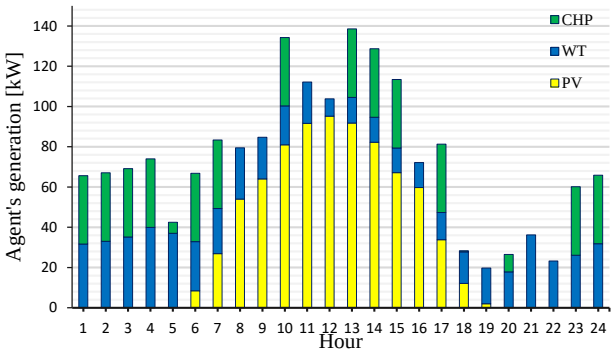

Fig. 6: Power generation amounts of agent 5 in 24 hours.

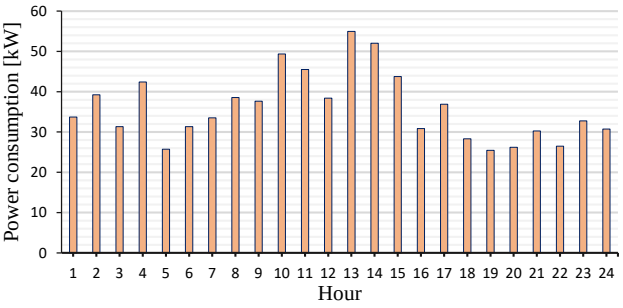

Fig. 7: Consumption power amounts of agent 5 in 24 hours.

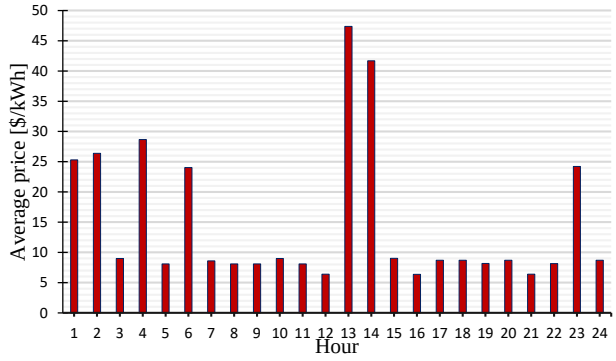

Fig. 8: The seller agents' average energy prices in 24 hours

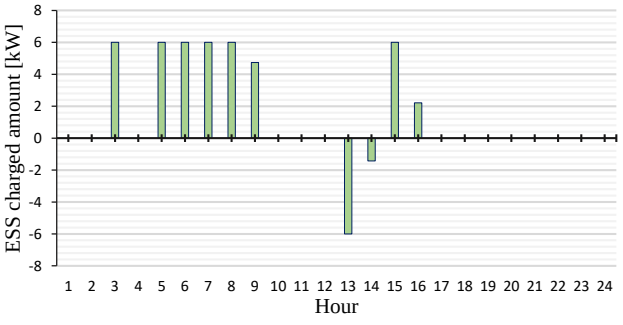

Fig. 9: Charging/discharging amounts of agent 5's ESS.

other hours can be justified similarly.

About the EV of agent 5, it is assumed that the initial EV charge is 10%, $EL^{ev}_{5,exit} = 0.85$, $E^{ev}_{5,cap} = 70kWh$, $\eta^{ev,d}_{5} = 1.05$, and he/she exits home after the 6th hour.

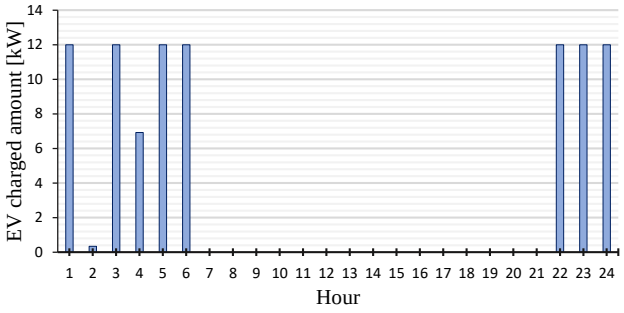

Fig. 10: Charging/discharging amounts of agent 5's EV.

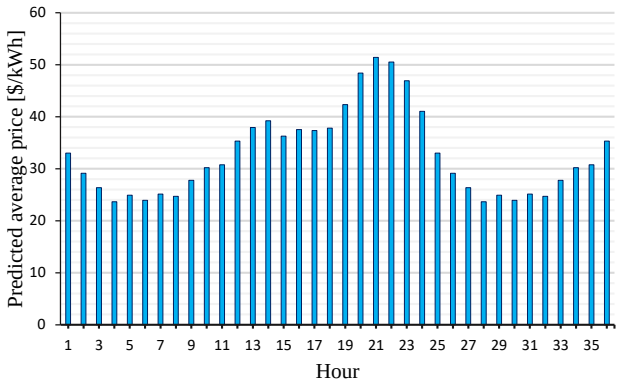

Fig. 11: Average power prices of future hours predicted by agent 5.

Therefore, his/her total charge amount of EV from the 1st to 6th hours should be equal to $(0.85-0.1)\times 70\times 1.05 = 55.125kWh$ which coincides with the amounts shown in Fig. 10. For the justification of EV charge/discharge amounts in Fig. 10, an argument similar to the ESS's charge/discharge amounts can be done. It is noteworthy to mention that although the discharge ability is enabled for agent 5, he/she did not discharge any amount of power in any hours of the day, according to Fig. 10. This is because, in the period of $[1,6]$ hours, he/she does not have any opportunities to discharge his EV due to the high amount of charge that he/she should do in total till the end of the 6th hour (i.e., $55.125kWh$). Moreover, in the period of [22,24], according to the prices shown in Figs. 8 and 11, it is beneficial for agent 5 to charge his/her EV at its maximum rate (which is assumed to be 12 kW per hour) because the energy prices in the current hours are less than the future hours in his/her opinion.

For the sake of investigating the convergence status of the prices in the proposed model, the prices of the agents 5, 6, 9, and 12 at the 15th hour are represented in Fig. 12 in all iterations. These agents have been selected as a sample of sellers at the 15th hour. According to this figure, the mentioned agents' prices have been converged appropriately through 756 iterations into $9\$/kWh$ approximately.

It should be noted that, as Fig. 12 shows, the converged prices of the mentioned agents are almost equal to each other. To find out the reason behind this, two cases are remarkable. First, if a seller agent rises his price into a value more than the others' prices, the buyer agents will decrease their purchase amounts from him/her, thus he/she has to decrease his/her

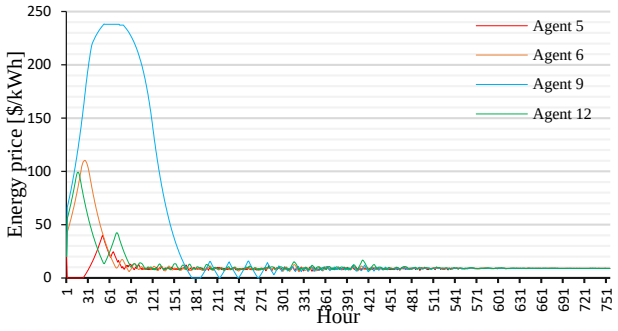

Fig. 12: The prices of a sample of sellers at the 15th hour in all iterations.

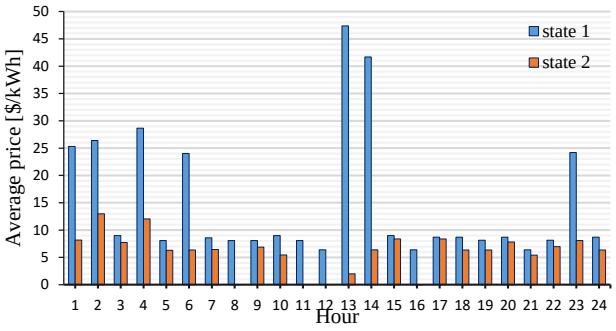

Fig. 13: Sellers average prices in 24 hours in states 1 and 2.

price again. Second, if the seller decreases his/her price to a value less than the others' prices, although the buyers will be motivated to buy more power amounts from him/her, this price will not be the optimum value for him/her because he/she will earn fewer benefits compared to the case that his/her price is just a little lower than the others. Therefore, the sellers will compete with each other and their final prices will be similar.

In addition to the aforementioned 24-hour simulation, named state 1 in this section, another similar simulation has been run for 24 hours, in which the values of $\beta_{n,t}$ for all agents in all hours have been decreased by 30% to analyze the sensitivity of prices to the values of $\beta_{n,t}$. In this context, the new simulation is named state 2. The averages of the sellers' prices for both state 1 and state 2 in 24 hours are shown in Fig. 13. As can be seen in the figure, the amounts of state 2 are lower than those of state 1 because when the amounts of $\beta_{n,t}$ decrease, the demand of seller agents diminishes. Thus, the prices come down due to the dominance of supply amounts over the demand amounts. In some hours such as the 8th and 11th, the energy prices are zero, which shows that the overall supply is much greater than the demand.

4. Conclusion

This paper provided a P2P framework to facilitate energy management in a multi-agent microgrid operating in the islanded mode. The proposed framework enables the power exchange among independent agents while addressing the privacy concern of private customers. Furthermore, it is considered that each agent can operate load demands, different kinds of distributed generation units, ESSs, and EVs, which will improve the flexibility of the agents participating in the P2P scheme. Finally, the proposed scheme is applied to a microgrid composed of nine agents operating different resources to investigate its effectiveness in islanded operating mode with a distributed structure.

CRediT Authorship Contribution Statement

Mahyar Tofighi-Milani: Data curation, Formal analysis, Investigation, Methodology, Resource, Software, Validation, Roles/Writing - original draft. **Sajjad Fattaheian-Dehkordi:** Conceptualization, Data curation, Methodology, Project administration, Validation. **Mahmud Fotuhi-Firuzabad:** Supervision, 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. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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