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A Novel Distributed Paradigm for Energy Scheduling of Islanded Multi-agent Microgrids

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ABSTRACT Restructuring in power systems has resulted in the development of microgrids (MGs) as entities that could be operated in grid-connected or islanded modes while managing the operation of their systems. On the other hand, privatization and integration of independently operated distributed resources in energy systems have caused the introduction of multi-agent structures. In this regard, new operational management methodologies should be employed by the MG operator (MGO) to efficiently operate the system while addressing the distributed nature of multi-agent structures. Accordingly, this paper aims to provide a new algorithm to operate an islanded multi-agent MG utilizing the peer-to-peer (P2P) management concept; which copes with the distributed nature of the system. Consequently, each agent would independently schedule its respective local resources, while participating in the hourly P2P market scheme. Moreover, MGO manages the power transactions among the agents. Furthermore, different types of power generation resources are modeled in the proposed optimization scheme while scenario-based stochastic optimization, as well as the condition-value-at-risk index, are deployed to address the uncertainty and the operational risk associated with the operational optimization of renewable energies. Finally, the developed framework is implemented on a 10-bus-MG test system to investigate its effectiveness in the management of the system and also on a 33-bus-MG test system to study its scalability.

INDEX TERMS Distributed energy resources, DERs, multi-agent microgrid, P2P operational optimization, peer-to-peer management, renewable energies, stochastic optimization.

ACRONYMS

DER	Distributed energy resource
MG	Microgrid
MGO	Microgrid operator
MAS	Multi-agent system
P2P	Peer-to-peer
MPC	Model predictive control
CVaR	Conditional value-at-risk
ESS	Energy storage system
EV	Electrical vehicle
PV	Photovoltaic
WT	Wind turbine
FC	Fuel cell
MT	Microturbine
CHP	Combined heat and power
DG	Diesel generator
CDF	Cumulative distribution function

I. INTRODUCTION

Recently, the high integration of independently operated distributed energy resources (DERs) as well as the local systems' concerns regarding the independency from the upstream power grids have resulted in significant transformations in the operation and planning procedures of the local systems; i.e., microgrids (MGs). In this regard, MGs, as entities thriving at a rapid pace, facilitate the integration of the independently operated agents, which may have different types of local resources and consumption parameters, into power systems [1]. Although the expansion of MGs brings lots of advantages for the entire power system; it would result in the complexity in the energy management of local systems, which should be handled in an efficient manner [2].

The energy management methods that have been employed in MGs could be classified into two general clusters of centralized and decentralized approaches. In the centralized methodologies, in order to manage the system, the MG operator (MGO) runs a centralized optimization problem that contains all the operational information of the system gents. Nevertheless, the decentralized approach enables each agent to independently run its own optimization problem with respect to its respective profits and objectives. Note that the centralized approach provides the global optimum response of the overall system, which would maximize the social welfare of the system. However, with the introduction of restructuring and privatization in power systems, there is a significant preference to deploy decentralized operational management approaches in energy systems. Furthermore, it is noteworthy that the decentralized approaches would address the privacy concerns of prosumers in the system [3], [4]. As a result, new efficient decentralized management approaches seem to be required in MGs by the expansion of the multi-agent system (MAS) concept which includes independent entities operating their respective resources [5], [6].

In recent years, several management concepts are employed by research works in order to develop decentralized operational frameworks in power systems. In this regard, implementing a decentralized peer-to-peer (P2P) market framework for managing energy trading in an islanded multi-agent MG seems to be an efficient and applicable methodology. In such a framework, each agent would be able to participate in the power market as a buyer/seller while maximizing its respective profit.

The P2P structure has been taken into consideration by many academic research works in order to facilitate the operation of MASs in power systems from different perspectives [7]. Reference [8] overviews several aspects associated with implementing P2P structures in MGs in order to discuss the challenging and critical points of the concept by considering different layers of the system. Authors in [7] have developed two mechanisms for the P2P market; i.e. “auction-based” and “bilateral contract-based” markets. In the first mechanism, prosumers offer bids in the market, while the distribution system operator clears the market and announces the prices. Moreover, after clearing the market, the prosumers have an opportunity to adjust their bids, and this process is continued until the convergence satisfaction. The second mechanism is similar to the first step, however, there is a platform instead of the market administration. In this platform, the offers are posted and agreements occur. Reference [9] overviews some solutions around decentralized P2P trading as well as its controlling issues. Moreover, this paper proposes certain business models for P2P structures and discusses some merits and demerits of them. Authors in [10] have proposed a method for the P2P trading market utilizing the double auction concept. In this context, agents set their supply and demand information, and finally strive to maximize their profit while determining the market price. Furthermore, [11] eliminates the role of central entities by implementing the P2P energy market in MGs. In this paper, seven factors of a P2P market that facilitates the efficient operation of the MG are also analyzed. Moreover, a continuous double auction in the P2P structure is taken into account in [12] in order to model the power market; while [13] considers a hierarchical P2P model structured in three levels; i.e. P2P transaction between nano-grids in an MG, P2P transaction between MGs within a multi-MG, and P2P transaction between multi-MGs.

Reference [14] has developed a P2P energy market in which the seller and buyer agents bid for the energy price that they want to trade. In this regard, seller agents begin to bid with the highest possible price and, as the algorithm proceeds, they reduce their prices gradually; while the buyers begin with the lowest price and then increase their offered bids. This paper has implemented a willingness function to model the effect of the time pressure associated with the market closure, historical records, and supply/demand data in the market. In the proposed market model in [15], the price of energy is firstly determined based upon the bids of the buyer and seller agents for the energy amount that they prefer to trade. Then a Bayesian game is conducted between the agents in order to ascertain the equilibrium point associated with the energy exchanges between agents considering DERs’ probability distribution. In addition, in [16], first, a non-cooperative game is conducted among the seller agents taking into account the energy demand of buyers in order to determine the amounts of selling energy. Afterward, the energy price is determined based on the proposed double auction between buyers and sellers utilizing the results of the non-cooperative game. In this regard, the obtained price from the auction market stage is used in the non-cooperative game and the results of the game are utilized in the auction market, iteratively. Note that previous research works in [7]–[9], [11]–[14], [16], [17] have not modeled the uncertainty associated with the operational scheduling of agents in the developed P2P market framework. Moreover, these works primarily focus on limited local resources operated by independent agents in the system. On the other hand, utilizing a model predictive control (MPC) method in order to improve the agents’ decision-making procedure as well as the conditional value-at-risk (CVaR) function to model the prediction risks of agents, have not been taken into account in these papers. It is noteworthy that the developed models in [18], [19] have merely considered the reactive power management in the system. In this regard, authors in [18] have utilized a distributed algorithm to limit the information exchange between neighboring agents of the system. Moreover, in [19], a compressive sensing technique is employed to compress the massive data exchange in the power system. Based on the above discussions, these references have not implemented the P2P transaction in energy systems, while this paper aims to model the P2P active power exchange in a multi-agent microgrid. The contributions of this paper can be also briefly rendered as the following points.

- Implementation and study of different local resources operated by independent agents

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considering the correlation between renewable energies in P2P market optimization.
- Implementation of the uncertainty of the agents' operational scheduling in the P2P market framework
- Implementation of the MPC method for a better decision-making procedure by agents
- Implementation of the CVaR function for prediction risk modeling

A simplified comparison of previously developed schemes with the proposed model in this paper is presented in Table 1.

TABLE 1. Taxonomy of research works on P2P management of Microgrids.

Refs	Reactive Power Management	Active Power Management	P2P Management	Uncertainty Modeling	Modeling Risk (CVaR)	Modeling Different Types of Local Resources
[1]	-	✓	-	✓	-	-
[7]–[17]	-	✓	✓	-	-	-
[18], [19]	✓	-	-	-	-	-
This paper	-	✓	✓	✓	✓	✓

Based upon the previous discussions, this work aims to develop a P2P market framework in an isolated multi-agent MG in order to operate the system taking into account its respective distributed nature. In the proposed approach, agents strive to maximize their own profits, while MGO evaluates the convergence as well as the demand-supply balance in the system. Furthermore, a stochastic optimization approach is employed in the proposed framework to address the uncertainty associated with the renewable energy sources (i.e., photovoltaic and wind power units) in optimization models of independent agents. Note that meteorological features are generally correlated in the geographical area where the multi-agent MG is located. In this regard, the Copula concept is taken into account to develop the scenarios associated with the power generation by RESs in different agents. Moreover, the MPC method is taken into consideration with the aim of modeling the operational characteristics of the future time intervals while optimizing each agent's operational scheduling in the current time interval [20]. In this regard, agents operating energy storage systems (ESSs) and electrical vehicles (EVs) would be able to optimize their resource scheduling in an efficient manner. Furthermore, the conditional value at risk (CVaR) concept is deployed in the optimization formulation of agents in order to address the risk associated with scenario-based stochastic optimization conducted by each agent. Note that while the previous research works have merely considered limited resources; this paper strives to study the effect of different kinds of power resources operated by independent agents in the operational management of the system. In this regard, in the proposed model, agents could manage a wide range of DERs including photovoltaic (PV), wind turbine (WT), fuel cell (FC), microturbine (MT), combined heat and power (CHP), diesel generator (DG), as well as ESSs and EVs. It is noteworthy that, in the proposed model, every agent would independently run an optimization problem to decide about its affairs such as the energy trades with other agents, power generation, and charging/discharging of ESS/EV units. Finally, the proposed algorithm would cope with the distributed nature of the system which would address the privacy concerns of independent agents in the system.

In this paper, the system modeling and respective pre-assumptions in the proposed scheme as well as the Copula-based scenario generation and mathematical model of generation units in each agent are represented in Sections II. A, II. B, and II. C, respectively. Moreover, modeling the cost function of agents is discussed in Section II. D. Furthermore, in Section II. E. the developed P2P market framework is explained in detail and the methods utilized for the convergence improvement are represented in this section. Finally, the proposed model is implemented on a 10-bus MG test system in order to discuss its effectiveness in Section III, followed by the conclusion in Section IV.

II. METHODOLOGY

A. SYSTEM MODELING

In this work, MGs are considered to be operated as an MAS owing to their alignment with the distributed nature of modern MGs as well as privacy-preserving advantages. In MASs, it is conceived that independent entities known as agents would manage their resources with the aim of maximizing their respective profits. Therefore, within an MAS framework, the decision-making process is distributed between the agents; in other words, the objectives of the agents may be different from each other and also from the global objective of the society [21]. In this regard, a simplified structure of multi-agent microgrids considered in this paper is represented in Fig. 1. In this respect, it is assumed that agents would be able to operate different types of DERs in order to develop a general P2P market framework. Finally, regarding the system presented in Fig. 1, the MG is assumed to be operated in an isolated mode.

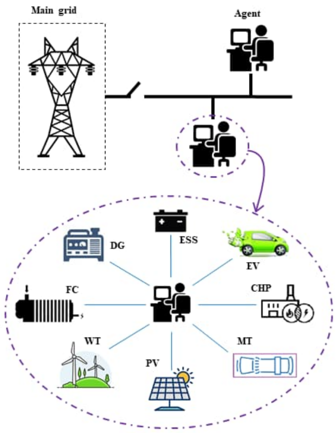

FIGURE 1. **A simplified model of the considered multi-agent microgrid.**

Based on the expansion of power generation resources such as renewable energies in local systems and intentions for independency from the upper-level network, the MG's agents would desire to trade energy together in order to maximize their profits. In other words, agents with an extra amount of energy prefer to sell their surplus power; while other agents want to purchase energy due to their energy shortages. This condition could benefit both the buyers and sellers; therefore, the development of local markets in MGs that facilitate the power exchanges among the agents seems to be necessary for modern energy systems. Consequently, in this paper, a new P2P market framework is proposed to manage the power trading among the independently operated agents which also copes with the conditions of the MG. In this structure, it is assumed that MGO would monitor the behavior of agents to assure the proper execution of trades, exchanges, and settlements in the market. In this paper, for the sake of convenience in the modeling of the proposed framework, three sets are considered for the agents, time intervals, and scenario numbers as $K = \{1, 2, \ldots, k\}$, $T = \{1, 2, \ldots, t\}$, and $S = \{1, 2, \ldots, s\}$, respectively. Hence, all over the context of this paper, *k*, *t*, and *s* would present the index of the agent, time interval, and scenario, correspondingly. In the next sections, first, the Copula-base scenario generation procedure for renewable energy sources is illustrated. Moreover, the overall cost function of system agents is obtained based on the mathematical operational modeling of their resources. Finally, the proposed algorithm for implementing the P2P market framework in the MG is presented considering the agents' optimization problems.

B. Copula-based Scenario Generation Utilizing K-Means Clustering Approach

In the developed P2P structure, stochastic optimization modeling is employed to consider the uncertainty of renewable energies in the operational optimization of system agents. Nevertheless, as mentioned, the uncertainty of renewable energies is initiated due to their dependence on meteorological characteristics. Note that the meteorological parameters are typically correlated in the geographical area of the multi-agent MG. In this regard, it is assumed that the MGO is the responsible entity for the scenario generation of renewable energies in each agent taking into account their corresponding correlation. In this context, the Gaussian Copula method is taken into consideration in this paper to demonstrate the correlation between power generation by renewable energies in system agents. In this model, Copula functions enable the formulation of multi-variable functions to show the correlation between stochastic variables. As a result, the three steps discussed in the following sub-sections are taken into account in order to generate the scenarios associated with the renewable energies in system agents.

1) MODELING THE STOCHASTIC DEPENDENCE:

In the Copula-base modeling, rank correlation (κ_r) is taken into account to measure the stochastic dependence among the respective decision variables. Consequently, the rank correlation between the random variables *X* and *Y* with the cumulative distribution functions (CDFs) of F_X and F_Y is modeled as below:

$$\kappa_r(X, Y) = \kappa(F_X(X), F_Y(Y)) \tag{1}$$

Where κ is a function that measures the linear correlation between $F_X(X)$ and $F_Y(Y)$.

2) MODELING THE COPULA-BASED CORRELATION:

In this paper, the Gaussian copula function, i.e., $G(u_1, u_2, ..., u_N)$, is taken into consideration to develop the multi-variable joint distribution $F(x_1, x_2, ..., x_N)$ based upon the CDF functions of its respective variables as below:

$$F(x_1, x_2, ..., x_N) = G(F_{x_1}(x_1), F_{x_2}(x_2), ..., F_{x_N}(x_N)) \tag{2}$$

3) K-MEANS BASED CLUSTERING APPROACH:

In the third step, first, *N* scenarios are generated in the domain of $[0,1]^N$ by utilizing the joint multiple-variable function, which is represented in (2). After that, the inverse-CDF function is taken into account to re-cast the variables to their corresponding primary domains. Furthermore, the *N* scenarios generated are partitioned into S categories, which are considered as the final scenarios to conduct the P2P management model. Note that the defined procedure in this section is employed to generate the operational scenarios for PV and WT units. Respectively, the correlation of solar irradiance and wind speed could be considered to measure the rank correlation as well as copula function formulation. After finalizing the scenarios, each agent employs its respective solar irradiance and wind speed in each of the scenarios to measure the output power by its renewable resources. It is noteworthy that, in the developed procedure, the copula model and correlation analysis could be modeled based on the accumulated power output of renewable energies in the system agents. Consequently, the finalized generated scenarios would show the power output by PV and WT units in each agent and so could be effortlessly allocated to the respective sources in the agent to conduct the agent operational optimization in the P2P management model. A more detailed illustration of the strategy employed for scenario generation as well as the clustering approach is presented in [22].

C. MATHEMATICAL MODELING OF GENERATION UNITS

1) OPERATIONAL COST OF PHOTOVOLTAICS/WIND TURBINES:

Operational and maintenance costs of PVs and WTs should be modeled by the agents in their respective cost functions as follows [17]:

$$f_{k,i}^{pv}(P_{k,i,t,s}^{pv}) = \chi_{k,i}^{pv} \cdot P_{k,i,t,s}^{pv} \tag{3}$$

$$f_{k,i}^{wt}(P_{k,i,t,s}^{wt}) = \chi_{k,i}^{wt} \cdot P_{k,i,t,s}^{wt} \tag{4}$$

$$P_{k,i,t,s}^{pv} \le \overline{P_{k,i}^{pv}}, P_{k,i,t,s}^{wt} \le \overline{P_{k,i}^{wt}} \tag{5}$$

In these equations, $f_{k,i}^{pv} / f_{k,i}^{wt}$ is the operational cost of agent k's PV/WT unit i. Moreover, $P_{k,i,t,s}^{pv} / P_{k,i,t,s}^{wt}$, $\chi_{k,i}^{pv}$ / $\chi_{k,i}^{wt}$, and $\overline{P_{k,i}^{pv}} / \overline{P_{k,i}^{wt}}$ represent the power production by the PV/WT at the time t and the scenario s, the maintenance cost per unit of the power generation by PV/WT, and the maximum possible amount of the power production by PV/WT, respectively. It is noteworthy that notation i in (3)-(5) shows the index of agent k's PV/WT units.

2) OPERATIONAL COST OF FUEL CELLS:

FCs conventionally consume some resources as their fuel and produce some products along with electrical energy. In this regard, a simple kind of FC combines oxygen and hydrogen as input resources and produces water in addition to electrical power [23]. Therefore, as long as an FC does not run out of fuel, it would continue the generation process. Respectively, the cost associated with the operation of FC units is dependent on the fuel cost and so is modeled as follows [17]:

$$f_{k,i}^{fc}(P_{k,i,t,s}^{fc}) = \left(\frac{\lambda^{fc}}{p^{fc} \cdot \eta_{k,i}^{fc}} + \chi_{k,i}^{fc}\right) P_{k,i,t,s}^{fc} \tag{6}$$

$$\underline{P_{k,i}^{fc}} \le P_{k,i,t,s}^{fc} \le \overline{P_{k,i}^{fc}} \tag{7}$$

Where, $f_{k,i}^{fc}$ and $P_{k,i,t,s}^{fc}$ present the operational cost associated with i_{th} FC in the agent k as well as its power generation at time t and scenario s. Moreover, λ^{fc}, p^{fc}, $\eta_{k,i}^{fc}$, $\chi_{k,i}^{fc}$, $\underline{P_{k,i}^{fc}}$, and $\overline{P_{k,i}^{fc}}$ represent the fuel cost per m^3, power produced per m^3 of consumed fuel, the FC's efficiency, the maintenance cost per unit of $P_{k,i,t,s}^{fc}$, and the minimum and maximum limits of the power production by the FC unit, respectively.

3) OPERATIONAL COST OF MICROTURBINES:

MT units are high-speed small-scale gas turbines that could be located in local systems and be operated by independent agents. The energy produced by an MT is in a mechanical form which would be transformed into electrical energy. Consequently, similar to FCs, costs associated with the operation of MTs are highly affected by their fuel costs. In this regard, the cost function of i_{th} MT unit of agent k could be defined as below [17]:

$$f_{k,i}^{mt}(P_{k,i,t,s}^{mt}) = \left(\frac{\lambda^{mt}}{p^{mt} \cdot \eta_{k,i}^{mt}} + \chi_{k,i}^{mt}\right) P_{k,i,t,s}^{mt} \tag{8}$$

$$\underline{P_{k,i}^{mt}} \le P_{k,i,t,s}^{mt} \le \overline{P_{k,i}^{mt}} \tag{9}$$

Where, $f_{k,i}^{mt}$, $P_{k,i,t,s}^{mt}$, and λ^{mt} indicate the MT's operational cost, its power generation, and fuel price, correspondingly. Furthermore, p^{mt}, $\eta_{k,i}^{mt}$, $\chi_{k,i}^{mt}$, $\underline{P_{k,i}^{mt}}$, and $\overline{P_{k,i}^{mt}}$ correspondingly represent the generated power amount per m^3 of the fuel consumption, the MT's efficiency, the maintenance cost per unit of $P_{k,i,t,s}^{mt}$, as well as the minimum and maximum limits of MT's power generation.

4) OPERATIONAL COST OF COMBINED HEAT AND POWER UNITS:

CHPs could simultaneously generate heat and electricity which enables them to be more economical compared with the MTs. In other words, utilizing the heat production of the MTs results in the improvement of their efficiency as well as decreasing their fuel costs. In this respect, the costs associated with the CHP units could be formulated as follows [17]:

$$f_{k,i}^{chp}(P_{k,i,t,s}^{chp}) = \left[\frac{\lambda^{mt}}{p^{mt} \cdot \eta_{k,i}^{mt}}\left(1 - \frac{r_k(\eta_{k,i}^{chp} - \eta_{k,i}^{e})}{\eta_{k,i}^{b}}\right) + \chi_{k,i}^{chp}\right] P_{k,i,t,s}^{chp} \tag{10}$$

$$\underline{P_{k,i}^{chp}} \le P_{k,i,t,s}^{chp} \le \overline{P_{k,i}^{chp}} \tag{11}$$

Where, $f_{k,i}^{chp}$ and $P_{k,i,t,s}^{chp}$ demonstrate the operational cost of the i_{th} CHP and its power generation. Moreover, $\chi_{k,i}^{chp}$, $\underline{P_{k,i}^{chp}}$, $\overline{P_{k,i}^{chp}}$, r_k, $\eta_{k,i}^{chp}$, $\eta_{k,i}^{e}$, and $\eta_{k,i}^{b}$ indicate CHP's maintenance cost per unit of $P_{k,i,t,s}^{chp}$, the minimum and maximum limits of CHP generation, the heat recovery factor, the total efficiency of the CHP, as well as the CHP's electrical efficiency and its boiler's efficiency, respectively. Finally, λ^{mt}, p^{mt}, and $\eta_{k,i}^{mt}$ are the parameters of the MT utilized in the optimization, which demonstrate the fuel price, the generated power amount per m^3 of the fuel consumption, and the efficiency of the MT, correspondingly.

5) OPERATIONAL COST OF DIESEL GENERATORS:

DGs are a type of DERs that utilize diesel fuel to produce electrical power. In this context, their relative operational costs could be obtained from the formulations stated below [24]:

$$f_{k,i}^{dg}(P_{k,i,t,s}^{dg}) = \begin{bmatrix} A_{k,i}(P_{k,i,t,s}^{dg})^2 + \\ B_{k,i}P_{k,i,t,s}^{dg} + C_{k,i} \end{bmatrix} + \chi_{k,i}^{dg} P_{k,i,t,s}^{dg} \tag{12}$$

$$\underline{P_{k,i}^{dg}} \le P_{k,i,t,s}^{dg} \le \overline{P_{k,i}^{dg}} \tag{13}$$

Where, $f_{k,i}^{dg}$, and $P_{k,i,t,s}^{dg}$ are the operational cost of i_{th} DG unit, and its respective power generation; while $\chi_{k,i}^{dg}$, $\underline{P_{k,i}^{dg}}$, and $\overline{P_{k,i}^{dg}}$ present the DG's maintenance cost per unit of $P_{k,i,t,s}^{dg}$, as well as the minimum and maximum limits associated with the DG's power generation, respectively. Note that $A_{k,i}$, $B_{k,i}$, and $C_{k,i}$ are fixed constants declared by the manufacturer.

D. MATHEMATICAL FORMULATION OF AGENTS' COST FUNCTIONS

This section aims to extract the overall costs of an agent and model it by one compact function. In this context, all kinds of costs associated with the operational management of an agent are presented in the following subsections, and then an overall function that models the cost of each agent while participating in the P2P market model is presented.

1) GENERATION COSTS OF AN AGENT:

In this paper, it is assumed that agents could operate six types of distributed power generation units including PV, WT, FC, MT, CHP, and DG. In this regard, the cost of an agent associated with generation units is simply obtained by summing generation units' costs as follows:

$$f_{k,t,s}^{gen} = \sum_{x \in X} \sum_{i \in I_n^x} f_{k,i}^{x}(P_{k,i,t,s}^{x}) \tag{14}$$

Where, $f_{k,t,s}^{gen}$ is the total generation cost, X presents the set of generation types defined as $X = \{pv, wt, fc, mt, chp, dg\}$, and I_n^x shows the set of distributed generation units in agent *n*.

2) OPERATIONAL COST OF ENERGY STORAGE SYSTEMS:

In the proposed scheme, it is considered that agents would be able to possess ESSs to enhance their flexibility against high prices in the system. This would also increase the overall flexibility of the system [1]. In this regard, the operational cost of ESSs and their relative constraints could be modeled as (15) – (18) [25].

$$f_{k,t,s}^{ESS} = \zeta_k^{ESS,c} P_{k,t,s}^{ESS,c} \Delta t + \zeta_k^{ESS,d} P_{k,t,s}^{ESS,d} \Delta t \tag{15}$$

$$0 \le P_{k,t,s}^{ESS,c} \le \overline{P_k^{ESS,c}}, 0 \le P_{k,t,s}^{ESS,d} \le \overline{P_k^{ESS,d}} \tag{16}$$

$$S_{k,t}^{ESS} = S_{k,t-1}^{ESS} + \eta_k^{ESS,c} P_{k,t,s}^{ESS,c} \Delta t - \eta_k^{ESS,d} P_{k,t,s}^{ESS,d} \Delta t \tag{17}$$

$$\underline{SL_k^{ESS}} S_{k,cap}^{ESS} \le S_{k,t}^{ESS} \le \overline{SL_k^{ESS}} S_{k,cap}^{ESS} \tag{18}$$

In these equations, $f_{k,t,s}^{ESS}$, $P_{k,t,s}^{ESS,c}$, $P_{k,t,s}^{ESS,d}$, $\zeta_k^{ESS,c}$, and $\zeta_k^{ESS,d}$ show the operational cost of the ESS, its charging and discharging amount, as well as the depreciated costs of the charging and discharging of the ESS unit, respectively. Moreover, $\overline{P_k^{ESS,c}}$, $\overline{P_k^{ESS,d}}$, $S_{k,t}^{ESS}$, $\eta_k^{ESS,c}$, and $\eta_k^{ESS,d}$ correspondingly declare the maximum limit of charging and discharging, energy level, and the charging and discharging efficiency of the ESS unit. Finally, $\underline{SL_k^{ESS}}$, $\overline{SL_k^{ESS}}$, and $S_{k,cap}^{ESS}$ present the minimum and maximum energy level as well as the capacity of the ESS unit, which are taken into account to assure the optimal lifetime of the ESS unit. It is important to note that in equation (17), $\eta_k^{ESS,c} \le 1$, while $\eta_k^{ESS,d} \ge 1$.

3) OPERATIONAL COST OF ELECTRICAL VEHICLES;

From the management point of view, EVs could improve the flexibility of the system. Similar to ESSs, the operational formulation of the EVs could be modeled as follows:

$$f_{k,t,s}^{EV} = \zeta_k^{EV,c} P_{k,t,s}^{EV,c} \Delta t + \zeta_k^{EV,d} P_{k,t,s}^{EV,d} \Delta t \tag{19}$$

$$0 \le P_{k,t,s}^{EV,c} \le \overline{P_k^{EV,c}}, 0 \le P_{k,t,s}^{EV,d} \le \overline{P_k^{EV,d}} \tag{20}$$

$$S_{k,t}^{EV} = S_{k,t-1}^{EV} + \eta_k^{EV,c} P_{k,t,s}^{EV,c} \Delta t - \eta_k^{EV,d} P_{k,t,s}^{EV,d} \Delta t \tag{21}$$

$$\underline{SL_k^{EV}} S_{k,cap}^{EV} \le S_{k,t}^{EV} \le \overline{SL_k^{EV}} S_{k,cap}^{EV} \tag{22}$$

In the developed formulation, $f_{k,t,s}^{EV}$ is the operational cost of the EV unit; while $P_{k,t,s}^{EV,c} / P_{k,t,s}^{EV,d}$ presents the charging/discharging power during the time interval Δt. Moreover, $\zeta_k^{EV,c} / \zeta_k^{EV,d}$ shows the depreciated cost of the charging/discharging of the EV unit, and $\overline{P_k^{EV,c}} / \overline{P_k^{EV,d}}$ indicates the maximum limit of the power charging/discharging. Moreover, $S_{k,t}^{EV}$ demonstrates the EV's energy level, and $\eta_k^{EV,c} / \eta_k^{EV,d}$ shows the efficiency of the EV unit charging/discharging. Finally, $\underline{SL_k^{EV}} / \overline{SL_k^{EV}}$ presents the minimum/maximum energy level of the EV unit, and $S_{k,cap}^{EV}$ demonstrates the EV's battery capacity. It is noteworthy that, similar to ESSs, in equation (21), $\eta_k^{EV,c} \le 1$, while $\eta_k^{EV,d} \ge 1$.

In order to model the time periods that the EV unit is connected to the grid, it is assumed that the agents arrive at home at the time t_k^{ar} and exit at t_k^{ex}. Furthermore, EVs could merely be charged at home. Finally, as presented in (23) and (24), it is presumed that the energy level of the EV's battery at t_k^{ar} is equal to $SL_k^{EV,ar}$, and the energy level at t_k^{ex} should be equal to or greater than $SL_k^{EV,ex}$. It is noteworthy that in the equations (19) to (22), $P_{k,t,s}^{EV,c}$ and $P_{k,t,s}^{EV,d}$ show the

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charging and discharging amount of the EV while the EV is connected to the grid at home.

$$S^{EV}_{k,t^{ar}_k} = SL^{EV,ar}_k \tag{23}$$

$$S^{EV}_{k,t^{ex}_k} \geq SL^{EV,ex}_k \tag{24}$$

4) MODELING THE POWER CONSUMPTION OF EACH AGENT:

In the proposed framework, the power consumption by agents' demands is modeled with the utility function. In this regard, the utility function presents the utility received by the agents while consuming energy. Two main types of utility functions exist for modeling the satisfaction that the agents earn by energy consumption including the quadratic utility function and logarithmic utility function. In this paper, a quadratic utility function is utilized in order for quantifying the utility of agents in which as an agent consumes more energy, the utility acquired by him would be increased. However, this utility increment would be decreased in higher amounts of consumption and in very high amounts of consumption the utility would be fixed. This is because when an agent begins to consume energy, his satisfaction highly increases but this increment of satisfaction diminishes gradually with the increment of consumption, and from a certain point, the increment of consumption has no effect on satisfaction enhancement for the agent. Respectively, $f^{utility}_{k,t,s}$ demonstrates the load utility function of the k_{th} agent at time t and scenario s could be obtained as follows [26], [27]:

$$f^{utility}_{k,t,s} = \begin{cases} \psi_{k,t} P^u_{k,t,s} - \dfrac{\gamma_k}{2}(P^u_{k,t,s})^2 & 0 \leq P^u_{k,t,s} \leq \dfrac{\psi_{k,t}}{\gamma_k} \\ \dfrac{1}{2}\dfrac{(\psi_{k,t})^2}{\gamma_k} & \dfrac{\psi_{k,t}}{\gamma_k} \leq P^u_{k,t,s} \end{cases} \tag{25}$$

$$\underline{P^u_{k,t}} \leq P^u_{k,t,s} \leq \overline{P^u_{k,t}} \tag{26}$$

Where, $\psi_{k,t} > 0$ is the parameter of consumption, $\gamma_k > 0$ shows a predetermined constant parameter, and $P^u_{k,t,s}$ models the power consumption which is considered to be between the minimum limit of $\underline{P^u_{k,t}}$ and the maximum limit of $\overline{P^u_{k,t}}$.

5) TRADING COSTS OF EACH AGENT:

Agents could trade with each other in the P2P market maximizing their profits with respect to their role; i.e., seller or buyer. In this regard, in order to model the costs/profits associated with the agents owing to their energy transactions, it is assumed that $f^{tr}_{j,t}$, $\lambda_{j,t}$, $P^{pur}_{ij,t}$, and $P^s_{j,t}$ represent the cost associated with the energy trading of agent j at time t, the power exchange price, the amount of power that agent j purchases from agent i, and the amount of power that agent j prefers to sell to other agents. In this regard, $f^{tr}_{j,t}$ could be formulated as follows:

$$f^{tr}_{j,t} = \left(\sum_{i \in K} \lambda_{i,t} P^{pur}_{ij,t} \right) - \lambda_{j,t} P^s_{j,t} \tag{27}$$

Note that $\lambda_{j,t}$, $P^{pur}_{ij,t}$, and $P^s_{j,t}$ are positive parameters. Moreover, the power purchased by agent j (i.e., $P^{pur}_{j,t}$) could be defined as follows:

$$P^{pur}_{j,t} = \sum_{\substack{i \in K \\ i \neq j}} P^{pur}_{ij,t} \tag{28}$$

Finally, in the proposed model, as equation (29) demonstrates, a system agent could not act as a seller and buyer at the same time. It is noteworthy that the constraint (29) is replaced by (30) in order to decrease the running time of the optimization problem.

$$P^{pur}_{j,t} \cdot P^s_{j,t} = 0 \tag{29}$$

$$P^{pur}_{j,t} + P^s_{j,t} = \left| P^{pur}_{j,t} - P^s_{j,t} \right| \tag{30}$$

6) OVERALL COST FUNCTION OF EACH AGENT AT THE PRESENT TIME INTERVAL:

Agents need to sum all their costs up within a single equation in order to be able to decide about their actions in the P2P market. In this regard, the overall cost function of agent k at the present time interval t (i.e., $f^N_{k,t,s}$) is derived as (31) by adding all the sub-functions discussed in previous parts.

$$f^N_{k,t,s} = f^{gen}_{k,t,s} + f^{ESS}_{k,t,s} + f^{EV}_{k,t,s} - f^{utility}_{k,t,s} + f^{tr}_{k,t} \tag{31}$$

It is noteworthy that the optimization conducted by the agent k for determining the resource scheduling at the current time interval that the P2P market is running would result in here-and-now decisions.

7) MODEL PREDICTIVE CONTROL APPROACH:

In order to improve the decision-making process by each agent, the MPC concept is employed in this paper. In this regard, in the developed scheme, agents consider the H_k time intervals in their optimization problems to decide the charging/discharging of their ESSs/EVs at the current time interval [28]. In this context, each agent would consider (32) to model the cost function at future time intervals.

$$f^F_{k,h,s} = f^{gen}_{k,h,s} + f^{ESS}_{k,h,s} + f^{EV}_{k,h,s} - f^{utility}_{k,h,s} + \lambda^F_{h,s} P^{F,pur}_{k,h,s} \tag{32}$$

Where, $f^F_{k,h,s}$ shows the total cost of agent k at the future time interval h and scenario s, $\lambda^F_{h,s}$ represents the predicted energy price at the future time interval h, and $P^{f,pur}_{k,h,s}$ is the amount of power that the agent k would purchase. Note that $P^{f,pur}_{k,h,s}$ could be either positive or negative. In this regard, when $P^{f,pur}_{k,h,s}$ is negative/positive, it means that the agent wants to sell/purchase power at the future time interval h. It is noteworthy that the agents would consider the predicted power generation by PV and WT units, power consumption, and the

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$\lambda^F_{h,s}$ at future time intervals. As mentioned, the scenarios associated with the power generation by renewable energies would be determined by the Copula method. Moreover, it is possible that agents utilize various prediction methods such as learning algorithms to amend their anticipations at future time intervals [29]. Finally, note that, in this paper, scenario-based stochastic optimization is taken into account in order to model the uncertainty associated with these operational parameters of future time intervals.

E. IMPLEMENTING THE DEVELOPED P2P MARKET FRAMEWORK

The overall flowchart of the proposed P2P market scheme which would be conducted in a step-wise manner at each time interval in order to manage the power transactions in multi-agent MGs is presented in Fig. 2. In this regard, the proposed algorithm would determine power exchanges among the system agents at the respective time interval. In the developed management scheme, first of all, agents should determine their preliminary prices for the first time that the algorithm is run; nevertheless, as the proposed procedure is conducted iteratively, they would be able to amend the preliminary prices in the future steps. The next steps of the flowchart would be illustrated in the upcoming subsections. In the simulation of the proposed model, without loss of generality, it is considered that all of the agents are sellers at the first iteration and they declare their selling prices. Nevertheless, note that $P^s_{k,t}$ would be equal to zero for buyer agents in the optimization problem because buyers need purchasing power rather than selling it. In other words, in order to simplify the application of the P2P model in multi-agent systems, at the first iteration, agents would be conceived as sellers, while they would amend their role based on the operational condition of the system in the future iterations. This role changing through the iterations is more explained within the updating prices procedure subsection of section E.

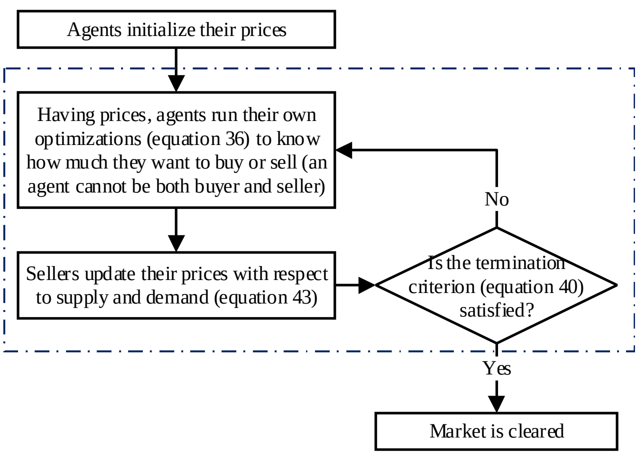

FIGURE 2. **The flowchart of the proposed P2P market in multi-agent MGs.**

1) OPTIMIZATION PROBLEM OF THE AGENTS:

After the initialization step in the flowchart, agents should run an optimization problem to decide about the scheduling of their resources. Moreover, agents should determine their roles as buyers or sellers and the respective amount of power to be purchased/sold. Furthermore, as previously mentioned, agents would consider future time intervals in order to utilize the MPC approach. In this regard, a scenario-based formulation is taken into account in the optimization modeling of agents in order to model the uncertainty associated with the prediction procedure. Respectively, each scenario would be associated with a probability to be employed in the optimization formulation. Therefore, if p_s indicates the probability of scenario s; the scenario-based optimization problem would be defined as follows:

$$Min\left\{\sum_{s\in S} p_s\left(f^N_{k,t,s} + \sum_{h=t+1}^{t+H_k-1} f^F_{k,h,s}\right)\right\}, \forall k\in K, \forall t\in T \tag{33}$$

Subject to the aforementioned constraints of (5), (7), (9), (11), (13), (16) - (18), (20) - (24), (26), (30), and:

$$\sum_{x\in X}\sum_{i\in I_n^x} P^x_{k,i,t,s} = \begin{pmatrix} P^u_{k,t,s} - P^{pur}_{k,t} + P^s_{k,t} + \\ P^{ESS,c}_{k,t,s} - P^{ESS,d}_{k,t,s} + P^{EV,c}_{k,t,s} - P^{EV,d}_{k,t,s} \end{pmatrix} \tag{34}$$
$$, \forall s\in S, \forall k\in K, \forall t\in T$$

$$\sum_{x\in X}\sum_{i\in I_n^x} P^x_{k,i,h,s} = \begin{pmatrix} P^u_{k,h,s} - P^{f,pur}_{k,h,s} + \\ P^{ESS,c}_{k,h,s} - P^{ESS,d}_{k,h,s} + P^{EV,c}_{k,h,s} - P^{EV,d}_{k,h,s} \end{pmatrix} \tag{35}$$
$$, \forall s\in S, \forall k\in K, \forall h\in \{t+1,\dots,t+H_k-1\}$$

Where, equations (34) and (35) respectively present the power balance constraints associated with the current time interval t and the future time interval h of system agents.

2) IMPLEMENTATION OF THE CVAR CONCEPT:

While modeling scenario-based stochastic optimization could address the uncertainty of the decision parameters associated with the future time intervals, the CVaR concept is taken into account to address the risk associated with the uncertainty of decision parameters. In this regard, based on the CVaR definition, in the case of considering α as a pre-determined parameter in the range of [0, 1], the expected value of the profits less than $(1-\alpha)$-quantile of the profit distribution would be equal to CVaR. In this regard, integrating this concept with the existing optimization problem enables the agents to manage their risks toward the uncertainty of decision parameters. As a result, the optimization problem associated with system agents could be formulated as follows:

$$Min\left\{\begin{aligned} &(1-\beta)\left[\sum_{s\in S}\rho_s\begin{pmatrix} f^N_{k,t,s} + \\ \sum_{h=t+1}^{t+H_k-1} f^F_{k,h,s}\end{pmatrix}\right] \\ &+\beta\left[v_{k,t} + \frac{1}{1-\alpha}\sum_{s\in S}\rho_s\cdot u_{k,t,s}\right]\end{aligned}\right\}, \forall k\in K, \forall t\in T \tag{36}$$

Subject to the aforementioned constraints of (5), (7), (9), (11), (13), (16) - (18), (20) - (24), (26), (30), (34) and:

$$-v_{k,t}+\left[\begin{array}{l} f^{N}_{k,t,s}+ \\ \sum_{h=t+1}^{t+H_k-1} f^{F}_{k,h,s}\end{array}\right]\le u_{k,t,s}, \forall s\in S, \forall k\in K, \forall t\in T \quad (37)$$

$$u_{k,t,s}\ge 0, \forall s\in S, \forall k\in K, \forall t\in T \quad (38)$$

Where β is the risk aversion factor, $v_{k,t}$ is an auxiliary variable, and $u_{k,t,s}$ is a non-negative variable for scenario s that is the maximum of $-v_{k,t}+\left[f^{N}_{k,t,s}+\sum_{h=t+1}^{t+H_k-1} f^{F}_{k,h,s}\right]$ and zero [30].

3) UPDATING PRICES PROCEDURE:

After the optimization step in the developed market algorithm presented in Fig. 2, agents update their prices considering the overall supply and demand requests in the market; which is formulated as follows:

$$\lambda_{k,t}(l+1)=\lambda_{k,t}(l)+\vartheta_k\left[P^{d}_{k,t}(l)-P^{s}_{k,t}(l)\right], \forall k\in K \quad (39)$$

In this equation, $\lambda_{k,t}(l)$ demonstrates the price of agent k in iteration l, $P^{d}_{k,t}(l)$ shows the total demand that is requested from the agent k in iteration l, and ϑ_k is the convergence factor. In this context, agents could independently determine their respective ϑ_k. As it is shown in (39), whenever an agent's total demand is greater/lower than its total supply, its price increases/decreases. As mentioned, $P^{s}_{k,t}(l)$ would be equal to zero for buyer agents. Therefore, according to equation (39), their price values would continuously be increased in the next iterations. Thus, since the price values of these agents are higher than the seller agents' prices in the upcoming iterations, the total purchase amount from these agents would be decreased gradually and reaches to zero. Consequently, buyer agents would have high price values and no one would purchase energy from them. This shows how buyer agents are managed in the proposed scheme; while their roles were automatically selected as sellers at the beginning of the proposed algorithm.

It is noteworthy that the determination of ϑ_k is dependent on every agent's own strategy for the price updating process and there is no limitation on it. As ϑ_k gets greater values, the deviations of price values increases but the accuracy of the optimum price values decreases. In this model, it is assumed that the agents choose lower values for ϑ_k when the iteration number is low and increase it gradually when the iteration number grows.

4) THE TERMINATION CRITERION:

Simply, in case the changes in prices of all the agents are negligible with a criterion of (ε) compared with the prices of the previous iteration, the algorithm would be considered as converged and the iterative model would be terminated. In this regard, this criterion could be formulated as:

$$\left|\lambda_{k,t}(l+1)-\lambda_{k,t}(l)\right|\le\varepsilon, \forall k\in K \quad (40)$$

F. CONVERGENCE IMPROVEMENTS

In order to amend the price convergence, some methods have been devised to be applied in the proposed algorithm. In this context, these methods are described in the rest of this section.

1) LIMITATIONS OVER THE CHANGES IN THE POWER PURCHASES AND PRICES:

In the proposed algorithm, as presented in (41), it is assumed that agents could merely change their purchase amounts in a limited range compared with the scheduling in the previous iteration of running the P2P market model. In this regard, agent j could alter its respective power purchase from agent i between two limits which are equal to δ_P percentage lower and higher than its power purchase amount in the previous iteration [31].

$$(1-\delta_P)P^{pur}_{ij,t}(l)\le P^{pur}_{ij,t}(l+1)\le(1+\delta_P)P^{pur}_{ij,t}(l), \forall j\in K \quad (41)$$

Similarly, in order to prevent the abrupt changes in the price values, every announced price would not be allowed to fluctuate more than δ_π percent of the announced price in the previous iteration; which is formulated as follows:

$$(1-\delta_\pi)\lambda_{k,t}(l)<\lambda_{k,t}(l+1)<(1+\delta_\pi)\lambda_{k,t}(l), \forall k\in K \quad (42)$$

2) LEARNING PROCESS:

Implementing the learning process in the price updating stage causes the (39) to be developed to (43) which takes into account the prices announced in the previous w iterations to improve the convergence.

$$\begin{aligned}\lambda_{k,t}(l+1)&=(1-\sigma_k)\left[\lambda_{k,t}(l)+\vartheta_k\left(P^{d}_{k,t}(l)-P^{s}_{k,t}(l)\right)\right]\\&+\sigma_k\sum_{i=l-w}^{l-1}\omega_{k,i}\lambda_{k,t}(i), \forall k\in K\end{aligned} \quad (43)$$

Where, σ_k and $\omega_{k,i}$ are the learning factor of agent k, and its weighting factor for $\lambda_{k,t}(i)$, respectively. Note that the learning factor is always in the range of $[0,1]$ and models the impact of the prices of the previous iterations [31].

III. CASE STUDY

In this section, two case studies are investigated: a 10-bus system for the sake of evaluating the proposed P2P market model within an islanded MAS and another 33-bus system in order for studying the scalability of the model. In this regard, a computer with 32 GB RAM and Core(TM) i7-4770 3.40GHz CPU is used in order for running a simulation written with MATLAB language utilizing a constrained nonlinear minimizer solver under the name of "fmincon" which is available in the optimization toolbox of MATLAB R2019a software.

Case 1: 10-bus system

In this case study, the proposed structure is applied to a 10-bus MG in order to analyze its effectiveness in the operational management of islanded multi-agent MGs utilizing a P2P market framework. In this simulation, it is assumed that the market is running hourly to determine the power exchanges between agents which are connected to each bus of the system. The test system and the considered local resources for each agent are presented in Fig. 3. Note that the operational characteristics of the local resources and pre-assumptions for implementing the P2P power market in the multi-agent test system are presented in [32].

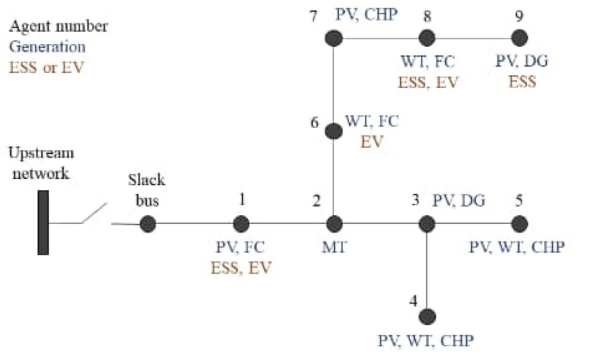

FIGURE 3. **The 10-bus test system utilized in the simulation study.**

The simulation is done for 24 hours of a sample day considering $\alpha = 0.7$ and $\beta = 0.2$ in order to investigate the effectiveness of the developed model in the operational management of the multi-agent test system. Considering the mentioned assumptions, the results of the simulation are represented in the rest of this section. Noted that the expected results of implementing the proposed model are presented and demonstrated in this section. In this regard, the summation of all the power exchanges between agents during the 24 hours of the day is shown in Fig. 4 as a chord diagram. This diagram shows the P2P graph of the obtained results in the market, in which almost all of the agents are trading energy with each other during the 24 hours. The Chord diagram of power exchanges is also depicted at hour 15 in Fig. 5. Moreover, agents 2, 4, 6, and 9 are selected to study their power trading status for 24 hours in Fig. 6. Accordingly, based on the obtained results, agent 2 is a buyer and agent 4 is a seller agent at all hours of the day; while agents 6 and 9 are buyers at some hours and sellers at the other hours of the day.

The average prices of the seller agents during the 24 hours of running the hourly P2P market framework are also demonstrated in Fig. 7. Regarding Fig. 7, the average prices at hours 2, 4, 8, 21, and 23 are higher than the other hours while running the P2P market model. This is based on the fact that the total supply power of seller agents is lower than the total requested power by buyer agents at these time intervals, which results in higher prices at these time intervals. Note that owing to the islanded operational mode of the MG, requested power by agents should merely be supplied by local power generation resources.

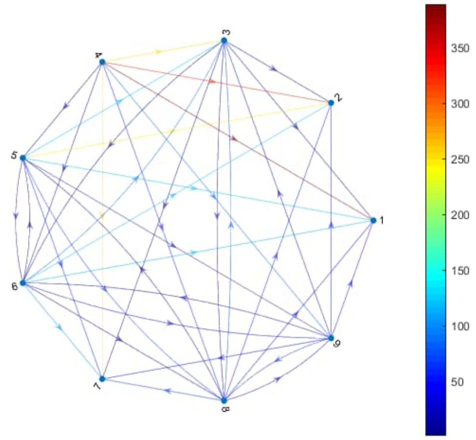

FIGURE 4. **Chord diagram of total power exchanges between the agents during the 24 hours in kW.**

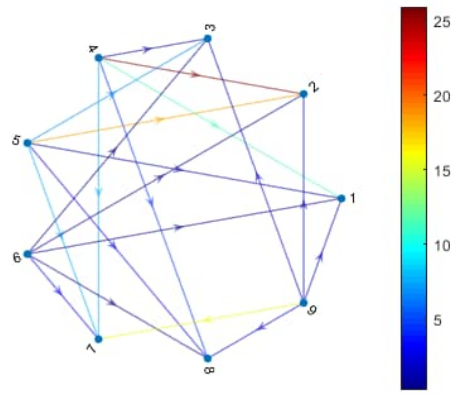

FIGURE 5. **Chord diagram of power exchanges between the agents at hour 15 in kW.**

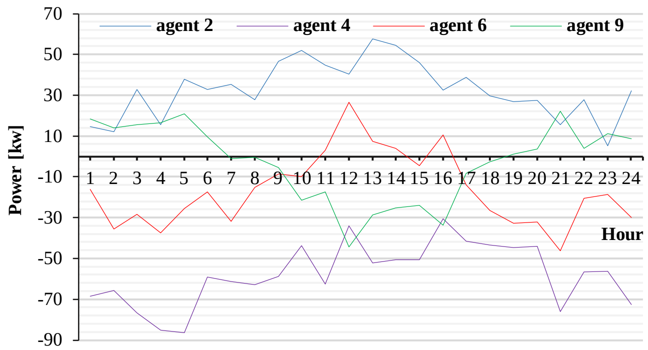

FIGURE 6. **Purchasing/selling power by agents 2, 4, 6, and 9 during 24 hours.**

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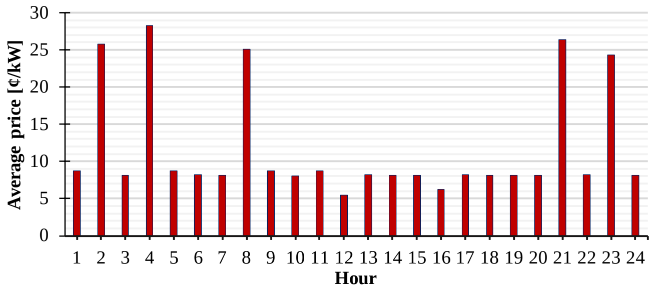

FIGURE 7. Average prices of sellers during 24 hours.

In the rest of this section, agent 8 is taken into account to inspect its operational scheduling during the 24 hours. In this regard, Fig. 8 indicates power generation by WT and FC of agent 8. Regarding the obtained results, the FC unit would not generate power at hours 12 and 16. This decision is rational due to the fact that $\left(\frac{\lambda^{fc}}{L^{fc}\cdot\eta^{fc}_{8,1}}+\chi^{fc}_{8,1}\right)=6.38\frac{¢}{kw}$; while, according to Fig. 7, only the power prices at hours 12 and 16 are lower than $6.38\frac{¢}{kw}$. Moreover, Fig. 9 demonstrates the power consumption of agent 8, while the charging/discharging of ESS and EV during 24 hours are shown in Figs. 10 and 11, respectively.

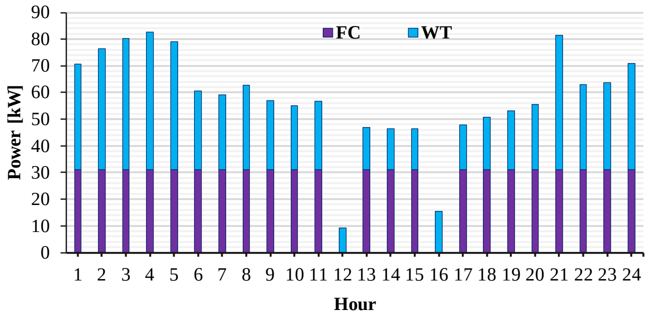

FIGURE 8. Power generation by WT and FC of agent 8.

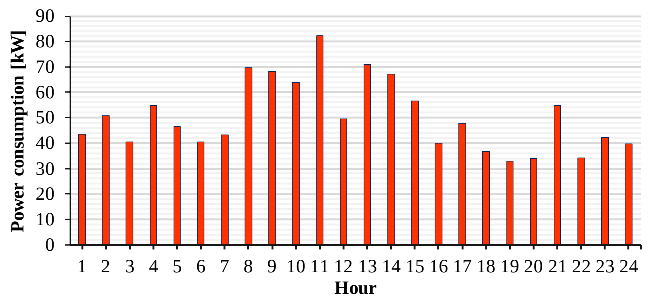

FIGURE 9. Power consumption of agent 8.

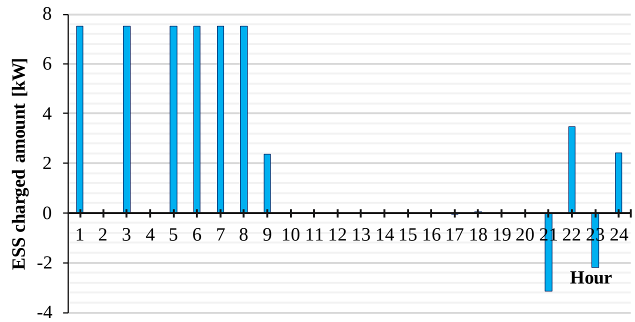

FIGURE 10. Charging/discharging of ESS unit of agent 8.

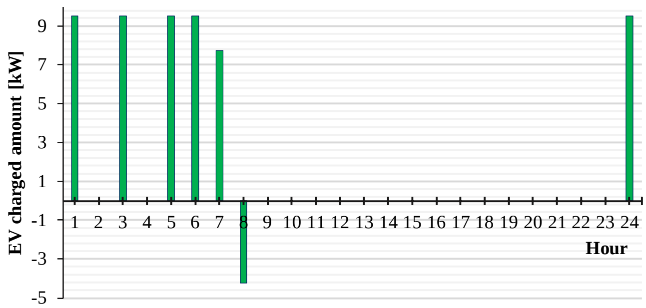

FIGURE 11. EV charging/discharging in agent 8.

The proposed model is also conducted considering $\beta=0$, $\beta=0.8$, and $\beta=1$ to study the effect of the risk factor in the developed operational management procedure. In this regard, Fig. 12 presents the proportional profit earned by agent 8 in hours 4, 16, and 21 considering different values of β. Regarding the obtained results, the total profit of agent 8 decreases as β increases; which means as the agent becomes more risk-averse, its respective profit would be decreased. In other words, the decrease in the agent profit would decrease the agent's risk associated with the uncertain parameters.

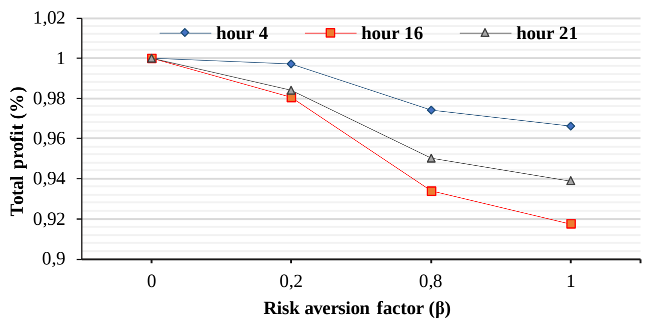

FIGURE 12. Relative comparison of total profit of agent 8 considering different risk factors.

Additionally, in order to investigate the convergence status of the proposed algorithm, the iterative announced prices by seller agents 4, 5, 6, and 9 in hour 15 are presented in Fig. 13. Regarding Fig. 13, all of the prices are approximately converged to 8.15¢; which is reasonable based on the competition among seller agents. In fact, if a seller agent increases its price to a higher value, the buyers would decrease their power purchasing amount from the agent. Moreover, lower prices will not be the optimum price for the agent taking into account the generation costs and other agents' benefits. Therefore, the seller agent strives to set its price to a value that is lower than the other sellers' prices marginally. Hence, as the results show in Fig. 13, all the prices are converged to almost the same value.

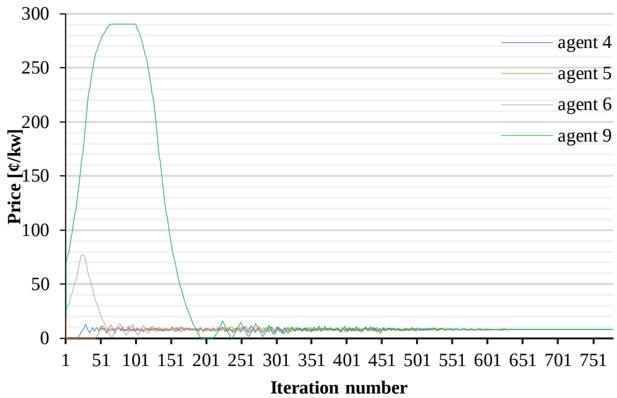

FIGURE 13. Convergence status in hour 15.

Case 2: 33-bus system

In the previous case study, the proposed model has been successfully tested on a small 10-bus MG and its various simulation results have been analyzed to show its effectiveness in the P2P management of the system. In this case study, in order to study its scalability, the model has been run on a 33-bus MG. The MG is assumed to be isolated from the upper-level network and 32 different agents are connected to the grid. The considered local resources for each agent of the test system are shown in Table 2. It is noteworthy that the operational data of the test system is presented in [32].

TABLE 2. Local resources of agents

Local resources	AGENT NUMBERS
PV	1, 3, 4, 5, 7, 9, 10, 12, 13, 14, 16, 18, 19, 21, 22, 23, 25, 27, 28, 30, 31, 32
WT	4, 5, 6, 8, 13, 14, 15, 17, 22, 23, 24, 26, 31, 32
FC	1, 6, 8, 10, 15, 17, 19, 24, 26, 28
MT	2, 11, 20, 29
CHP	4, 5, 7, 13, 14, 16, 22, 23, 25, 31, 32
DG	3, 9, 12, 18, 21, 27, 30
ESS	1, 8, 9, 10, 17, 18, 19, 26, 27, 28
EV	1, 6, 8, 10, 15, 17, 19, 24, 26, 28

In the rest of this subsection, the related results are presented assuming $\alpha = 0.7$ and $\beta = 0$. It should be noted that the study results are conducted for the 13th hour as a random sample of 24 hours of a day. In this regard, Fig. 14. shows the chord diagram of agents' power exchanges at the 13th hour. Note that the energy exchanges less than 2 kW are omitted from Fig. 14 for the sake of simplicity. Moreover, Fig. 15 demonstrates the amount of energy purchased by buyers and the amounts of sold power by sellers, simultaneously. Based on the obtained results, the total amount of sold power is equal to the total amount of purchased power by buyers. Furthermore, Fig. 16 indicates the selling price of three sample seller agents (i.e., 4th, 14th, and 27th agent) at hour 13 in all iterations, which have converged greatly to approximately 8.18¢/kw. The convergence status can be also inferred from Fig. 15, in which the balance of total sold and purchased power is approved. These results show the ability of the proposed model in the P2P management of multi-agent MGs.

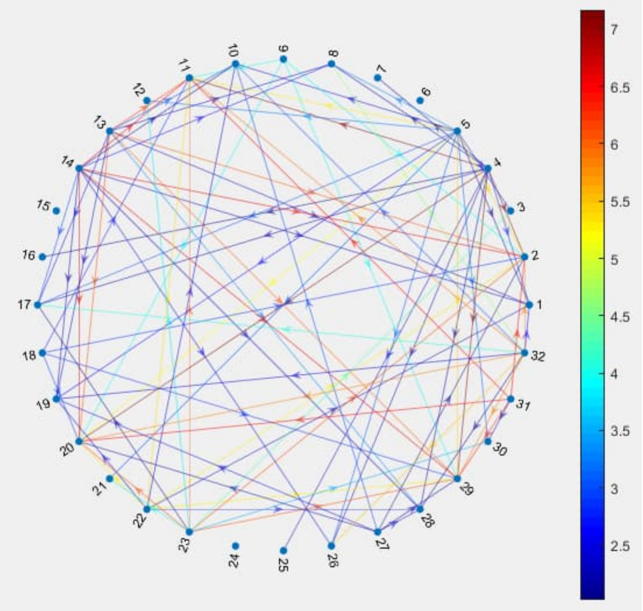

FIGURE 14. Chord diagram of power exchanges between the agents at 13th hour in kW.

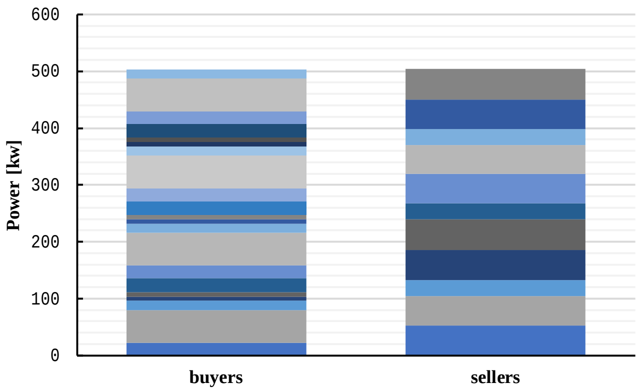

FIGURE 15. The amount of energy exchanged between buyers and sellers in kw.

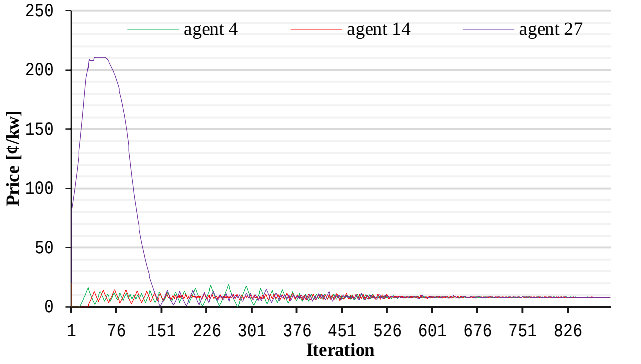

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FIGURE 16. The price of sample sellers in various iterations.

Additionally, the power generated by PV, WT, and other types of generation units (which are indicated by X) for each agent are represented in Fig. 17. Moreover, the power consumption by different agents is also shown in Fig. 17. It is noteworthy that X can be FC, MT, CHP, or DG according to the local resources of each agent.

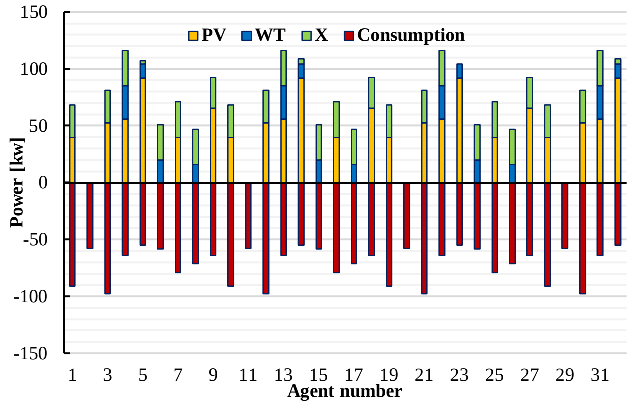

FIGURE 17. Generation and consumption amounts of agents at 13th hour.

IV. CONCLUSION

Based upon the current restructuring trend in power systems, MGs with multi-agent structures would play a key role in the integration of independently operated local resources into power systems. Accordingly, in this paper, a new framework based on the P2P concept is developed in order to optimize the power exchanges among agents in an islanded MG. In this regard, agents would optimize the operation of different types of distributed power generation sources while participating in the P2P market organized by the MGO. Moreover, stochastic optimization is employed in the optimization model developed for each agent in order to address the uncertainty associated with the decision parameters, whereas the CVaR index is taken into account to model the risk associated with the scenario-based optimization modeling.

The proposed P2P framework is implemented on a 10-bus MG test system with a multi-agent structure in order to analyze its application in the operational management of MGs with distributed nature. Finally, the simulation results show the ability of the proposed approach in the operational management of the multi-agent islanded MGs while addressing the privacy concerns of the independent agents.

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