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RESEARCH ARTICLE

A Real-Time Simulation for P2P Energy Trading Using a Distributed Algorithm

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ABSTRACT Increasing the deployment of Renewable Energy Resources (RES), along with innovations in Information and Communication Technologies (ICT), would allow prosumers to engage in the energy market and trade their excess energy with each other and with the main grid. To ensure an efficient and safe operation of energy trading, the Peer-to-Peer (P2P) energy trading approach has emerged as a viable paradigm to provide the necessary flexibility and coordinate the energy sharing between a pair of prosumers. The P2P approach is based on the concept of decentralized energy trading between prosumers (i.e., production capabilities or energy consumers). However, security protection and real-time transaction issues in the P2P market present serious challenges. In this paper, we propose a decentralized P2P energy trading approach for the energy market with high penetration of RE. First, the P2P energy market platform proposed coordinating the energy trading between energy providers and consumers to maximize their social welfare. A distributed algorithm is applied to solve the market-clearing problem based on the Alternating Direction Method of Multipliers (ADMM). In this way, the computational complexity can be reduced. Furthermore, a P2P Manager (P2PM) utility is introduced as an entity to solve the synchronization problem between peers during the market clearing. Finally, through a real-time application using Hardware-In-the-Loop (HIL), the effectiveness of the proposed P2PM is verified in terms of synchronizing the market participants and improving the power transaction.

INDEX TERMS Peer-to-peer, energy market, energy trading, distributed algorithm, alternating direction method of multipliers.

I. INTRODUCTION

In response to the urgent call to reduce greenhouse gas emissions globally, there has been a surge in the development and implementation of Renewable Energy (RE) sources such as solar and wind power. These sources, which are variable in nature, are increasingly being used to produce electricity. Additionally, there is a growing trend towards electrifying various sectors traditionally powered by fossil fuels, including transportation, commercial, and industrial sectors [1]. This development is expected to continue growing in order to meet environmental and sustainable targets. In the face of this development, power grids and energy markets are facing significant challenges with respect to their operation

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and design [2]. One major challenge relates to the fluctuation and power dispatch in RE resources, which create a balance management issue and reduce the power quality and reliability. In this context, the current wholesale markets lack the capability to react to the fluctuation and intermittent power generation from RES, which has led to the opening up of a Local Energy Market (LEM) for different participants in the distribution system [3].

In order to fulfill the power balance and enhance social welfare, LEM is utilized to motivate small-scale players, such as consumers and prosumers, to participate in trading their energy with one another in the community. Prosumers are defined as new players in the LEM that have changed conventional energy markets, where players can consume and produce electricity [4]. The interaction between different prosumers and energy market participants has been modeled using a variety of LEM designs that have been presented in the literature. The most widely used LEM models include Transactive Energy (TE), Community Self-Consumption (CSC), and Peer-to-Peer (P2P) energy trading [5].

P2P energy trading is recognized as an efficient solution for promoting the adaptation of REs and organizing transactions among a large number of peers. The P2P approach allows for flexibility among market participants, where surplus power from different small-scale REs and Energy Storage Systems (ESS) are traded locally. P2P electricity trading enables energy prosumers to benefit from selling surplus power to consumers and the main network. Moreover, it optimizes the benefits of decentralized power generation by reducing transmission losses and enhancing electricity supply stability. Notably, the P2P energy transaction paradigm can be arranged in two ways: centralized or decentralized (peer-centric) [6].

On the one hand, centralized P2P energy trading ensures the contracted transaction and unified pricing transaction. The P2P transactions are cleared in a centralized manner through the central entity, and the energy sharing between peers is fully controlled by a central unit in charge of implementing the market mechanism [6]. Several researchers have conducted the application of centralized P2P approaches for driven LEM. For example, in [7], a scalable market model for centralized P2P energy trading utilizing bilateral contract networks, which offered effective energy trading in an island microgrid, was presented. The system assumes a cluster of energy providers (two diesel generators) and customers using green energies, flexible or inflexible loads. The supplier agent operates all energy and finance between the energy providers and the prosumers. Based on the power provided, the demand, and grid buying and selling prices, the intermediate agents calculate the clearing price for the purchase of energy. In [8], a centralized entity called a P2P Market Operator (P2PMO) for the LEM was proposed, which facilitates the energy exchange in a P2P energy market for the microgrid network. P2PMO is assumed to reduce the congestion in the distribution system and balance energy supply and demand in a local community. Moreover, an iterative algorithm based on game theory is proposed in a community of prosumers to increase the social benefits of each prosumer and the microgrids community. It was proposed in [9] that an independent entity serve as an energy trading coordinator and monitor its execution. The LEM model was developed to determine the price at which energy prosumers should sell their electrical energy and to optimize their profit. The findings suggested that the suggested P2P energy trading model is able to save Photovoltaic (PV) prosumers' costs and enhance the sharing of PV energy. A centralized P2P energy trading model among households is suggested in [10]. A centralized manager gathers the data from households and solves an optimization problem, which increases the financial incomes for rooftop PV batteries and diesel generator (DG) in P2P energy trading conditions. The suggested model demonstrates that the interactions among P2P trading stakeholders using larger PV systems with battery storage can save up to 28% of energy during the weekdays. Even though the findings are positive, there are some limits to using the centralized energy trading mechanism. In particular, it requires a trusted entity to operate the status of the market players and energy production/consumption schedule. For privacy concerns, the end prosumer may decline to share sensitive data. On the other hand, the market players in decentralized P2P energy trading are able to engage in negotiations or transactions with each other completely without an intermediate. They can fully manage their energy sharing to maximize their benefits or increase their personal interests. Decentralized P2P energy trading improves market participants' transparency, secures data privacy, and promotes privacy-sensitive prosumers to participate in the LEM [11]. Many papers in the literature use the decentralized approach to trade energy between multiple buyers and sellers in an LEM [12]. In [12], a fully decentralized P2P energy trading utilizing the Alternating Direction Method of Multipliers (ADMM) procedure was developed. The author presented the concept of prosumers with a decentralized learning technique for tuning parameters of the cost function of each peer to obtain the best energy sharing to increase social welfare. In this manner, the peers decide the offers and bids based on their objective function. Reference [13] proposed a model for estimating maximum and minimum energy trading prices for energy prosumers and consumers that guaranteed their financial benefits and suggested a P2P energy trading technique considering the power demand and response, which can increase the earnings of the energy prosumer. Reference [14] applied a competitive game theory for market clearing for the P2P energy model. The market mechanism is designed to ensure the convergence to an economically efficient operation. It provides prosumers and consumers with financial incentives to make transactions with each other before dealing separately with the power network. In [15] addressed the deep reinforcement learning based multi-agent to address the decentralized P2P energy trading problem and energy exchange policies for multi-microgrids system. Specifically, interconnected domestic, commercial, and industrial multi-microgrids in a local community are investigated to reduce the operational cost of the community. Numerical analysis indicates that prosumers' financial gains may be enhanced via P2P scheme-based multi-agent systems, and that the price of the carbon tax can affect operating expenses and greenhouse gas emissions.

II. RELATED WORK

P2P trading is an emerging method that allows network participants to exchange resources with each other and has become an area of interest for research in order to advance the efficient use of local resources. The literature on the development of market mechanisms for P2P energy trading has received more attention recently using the optimization approach and iterative methods that we will apply within the scope of this research. In [16], the impact of self-sufficiency, smaller payback periods, and economical utilization of energy resources were examined using a Mixed-Integer Linear Programming (MILP) optimization approach designed from the use of PV and BESS. The suggested model allows consumers to provide energy at the most cost-effective rate within the suggested system via the P2P energy marketplace. In [17], an iterative uniform-price auction mechanism was proposed for P2P energy trading in community microgrids. The prosumers and consumers submit their asks and bids and iteratively adjust their prices based on the utility-maximizing point until the convergence state is reached, which can define the clearing price and energy allocation. In [18], a Relaxed Consensus and Innovation (RCI) technique is introduced to address the multi-bilateral economic dispatch problem for P2P transactions. The RCI is designed for distributed implementation that was investigated in different energy providers, four domestic and two industrial consumers, adhering to a decentralized approach that upholds participants' privacy and enhances data security. In [19], iterative mechanisms based on the negotiation method have been proposed, which the prosumers use to reach an agreement on an energy contract in terms of prices and energy supply in the intra-day and day-ahead P2P markets. Simulation case studies are implemented and demonstrated for the IEEE European Low Voltage Test Feeder. The results suggested that the proposed negotiation mechanism allows the prosumers to make autonomous utility/maximizing decision. To solve the heavy computational burden problem for P2P market mechanisms in real-time, the authors in [20] introduced a novel online optimization framework with the aim of enabling real-time operations within the P2P market. This framework relies on the concept of online social welfare maximization using the online consensus ADMM approach, which only performs one iteration for each agent at every step. In [21], a P2P energy trading model utilizing an iterative double auction approach was introduced. This mechanism is applied to extract hidden information from all participants to maximize social welfare. In this process, buyers and sellers adapt their asks and bids to optimize their individual profits based on their past transactions of the quantity of energy and the clearing price, all while operating with limited knowledge about the overall market dynamics. The authors in [22] applied a two-stage optimization methodology to determine the most advantageous strategies for maximizing utilities in P2P energy-sharing trading. In the initial optimization stage, the decision about participation in P2P energy-sharing trading has been considered for maximizing the social utility function. Simultaneously, the optimal quantities of energy to be exchanged are calculated. In the subsequent optimization stage, an analysis of the optimal trading payments using a payment bargaining model is conducted. Both of these optimization challenges are addressed using separate distributed algorithms. Reference [23] cleared the hybrid P2P energy trading market using an iterative approach based on the ADMM technique. The privacy of the energy prosumers will be preserved using the suggested algorithm. The prosumer is able to request or bid on pricing and share information about their energy use with other prosumers. Distributed energy resource (DER) operating conditions, grid costs, and precise biddings are not disclosed. In [8] two iterative methods are suggested for carrying out the games in a way that ensures each game has an equilibrium state. The findings demonstrate that P2P energy trading offers substantial financial and technical advantages to the community and is becoming an attractive alternative to expensive ESS.

Most previous studies merely presented the decentralized mechanism and iterative approach as a concept that should be used in microgrids for energy trading. However, these studies lacked the practical implementation necessary to evaluate its actual performance. Specifically, there is a challenge during practical implementation while attempting to transmit and receive data among peers. This challenge leads to synchronization problems, particularly concerning iterative algorithms such as ADMM. Hence, how the distribution algorithm for market clearing works and the communication between the market players in practice for microgrid energy trading has remained unconsidered. In this paper, we consider a decentralized P2P energy trading in which each prosumer is capable of trading the excess energy with other prosumers. Similar to the study in [12], we include an entity in the microgrid community called ''P2P Manager (P2PM)'' to ensure synchronized, safe, and reliable operation of the system. Moreover, we formulate market clearing as a distribution problem in which peers have coupling objective functions and constraints to maximize social welfare. The major contributions of this paper are summarized as follows:

- An energy trading strategy is developed to improve prosumers' involvement in P2P trading by integrating their financial goals, their own information, and the market information that the microgrid community,

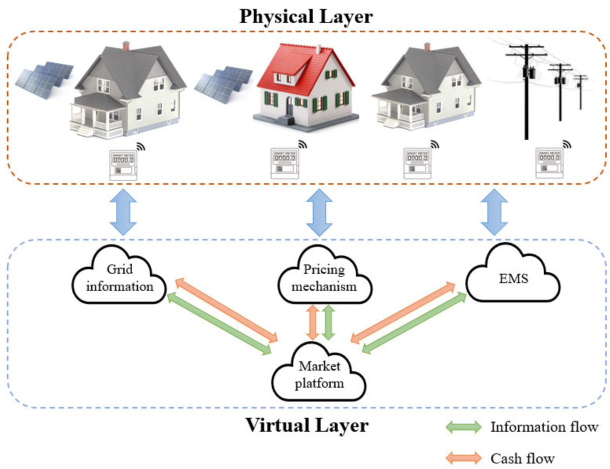

FIGURE 1. Structure of a decentralized P2P energy trading in LEM in microgrid system.

- Performs real-time testing using Hardware-In-the-Loop (HIL) for LEM from different prosumers and consumers and evaluates the performance of the distributed algorithm.
- Implementation of a multi-agent-based ADMM algorithm and control of this system using a comprehensive Information and Communication Technologies (ICT) protocol.

The paper is structured as follows. In section II, the objective function for the prosumers is described. In section III, details regarding the proposed P2PM, as well as the topology of the system under study, are presented. The real-time simulation results are discussed in section IV. Finally, section V concludes the paper.

III. P2P ENERGY TRANSACTION-BASED LEM STRUCTURE

This work considers the bilateral P2P energy trading in a power system. An example of the conceptual model of the P2P energy trading in the LEM is displayed in Figure 1. Prosumers can both produce and consume power using their own assets, e.g., rooftop solar panels, batteries, and thermal storage, to name a few, as well as load.

Under the common structure of the P2P energy trading market, each prosumer is called a peer or agent. The prosumers can share their surplus energy with other peers rather than selling it directly to the main grid. P2P energy trading among prosumers is facilitated through a two-layer platform. The physical platform layer enables data collection and energy transfer from sellers to buyers once a trading agreement has been established on the virtual layer platform. The virtual layer of the platform offers a secure network environment that allows prosumers to determine their energy trading parameters.

The agents in the community microgrid are considered the physical layer. All agents are connected to one another through bidirectional energy and information flow structure, and the entire community is connected to the utility grid at the Point of Common Coupling (PCC) to balance the individual overall energy surplus and energy demand. Each agent is equipped with a smart meter to record the energy data, e.g., real-time demand and available power capacity. Moreover, the smart meter sends private information to the Energy Management System (EMS) in each agent for processing. Each agent determines the distribution locational marginal prices associated with day-ahead using the utility functions in a quadratic form, considering the uncertainty associated with upstream energy prices, local power generation, and load profile. In addition, the smart meter is installed with the grid at the PCC to assess the performance of the energy trading with the main grid, such as the total quantity of energy sold to or bought from the main grid. In such implementations of P2P energy trading, the communication infrastructure is essential in enabling all market participants to communicate with one another and facilitate the exchange of information within the network. Different P2P communication frameworks have been proposed in the literature, including structured, unstructured, and hybrid architectures.

The virtual layer platform supports the idea that all prosumers have equal access to the P2P market, where a specific market mechanism is applied to match the power demand from the buyer and the surplus power offered by the seller. This is difficult in practice due to the inherent interactions among market players, which significantly impact overall stability and accuracy between the physical and virtual layers of the test system. In this study, our primary attention will be on the virtual layer to validate the previous theoretical claims of a P2P energy market by conducting a detailed real-time simulation using HIL. Furthermore, we highlight the scalability and performance of the communication infrastructure that supports the proposed P2P energy market on a community microgrid.

A. THE MATHEMATICAL DESIGN OF THE PROPOSED MARKET

In this paper, we assume a set of all players $\mathcal{N}$ in the LEM consists of a union to finite and disjoint sets: a set of sellers $\mathcal{N}_S = \{1, 2, \ldots, N_S\}$, and a set of buyers $\mathcal{N}_B = \{1, \ldots\ldots, N_B\}$, are indexed by $S = \{1, 2, 3, \ldots, i\}$, and $B = \{1, 2, 3, \ldots, j\}$, respectively. Notably, $\mathcal{N}_S \bigcup \mathcal{N}_B = \mathcal{N}$, and $\mathcal{N}_S \bigcap \mathcal{N}_B = \emptyset$. Each agent behaves freely and independently in the proposed LEM to maximize individual welfare. Figure 2 represents the LEM process to maximize the individual welfare of each seller and buyer.

The objective function in the P2P is to maximize the welfare of all market players where sellers sell their excess energy to buyers. The mathematical formulation for social welfare maximization is given by:

$$max = \left(\sum_{i=1}^{N_S} WS_i + \sum_{j=1}^{N_B} WB_j \right), \tag{1}$$

where WS_i and WB_j represent the social welfare of each seller i and buyer j, respectively.

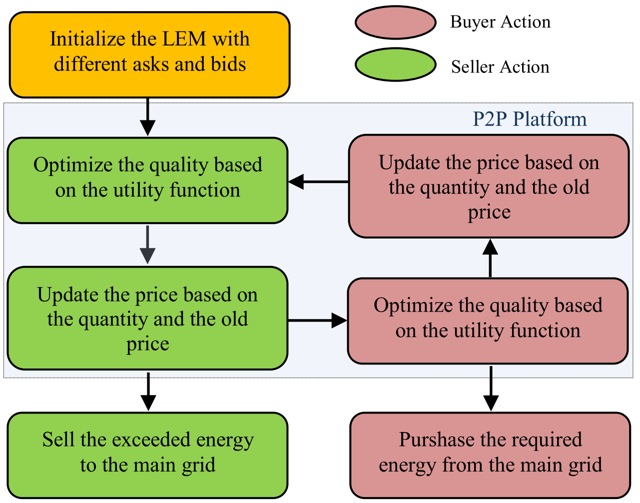

FIGURE 2. **Summary of LEM to maximize individual welfare.**

The mathematical model of the social welfare of the seller and buyer can be described in Eqs (2) and (3), respectively.

$$WS_i = \sum_{j\in\mathcal{N}_B} \left(P_{ij}.\lambda_{ij}\right) - P_i\left(x_i\right), \tag{2}$$

$$WB_j = P_j(x_j) - \sum_{i\in\mathcal{N}_S} \left(P_{ji}.\lambda_{ji}\right), \tag{3}$$

P_{ij} and P_{ji} are the energy trading between the seller i and buyer j, where: $x_i = \sum_{j\in\mathcal{N}_B} P_{ij}$ and $x_j = \sum_{j\in\mathcal{N}_S} P_{ji}$. Meanwhile, λ_{ji} is the vector of price estimates for energy trading. The cost/rate associated with the power generation $P_i(x_i)$ and power consumption $P_j(x_j)$ are usually modeled by a quadratic function and given by Eqs (4) and (5), respectively. The power transaction between agents i and j is denoted by P_{ij}, where $P_{ij} > 0$ and $P_{ij} < 0$ imply agent i sells power to and buys power from prosumer j, respectively:

$$P_i\left(x_i\right) = \alpha_i {x_i}^2 + \beta_i x_i, \tag{4}$$

$$P_j\left(x_j\right) = \alpha_j {x_j}^2 + \beta_j x_j, \tag{5}$$

where α_i, β_i and α_j, β_j are predetermined positive constants for each seller i and buyer j, respectively. The sold energy x_i by seller i and purchased energy x_j by buyer j is constrained by Eq (6) and (7), respectively.

The global constraints for each seller and buyer are given by:

$$x_i = \sum_{i\in\mathcal{N}_B} x_{ij}, \tag{6}$$

$$x_j = \sum_{i\in\mathcal{N}_S} x_{ji}, \tag{7}$$

where Eqs (6) and (7) represent the total amount of energy delivered and received by the seller i and buyer j, respectively.

The local constraints for each seller and buyer are given by:

$$x_{i,\ min} \leq x_i \leq x_{i,\ max}, \tag{8}$$

$$x_{j,\ min} \leq x_j \leq x_{j,\ max}, \tag{9}$$

where $x_{i,\ max}$, and $x_{i,\ min}$ represent the maximum and minimum energy provided by the seller i. $x_{j,\ max}$, and $x_{j,\ min}$ represent the maximum and minimum energy demand by the buyer j. Note that a positive value corresponds to the energy sold by the seller i and a negative value to the purchased energy by the buyer j.

B. MARKET CLEARING-BASED DISTRIBUTION ALGORITHM

The consensus ADMM is widely applied to solve convex problems in microgrid applications such as voltage control [24], power flow distribution [25], cyber security [26], EMS [27], and energy trading [26]. In the context of P2P trading, the market clearing process raises certain issues when centralized methods are used. These methods require access to information from all participants, which can lead to computational overheads and privacy concerns. Therefore, the ADMM approach has been proposed as a solution to these problems. ADMM is a highly effective strategy for resolving problems where the objective and constraints are spread across multiple agents. Each agent is responsible for managing its own objective function and constraint term internally. To formulate the ADMM, consider agents i and j in a networked system, indexed by $\{1,\ 2,\ 3,\ \ldots, N\}$ and $\{1,\ 2,\ 3,\ \ldots, M\}$, respectively. Each agent possesses a local private convex objective function and a local optimal solution denoted by $f(x_i)$ and $g(z_i)$, where $x_i \in \mathbb{R}^N$ and $z_i \in \mathbb{R}^M$ are the variables being optimized. Both $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $g : \mathbb{R}^m \rightarrow \mathbb{R}$ are convex functions. The goal of distributed optimization is to minimize a global objective function that is the sum of the objective functions of all agents in $f(x_i)$ and $g(z_j)$:

$$\begin{aligned} &Minimize \sum_{i=1}^{N} f(x_i) + \sum_{j=1}^{M} g(z_j), \\ &\text{subject to: } Au - Bv = 0. \end{aligned} \tag{10}$$

In the above expression, $A \in \mathbb{R}^{l\times N}$ and $B \in \mathbb{R}^{l\times M}$ are constant matrix and vector. Meanwhile, $u = (x_1, x_2, \ldots, x_N)$ and $v = (z_1, z_2, \ldots, z_M)$ are the set of the variables for each x_i and z_j, respectively. Since the constraint is that all the local variables should agree, i.e., be equal, this is called a global consensus problem [28]. The augmented Lagrangian function, based on the global variable consensus of the constraints, can be written as:

$$\begin{aligned} \mathcal{L}_\rho\left(x, z, \lambda\right) = &\sum_{i=1}^{N} f\left(x_i\right) + \sum_{j=1}^{M} g\left(z_j\right) + \underbrace{\lambda^T \cdot (Au - Bv)}_{①} \\ &+ \underbrace{\frac{\rho}{2}\|Au - Bv\|_2^2}_{②}, \end{aligned} \tag{11}$$

where ① and ② are the loss and regularization functions, respectively. λ represents the multiplier associated with the equality constraint, and $\rho > 0$ is the penalty parameter. The variables x, z, and λ are updated separately and sequentially by following the iterative scheme:

The convergence properties of the ADMM to meet the constraint are referred to in [28] and [29]. The stopping criteria for the iteration could be defined as follows:

$$x_1^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho \left((x_1, x_2, \ldots, x_N), v^k, \lambda \right),$$
$$x_2^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho ((x_1^{k+1}, x_2, \ldots, x_N), v^k, \lambda),$$
$$\vdots$$
$$x_n^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho ((x_1^{k+1}, x_2^{k+1}, \ldots, x_N), v^k, \lambda),$$
$$z_1^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho \left(u^{k+1}, (z_1, z_2, \ldots, z_M), \lambda \right),$$
$$z_2^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho \left(u^{k+1}, \left(z_1^{k+1}, z_2, \ldots, z_M \right), \lambda \right),$$
$$\lambda_{i,j}^{k+1} = \lambda_{i,j}^k + \rho (A u^{k+1} - B v^{k+1}),$$

When these criteria become less than the specified factor, it could be considered that the ADMM algorithm has converged to the optimal solution.

$$r^{k+1} = \left\| A u^{k+1} - B v^{k+1} \right\|,$$
$$s^{k+1} = \rho \left\| A^T B (v^k - v^{k+1}) \right\|,$$

C. ADMM FOR SOLVING THE PROPOSED OPTIMIZATION PROBLEM

In the following, a distributed algorithm based on the ADMM approach is proposed to solve the mathematical equation on (1). This approach allows each player in the LEM to solve its sub-problem locally while sharing information only with the matched peers to converge to the optimal solution for clearing the market. In the distributed algorithm, the market player needs to share limited information to achieve the P2P energy trading consensus, thus enhancing the privacy level of the market participants, pricing curves, and preferences. The ADMM approach is performed in an iterative manner to obtain the clearing price that maximizes the social welfare of each individual. The problem in Eq (1) is convex. Before decomposing the global problem in Eq (1) into subproblems, the Lagrangian multipliers are applied to decouple the global and local constraints as described in Eqs (6), (7), (8), and (9), respectively. The Lagrangian multipliers of Eq (1) are given by:

$$\mathcal{L}_\rho \left(P_{ij}, P_{ji}, \lambda_{ji}, \lambda_{ij} \right) = \sum_{j=1}^{N_B} WB_j - \sum_{i=1}^{N_S} WS_i + \sum_{i=1}^{N_S} \sum_{j=1}^{N_B} \lambda_{ji}. \left(P_{ji} - P_{ij} \right) - \sum_{j=1}^{N_B} \sum_{i=1}^{N_S} \lambda_{ij}. \left(P_{ij} - P_{ji} \right) + \frac{\rho}{2} \left\| P_{ji} - P_{ij} \right\|_2^2, \quad (12)$$

Note that the local constraints in (7) and (8) for the seller and buyer, respectively, can be solved locally. An iteration of the ADMM for the optimal solution follows these steps:

$$P_{ij}^{k+1} = \underset{P_{ij} \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho \left(P_{ij}, {P_{ji}}^k, {\lambda_{ji}}^k, {\lambda_{ij}}^k \right), \quad (13)$$
$$P_{ji}^{k+1} = \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho ({P_{ij}}^{k+1}, P_{ji}, {\lambda_{ji}}^k, {\lambda_{ij}}^k), \quad (14)$$
$${\lambda_{ji}}^{k+1} = {\lambda_{ji}}^k - \rho (P_{ij}^{k+1} - P_{ji}^{k+1}), \quad (15)$$
$${\lambda_{ij}}^{k+1} = {\lambda_{ij}}^k - \rho \left(P_{ji}^{k+1} - P_{ij}^{k+1} \right). \quad (16)$$

Each peer will repeat its algorithm to meet the stopping criteria. Stopping criteria for sellers and buyers for the market clearing are given as follows, respectively:

$$\left| {\lambda_{ji}}^{k+1} - {\lambda_{ji}}^k \right| \leq \epsilon, \quad (17)$$
$$\left| {\lambda_{ij}}^{k+1} - \lambda_{ij} \right| \leq \mu. \quad (18)$$

where ϵ and μ are small positive numbers, under the guidance of this framework, the global pseudo code of the ADMM-based algorithm is illustrated in Algorithm 1.

Algorithm 1 Market Clearing Algorithm

Initialization: Initialize variable λ, ρ, ϵ, and P.
While: $\left| \lambda_{ji}^{k+1} - \lambda_{ji}^k \right| \leq \epsilon$ and $\left| \lambda_{ij}^{k+1} - \lambda_{ij} \right| \leq \mu$
  for all $i \in N_s$ ## Sellers
    Update the value of λ using Eq (15)
    Update the value of P using Eq (13)
  end
  for all $i \in N_b$ ## Buyers
    Update the value of λ using Eq (16)
    Update the value of P using Eq (14)
  end
end

IV. P2P MANGER MODEL FOR A DECENTRALIZED SYSTEM

In the proposed decentralized P2P energy trading mechanism, each peer is supposed to be a rational agent who makes the most beneficial decisions and tries to maximize the individual welfare based on their objective function. As discussed before, by applying the decentralized solution and decomposing the objective function of the centralized function, all players participate in solving their own local welfare maximization problem using Eqs (13) and (14) through an iterative process. In practice, ensuring effective communication and operative processing of information among all participants within the LEM presents a formidable challenge when aiming to attain the optimal solution in each iterative phase due to the computational burden and the numerosity and complexity of the participants. In other words, it is imperative that every player receives the appropriate value during each iteration for the market clearing. In this study, a P2PM is introduced to synchronize the iteration process between the market players, as illustrated in Figure 3. In this framework, the P2PM has

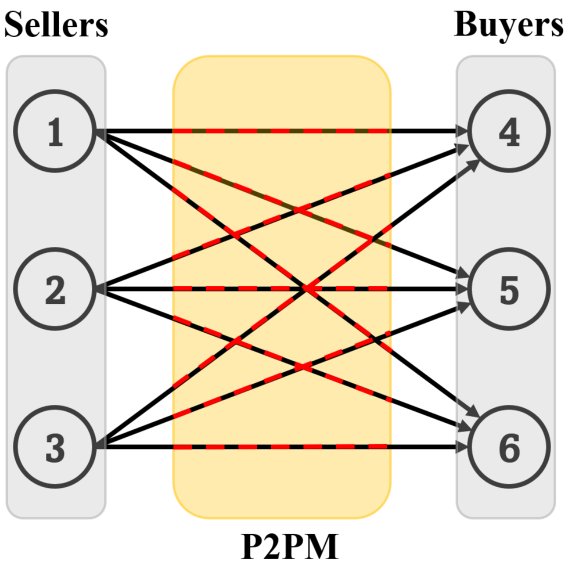

FIGURE 3. P2P structure for the LEM.

Algorithm 2 The Proposed Synchronization Algorithm for Each Agent

Initialization: Initialize the parameters of $i = 0$, ρ, ϵ, and μ.
Initialize the port of sending data of each agent $\boldsymbol{n}$
Initialize the port of receiving data of each agent $\boldsymbol{n}$
Initialize the message structure for packing and unpacking

While 1:
Receive the data from receiving data ports of the quantity power for other agents and synchronization mode signal.
Unpack the received data
Receive λ from the receiving port
Unpack the received data of λ
Optimize and update the value of power according to Eq (13)
Wait for (3 second)
If synchronization mode = 1:
$i = i + 1$
Send the optimal value via sending data port
Wait for (3 second)
Update the value of λ
Calculate $\left|\lambda_{ji}^{k+1} - \lambda_{ji}^{k}\right|$
If $\left|\lambda_{ji}^{k+1} - \lambda_{ji}^{k}\right| \leq \epsilon$
Break;

the following functionalities: making the problem computationally tractable, ensuring the overall market mechanism and the communication between the peers, and guaranteeing the synchronizing of the computation process.

Real-time simulation for the LEM system is essential for analyzing the testability and evaluating the market participants in real-time. Therefore, we propose a Stateflow-based method for the P2PM to conquer the drawbacks of other P2P models in terms of synchronization. The Stateflow-based method for the P2PM can possess the functions of modeling the internal state transition and logic execution processes of the LEM and the system under test with the interaction between the agents. Moreover, it incorporates the in-depth modeling of internal hierarchical logic, which can dynamically guarantee synchronization in each iteration. An example of the Stateflow model representing the P2PM for six agents is portrayed in Figure 4.

A system's stateflow model offers a graphical depiction of how the system transitions between different states based on its current conditions. Only when the system meets every parameter requirement listed for every state will the system proceed to an individual state. In the case of 6 agents, there are seven states in the Stateflow model: *INITIAL STATE:* represents the initial state where the synchronization mode of each agent is not activated (equal to 0). Once the iteration i for agent $n ==$ agent $n + 1$, the state will jump from the state *INITIAL* to *PASSn STATE,* and the synchronization mode for agent n is activated, and agent $n - 1$ is disactivated. In *PASSn STATE:* the P2PM ensures the delivery and provides accurate data, as well as maintains a signal synchronization mode for each agent n.

As described in the previous section, the behavior of each agent n is developed individually. Only communication protocol between agents ensures the cohesion of the system. The interaction of each agent n in the LEM is represented by Algorithm 2. In the context of the delay mentioned in the algorithm, it plays a significant role in ensuring the proper functioning and synchronization of the system. After the optimization and update of power according to Eq (13), if the synchronization mode equals 1. After sending the optimal value via the sending data port. This delay could be interpreted as a buffer period that allows each agent to adequately process the received data and prepare for the next state transition. It ensures that the system does not rush into the next state before all agents have accurately updated their parameters, thereby maintaining the integrity of the data and the synchronization among the agents. Moreover, this delay might also serve as a form of error-checking mechanism. If an agent fails to receive or process the data within this time window, it could indicate a problem in the system that needs to be addressed. Using the delay component contributes to the robustness and reliability of the system's performance. It ensures that each agent has sufficient time to update its state and maintain synchronization with the other agents, thereby enhancing the overall efficiency and accuracy of the system.

V. REAL-TIME SIMULATION MODEL AND RESULTS

A. SIMULATION SETUP

Our test system is a HIL real-time simulation platform built on the "Speedgoat" real-target machine. This platform allows us to simulate the LEM in real-time and test the validity of the proposed Peer-to-Peer Manager (P2PM).

The HIL tests consider communication challenges and limitations in controller computation, making their results more practical. These tests are often favored due to their

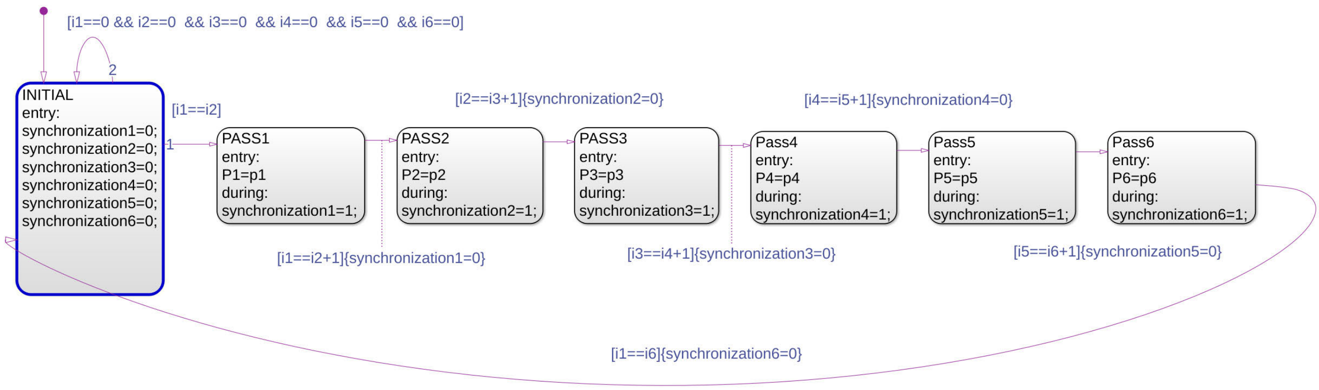

FIGURE 4. **A Stateflow example of P2PM model for LEM.**

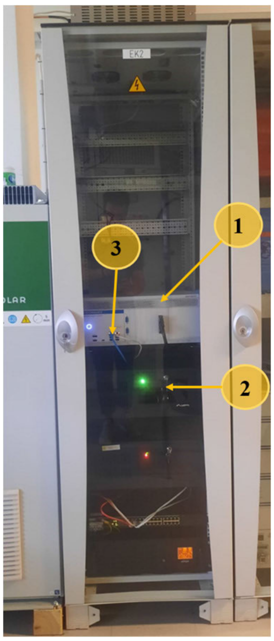

FIGURE 5. **Online hardware-in-the-loop testing setup. (1) Real-target machine. (2) Host server. (3) UDP communication port.**

cost-effectiveness and speed compared to field or laboratory experiments, leading to their frequent use before creating a prototype LEM.

The Simulink Real-Time Explorer is used to run the P2PM model and make it operate in the Speedgoat real-time simulator. An agent's activity may be graphically encoded through the use of Simulink's state-flow library to create his state-flow diagram. This strategy works extremely well in large systems with well-developed communications when the suggested solution does not yet call for such language.

The communications required between market participants were also modeled explicitly on a multi-agent base. To perform this, different agents were simulated in Python language and interfaced internally to a central computer hosting. This setup allows the effects of communication delays and data loss on system operations to be directly incorporated. The CVXPY v.1.2.1 library is used for each agent as the programming tool for solving the LEM sub-problem.

In the conducted real-time simulation, communication between agents is cabled using the User Datagram Protocol (UDP) with different virtual communication ports. Each agent has one output port for sending information to the P2PM and one input port for receiving data from the P2PM.

UDP is a communication protocol used over the Internet for transmitting data. Unlike Transmission Control Protocol (TCP), UDP is connectionless, meaning it does not establish a connection before transmitting data. This makes UDP faster and more efficient, especially for applications that require real-time data transmission, such as video streaming or online gaming.

In our system, UDP plays a crucial role in facilitating communication between agents. When an agent needs to send information, it sends a UDP datagram to the P2PM via its output port. The P2PM receives this datagram, processes the information, and then sends a response to the agent via the agent's input port. This process happens in real-time, ensuring that all agents can communicate effectively and make decisions based on the most up-to-date information.

The test system is designed to be scalable and robust, capable of handling multiple agents and complex communication protocols. It is also flexible, allowing for modifications and improvements as the study continues to refine our P2PM model.

B. SIMULATION RESULTS

This section presents the numerical results for the performance evaluation of the proposed distributed algorithm based on P2PM for LEM through a case study. Due to the novelty of the proposed approach, a numerical study is conducted for a small-scale system to analyze the model behavior more accurately. Therefore, a system of six prosumers is considered with the parameters given in Table 1.

The sellers in this system are equipped with RE resources. Their power output lower bounds are set to 0.01, indicating

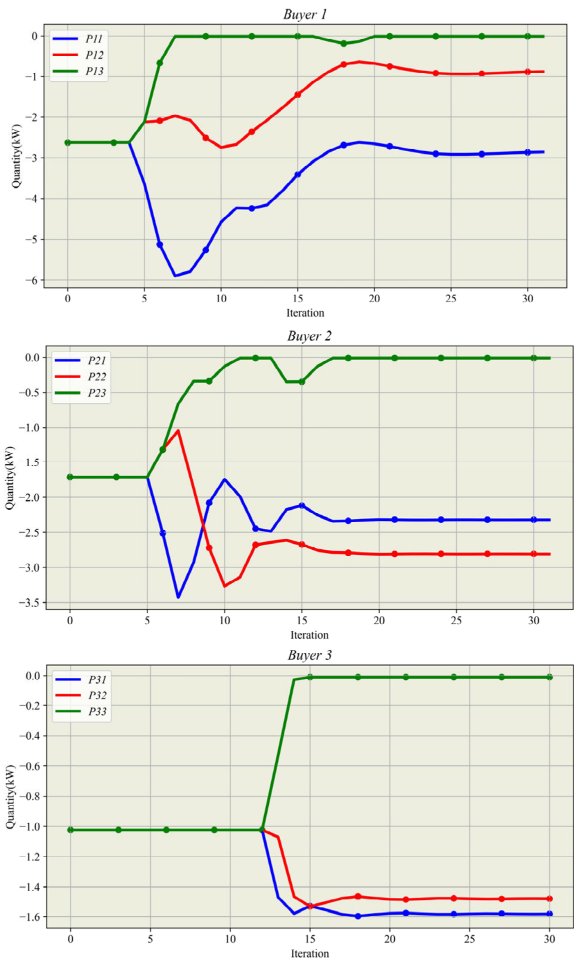

FIGURE 6. Online energy transactions between the buyers and sellers.

that they can cease power production if necessary. The upper bounds, denoted by x_{max}. On the other hand, the buyers are residential houses fitted with controllable loads. The upper bounds for these buyers are set to -0.01, signifying that the minimum energy demand for these houses is x_{min}. This setup allows us to effectively analyze and manage the energy demands and supplies within this microgrid system.

To analyze the feasibility of the P2PM, we used an ADMM-based distributed market clearing method, as introduced in [12], which has proven effective in similar studies and could provide valuable insights for our analysis. The main parameters of the ADMM algorithm are set as $\rho = 1$ and $\epsilon = \mu = 10^{-4}$. The initial values of Lagrange multipliers are zero. Following this, we demonstrate the sequential implementation procedure of market trading within a single timeslot.

1) POWER TRANSACTION AND THE CONVERGENCE OF THE MARKET MECHANISM

The performance of the LEM for energy trading between each buyer and seller is presented in Figure 6. It can be observed from Figure 6 that the traded energy quantities reached the

TABLE 1. Agents' parameters of a simple case study.

Prosumer	Index	α_i (¢/kWh^2)	β_j (¢/kWh)	x_{min} (kWh)	x_{max} (kWh)
Buyer	**1**	0.072	8.21	-7.88	-0.01
	2	0.084	11.21	-5.14	-0.01
	3	0.045	13.24	-3.07	-0.01
Seller	**1**	0.084	5.21	0.01	6.77
	2	0.075	6.35	0.01	5.17
	3	0.051	7.98	0.01	4.42

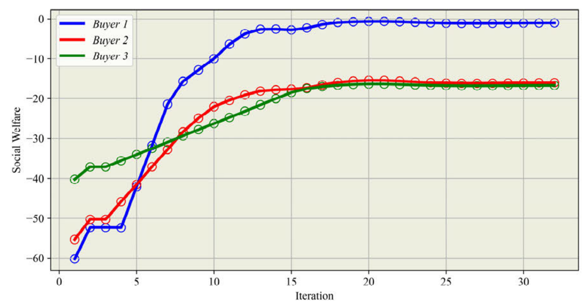

FIGURE 7. Evolution of objective value for the buyers.

global optimal point after a certain number of iterations and instantaneous fluctuation. It can be observed from the figure that the seller did not participate in the LEM.

In order to better illustrate that the LEM is maximizing the social welfare of each market player when solving the market clearing problem, we provide Figure 7. As a result, the optimal values for buyer 1, buyer 2, and buyer 3 are -1.0, -15.95, and -16.66, respectively.

The evolution of the negotiations through the LEM from each buyer is plotted in Figure 8. to illustrate the convergence behavior. It clearly indicates that the energy prices of all successful transactions are equal since the communication graph between successfully traded peers is connected. Based on the comparison of results in Figures 6 and 8, it can be observed that the price offered by seller 3 is higher than that of sellers 1 and 2. As a result, seller 3 did not engage in LEM, which imposes a significant cost for energy transactions.

2) CONVERGENCE AND SENSITIVITY EVALUATION

This section illustrates the convergence and sensitivity analysis for the LEM in the real-time simulation. To analyze the negotiation mechanism's convergence performance, the value of total primary residuals with time is measured in each iteration. The convergence process of the LEM for the market clearing with time is displayed in Figure 9. The figure illustrates that our algorithm performs well even when a delay of 3 sec is added, particularly in terms of the convergence rate. Notably, it requires only a few dozen iterations to reach convergence, which is 32 iterations. Furthermore, the computational time required for solving the sub-problem for each player is 96.103 seconds. The global operation for clearing the market is also efficient, taking around 414.618 seconds.

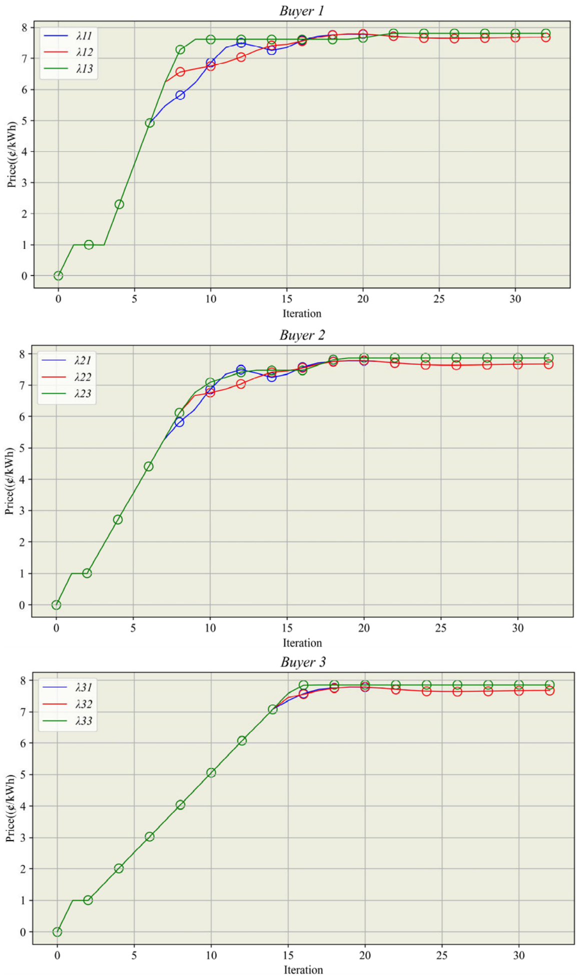

FIGURE 8. Online pricing exchange between the buyers and sellers.

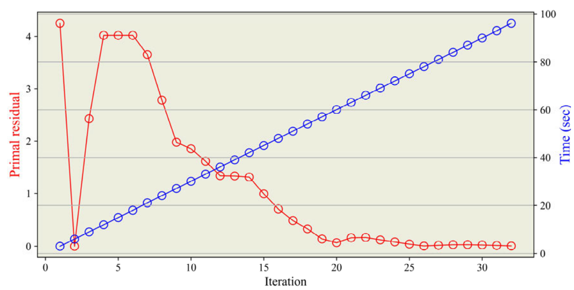

FIGURE 9. Convergence process for primal residual.

As described above, the mechanism used for market clearing is based on the ADMM algorithm, where ρ serves as its primary control parameter. The convergence of ADMM for any value of ρ has been validated by Boyd et al. [28]. However, to ensure a reasonable number of iterations, it is required to set the ρ value between 0.1 and 10 for our algorithm. This range helps optimize the performance and efficiency of the algorithm.

Figure 10 illustrates the convergence performance of the market clearing approach for buyer 1 in different values of the penalty parameter ρ. For evaluation, the values of 0.1, 1.0 and 10 have been proposed for testing. It can be noted that different choices of ρ can make a difference in the objective function value and number of iterations for convergence. Consequently, our technique exhibits good convergence rate performance and is not too dependent on the value of ρ, with the exception of the first few iterations.

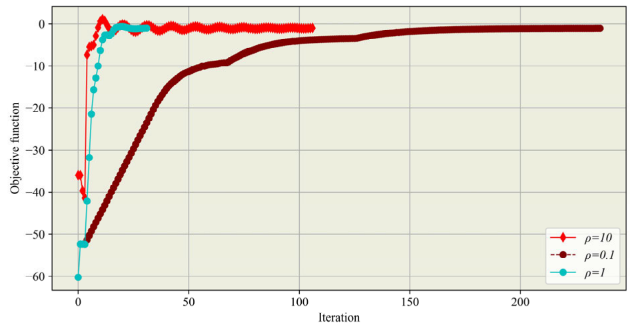

FIGURE 10. Computational performance under different penalty parameters.

VI. CONCLUSION

P2P energy trading presents a promising solution for coordinating future smart grids. It encourages prosumers in the community microgrid to maintain a local supply-demand equilibrium through LEM. Moreover, the competitive mechanisms established between buyers and sellers encourage a more effective pricing system and economic benefits than traditional methods. However, the practical application of LEM introduces challenges due to the underlying interactions within the participants. In this paper, we have designed a decentralized LEM that provides prosumers with opportunities to actively participate in the P2P market platform. The proposed framework includes a P2PM, which makes the problem computationally tractable, ensures the overall market mechanism and communication between the peers, and guarantees the synchronization of the computation process. The market participants were classified into sellers and buyers. The clearing price problem for the LEM was formulated as an aggregated welfare maximization problem. The global objective function is decomposed by sub-problems, and each sub-problem is solved by each agent based on the KKT conditions. A privacy-preserving method is designed to protect agents' private information using the ADMM approach.

The effectiveness of the proposed P2PM is verified through a real-time application using HIL. The results successfully revealed that P2PM has been verified in terms of enhancing power transactions and achieving synchronization among market participants in real-time applications. We applied convergence and sensitivity evaluation to assess the performance of the ADMM within the context of P2PM. This approach provides a comprehensive analysis of the algorithm's effectiveness, examining how it behaves under different conditions and how sensitive it is to changes in the input parameters.

By doing so, we can ensure that the P2PM is not only efficient but also robust and reliable for various scenarios in real-world applications.

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