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RESEARCH ARTICLE

A Competitive Framework for the Participation of Multi-Microgrids in the Community Energy Trading Market: A Case Study

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ABSTRACT An increase in the deployment of Distributed Energy Resources (DERs) and Renewable Energy (RE) resources is a promising paradigm in the decentralized energy era. It has motivated multi-Microgrids (MGs) to trade energy directly with others in the Local Energy Market (LEM), as well as with the main grid. The LEM has become a popular platform that covers several shortcomings of surplus/deficient energy, which can also manage the increasing connection of multi-microgrids, meet internal balance, and maximize the social welfare of the community Microgrid (MG). Moreover, in the LEM, the MGs would like to provide some payoff to encourage each other to exchange their energy locally. However, designing an appropriate market framework, privacy protection, and the community's unbalanced energy supply and demand is challenging. To cope with these challenges, in this study, an LEM for a multi-microgrid system is designed to maximize the social welfare of the community, and a decentralized clearing algorithm based on the Alternating Direction Method of Multipliers (ADMM) is proposed for local market clearing and privacy protection. The Community Manager (CM) is used as an intermediate coordinator between the interconnected MGs. This way, the computation process will be completely distributed, and the privacy of each MG will be protected. Moreover, considering the utility function for the consumers and energy providers, an equivalent cost model based on internal pricing is proposed to state the willingness of the utility and motivate the participants to join LEM. Finally, an illustrative example and a case study are used to demonstrate the efficiency and effectiveness of the proposed design of LEM and algorithm in terms of social welfare and power balance. In our study, we found that by using dynamic pricing in conjunction with our proposed model, the social welfare of the energy community can be increased by 14.25%. This demonstrates the significant economic benefits and effectiveness of our approach in the Local Energy Market (LEM).

INDEX TERMS Local energy market, alternating direction method of multipliers, multi-microgrids, community manager, energy transaction.

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I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

The fundamental transition in the use of local Distributed Energy Resources (DERs) driven by Renewable Energy (RE), along with intelligent infrastructures, enables the prosumers to become an active entity in the Microgrid (MG) with local generation sources, which continuously consider the management of energy generation and consumption [1]. Unlike traditional consumers, prosumers can behave as buyers or sellers depending on their power generation, load profile, and electricity pricing. Moreover, they can have a vital role in achieving energy balance in an MG [2]. The integration of prosumers into MGs has several advantages, such as motivating self-consumption and reducing dependency on the grid, demand peak shaving, reducing greenhouse gas emissions, and enhancing the penetration of RE resources [3]. Therefore, to enable prosumers to profit from selling additional electricity they generate to other prosumers or the grid utility, various self-consumption regulations have been established using different plans, including Feed-in-Tariffs (FiT) and net-metering [4].

Recently, improvements achieved in Information and Communication Technology (ICT) at the power grid, particularly at the distribution level, have permitted prosumers to interact directly with the wholesale electricity market to participate in various subsequent trading floors. This includes Day-Ahead (DA) and Real-Time (RT) markets. To deal with the recent challenges, including the uncertainties associated with intermittent power generation for the prosumer, several Local Energy Markets (LEM) designs are proposed as alternative solutions for coordinating the prosumers' energy. It is related to the more active participation of the demand side, maximizing individual prosumers' benefits and market bidding structures, including enabling access to trade flexibility services to Distribution System Operators (DSOS) and Transmission System Operators (TSOS) [5]. However, an important challenge in developing reliable LEM processes for prosumers is motivating consumers to participate in the LEM to meet their power demand. Therefore, economic and behavioral considerations should be considered when designing the LEM for all the players in the local market to motivate them to participate actively [6]. To this end, the user welfare (or willingness to pay) function has been widely used in LEM to achieve customers' active participation and expose an efficient price signal [7]. For example, the study in [8] presented the cost function determined by the DA market price from each consumer. Prices for both mean and standard deviation on the basis of the DA market from the annual wholesale market price are calculated using identical hour intervals to indicate the grid parameter for the consumer to get involved in energy exchange. The willingness price for participating in energy sharing is designed in [9] using dynamic market information considering the total power demand, the total supply, and the purchasing/selling prices from/to the utility grid. References [10] and [11] represented the willingness to pay for the energy of the buyer prosumer as a quadratic function. The predetermined parameters for the benefit function indicate the marginal (reservation) price of each consumer. Following this perspective, every player can participate in the LEM based on the causal relationships among energy price, energy supply, and benefit growth during a given period.

Generally, the operation of the LEM can be divided into two categories: energy trading pricing and participants' energy scheduling. On the one hand, research has been conducted by [12] to create an energy trading mechanism by providing a pricing approach derived from trading the price of energy from a negotiation technique to enhance the benefits of small and large scale for prosumers. Reference [13] introduced a method considering the Supply and Demand Ratio (SDR) to estimate the price optimally by taking into account the consumption and generation flexibility of prosumers. A dynamic RT pricing mechanism is introduced in [14] to enable all stakeholders, including Electric Vehicles (EVs) and Home Energy Management Systems (EMS), to obtain an optimal price. On the other hand, LEM permits scheduling the MG production and consumption with minimum information shared and transmitted by production units, such as the study in [14]; the LEM is proposed for energy scheduling with an EMS to decrease the cost of operations and maximize the utilization of DERs. In [15], DA energy scheduling using the LEM is proposed for the optimal operational planning of prosumers and grid-connected.

B. RELATED WORK

From the market structure perspective, there are three different categories of LEM structures for Transactive Energy (TE) that, after self-use, energy consumers may manage and benefit from excess energy [4]. The first one presents direct electrical energy transactions between the prosumer and the consumer without any central operator and is named the peer-to-peer (P2P) market. The second one presents electricity collectives or community-based markets, which rely on a Community Manager (CM) to manage the power-sharing and maximize the social welfare inside the community or group of prosumers or MGs. Meanwhile, a third category is the hybrid model market, which can be operated as a hybrid of both aforementioned models [16].

Due to the significance of this subject, numerous research has been conducted on how prosumers can profit from TE in different LEM structures. First, several studies on the Peer to Peer (P2P) market have analyzed revenues that consumers could make through participating in P2P markets. The concept of P2P energy trading between residential and commercial multi-energy systems is discussed in [17] to evaluate the economic benefit allocation for prosumers. The optimal TE and the fair price for P2P trading are selected to minimize the cost of energy and maximize the social welfare of the market participants. The study by [18] suggested a LEM architecture combining the advantages of P2P energy trading and distribution locational marginal pricing. Hence, integrating the locational pricing in the LEM allows a scalable method to coordinate demand, considering different constraints and losses for the prosumers to increase their profit. Meanwhile, the P2P approach enables market participants to engage in negotiations on bilateral energy transactions that will benefit both parties. In order to decrease the expenses related to power losses, the work reported in [1] created a P2P energy market platform that organizes trade between prosumers employing battery energy storage and the wholesale electricity market. The purpose of using local energy is to encourage prosumers to improve peak shaving and decrease the requirement for balancing at the transmission system level. The study presented in [19] investigated the external P2P energy trading in LEM within interconnected residential, commercial, and industrial MG systems. This interaction saves energy bills for the prosumers and achieves higher energy utilization of multi-vector energies (electricity, heat, and natural gas). The study in [20] suggested an approach that would allow prosumers to select the most effective strategies for TE of internal response and external P2P trading simultaneously. The suggested solution allows prosumers to reduce their energy bills and investment costs while becoming less dependent on grid utilities and, therefore, aggregate into a sustainable energy system. The work in [21] investigated energy scheduling using a two-stage optimization approach to increase its benefit in the P2P energy market. During the initial phase, the participant prosumers in the P2P energy-sharing trading determine the optimal quantity of exchanged energy. The most appropriate associated price mechanism was examined and suggested using a payment negotiation model in the next stage.

Second, some research studies were conducted to assess the use of the community energy market in the interest of collective social welfare. Most of these investigations discovered that prosumers' participation in the community energy market is economically feasible. For example, the study by [22] established the energy scheduling issue under unpredictability regarding clean energy production and energy storage technologies for a community-based energy market. For an energy community considering power network limits, the price is established on a DA clearing mechanism basis. Research by [23] presented a community market for MGs based on a standard auction market. In this market, the seller and buyer submit their bids and asks by announcing their available surplus energy and their benefits models. The focus is on the prosumers of MGs getting profit from their excess resources or sharing their resources to reduce the overall cost of acquiring their demand. The authors in [24] proposed an RT energy sharing and management in the community-level energy system based on two-layered sub-problems. The electricity price in a community market is calculated based on local observation and RT appliance scheduling to reduce the prosumers' daily costs. A study in [25] merged different RE sources, flexible and non-flexible loads, EVs, Hydrogen Vehicles (HV), and a Hydrogen Storage System (HSS) in a community energy market based on a matching and clearing approach. The LEM is organized at the distribution level, where the prosumers can participate in the LEM or trade with DSO. The authors in [26] proposed a framework for scheduling a multi-MG system in a community energy market considering the uncertainty of the RE resources and loads. The proposed framework can achieve optimal energy and ancillary service scheduling within each MG and facilitates fair energy trading among the MG community. In [8], the energy collectives and fairness model for a community electricity market, where the market players are represented as a single community, is introduced. The proposed model achieves the optimal economic power dispatch for the community and different collective agreements for the physical constraints. The research in [27] thoroughly compared the characteristics of the community and P2P market designs in terms of social welfare, total payment, and energy trading volume. The results suggested that the community-based energy market can ensure that prosumers are satisfied, resulting in higher energy trading volume and social welfare.

Third, several studies have been conducted to conduct efficient application of the hybrid P2P energy trading in TE, such as [3], which aimed to create an electricity trading scheme by suggesting a pricing approach for the hybrid P2P energy market. Using the suggested hybrid system, prosumers are able to engage in a variety of markets, particularly the wholesale market, rather than sequential participation to maximize their benefits. Furthermore, the Direct Load Flow (DLF) program is conducted to incorporate the power line constraints in energy trading of the market players. In [28], the authors integrated a P2P energy trading scheme that can assist a centralized market operator in minimizing the energy demand during peak hours. The prosumers form a suitable coalition with consumers to participate in P2P energy trading to meet their energy demands. On the other hand, the centralized market operator acts as an intermediary between the peers and the superior power system. The work presented in [29] developed a hybrid P2P energy market consisting of conventional pool-based and P2P configurations. Individual cost minimization is possible for each energy prosumer due to the hybrid P2P energy-sharing market, and the social cost of the whole market is also reduced. The work presented in [30] introduced a hybrid energy trading mechanism based on the formed communities, considering the energy loss and wheeling charging at the local trading level. The market model can be adapted to large-scale trading participants efficiently in a distributed way to maximize the prosumer benefits. In [31], an integration of prosumers in the hybrid market using the generic supply-demand function method is proposed. This interaction provides incentives for individual prosumers to participate in the LEM and permits prosumers to freely decide whether they will buy or sell based on their purchase desire.

C. RESEARCH GAPS AND MAIN CONTRIBUTION

Although studies, as mentioned earlier, have considered framework design for energy scheduling and trading of prosumers in LEM, the joint consideration of the prosumer willing to participate in the LEM to optimize their profit has not been undertaken. In contrast, prosumers might have different responses and decisions during the participation. Moreover, the literature also lacks modeling of different types of prosumers, such as PV systems, to participate in the LEM energy trading, where the parameters of participants are predetermined. Different from these research studies, this paper distinguishes itself in the existing body of research by jointly considering the willingness of prosumers to participate in the Local Energy Market (LEM) to optimize their profit. Unlike previous studies, a symmetric model for the prosumer is proposed that aligns with reality and encourages participation in LEM. The willingness to participate is modeled based on real-dynamic market information using the SDR of energy sharing and the retail market price, providing an adequate trading design to incentivize active participation. The main contributions and novelty of this research paper are:

- **LEM for Multi-MGs:** The LEM for multi-MGs is considered where each MG can sell and buy energy from the main grid and directly trade with other MGs mediated by the CM.
- **Design of a Competitive Framework:** A competitive framework for the participation of multi-MGs in the community energy trading market, which is more realistic in the foreseeable future, is designed.
- **Mathematical and Technical Formulation:**The mathematical and technical formulation of the interaction of local energy providers and the demand of the sellers and buyers with the MG CM is described.
- **LEM Clearing Problem Solution:** The LEM clearing problem is addressed by designing a specific iterative process based on a distributed algorithm using the Alternating Direction Method of Multipliers (ADMM). This algorithm reduces the complexity of the market clearing model and efficiently utilizes a private topology for exchanging information between market participants

The remainder of this paper is organized as follows. Section II introduces the market structure, and Section III presents the modeling of the utility function using the internal price. The mechanism and architecture of the proposed LEM is introduced in Section IV. The numerical experiments are presented in Section V, and the conclusions are in Section VI.

II. MARKET STRUCTURE

The energy-sharing model and control mechanism are first presented in this section, followed by formulating the problem corresponding to the classification of the participants in the LEM and determining the internal price addressed by the SDR.

A. ENERGY SHARING MODEL

MGs provide a new economic and control mechanism, where multiple MGs can trade electricity with the grid utility using centralized energy retailers and trade energy among themselves using a LEM. To facilitate the community-based trade of multiple MGs, we proposed a local electricity market design composed of two energy entities: a main grid and multiple MGs. Figure 1 depicts the schematic of the proposed framework of LEM with two individual transactive MGs. Each MG is composed of different prosumers (loads and DER) and MG operators. All the MGs are connected to one another through the bidirectional power-sharing system, and the whole community of the MGs is connected to the grid utility via a Point of Common Coupling (PCC). The grid meter is placed at the PCC with the external utility grid to measure the energy exchanged between the grid utility and the MGs community. Each prosumer in an MG is equipped with a local bidirectional meter that measures the energy that the specific prosumer. This meter measures the prosumer's generation, consumption, and energy transactions with other prosumers and sends information to the MG operator. Each MG's energy resource capacities, preferences, surplus, and energy demand are private information. MG operator is adopted in this framework to deal with the practical issues of collecting information, managing massive prosumers, and solving the centralized problem in the LEM. The MG operator manages their data and sends the information to the CM. The CM classifies the MG and coordinates the clearing process. This coordination task implies sending information to the MG operator and receiving information back from them. The community-based market, which is operated by the CM, has access to the retail energy market to trade energy with the grid utility.

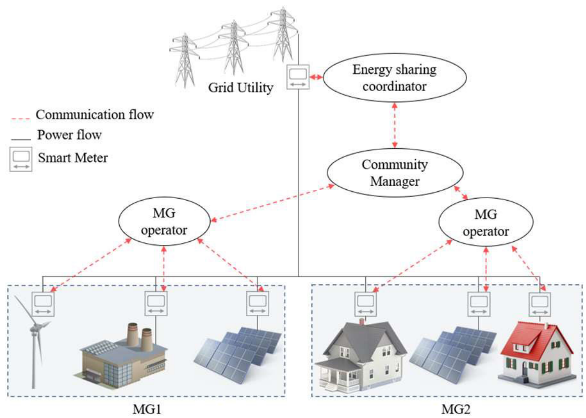

FIGURE 1. Shows the LEM energy trading paradigm among two- MGs with the internal network, prosumers, and meters.

Take the DA energy market as a research problem in this study. The main steps and the action sequence of the LEM mechanism are illustrated in Figure 2. The transaction occurs in two markets. The main market is called the retail market, which is operated by the retail market operator. The submarket is called the LEM for the MG community, which is coordinated by the CM. The DA problem was solved the day before the actual power exchanges in the LEM and

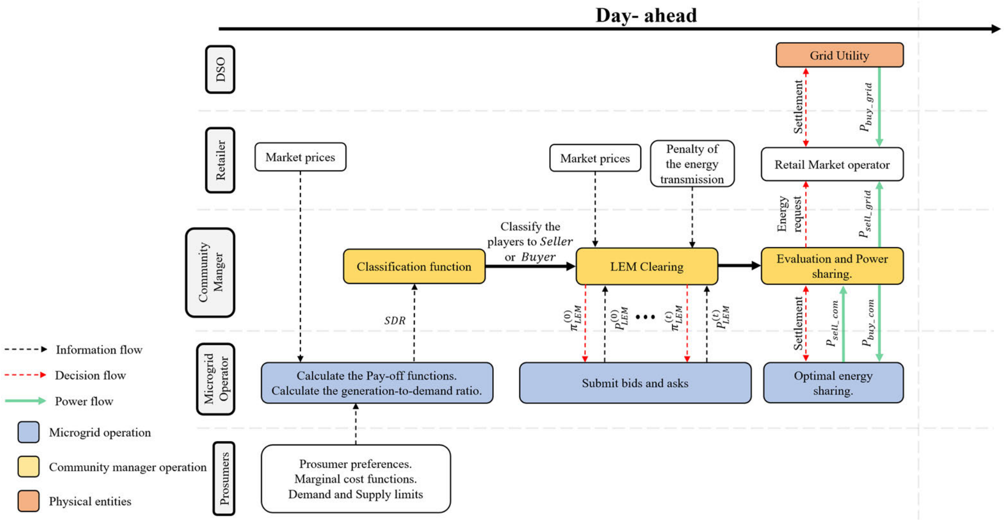

FIGURE 2. **The sequence of actions for the proposed LEM.**

retail market occurred. All MGs should follow the market mechanism to suggest the optimal power and price to the community, where the final goal is to maximize their social welfare.

As the first step in the proposed framework, each MG operator collects the preferences information related to their prosumers. In parallel, the retail market operator also provides technical information on the retail market prices to the MG operator. Once the MG operator receives this information, the SDR, the willing-pay function for the consumers, and the utility cost functions are determined, as detailed in Section III. Note that the utility function is calculated based on real-dynamic values to encourage all the prosumers to join the LEM. From the view of the MG operator, self-consumption of energy is still the first choice for their consumers. Next, each MG operator sends the SDR to the CM to classify the MG in the community as either buyer or seller. The interaction between the sellers and the buyers in the community is conducted by the CM. The CM coordinates the clearing process by including other factors, such as the retail energy price and the penalty of energy transmission. The market is cleared after an iterative process by sending information to the MG operators and receiving information back. Each MG operator adapts its offering/bidding parameters to avoid any loss. After clearing the market, the CM broadcasts the clearing results and sends an energy request to the retailer market operator either to buy or sell energy to the grid utility. Then, the retailer market operator accumulates energy requests from the CM to sell or purchase the energy from the MG community. Meanwhile, the CM sends information to the MG operator. This way, the MG operator determines the optimal operation by a cooperative energy and share scheduling model, in which energy from the grid utility and community can be cooperatively utilized among consumers. This process provides a fair distribution of the sharing benefits.

B. PROBLEM FORMULATION

The study considers an energy community that consists of a set of residential MGs. Each MG has on-site variable-scaled PV systems and regular loads to serve. To formulate the problem, let $\mathcal{N} = \{1, 2, 3, \ldots, N\}$ denote the set of the MGs in the community, and $N \triangleq |\mathcal{N}|$ represents the total number of MGs in the community. Each MG n in the community can be defined as follows: $MG^n = \{MG^1, MG^2, MG^3, \ldots, MG^N\}$, where $n \in \mathcal{N}$. Let us consider the local energy generator P and the energy consumption C in each MG n are indexed by $\mathcal{G} = \{1, 2, 3, \ldots, G\}$ and $\mathcal{D} = \{1, 2, 3, \ldots, D\}$, respectively. The sets of the local energy resources and the energy consumption in each MG n are defined as $P_g^n = \{P_1^n, P_2^n, P_3^n, \ldots, P_G^n\}$ and $C_d^n = \{C_1^n, C_2^n, C_3^n, \ldots, C_D^n\}$, where $G \triangleq |\mathcal{G}|$ and $D \triangleq |\mathcal{D}|$ represent the total number of local energy generators and consumers, respectively. The MGs in the community are classified according to their type of energy sharing. Note that the classification is based on predicted energy generation and consumption. Specifically, when an MG predicts the total power generation is larger than its total power demand, it is classified as a seller. Otherwise, the MG is considered to be a buyer. In this study, the SDR approach is applied. The SDR for a MG $n \in \mathcal{N}$ is defined as follows:

$$SDR^n = \frac{\sum_{g=1}^{G} P_g^n}{\sum_{d=1}^{D} C_g^n}, \text{ where } n = \{1, 2, 3, \ldots, N\} \quad (1)$$

We identify $\mathcal{S} = \{1, 2, 3, \ldots, S\}$ as the set of sellers when $SDR^n \geq 1$, and $\mathcal{B} = \{1, 2, 3, \ldots, B\}$ as the set of buyers when $SDR^n < 1$. Here, $S \triangleq |\mathcal{S}|$ and $B \triangleq |\mathcal{B}|$ represent the total number of sellers and buyers, respectively. Therefore, $\mathcal{S} \cup \mathcal{B} = \mathcal{N}$ and $\mathcal{S} \cap \mathcal{B} = \emptyset$. $\imath$ and $\jmath$ represent the index of the sellers and the buyers in the set $\mathcal{S}$ and $\mathcal{B}$, respectively. The seller MGs can participate in this LEM, depending on the amount of their energy surplus. Note that the self-consumption of energy is the first choice for the MG. Thus, when $SDR^n = 1$, the MG n is not required to participate in the LEM.

Generally, the export price from the utility grid is lower than the import price to encourage local energy sharing. The prosumers can participate in the MG using an internal price to maximize their own profit and reduce the impact on the utility grid. In this work, we defined Pr^n as the internal price model for each MG n. The principle of formulating the internal price Pr^n is based on the SDR^n of MG and RT price from the grid utility [13]. It should be noted that the price at which energy is purchased internally should not exceed the price of energy imported from the grid utility, and the price at which it is sold should not be less than the price at which it is sold to the grid utility. The internal buying and selling prices for each MG n are given in Eq. (2) and (3), respectively.

$$Pr^n_{sell} = \begin{cases} \dfrac{\pi^{grid}_{sell} \cdot \pi^{grid}_{buy}}{\left(\pi^{grid}_{sell} - \pi^{grid}_{buy}\right) \cdot SDR^n + \pi^{grid}_{sell}}, & 0 \le SDR^n \le 1 \\ \pi^{grid}_{sell}, & SDR^n > 1 \end{cases} \tag{2}$$

$$Pr^n_{buy} = \begin{cases} Pr^n_{sell} \cdot SDR^n + \pi^{grid}_{buy}\left(1 - SDR^n\right), & 0 \le SDR^n \le 1 \\ \pi^{grid}_{sell}, & SDR^n > 1 \end{cases} \tag{3}$$

where Pr^n_{sell}, Pr^n_{buy} represent the internal buying and selling prices, respectively. π^{grid}_{sell}, and π^{grid}_{buy} represent the selling and buying price from the grid utility. As illustrated in Eqs. (2) and (3), the internal price is inversely proportional to the variable SDR. In other words, the internal selling price becomes high with the lower SDR and vice versa. When $SDR^n > 1$, the power surplus of the MG n is sold to the consumers and the community at the price π^{grid}_{sell}. In this case, setting Pr^n_{buy} as low as possible can encourage the MGs and community to increase consumption using the internal generation (e.g., through a demand response program) and reduce the impact on the grid utility. When $0 \le SDR^n \le 1$, the price of energy bought by the community from the MG n is between π^{grid}_{sell} and π^{grid}_{buy}, and it continues to decrease with the increase of SDR.

The reason for introducing the internal price in this study is that we have taken advantage of the SDR pricing mechanism in the TE framework by modeling the utility function formulations for the combination of power supply and energy consumption to increase social welfare. In the next sections, we present the main contribution of this study, which is divided into three main subsections: the methodology, prosumers model, and markets.

III. MODELLING OF THE UTILITY FUNCTION USING THE INTERNAL PRICE

The utility function is a mathematical representation of the individual's benefit from providing or consuming an energy service. The concept of the utility function is widely applied in the field of "Microeconomics" to describe the satisfaction

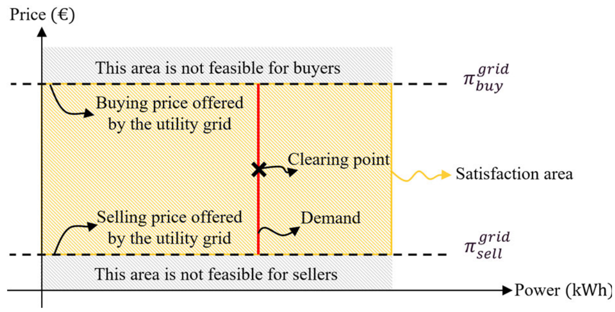

FIGURE 3. Satisfaction area for the sellers and energy buyers.

of the prosumers based on the decision-making process. In the energy market, the prosumers are satisfied when they purchase and sell their energy in LEM between π^{grid}_{sell}, and π^{grid}_{buy}, as displayed in Figure 3. However, quantifying these benefits and representing the level of satisfaction of a prosumer as a function when it consumes or provides a certain amount of energy might be difficult due to the time and quantity of consumption and uncertainties of the local energy resources. In this context, we propose a dynamic utility function by generalizing the SDR pricing mechanism to consider the situation where prosumers can flexibly change their behavior in RT to increase their profit. The utility to a prosumer consists of two parts: the utility of energy consumption and supply, which a quadratic function can capture.

A. MODELLING OF ENERGY CONSUMPTION

As discussed above, we have employed the utility function for consumption modules to evaluate the willingness to pay for energy demand. All consumer certainly can gain some benefits in the utilization of more power for their desired activities until they approach the limited demand. The power demand for consumers can usually be classified into two categories: non-flexible and flexible demand. Suppose that the total demand for consumers, C^n_d, is the sum of the flexible and non-flexible demand. Thus, for any C^n_d, the following relationship must be satisfied:

$$C^n_{d\_min} \le C^n_d \le C^n_{d\_max} \tag{4}$$

where $C^n_{d\_min}$ and $C^n_{d\_max}$ represent the minimum and maximum power demand, respectively for each consumer d in MG n.

There are different types of utility functions frequently applied for modeling the energy consumption. A quadratic function is one of the popular forms of the utility function used in line with the vast majority of the literature [6], [8] to describe electricity consumption patterns of the consumer satisfaction. The motivation behind choosing the quadratic utility function is that it is closely related to the utility function described in [32], which leads to a proportionally fair demand response program. Quadratic utility function for the consumer C^n_d Can be expressed as follows:

$$\psi(C^n_d) = \frac{1}{2}\alpha^n_d \left(C^n_d\right)^2 + \beta^n_d C^n_d + \gamma^n_d \tag{5}$$

where $\psi(C_d^n)$ is the utility function of the consumer d in the MG n. α, β, $\gamma > 0$ are predetermined parameters. These parameters describe how the rate of change of consumer's utility changes as consumption changes.

In Eq. (5), The utility function U is used by the literature [10], exploit the derivative function of $\psi(C_d^n)$ to calculate the marginal cost function. By assuming the constant parameter γ is zero, the marginal cost function is given as:

$$\frac{\partial\psi(C_d^n)}{\partial C_d^n} = \alpha_d^n\left(C_d^n\right) + \beta_d^n = \pi^* \tag{6}$$

π^* denotes the marginal cost of the utility function $\psi(C_d^n)$. In order to combine the advantage of the aforementioned function and the internal price for the consumer, we consider that the internal price for Pr_{buy}^n represents the marginal price π^*. This amount describes the change in the total cost that arises when the energy consumption is incremented by a unit. Therefore, the marginal cost is mathematically expressed as:

$$\alpha_d^n\left(C_d^n\right) + \beta_d^n = Pr_{buy}^n \tag{7}$$

Eq. (7) quantifies the variation of the trajectory with respect to the constant parameters α and β. This quantification is used to update the model parameters in order to minimize the residual error that measures the mismatch between the derivative function and the marginal cost. An approximation to a known curve can be discovered by sampling the curve and interpolating linearly between the minimum and maximum power demand. The linear regression model is applied to define the optimal parameters for minimizing the residual error. The objective function is given by the following formula:

$$\underset{\alpha_d^n\geq 0,\beta_d^n\geq 0}{Minimize}\ 1/2 \sum_{C_d^n=C_{d\_min}^n}^{C_{d\_max}^n}\left(\left(\alpha_d^n\left(C_d^n\right)+\beta_d^n\right)-Pr_{buy}^n\right)^2 \tag{8}$$

The optimization problem in Eq. (8) is solved for limitation of the power demand of C_d^n, starting from $C_{d\_min}^n$ to the maximum demand $C_{d\_max}^n$. The decision variables in the MG operator are α_d^n and β_d^n, which captures the dynamic weight of energy consumption utility and the dynamic energy consumption preference of consumers. More specifically, the lower value of the parameters α_d^n, β_d^n, the more consumers benefit from the DR program. By doing so, the consumers express their willingness to pay a price premium if they can be ensured.

B. MODELLING OF POWER SUPPLY

In the literature [6], in order to evaluate the pricing models for the supply utility, the quadratic function $\varphi(\cdot)$ is often used to (approximately) model the operation cost that comes from supply unit. The cost function of the supply utility represents the cost associated with providing the offered energy to the community of the grid utility, which arises from operation costs (e.g., fuel, startup and shutdown cost, levelized cost) and maintenance costs. The quadratic function of the power

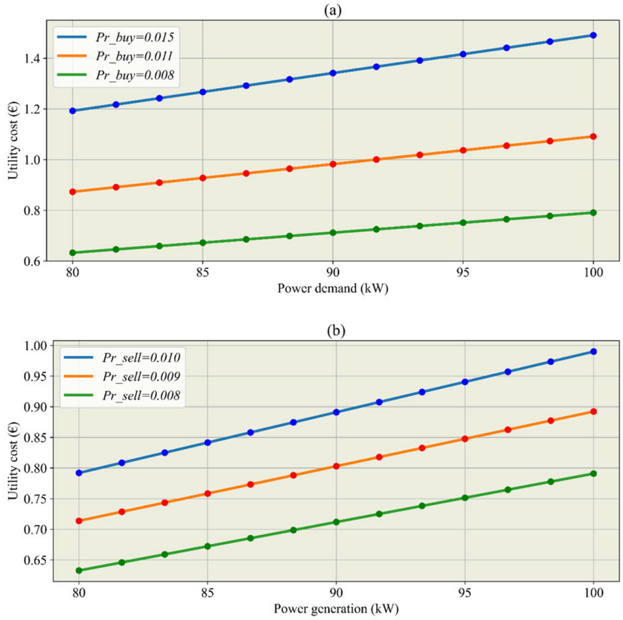

FIGURE 4. Prosumer utility as a function of energy consumption and energy supply for various internal price.

supply can be expressed as:

$$\varphi\left(P_g^n\right) = \frac{1}{2}\alpha_g^n\left(P_g^n\right)^2 + \beta_g^n P_g^n + \gamma_g^n \tag{9}$$

$$P_{g\_min}^n \leq P_g^n \leq P_{g\_max}^n \tag{10}$$

where α_g^n, β_g^n, γ_g^n represent the constant parameters of the supply utility g in each MG n. $P_{g\_min}^n$ and $P_{g\_max}^n$ represent the minimum and maximum power supply, respectively, for each local energy provider g in MG n. Generally, the supply utility functions of the energy provider only include their operation cost. That is unlikely to be very rational considering the fact that the energy provider certainly can get some benefits in the TE and be encouraged to participate in the LEM. Therefore, the dynamic internal price is proposed to formulate an initiative model for the local energy provider. Assuming that the marginal cost of the supply utility is given as follow:

$$\frac{\partial\varphi\left(P_g^n\right)}{\partial P_g^n} = \alpha_g^n\left(P_g^n\right) + \beta_g^n = Pr_{sell}^n \tag{11}$$

The mathematical expression to identify the constant parameters of the supply utility can be described as:

$$\underset{\alpha_g^n\geq 0,\beta_g^n\geq 0}{Minimize}\ 1/2 \sum_{P_g^n=P_{g\_min}^n}^{P_{g\_max}^n}\left(\left(\alpha_g^n\left(P_g^n\right)+\beta_g^n\right)-Pr_{sell}^n\right)^2 \tag{12}$$

The optimization problem in Eq. (12, namely, minimizing the curve error to find the decision variables α_g^n and β_g^n where the derivative function of $\varphi\left(P_g^n\right)$ is equal to the marginal cost Pr_{sell}. Figure 4. depicts an example of the consumer's d and local energy source g in the MG n as a function of $\psi(C_d^n)$, and $\varphi\left(P_g^n\right)$ for a given upper and lower bound with different values of internal price Pr_{buy}^n and Pr_{sell}^n, respectively.

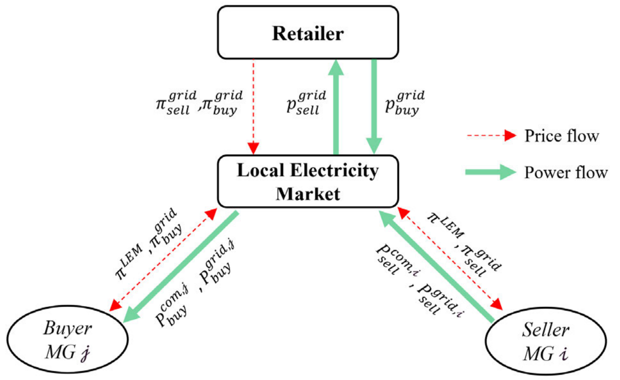

FIGURE 5. A block diagram of the interaction between the MGs, the LEM, and the retailer.

IV. MECHANISM AND ARCHITECTURE OF THE PROPOSED LEM

In this section, the LEM among multiple MGs is established. The architecture of the energy-sharing system in this paper is illustrated in Figure 5, consisting of three components: the MG operator, LEM, and the retailer. The proposed LEM divides the MGs into sellers and buyers during the scheduling period. As discussed in Section II, such classification is performed based on each MG's net production and demand obtained from the total generation and local energy demand of its total assets. Note that the classification is based on predicted electricity generation and consumption. A distributed iteration algorithm is proposed to analyze and realize market clearing further to determine the DA LEM prices and energy trading amounts of MGs.

A. WELFARE FUNCTION FOR SELLER

According to the definition of social welfare definition, in a LEM where the seller i in the market offers their surplus energy for trading with buyers under the supervision of a CM, the social welfare of the seller i can be modeled by summation of the benefits of the seller which describes their satisfaction level from selling their energy. Therefore, seller i can be modeled in two parts: (1) the economic benefits of selling excess electricity to LEM and grid, and (2) the seller's satisfaction due to energy consumption. The social welfare of the seller is modeled in Eq. (13).

$$\begin{aligned} WS_i(P_{sell}^{com,i}, P_{sell}^{grid,i}, \pi^{LEM}) &= P_{sell}^{com,i}.\pi^{LEM} + P_{sell}^{grid,i}.\pi_{sell}^{grid} \\ &+ \left(\sum_{g=1}^{G} \psi(C_d^i) - \sum_{g=1}^{G} \varphi\left(P_g^i\right)\right) \end{aligned} \tag{13}$$

Here, WS_i represents the social welfare of the seller i, composed of three terms. The first term is the revenue from selling energy to the community. The second term represents the revenue from selling energy to the grid. The third term described the cost of the prosumer's utility for the seller i. π^{LEM} describes the clearing price for the LEM. $P_{sell}^{com,i}$ represents the sold power to the community. $P_{sell}^{grid,i}$ represents the sold power to the grid. A set of technical constraints should be considered for the seller, which are expressed in the following:

$$\sum_{g=1}^{G} P_g^i - \sum_{d=1}^{D} C_d^i > 0 \tag{14}$$

$$\sum_{g=1}^{G} P_g^i - \sum_{d=1}^{D} C_d^i = P_{sell}^{com,i} + P_{sell}^{grid,i} \tag{15}$$

Constraint (14) guarantees that the local energy generation of each seller i is higher than the total consumption. Constraint (15) demonstrates the energy balance for local sellers i including the energy sharing with the community $P_{sell}^{com,i}$ and utility grid $P_{sell}^{grid,i}$.

B. WELFARE FUNCTION FOR BUYER

As mentioned above, buyer agents are those who need to buy some power at a certain time slot. Buyer satisfaction level describes the buyer's welfare, which is determined by the difference between the benefits of the local user utility and payment of the power from the local energy provider, community, and grid utility. The following relation describes the total welfare of the buyer j:

$$\begin{aligned} WB_j(P_{buy}^{com,j}, P_{buy}^{grid,j}, \pi^{LEM}) &= \sum_{g=1}^{G} \psi(C_d^j) - \sum_{g=1}^{G} \varphi\left(P_g^j\right) \\ &- P_{buy}^{com,j}.\pi^{LEM} - P_{buy}^{grid,j}.\pi_{buy}^{grid} \end{aligned} \tag{16}$$

Here, WB_j describes the social welfare of the seller j in the community, while $P_{buy}^{com,j}$ is the amount of power buyer j purchased from the community. $P_{buy}^{grid,j}$ is the amount of power the buyer purchased from the utility grid. It should be noted that buyer welfare can be a negative value in instances when the utility it gets is lower than the purchasing prices. The power balance is constrained by each buyer j constraints given by:

$$\sum_{d=1}^{D} C_d^j - \sum_{g=1}^{G} P_g^j > 0 \tag{17}$$

$$\sum_{d=1}^{D} C_d^j - \sum_{g=1}^{G} P_g^j = P_{buy}^{com,j} + P_{buy}^{grid,j} \tag{18}$$

where the inequality constraint (17) guarantees the total demand of each buyer j is higher than the local power generation, while the constraint (18) ensures the power balance for the buyer j, where the left-hand side of the constraint represents the imported power from the buyer j, and the right-hand side defines the summation of the injected power from the community $P_{sell}^{com,j}$ and the grid utility $P_{sell}^{grid,j}$.

C. COMMUNITY OBJECTIVE FUNCTION

Following the elaborations on the sections above, a generic framework for the LEM is conceptualized to achieve the social welfare of the community. The CM manages the community to maximize the total social welfare of all sellers and buyers, where minimal financial costs typically represent the highest social welfare. When $\mathcal{S} \cup \mathcal{B} = \mathcal{N}$, mathematically, the objective function of the community to maximize social welfare is as follows:

$$\underset{P_{sell}^{com,\imath},P_{sell}^{grid,\imath},\pi_{sell}^{com},P_{buy}^{com,\jmath},P_{buy}^{grid,\jmath},\pi_{buy}^{com}}{Maximize} \sum_{\imath=1}^{S} WS_{\imath}\left(P_{sell}^{com,\imath}, P_{sell}^{grid,\imath}\right) + \sum_{\jmath=1}^{B} WB_{\jmath}\left(P_{buy}^{com,\jmath}, P_{buy}^{grid,\jmath}, \pi_{buy}^{com}\right) - C_{penalty}^{grid} \cdot P^{com} \tag{19}$$

$$S.t.\ \pi_{buy}^{com} \le \pi_{buy}^{grid} \tag{20}$$

$$\pi_{sell}^{com} \ge \pi_{sell}^{grid} \tag{21}$$

$$\sum_{\jmath=1}^{S} P_{buy}^{com,\jmath} = \sum_{\imath=1}^{B} P_{sell}^{com,\imath} \tag{22}$$

$$\pi_{sell}^{com} = \pi_{buy}^{com} \tag{23}$$

The objective function (18) is composed of two terms. The first term is the summation of the optimization problems (13) and (16) for the sellers and buyers, respectively. The second term represents the network charge from the grid utility to the community, where $C_{penalty}^{grid}$ describes the network usage fee for both the sellers and buyers. P^{com} is the total energy sharing in the community. π_{buy}^{com}, π_{sell}^{com} describe the buying and selling prices for the buyer and seller in the LEM, respectively. Constraints (20) and (21) set limits to the energy prices of the buyer and seller, respectively. Constraints (22) and (23) impose the balance of the power-sharing and the clearing price within the community, respectively.

D. DECENTRALIZED CLEARING MECHANISM

In the proposed formulation in (18), the first term problem is a quadratic program formulation composed of a cooperative solution of the participants in the LEM. The sellers and buyers in the LEM have separable objectives (13) (16). The coupling constraint is the balance of the power-sharing and the price constraint in (24) and (25), which contains variables from both the clearing price and the total power-sharing. This problem can be implemented in a centralized manner using a supervisory entity such as the CM. However, the CM requires the information of all players to solve this problem, including the utility function, clearing price, power demand, and supply. Since the market players are independent, the centralized approach is not suitable to solve the proposed optimization problem in order to protect the privacy and security of each market player subject and improve the calculation speed of massive data. Moreover, the centralized approach is subject to performance limitations, such as the scalability and limited flexibility to clear the LEM. Therefore, the market players need to share limited information to achieve a decentralized energy trading consensus. As a result, we employ the distributed algorithm based on ADMM to clear the LEM and determine the optimal energy sharing among the market players. ADMM offers benefits if a problem is separable in local optimization subproblems. ADMM is applied in decentralized optimization to solve problems in a distributed manner.

In this section, the concept of ADMM is briefly discussed and then designed to solve the problem (18), which has many advantages over a centralized approach in terms of privacy and the computation burden, to name a few. Moreover, the proposed distributed approach can be proved to converge to the optimal solution for the market clearing problem.

1) GLOBAL VARIABLES CONSENSUS ADMM FORMULATION

The consensus ADMM is widely used in diversifying areas in MG applications such as cybersecurity and energy trading. Its convergence was proved when different blocks of variables were updated. It is also a strongly desirable method for solving problems in which the objective and constraints are distributed across multiple agents. Each agent only has to handle its own objective function and constraint term, plus a quadratic term, which is updated each iteration. To formulate the ADMM, let i and j agents in a networked system which are indexed by $\{1, 2, 3, \ldots, N\}$ and $\{1, 2, 3, \ldots, M\}$, respectively. Each of these agents has a local private convex objective function and local optimal solution of $f(x_i)$ and $g(z_i)$, where $x_i \in \mathbb{R}^N$ and $z_i \in \mathbb{R}^M$ are the optimization variables. $f : \mathbb{R}^n \rightarrow \mathbb{R}$ and $g : \mathbb{R}^m \rightarrow \mathbb{R}$ are convex functions. The objective of distributed optimization is to minimize a global objective function, which is a sum of the objective functions of all agents in $f(x_i)$ and $g(z_j)$:

$$\begin{aligned} &Minimize \sum_{i=1}^{N} f_i(x_i) + \sum_{j=1}^{M} g_j(z_j) \\ &Au - Bv = 0 \end{aligned} \tag{24}$$

In the above expression, $A \in \mathbb{R}^{l \times N}$ And $B \in \mathbb{R}^{l \times M}$ are constant matrix and vector. $u = (x_1, x_2, \ldots, x_N)$ 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 ref to [34]. The augmented Lagrangian function, based on the global variable consensus of the constraints, can be written as:

$$\mathcal{L}_{\rho}(x, z, \lambda) = \sum_{i=1}^{N} f_i(x_i) + \sum_{j=1}^{M} g_j(z_j) + \underbrace{\lambda^T \cdot (Au - Bv)}_{①} + \underbrace{\frac{\rho}{2} \|Au - Bv\|_2^2}_{②} \tag{25}$$

where ① and ② are the loss and regularization function, respectively. λ is 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:

$$\begin{aligned}
x_1^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho((x_1, x_2, \ldots, x_N), v^k, \lambda) \\
x_2^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho((x_1^{k+1}, x_2, \ldots, x_N), v^k, \lambda) \\
&\;\;\vdots \\
x_n^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho((x_1^{k+1}, x_2^{k+1}, \ldots, x_N), v^k, \lambda) \\
z_1^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho(u^{k+1}, (z_1, z_2, \ldots, z_M), \lambda) \\
z_2^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho(u^{k+1}, (z_1^{k+1}, z_2, \ldots, z_M), \lambda \\
&\;\;\vdots \\
z_M^{k+1} &= \underset{x_i \in \mathbb{R}^N}{argmin}\, \mathcal{L}_\rho(u^{k+1}, (z_1^{k+1}, z_2^{k+1}, \ldots, z_M), \lambda) \\
\lambda^{k+1} &= \lambda^k + \rho(Au^{k+1} - Bv^{k+1})
\end{aligned} \tag{26}$$

The convergence properties of the ADMM to meet the constraint can be referred to in [34] and [35]. The stopping criteria for the iteration could be defined as follows:

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

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

2) ADMM FOR SOLVING THE PROPOSED OPTIMIZATION PROBLEM

Since the objective function (18) maximizes the community's total social welfare, we first term the problem for market clearing. Subsequently, we determine the payments among the grid utility based on the solution of the term in the objective function (18). We consider each seller and buyer as an individual agent in the community, which are indexed in sets of $\{1, 2, 3, \ldots, S\}$ And $\{1, 2, 3, \ldots, B\}$, respectively. In order to decompose the optimization problem in (18) based on the ADMM rules (24), the augmented Lagrangian is written as below:

$$\begin{aligned}
&\mathcal{L}_\rho(P_{sell}^{com,i}, \pi_{sell}^{com}, P_{buy}^{com,j}, \pi_{buy}^{com}, \lambda) \\
&= -\left(\sum_{i=1}^{S} WS_i \left(P_{sell}^{com,i}, \pi_{sell}^{com}\right) + \sum_{j=1}^{B} WB_j \left(P_{buy}^{com,j}, \pi_{buy}^{com}\right) \right) \\
&\quad + \lambda^T (Au - Bv) + \frac{\rho}{2} \|Au - Bv\|_2^2
\end{aligned} \tag{27}$$

where

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
$$B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
$$u = \begin{bmatrix} \sum_{j=1}^{S} P_{buy}^{com,j} \\ \pi_{buy}^{com} \end{bmatrix}$$
$$v = \begin{bmatrix} \sum_{i=1}^{B} P_{sell}^{com,i} \\ \pi_{sell}^{com} \end{bmatrix}$$

According to (22) and (23), u and v, are the variable vector for the seller and buyer, respectively. A and B describe the constant constraints for the vector u and v, respectively. In ADMM iterations, we alternately optimize the augmented Lagrangian function of each seller i to obtain the optimal variable of $P_{sell}^{com,i}$ and π_{sell}^{com}, and each buyer j to obtain the optimal variable $P_{buy}^{com,|}$ and π_{buy}^{com}. In this respect, the local variables in (14) and (15) for the seller while (17) and (18) for the buyer are solved locally.

The ADMM approach has communication links between each agent, which means that the potential privacy risk still exists. Regarding the proposed LEM mechanism, the ADMM process for the sellers and buyers is conducted separately, which would improve computational efficiency and privacy preservation. In this study, we introduced the functions M and N at the CM level to transform the loss and regularization function to a single function in each update between the sellers and buyers, respectively, as indicated in (28) and (29).

$$M(X^{k+1}) = \boldsymbol{A}' \cdot X + \boldsymbol{B}' = \lambda^T \cdot (Au - Bv^k) + \frac{\rho}{2} \left\| Au - Bv^k \right\|_2^2 \tag{28}$$

$$\begin{aligned}
N(X^{k+1}) = \boldsymbol{A}'' \cdot X + \boldsymbol{B}'' &= \lambda^T \cdot (Au^{k+1} - Bv) \\
&\quad + \frac{\rho}{2} \left\| Au^{k+1} - Bv^k \right\|_2^2
\end{aligned} \tag{29}$$

where X represents the variable of the next update of each agent. $\boldsymbol{A}'$, $\boldsymbol{A}''$, $\boldsymbol{B}''$ And $\boldsymbol{B}'$ Are a constant value. k is the iteration number of the ADMM.

Seller$i$- update:

At the iteration $(k + 1)$, the update for the variable $\left(P_{sell}^{com,i}, \pi_{sell}^{com}\right)^{k+1}$ Of each seller i is formulated as below:

$$\underset{P_{sell}^{com,i}, \pi_{sell}^{com}}{Minimize} \left(-WS_i \left(P_{sell}^{com,i}, \pi_{sell}^{com}\right) + \boldsymbol{A}' \cdot \begin{pmatrix} P_{sell}^{com,i} \\ \pi_{sell}^{com} \end{pmatrix} + \boldsymbol{B}' \right)$$

Subject to: (14) and (15). (30)

Buyer j- update:

At the iteration $(k + 1)$, the update for the variable $\left(P_{buy}^{com,\rangle}, \pi_{buy}^{com}\right)^{k+1}$ Of each buyer j is formulated as below:

$$\underset{P_{sell}^{com,i}, \pi_{sell}^{com}}{Minimize} \left(-WS_i \left(P_{sell}^{com,i}, \pi_{sell}^{com}\right) + \boldsymbol{A}' \cdot \begin{pmatrix} P_{sell}^{com,i} \\ \pi_{sell}^{com} \end{pmatrix} + \boldsymbol{B}' \right)$$

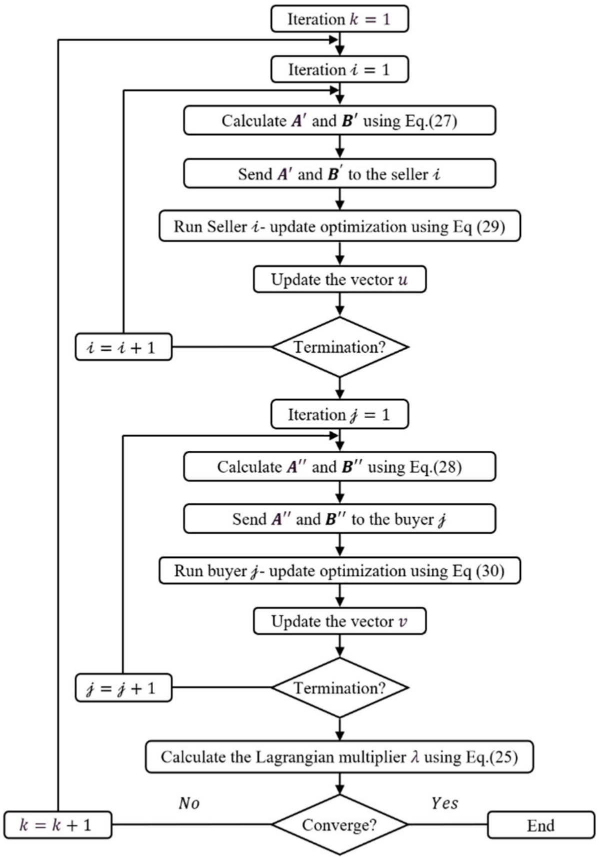

FIGURE 6. Information flow between the CM and the market participant.

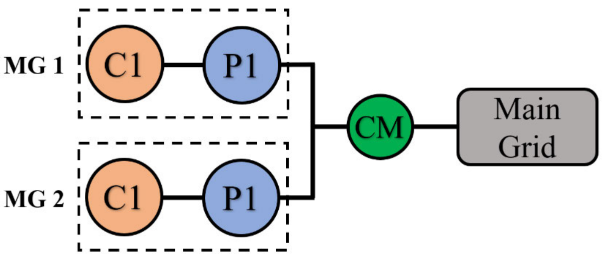

FIGURE 7. The single-line diagram for the illustrative example.

Subject to: (17) and (18) (31)

The implementation procedure of the proposed framework from the CM perspective is shown in Figure. 6.

The first iteration is dedicated to the seller, the second to the buyer, and the third updates the Lagrangian multiplier in accordance with equation (26).

V. NUMERICAL EXPERIMENTS

This section summarizes the findings of this paper and presents the numerical results related to the mathematical models and the decentralized algorithm previously described. For ease of illustration, we report results on a simple illustrative example to demonstrate the proposed design of the LEM. Then, we apply the proposed design over a real case study in a residential area in Latvia, considering different pricing packages provided by the retailer. The simulations were performed

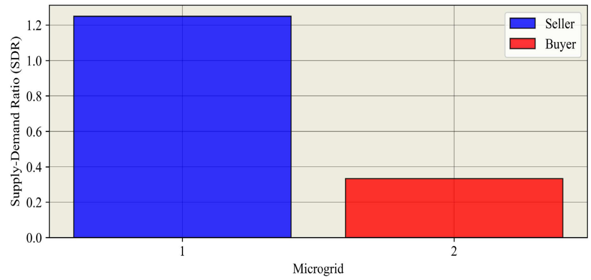

FIGURE 8. The supply and demand ratio (SDR) for MG① and MG②.

within a Python 3.7 environment, using CVXPY to model the objective functions using the CPLEX. A Personal Computer (PC) was used for the experiments with a CPU Intel Core i5 1135G7 2.30 GHZ and 32GB of RAM.

A. ILLUSTRATIVE EXAMPLE

The numerical result of the illustrative example is conducted in a fully connected 2 MG system with a main grid. Each MG is composed of 1 consumer and 1 energy provider, which possess a PV system. The CM takes the place of managing the MG community. The single-line diagram is illustrated in Figure 7. Since the proposed method evaluates the willingness of the utilities to participate in LEM, we choose a single timeslot of the energy generation and demand for demonstration. The level of the power generation and the power demand are assumed to be [0, 5] kW and [2, 4] kW for MG① and [0, 2] kW and [2, 6] kW for MG②, respectively. We set the electricity retail prices for π_{buy}^{grid} and π_{sell}^{grid} are 19.01 ¢/kW and 8.7¢/kW, respectively. We assumed the grid tariff in energy terms is 0.01 ¢/kW. It is also important to note that the capacity subscription tariff costs, e.g., (fixed cost, static and dynamic capacity cost, …) are excluded.

Following the steps mentioned in section II-A., each MG calculates locally the SDR value, internal price, and the utility function for the consumer and the energy provider using Eqs. (8) and (12), respectively. The SDR of each MG is illustrated in Figure 8. As illustrated, the MG① behaves as a seller and the MG② as a buyer. Since the internal price is calculated based on the SDR ratio, different SDRs will provide different internal prices. Figure 9. represents the value of the internal prices for each MG.

It can be observed that the MG① is willing to participate in the LEM by selling and purchasing at the price of 8.7¢/kw. On the other hand, MG② indicates the willingness to participate at the price of 13.6¢/kw and 17.3¢/kw for selling and buying, respectively. Table 1. Describes the parameter values of the convex function of the utilities based on the internal price for a competitive LEM. These parameters dynamically reflect the profit of each MG in the LEM.

Figures 11, and 12 represent the curves of utility function for the seller "MG①" and the buyer "MG②". The CM coordinates the market clearing using an iterative process after classifying the players based on SDR values. The iterative process to solve the clearing problem is portrayed in Fig. 12.

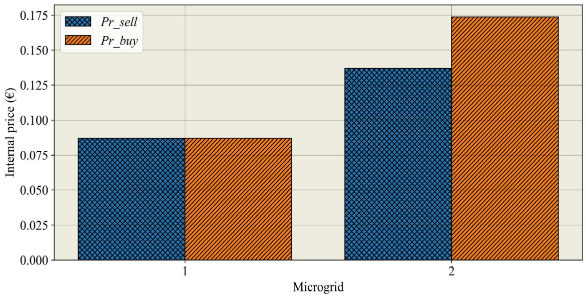

FIGURE 9. The internal prices for each MG.

TABLE 1. Parameter of the utility function for each MG.

	Prosumer index	P_{min}	P_{max}	C_{min}	C_{max}	α (¢/kw2)	β (¢/kw)
MG①	P=1	0	5	-	-	0.0057	8.698
	C=1	-	-	2	4	0.0105	8.696
MG②	P=1	0	2	-	-	0.0237	13.68
	C=1	-	-	2	6	0.0058	17.36

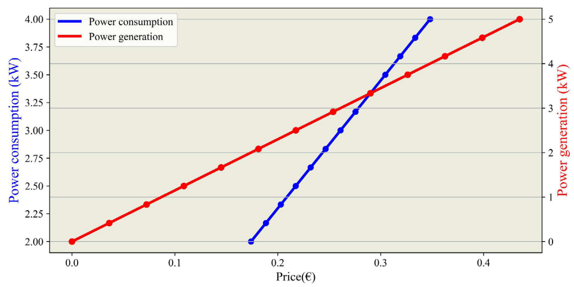

FIGURE 10. The utility curves of the power utility for the MG①.

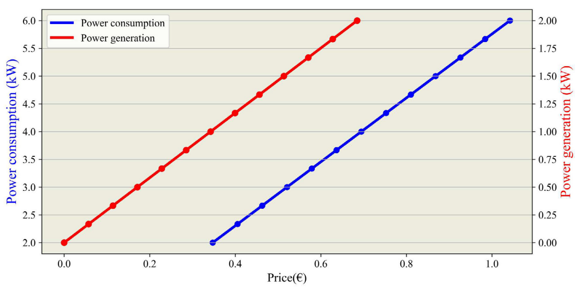

FIGURE 11. The utility curves of the power utility for the MG②.

As illustrated, the initial tentative price for the energy traded in the LEM is broadcasted from the seller "MG①" and the buyer "MG②". Meanwhile, the LEM prices stay in the range of the selling and purchasing the energy from the retail market. After 33 iterations, the market is fully cleared at price of 13.86¢/kw.

Fig. 13. represents the total surplus power supply and demand for the seller and buyer in the LEM. Fig. 14. And 15, illustrates the optimal energy sharing of the community which is realized through the proposed LEM design. Fig. 14. represents the convergence of the power in the community, which verifies that the total traded energy between the seller and the buyer is the same. It is noticeable that the sellers are urged to be motivated and incentivized to sell their surplus

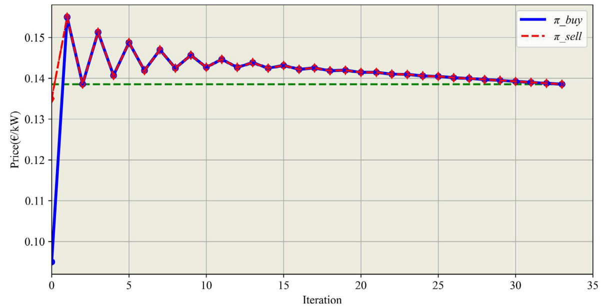

FIGURE 12. Clearing price process for the LEM.

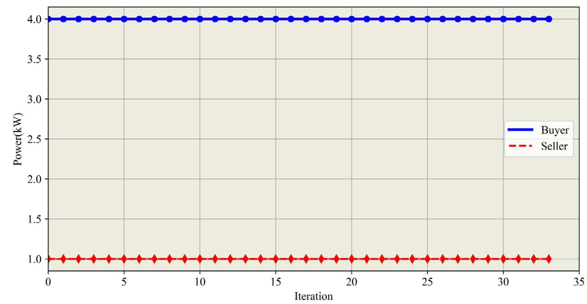

FIGURE 13. The total surplus power supply and demand of the seller and buyer in LEM.

energy in the community rather than grid utility, because the selling price in the LEM is higher than the grid utility. The total amount of energy purchased from and sold to the utility grid for the buyer and seller is shown in Fig. 15. As observed, the total amount of energy purchased from the grid by the buyer is significantly reduced with the application of LEM trading, where the buyer attempted to purchase the power from the community to increase their social welfare. The proposed mechanism allows prosumers to benefit maximally from their participation in the LEM.

An CM operates the community of the MG to maximize their social welfare, by optimizing the energy transaction and the interactions among the sellers and buyers and with the grid utility. Fig. 16. illustrate the convergence of the seller and buyer to maximize their individual welfare. Since maximizing the social welfare is implicitly related to minimizing the operation cost for each player, the convergence is ensuring that no entity is penalized with respect to acting individually. Moreover, it has been demonstrated that the clearing price not only maximizes the social welfare for the players, but also the payoff for energy provider.

In the context of the efficiency of the proposed algorithm for market clearing, we perform our algorithm to solve the objective function on different parameters of $\rho = 40$, 10, 2, and 0.5. From Fig. 17, we can see those different choices of ρ can make a difference at the beginning of the algorithm, and after several iterations it can converge to the optimal value. Therefore, our algorithm has good performance in convergence rate and is not too sensitive to the value of ρ, except for the first several iterations.

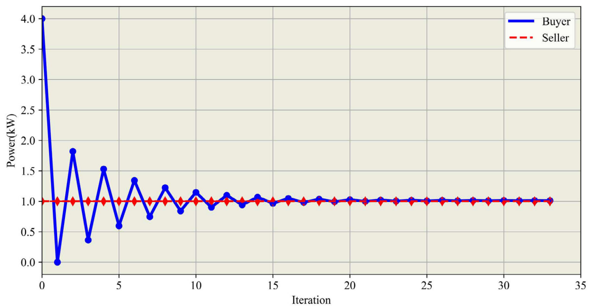

FIGURE 14. Traded energy by seller and buyer in LEM.

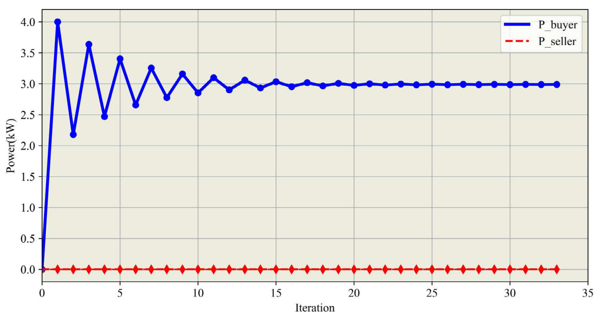

FIGURE 15. Traded energy with the main grid.

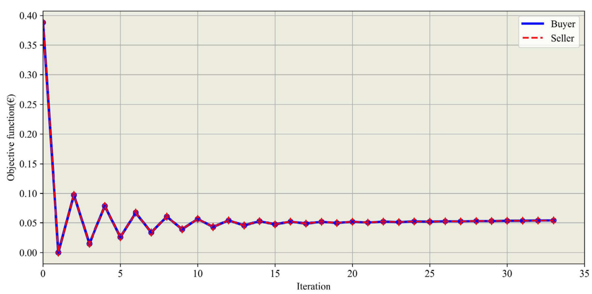

FIGURE 16. Curves of the welfare level for the seller and buyer.

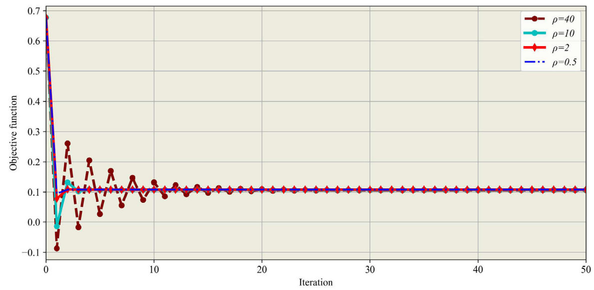

FIGURE 17. Evaluation of the objective function for different ρ.

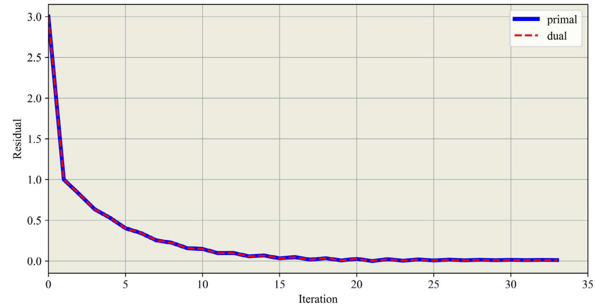

FIGURE 18. The supply and demand ratio (SDR) for the community.

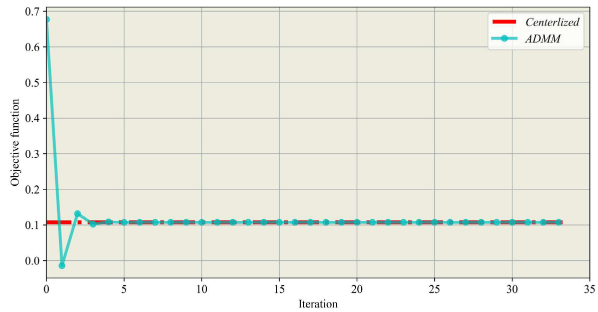

FIGURE 19. The supply and demand ratio (SDR) for the community.

The market clearing problem is solved by the proposed algorithm based on the ADMM algorithm in an iterative process. In this work, the primal and dual convergence is defined as 0.001, and the penalty ρ is set as 10. Figure 18. displays the aggregated primal and dual residual at each iteration. It depicts that the proposed algorithm can only converge to the specified thresholds after a few iterations only.

The centralized solution is obtained by directly solving the market clearing model with the Pyomo IPOPT solver. The iteration process of the objective value is displayed in Figure 19, demonstrating that the ADMM-based algorithm can reproduce the optimal outcomes obtained from centralized optimization. The computation times to solve the objective function are 0.1691 (s) and 3.218 (s) for the centralized and the proposed ADMM method, respectively. Meanwhile, the maximum solution time for the seller and buyers' sub-problems is 0.0633 (s). As it can be observed, the proposed ADMM approach needs more computation time than the centralized approach, and it can maintain privacy information protection, i.e., the CM does not need to have access for the preferences of each MG participating in the LEM.

B. CASE OF STUDY

A case study of an actual segment of an electricity distribution system of a residential area in the city of Riga, Latvia, is used for the testing of the developed framework [36]. There are four MG connected with the grid utility, and each MG is composed of different DERs (loads and PV1 systems), as displayed in Figure 20. All those DERs have PV capacity between [0, 11] kW and energy consumption between [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], and [26] kW. Figure 21 Represents the SDR of each MG. In order to elaborate the proposed LEM, fixed-rate pricing and dynamic pricing are considered. Table 2 represents the characteristics of the pricing packages from the retailer. We assume the spot market price is 10 ¢/kW and the fixed price for selling is 6.75 ¢/kW. We set our algorithm at the criteria stop at 10^{-5}.

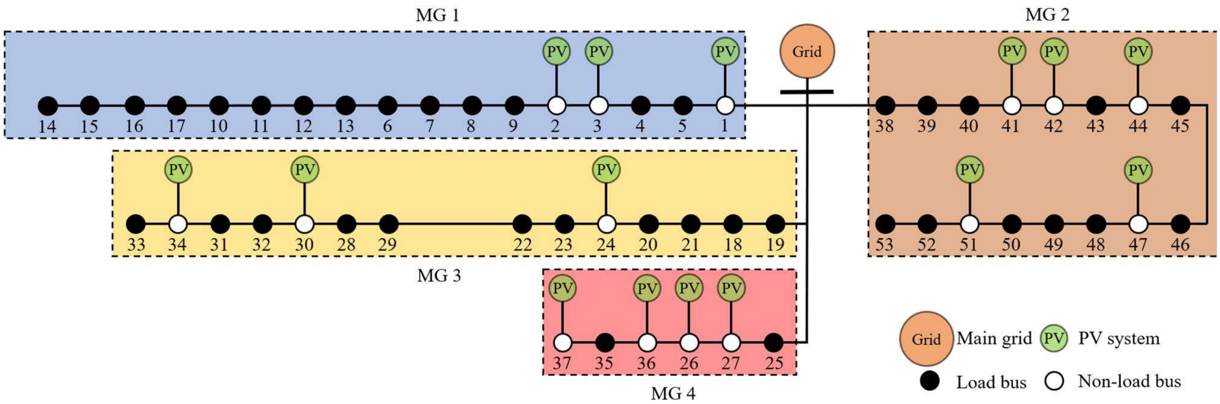

FIGURE 20. The topology of the case of study.

TABLE 2. The characteristics of the pricing packages.

	Dynamic pricing	Fixed-rate pricing
Seller margin (¢/kw)	0.55	-
Monthly fee for selling (€/month)	1.99 €	3.99 €
Purchaser margin (¢/kw)	0.75	0.75
Monthly fee for purchasing (€/month)	-	-

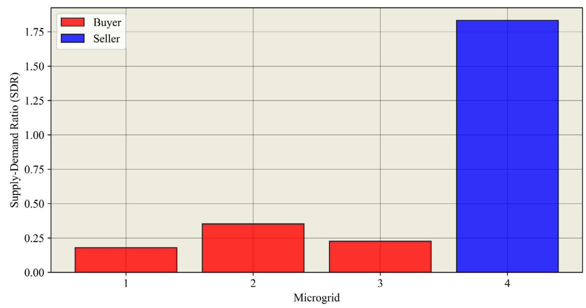

FIGURE 21. The supply and demand ratio (SDR) for the community.

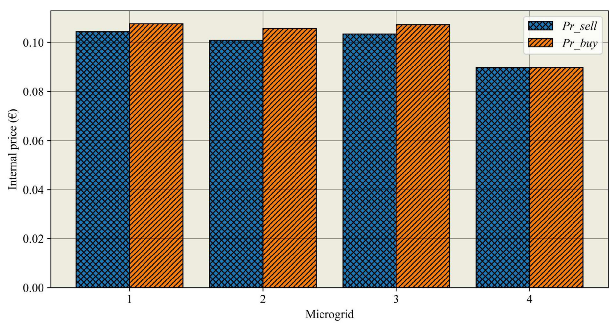

FIGURE 22. The internal pricing for the MGs using the dynamic pricing.

According to the proposed scheme, the utility functions for each MGs are directly influenced by the pricing package. The impact of the internal pricing using the dynamic and the fixed rate pricing at the LEM is depicted in Figures 22 and 23, respectively. According to Figures 22 and 23, the internal price of the MGs using dynamic pricing is higher

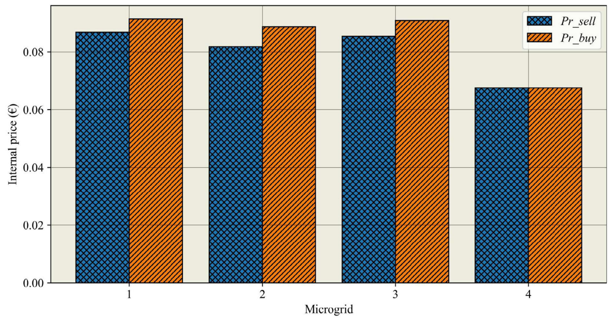

FIGURE 23. The internal pricing for the MGs using the fixed rate pricing.

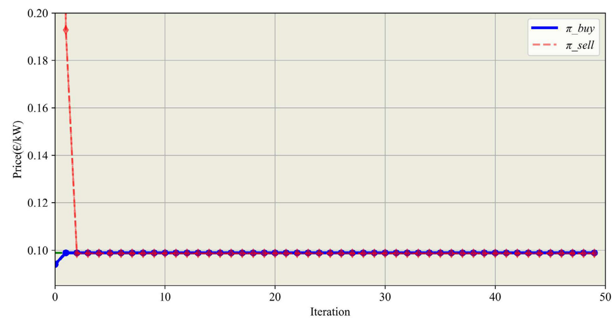

FIGURE 24. Clearing process under the dynamic pricing.

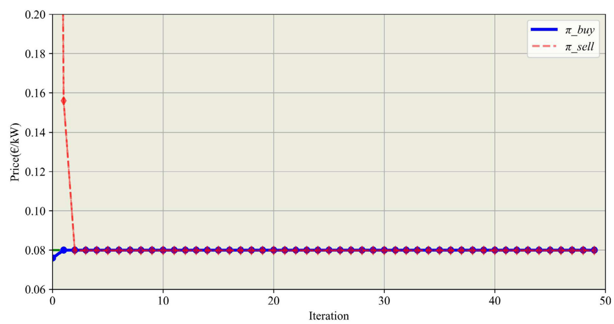

FIGURE 25. Clearing process under the fixed rate pricing.

than fixed-rate pricing. Thus, the utility coefficients for the consumers and energy providers in each MG using dynamic pricing are higher than fixed-rate pricing.

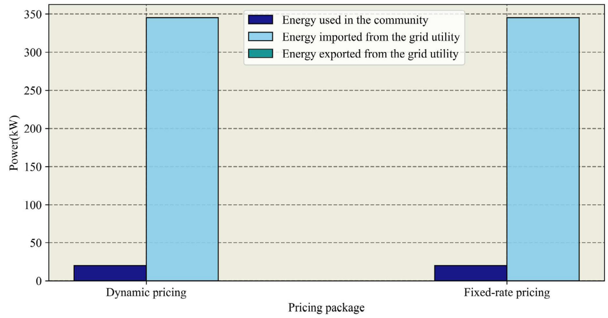

FIGURE 26. Total power exchange of community using the dynamic pricing and Fixed-rate pricing.

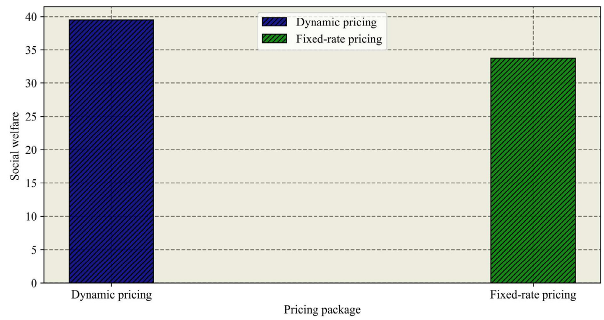

FIGURE 27. Comparison of the social welfare using dynamic pricing and Fixed-rate pricing.

Fig 24 and Fig 25, show the market clearing process using the proposed LEM design under the dynamic and fixed-rate pricing. Where it can be verified that in the π_{sell}^{com}, and π_{buy}^{com} Between seller and buyer they will reach convergence. Also, the clearing price satisfies pricing's constraints, it means that a MG④ cannot offer a price higher than retailer's selling price and the MG①, MG②, and MG③ cannot ask for an energy at a price lower than retailer's purchasing price. As can be noted the clearing price is 9.86 ¢/kw for the dynamic pricing and 7.98 ¢/kw for the fixed rate pricing.

The total power exchange for the community using the dynamic and fixed rate pricing is demonstrated in Figure 26. As expected, the exchange energy amount to the main grid for both packages is similar, equal to zero. The reason is that the amount of energy exchanged in the LEM is insufficient to meet the community's self-demand. The CM never sells electricity to the main grid since the electricity purchasing price of the main grid is always no higher than that of the LEM. The community also needs to purchase energy of 345.21 kW from the main grid to satisfy their power demand, which is 365 kW.

Figure. 27. illustrates the economic benefit of the community from the view of social welfare. As can be observed, the changes in social welfare and the total trading payment mainly depend on the pricing, and they increase and decrease with the increase in pricing in the LEM. Obviously, the community enjoys the highest social welfare when using dynamic pricing. The reason is that the sellers benefit more when the LEM price is high, and the buyers can enjoy more at a lower price.

VI. CONCLUSION

In recent years, extensive research has been conducted to explore MGs to establish a fully competitive market between prosumers. Nevertheless, ensuring the secure and efficient operation of MGs necessitates the implementation of advanced market designs and private topology for exchanging information. In this research, an LEM framework involving energy trading for multi-MGs connected with the main grid is proposed. This framework provides chances for interconnected MGs to utilize the surplus energy in the community to increase their social welfare. The MGs, as in the community, were classified into sellers and buyers based on their SDR. Consequently, the willingness to participate in a LEM is modeled based on real-dynamic market information using the internal pricing method and the retail market price, which provide an adequate trading design to incentivize players to participate actively in the trading process. The objective function for the sellers and the buyers is reformulated as a distributed convex optimization problem. The CM plays a role as an intermediate coordinator between the sellers and buyers for market clearing. The LEM clearing problem relied on a specific iterative process ADMM algorithm to protect the privacy and security of each market player. Implemented case studies verified that the proposed framework could help multi-MGs trade power locally to meet their own power requirements with minimum cost. Moreover, the convergence of the proposed ADMM approach was proved, and the comparison with the centralized approach was also examined. The proposed approach obtains the optimal result in a reasonable number of iterations. It provides the same value of social welfare as demonstrated in the centralized approach, while it needs lower information exchange. Our study found that by using dynamic pricing in conjunction with our proposed model, the social welfare of the energy community can be increased by 14.25%. This demonstrates the significant economic benefits and effectiveness of our approach in the Local Energy Market (LEM).

However, a limitation of our work is that the algorithm takes many iterations to converge to the clearing price, which increases the computation cost and may cause some communication delay. In future work, we plan to focus more on improving the algorithm based on the second derivative model to make it converge faster and provide more privacy.

REFERENCES

[1] T. Morstyn and M. D. McCulloch, "Multiclass energy management for peer-to-peer energy trading driven by prosumer preferences," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4005–4014, Sep. 2019, doi: 10.1109/TPWRS.2018.2834472.

[2] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6087–6097, Aug. 2019, doi: 10.1109/TIE.2018.2874578.

[3] M. Khorasany, Y. Mishra, and G. Ledwich, "Hybrid trading scheme for peer-to-peer energy trading in transactive energy markets," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 2, pp. 245–253, Jan. 2020, doi: 10.1049/iet-gtd.2019.1233.

[4] T. AlSkaif, J. L. Crespo-Vazquez, M. Sekuloski, G. van Leeuwen, and J. P. S. Catalão, "Blockchain-based fully peer-to-peer energy trading strategies for residential energy systems," *IEEE Trans. Ind. Informat.*, vol. 18, no. 1, pp. 231–241, Jan. 2022, doi: 10.1109/TII.2021.3077008.

[5] X. Jin, Q. Wu, and H. Jia, "Local flexibility markets: Literature review on concepts, models and clearing methods," *Appl. Energy*, vol. 261, Mar. 2020, Art. no. 114387, doi: 10.1016/j.apenergy.2019.114387.

[6] M. Khorasany, A. Najafi-Ghalelou, and R. Razzaghi, "A framework for joint scheduling and power trading of prosumers in transactive markets," *IEEE Trans. Sustain. Energy*, vol. 12, no. 2, pp. 955–965, Apr. 2021, doi: 10.1109/TSTE.2020.3026611.

[7] M. N. Faqiry, L. Edmonds, H. Wu, and A. Pahwa, "Distribution locational marginal price-based transactive day-ahead market with variable renewable generation," *Appl. Energy*, vol. 259, Feb. 2020, Art. no. 114103, doi: 10.1016/j.apenergy.2019.114103.

[8] F. Moret and P. Pinson, "Energy collectives: A community and fairness based approach to future electricity markets," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 3994–4004, Sep. 2019, doi: 10.1109/TPWRS.2018.2808961.

[9] Y. Tao, J. Qiu, S. Lai, and J. Zhao, "Integrated electricity and hydrogen energy sharing in coupled energy systems," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 1149–1162, Mar. 2021, doi: 10.1109/TSG.2020.3023716.

[10] G. Hug, S. Kar, and C. Wu, "Consensus + innovations approach for distributed multiagent coordination in a microgrid," *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 1893–1903, Jul. 2015, doi: 10.1109/TSG.2015.2409053.

[11] W. Liu, Q. Wu, F. Wen, and J. Østergaard, "Day-ahead congestion management in distribution systems through household demand response and distribution congestion prices," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2739–2747, Nov. 2014, doi: 10.1109/TSG.2014.2336093.

[12] F. Lezama, J. Soares, P. Hernandez-Leal, M. Kaisers, T. Pinto, and Z. Vale, "Local energy markets: Paving the path toward fully transactive energy systems," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4081–4088, Sep. 2019, doi: 10.1109/TPWRS.2018.2833959.

[13] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, Sep. 2017, doi: 10.1109/TPWRS.2017.2649558.

[14] M. Marzband, A. Sumper, J. L. Domínguez-García, and R. Gumara-Ferret, "Experimental validation of a real time energy management system for microgrids in islanded mode using a local day-ahead electricity market and MINLP," *Energy Convers. Manage.*, vol. 76, pp. 314–322, Dec. 2013, doi: 10.1016/j.enconman.2013.07.053.

[15] S. Lilla, C. Orozco, A. Borghetti, F. Napolitano, and F. Tossani, "Day-ahead scheduling of a local energy community: An alternating direction method of multipliers approach," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 1132–1142, Mar. 2020, doi: 10.1109/TPWRS.2019.2944541.

[16] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, and E. Sorin, "Peer-to-peer and community-based markets: A comprehensive review," *Renew. Sustain. Energy Rev.*, vol. 104, pp. 367–378, Apr. 2019, doi: 10.1016/j.rser.2019.01.036.

[17] R. Jing, M. N. Xie, F. X. Wang, and L. X. Chen, "Fair P2P energy trading between residential and commercial multi-energy systems enabling integrated demand-side management," *Appl. Energy*, vol. 262, Mar. 2020, Art. no. 114551, doi: 10.1016/j.apenergy.2020.114551.

[18] T. Morstyn, A. Teytelboym, C. Hepburn, and M. D. McCulloch, "Integrating P2P energy trading with probabilistic distribution locational marginal pricing," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3095–3106, Jul. 2020, doi: 10.1109/TSG.2019.2963238.

[19] T. Chen, S. Bu, X. Liu, J. Kang, F. R. Yu, and Z. Han, "Peer-to-peer energy trading and energy conversion in interconnected multi-energy microgrids using multi-agent deep reinforcement learning," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 715–727, Jan. 2022, doi: 10.1109/TSG.2021.3124465.

[20] H. Yao, Y. Xiang, S. Hu, G. Wu, and J. Liu, "Optimal prosumers' peer-to-peer energy trading and scheduling in distribution networks," *IEEE Trans. Ind. Appl.*, vol. 58, no. 2, pp. 1466–1477, Mar. 2022, doi: 10.1109/TIA.2021.3133207.

[21] A. Jiang, H. Yuan, and D. Li, "A two-stage optimization approach on the decisions for prosumers and consumers within a community in the peer-to-peer energy sharing trading," *Int. J. Electr. Power Energy Syst.*, vol. 125, Feb. 2021, Art. no. 106527, doi: 10.1016/j.ijepes.2020.106527.

[22] J. L. Crespo-Vazquez, T. AlSkaif, Á. M. González-Rueda, and M. Gibescu, "A community-based energy market design using decentralized decision-making under uncertainty," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 1782–1793, Mar. 2021, doi: 10.1109/TSG.2020.3036915.

[23] P. Shamsi, H. Xie, A. Longe, and J.-Y. Joo, "Economic dispatch for an agent-based community microgrid," *IEEE Trans. Smart Grid*, vol. 7, no. 5, pp. 2317–2324, Sep. 2016, doi: 10.1109/TSG.2015.2487422.

[24] L. Yan, X. Chen, Y. Chen, and J. Wen, "A hierarchical deep reinforcement learning-based community energy trading scheme for a neighborhood of smart households," *IEEE Trans. Smart Grid*, vol. 13, no. 6, pp. 4747–4758, Nov. 2022, doi: 10.1109/TSG.2022.3181329.

[25] Y. Xiao, X. Wang, P. Pinson, and X. Wang, "A local energy market for electricity and hydrogen," *IEEE Trans. Power Syst.*, vol. 33, no. 4, pp. 3898–3908, Jul. 2018, doi: 10.1109/TPWRS.2017.2779540.

[26] Y. Liu, Y. Li, H. B. Gooi, Y. Jian, H. Xin, X. Jiang, and J. Pan, "Distributed robust energy management of a multimicrogrid system in the real-time energy market," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 396–406, Jan. 2019, doi: 10.1109/TSTE.2017.2779827.

[27] C. Liu and Z. Li, "Comparison of centralized and peer-to-peer decentralized market designs for community markets," *IEEE Trans. Ind. Appl.*, vol. 58, no. 1, pp. 67–77, Jan. 2022.

[28] W. Tushar, T. K. Saha, C. Yuen, T. Morstyn, Nahid-Al-Masood, H. V. Poor, and R. Bean, "Grid influenced peer-to-peer energy trading," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1407–1418, Mar. 2020, doi: 10.1109/TSG.2019.2937981.

[29] Y. Xia, Q. Xu, and F. Li, "Grid-friendly pricing mechanism for peer-to-peer energy sharing market diffusion in communities," *Appl. Energy*, vol. 334, Mar. 2023, Art. no. 120685, doi: 10.1016/j.apenergy.2023.120685.

[30] L. Ma, L. Wang, and Z. Liu, "Multi-level trading community formation and hybrid trading network construction in local energy market," *Appl. Energy*, vol. 285, Mar. 2021, Art. no. 116399, doi: 10.1016/j.apenergy.2020.116399.

[31] Y. Chen, S. Mei, F. Zhou, S. H. Low, W. Wei, and F. Liu, "An energy sharing game with generalized demand bidding: Model and properties," *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2055–2066, May 2020, doi: 10.1109/TSG.2019.2946602.

[32] P. Samadi, H. Mohsenian-Rad, R. Schober, and V. W. S. Wong, "Advanced demand side management for the future smart grid using mechanism design," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1170–1180, Sep. 2012, doi: 10.1109/TSG.2012.2203341.

[33] B. Cornélusse, I. Savelli, S. Paoletti, A. Giannitrapani, and A. Vicino, "A community microgrid architecture with an internal local market," *Appl. Energy*, vol. 242, pp. 547–560, May 2019, doi: 10.1016/j.apenergy.2019.03.109.

[34] S. Boyd, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Found. Trends Mach. Learn.*, vol. 3, no. 1, pp. 1–122, 2010, doi: 10.1561/2200000016.

[35] J. Gallier and J. Quaintance, *Fundamentals of Optimization Theory With Applications to Machine Learning*. Philadelphia, PA, USA: University of Pennsylvania, 2019.

[36] T. Korõtko, F. Plaum, T. Häring, A. Mutule, R. Lazdins, O. Borsčevskis, A. Rosin, and P. Carroll, "Assessment of power system asset dispatch under different local energy community business models," *Energies*, vol. 16, no. 8, p. 3476, Apr. 2023, doi: 10.3390/en16083476.

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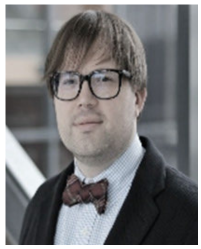

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