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Research Article

Novel Architecture for Transactive Energy Management Systems with Various Market Clearing Strategies

S. L. Arun,[1] **Kishore Bingi**,[2] **R. Vijaya Priya**,[1] **I. Jacob Raglend**,[1] **and B. Hanumantha Rao**[3]

[1]*School of Electrical Engineering, Vellore Institute of Technology, Vellore, India*
[2]*Department of Electrical and Electronic Engineering, Universiti Teknologi PETRONAS, 31750 Seri Iskandar, Malaysia*
[3]*School of Electrical and Electronic Engineering, University College Dublin, Dublin, Ireland*

Correspondence should be addressed to Kishore Bingi; bingi.kishore@ieee.org

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The recent advancements in demand-side management techniques add significant benefits to the distribution systems. One such technique is transactive energy management systems (TEMS) which motivate the energy end-users to take part in local energy trading. The end-users can effectively increase the monetary benefits by trading the surplus generation/demand within the local energy market (LEM). The LEM operator frames a viable market clearing strategy to fix the market clearing price to enhance the monetary benefits of all the market players. In this study, LEM architecture with different market clearing strategies is proposed for TEMS to ensure profitable power transactions between the neighboring end-users. An optimal energy management algorithm is also proposed for time scheduling the operation of flexible loads and batteries, considering dynamics in end-users' behavior, variations in utility parameters, and the intermittent nature of renewable power generation. Further, an optimal load scheduling algorithm is developed at the end-users' premises to improve the profits in the LEM. Correspondingly, the trading strategies are extended to increase market reliability by penalizing participants for their abnormal activities in energy trading. The proposed framework is validated with different case studies considering ten residential participants in a locality.

1. Introduction

Demand side management (DSM) techniques are proven to achieve remarkable benefits in smart distribution systems [1]. For instance, the end-users can avail considerable incentives from the grid operator by actively responding (demand response) to the utility DSM control schemes. An energy management system helps the end-users easily track and regulate the operation of home appliances to avail the maximum economic benefits [2]. Also, the end-users can further minimize their electricity bill by significantly reducing and meeting the demand through energy storage devices, especially during peak intervals. Since these storage devices are charged from the grid, they may not result in a substantial reduction in the electricity bill, especially when the utility charges at a flat-rate tariff. As an alternate solution, the end-users adopt in-house renewable energy resources (RERs), for instance, rooftop solar photovoltaic (PV) arrays and small wind turbines, to meet the residential demand either partly or entirely. Nevertheless, the power generation from the RERs is site-specific and profoundly intermittent. Henceforth, the net demand profile of such residential buildings is highly unpredictable.

On the other hand, utilities encourage the end-users to trade their excess power generation to the utility with considerable incentives and call these types of users as prosumers. Generally, prosumers prefer to export the excess generation into the grid during peak intervals to enhance electricity bill savings. Further, to reduce their dependency on the grid during high price intervals, prosumers optimally reschedule the operation of home appliances for low-price intervals. To enhance the control mechanism of home appliance operation, the smart energy management system (SEMS) is indispensable [2]. Generally, SEMS is devised to schedule the operating time of household appliances concerning end users' requirements, utility operational dynamics, and the intermittent nature of RERs.

1.1. Literature Review. Several research works have been addressed in the literature to schedule household appliances through energy management systems optimally. To lower the residential consumer's electricity bill, a load scheduling algorithm using a mixed-integer linear program is proposed in [3]. Considering the uncertainty of home appliances' operation times, energy storage systems, and the sporadic nature of renewable energy generation, an efficient energy management scheme is devised in [4]. A DSM with prosumer participation is developed in [5], where the consumer's electricity bill is reduced by exporting power to the utility. Also, the residential electricity demand pattern is synthesized based on the probability of appliances' times of operation. Incorporating RERs and electric vehicles with appropriate DSM in residential buildings substantiates microgrid stability and lessens utility dependence [6]. A load scheduling algorithm to maximize operational savings as a primary objective function is discussed in [7], employing a simple linear program. In [8], an optimization technique is presented to schedule the load demand of PV-installed residential buildings as the output power variation is unpredictable.

The feed-in tariff (FiT) scheme in the traditional market is intended to motivate small-scale prosumers. However, the number of new installations over a decade increased unexpectedly. The governing bodies started to decrease the FiT price significantly, which resulted in a lengthy investment pay-back period for prosumers. FiT schemes have been discontinued in some parts of the world, like the state of Queensland in Australia [9]. As the distribution grid operators face additional operational challenges with integrating RERs-based residential buildings [10], utilities are showing a lack of interest in purchasing surplus generation from the end-users. However, few utilities regulate end-users' support by initiating a time-varying power injection limit (PIL) [11]. In this regulation, an end-user benefits economically by injecting the excess generation into the grid without exceeding the predefined utility PIL. In such scenarios, the excess power generation beyond the utility PIL should either be stored in the battery for subsequent usage or drained via a dump load. Further, the end-users are recommended to lessen the power evacuation from RERs by disconnecting the in-house resources from the system when the surplus power generation exceeds PIL.

Although introducing PIL at the end-user premises significantly reduces the operational difficulties of utilities, this regulation may decrease the profit gained by the end-user. Further, the generated green energy may not be fully utilized when surplus generation exceeds the utility PIL. Hence, the PIL constraint indirectly restricts the installation capacity of in-house RERs at the end-user side. To overcome this limitation, end-users are preferred to participate in transactive energy management systems (TEMS) [12, 13]. TEMS is an advanced technique in DSM schemes that intend to develop a deregulated market between the end-users to trade their excess generation and demand with neighboring users to attain more profit compared to utility [14]. This kind of market is called the local energy market (LEM).

In [15], a game theory-based reverse auction model is developed as a multiagent system including prosumers of the corresponding locality and utility. However, neither the prosumers are modeled as individual agents, nor the flexible loads are considered. An individual agent-based simulation environment is structured in [16] to share the energy among participants in the community energy market. In such a community, a recursive least squares learning algorithm is framed to find the dynamic pricing and initiate decision-making. Nevertheless, modeling of flexible loads is not considered in the considered work. In [17], a peer-to-peer (P2P) energy trading technique is devised between electric vehicles. A game theory method is employed in the considered work to maintain the dynamic equity between demand and supply at peak and off-peak intervals. A similar game theory approach is discussed in [18], which has initiated a P2P energy trading technique considering a multi-agent coordinated zone-based energy trading network. Also, this study details the energy trading between prosumers in the smart neighborhood.

In [19], a P2P energy sharing mechanism is developed using a game theory method for off-grid and on-grid microgrid systems. A game-theory method based on a bilevel optimization algorithm and a two-stage distributed optimization algorithm using Nash bargaining is discussed in [20, 21], respectively, for P2P power trading. Different P2P power trading techniques are explained in [22–24]. A novel multilevel transactive energy optimization model is proposed in [25] for the optimal scheduling of distributed generation units within the considered virtual power plant (VPP). The model supports energy transfers inside a specific VPP as well as between the linked VPPs. Further, a block-chain-based smart contract layer is being developed to automate and store the energy transaction information. In [26], a market model based on the double auction technique is developed to facilitate P2P energy trading. The proposed market architecture's benefits are highlighted by comparing it with the manager-based centralized energy market in terms of social welfare, total payment, and energy trade volume outcomes. The overview of blockchain-based decentralized energy market architecture and its components for TEMS is detailed in [27]. Consecutively, the blockchain-based intra- and inter-VPP-P2P energy market is realized in [28]. Besides mixed-integer linear programming-based optimization, it is proposed to compute the optimal cost for energy exchange.

A comprehensive review of transactive energy systems is presented in [29], emphasizing the control techniques, topologies, and simulators available for the design, assessment, and analysis of the systems. Further, a hierarchical framework which comprised four main levels is used to evaluate the transactive energy control strategies and controller's concepts. A decentralized architecture is developed in [30] to integrate the retail and wholesale energy markets in the context of wind and demand uncertainty, as well as the financial risks provided by these sources. The results of simulation studies show that the suggested structure has a strong potential to create integrated power markets with maximum performance and efficiency despite multiple system restrictions. The impact of numerous uncertainties (created by pricing, generation, and demand) on direct energy trading is examined in [31]. Additionally, a Nash bargaining game-based direct transactive energy trading framework is implemented to mitigate the effects of uncertainty. A detailed evaluation of previous research studies and pilot projects on P2P energy trading in terms of implementation approaches with mathematical formulations is presented in [32].

1.2. Research Gap and Motivation. Based on the literature survey, it is foreseen that the optimum scheduling of flexible loads and batteries, including the expected renewable generation and utility dynamics, results in significant savings in end-users' electricity bills. Further, injecting excess power into the utility, especially during peak intervals, assures end-users of high incentives from the utility. Additionally, the active participation of end-users in energy trading under LEM increases the profit considerably. On the other hand, developing suitable market clearing strategies by the LEM operators (LEMO) attracts many end-users to participate in transactive energy systems, increasing the installation and optimal utilization of RERs.

An optimal energy management algorithm is developed in this study to enhance the operational and monetary perks of end-users and utilities. The algorithm is framed to control the operating time of flexible loads and batteries, considering end-users' operational dynamics and requirements, utility parameter variations, and renewable power generation. Further, the scheduling method has been upgraded to assist the end-users in taking part in LEM. The upgraded system optimally determines the expected demand/generation for the upcoming intervals based on the dynamics of end-users' behavior and climatic changes. In addition, the proposed system reschedules the operations of home appliances in real time to reduce the forfeit imposed by the market operator for not supporting the grid with quoted power. LEM is also devised with different market clearing strategies to manage the power trading between the neighboring end-users. The proposed LEM scheme ensures the individuals' profit in energy trading based on their participation and consistency in quoted demand. Further, the proposed LEM scheme identifies the abnormal activities of participants in quoted power and penalizes them accordingly.

1.3. Contributions and Paper Organization. The major contributions of this study are described as follows:

(1) An optimal energy management algorithm is proposed for time scheduling the operation of flexible loads and batteries considering
  (a) Dynamics in end-users' behavior
  (b) Variations in utility parameters (consumer demand limit and PIL)
  (c) Intermittent nature of renewable power generation
(2) An energy trading algorithm is developed to enable the participants to participate in LEM to enhance their profits through transactive energy.
(3) A new local energy market with different market clearing strategies is presented to ensure profitable power transactions between the neighboring end-users
(4) The proposed trading strategies are extended to increase the market's reliability by penalizing the participants for their abnormal activities in energy trading

The remaining sections of the manuscript are organized as follows: the detailed architecture of the proposed local energy market and the mathematical modeling of the end-user's demand pattern are discussed in Section 2; as part of the P2P energy market, two different pricing strategies are developed in Section 3; the proposed market clearing strategies are validated through case studies in Section 4. The conclusions and future scope are given in Section 5.

2. Architecture of the Local Energy Market

A group of residential consumers and prosumers in close proximity forms a LEM. In LEM, the market participants (consumer/prosumer) are encouraged to trade their surplus generation/demand within the locality along with the upstream utility grid. The proposed conceptual architecture of LEM is shown in Figure 1, which consists of market participants, LEMO, and a utility grid. The objective of LEMO is to maintain a real-time balance between local demand and generation with the appropriate pricing strategies within the locality. This led to the development of TEMS with different market clearing strategies within the locality.

Nowadays, residential consumers are intelligently operating electrical and electronic household appliances to fulfill their tasks timely. Based on the operating pattern, residential loads are categorized into two groups: nonflexible loads (NFLs) and flexible loads (FLs). The loads which are essential and anticipated to respond instantly are classed as NFLs. The inherence and comfort highly persuade the end-user's operational profiles of the NFLs. Loads that are flexible to operate between user-defined periods are categorized under FLs. The net demand of an end-user $n\ (n \in \mathcal{N} \triangleq [1, 2, \ldots, N])$ for the time interval $t\ (t \in \mathcal{T} \triangleq [1, 2, \ldots, T])$ is as ND_n^t, and it is mathematically expressed as follows:

$$\mathrm{ND}_n^t = \mathrm{NFL}_n^t + \mathrm{FL}_n^t + \mathrm{ES}_n^t - \mathrm{DG}_n^t, \quad \forall n \in \mathcal{N}; \forall t \in \mathcal{T}, \tag{1}$$

where

(i) N is the locality's cumulative end-users
(ii) T is the maximum number of time intervals over a period
(iii) NFL_n^t and FL_n^t represent the overall demand of the entire NFLs and FLs, respectively

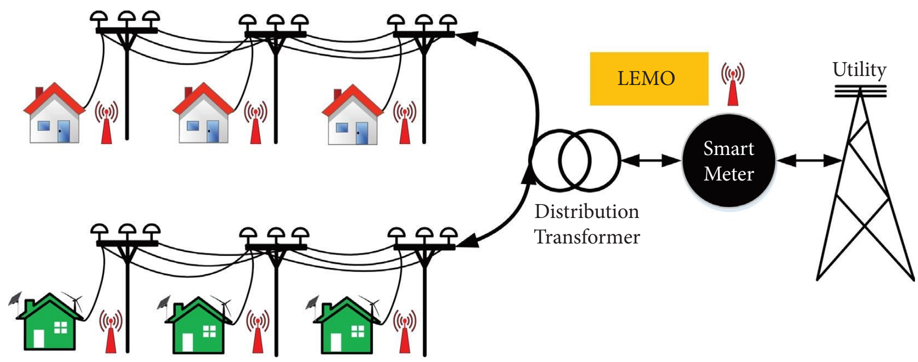

FIGURE 1: Conceptual diagram of the local energy market.

FL_n^t can be computed as follows:

$$\mathrm{FL}_n^t = \sum_{l\in\mathrm{FLs}} \mathcal{S}_{l,n}^t \cdot P_{l,n}, \tag{2}$$

where $\mathcal{S}_{l,n}^t$ denotes operating status of flexible load l during an interval t. The value of $\mathcal{S}_{l,n}^t$ is assigned to 0 and 1 for the respective load status of OFF and ON. $P_{l,n}$ represents the power rating of flexible load l.

ES_n^t refers to the battery power exchange during different modes of battery operation, and it is described as follows:

$$\begin{aligned}
&\mathrm{ES}_n^t > 0; \left\{\begin{matrix} \mathfrak{B}_{C,n}^t = 1, \mathfrak{B}_{D,n}^t = 0, \mathfrak{B}_{F,n}^t = 0 \\ \text{Battery in charging mode} \end{matrix}\right\},\\
&\mathrm{ES}_n^t < 0; \left\{\begin{matrix} \mathfrak{B}_{C,n}^t = 0, \mathfrak{B}_{D,n}^t = 1, \mathfrak{B}_{F,n}^t = 0 \\ \text{Battery in di scharging mode} \end{matrix}\right\},\\
&\mathrm{ES}_n^t = 0; \left\{\begin{matrix} \mathfrak{B}_{C,n}^t = 0, \mathfrak{B}_{D,n}^t = 0, \mathfrak{B}_{F,n}^t = 1 \\ \text{Battery in floating mode} \end{matrix}\right\},
\end{aligned} \tag{3}$$

where $\mathfrak{B}_{C,n}^t$, $\mathfrak{B}_{D,n}^t$, and $\mathfrak{B}_{F,n}^t$ are battery operating mode status during charging, discharging, and floating, respectively.

DG_n^t represents the power generation from installed in-house distributed energy resources. These days, residential buildings are mostly equipped with renewable power generation systems such as rooftop solar PV or small wind turbines. Hence, considering the RERs, the total power generation (DG_n^t) can be computed as follows:

$$\mathrm{DG}_n^t = P_{\mathrm{PV},n}^t + P_{\mathrm{WT},n}^t, \tag{4}$$

where $P_{\mathrm{PV},n}^t$ and $P_{\mathrm{WT},n}^t$ represent the installed solar PV and wind turbine power generation, respectively.

Currently, utilities are introducing various electricity pricing schemes as part of the DSM program to maintain a flat load profile. One such pricing scheme is real-time pricing (RTP), where the end-user will be informed about the interval's electricity price and other incentives just before the interval begins [33]. Hence, the prediction strategies of end-users play a vital role in reducing end-users' electricity bills. The total electricity bill of any user $n(\mathrm{TEB}_n)$ will be computed based on the utility cost function as expressed in

$$\mathrm{TEB}_n = \sum_{t=1}^{T} \mathbb{C}^t\left(\mathrm{ND}_n^t\right), \tag{5}$$

$$\mathbb{C}^t\left(\mathrm{ND}_n^t\right) = \begin{cases} \mathrm{GSP}^t \cdot \mathrm{ND}_n^t \cdot \Delta t; & \text{if } 0 \le \mathrm{ND}_n^t \le \mathrm{CDL}^t,\\ \left(\begin{matrix} \mathrm{GSP}^t \cdot \mathrm{CDL}^t \cdot \Delta t + \\ \left(\mathrm{ND}_n^t - \mathrm{CDL}^t\right) \cdot \beta^t \cdot \mathrm{GSP}^t \cdot \Delta t \end{matrix}\right); & \text{if } \mathrm{ND}_n^t > \mathrm{CDL}^t,\\ \mathrm{GBP}^t \cdot \mathrm{ND}_n^t \cdot \Delta t; & \text{if } \mathrm{ND}_n^t < 0, \end{cases} \tag{6}$$

where GSP^t and GBP^t are the t^{th} interval grid selling and buying prices, respectively. CDL^t represents the consumer demand limit (CDL) for the interval t, which the grid operator imposes to regulate the energy utilization at the consumer zone [34].

The consumer will be fined only when the total demand exceeds the utility-defined CDL. Hence, the electricity bill will be increased based on the CDL factor (β^t) of that interval (t). To limit the usage of the peak power plant and increase profit, the utilities are imposing higher energy prices during peak intervals. Further, the end-users are also incentivized by the utilities to export their surplus, especially during peak intervals. Hence, the prosumers are showing more interest in optimally altering their demand pattern to avail of possible utility benefits. This optimal scheduling problem can be analytically calculated considering the objective function as minimizing the overall debt of the electricity bill as expressed in

$$\min . \left(\mathrm{TEB}_n = \sum_{t=1}^{T} \mathbb{C}^t \left(\mathrm{ND}_n^t \right) \right), \tag{7}$$

subject to

$$\mathcal{S}_{l,n}^t = 0 \quad t \notin \Psi_{l,i} \forall l \in \mathrm{FL}, \tag{8}$$

$$\sum_{t=1}^{T} \mathcal{S}_{l,n}^t = \lambda_{l,n} \forall l \in \mathrm{FL}, \tag{9}$$

$$\mathfrak{B}_{C,n}^t + \mathfrak{B}_{D,n}^t + \mathfrak{B}_{F,n}^t = 1 \forall t \in T, \tag{10}$$

$$\mathrm{SoC}_{\min,n} < \mathrm{SoC}_{B,n}^t < \mathrm{SoC}_{\max,n}, \tag{11}$$

$$\mathrm{ES}_{\min,n} < \left| \mathrm{ES}_n^t \right| < \mathrm{ES}_{\max,n}, \tag{12}$$

where $\Psi_{l,n}$ is the user-predefined time for flexible load l and $\lambda_{l,n}$ is the number of intervals needed to fulfill the flexible load l task. Battery operational parameter $\mathrm{SoC}_{B,n}^t$ represents the feasible state of charge (SoC) at the beginning of the time interval t. The minimum and maximum SoC boundary values are represented as $\mathrm{SoC}_{\min,n}$ and $\mathrm{SoC}_{\max,n}$, respectively. Similarly, the battery power exchange minimum and maximum boundaries are given as $\mathrm{ES}_{\min,n}$ and $\mathrm{ES}_{\max,n}$, respectively.

The distribution grid operators face many operational challenges due to the high penetration of grid-connected small-scale RERs. Hence, the utilities regulate the end users' support by introducing a time-varying PIL. To utilize the maximum amount of generated renewable power and to increase the economic profit through energy export, the end-users are expected to optimally schedule their household appliances with due consideration to the dynamics in renewable energy generation. Accounting for this, the objective function defined in (7) is updated with the modified cost function as shown in

$$\mathbb{C}^t\left(\mathrm{ND}_n^t\right) = \begin{cases} \mathrm{GSP}^t \cdot \mathrm{ND}_n^t \cdot \Delta t; & \text{if } 0 \le \mathrm{ND}_n^t \le \mathrm{CDL}^t, \\ \left(\begin{array}{c} \mathrm{GSP}^t \cdot \mathrm{CDL}^t \cdot \Delta t + \\ \left(\mathrm{ND}_n^t - \mathrm{CDL}^t\right) \cdot \beta^t \cdot \mathrm{GSP}^t \cdot \Delta t \end{array} \right); & \text{if } \mathrm{ND}_n^t > \mathrm{CDL}^t, \\ \mathrm{GBP}^t \cdot \mathrm{ND}_n^t \cdot \Delta t; & \text{if } \left(-\mathrm{PIL}^t\right) \le \mathrm{ND}_n^t < 0, \\ \mathrm{GBP}^t \cdot \left(-\mathrm{PIL}^t\right) \cdot \Delta t; & \text{if } \mathrm{ND}_n^t < \left(-\mathrm{PIL}^t\right). \end{cases} \tag{13}$$

In addition to the constraints discussed from (8) to (12), the modified objective function is also subjected to the power injection constraint. The constraint imposes that the excess energy shared with the utility during a particular interval (t) should not exceed the utility's predefined power export limit of that interval (PIL^t). The hard constraint shall be mathematically expressed as follows:

$$\mathrm{ND}_n^t \ge \left(-\mathrm{PIL}^t\right), \quad \forall t \in T. \tag{14}$$

To overcome the limitation due to utility PIL, it is preferred that the end-users take part in TEMS. As part of TEMS, the LEM operator invites the end-users to trade the power (surplus generation/demand) within the locality. The expected net demand END_n^t of any participant n for the time interval t is computed as follows:

$$\mathrm{END}_n^t = \mathrm{ENFL}_n^t + \mathrm{EFL}_n^t + \mathrm{EES}_n^t - \mathrm{EDG}_n^t \forall n \in \mathcal{N}; \forall t \in \mathcal{T}, \tag{15}$$

where ENFL_n^t represents the expected nonflexible load demand for interval t, which will be decided based on the users' comfort and desire.

EFL_n^t and EES_n^t are the expected demands of flexible load and battery banks which can be obtained as the result of the optimal scheduling problem defined in (7) and (13). EDG_n^t is the expected power generation from in-house RERs, which can be predicted either by devising a dedicated algorithm or analyzing the local renewable resources variables such as solar irradiation, atmospheric temperature, and wind speed provided by the LEM operator. Based on the quoted demand of individuals, the LEM operator will clear the market so that all the localities and the grid participants would benefit.

End-users' active participation will build successful TEMS. Further, adopting suitable marketing strategies for LEM may increase the participants' interest in TEMS. The LEM should be designed with due consideration for participants' consumption patterns and utility dynamics in operational parameters (selling price, buying price, CDL, and PIL). However, the developed LEM should deliver adequate economic benefit to the participants without violating the utility power constraints. Different market strategies are proposed in the upcoming section to have a profitable power transaction between participants through TEMS.

3. Local Energy Market Pricing Strategies

The reliability of any LEM is merely based on the pricing strategy used to clear the market. Therefore, the proposed LEM shall be managed by either a utility or a third party in this work. However, the utility considers all the end-users participating in LEM as single users whose power demand varies continuously. Hence, the individual users' utility constraint parameters, such as CDL and PIL, should be aggregated. This study proposes two different market clearing strategies: average market clearing (AMC) and generation-to-demand ratio-based market clearing (GDRMC) strategies.

3.1. Average Market Clearing (AMC) Strategy. Let us consider a locality where all the users participate in LEM. Considering individuals' expected net demand, the aggregated locality demand (TDE^t), locality generation (TGE^t), and locality net demand (LND^t) for an interval t can be calculated as follows:

$$\begin{aligned}\mathrm{TDE}^t &= \sum_{N\in\mathcal{N}} \mathrm{END}_n^t \forall\, \mathrm{END}_n^t \geq 0,\\ \mathrm{TGE}^t &= \sum_{N\in\mathcal{N}} \left|\mathrm{END}_n^t\right| \forall\, \mathrm{END}_n^t < 0,\\ \mathrm{LND}^t &= \mathrm{TDE}^t - \mathrm{TGE}^t = \sum_{N\in\mathcal{N}} \mathrm{END}_n^t.\end{aligned} \tag{16}$$

The computed value of LND^t expresses the entire locality's grid dependency. Hence, two substrategies are proposed under AMC for different values of LND^t.

3.1.1. AMC Strategy-1: $\mathrm{LND}^t \geq 0$. When the locality's total demand is more than its total generation ($\mathrm{TDE}^t \geq \mathrm{TGE}^t$), the locality will act as an importer for utilities. The locality should depend on the grid to meet the excess demand in this scenario. However, LEM allows the exporter (having excess generation) and importer (having excess demand) to trade the surplus power with others for more profit than the utility. The exporter market clearing price ($\lambda_{\mathrm{sell}}^t$) for an interval t under AMC strategy-1 is expressed as follows:

$$\lambda_{\mathrm{sell}}^t = \frac{\mathrm{GSP}^t + \mathrm{GBP}^t}{2}. \tag{17}$$

Based on the computed price of $\lambda_{\mathrm{sell}}^t$, importer market clearing price (λ_{buy}^t) for an interval t under AMC strategy-1 can be calculated as follows:

$$\lambda_{\mathrm{buy}}^t = \begin{cases} \dfrac{\left(\mathrm{LND}^t \times \mathrm{GSP}^t\right) + \left(\lambda_{\mathrm{sell}}^t \times \mathrm{TGE}^t\right)}{\mathrm{TDE}^t} & \text{if } \left|\mathrm{LND}^t\right| \leq \left(N \times \mathrm{CDL}^t\right),\\[2ex] \dfrac{\left(N \times \mathrm{CDL}^t \times \mathrm{GSP}^t\right) + \left(\lambda_{\mathrm{sell}}^t \times \mathrm{TGE}^t\right)}{\left(N \times \mathrm{CDL}^t\right)} & \text{if } \left|\mathrm{LND}^t\right| > \left(N \times \mathrm{CDL}^t\right).\end{cases} \tag{18}$$

3.1.2. AMC Strategy-2: $\mathrm{LND}^t < 0$. When the total generation of a locality is more than the total demand ($\mathrm{TGE}^t > \mathrm{TDE}^t$), the locality will act as an exporter of utility. Further, the locality is allowed to share the surplus generation with the grid until the magnitude of LND^t reaches the aggregated value of all participants' PIL. The (λ_{buy}^t) under AMC strategy-2 is expressed as follows:

$$\lambda_{\mathrm{buy}}^t = \frac{\mathrm{GSP}^t + \mathrm{GBP}^2}{2}. \tag{19}$$

Based on the computed price of λ_{buy}^t, the $\lambda_{\mathrm{sell}}^t$ for an interval t under AMC strategy-2 can be calculated as follows:

$$\lambda_{\mathrm{sell}}^t = \begin{cases} \dfrac{\left(\mathrm{TDE}^t \times \lambda_{\mathrm{buy}}^t\right) + \left(\mathrm{LND}^t \times \mathrm{GBP}^t\right)}{\mathrm{TGE}^t}; & \text{if } \left|\mathrm{LND}^t\right| \leq \left(N \times \mathrm{PIL}^t\right),\\[2ex] \dfrac{\left(\mathrm{TDE}^t \times \lambda_{\mathrm{buy}}^t\right) + \left(N \times \mathrm{PIL}^t \times \mathrm{GBP}^t\right)}{\left(N \times \mathrm{PIL}^t\right)}; & \text{if } \left|\mathrm{LND}^t\right| > \left(N \times \mathrm{PIL}^t\right),\end{cases} \tag{20}$$

The proposed AMC strategy is simple; hence, the computational time for market clearing is less for any number of participants. Further, the AMC-based LEM is easily predictable, making the participants more interested in energy trading. However, the exporters (in AMC strategy-1) and importers (AMC strategy-2) have more profit irrespective of the amount of contribution in the locality net demand. To overcome this weakness and make profitable transactions for all participants, the generation-to-demand ratio is proposed as a market clearing approach in the following subsection.

3.2. GDR-Based Market Clearing Strategy. Considering the net demand of individual participants, the locality generation-to-demand ratio (GDR) for an interval t can be computed as follows:

$$\mathrm{GDR}^t = \frac{\mathrm{TGE}^t}{\mathrm{TDE}^t}. \quad (21)$$

The value of GDR^t decides the nature of locality with respect to utility as an importer $(\mathrm{GDR}^t < 1)$ or exporter $(\mathrm{GDR}^t > 1)$. Hence, two strategies are proposed under the generation-to-demand ratio market clearing (GDRMC) strategy.

3.2.1. GDRMC Strategy-1. When the locality acts as an importer for utility $(\mathrm{GDR}^t < 1)$, the market clearing price for exporters and importers of the locality can be computed as follows:

$$\begin{aligned}\lambda_{\mathrm{sell}}^t &= \frac{\mathrm{GSP}^t + \mathrm{GBP}^t\left(1 - \mathrm{GDR}^t\right)}{2},\\ \lambda_{\mathrm{buy}}^t &= \left(\lambda_{\mathrm{sell}}^t \times \mathrm{GDR}^t\right) + \left(\mathrm{GSP}^t\left(1 - \mathrm{GDR}^t\right)\right).\end{aligned} \quad (22)$$

The demand of individual importers highly influences the economic benefit of the individual participants in the proposed strategy. Further, quoting more demand in LEM may lead to nonprofitable trading. Hence, the proposed strategy will be used only when the net locality demand is maintained within the utility's defined locality demand limit. If the demand constraint is violated, the importers are restricted from sharing the excess demand in LEM. Considering this limitation, the proposed GDRMC strategy-1 is modified concerning the importer demand limit. The modified generation-to-demand ratio for an interval t is computed as follows:

$$\mathrm{MGDR}^t = \frac{\mathrm{TGE}^t}{N \times \mathrm{CDL}^t}. \quad (23)$$

Considering MGDR^t, the market clearing price for the exporter $(\lambda_{\mathrm{sell}}^t)$ and the importer $(\lambda_{\mathrm{buy}}^t)$ of an interval t can be calculated as follows:

$$\begin{aligned}\lambda_{\mathrm{sell}}^t &= \frac{\mathrm{GSP}^t + \mathrm{GBP}^t\left(1 - \mathrm{MGDR}^t\right)}{2},\\ \lambda_{\mathrm{buy}}^t &= \left(\lambda_{\mathrm{sell}}^t \times \mathrm{MGDR}^t\right) + \left(\mathrm{GSP}^t\left(1 - \mathrm{MGDR}^t\right)\right).\end{aligned} \quad (24)$$

3.2.2. GDRMC Strategy-2. When the value of GDR^t is greater than 1, the locality will act as an exporter concerning utility, and the market clearing prices for importers and exporters can be calculated as given in (25) and (26), respectively:

$$\lambda_{\mathrm{buy}}^t = \frac{\mathrm{GSP}^t - \mathrm{GBP}^t\left(1 - 1/\mathrm{GDR}^t\right)}{2}, \quad (25)$$

$$\lambda_{\mathrm{sell}}^t = \frac{\lambda_{\mathrm{buy}}^t + \mathrm{GBP}^t\left(\mathrm{GDR}^t - 1\right)}{\mathrm{GDR}^t}. \quad (26)$$

Consequentially, the utilities are imposing time-varying PIL limits to reduce operational difficulties. Hence, the exporters are constrained to trade their excess generation by considering the utility-defined locality net export limit. The modified GDR for the locality when the net export exceeds the utility limit can be computed as follows:

$$\mathrm{MGDR}^t = \frac{N \times \mathrm{PIL}^t}{\mathrm{TDE}^t}. \quad (27)$$

Subsequently, the market clearing prices for importers and exporters can be calculated as expressed in (28) and (29), respectively:

$$\lambda_{\mathrm{buy}}^t = \frac{\mathrm{GSP}^t - \mathrm{GBP}^t\left(1 - 1/\mathrm{GDR}^t\right)}{2}, \quad (28)$$

$$\lambda_{\mathrm{sell}}^t = \frac{\lambda_{\mathrm{buy}}^t + \mathrm{GBP}^t\left(\mathrm{MGDR}^t - 1\right)}{\mathrm{MGDR}^t}. \quad (29)$$

Considering different pricing strategies, the traded electricity bill of participant n during a trading interval t can be computed as follows:

$$\mathrm{TEB}_n^t = \begin{cases} \mathrm{ND}_n^t \cdot \lambda_{\mathrm{buy}}^t \cdot \Delta t; & \left\{ \begin{array}{l} \left\{ \begin{array}{l} \mathrm{ND}_n^t \geq 0 \\ \mathrm{TDE}^t \leq \left(N \times \mathrm{CDL}^t \right) \end{array} \right. \\ \text{or} \\ \left\{ \begin{array}{l} 0 \leq \mathrm{ND}_n^t \leq \dfrac{N \times \mathrm{CDL}^t}{N_I} \\ \mathrm{TDE}^t > \left(N \times \mathrm{CDL}^t \right), \end{array} \right. \end{array} \right. \\ \left[\begin{array}{c} \dfrac{N \times \mathrm{CDL}^t}{N_I} \cdot + \\ \lambda_{\mathrm{buy}}^t \left(\mathrm{ND}_n^t - \dfrac{N \times \mathrm{CDL}^t}{N_I} \right) \cdot \beta^t \cdot \mathrm{GSP}^t \end{array} \right] \cdot \Delta t; & \left\{ \begin{array}{l} \mathrm{ND}_n^t > \dfrac{N \times \mathrm{CDL}^t}{N_I} \\ \mathrm{TDE}^t > \left(N \times \mathrm{CDL}^t \right), \end{array} \right. \\ \mathrm{ND}_n^t \cdot \lambda_{\mathrm{sell}}^t \cdot \Delta t; & \left\{ \begin{array}{l} \mathrm{ND}_n^t < 0 \\ \mathrm{TGE}^t \leq \left(N \times \mathrm{PIL}^t \right) \end{array} \right. \text{or} \left\{ \begin{array}{l} -\dfrac{N \times \mathrm{PIL}^t}{N_E} \leq \mathrm{ND}_n^t < 0 \\ \mathrm{TGE}^t > \left(N \times \mathrm{PIL}^t \right), \end{array} \right. \\ -\dfrac{N \times \mathrm{PIL}^t}{N_E} \cdot \lambda_{\mathrm{sell}}^t \cdot \Delta t; & \left\{ \begin{array}{l} -\dfrac{N \times \mathrm{PIL}^t}{N_E} > \mathrm{ND}_n^t \\ \mathrm{TGE}^t > \left(N \times \mathrm{PIL}^t \right). \end{array} \right. \end{cases} \tag{30}$$

The proposed market strategies are developed based on the participants' quoted demand. The quoted electricity demand of individual participants merely depends upon the accurate prediction of RERs and the optimal scheduling of flexible loads. However, the user cannot maintain the quoted demand strictly for all the trading intervals due to sudden changes in end-users' requirements. Hence, false demand quotations may ruin the LEM's profitable power trading in TEMS. To overcome this issue, a trading agreement violation cost (Γ_n^t) is introduced for the calculation of the electricity bill. Further, the deviation in quoted demand may increase or decrease the trading electricity bill. The change in electricity bill is referred to as the deviation cost (DC_n^t). The values of Γ_n^t and DC_n^t for any user n during an interval t can be computed with due consideration to actual net demand (AND_n^t), quoted demand, market clearing prices, and false data penalty rate (δ^t) as shown in

$$\Gamma_n^t = \left| \left(\mathrm{AND}_n^t - \mathrm{END}_n^t\right) \cdot \frac{\lambda_{\mathrm{buy}}^t + \lambda_{\mathrm{sell}}^t}{2} \cdot \delta^t \right|, \tag{31}$$

$$\mathrm{DC}_n^t = \begin{cases} \left(\mathrm{AND}_n^t - \mathrm{END}_n^t\right) \cdot \lambda_{\mathrm{buy}}^t; & \text{if } \mathrm{AND}_n^t > 0 \quad \mathrm{END}_n^t > 0 \\ \left(\mathrm{AND}_n^t - \mathrm{END}_n^t\right) \cdot \lambda_{\mathrm{sell}}^t; & \text{if } \mathrm{AND}_n^t < 0 \quad \mathrm{END}_n^t < 0 \\ \left(\mathrm{AND}_n^t \cdot \lambda_{\mathrm{sell}}^t\right) - \left(\mathrm{END}_n^t \cdot \lambda_{\mathrm{buy}}^t\right); & \text{if } \mathrm{AND}_n^t < 0 \quad \mathrm{END}_n^t > 0 \\ \left(\mathrm{AND}_n^t \cdot \lambda_{\mathrm{buy}}^t\right) - \left(\mathrm{END}_n^t \cdot \lambda_{\mathrm{sell}}^t\right); & \text{if } \mathrm{AND}_n^t > 0 \quad \mathrm{END}_n^t < 0. \end{cases} \tag{32}$$

Considering the trading electricity bill, deviation cost, and agreement violation cost, the net electricity bill of a user during a trading interval can be computed as follows:

$$\mathrm{EB}_n^t = \mathrm{TEB}_n^t + \mathrm{DC}_n^t + \Gamma_n^t. \tag{33}$$

4. Simulation Study

The proposed market strategies are validated concerning various case studies to emphasize the significance of TEMS on the end-user's electricity bill savings.

4.1. Study Environment. The considered locality consists of ten residential prosumers actively participating in TEMS. Currently, residential buildings are furnished with a numerous modern electrical equipment to make life easier. The most common and essential appliances and their power ratings are given in Table 1 [35].

To lessen the dependency on the grid and improve electricity bill savings, residential consumers are recommended to build in-house RERs. Considering various resources, for instance, residential consumers highly prefer renewable power generation using rooftop solar PV and small wind turbines. Further, the residents are interested in battery storage to reduce the electricity bill by meeting essential demands during peak intervals [24]. The RERs and batteries are optimally sized with due consideration to the total investment cost, space availability, and intermittence in renewable resources as formulated in the author's previous work [35]. The variations in utility energy selling and buying prices over a month are depicted in Figure 2. For a better view of utility dynamics, per day variations in electricity prices are given in Figure 3. The utility CDL factor for crossing CDL is considered as 2.5 times the nominal cost. The false data penalty rate for violating the trading agreement (not supporting the grid with quoted generation/demand) is 0.2.

On account of the end-users' comfort and desire, the operation of various household appliances is optimally scheduled by solving the objective function defined in (7), subject to the constraints given in (8)–(12) and (14). Considering the individual user inside the studied locality, the optimal demand pattern and available generation from RERs over a month are shown in Figure 4.

4.2. Study Results. The economic analysis of individual participants is evaluated in the following cases: prosumers under the peer-to-grid (P2G) scheme without PIL (Case 1); prosumers under the P2G scheme with PIL (Case 2); prosumers under the P2P scheme with the AMC strategy (Case 3); and prosumers under the P2P scheme with the GDRMC strategy (Case 4). The participants' per day electricity bills for different cases are shown in Figure 5. To show the effectiveness of the proposed architecture, the study is extended for a period of one month and the monthly electricity bills for different cases are listed in Table 2.

In-house RER installation merely depends on the consumers' economic background and space availability. Few consumers in the locality may not afford it. However, those users can also actively participate in LEM as consumers and reduce their electricity bills significantly. To validate this, the simulation study has been extended to the locality in which 50% of the residential buildings are not installed with any additional energy resources. The monthly electricity bill of all the participants under different market cases is listed in Table 3.

Active participation and accurate prediction of expected electricity demand significantly increase the participants' profits. However, deviations in the quoted electricity demand and injecting false data will severely affect the electricity market. Hence, the market operators introduce trading agreement violation costs to regulate the participant's deviations from the quoted demand. To validate this, the case study is evaluated for a trading interval considering

Table 1: Household appliances.

S. no.	Load	Power (kW)	Type
1	Fan	0.10	NFL
2	Lighting	0.02	NFL
3	Television	0.25	NFL
4	Mobile and laptop charger	0.05	NFL
5	Air conditioner	1.0	NFL
6	Refrigerator	0.5	NFL
7	Cloth washer	0.8	FL
8	Cloth dryer	2.2	FL
9	Dish washer	1.5	FL
10	Well pump	1.2	FL
11	PHEV charging	2.3	FL

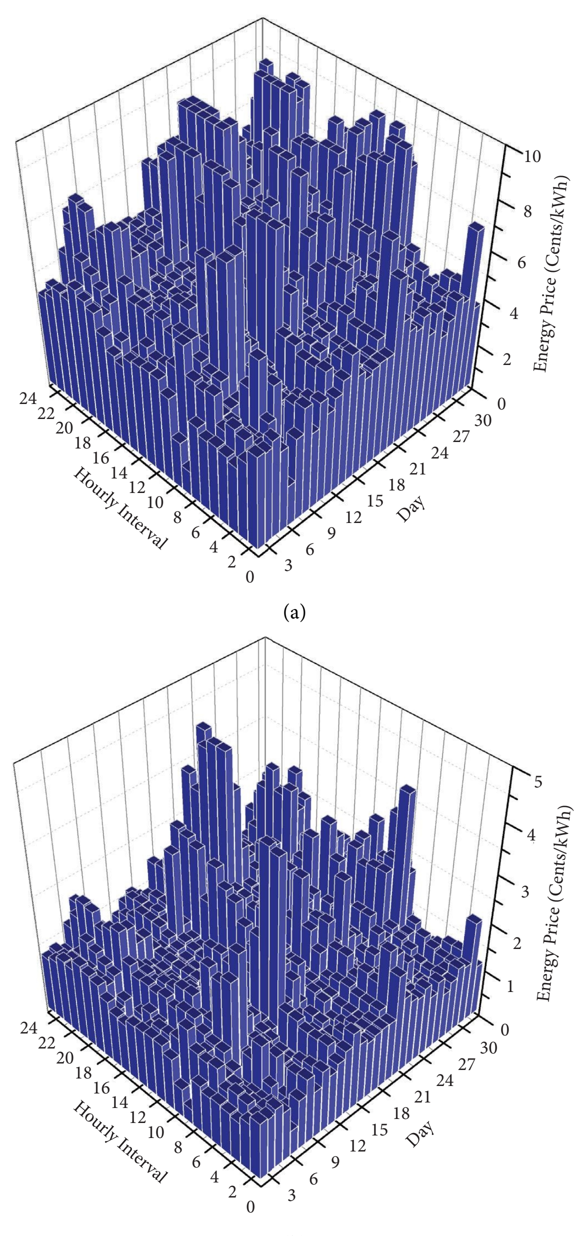

Figure 2: Utility monthly electricity price variation. (a) Selling price. (b) Buying price.

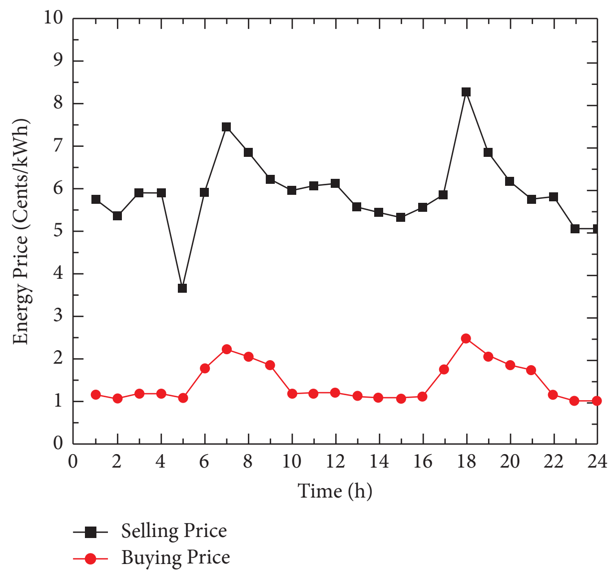

Figure 3: Utility energy price variation.

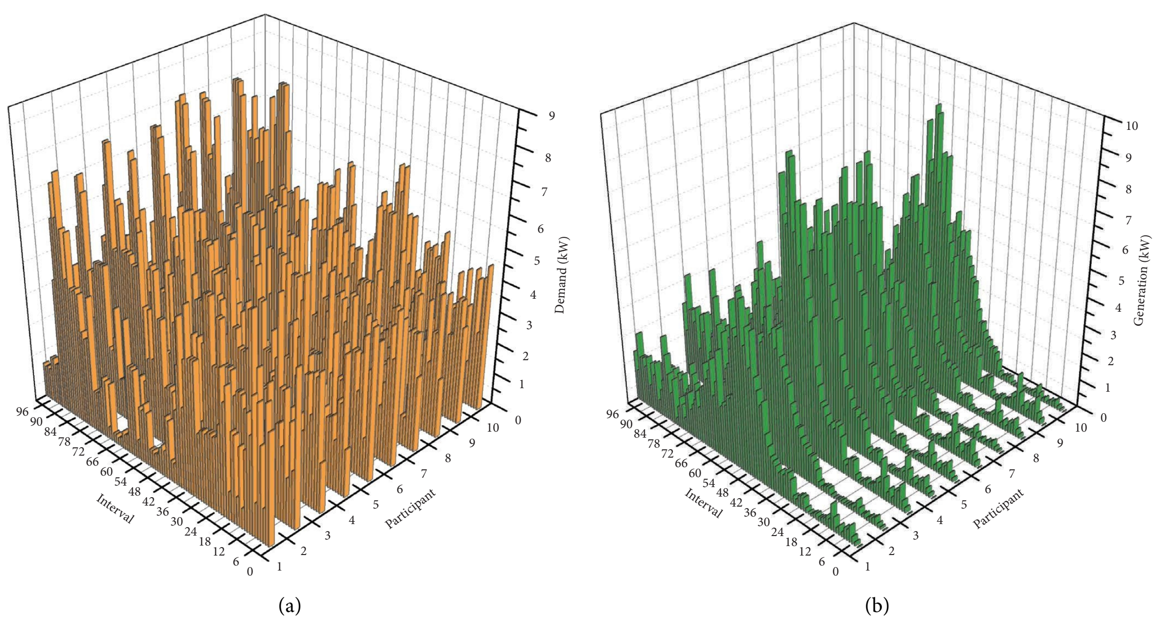

Figure 4: Monthly variations. (a) Optimal demand pattern. (b) Available generation.

different deviations, and the corresponding results are tabulated in Tables 4 and 5.

4.3. Discussions. The outcomes shown in Tables 2 and 3 express the economic significance of the transactive energy systems in the smart grid paradigm. Cases 1 and 2 are examined using the P2G scheme, whereas Cases 3 and 4 are evaluated using the P2P scheme. Furthermore, in Case 1, the participants saved more money on their electricity bills since the utility provides unconditional grid assistance. However, in order to address operational issues caused by the significant penetration of small scale in-house RERs, utilities are placing numerous constraints in the P2G system. Case 2 results show that implementing grid limits such as the PIL constraint has a detrimental impact on end consumers' electricity bills. Participants in P2P schemes using AMC (Case 3) and GDRMC (Case 4) approaches save significantly more than in P2G schemes (Case 2). Furthermore, the percentage reductions in electricity bill for the AMC and GDRMC schemes compared to the P2G scheme demonstrate the usefulness of the recommended market strategies. Participants can increase this proportion by optimizing the timing of domestic appliance use while considering end-user dynamics, power generation from in-house RERs, utility limits, and predicted market net demand. Aside from the

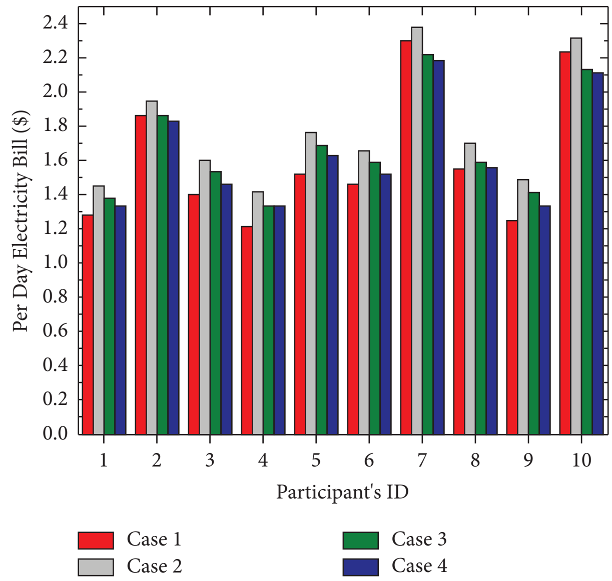

Figure 5: Participants' per day electricity bill.

Table 2: Participants' monthly electricity bill.

PID	Case-1	Case-2	Case-3		Case-4	
	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{S}_{\text{PID}}$ (%)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{S}_{\text{PID}}$ (%)
1	96.53	98.91	94.8	4.16	92.76	6.22
2	97.67	100.18	96.16	4.02	93.78	6.39
3	78.07	85.17	82.17	3.53	79.55	6.6
4	81.59	87.23	84.22	3.46	81.48	6.6
5	79.96	87.12	83.34	4.34	80.52	7.58
6	82.96	87.49	84.05	3.94	81.62	6.71
7	99.87	101.85	96.4	5.36	94.42	7.3
8	85.66	90.21	87.13	3.42	84.61	6.21
9	80.25	86.04	83.25	3.25	80.76	6.14
10	99.14	101.61	97.28	4.27	94.96	6.55

PID: participant's ID. $\mathscr{B}_{\text{PID}}$: participant's monthly electricity bill. $\mathscr{S}_{\text{PID}}$: percentage saving of electricity bill when compared to Case-2.

Table 3: Participants' monthly electricity bill.

PID	Case-1	Case-2	Case-3		Case-4	
	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{S}_{\text{PID}}$ (%)	$\mathscr{B}_{\text{PID}}$ (\$)	$\mathscr{S}_{\text{PID}}$ (%)
1	96.53	98.91	94.9	4.06	90.4	8.61
2	97.67	100.19	95.49	4.7	91.75	8.43
3	78.07	85.17	78.97	7.28	75.53	11.32
4	81.59	87.23	81.4	6.69	77.95	10.64
5	79.96	87.13	79.88	8.33	76.43	12.29
6	148.93	148.93	135.13	9.27	125.58	15.68
7	147.26	147.26	133.44	9.39	124.54	15.43
8	149.81	149.81	136.25	9.06	127.17	15.12
9	150.76	150.76	137.3	8.93	127.91	15.16
10	153.74	153.74	139.58	9.22	129.76	15.6

economic benefits, the recommended strategies protect end-users' privacy by supporting them in sharing just demand information.

The extended case study assumes that 50% of the community's participants do not have any in-house RERs, and the recommended techniques result in considerable

TABLE 4: Penalty analysis for fault data injection attack under the AMC strategy.

UEM	GSP = 5.4 cents/kWh GBP = 1.6 cents/kWh		LND = 4 kW CDL = 3 kW		LEM	λ_{sell}^{t} = 3.5 cents/kWh λ_{buy}^{t} = 4.4 cents/kWh	
PID	END (kW)	EEBill (cents)	AND (kW)	UEBill (cents)	TEBill (cents)	P-cost (cents)	TEB (cents)
1	1.5	6.6	1.7	9.18	7.48	0.24	7.72
2	−1	−3.5	−0.8	−1.28	−2.8	0.24	−2.56
3	1.5	6.6	1.5	8.1	6.6	0	6.6
4	2	8.8	2.5	13.5	11	0.6	11.6
5	−1.5	−5.25	0.5	2.7	2.2	2.37	4.57
6	2.5	11	1.5	8.1	6.6	1.19	7.79
7	0.5	2.2	0.8	4.32	3.52	0.36	3.88
8	−2	−7	−2	−3.2	−7	0	−7
9	−0.5	−1.75	−1.8	−2.88	−6.3	1.55	−4.75
10	1	4.4	1	5.4	4.4	0	4.4

EEBill: expected electricity bill under P2P scheme. UEBill: expected electricity bill under P2G scheme. TEBill: trading electricity bill; P-cost-agreement violation cost.

TABLE 5: Penalty analysis for fault data injection attack under the GDRMC strategy.

UEM	GSP = 5.4 cents/kWh GBP = 1.6 cents/kWh		LND = 4 kW CDL = 3 kW		LEM	λ_{sell}^{t} = 3.1 cents/kWh λ_{buy}^{t} = 4.2 cents/kWh	
PID	END (kW)	EEBill (cents)	AND (kW)	UEBill (cents)	TEBill (cents)	P-cost (cents)	TEB (cents)
1	1.5	6.3	1.7	9.18	7.14	0.22	7.36
2	−1	−3.1	−0.8	−1.28	−2.48	0.22	−2.26
3	1.5	6.3	1.5	8.1	6.3	0	6.3
4	2	8.4	2.5	13.5	10.5	0.55	11.05
5	−1.5	−4.65	0.5	2.7	2.1	2.19	4.29
6	2.5	10.5	1.5	8.1	6.3	1.1	7.4
7	0.5	2.1	0.8	4.32	3.36	0.33	3.69
8	−2	−6.2	−2	−3.2	−6.2	0	−6.2
9	−0.5	−1.55	−1.8	−2.88	−5.58	1.43	−4.15
10	1	4.2	1	5.4	4.2	0	4.2

electricity bill reductions for both prosumers and consumers. These findings support the viability of the proposed P2P energy market. Furthermore, the computations required by the suggested market strategies are straightforward for any number of players which makes the real-time implementation of LEMO simple. Finally, the penalty analysis findings in Tables Z and W demonstrate the impact of erroneous demand quotations on the electricity bill. Participants are penalized based on the percentage divergence from the real demand. Furthermore, the participants' misleading data have a significant influence on the market clearing parameters λ_{sell}^{t} and λ_{buy}^{t}. However, the participant is strongly penalized to make up for the economic loss. This expense can be used for operation and maintenance by the LEMO and/or grid operator. Even if any advanced computing technique precisely anticipates the predicted demand and generation of the participants, variations in the user demand pattern are unavoidable. Participants must reschedule battery operations depending on market conditions to overcome variances and thereby decrease penalty costs.

5. Conclusions and Future Scope

An optimal scheduling algorithm is proposed at the end-users' premises, considering the depreciation of the total electricity bill as the objective function. Considering the end-user's requirements, utility dynamics, and expected generation from the installed in-house RERs, the proposed algorithm assisted the end-user in controlling the operation of flexible loads and batteries. Further, the end-users are motivated through the transactive energy technique to share the surplus generation/demand with other participants in the community for a higher profit than the utility. To manage the local energy trading, a framework for the locality electricity market is also proposed with two strategies: an average market clearing strategy and a generation-to-demand ratio-based market clearing strategy. The proposed architectures are validated through various case studies considering ten residential participants. Compared to the P2G approach with utility-defined PIL, the AMC technique increases the community average savings in participants' monthly electricity bills by 3.97%. However, by using the

GDRMC approach, the average percentage savings is increased to 6.63%. Furthermore, the percentage savings for the community with 50% of participants who do not own any in-house RERs are 7.69% and 12.83% for AMC and GDRMC approaches, respectively. These findings highlight the significance of TEMS in improving end-user social welfare. Furthermore, the penalty analysis for fault data injection threats to provide the cyber security and reliability of the P2P energy market.

Since the recommended techniques anticipate cooperation from all players, the profit obtained by each member during every trading interval is restricted in relation to the community's net demand. When community demand exceeds generation, importers may not get significant economic gains from LEM. On the other hand, exporters may earn less when the generation is higher. In the future, as an extension of this work, TEMS shall be developed with more complex market clearing strategies to overcome the abovementioned issue. Besides, with the proposed centralized power management system, the third-party agent (LEMO) is required to coordinate the power balance between local generation and demand. Hence, a decentralized system can be incorporated to eliminate third-party intervention (LEMO) while implementing P2P power trading in a microgrid community.

Nomenclature

AMC: Average market clearing
CDL: Consumer demand limit
DSM: Demand side management
FiT: Feed-in tariff
FLs: Flexible loads
GDR: Generation-to-demand ratio
GDRMC: Generation-to-demand ratio-based market clearing
LEM: Local energy market
LEMO: Local energy market operator
NFLs: Nonflexible loads
PIL: Power injection limit
PID: Participant's ID
P2G: Peer-to-grid
P2P: Peer-to-peer
RERs: Renewable energy resources
RTP: Real-time pricing
SEMS: Smart energy management system
SoC: State of charge.
TEMS: Transactive energy management systems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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