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Framework of locality electricity trading system for profitable peer-to-peer power transaction in locality electricity market

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Abstract: This paper proposes an architecture of locality electricity market (LEM) for peer-to-peer (P2P) energy trading among a group of residential prosumers (consumers and producers) with renewable energy resources, smart meters, information and communication technologies, and home energy management systems in a smart residential locality. Prosumers may sell(buy) their excess generation(demand) in LEM at a profitable prices compared to the utility prices in P2P fashion. In order to manage the trading in LEM, a common portal named as locality electricity trading system (LETS) is introduced. The purpose of LETS is to prepare a trading agreement between the participants by fixing a price for every deal based on the quoted price and day-ahead power trading schedule given by the participants. An enhanced intelligent residential energy management system (EIREMS) is proposed at the prosumers' premises to enable their participation in the day-ahead energy trading process and in real-time scheduling of schedulable loads and battery for reducing the electricity bill with due consideration to the operational constraints and LETS agreement. The performances of proposed LETS and EIREMS are validated through a few case studies on a locality with ten prosumers. The proposed methodology endorses marginal economic benefit for all the participants.

1 Introduction

1.1 Background and motivation

Recent advancements in electronics, information and communication technologies help us to upgrade the existing electric power grid as a smart grid [1]. Under the smart grid environment, power system operations are effectively monitored and controlled through intelligent electronic devices that are featured with a two-way cyber-secure communication facility. Demand-side management (DSM) is an encouraging approach adopted by many utilities to balance generation and demand under the smart grid environment. In DSM, the utilities enforce the consumers to alter/reduce their demand by imposing incentives/penalties [2]. Demand response (DR) program is a part of the DSM [3] in which utility provides an opportunity to the consumers to reduce their electricity bill. Nowadays, few utilities are following real-time pricing (RTP) and maximum demand limit (MDL) so as to reduce the peak-to-average ratio [4]. In RTP, the utility energy price varies at different intervals of a day and is announced just before an interval begins. In the MDL scheme, the consumers have to pay a higher price for drawing power beyond MDL. The depletion of conventional resources and the increase in usage of electricity make the utilities to focus on renewable power generation (RPG) units as an alternative way to handle the escalating electric demand. However, grid integration of large-scale RPG units suffers from various installation and operational constraints. In addition to this, the utilities have to manage the intermittent nature of renewable resources in real-time. Therefore, the utilities motivate the residents to install small scale renewable power sources to increase the self-sustainability and hence to reduce their electricity bill [5].

Nowadays, the home energy management system (HEMS) effectively manages the smart and non-smart household appliances and power from RPG units to minimise the electricity cost under the smart grid paradigm [6]. If excess power is available, it can be sold to the grid. Consequentially, the utility may face operational complexities if a large number of prosumers export their excess power to the grid. In order to avoid such circumstances, the utility proposes a power injection limit (PIL). The additional available power beyond the PIL shall be either stored in an energy storage device such as a battery for future use or dissipated through a dump load by the prosumers [7]. Costanzo *et al.* [8] developed a load management model to improve the reduction in electricity bills by maintaining the total demand under utility defined MDL. Pipattanasomporn *et al.* [9] presented an intelligent home energy management system, which schedules the households based on their preset priority. Adika and Wang [10] developed a prosumer-based DSM scheme to increase the profit by encouraging them to participate in the electricity market. Wang *et al.* [11] proposed a robust optimisation model to tackle the intermittent nature of PV power generation in the household demand schedule. Mohsenian-Rad *et al.* [12] framed a game for energy consumption scheduling of individual consumers. Chen *et al.* [13] formulated a game for the DSM program based on the energy consumption pattern of consumers and electricity billing. Chai *et al.* [14] proposed a new DR management scheme with multiple utilities and the model was developed with a two-level game approach. Maharjan *et al.* [15] proposed a Stackelberg game between the electric utility companies and end consumers to increase the economic profit of utility and reduce the electricity bill of end-user. Following this, various game-theory-based DR models were reported in the literature [16–18]. La *et al.* [19] presented a market-based mathematical algorithm for power management between intelligent buildings.

This is the background of DSM and DR implementations under the peer-to-grid (P2G) paradigm. In P2G, the prosumers always depend upon the utility to sell their excess power and hence the installation capacity of an in-house RPG is restricted by PIL and hence the pay-back period is more. It is anticipated that the economic profit of the prosumers may increase if the available power beyond PIL is traded with neighbouring consumers. Hence, the locality electricity markets at the distribution side of the power system network motivate and lift-offs a new paradigm shift from DR to transactive energy (TE) under the P2P paradigm.

1.2 Relevant literature review

The trading of energy between prosumers is called peer-to-peer (P2P) energy trading. Wang *et al.* [20] proposed a game-theory based model for energy trading in the smart grid. Cintuglu *et al.*

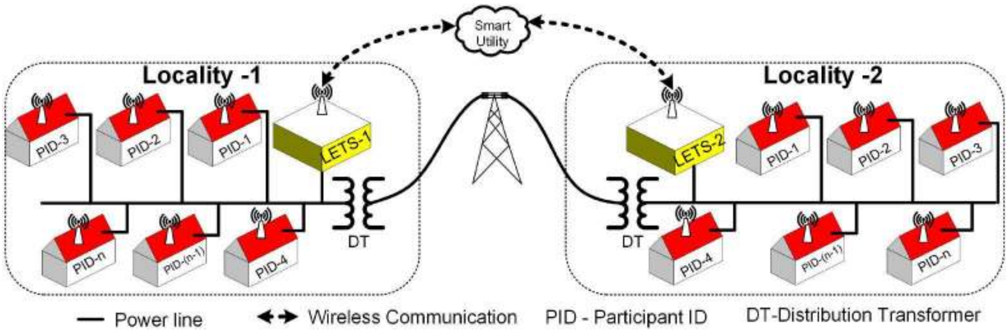

Fig. 1 *Smart localities for electricity trading*

[21] proposed a reverse auction model using game-theory for implementing energy sharing among prosumers under a competitive market environment. Liu *et al.* [22] presented an optimisation to improve the usage of power from renewables and to minimise the overall energy cost while implementing P2P energy trading among neighbouring microgrids at the distribution side considering practical constraints. Long *et al.* [23] proposed different market-clearing mechanisms for P2P energy sharing among prosumers. Kang *et al.* [24] proposed the P2P energy trading model among PHEVs under a smart grid environment using consortium blockchain. Khorasany *et al.* [25] presented a TE market platform for P2P energy trading among a group of prosumers and consumers; the market-clearing mechanism is designed using an auction approach. Alam *et al.* [26] proposed the first optimal model to integrate DSM with P2P energy trading to minimise household energy cost. Liu *et al.* [27] proposed an energy trading model for microgirds of P2P prosumers using the supply-to-demand ratio (SDR) mechanism, in which the internal prices are the function of SDR. The drawback of this model is the convergence problem, which affects DR. Ning *et al.* [28] presented a non-cooperative bidding strategy among microgrids to raise microgrids' profit and renewable source utilisation while implementing P2P energy trading. Thakur *et al.* [29] proposed a blockchain-based P2P energy trading platform using double auctions. Lezama *et al.* [30] presented an integrated TE system for implementing P2P energy trading to reduce energy costs in local electricity markets. Paudel *et al.* [31] proposed a game-theory based model for P2P energy trading between the prosumers in a residential community. Wang *et al.* [32] developed an optimisation model to implement P2Penergy trading using IBM Hyperledger blockchain-based architecture. Baroche *et al.* [33] presented a P2P electricity market with network charges while implementing P2P energy trading using a game-theoretic approach. Khorasany *et al.* [34] presented a market platform for P2P energy trading under a TE environment using the auction-based approach. Morstyn *et al.* [35] proposed bilateral contract networks as a scalable market design for P2P energy trading; this ensures the real-time balance between demand and generation and reduces the energy cost using multi-agent systems. Sorin *et al.* [36] presented a P2P market structure for multi-bilateral trading with product differentiation using a consensus-based approach. Baez-Gonzalez *et al.* [37] presented P2P energy exchange structures between prosumers in the same microgrid using continuous double auctions. Morstyn and McCulloch [38] proposed the P2P energy market platform based on the multi-class energy management system. This mechanism ensures data privacy, scalability, reduced energy cost. Guerrero *et al.* [39] proposed a methodology to assess the impact of P2P energy trading on network constraints using blockchain technology. Mihaylov *et al.* [40] proposed the P2P energy trading model using blockchain. Cryptocurrencies like bitcoin inspire the retail electricity market to create a decentralised system while implementing P2P energy trading in microgrids [29, 41–45].

1.3 Contributions

The aforementioned literature did not consider the categorisation of loads based on interruptibility and schedulability, modelling of expected power demanded by household appliances to predict the day-ahead load demand, and the impact of the level of participation of prosumers in trading on the economic benefit of the individual and the group of prosumers. In this study, the loads are modelled properly and the dynamics of non-schedulable loads are considered while implementing the P2P energy trading under the TE paradigm. A locality electricity trading system (LETS) is proposed for enabling power trading between residents through a locality electricity market (LEM). In the proposed method, a group of prosumers cooperates with each other by trading their excess generation/demand to minimise the grid dependency of the entire locality and reduce their energy bills. Based on the individual's energy price and available power for trading, the LETS develops a trading agreement between the participants. An enhanced intelligent residential energy management system (EIREMS) is developed to enable the residents to participate in LEM. Further, the EIREMS schedules the schedulable loads in real-time while considering the non-schedulable load's demand, utility price and MDL variations, available renewable energy and trading agreement with others. The electrical connections of distribution microgrids between the utility and residents are depicted in Fig. 1. Since all the participants in the locality cooperate with each other, the smart utility considers the entire locality as a single prosumer. The PIL of the entire locality (APIL) is computed by aggregating the PIL of all the prosumers. Hence, the prosumers are economically benefited by exporting power to the utility until the net export of locality reaches APIL. LETS instructs the prosumers to limit the power export to the grid when the net export exceeds APIL. Rescheduling the operation of households, reducing the power extraction from renewable resources and finally using the dump loads are recommended methods to limit the power exported to the smart utility.

The major contributions of this paper are as follows:

i. Presenting an architecture of EIREMS at the participants' premises to enable them to participate in the locality electricity market.
ii. Presenting an iterative day-ahead demand scheduling using a binary genetic algorithm as an optimisation tool to minimise the electricity bill while considering the variations in aggregated locality electricity net demand.
iii. Presenting a real-time demand scheduling for household appliances while considering the dynamics of non-schedulable loads, the comfort of the user, renewable power generation availability, variations in utility parameters (MDL and PIL) and day-ahead power trading agreement with others.

2 Architecture of the proposed system

The household appliances of the residential consumers are categorised based on the interruptibility and schedulability as non-interruptible and non-schedulable loads (NINSLs), interruptible and non-schedulable loads (INSLs), and schedulable loads (SLs). A NINSL has to provide its service as soon as the user switches it ON. The entertainment loads such as television, home theatres, home decorators and essential loads such as fan, light and mobile/laptop charger are under this category. The temperature-controlled households are classified under the INSL category. These loads need to maintain the operating temperature around the setpoint

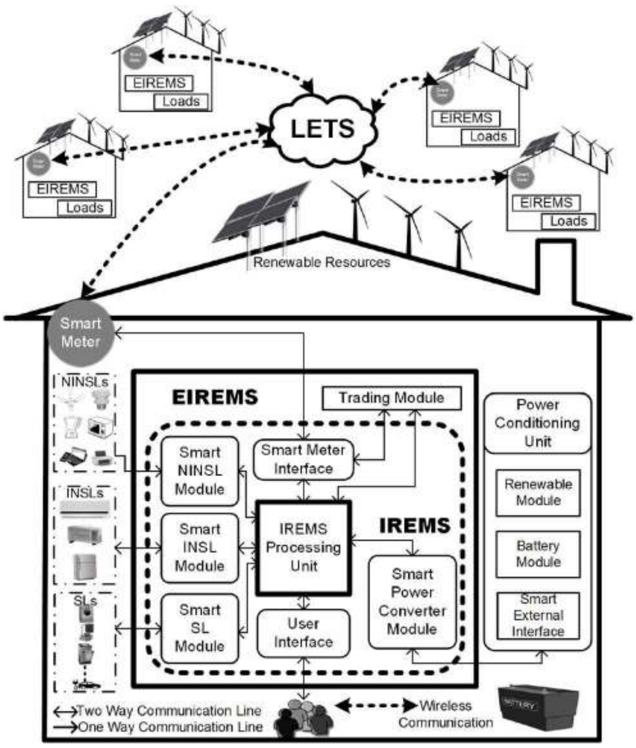

Fig. 2 *Architecture of proposed EIREMS*

value assigned by the user. When the difference between the actual and setpoint values is beyond the manufacturer's defined tolerance limit, the INSL starts to consume its rated power in order to reduce the difference. Air-conditioner, refrigerator and space heater are a few examples of INSL. The third category of loads, SLs, has a prefixed time span to complete the task. Washing machine, dishwasher, well pump, plug-in hybrid electric vehicle (PHEV) and food grinder are under this category. The boundaries of the time span of an SL are load starting interval (β_l) (in which the particular SL l is added in scheduling) and load ending interval (η_l) (on or before which interval the task of SL l should be completed). The artificial intelligence system of modern SLs helps to predict the number of intervals (Ω_l) required to complete a particular task (by SL l) from the initial conditions such as existing water level in the overhead tank for smart well pump operation and weight of cloths inserted into a smart washing machine. The user has to maintain the relationship $\eta_l - \beta_l \geq \Omega_l$ while assigning the boundary of the time span for the operation of SL. The SLs are further classified as non-interruptible SLs (NISLs) and interruptible SLs (ISLs). A NISL should operate continuously once it starts its service, whereas an ISL can operate either continuously or discontinuously in the given time span. NISL and ISL are distinguished by its pre-emptive status (ρ), it is 1 for NISL and 0 for ISL. Moreover, as discussed in Section 1, residential consumers have recently been focusing on the installation of small-scale renewable power generation units such as photovoltaic (PV) systems and small wind turbines for being self-sustained and to reduce the electricity bill. Further, energy storage devices such as a battery are preferred by several consumers for tackling the intermittency in renewable power generation and providing power backup.

The architecture of the proposed EIREMS is shown in Fig. 2, in which the IREMS presented in [7] is a sub-system. IREMS consists of smart NINSL module, smart INSL module and smart SL module to facilitate the transfer of data and control signals between the processing unit and NINSLs, INSLs and SLs, respectively. Further, it has a smart meter interface and a user interface. The IREMS receives the timely updates of utility parameters through the smart meter interface. The smart meter has two-way communication with the utility. Smart NINSL module aggregates demand of all NINSLs and deliver an alert message when the total NINSLs demand exceeds the consumer set limit. Smart INSL module collects INSL parameters such as set point temperature, tolerance limit, rated power, standby power, and user status of the load (switch ON/OFF) from all the INSLs. Further, it delivers the operational instruction (RUN/STAND-BY) generated by the processing unit to INSLs. Smart SL module obtains the information like load initialisation interval, load dead interval, computational intervals and preemptive status from all SLs and delivers the control signals to SLs as per the instruction received from the processing unit. The user interface present in the IREMS reads the maximum limit of power consumption by NINSLs and extended tolerance limits for INSLs decided by the user. Moreover, the user interface can be used to display warning messages and other information such as electricity bills, power consumption by different kinds of loads. However, the functioning of the smart power converter module is extended to transfer the information about power generation from renewable sources to IREMS processing unit. Using this real-time information and the past history data, IREMS predicts the possible renewable power generation of upcoming intervals. Considering the present and predicted renewable power, IREMS schedules the operation of SLs and batteries.

IREMS does not control any NINSL because time scheduling of a NINSL may disturb the comfort of the user. The smart NINSL module of IREMS aggregates the demand of all NINSLs and delivers an alert message whenever this demand exceeds the limit set by the user. The total demand by all NINSLs is taken into account for energy trading and effective scheduling of other loads by IREMS. The smart INSL module collects the operational parameters and status of all INSLs and delivers the appropriate instruction (run/stand-by) generated by IREMS processing unit to individual INSL. The smart SL module gathers the operational parameters of SLs (β_l, η_l, Ω_l, ρ_l and power rating) and delivers the control signal (ON/OFF) to individual SL. The smart power converter module stores the battery parameters such as ampere-hour rating, voltage rating, state-of-charge (SoC), charging and discharging current boundary limits. Further, it controls the battery operations through a power conditioning unit and updates the available renewable power generation in real-time. The IREMS processing unit computes the optimal schedule of SLs and battery to achieve the objective of minimum electricity bill and delivers the control instructions to smart SL and smart power converter modules.

3 Problem formulation

3.1 Day-ahead scheduling

3.1.1 Participant's day-ahead trading strategy: Every prosumer in a locality has an objective to reduce his/her daily expected electricity bill (EEB) payable to the utility by sharing his/her own demand and generation with other prosumers of the locality by participating in the locality electricity market. However, the trading process will be successful only if the total locality expected net demand (LEND) is minimised. The positive value of minimised LEND indicates that the locality has excess demand, which has to be drawn from the utility. The negative value of minimised LEND indicates that the locality has excess generation, which has to be fed to the utility grid. Hence, depending on the magnitude and sign of LEND, the participants may increase or decrease their individual net demand during trading. This ensures the self-sustainability and individual profit of the participants of the locality. This scenario is formulated mathematically as a multi-objective optimisation problem. The parameters such as operating status of SLs, mode of operation and power exchange of battery are chosen optimally while considering the user's comfort and operational constraints of households. This day-ahead optimal demand scheduling problem is solved using a genetic algorithm. The mathematical representation of the objective function is given as

$$\text{minimize}\left(w_1 * \overline{\text{EEB}_n} + w_2 * \left|\overline{\text{LEND}}\right|\right) \tag{1}$$

where w_1 and w_2 are the weighting factors. $\overline{\text{EEB}_n}$ and $\overline{\text{LEND}}$ are normalised values of $\text{EEB}_{(n,\Theta)}$ and $\text{LEND}_{(\Theta)}$, respectively, with respect to the chosen maximum values attained during the past history of days. All the participants simultaneously perform this optimal scheduling process and export their trading schedule to LETS. Based on the updated results, the scheduling process is repeated on a trial basis until a convergence criterion is met, hence the trial count Θ is used. The necessary condition for assigning values for the weighting factors is $w_1 + w_2 = 1$. The total EEB of a day for the participant $n(n \in \mathcal{N} \triangleq [1, 2, \ldots, N])$ (N is the maximum number of participants in the locality) in the trial Θ is expressed as

$$\text{EEB}_{(n,\Theta)} = \sum_{t=1}^{T} \left(\mathbb{C}_U^t\left(\left(1 - \vartheta_n^t\right) * \text{EP}_{(\text{Net},n)}^t\right) + \mathbb{C}_P^t\left(\text{TP}_{(n,\Theta)}^t\right)\right) \tag{2}$$

where $\mathbb{C}_U^t\left(\left(1 - \vartheta_n^t\right) * \text{EP}_{(\text{Net},n)}^t\right)$ and $\mathbb{C}_P^t\left(\text{TP}_{(n,\Theta)}^t\right)$ are the price functions of the utility and prosumer, respectively, during the trading interval $t(t \in \mathcal{T} \triangleq [1, 2, \ldots, T])$ (T represents the maximum number of intervals in a day). The participant power trading schedule (PPTS) expresses the trading between participant n and other participants in the locality. Each element of PPTS, the trading power during the interval t is computed as

$$\begin{gathered}\left(\text{TP}_{(n,\Theta)}^t \in \text{PPTS} \overset{\Delta}{=} [\text{TP}_{(n,\Theta)}^1, \text{TP}_{(n,\Theta)}^2, \ldots, \text{TP}_{(n,\Theta)}^T]\right) \\ \text{TP}_{(n,\Theta)}^t = \vartheta_n^t * \text{EP}_{(\text{Net},n,\Theta)}^t\end{gathered} \tag{3}$$

where $\text{EP}_{(\text{Net},n,\Theta)}^t$ is the sum of expected net demand of all households during the interval t for participant n and it is calculated as

$$\begin{aligned}\text{EP}_{(\text{Net},n,\Theta)}^t = \text{EP}_{(\text{NINSL},n)}^t + \text{EP}_{(\text{INSL},n)}^t + \text{EP}_{(\text{SL},n,\Theta)}^t \\ + \text{EP}_{(B,n,\Theta)}^t - \text{EP}_{(\text{RPG},n)}^t\end{aligned} \tag{4}$$

where $\text{EP}_{(\text{NINSL},n)}^t$, $\text{EP}_{(\text{INSL},n)}^t$, $\text{EP}_{(\text{SL},n,\Theta)}^t$, $\text{EP}_{(B,n,\Theta)}^t$ and $\text{EP}_{(\text{RPG},n)}^t$ are the expected total demand of NINSLs, INSLs, SLs, battery and expected renewable power generation, respectively, of participant n during the interval t. ϑ_n^t is an user-defined power-sharing factor. This factor is introduced for effective, profitable and secure trading. The expected total demand of different households is computed as follows: As discussed in the architecture section, EIREMS cannot control the NINSLs operation and hence all NINSLs are aggregated and considered as a single load whose demand is varying continuously. Further, a participant may arrive at his/her day-ahead NINSL demand schedule based on the expected comfort and desire to use NINSLs and also by using the demand schedules of previous days. The expected demand for NINSLs for participant n during the interval t is obtained as

$$\text{EP}_{(\text{NINSL},n)}^t = \eta^t * P_{(\text{NINSL},n,\text{Avg})}^t \tag{5}$$

where η^t is the user-defined comfort factor and $P_{(\text{NINSL},n,\text{Avg})}^t$ is similar day average demand of NINSLs over a user-defined number of weeks during the interval t. The expected total demand for INSLs for participant n during the interval t is expressed as

$$\text{EP}_{(\text{INSL},n)}^t = \sum_{a=1}^{A_n} \left(\text{ex}_a^t * P_{(\text{INSL},a)}\right) \tag{6}$$

where ex_a^t describes the expected operating status ($\text{ON} = 1, \text{OFF} = 0$) of the INSL a ($a \in \mathcal{A}_n \triangleq [1, 2, \ldots, A_n]$) during the interval t and A_n is the maximum number of INSLs in residence. The power rating corresponding to INSL a is $P_{(\text{INSL},a)}$. The expected operating status of an INSL is influenced by variations in weather conditions and the availability of people in residence from time to time. The expected total demand for SLs of a participant n is expressed as

$$\text{EP}_{(\text{SL},n,\Theta)}^t = \sum_{b=1}^{B_n} \left(\text{es}_{(b,\Theta)}^t * P_{(\text{SL},b)}\right) \tag{7}$$

where $\text{es}_{(b,\Theta)}^t$ is the expected operating status ($\text{ON} = 1, \text{OFF} = 0$) of the SL b ($b \in \mathcal{B}_n \overset{\Delta}{=} [1, 2, \ldots, B_n]$) during the interval t and B_n is the maximum number of SLs in residence. The rated power of SL b is $P_{(\text{SL},b)}$. Perfection in the computation of the expected total demand of SLs can be obtained if the number of SLs to be operated in the following day and their time span of operation are decided in prior. Further, this would lead the participant to attain more profit in the trading process. Incorporating the battery demand pattern into the net expected demand would definitely improve the participant energy trading strategy. The mode of operation and power exchange of battery in any interval depends predominantly on the available RPG and utility parameters such as electricity price, MDL and PIL. The expected battery net power is computed as

$$\text{EP}_{(B,n,\Theta)}^t = \text{eb}_{(\Theta)}^t * \left(\text{EBP}_{(\Theta)}^t\right) \tag{8}$$

where $\text{EBP}_{(\Theta)}^t$ is the net expected battery power exchange and $\text{eb}_{(\Theta)}^t$ is the mode of operation of battery during the interval t and is expressed as

$$\text{eb}_{(\Theta)}^t = \begin{cases} -1 & \text{Discharging} \\ 0 & \text{Floating} \\ 1 & \text{Charging} \end{cases} \tag{9}$$

The expected renewable power generation by the participant n during the interval t is calculated as

$$\text{EP}_{(\text{RPG},n)}^t = \text{EP}_{(\text{PV},n)}^t + \text{EP}_{(\text{WT},n)}^t \tag{10}$$

where $\text{EP}_{(\text{PV},n)}^t$ and $\text{EP}_{(\text{WT},n)}^t$ are the expected solar PV and wind power generation during the interval t, respectively. The solar power generation is depending on the available amount of solar irradiation and ambient temperature with respect to time t, and it is calculated using the following equations:

$$\text{EP}_{(\text{PV},n)}^t = D_{\text{PV}}\, P_{\text{STC}}\left(\frac{E_A^t}{E_{\text{STC}}}\right)\left(1 + \left(T_C^t - T_{\text{STC}}\right)C_T\right) \tag{11}$$

$$T_C^t = T_A^t + \left(\frac{\text{NOCT} - 20}{0.8}\right) * E_A^t \tag{12}$$

where $\text{EP}^t_{(\text{PV},n)}$ is the output power in kW, D_{PV} is the de-rating factor of solar panel, P_{STC} is the PV power (kW_p) at standard test condition (STC), E_A^t is the averaged solar irradiation in kW/m^2 during interval t. E_{STC} is the solar irradiation at STC ($1\,\text{kW/m}^2$), T_C^t is the PV cell temperature during interval t in °C, T_{STC} is the temperature at STC in °C, C_T is the PV cell temperature coefficient, NOCT is the normal operating cell temperature in °C and T_A^t is the averaged ambient temperature during interval t in °C. The total expected wind power generation is highly depending on wind speed, and it is calculated using the following equations:

$$\text{EP}^t_{(\text{WT},n)} = 0.5\rho A_w (\nu^t)^3 C_p \tag{13}$$

where $\text{EP}^t_{(\text{WT},n)}$ is the power generated (kW) by wind turbine during the interval t, air density (kg/m^3) is ρ, swept area (m^2) is A_w, ν^t is the averaged wind velocity (m/s) during the interval t and C_p is the power coefficient. The accuracy of the expected renewable power generation relies completely on the precise prediction of weather in the locality. Weather prediction can be done either by the individual participant or by the LETS and communicated to the participants through a smart meter. The computation of expected renewable power generation is essential and plays a vital role in the success of the trading process. In order to reduce the complexity, the present work assumes that weather prediction is performed by the LETS using an artificial neural network (ANN) [46, 47]. The other objective of the participant, which is minimising the LEND, is expressed as

$$\text{LEND}_{(\Theta)} = \sum_{t=1}^{T} \left[\text{TP}^t_{(n,\Theta)} + \text{ALD}^t_{(\Theta-1)} - \text{TP}^t_{(n,\Theta-1)}\right] \tag{14}$$

where $ALD^t_{(\Theta-1)}$ is the aggregated locality net demand during the interval t $\left(\text{ALD}^t \in \text{ALDS} \overset{\Delta}{=} [\text{ALD}^1, \text{ALD}^2, \ldots, \text{ALD}^T]\right)$ and it is computed by LETS using (15).

In order to manage the trading between participants by minimising the objective (14), every participant has to update his/her day-ahead PPTS to LETS simultaneously. The profit of every participant in LEM merely depends upon the individual cooperation with others. Every participant should be aware of the market strategy of LETS before announcing his/her bidding price because the allocation of market share to every participant by LETS is highly influenced by the participant's quoted bidding price. Considering the social benefit and reliable market operation, LETS permits the participants to announce their energy prices only once. However, LETS helps the participants by providing the history information of the price and PPTS of all the participants. The steps followed by an individual participant during day-ahead trading are presented in Algorithm 1.

Algorithm 1: Steps followed for P2P energy trading in LEM

1. Transmit the day-ahead participant's power trading schedule and bidding price set of participant n to LETS: $\{\text{PPTS}^{(0)}_{(n)}, \Theta \leftarrow 0; P_b\}$.
2. After receiving the day-ahead PPTS from all participants, LETS calculates the day-ahead ALDS, SALDS and broadcast this information to all participants: $\{\text{ALDS}^{(0)}_{\text{LEM}}, \text{SALDS}^{(0)}_{\text{LEM}}; \Theta \leftarrow 0\}$.
3. After receiving the day-ahead ALDS, SALDS from LETS, participants perform the optimisation to minimise the electricity bill and updates the PPTS.
4. Update the trial count: $(\Theta + 1) \leftarrow \Theta$.

   Repeat steps 1–3 until convergence

   Convergence criteria:

   $$\left|\text{SALDS}^{(\Theta)}_{\text{LEM}} - \text{SALDS}^{(\Theta-1)}_{\text{LEM}}\right| < \varepsilon \,\Big|\, \Big|\Theta = \Theta_{\max}$$

   $$\text{SALDS}^{(\Theta)}_{\text{LEM}} = \sum_{t}\sum_{n=1}^{N} \text{TP}^t_{(n,\Theta)} \quad t \in T_g$$

   where $\text{SALDS}^{(\Theta)}_{\text{LEM}}$ is the sum of aggregated locality net demand schedule (ALDS) of LEM in all T_g during the trial Θ. T_g is a set of intervals with a considerable amount of renewable power generation. In the present study T_g includes all the intervals from 08 AM to 06 PM, and $\Theta_{\max}$ is the maximum number of trial counts.
5. Calculate the profitable trading price using (18), and day-ahead EEB using (2) over finalised PPTS of participant n.

3.1.2 LETS day-ahead trading strategy: A LETS is a non-profited, intermediate market operating agent, it will manage the trading between the participants in the locality electricity market. The utility distribution system operators may also act as LETS. The functions of LETS are collecting day-ahead participants power trading schedule and corresponding bidding price information, computing day-ahead ALDS for entire locality and broadcasts this information to all participants, prioritising participants based on their individual quoted price and demand to calculate the market-clearing price, and developing the trading agreement. In each trial of the trading process, LETS receives the participants power trading schedule from all the participants and computes the ALDS. The aggregated locality net demand during the interval t at the end of the trial Θ is calculated using the following equation:

$$\text{ALD}^t_{(\Theta)} = \sum_{n=1}^{N} \text{TP}^t_{(n,\Theta)} \tag{15}$$

LETS broadcasts the value of ALDS to all the participants for computing LEND in the subsequent trial using (14). All the participants of LEM would have the interest to sell their excess generation at a higher price and to meet their demand at a lower price compared to the utility price. In order to regulate the LEM, LETS acts as a common portal to which every participant informs his/her final day-ahead PPTS and decided price at the end of the trading process as given in Algorithm 1.

3.1.3 Market-clearing mechanism: The market-clearing mechanism is designed by calculating the price of the deal during the interval t. Based on the final PPTS, LETS categorises the participants as importer (having excess demand) or exporter (having excess generation). LETS further prioritises the participants based on the quoted trading price. The highest price in the importer set and the lowest price in the exporter set are given the highest priority. Consequently, the lowest and the highest prices in the importer set and exporter set, respectively, are given the lowest priority. When two or more participants quote the same price in either set, the highest priority is given to the higher power trader. High priority participants get more chance to sell/buy their excess generation/demand through LEM. The prioritisation by LETS for exporter set (participant IDs: P, Q, R and S) and importer set (participant IDs: X, Y and Z) with the quoted price C^t_{PID} and trading power TP^t_{PID} for the interval t is shown in Fig. 3. LETS transforms the trading information into matrices ($\mathbb{E}$-Matrix and $\mathbb{I}$-Matrix) which contain the participant ID (PID), trading power (TP), quoted price (QP), available trading power (ATP) and transaction amount (TA). The mathematical representation of the matrices are given as

$\mathbb{E}^t$−Matrix

$$
= \begin{bmatrix} \textbf{PID} & \textbf{TP} & \textbf{QP} & \textbf{ATP} & \textbf{TA} \\ P & \mathrm{TP}_P^t & C_P^t & \mathrm{ATP}_{(P,k_e)}^t & \mathrm{TA}_P^t(C_P^t, \mathbb{I}^t) \\ Q & \mathrm{TP}_Q^t & C_Q^t & \mathrm{ATP}_{(Q,k_e)}^t & \mathrm{TA}_Q^t(C_Q^t, \mathbb{I}^t) \\ R & \mathrm{TP}_R^t & C_R^t & \mathrm{ATP}_{(R,k_e)}^t & \mathrm{TA}_R^t(C_R^t, \mathbb{I}^t) \\ S & \mathrm{TP}_S^t & C_S^t & \mathrm{ATP}_{(S,k_e)}^t & \mathrm{TA}_S^t(C_S^t, \mathbb{I}^t) \end{bmatrix} \tag{16}
$$

$\mathbb{I}^t$−Matrix

$$
= \begin{bmatrix} \textbf{PID} & \textbf{TP} & \textbf{TP} & \textbf{ATP} & \textbf{TA} \\ X & \mathrm{TP}_X^t & C_X^t & \mathrm{ATP}_{(X,k_i)}^t & \mathrm{TA}_X^t(C_X^t, \mathbb{E}^t) \\ Y & \mathrm{TP}_Y^t & C_Y^t & \mathrm{ATP}_{(Y,k_i)}^t & \mathrm{TA}_Y^t(C_Y^t, \mathbb{E}^t) \\ Z & \mathrm{TP}_Z^t & C_Z^t & \mathrm{ATP}_{(Z,k_i)}^t & \mathrm{TA}_Z^t(C_Z^t, \mathbb{E}^t) \end{bmatrix} \tag{17}
$$

In these matrices, k_e represents a deal of an exporter and k_i represents a deal of an importer. The power exchange between an exporter and an importer is hereafter referred to as a deal. For every deal, the available trading power of both exporter and importer decreases. The deals between a particular exporter/importer with other importers/exporters continue till the available trading power of the particular exporter/importer attains zero. An appropriate scheme may be adopted by LETS for calculating the price of deal (PoD). However, in the present work, a simple average pricing scheme is employed, as given in (18). The PoD for a deal between the importer X and the exporter P is calculated as

$$
\mathrm{PoD}_{P,k_e}^t = \mathrm{PoD}_{X,k_i}^t = \frac{C_P^t + C_X^t}{2} \tag{18}
$$

The transaction amount of a participant is calculated by adding the PoD of all the deals $(k_e(k_i) = 1, 2, \ldots, K$, where K is the maximum number of deals of an exporter (importer)) of that participant and it is expressed as

$$
\mathrm{TA}_{\mathrm{PID}}^t = \sum_{k=1}^{K} \left(\mathrm{PoD}_{\mathrm{PID},k}^t\right) \tag{19}
$$

In (19), $k = k_e(k_i)$ if PID is an exporter (importer). The basic steps followed by LETS for the market-clearing mechanism are given in Fig. 4.

3.2 Participant's daily real-time scheduling

The day-ahead scheduling of households for participating in LEM reduces the electricity cost of the participants. However, the comfort of the residents is completely depends upon their desire and hence the participants may deviate from the day-ahead schedule in real-time. This deviation results in either penalty or incentive to that participant during the interval t. The penalty/incentive for the deviation in the real-time schedule is charged at the utility price. The proposed EIREMS manages the time-varying household demand with scheduled trading power in real-time. The objective of the EIREMS is a minimisation of total electricity bill payable to the utility while considering the power consumption dynamics of non-SLs (NINSLs and INSLs), operational constraints of SLs, intermittence in RPG, scheduled trading power and utility operational parameters such as electricity price, MDL and PIL. The proposed EIREMS optimally time schedules the SLs, mode of operation and power exchange of battery in each interval t to attain minimum electricity bill while satisfying the power trading constraint. The mathematical formulation of the objective function of EIREMS is

$$
\min \sum_{t=1}^{T} \mathbb{C}_U^t\left(P_{\mathrm{Tot}}^t\right) \tag{20}
$$

$$
P_{\mathrm{Tot}}^t = \left(P_{\mathrm{NINSLs}}^t + P_{\mathrm{INSLs}}^t + P_{\mathrm{SLs}}^t + P_B^t - P_{\mathrm{RPG}}^t - \mathrm{TP}^t\right) \tag{21}
$$

where P_{NINSLs}^t, P_{INSLs}^t, P_{SLs}^t, P_B^t, P_{RPG}^t are expected demand of NINSLs, INSLs, SLs, battery and renewable during the interval t, respectively. The proposed objective function is subjected to various hard and soft constraints. The hard constraints are as follows: SLs can operate only in between the starting and ending time intervals defined by the user; SLs should operate only for a given number of intervals required to complete the particular task (λ_l); NISLs should operate continuously. These constraints should be satisfied while scheduling SLs [7]. The hard constraints are mathematically expressed as

$$
\begin{aligned} s_l^t = 0; \quad t < \beta_l, \forall l \in \mathcal{SL} \\ s_l^t = 0; \quad t > \eta_l, \forall l \in \mathcal{SL} \end{aligned} \tag{22}
$$

$$
\sum_{t=1}^{T} s_l^t = \lambda_l \quad \forall l \in \mathcal{SL} \tag{23}
$$

$$
\sum_{\theta=0}^{\upsilon-1} \prod_{\mu=\beta_l+\theta}^{\beta_l+\omega_l+\theta-1} s_l^\mu \rho_l = \rho_l \tag{24}
$$

$$
\upsilon = \eta_l - \beta_l - \omega_l + 2 \tag{25}
$$

Simultaneously, the power drawn from the grid shall be maintained below the utility defined MDL, $P_{\max}^t$ to avoid excess payment. Consumers can violate this constraint by paying more electricity bills to the utility. Hence, it is considered as a soft constraint. The power demand constraint is expressed as

$$
P_{\mathrm{Tot}}^t \le P_{\max}^t \tag{26}
$$

In addition to the load management, the scheduling algorithm decides the mode of operation and power exchange of battery to avoid the penalty by fulfilling the trading agreement. Hence, the scheduling algorithm considers battery operational constraints such as the SoC of battery at any interval should be within its minimum and maximum limits, the charging and discharging currents of the battery should not exceed its minimum and maximum limits. These battery constraints are also hard constraints. As discussed in

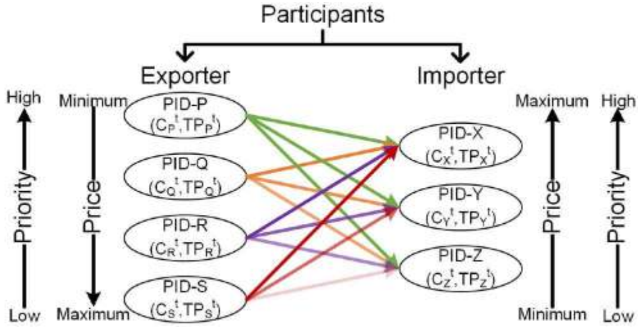

Fig. 3 *Prioritisation of participants by LETS*

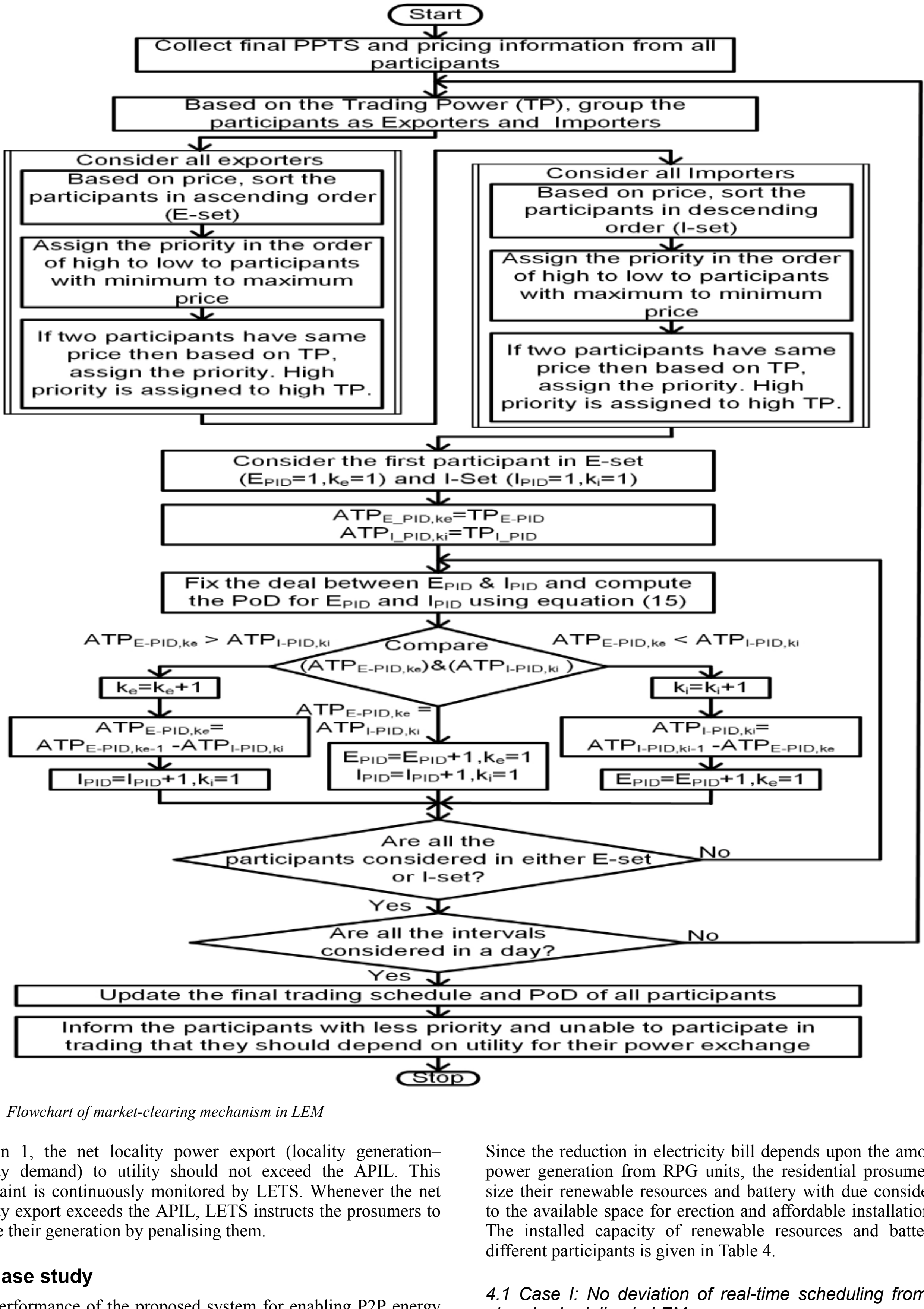

Fig. 4 *Flowchart of market-clearing mechanism in LEM*

Section 1, the net locality power export (locality generation–locality demand) to utility should not exceed the APIL. This constraint is continuously monitored by LETS. Whenever the net locality export exceeds the APIL, LETS instructs the prosumers to reduce their generation by penalising them.

4 Case study

The performance of the proposed system for enabling P2P energy trading between the residents of a locality through LEM is validated by carrying out a few case studies with 10 residential prosumers as participants. Every participant is equipped with various household appliances to fulfil their basic needs. The details of different types of household appliances along with their power rating, are taken from [48] and shown in Tables 1–3. The operating duration of appliances is varied from participant to participant. Since the reduction in electricity bill depends upon the amount of power generation from RPG units, the residential prosumers can size their renewable resources and battery with due consideration to the available space for erection and affordable installation cost. The installed capacity of renewable resources and battery for different participants is given in Table 4.

4.1 Case I: No deviation of real-time scheduling from day-ahead scheduling in LEM

This case study considers that real-time scheduling does not deviate from the day-ahead scheduling. The utility defined electricity prices are collected from [7]. The excess payment for exceeding the MDL is taken as 2.5 times of normal electricity price. The monthly electricity bill of the participants while employing the trading based scheduling algorithm (TSA) is

Table 1 Non-interruptible and non-SLs

S. no.	Load	Power, kW	Duration, h	Qty[a]
1	fan	0.10	00.00– 06.00	4
			06.00–09.00	2
			17.00–21.00	2
			21.00–24.00	4
2	fluorescent lamp	0.04	05.00–07.00	3
			18.00–22.00	6
3	CFL	0.02	00.00–05.00	4
			05.00–07.00	8
			18.00–22.00	8
			22.00–24.00	4
4	television	0.25	06.00–08.00	1
			17.00–22.00	1
5	mobile/laptop charging	0.05	06.00–08.00	2
			17.00–19.00	2

[a]Qty – Quantity varies from participant to participant.

Table 2 Interruptible and non-SLs

S. no.	Load	Power, kW	Duration[a], h
1	air conditioner	1.0	00.00–05.00
			17.00–19.00
			21.00–24.00
2	refrigerator	0.5	00.00–24.00
3	water heater	2.0	05.00–9.00
			18.00–22.00

[a]Duration – duration varies from participant to participant.

Table 3 Schedulable loads

S. no.	Load	Power, kW	ζ_l	Time span[a], h		ω_l
				Start	End	
1	cloth washer	0.8	1	08.00	13.00	2
2	cloth dryer	2.2	1	13.00	19.00	1
3	dish washer	1.5	0	08.00	12.00	1
				14.00	18.00	1
				21.00	24.00	1
4	well pump	1.2	0	00.00	06.00	1
				09.00	18.00	1
5	PHEV charging	2.3	0	00.00	05.00	2
				21.00	24.00	1
6	grinder	0.5	1	13.00	18.00	1

[a]Time span – time span varies from participant to participant.

Table 4 Participants' RER and battery sizes

PID	Solar PV panel (each rated as 0.1 kW)	Wind turbine (each rated as 1 kW)	Battery (each rated as 12 V, 75 Ah)
1	30	2	4 in series
2	50	1	2 in series
3	56	3	4 in series
4	60	2	2 in series
5	70	2	4 in series
6	36	3	4 in series
7	40	1	2 in series
8	50	2	2 in series
9	46	3	4 in series
10	50	1	2 in series

calculated and presented in Table 5. Further, the monthly electricity bill of the participants with no scheduling algorithm (NSA) (EIREMS is not present and hence no scheduling and no trading) and optimisation-based scheduling algorithm (OSA) (IREMS is present and hence optimisation based scheduling is done but no trading [7]) are presented in Table 5 for better comparison. These results confirm that all the participants are economically benefited by the proposed TSA. Further, the percentage of total excess generation shared with others over a period of one month is given in Table 5. Fig. 5 shows the energy exchange between prosumers

Table 5 Comparison of monthly electricity bills using different algorithms

PID	NSA, $	OSA, $	TSA, $	EGS[a], %
1	141	109	98	18
2	144	108	100	22
3	127	90	83	9
4	133	93	88	13
5	130	90	82	9
6	129	96	88	12
7	145	108	101	31
8	132	97	89	16
9	131	93	85	10
10	149	107	100	25

[a]EGS – excess generation shared in trading.

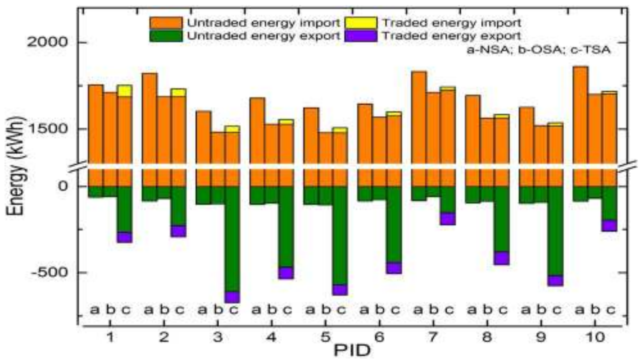

Fig. 5 *Energy exchange of participants*

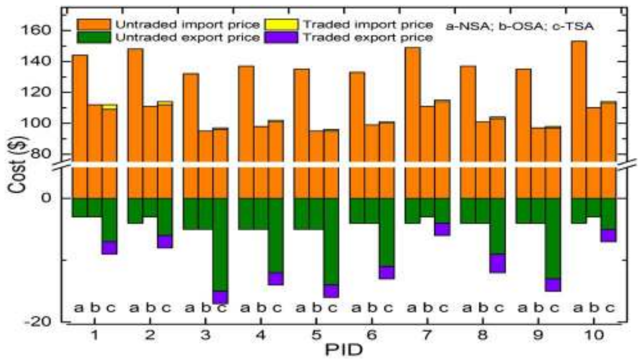

Fig. 6 *Revenue exchange of participants*

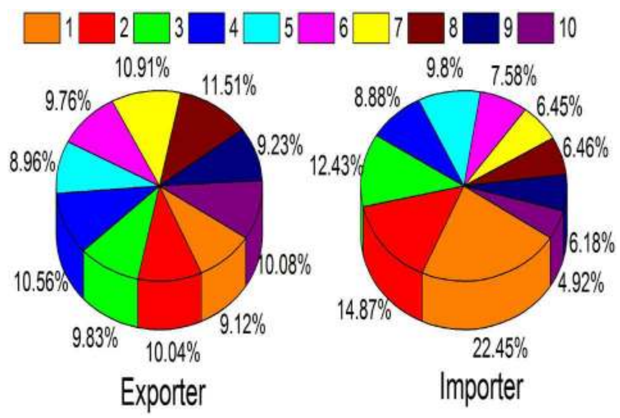

Fig. 7 *Prosumer participation in trading over a month*

and utility (un-traded import/export) and between different prosumers (traded import/export) while employing NSA, OSA and TSA. The electricity bills without and with the trading process are presented in Fig. 6. Further, the percentage contribution by individual participants in the import and export processes of LEM is shown as a pie-chart in Fig. 7.

From the simulation results, it is confirmed that the trading process reduces the electricity bill of all the participants in the locality compared to NSA and OSA methods. All the prosumers share a very minimum fraction of their excess generation in the trading process, as given in Table 5. The reduction in electricity bills will increase if this fraction increases. It can be observed from Fig. 6 that in the bar graphs corresponding to TSA, purple colour represents the cost of power exported to the neighbourhood and the green colour represents the cost of power exported to the grid. Similarly, yellow and orange colours represent the cost of power imported from the neighbourhood and the grid. It can be understood from this case study that the increase in purple and yellow colour portions would result in more amount of power trading among the participants of the LEM. This increase in power trading would further result in more economic benefit to the participants.

The installation of RPG units in residential buildings merely depends upon the participant's interest and financial ability. All the consumers in a locality may not afford it. However, the proposed methodology extends the opportunity to such consumers to reduce their electricity bills by sharing their demand with other exporters in the locality. The case study is extended by considering that a part of the participants in the locality are not equipped with RPG units. Five participants (PID – 1, 2, 3, 4 and 5) of the locality are considered to be prosumers whereas the remaining five participants (PID – 6, 7, 8, 9 and 10) are consumers. The monthly electricity bills of all the participants for this case are computed and presented in Table 6 along with the electricity bills when NSA and OSA methodologies are employed [7]. From these results, it can be understood that the proposed trading methodology provides significant economic benefits for all types of consumers in a locality.

4.2 Case II: With deviation in real-time scheduling from day-ahead scheduling in LEM

Deviation in LETS agreement by participants in real-time leads to penalty/incentive in LEM. The reasons for deviations of a participant from the LETS agreement are error in prediction of parameters such as demand variation, renewable power generation variation, electricity price and MDL during day-ahead scheduling; sudden changes in consumer behaviour in real-time. The penalty/incentive is depending upon the magnitude of deviation from the day-ahead scheduled trading power. Considering a typical case, in which an exporter agrees to share his/her generation with an importer during a particular trading interval. Due to the sudden changes in demand for non-SLs, the exporter is unable to share his/her scheduled trading power. However, LETS decides the trading power and transaction amount of all the participants at the end of the day-ahead trading process. Hence, the exporter has to purchase his/her unmet trading power (scheduled trading power – his/her own excess generation) from the utility. Considering another case, in which an importer has to share his/her excess demand with an exporter. Due to the sudden increase in RPG and/or decrease in non-SLs usage, the total demand of the importer reduces from the scheduled trading power. However, the concerned importer has to pay the transaction amount as per the LETS agreement. These deviations can be reduced by increasing the accuracy of day-ahead prediction. In order to show the impact of real-time schedule deviation from the day-ahead schedule in trading agreement, the following case study has been considered. The duration of the trading interval is taken as 1 h in this case. Let us consider a locality with two participants A and B. At the end of the final trial the participants settled with the following exchange details as shown in Table 7. From these details, LETS develops the final agreement for that interval t. The market-clearing price (cents/kWh) of the deal is calculated using (24)

$$\mathrm{PoD} = \frac{3+6}{2} = 4.5 \tag{27}$$

Table 6 Monthly electricity bills of prosumers and consumers

PID	NSA, $	OSA, $	TSA, $
1	141	109	88
2	144	108	95
3	127	90	73
4	133	93	77
5	130	90	72
6	194	165	141
7	192	163	143
8	193	166	139
9	199	168	137
10	200	170	153

Table 7 Power exchange details of participants *A* and *B* during the interval *t*

	Participant *A*	Participant *B*	Utility
excess generation, kW	1	—	—
excess demand, kW	—	1	—
selling price, cents/kWh	3	—	8
buying price, cents/kWh	—	6	2

The transaction amount of this deal = 1 kW * 4.5 cents/kWh*1 h = 4.5 cents. This 4.5 cents is credited (−4.5 cents) for participant A and debited (+4.5 cents) for participant B through the day-ahead locality electricity market. This transaction amount is fixed and used for real-time electricity bill computation. The net power (net demand for which he/she gets penalty/incentive) of a participant considering the impact of dynamics in consumer behavior and renewable power generation on the trading agreement is computed as

$$\mathrm{PP}^t_{\mathrm{Tot}} = \left[P^t_{\mathrm{NINSLs}} + P^t_{\mathrm{INSLs}} + P^t_{\mathrm{SLs}} + P^t_B - P^t_{\mathrm{RPG}} - \mathrm{TP}^t\right]$$

This case study is analysed with the following different scenarios in real-time.

4.3 Scenario 1: real-time demand/generation schedule is equal to the predicted day-ahead demand/generation schedule

According to the day-ahead trading agreement, the trading power of participants is

$$\mathrm{TP}^t_A = -1\,\mathrm{kW}, \quad \mathrm{TP}^t_B = 1\,\mathrm{kW}$$

$$\text{Hence, } \mathrm{PP}^t_{\mathrm{Tot},A} = 0\,\mathrm{kW}, \quad \mathrm{PP}^t_{\mathrm{Tot},B} = 0\,\mathrm{kW}$$

The total electricity bill of the individual participants during the interval *t* is

$$\mathrm{TEB}^t_A = \mathrm{TA}^t_A + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},A}\right) = -4.5 + 0 = -4.5\,\text{cents}$$

$$\mathrm{TEB}^t_B = \mathrm{TA}^t_B + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},B}\right) = 4.5 + 0 = 4.5\,\text{cents}$$

In this scenario, both the participants are not experiencing any deviation in real-time schedules from the day-ahead schedule, so no penalty/incentive to participants *A* and *B*.

4.4 Scenario 2: real-time demand/generation schedule decreases from day-ahead predicted demand/generation schedule

4.4.1 Real-time renewable power generation of participant A decreases by 0.5 kW from the day-ahead generation: According to the day-ahead trading agreement, the trading power of participants is

$$\mathrm{TP}^t_A = -1\,\mathrm{kW}, \quad \mathrm{TP}^t_B = 1\,\mathrm{kW}$$

In this case

$$\mathrm{PP}^t_{\mathrm{Tot},A} = 0.5\,\mathrm{kW}, \quad \mathrm{PP}^t_{\mathrm{Tot},B} = 0\,\mathrm{kW}$$

The total electricity bill of the individual participants during the interval *t* is

$$\mathrm{TEB}^t_A = \mathrm{TA}^t_A + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},A}\right) = -4.5 + (0.5 * 8) = -0.5\,\text{cents}$$

$$\mathrm{TEB}^t_B = \mathrm{TA}^t_B + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},B}\right) = 4.5 + 0 = 4.5\,\text{cents}$$

In order to follow the agreement, A purchased 0.5 kW from the utility at the cost of 4 (=0.5 × 8) cents. Hence participant A incurred a loss (penalty) of 4 cents because of deviation.

4.4.2 Real-time demand of participant B decreases by 0.5 kW from the day-ahead prediction: According to the day-ahead trading agreement, the trading power of participants is

$$\mathrm{TP}^t_A = -1\,\mathrm{kW}, \quad \mathrm{TP}^t_B = 1\,\mathrm{kW}$$

In this case

$$\mathrm{PP}^t_{\mathrm{Tot},A} = 0\,\mathrm{kW}, \quad \mathrm{PP}^t_{\mathrm{Tot},B} = -0.5\,\mathrm{kW}$$

The total electricity bill of the individual participants during the interval *t* is

$$\mathrm{TEB}^t_A = T^t_A + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},A}\right) = -4.5 + 0 = -4.5\,\text{cents}$$

$$\mathrm{TEB}^t_B = T^t_B + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},B}\right) = 4.5 + (-0.5 * 2) = 3.5\,\text{cents}$$

Though the demand of participant B decreases by 0.5 kW, in order to follow the trading agreement, B buys 1 kW from A at the cost of 4.5 cents and sells 0.5 kW to the utility at the cost of 1 (=0.5 × 2) cents. The net amount that B needs to pay is 3.5 cents. This is obvious that the reduction in demand will reduce the electricity bill.

4.5 Scenario 3: real-time power generation of participant A increases by 1 kW and real-time demand of participant B increases by 1 kW

According to the day-ahead trading agreement, the trading power of participants is

$$\mathrm{TP}^t_A = -1\,\mathrm{kW}, \quad \mathrm{TP}^t_B = 1\,\mathrm{kW}$$

In this case

$$\mathrm{PP}^t_{\mathrm{Tot},A} = -1\,\mathrm{kW}, \quad \mathrm{PP}^t_{\mathrm{Tot},B} = 1\,\mathrm{kW}$$

Utility buying and selling prices are 2 and 8 cents/kWh, respectively. The total electricity bill of the individual participants during the interval t is

$$\mathrm{TEB}^t_A = \mathrm{TA}^t_A + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},A}\right) = -4.5 + (-1 * 2) = -6.5\,\mathrm{cents}$$

$$\mathrm{TEB}^t_B = \mathrm{TA}^t_B + \mathbb{C}^t_U\left(\mathrm{PP}^t_{\mathrm{Tot},B}\right) = 4.5 + (1 * 8) = 12.5\,\mathrm{cents}$$

Though the real-time generation of participant A increases by 1 kW and real-time demand of participant B increases by 1 kW, they cannot trade this additional generation/demand in real-time because of the day-ahead trading agreement. Participant A sells the increased generation of 1 kW to the utility at the cost of 2 (=1 × 2) cents and participant B buys the additional demand of 1 kW from the utility at the cost of 8 (=1 × 8) cents. If the day-ahead prediction of demand and generation is precise, then participant A (participant B) would have earned (spent) 9 cents instead of 6.5 cents (12.5 cents) by trading 2 kW generation (demand) in LEM.

4.6 Case III: impact of user-defined parameters in the modelling of expected demand of household appliances

Based on the interruptibility and schedulability, the household appliances are categorised into NINSLs, INSLs and SLs. The modelling of power demanded by these loads is shown in Section 3.1.1 of the manuscript. Mathematical modelling of expected power demanded by these household appliances is very much required to predict the day-ahead expected total demand, and it will impact the day-ahead EEB. The day-ahead expected power demand of NINSLs is calculated using (5), where the user-defined comfort factor will impact the EEB and is shown in Table 8. The optimal value of the NINSLs user-defined factor is 1.5, which gives minimum daily EEB (cents) for all participants. Further, the increase or decrease in NINSLs demand in real-time from day-ahead predicted demand will impact the electricity bill, which is explained in case study-II. The day-ahead expected power demand of INSLs is calculated using (6), the power consumption of INSLs is influenced by the weather conditions, if there are any uncertainties in weather conditions and if the temperature is beyond/below the set point temperature of cooling/heating INSLs then the operating status of that INSLs will change in real-time. Hence the real-time demand schedule varies from day-ahead demand schedules of the participant. Therefore, the participant should pay the penalty for the change in demand, and this scenario is explained in case study-II.

The day-ahead expected power demand of SLs is calculated using (7), the day-ahead scheduling algorithms of EIREMS schedules the SLs between pre-opted user-defined intervals. If the participants willing to shift the SLs from pre-opted intervals to any intervals, then they get more economic benefits in the P2P market. Shifting of SLs from pre-opted intervals leads to shifting of loads from periods with less renewable power generation to periods with more generation. The effect of time constraints of SLs on the aggregated locality net demand is shown in Fig. 8, and the day-ahead electricity cost is shown in Fig. 9. Different values of user-defined weighting factor in (1) and comfort factor in (5) affect the EEB of prosumers and are shown in Table 8. The optimal values of η, w_1, w_2 are 1.5, 0.7 and 0.3, respectively.

5 Conclusion

In this paper, trading based individual demand scheduling of a group of prosumers in a smart locality is presented. The proposed methodology inspires the prosumers to actively participate in LEM to sell/buy their excess generation/demand at a profitable price compared to the utility price. A trading algorithm has been devised to arrive at the price of every deal between the participants of LEM using the proposed LETS. The trading algorithm gives an

Table 8 Day-ahead electricity bill (cents) for different user-defined parameters

η	0.75	1	1.25	**1.5**	1.2	2.0	1.2	1.2	1.2
w_1	0.7	0.7	0.7	**0.7**	0.7	0.7	0.1	0.3	0.5
w_2	0.3	0.3	0.3	**0.3**	0.3	0.3	0.9	0.7	0.5
P-1	158	201	175	133	171	155	184	234	176
P-2	157	197	172	132	176	201	188	242	173
P-3	162	197	174	137	160	172	172	249	178
P-4	158	190	169	131	173	141	190	234	173
P-5	159	201	172	140	162	168	181	244	176
P-6	160	198	174	139	172	173	183	234	176
P-7	155	195	172	139	170	236	186	244	175
P-8	162	201	177	140	169	182	185	248	176
P-9	152	201	173	140	174	156	181	236	179
P-10	155	196	171	138	173	231	183	233	171

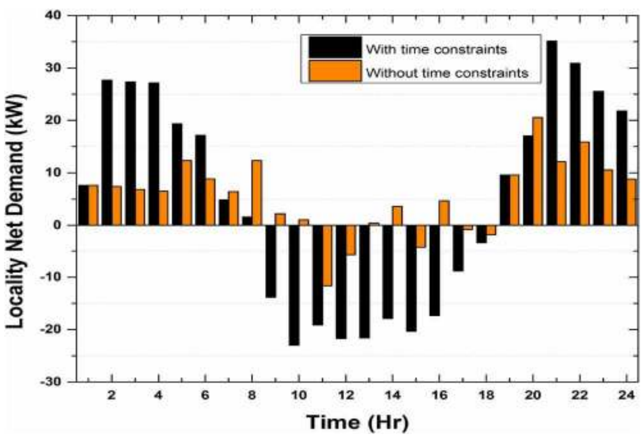

Fig. 8 *Aggregated locality net demand with and without time constraints on SLs*

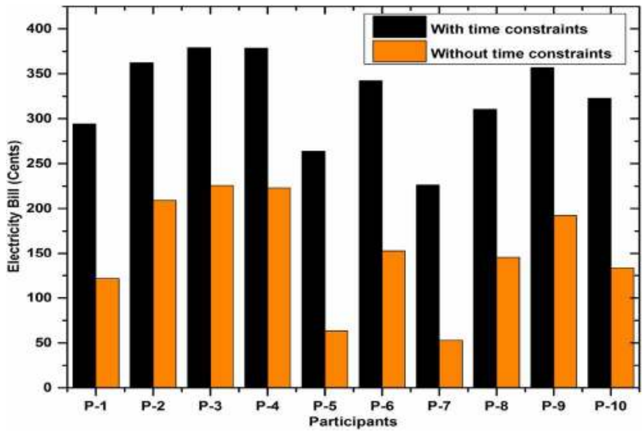

Fig. 9 *Electricity bill of participants with and without time constraints on SLs*

opportunity to every participant to update his/her power trading schedule iteratively considering the minimisation of his/her electricity bill and net power exchange between the locality and utility. At the end of this process, LETS prioritises the exporting and importing participants based on their quoted price. Later, LETS arrives upon the amount of power exchange and price of every deal. LETS informs the final power trading schedule and its associated price to the participants. The trading module present in the EIREMS takes part in the trading process. Further, the processing unit of EIREMS schedules the schedulable load and battery in real-time to reduce the electricity bill with due consideration to the operational constraints and LETS day-ahead agreement.

The proposed methodology is validated through different case studies. The study results demonstrate that the proposed trading methodology provides significant profit to all the participants of LEM compared to when they individually exchange power only with the grid. Further, the results obtained from the extended case study justify the efficacy of the proposed methodology for providing economic benefits even to the participants without any in-house renewable generation units. The simulation results demonstrate that, the proposed framework can effectively manage the renewable generation units in the locality and encourages the prosumers to participate in the TE-based DR under the P2P paradigm (TSA) compared to the P2G paradigm (NSA, OSA) to get more economic benefits. Case study-I results demonstrate that the participants in P2P are economically benefited and the local power generation is utilised to the local SLs when the participants' real-time scheduling does not deviate from the day-ahead scheduling in the LEM. Case study-II results demonstrate that the participants in P2P are penalised/incentivised under different scenarios when the participants' real-time scheduling deviates from the day-ahead scheduling in the LEM and scenario 3 of this case study demonstrates that even though there is equal excess generation and demand, they cannot trade because of the trading agreement. Case study-III results illustrate the impact of user-defined factors of household appliances on the electricity bills in LEM, if the participants are willing to shift the SLs from pre-opted intervals, then they get more marginal revenues. Realisation of EIREMS using single-board computers such as Raspberry PI and prototype implementation of P2P energy trading in a residential community of Indian smart city is the scope of future work.

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