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RESEARCH ARTICLE

Credit Rating-Based Transactive Energy System With Uncertainties in Energy Behavior

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ABSTRACT In recent years, the evolution of demand-side management techniques has ushered in substantial improvements for distribution systems. Among these advancements, the Transactive Energy System (TES) emerges as a promising innovation, empowering end-users by facilitating surplus generation/demand trading within local energy markets. However, in contrast to the wholesale electricity markets of conventional grids, TES integrates a significant share of small-scale prosumers and highly variable intermittent Distributed Energy Resources (DERs), introducing elevated market uncertainties. In this conditions the economic stability of TES hinges on active and credible participant engagement. The central challenge lies in addressing uncertainties surrounding the energy requirements of community participants and incentivizing their involvement. To address these challenges, this paper introduces a novel market clearing strategy based on credit ratings. This strategy aims to mitigate uncertainties while motivating credible participants through substantial savings on their electricity bills. Further this paper presents final demand response consideration, among a group of participants in a TES using an auction-theoretic approach which increases monetary gains. The effectiveness of this proposed methodology is validated through comprehensive case studies involving multiple households within a community. The results are highly promising, with participating households realizing monthly savings of 17.18%, 16.11%, 20.7%, and 23.22% on their electricity bills when compared to the latest transactive energy exchange method. These tangible outcomes underscore the significant positive impact achievable through the implementation of our proposed market clearing approach and demonstrate the substantial increase in monthly savings for participants across various scenarios.

INDEX TERMS Credit rating, demand response management, energy trading, smart grid, transactive energy.

ABBREVIATIONS

BCS	Buyer Credit Score.
CEE	Community Energy Expert.
DSO	Distributed System Operator.
INSLs	Interruptible and Non Schedulable Loads.
IREMS	Intelligent Residential Energy Management System.
LTES	Locality Transactive Energy System.
MDL	Maximum Demand Limit.
NSL	Non Schedulable Loads.
NINSLs	Non-Interruptible and Non-Schedulable Loads.
NISLs	Non-Interruptible Schedulable Loads.
P2P	Peer-to-Peer.
PIL	Power Injection Limit.
RPG	Renewable Power Generation.
RTP	Real Time Pricing.
SCS	Seller Credit Score.
SLs	Schedulable Loads.

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NOMENCLATURE

Sets and Indices

A_m	Data Set of SLs.
$A^n_{i,b}$	Data Set of buyer i upto n^{th} interval.
$A^n_{j,s}$	Data Set of seller j upto n^{th} interval.
B_m	Data Set of NSL.

C_m	Data Set of NINSLs.
i	Buyer.
j	Seller.
M	Set of participants.
N	Set of intervals.

Parameters

$\lambda_{ig,b}^{n}$	Utility buying price in n^{th} interval.
$\lambda_{jg,s}^{n}$	Utility selling price in n^{th} interval.
$\psi_{i,b}$	Power extraction limiting factor.
$\psi_{j,s}^{n}$	Power injection limiting factor.
Υ	Priority factor.
σ_{i}^{n}	Scaling factor.
$CCS_{i,bt}^{n}$	Desired credit score.

Variables:

$\lambda_{i,b}^{n}$	Bidding price of i^{th} buyer in n^{th} interval.
λ_{itavg}^{s}	Market clearing price.
$\lambda_{j,s}^{n}$	Offred price of j^{th} seller n^{th} interval.
$AP_{i,b}^{n}$	Actual i^{th} buyer power in n^{th} interval.
$AP_{j,s}^{n}$	Actual j^{th} seller power in n^{th} interval.
$CS_{i,b}^{n}$	Credit score of buyer i in n^{th} interval.
$CS_{j,s}^{n}$	Credit score of seller j in n^{th} interval.
M_{b}^{n}	Total number of buyers in n^{th} interval.
M_{s}^{n}	Total number of sellers in n^{th} interval.
n	Market interval.
$P_{i,b}^{n}$	Modified maximum power bid of i^{th} buyer in n^{th} interval.
$P_{j,s}^{n}$	Modified maximum power offer of j^{th} seller in n^{th} interval.
$R_{i,b}^{n}$	Coated bid power by buyer i in n^{th} interval.
$R_{i,b}^{n}$	Coated offer power by seller j in n^{th} interval.
$SP_{i,b}^{n}$	Scheduled i^{th} buyer power in n^{th} interval.
$SP_{j,s}^{n}$	Scheduled j^{th} seller power in n^{th} interval.
$U_{i,b}^{n}$	Variance value of buyer i in $(n-1)^{th}$interval.
$U_{i,b}^{n}$	Variance value of seller j in $(n-1)^{th}$ interval.
$V_{i,b}^{n}$	Variance value of buyer i in n^{th} interval.
$V_{j,s}^{n}$	Variance value of seller j in n^{th} interval.
$X_{i,b}$	Calculated data value of buyer i in n^{th} interval.
$X_{j,s}^{n}$	Calculated data value of seller j in n^{th} interval.
$y_{i,b}^{n}$	Cleared power bid of i^{th} buyer in n^{th} interval.
$y_{j,s}^{n}$	Cleared power offer of j^{th} seller in n^{th} interval.
$Z_{i,b}^{n}$	Credible factor of buyer i in n^{th} interval.
$Z_{j,s}^{n}$	Credible factor of seller j in n^{th} interval.
$CCS_{i,b}^{n}$	Calculated credit score of i^{th} buyer in n^{th} interval.
$CCS_{j,s}^{n}$	Calculated credit score of j^{th} seller in n^{th} interval.

I. INTRODUCTION

In the 21^{st} century, the evolving paradigm of electronics, computing, and communication technologies allows us to convert the traditional electric power system into a smart grid [1]. In smart grid, power system operations are efficiently monitored and managed by intelligent electronic equipments featured with a bidirectional cyber-secure communication facility. Demand-Side Management (DSM) is an evolution strategy used by numerous utilities to balance generation and demand in the context of smart grid [2], where utilities use incentives and penalties to force the energy consumers to change or lower their demand.

A. BACKGROUND AND MOTIVATION

The Demand Response (DR) program [3] is a creative component of DSM that allows customers to lower their electricity rates. As part of DSM scheme, few utilities currently use Maximum Demand Limitations (MDL) and Real-Time Pricing (RTP) to minimize the grid peak-to-average ratio [4]. Consumers will be penalized under the MDL approach if their energy use exceeds the utility's predetermined limit. Presently, utilities are increasingly focusing on Renewable Power Generation (RPG) units as an alternative for regulating the rising energy demand caused by the depletion of traditional resources and the rise in electricity use. However, these RPG units have several installation and operational constraints. Hence, utilities must be upgraded to handle the unpredictable nature of renewable energy resources. On the other hand, utilities are constantly encouraging the end users to install small-scale RPG units in order to promote self-sustainability and reduce electricity bills [5].

In the growth of smart grid, the Home Energy Management Systems (HEMS) successfully regulates both smart and non-smart residential appliances, as well as power generation from RPG units, to save electricity bills [6]. Further, end-users are encouraged to barter excess power generation to utilities in exchange for substantial incentives, and these users are referred to as prosumers [7]. In general, prosumers want to export excess energy into the grid during peak periods to maximize electricity bill savings. However, utilities are encountering significant operational challenges as a result of the increased penetration of small-scale prosumers. Hence, utilities are implementing Power Injection Limits (PIL) to regulate the prosumers grid integration. Any surplus power generated by a prosumer over the PIL should be stored in an energy storage devices [7] or dissipated through dump load. This restriction will indirectly limit RPG units installation. To overcome the PIL constraint, end users opt to engage in the Peer-to-Peer (P2P) energy market, where they may share their excess generation with neighboring users for a higher return than the utility. P2P provides several advantages, including high integration of economically feasible distributed green energy sources, energy storage devices, mobile energy storage devices in the form of electric vehicles, cost-effectiveness, quality electricity, and educating customers about demand response schemes [8]. Participants in P2P energy trading may default quoted energy, owing to fluctuations in electricity prices and human greed [9].

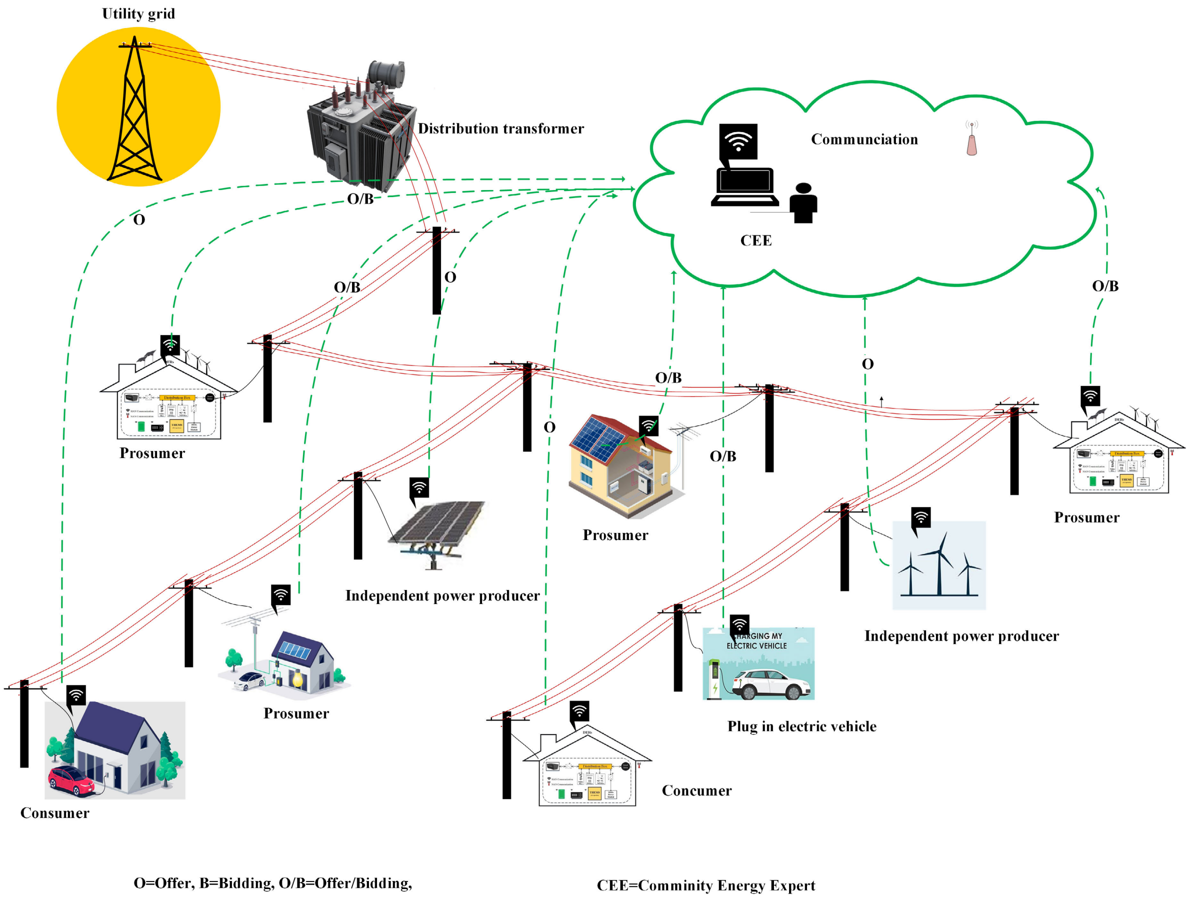


FIGURE 1. **Conceptual model of a transactive energy connection setup.**

Since the electricity markets are typically forward markets uncertainty in distributed renewable energy output and demand may result in real-time default energy behavior [10]. This might result in the failure of P2P whole electrical market [11]. Consider the following scenario: a prosumer agrees to commit a given quantity of energy for a particular period and receives money from the seller for that energy. However, it is conceivable that the actual energy supplied to the buyer is less than the amount committed. Similarly, buyer consumption power may differ from what was negotiated. Such a market result will obviously be sub-optimal and unfit for market sustainability. As a result, establishing a solid credit rating system is necessary for regulating unpredictable energy behavior. A credit rating, in the context of our research, refers to an assessment and evaluation of participants' performance and reliability within the transactive energy market based on their energy behavior. It quantifies the extent to which participants adhere to their energy agreements and fulfill their scheduled energy commitments. In this work Fig. 1 represents a conceptual model illustrating the setup of an electrical connection within the transactive energy system. It showcases the key components and their interconnections, providing a visual representation of the underlying infrastructure.

B. RELEVANT LITERATURE REVIEW

Numerous efforts were dedicated to crafting cost-effective and proficient energy trading mechanisms within the market in [12], [13] and [14]. One approach involved a distributed energy management system that promoted collaboration between energy suppliers and users, aiming to enhance societal well-being [15]. Haghifam et al. introduced a Stackelberg game-based approach for optimizing the participation of multiple stakeholders in the day-ahead energy market [16]. In another study, Bhattacharya et al. conducted an in-depth analysis of the impact on unit energy prices when participants exhibit enhanced flexibility [17]. Further, Gokcek et al. presented an innovative dual bidding strategy that effectively incorporates considerations for both intra and inter-community-based energy trading [18]. Azim et al. demonstrated a peer-to-peer energy trading system using a coalition graph and local voltage management [19], while Wang and Huang explored the promotion of active energy trade through a coalition-forming incentive mechanism based on Nash bargaining theory [20]. Kareem et al. introduced a Multi-Settlement quasi-ideal P2P trading framework that integrates bilateral contracts, a double-auction Vickrey-Clarke-Groves (VCG) mechanism, and trading functionalities with the main grid [21]. The VCG mechanism promotes truthful bidding by participants and eliminates market power exercise. However, this framework lacks the budget balance property. In another approach, Zhenwei et al. proposed a high-efficiency and incentive-compatible P2P energy trading mechanism within a blockchain environment [22]. This mechanism offers efficiency and incentives but faces scalability challenges that need to be addressed for broader implementation. To tackle the budget deficit issue in P2P energy trading, Lazaros et al. proposed an incentive-compatible mechanism that combines the VCG method with a post-budget redistribution scheme [23]. This approach aims to partially recover budget deficits and enhance the overall incentive compatibility of the system. Baroche et al. utilized externally allocated grid-related charges [24]. Furthermore, Bokkisam et al. introduced a periodic iterative double auction strategy with demand response in the transactive pooled market [25]. In a recent study, Arun et al. emphasized strategies focused on the supply-to-demand ratio to enhance market liquidity for residential-based TES [26]. However, concerns arose regarding the uncertainty and default behavior associated with energy sharing, potentially undermining the energy market [27]. To address these concerns, Yang et al. proposed a priority order based on prosumers' credit rating points, giving priority to excellent prosumers [28]. However, in this paper, the author suggested directly assigning a credit score to prosumers, which could potentially result in high credit rating prosumers being prioritized in peer matching. This raised concerns about missed opportunities for low-cost energy offers or bids, leading to potential decreases in social welfare. In [29], the authors introduced an intriguing concept called the Market Reputation Index (MRI) for sellers, where higher MRI sellers received bigger rewards during market clearing. This proposal held promise for enhancing market dynamics and promoting efficiency. However, the author's suggestion of using a uniform weighting factor raised questions about the optimal implementation of this reward mechanism. Khorasany et al. suggested prioritizing peer matching based on trade partner reputation and distance but did not provide a precise mathematical approach, making the recommendation insufficiently feasible [30]. In another study [31], a method for calculating the net reputation value (NRV) or MRI was proposed, but it was considered unfair to penalize customers with strong credit points for failing to meet requirements. Other approaches included trading priority values based on reputation and selling price [32], and credit scores for sellers determined using logistic regression and default energy behavior [33]. Xia et al. developed a pricing strategy for output energy when low liquidity was present but mainly focused on flexible reserve resources [34]. In another study, a fuzzy-based multi-objective programming model was developed [35] to effectively handle uncertainties associated with demand and capacity in renewable distributed generation sources. Zhang et al. suggested a demand response technique to mitigate uncertainty, but controlling loads in real-time could compromise market players' comfort and autonomy [36]. Azim emphasized, "It is crucial to develop a comprehensive strategy addressing uncertainty and default behavior in reputation assessment and calculating prosumer credit ratings based on energy behavior and uncertainties. Establishing a trustworthy system or index to track and assess prior performance is essential for fostering trust and ensuring the integrity of the transactive energy market. Improving the effectiveness and reliability of peer-to-peer (P2P) energy trading requires addressing uncertainty, developing specific calculation methods, and implementing a robust reputation evaluation system" [11]. Additionally, Frei stated that "market liquidity also significantly impacts transactive energy markets, facilitating ease, efficiency, and successful transactions between participants" [37]. Furthermore, Kuno emphasized that "Higher liquidity brings benefits such as increased market participation, improved price discovery, and enhanced market efficiency" [38]. Prosumer groups with similar generation and demand profiles often have high absolute net demand, leading to the exportation or importation of energy from the grid, as highlighted in previous research [7]. In a more recent study, Arun stated that "The quantity of energy exchanged among prosumers directly impacts the reduction in the electricity bill" [39]. This underscores the need for a proper method to increase market liquidity.

C. PROBLEM DESCRIPTION AND METHODOLOGY

The previous research studies lacked a specific calculation method for a credit-based transactive energy market. Additionally, the existing demand response strategies have not yielded a substantial increase in market liquidity. Moreover, these studies failed to introduce the concept of final demand response as a means to effectively enhance market liquidity. Most of the existing literature relied on the default energy concept, which assumes that the actual supplied energy is less than the scheduled energy. However, in real-time, the supplied energy can be more. Furthermore, the assessment of participants' credit rating was not conducted continuously within each time interval. The priority order of peer matching based on credit rating could potentially reduce social welfare. In order to tackle these gaps, a peer-to-peer electricity trading model is proposed, integrating credit management rooted in participants' uncertain energy patterns, alongside a conclusive demand response technique aimed at reducing the overall net demand. In the proposed auction method, end users are assigned a credit rating based on the scheduled energy and actual energy in each trading interval. To maintain participants' credit ratings and adjust bids or offers accordingly, the Community Energy Expert (CEE) is introduced as a common portal. The credit management aspect of our model penalizes uncertain energy behavior, aiming to minimize uncertainties in the electricity market. Additionally, power exchange limits are proposed based on the credit score of prosumers. Users with a low credit rating will face appropriate penalties, which

TABLE 1. Important references related to research gap.

References	Demand response	Credit rating	Motivating credible participants	Uncertainty in energy-reducing approach
[25]	Day-ahead load scheduling based on utility prices	Not considered	Not considered	Not considered
[26]	Considered demand response based on utility Prices	Not considered	Not considered	Not considered
[28]	Not considered	Directly assigned credit Ratings	Priority is given to high-credit participants for peer matching, decreasing social welfare	Not considered
[29]	Partial load scheduling	Uniform weighting factor without specific calculation	With Load shedding and power injection regulation for low reputation participants	Considered centralized controllable energy storage for uncertainty in energy mitigation
[30]	No classified residential load scheduling	Reputation factor proposed with direct weighting factors	Priority in peer matching	Not considered
[31]	Not considered	Directly assigned reputation factor	Priority in ranking order for peer matching	Not considered
[32]	Not considered	No specific calculation for weighting factor	Trading priority values based on reputation and selling Price	Not considered
[33]	Not considered	Default energy-based credit rating	Biased clearing price towards high credit participants	Not considered
[34]	Not considered	Not considered	Not considered	Considered flexible resources
Proposed approach	Demand response based on locality net demand in real time	Efficient credit rating	Priority of credible energy	Power exchange limits will discourage uncertainty in energy from a behavioral point of view

supplement the power exchange limit and help mitigate the uncertainty. Furthermore, the feasibility of the proposed P2P electricity trading mechanism is verified by using multiple households with different scenarios. All participants in the Local Transactive Energy System (LTES) are assumed to be equipped with an intelligent residential energy management system, enabling profitable energy trading with others. In this work, Table 1 illustrates the proposed approach in comparison to existing approaches while referencing important literature related to the research gap.

D. CONTRIBUTIONS

In this study, significant contributions are presented with the objective of enhancing the local transactive energy trading system. It begins by introducing a comprehensive framework designed to incorporate a demand response strategy based on locality net demand. This innovative framework enhances market liquidity and energy transactions among participants within localized areas. Furthermore, this study introduces an efficient credit rating management system, complete with a specific calculation method. By assigning credit ratings based on scheduled energy and actual energy consumption within each trading interval, it establishes a robust mechanism for evaluating and managing participant credibility, ensuring trust among participants and reliability in energy trading. Additionally, this research introduces a novel market clearing strategy that considers participants' credibility scores. This innovative approach to market clearing aims to optimize overall social welfare within localities. By factoring in participants' credit ratings when determining market outcomes, the proposed strategy encourages responsible energy behavior and discourages unreliable trading practices. Consequently, it significantly contributes to the stability and effectiveness of the local transactive energy market. To further validate these contributions, the research also conducts a comparative analysis of the proposed method with existing transactive energy market clearing mechanisms, providing valuable insights.

The major contributions of the paper are as follows:

1) Development of a framework for the local transactive energy system, incorporating a demand response strategy based on locality net demand. This framework facilitates lucrative energy transactions among locality participants.
2) Introduction of an efficient credit rating management system that considers participants' uncertainty in energy trading behavior. This system will track the energy trading history of participants.
3) Incorporating power exchange limits based on participants' credibility scores into the market clearing mechanism, with the aim of reducing uncertainty from a behavioral perspective in energy trading.
4) Validating the effectiveness of the proposed methodology involved conducting several case studies with multiple household participants within a LTES.

E. PAPER ORGANIZATION

This paper follows a structured approach, beginning with Section II, which introduces a locality-based transactive energy system architecture. Section III outlines the mathematical models for each sub-system within the transactive energy system. In Section IV, a detailed description of the transactive energy trading mechanism is provided. Section V presents the simulation results derived from various case studies. Finally, Section VI summarizes the study's conclusions, emphasizing the significant findings.

II. ARCHITECTURE OF LOCALITY TRANSACTIVE ENERGY SYSTEM (LTES)

Fig. 2 depicts the architecture of the proposed LTES, which involves utility providers, CEE (Community Energy Expert), and trading participants (prosumers and consumers). LTES allows participants to exchange their net demand (the difference between electricity demand and generation) with neighboring participants at the market clearing price, offering an alternative to relying solely on utility providers to minimize electricity bills. CEE acts as a network operator, retail electricity broker, and mediator of the local electricity market. The participants' household appliances are categorized into three types based on interpretability and schedulability: Non-Interruptible and Non-Schedulable Loads (NINSLs), Interruptible and Non-Schedulable Loads (INSLs), and Schedulable Loads (SLs). NINSLs, such as televisions, home theaters, home decorators, fans, lights, mobile and laptop chargers, provide immediate service upon activation. INSLs consist of temperature-controlled appliances that maintain the operating temperature around a user-defined setpoint value. If the actual temperature deviates beyond the manufacturer's tolerance limit, the INSLs consume their rated power to reduce the difference. Examples of INSLs include air conditioners, refrigerators, and space heaters. SLs have specific time frames for completing tasks and include appliances like washing machines, dishwashers, well pumps, plug-in hybrid electric vehicles (PHEVs), and food grinders. Modern SLs employ artificial intelligence systems to predict the necessary intervals for completing tasks based on initial conditions, such as the water level in the overhead tank for smart well pump operation or the weight of clothes in a smart washing machine. SLs can be further categorized as Non-Interruptible SLs (NISLs) and Interruptible SLs (ISLs). NISLs operate continuously once activated, while ISLs can operate continuously or discontinuously within a given time span. Residential consumers have shown increasing interest in installing small-scale RPG units, such as solar PV systems and small wind turbines, to achieve self-sustainability and reduce electricity bills. Additionally, many consumers favor energy storage devices like batteries to address the intermittent nature of RPG and provide backup power. In this study, a residential building equipped with solar PV and small wind power generation is considered, and the battery backup manages the intermittency of renewable energy resources (RER).

In the LTES, participants share their generation offers or demand bids prior to the trading period in order to obtain economic benefits. However, the CEE adjusts the submitted bids according to power exchange limits derived from credit ratings. Subsequently, the CEE optimally calculates the market clearing price and facilitates the settlement of transactions between participants. In the restructured energy market, the role of CEE is taken over by a Distributed System Operator (DSO), which is a non-profit market operator and part of the DSO that integrates local distributed energy resources, implements demand response measures to improve LTES reliability, and controls energy prices. The proposed LTES operates as a real-time market, enabling more end users to participate with reduced uncertainty regarding energy behavior. To support participants in making profitable trades, an intelligent residential energy management system is installed at the end user's premises. The credit rating-based LTES process is illustrated in Fig. 3. as a flow diagram.

A. CREDIT RATING SYSTEM

The proposed LTES categorizes participants as sellers (with excess generation) and buyers (with surplus demand) based on their quoted trading demand. To establish a credit rating-based LTES, two performance indices are introduced: Seller Credit Score (SCS) and Buyer Credit Score (BCS). The SCS is computed by comparing the quoted trade generation with the actual energy delivered during the trading interval. Similarly, the BCS is determined by comparing the quoted demand with the actual energy consumed during the trading interval. The SCS reflects the participants' ability to uphold their committed generation supply in agreement with the energy delivered, while the BCS indicates their ability to maintain energy consumption in line with the agreed demand.

Accurate calculation of the credit scores involves assigning appropriate weighting factors, which consider both past credit scores and the scores from the current trading interval. These weighting factors are determined to ensure the maximum likelihood estimation, thereby justifying the precise calculation of the credit scores. The mathematical explanation of this weighting concept will be elaborated in the upcoming section.

III. MATHEMATICAL MODELING OF CREDIT RATING BASED LTES

A. UTILITY MODEL

The utility is regarded as a static participant. Furthermore, the utility can behave as a seller (net demand > 0) or buyer (net demand ≤ 0) dependent on the locality net demand (buyers demand - sellers generation). In general, utilities buy surplus generation from LTES at predetermined energy rates. This pricing structure is known as the Feed-in-Tariff (FiT) scheme [8]. Similarly, the utility sells the energy to LTES at the retail price. Let us assume that $\lambda_{U,b}^{n}$ and $\lambda_{U,s}^{n}$ are the utility's buying and selling prices for trading interval n, respectively. Further, these prices will remain same for the duration of the trading interval.

B. PARTICIPANT MODEL

Nowadays, residential buildings are outfitted with a variety of electrical gadgets to help residents do their tasks quickly and conveniently. Let $M = [1, 2, \ldots m]$ is a set of players willing to participate in the LTES and the set of trading interval over a given period is taken as $N = [1, 2, \ldots, n]$. Participants

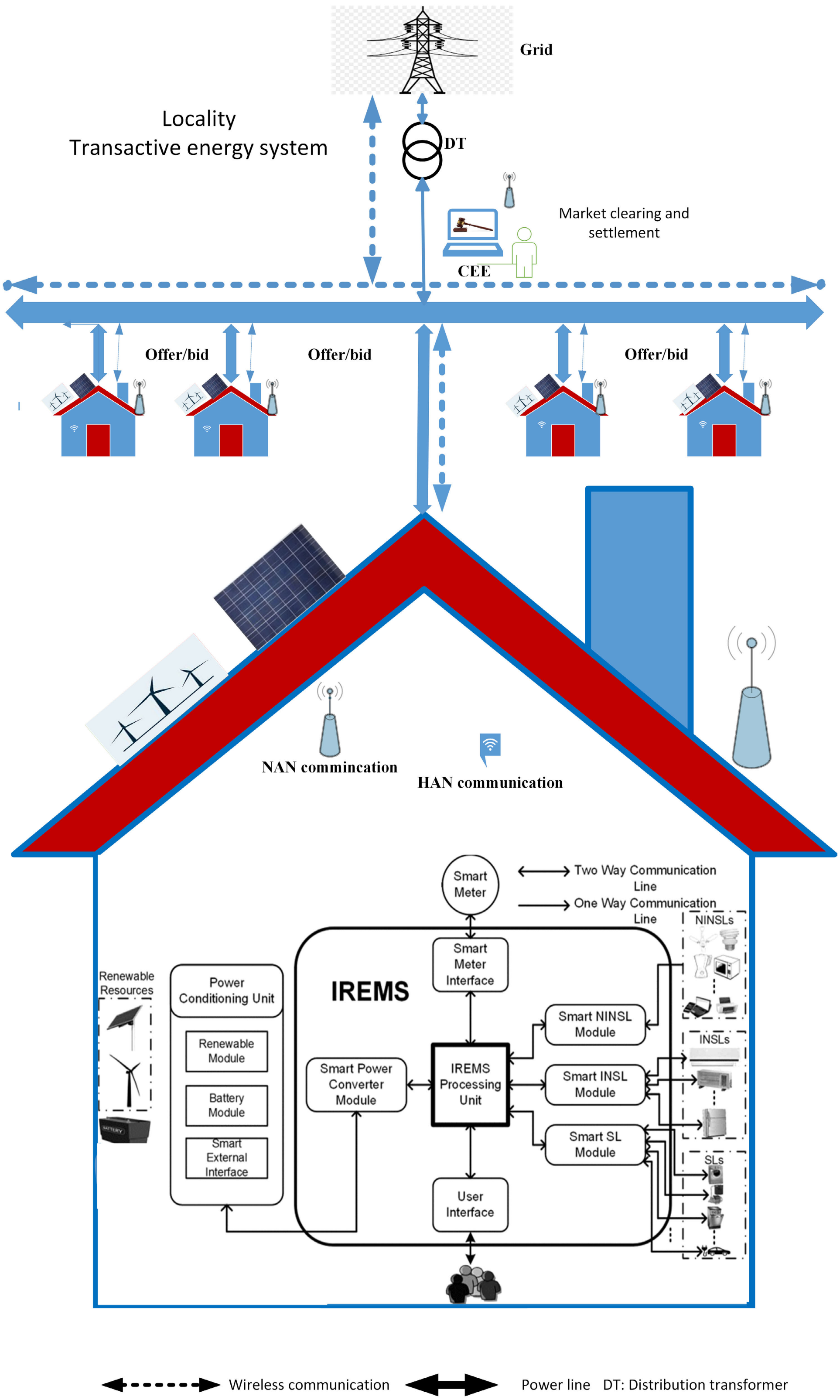


FIGURE 2. Proposed LTES architecture.

can forecast their expected net demand (expected demand - expected generation) pattern for the upcoming intervals based on end-user behavior dynamics, energy consumption history data, and CEE forecasted weather data. Let $pd^{n}_{m,SLs}$,

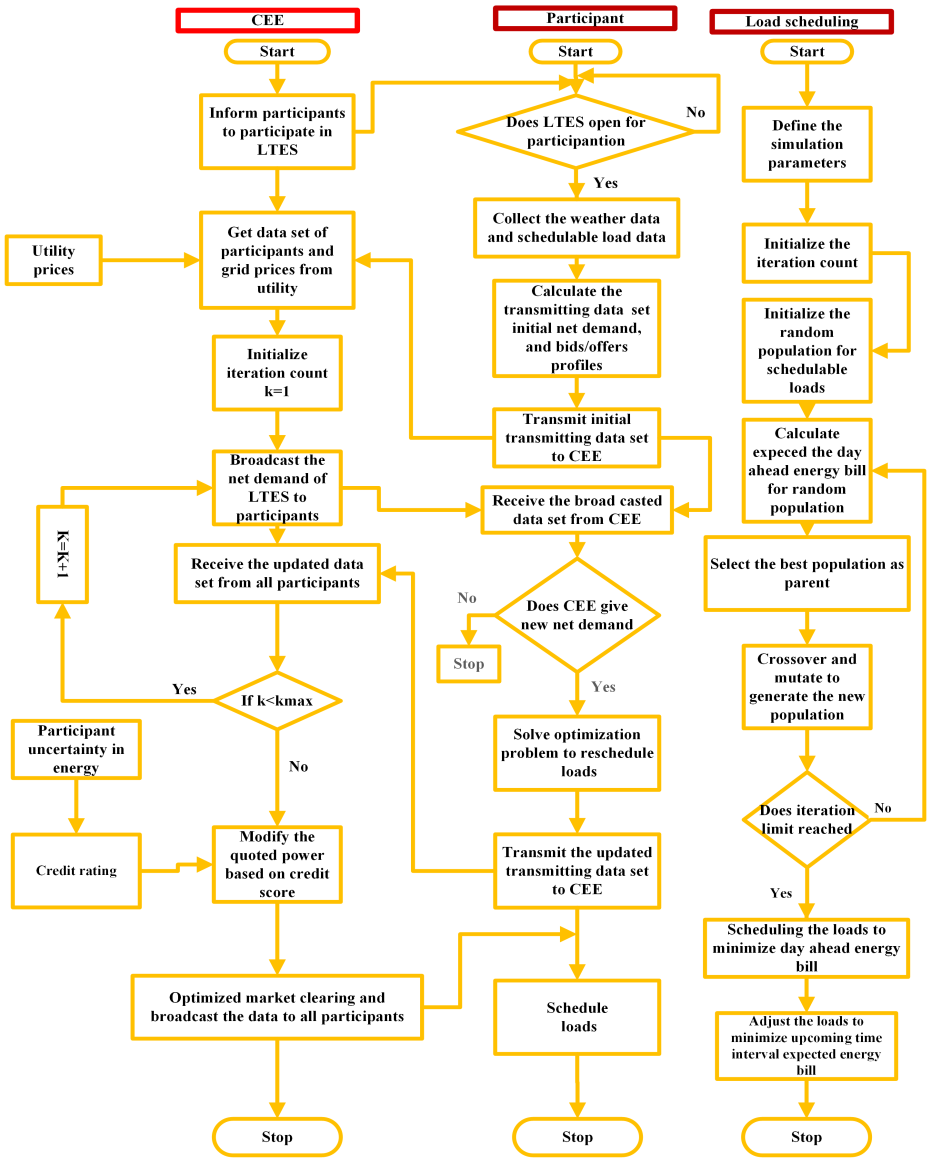


FIGURE 3. LTES flow mechanism.

$pd^n_{m,INSLs}$, $pd^n_{m,NINSLs}$ and nd^n_m indicate the power demand (kW) of SLs, INSLs, NINSLs and aggregated demand of the participant $m \in M$ during the trading interval $n \in N$, respectively. These variables can be computed using (1)-(4) [7].

$$pd^n_{m,SLs} = \sum_{a=1}^{A_m} \left(S^n_{a,SL} * P^n_{a,SL}\right) \ \forall m \in M \ \forall n \in N \quad (1)$$

$$pd^n_{m,INSLs} = \sum_{b=1}^{B_m} \left(S^n_{b,INSL} * P^n_{b,INSL}\right) \ \forall m \in M \ \forall n \in N \quad (2)$$

$$pd^n_{m,NINSLs} = \alpha^n \sum_{c=1}^{C_m} APD^n_{c,NINSL} \ \forall m \in M \ \forall n \in N \quad (3)$$

$$td^n_m = \left[pd^n_{m,SLs} + pd^n_{m,INSLs} + pd^n_{m,NINSLs}\right] \quad (4)$$

where A_m,B_m and C_m are the available number of SLs, INSLs, and NINSLs in the considered residential building, respectively. The $P^n_{a,SL}$ and $P^n_{b,INSL}$ are represented as the rated power of SL and INSL, respectively. In equation (3) α^n is a user defined factor and APD^n_{NINSL} is the average power demand of NINSL in similar days over the used defined past weeks. The S^n_{SL} and S^n_{INSL} are the operating status of SL and INSL, respectively. When the appliance is turned ON, the operating status is presumed to be 1, otherwise it is 0. The symbols $pg^n_{m,PV}$, $pg^n_{m,WIND}$, and tg^n_m represent the generated electric (kW) from the participant m's photovoltaic (PV) system, wind-based electricity generator, and the combined renewable energy generation, respectively. These variables can be computed using (5)-(8) [7]. The aggregated demand and generation will be used to calculate the net demand of participant m for the interval n as expressed in (9).

$$pg^n_{m,PV} = F_C P_{STC} \left(\frac{G^n_{AVG}}{G^n_{STC}}\right) \left(1 + \left(T^n_C - T_{STC}\right) \alpha_C\right) \quad (5)$$

$$T_C^n = T_{AVG}^n + \left(\frac{NOCT - 20}{0.8}\right) * G_{AVG}^n \quad (6)$$

$$pg_{m,WIND}^n = 0.5\rho A_w \left(v^n\right)^3 * C_P \quad (7)$$

$$tg_m^n = \left[pg_{m,PV}^n + pg_{m,WIND}^n\right] \quad \forall m \in M, n \in N \quad (8)$$

$$nd_m^n = \left[td_m^n - tg_m^n\right] \quad \forall\, m \in M, n \in N \quad (9)$$

In the equation, F_c and P_{STC} represent the de-rating factor and nominal power (in kW_p) under the Standard Test Condition (STC) of the PV array, respectively. The variables G_{AVG}^n, T_C^n, and T_{AVG}^n correspond to the average solar radiation (kW/m^2), temperature of the PV cell ($^\circ C$), and averaged ambient temperature (in $^\circ C$) during interval $n \in N$, respectively. GSTC represents the solar radiation at the STC (1 kW/m^2), TSTC denotes the STC temperature (25°C), α_C represents the temperature coefficient of the PV cell, and NOCT signifies the normal operating cell temperature (48°C). The variables A_w and ρ denote the swept area (m^2) and air density (kg/m^2) of the wind turbine, respectively. The variable v^n represents the wind velocity (in m/s), and C_p corresponds to the maximum power coefficient. Market players have the option to forecast their own generation using the day-ahead weather forecasting information provided by either TESO's or any third-party models. Generally, methods like artificial neural networks (ANN) are used in weather forecasting [7]. The participants in this work employ a dynamic bidding strategy, which involves determining their bidding quantities and prices using various self-analysis methods, as mentioned in reference papers [39] and [40]. These approaches leverage data from the utility or third-party sources to inform their decision-making process. It is worth noting that the bidding strategy in this study is user-defined, enabling participants to customize and modify their strategies according to their specific requirements and preferences. The objective function of participant $m \in M$ is defined as

$$\min \sum_{n=1}^{N} (\lambda_{mp}^n [OD_m^n - OG_m^n] - (nd_m^n - [OD_m^n - OG_m^n])\lambda_u^n) \quad (10)$$

subject to following constraints

$$S_{sl}^n = \begin{cases} 1 & \forall \text{n} \in [e_{sl}, f_{sl}] \quad \forall sl \subset \text{SLs} \\ 0 & \text{else} \end{cases} \quad (11)$$

$$\sum_{q=t}^{f_{sl}} S_{sl}^q = c_{sl}^q \quad \forall sl \in \text{SLs} \quad, \forall n \in [e_{sl}, f_{sl}] \quad (12)$$

$$\sum_{x=0}^{f_{sl}-e_{sl}-d_{sl}+l} \quad \prod_{y=e_{sl}+x}^{e_{sl}+d_{sl}+x-l} [S_{sl}^y \star ps_{sl}] = ps_{sl} \quad (13)$$

The variable OD_m^n denotes the optimal demand energy provided by the utility, whereas OD_g^n represents the optimal generation energy provided by the utility. The variable λ_{mp}^n signifies the expected unit energy price provided by the utility in the market clearing process. Furthermore, nd_m^n corresponds to the net demand of participant m during the n^{th} time interval.

The objective function relies on several factors, including the operating status (ON/OFF) of schedulable loads, the market-clearing price, and the net demand of the participant. Moreover, we utilize the variables e_{sl}, f_{sl}, and ps_{sl} to represent the starting time interval, dead time interval, and preemptive status of a particular schedulable load sl belonging to the set SL. The variable S_{sl}^t indicates the on/off status of sl during the time interval n, where n belongs to the set N. Furthermore, c_{sl}^q denotes the remaining intervals required to complete the task associated with sl within the interval $n \in [e_{sl}, f_{sl}]$. Equation (13) represents a preemptive constant specific to the schedulable loads in the set SLs.

In the case where the net demand $nd_m^n \geq 0$ during interval $n \in N$, the participant considered as a buyer. Conversely, if $nd_m^n < 0$, the participant functions as a seller. The bidding and offering prices are represented as $\lambda_{m,b}^n$ and $\lambda_{m,s}^n$, respectively.

$$\lambda_{m,b}^n = \begin{cases} \lambda_{U,buy}^n \leq \lambda_{m,b}^n \leq \lambda_{U,sell}^n & \text{if } nd_m^n \geq 0 \\ 0 & \text{else} \end{cases} \quad (14)$$

$$\lambda_{m,s}^n = \begin{cases} 0 & \text{if } nd_m^n \geq 0 \\ \lambda_{U,buy}^n \leq \lambda_{m,s}^n \leq \lambda_{U,sell}^n & \text{else} \end{cases} \quad (15)$$

where exporting utility energy cost is $\lambda_U^{buy,n}$ and importing utility energy cost is $\lambda_U^{sell,n}$, respectively. After determining the price and predicting their future time interval net demand profile, all participants' complete data sets are sent to the CEE. The participant $m \in M$, sending data set is specified as

$$T_m^n \triangleq [ND_m^n; BP_m^n; OP_m^n] \quad \forall m \in M \quad (16)$$

For each participant $m \in M$, the sets ND_m^n, BP_m^n, and OP_m^n represent the initial net demand, bidding price, and offering price, respectively. After obtaining the transmission data set from all participants, CEE calculates the locality net demand and broadcasts it to all participants. The receiving data set of participant $m \in M$ is defined as follows.

$$R_m^n \triangleq [LND_k^n] \quad \forall m \in M \quad (17)$$

Here locally net demand for the k^{th} beneficial choice in the n^{th} interval is denoted by LND_k^n. Upon receiving the data set from the CEE, each participant employ an optimization algorithm [39] to optimize electricity bills and achieve demand response (DR) using dynamic price signals. The participants then transmit their updated information to the CEE through a revised transmitting data set. The revised transmitting data set is specific to participant m from the set M and includes the updated net demand, bidding price, and offering price. This process of the locality net demand response strategy is repeated a finite number (k) of times, as determined by the CEE based on the forward market structure. The final data set for participant $m \in M$ is represented as T_m^n:

$$T_m^n \triangleq [\hat{ND}_m^n; \hat{BP}_m^n; \hat{OP}_m^n] \quad \forall m \in M \quad (18)$$

Here, $\hat{ND}_m^n$, $\hat{BP}_m^n$, and $\hat{OP}_m^n$ are the updated sets of net demand, bidding price, and offering price for participant $m \in M$, respectively. These updates reflect the optimized choices made by participants to ensure efficient energy consumption and cost savings.

C. CEE MODEL

CEE is a centralized market operator whose duties include forecasting meteorological data, building communication networks, disseminating information to participants, deciding internal market clearing prices, and maintaining the real-time power balance in the community micro grid. The market clearing price and quantities in the market time-line are calculated in this study using a linear optimization technique. In order to monitor the negotiation between buyers and sellers, the CEE serves as an interface. The LTES receives simultaneous submissions of all generating offers and demand bids. As a result, nobody is aware of other people's bids or offers.

D. CREDIT RATING BASED DOUBLE SIDE AUCTION MODEL

In the proposed distributed electric energy trading platform, a credit rating based double side auction model ensures fair and efficient energy trading while preventing malicious quotations from prosumers that could disrupt the market. The double side auction model, a well-established mechanism in various trading scenarios, involves simultaneous bidding from both buyers and sellers in a transparent manner. Prior to each round of transactions, the trading platform displays the highest reference price and the lowest reference price. Participants are only allowed to trade with other prosumers if their quoted price falls within these reference price limits. This mechanism helps maintain order and fairness in the distributed power trading market. It's important to note that the utility energy tariff in each time interval serves as the boundary limit for the price quotations of participants.

All participants in an LTES are driven to minimize their utility bill by sharing excess generation or demand with other participants. However, the success of LTES is solely dependent on the magnitude of the locality's net demand. A positive net demand value indicates that LTES has excess demand that must be drawn from the utility grid, whereas a negative net demand value indicates that LTES has excess generation that must be fed to the utility grid. Participants in this proposed real-time LTES have finite beneficial alternatives provided by CEE to rearrange the operating pattern of their household appliances within a certain time frame. As a result, depending on the quantity and sign of locality net demand, players may actively modify their net demand. Eventually, the CEE will use appropriate market clearing mechanisms to maximize participants social welfare. As a consequence, the individual participant's profit and LTES's self-sustainability will be strengthened. The uncertainty in users' energy usage will have a detrimental influence on LTES social welfare and stability. Hence, in the proposed LTES, power injection limits are recommended for sellers and power extraction limits are proposed for buyers depending on the credit ratings of individual participants. Further, these limits will force the participants to reduce the uncertainties. This scenario is analytically expressed as a linear optimization problem. The goal of the optimization process is to establish a single market-clearing price and the best demand-generation plans for each time period. The mathematical representation of the objective function is given in (19).

$$\max_{\lambda_{i,b}^n,\lambda_{j,s}^n,y_{i,b}^n,y_{j,s}^n} \sum_{i=1}^{M_b^n} \lambda_{i,b}^n y_{i,b}^n - \sum_{j=1}^{M_s^n} \lambda_{j,s}^n y_{i,s}^n \tag{19}$$

$$\text{s.t.} \sum_{i=1}^{M_b^n} y_{i,b}^n - \sum_{j=1}^{M_s^n} y_{j,s}^n = 0 \tag{20}$$

$$0 \le y_{i,b}^n \le p_{i,b}^n \quad i = 1, \ldots, M_b^n \tag{21}$$

$$0 \le y_{j,s}^n \le p_{j,s}^n \quad j = 1, \ldots, M_s^n \tag{22}$$

where $\lambda_{i,b}^n y_{i,b}^n$ and $\lambda_{j,s}^n y_{i,s}^n$ indicate the revenue of the buyer and seller, respectively. The relationship between demand and generation is described as an equality constraint in (20). Furthermore, in (21) and (22), the limitations for buyer demand and seller generation are described as boundary constraints. Here $p_{i,b}^n$ and $p_{j,s}^n$ are maximum power constraints of buyer and seller respectively.

The quantity of modified demand and generation depending on credit rating during a trading period n are represented as $p_{i,b}^n$ and $p_{j,s}^n$, respectively, and will be calculated using (23) and (24).

$$p_{i,b}^n = \psi_{i,b}^n R_{i,b}^n \tag{23}$$

$$p_{j,s}^n = \psi_{j,s}^n R_{j,s}^n \tag{24}$$

Here $R_{i,b}^n$ and $R_{j,s}^n$ represent the participants' quoted bid and offer during a trading interval n. CEE will assign $\psi_{i,b}^n$ and $\psi_{j,s}^n$ as power extraction and power injection restriction factors to individual participants depending on their uncertain energy behavior. The steps involved in the computation of these factors will be discussed in the upcoming subsection.

E. COMPUTING PARTICIPANTS' CREDIT RATING

In the proposed LTES, the notations $CCS_{i,b}^n$ and $CCS_{j,s}^n$ are taken as Calculated Credit Score (CCS) for buyer i and seller j during trading interval n, respectively. The CCS for any trading interval n can be mathematically computed with due consideration to the previous interval CCS and present interval credit points as shown in (25) and (26).

$$CCS_{i,b}^n = Z_{i,b}^n CS_{i,b}^n + \left(1 - Z_{i,b}^n\right) CCS_{i,b}^{(n-1)} \tag{25}$$

$$CCS_{j,s}^n = Z_{j,s}^n CS_{j,s}^n + \left(1 - Z_{j,s}^n\right) CCS_{j,s}^{(n-1)} \tag{26}$$

where $CS_{i,b}^n$ and $CS_{j,s}^n$ be the n^{th} trading interval credit score for buyer i and seller j, receptively. $Z_{i,b}^n$ and $Z_{j,s}^n$ are represented as credible factor for buyer i and seller j, receptively which are expected to satisfy the boundary constraints such as $0 \leq Z_{i,b}^n \leq 1$ and $0 \leq Z_{j,s}^n \leq 1$. The value of the credibility factor shows the importance of the current interval credit score (CS) when compared to the end user's previous CSS. Furthermore, these credible factors will be estimated using the maximum likelihood estimate [41], yielding a weightage balance of $CS_{i,b}^n$ and $CCS_{i,b}^{(n-1)}$ for buyer and $CS_{j,s}^n$ and $CCS_{j,s}^{(n-1)}$ for the seller. These credible factors can be expressed mathematically as given in (27) and (28).

$$Z_{i,b}^n = \frac{V_{i,b}^n}{U_{i,b}^n + V_{i,b}^n} \tag{27}$$

$$Z_{j,s}^n = \frac{V_{j,s}^n}{U_{j,s}^n + V_{j,s}^n} \tag{28}$$

where $V_{i,b}^n$ and $V_{j,s}^n$ are the variances of participants energy data $\{X_{i,b}^1, \ldots, X_{i,b}^{(n-1)}\} \in A_{i,b}^{n-1}$ for buyer and $\{X_{j,s}^1, \ldots, X_{j,s}^{(n-1)}\} \in A_{j,s}^{n-1}$ for seller, respectively. Further, these variances are computed without considering the current interval energy data. Similarly, $U_{i,b}^n$ and $U_{j,s}^n$ represent the variance of participants energy data $\{X_{i,b}^1, \ldots, X_{i,b}^{(n)}\} \in A_{i,b}^n$ for buyer and $\{X_{j,s}^1, \ldots, X_{j,s}^{(n)}\} \in A_{j,s}^n$ for seller, respectively. Further, these variances are computed by considering the current interval energy data.

$$V_{i,b}^n = Var\left(A_{i,b}^{n-1}\right) \tag{29}$$

$$V_{j,s}^n = Var\left(A_{j,s}^{n-1}\right) \tag{30}$$

$$U_{i,b}^n = Var\left(A_{i,b}^n\right) \tag{31}$$

$$U_{j,s}^n = Var\left(A_{j,s}^n\right) \tag{32}$$

The computed variances of participant data ($X_{i,b}^n$, $X_{i,s}^n$) illustrate the dynamics of electricity trading involving participants and the utility. The presence of uncertainties in trading electricity among participants necessitates a priority mechanism to minimize penalties. To address this, the introduction of a priority factor becomes pivotal, enabling adjustable weightage as decided by CEE. The mathematical modeling of the suggested computation are expressed in (33) and (34).

$$X_{i,b}^n = \Upsilon P_{it,b}^n \lambda_{itavg}^n t + P_{ig,b}^n \lambda_{ig,b}^n t \tag{33}$$

$$X_{j,s}^n = \Upsilon P_{jt,s}^n \lambda_{jtavg}^s t + P_{jg,s}^n \lambda_{jg,s}^n t \tag{34}$$

where $P_{it,b}^n$ and $P_{ig,b}^n$ are the i^{th} buyer participant's buying power through P2P energy trading and Peer-to-Grid (P2G) scheme, respectively. λ_{itavg}^n and $\lambda_{ig,b}^n$ are the P2P average market clearing unit cost and P2G grid selling price, receptively. Similarly, $P_{jt,s}^n$, $P_{ig,s}^n$, λ_{jtavg}^n and $\lambda_{ig,s}^n$ are expressed as the j^{th} seller participant's selling power through P2P scheme, P2G scheme, P2P average market clearing unit cost and P2G grid buying price, respectively. Since the high demand intervals will have more impact on credit score variations, the average unit cost of participants has given more importance to compute the energy data. Further, CEE will decide the priority factor Υ to trade the energy among end users compared to grid. The current interval credit score of buyer ($CS_{i,b}^n$) and seller ($CS_{i,b}^n$) can be computed mathematically by using (35) and (36), respectively.

$$CS_{i,b}^n = \begin{cases} \dfrac{AP_{j,s}^n}{SP_{j,s}^n}100 & \text{if } 0 \leq AP_{j,s}^n \leq SP_{j,s}^n \\ \left(2 - \dfrac{AP_{j,s}^n}{SP_{j,s}^n}\right)100 & \text{if } 2SP_{j,s}^n \geq AP_{j,s}^n > SP_{j,s}^n \\ 0 & \text{otherwise} \end{cases} \tag{35}$$

$$CS_{j,s}^n = \begin{cases} \dfrac{AP_{j,s}^n}{SP_{j,s}^n}100 & \text{if } 0 \leq AP_{j,s}^n \leq SP_{j,s}^n \\ \left(2 - \dfrac{AP_{j,s}^n}{SP_{j,s}^n}\right)100 & \text{if } 2SP_{j,s}^n \geq AP_{j,s}^n > SP_{j,s}^n \\ 0 & \text{otherwise} \end{cases} \tag{36}$$

where $AP_{i,b}^n$ and $RP_{i,b}^n$ are the i^{th} buyer's actual demand and P2P stated demand in real time, receptively. Similarly, $AP_{j,s}^n$ and $SP_{j,s}^n$ are the j^{th} seller's actual surplus generation and P2P agreed generation.

F. POWER EXCHANGE LIMITING FACTORS

The mathematical modeling of power exchange limiting factors is based on the proportional relationship between the credit rating difference and the desired or target rating. The actual credit rating for a buyer can be denoted as $CCS_{i,b}^n$, while the target credit rating is represented as $CCS_{i,bt}^n$. Similarly, for a seller, the actual credit rating is given by $CCS_{j,s}^n$, and the target credit rating is denoted as $CCS_{j,st}^n$. The calculation of the n^th interval power injection limit takes into account the credit score of the $(n-2)^{th}$ interval, considering its significance in addressing time complexity within real-time market situations. This concept can be succinctly expressed as follows:

$$\psi_{i,b}^n = 1 - \sigma_i^n \star \frac{(CCS_{i,bt}^n - CCS_{i,b}^{n-2})}{CCS_{i,bt}^n} \tag{37}$$

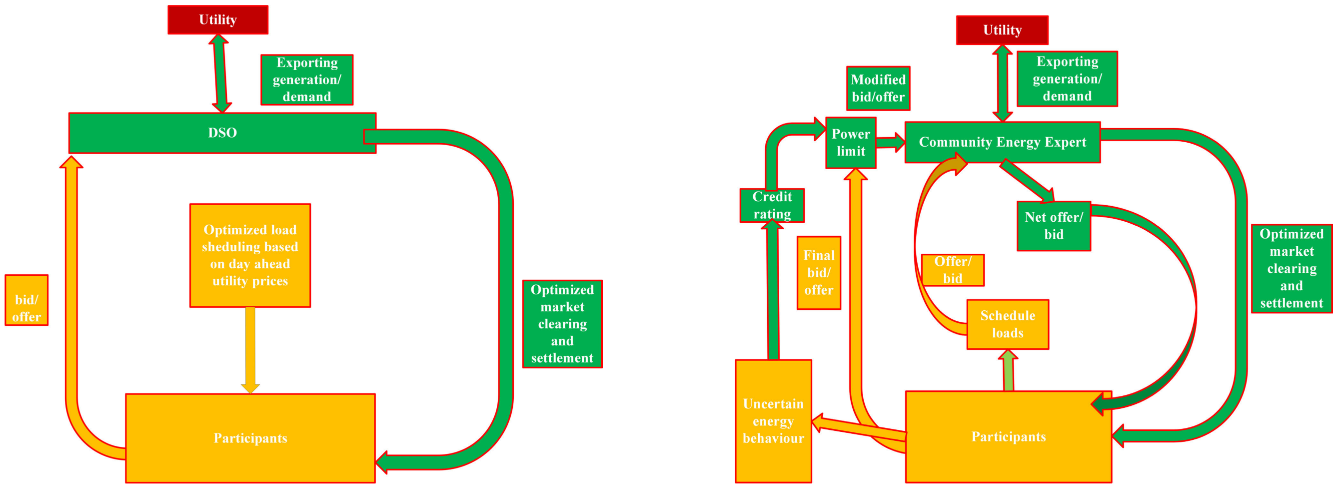
$$\psi_{j,s}^n = 1 - \sigma_j^n \star \frac{(CCS_{j,st}^n - CCS_{j,s}^{n-2})}{CCS_{j,st}^n} \tag{38}$$

Here, the σ_i^n and σ_j^n represents a scaling factor that determines the magnitude of the power exchange limiting factor. The larger the scaling factor, the higher the penalty for larger deviations from the target credit rating. The term $(CCS_{i,bt}^n - CCS_{i,b}^{n-2})$ represents the difference between the target and actual credit ratings for buyer. If the actual rating is equal to the target rating, then power exchange limiting factor is one.

IV. TRANSACTIVE ENERGY TRADING METHODOLOGY

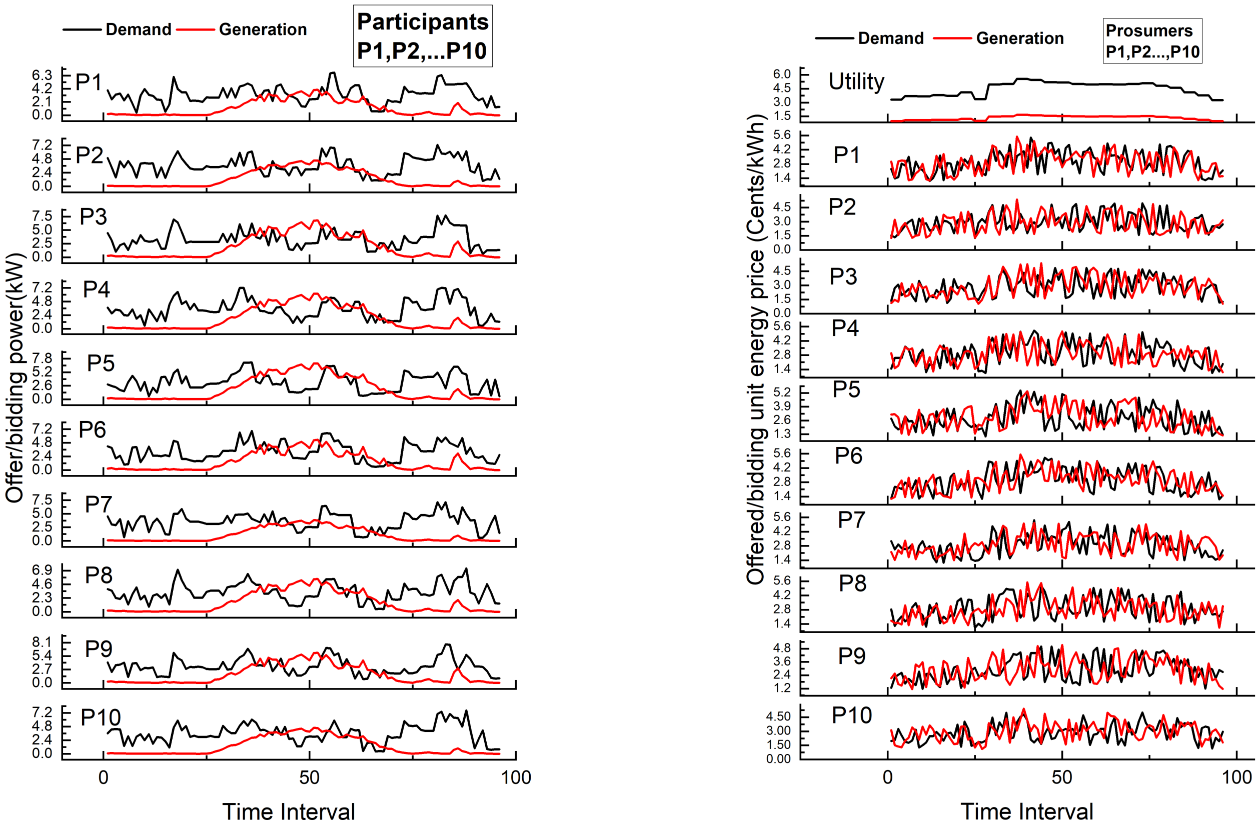
A. EXISTING ENERGY TRADING APPROACH

Fig.4a provides a visual representation of the sequential procedures entailed in enabling energy trading through



(a) (b)

FIGURE 4. Conceptual comparison of TES framework (a) Existed. (b) Proposed.



(a) (b)

FIGURE 5. Participant one day offer/bidding (a) Power. (b) Price.

established methodologies. The process commences with the Distribution System Operator (DSO) initiating their engagement in the market, thereby attracting participants with self-interest in energy trading. Subsequently, each participant engages in resolving an optimization problem aimed at minimizing their projected electricity expenses, which are contingent on day-ahead utility pricing. This optimization process often encompasses adjustments to the operational schedules of specific appliances through a variety of optimization algorithms. Following the completion of the optimization tasks, all market participants proceed to update their transmitted datasets, subsequently transmitting

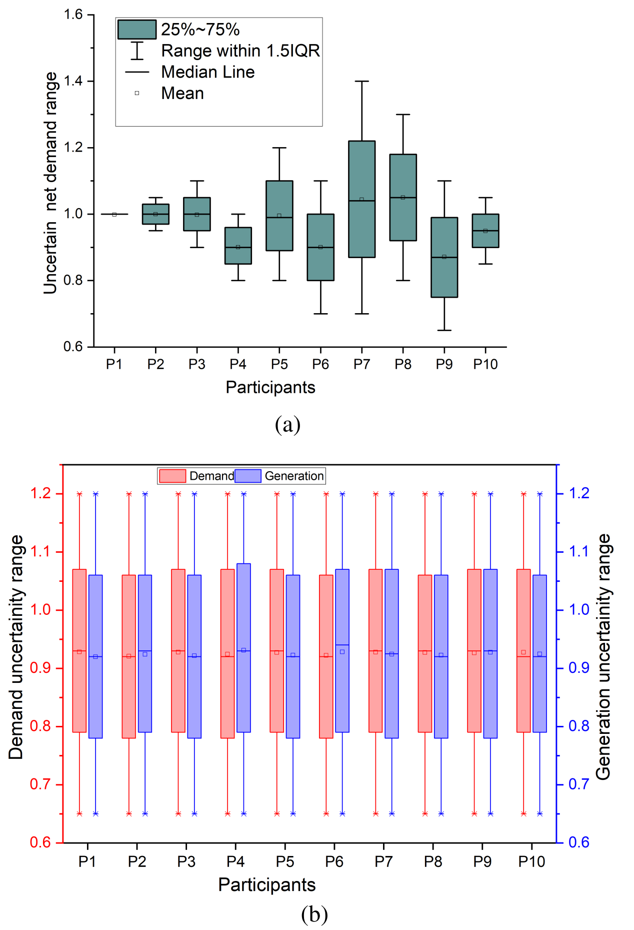


FIGURE 6. **Participants offered/bidding uncertainty range. (a) Case study 1-3. (b) Extended case study.**

them back to the DSO. Once the DSO has received the final datasets from all participants, it proceeds to compute the market-clearing quantity and corresponding price. Any surplus energy not cleared by end-users is routed to the utility at predefined rates, and this data is subsequently disseminated to all participants.

B. PROPOSED ENERGY TRADING APPROACH

Figures 3 and 4b illustrate the sequential steps involved in facilitating energy trading within the LTES. Initially, the LTES opens the market for participation, attracting self-interested participants who wish to engage in energy trading. All the participants simultaneously transmit their data sets to CEE. Once the CEE receives data from all participants, it initializes the iteration count (k) and broadcasts the net demand information to all participants. Upon receiving this net demand data, the IREMS of each participant solves an optimization problem to minimize their expected upcoming electricity bill. This optimization may involve adjusting the operating intervals of certain appliances (represented as SLs) using a binary genetic algorithm (BGA) [40]. After the optimization process, all the market participants update their transmitting data sets and transmit them back to the LTES. Participants then await the updated net demand data. This iterative process continues until the convergence criterion is met. The iteration process terminates either when the community generation is nearly fully utilized for community demands or when the maximum number of iterations, determined by the LTES, is reached. Upon receiving the final data set from the participants, the CEE modifies it by multiplying the power exchange limits, which are determined based on the credit scores calculated in the previous interval. Subsequently, the CEE calculates the market-clearing quantity and price by solving optimization problem defined in (19)-(22). Uncleared energy among end users is exported to the utility at predefined prices, and this dataset is broadcasted to the participants.

V. CASE STUDY

In this section, the feasibility and performance of the proposed LTES are validated by various case studies with ten residential end users as participants.

A. SIMULATION SETUP

The details of different type of household appliances along with power rating, and renewable generation are taken from [40]. The utility defined energy selling and buying prices are taken from [39]. In order to have efficient trading, the duration of trading interval for the proposed LTES is assumed to be 15 minutes. The individual participants generation and demand pattern of a particular day is depicted in Fig.5a. Further, the offer and bidding price of the participants is illustrated in Fig. 5b. In the proposed research, the initial default energy behavior of participants over a month is taken randomly because it depends on person greediness, stochastic generation and demand which is shown in Fig.6a. MATLAB is used with the following computer configuration to develop and analyze the entire community's transactive energy market: 16 GB of RAM with a 3 GHz Intel Core i5 CPU.

B. CASE STUDY ENVIRONMENT

This section presents the simulation environment of various case studies to compare the performance of the proposed credit based TEM with different TEM available in the literature. Four case studies are presented in this work: Case-I-Ten prosumers with uncertainty energy behavior; Case-II-Five prosumers and Five consumers with uncertainty energy behavior; Case-III-Ten prosumers with uncertain energy behavior and two final demand response choices. Extended Case Study-Ten prosumers with more uncertain energy behavior than Case-III and two final demand response choices. Each case study takes into consideration the following scenarios:

1) Participants in P2G scheme with utility predefined electricity selling and buying prices.
2) Participants in P2P energy trading without credit rating based LTES.

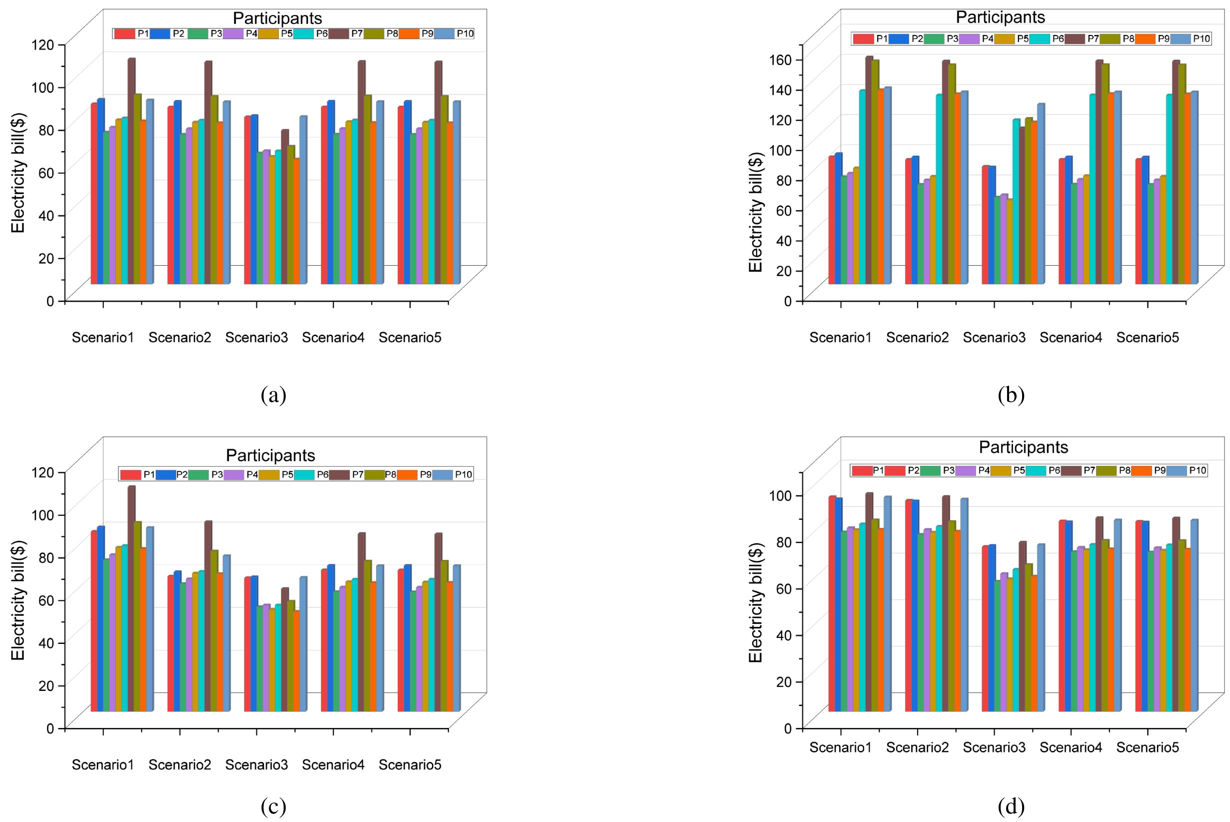


FIGURE 7. Participants monthly electricity bill. (a) Case-1 (b) Case-2 (c) Case-3 (d) Extended case study.

3) Participants in P2P energy trading with credit rating-based LTES and utility-set power injection/ extraction restrictions.
4) Participants in P2P energy trading with credit rating based LTES and TEM-set import/export restrictions.
5) Participants in P2P energy trading with priority based LTES by considering the credit rating.

In the proposed case studies, the penalty unit price for participants energy uncertainties are listed in Table. 2. Further, the utility related charges for scenario 2 to 5 are considered as $0.01\$/kWh$ [24] and the value of priority factor (Υ) is taken as 2. To simplify the computational processes and provide the participants with greater flexibility in deciding power exchange limits, a classification system based on credit scores has been implemented. The participants are divided into seven grades, as outlined in Table 3. For instance, Grade A comprises participants with credit scores between 91 and 100. In this scenario, the highest value in the credit score range is employed for calculating power exchange limits.In the case study environment, the limits assigned to buyers are determined using (37), while the limits assigned to sellers are calculated using (38). The scaling factors σ_i^n and σ_j^n are both set to one in this calculation. Furthermore, the desired credit rating values ($CCS_{i,bt}^n$, $CCS_{j,st}^n$) are set as 100. These values are generally determined by the CEE considering the reserve capacity and the necessary level of uncertainty mitigation.

TABLE 2. Considered penalty price for uncertainty in energy.

Uncertainty in energy	Unit price (cents/kWh)
Decreased demand	0.5*(Utility buying price)
Decreased generation	2*(Utility selling price)
Increased demand	2*(Utility selling price)
Increased generation	0.5*(Utility buying price)

TABLE 3. Participant classification by credit score.

Credit score	91-100	81-90	71-80	61-70	51-60	41-50	below 40
Grades	**A**	**B**	**C**	**D**	**E**	**F**	**G**

Similar considerations are applied to participants in the other grades, leading to the determination of appropriate power exchange limiting factors. These factors define the maximum power injection limit ($\psi_{j,s}^n$) for sellers and the maximum power extraction limit ($\psi_{i,b}^n$) for buyers.

C. TRANSACTIVE ENERGY MARKET ENVIRONMENT IN CASE STUDIES

The proposed market is a forward market in which a day is split into 15-minute intervals, resulting in 96 slots every day. Further, the LTES participants are supposed to be

TABLE 4. Comparing the monthly uncertainty energy under various scenarios in case I and case II.

Energy uncertainty	Case I					Case II				
	Scenario1	*Scenario2*	***Scenario3***	*Scenario4*	*Scenario5*	*Scenario1*	*Scenario2*	***Scenario3***	*Scenario4*	*Scenario5*
DDWU	943.36	931.73	**60.47**	936.31	932.1	1294.18	1235.41	**83.18**	1256.07	1237.82
DDIT	0	11.63	**0.76**	7.04	11.25	0	58.76	**4.13**	38.11	56.35
DGWU	258.58	244.97	**16.38**	249.98	245.43	96.91	60.14	**2.60**	71.00	60.35
DGIT	0	13.60	**0.81**	8.59	13.14	0	36.77	**1.27**	25.91	36.55
IDWU	504.75	504.75	**39.50**	504.75	504.75	687.07	687.07	**56.311**	687.07	687.07
IGWU	124.93	124.93	**8.85**	124.93	124.93	50.34	50.34	**1.69**	50.34	50.34

DDWU=Decreased demand with utility; DDIT=Decreased demand inside TEM; DGWU=Decreased generation with utility;
DGIT=Decreased generation inside TEM IDWU=Increased demand with utility; IGWU=Increased generation with utility.

TABLE 5. Demand response strategy with net LTES net demand (kW).

	P1		P2		P3		P4		P5		P6		P7		P8		P9		P10		
DRS	D	G	D	G	D	G	D	G	D	G	D	G	D	G	D	G	D	G	D	G	LND
Intial	2.81	-0.49	3.39	-0.55	2.81	-0.82	2.96	-0.75	3.03	-0.84	2.41	-0.65	3.15	-0.46	3.54	-0.67	2.79	-0.74	2.96	-0.55	23.33
	⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓
FDR	2.2	-0.49	3.1	-0.55	2	-0.82	2.4	-0.75	2.8	-0.84	2.1	-0.65	2.95	-0.46	2.86	-0.67	2.54	-0.74	2.33	-0.55	18.76
	⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓
SDR	2.12	-0.49	3.01	-0.55	2.12	-0.82	2.25	-0.75	2.61	-0.84	1.98	-0.65	2.84	-0.46	2.76	-0.67	2.48	-0.74	2.12	-0.55	17.77
FB	**1.63**		**2.46**		**1.3**		**1.5**		**1.77**		**1.33**		**2.38**		**2.09**		**1.74**		**1.57**		**17.7**
Intial	2.61	-4.04	2.99	-4.52	2.64	-6.78	2.19	-6.18	1.99	-6.9	3.19	-5.35	2.54	-3.8	2.59	-5.47	3.19	-6.06	3.04	-4.52	-26.65
	⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓
FDR	3	-4.04	3.2	-4.52	2.8	-6.78	3.4	-6.18	3.2	-6.9	3.8	-5.35	3.6	-3.8	3.4	-5.47	4.19	-6.06	3.7	-4.52	-19.33
	⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓		⇓
SDR	3.4	-4.04	3.8	-4.52	4	-6.78	3.2	-6.18	2.5	-6.9	3.9	-5.35	3.2	-3.8	3.6	-5.47	3.3	-6.06	3.9	-4.52	-18.82
FB	**-0.64**		**-0.72**		**-2.78**		**-2.98**		**-4.4**		**-1.45**		**-0.6**		**-1.87**		**-2.76**		**-0.62**		**-18.8**

D=Demand ; DRS=Demand response stages; FB=Final bidding ;
FDR=First demand response; G=Generation ; LND=Locality net demand;
SDR=Second demand response.

rational, as stated in [24], i.e., always making the best decisions objectively, and non-strategic. The market offering and bidding power began five minutes before the actual energy trading period. Prosumers first disclose their surplus demand or generation to CEE. The CEE computes the community net demand (demand - generation) using the quoted demand of individual prosumers and disclose it to all prosumers in the community. Within the first two minutes, all prosumers have two beneficial options with a one-minute time frame to rearrange their loads based on community net demand. Prosumers send their final bids to CEE, which then adjusts them according to individual credit ratings. This approach uses the latest credit rating as a reference for setting power limits. CEE has further optimized market clearing and communicates successful bids and offers to all participants. Finally, the uncleared prosumers' generation or demand will be shared with the grid at utility stated pricing.

TABLE 6. Comparing the monthly electricity bill with the previously proposed mechanisms in case-III.

EB	P2G	AMC	GDR	PIDA	VCG	Scenario 3	Scenario 4	Scenario 5
P1	84.26	82.77	75.84	77.81	78.74	62.54	66.23	66.21
P2	86.36	85.42	76.93	75.02	84.62	62.99	68.35	68.33
P3	70.97	69.94	65.74	63.64	64.26	48.96	56.01	55.93
P4	73.38	72.6	67.38	65.18	68.95	49.8	58.11	58.07
P5	76.83	75.7	66.67	64.42	67.06	47.73	60.73	60.55
P6	77.64	76.63	67.24	65.3	69.24	49.78	61.84	61.84
P7	105.21	103.87	77.12	75.54	83.81	57.48	83.26	83.08
P8	88.49	87.75	69.7	67.69	72.27	51.51	70.36	70.28
P9	76.24	75.44	66.6	64.61	66.07	46.76	60.24	60.36
P10	86.09	85.25	77.82	75.97	84.58	62.68	68.22	68.22

EB=Electricity Bill; P2G=Peer to grid; AMC=Average Market Clearing; GDR= Generation to demand ratio;
PIDA=Periodic iterative double auction; VCG=vickrey clarke groves

TABLE 7. Comparing the monthly uncertainty energy under various scenarios in extended case study.

Energy uncertainty	Case IV				
	Scenario1	*Scenario2*	***Scenario3***	*Scenario4*	*Scenario5*
DDWU	1772.84	1750.96	**173.09**	1751.30	1752.18
DDIT	0	21.88	**2.04**	21.54	20.65
DGWU	428.4	404.94	**40.43**	405.22	414.75
DGIT	0	23.45	**2.15**	23.17	13.64
IDWU	585.85	585.85	**57.21**	585.85	585.85
IGWU	150.65	150.65	**66.70**	150.65	150.65

DDWU=Decreased demand with utility; DDIT=Decreased demand inside TEM; DGWU=Decreased generation with utility;
DGIT=Decreased generation inside TEM
IDWU=Increased demand with utility;
IGWU=Increased generation with utility.

D. COMPARATIVE ANALYSIS

1) CASE STUDY-I

In this study, the credit rating based LTES is validated by considering ten residential end users as energy trading participants. However, participants demand response in two beneficial choice is not taken into account. Hence, the offers/bid quoted by the participants at the starting of the trading is considered as final values to clear the energy market.

The simulation findings shown in Fig. 7a demonstrate that the participants' electricity bills are lower in scenario 3 when compared to other scenarios. Furthermore, in scenario 3, the monthly participant power uncertainty is greatly decreased, as seen in Table. 6. Although the power uncertainties in scenarios 4 and 5 are lower than in scenario 2, the reductions in participants' electricity costs are not great. In the proposed method, that means in scenario 3, locality total monthly electricity bill savings are 17.18% compared to scenario 2, which represents the conventional transactive energy method.

2) CASE STUDY-II

The deployment of in-house renewable energy-based power generation will only be determined by the user's wealth and the available space at the installation location. Some users may be unable to afford it. The suggested LTES technique encourages these users to trade their demand for a lower price than utility. In this case study, 50% of the participants (P1, P2, P3, P4, and P5) are considered as residential prosumers, while the remaining 50% (P6, P7, P8, P9, and P10) are considered as residential customers in order to validate the credit rating based LTES. However, participants' demand response in two beneficial choices is ignored. The simulation findings in Fig. 7b show that scenario 3 have lower electricity bills than all other scenarios. Furthermore, it reduces the prosumer's monthly uncertain energy, as shown in table 5. Despite the fact that there is less uncertainty in scenarios 4 and 5 than in scenario 2, the electricity bills are nearly same to that in scenario 1 since the utility and LTES impose equal penalties. Based on the results, when comparing scenario 3 with scenario 2, the total locality's monthly electricity bill savings is 16.11%.

3) CASE STUDY-III

This case study assumes that all prosumers have two beneficial choices for rescheduling their loads within a time frame of one minute for each option. Further, the net demand of community will be announced by utility to increase the economic benefit of participants. In order to have better view of study, Table 5 illustrate the changes in participants quoted demand with respect to the demand response economic choices. It is presumed that all the participants has similar demand response strategies to alter their demand pattern. CEE will clear the energy market based on the quoted demand of individual participants and computed credit rating of them. The monthly electricity bills of the participants are computed for different scenarios and depicted in Fig. 7c. According to the results, scenario 3 provides a lower electricity bill than the other scenarios. Further, the uncertainties are reduced in scenario 3 by rejecting the set of offers and bids based on the credit ratings. However, scenarios 4 and 5 give lower electricity bills compared to scenarios 1 and 2 without rejecting any set of the offers or bids. Based on the results, when comparing scenario 3 with scenario 2, the total monthly savings on the electricity bill for the locality is 20.07%. Additionally, the proposed method is compared with existing mechanisms in the literature related to demand response-based transactive energy market clearing mechanisms, as presented in Table 5. In this comparison, the P2G market clearing mechanism is considered from reference [39], the Average Market Clearing (AMC) Strategy, and the Generation-to-Demand Ratio (GDR) based market clearing strategy are considered from reference [26], the Periodic Iterative Double Auction (PIDA) clearing mechanism is considered from [25], and the Vickrey Clarke Groves (VCG) mechanism is considered from [21]. According to the results, the proposed method is consistently offering lower electricity bills compared to all other existing mechanisms. In this study, a novel demand response strategy is being introduced to increase market liquidity, which specifically reducing electricity bills. In the GDR strategy, sellers are benefiting during high-demand periods, while buyers are benefiting during low-demand periods. The PIDA strategy is providing lower electricity bills for participants who are rescheduling loads based on the prices declared by the CEE. The VCG mechanism is yielding lower electricity bills for high marginal contribution players. In addition, within the proposed method's credit rating priority approach, credible players experience higher monetary gains in scenario 3 when compared to all other methods.

4) EXTENDED CASE STUDY

The case study - III is extended for diverse uncertainty energy behavior in participants' demand and generation as shown in Fig. 6b to further demonstrate the efficacy of the suggested methodologies. Table 7 shows the monthly aggregated uncertainty for various scenarios and Fig. 7d also depicts the participants' monthly electricity bills. The observations indicate that scenario 3 resulted in a lower electricity bill than the other scenarios. Based on the results, scenario 3 represents a monthly saving of 23.22% in the total locality electricity bill compared to latest transactive energy method scenario 2.

VI. CONCLUSION

In this paper, the key issue in locality transactive energy market such as participants uncertain energy behavior is addressed. The proposed methodology assists the participants to reduce their uncertain energy behaviors based on the credit score. The CEE computes the individuals' credit score with due consideration to the deviation in LTES quoted demand and actual demand. CEE optimally cleared the energy market in a way beneficial to all LTES participants. Further, the CEE penalizes the participants for their default energy behavior. The effectiveness and efficiency of the proposed credit rating-based locality transactive energy market are validated through various case studies. A comparative analysis is performed with due consideration to the various power injection and extraction limits imposed by transactive energy market operators and utility to demonstrate the necessity of uncertainty demand or generation mitigation. One key aspect of the suggested technique is that it may eliminate participants who do not lower their energy uncertainty as early as possible. As a result, participants are self-motivated to minimize their default energy behavior to enhance their electricity bill savings. Simultaneously, the proposed P2P energy market's reliability and sustainability would also be enhanced. Future research will be able to analyze the power quality and stability issues related to energy default behavior.

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.

REFERENCES

[1] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart grid—The new and improved power grid: A survey," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 4, pp. 944–980, 4th Quart., 2012.

[2] B. P. Esther and K. S. Kumar, "A survey on residential demand side management architecture, approaches, optimization models and methods," *Renew. Sustain. Energy Rev.*, vol. 59, pp. 342–351, Jun. 2016.

[3] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy*, vol. 36, no. 12, pp. 4419–4426, Dec. 2008.

[4] K. Herter, "Residential implementation of critical-peak pricing of electricity," *Energy Policy*, vol. 35, no. 4, pp. 2121–2130, Apr. 2007.

[5] A. Fraija, K. Agbossou, N. Henao, S. Kelouwani, M. Fournier, and S. S. Hosseini, "A discount-based time-of-use electricity pricing strategy for demand response with minimum information using reinforcement learning," *IEEE Access*, vol. 10, pp. 54018–54028, 2022.

[6] S. Singh, A. Roy, and M. P. Selvan, "Smart load node for nonsmart load under smart grid paradigm: A new home energy management system," *IEEE Consum. Electron. Mag.*, vol. 8, no. 2, pp. 22–27, Mar. 2019.

[7] B. H. Rao, S. L. Arun, and M. P. Selvan, "An electric power trading framework for smart residential community in smart cities," *IET Smart Cities*, vol. 1, no. 2, pp. 40–51, Dec. 2019.

[8] E. A. Soto, L. B. Bosman, E. Wollega, and W. D. Leon-Salas, "Peer-to-peer energy trading: A review of the literature," *Appl. Energy*, vol. 283, Feb. 2021, Art. no. 116268.

[9] K. Zhou, J. Chong, X. Lu, and S. Yang, "Credit-based peer-to-peer electricity trading in energy blockchain environment," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 678–687, Jan. 2022.

[10] W. Tan, L. Li, Z. Zhou, Y. Yan, T. Zhang, Z. Zhang, Z. Lin, and L. Yang, "Blockchain-based distributed power transaction mechanism considering credit management," *Energy Rep.*, vol. 8, pp. 565–572, Aug. 2022.

[11] M. I. Azim, W. Tushar, T. K. Saha, C. Yuen, and D. Smith, "Peer-to-peer kilowatt and negawatt trading: A review of challenges and recent advances in distribution networks," *Renew. Sustain. Energy Rev.*, vol. 169, Nov. 2022, Art. no. 112908.

[12] Y. B. Heng, V. K. Ramachandaramurthy, R. Verayiah, and S. L. Walker, "Developing peer-to-peer (P2P) energy trading model for Malaysia: A review and proposed implementation," *IEEE Access*, vol. 10, pp. 33183–33199, 2022.

[13] H. Zein, Y. Sabri, and A. Mashar, "Implementation of electricity competition framework with economic dispatch direct method," *TELKOMNIKA (Telecommun. Comput. Electron. Control)*, vol. 10, no. 4, p. 667, Dec. 2012.

[14] H. Zein, Y. Sabri, and E. Dermawan, "Determining LBMP through optimal power flow in the electric power business," *TELKOMNIKA Indonesian J. Electr. Eng.*, vol. 12, no. 7, pp. 5086–5095, Jul. 2014.

[15] M. F. Zia, M. Benbouzid, E. Elbouchikhi, S. M. Muyeen, K. Techato, and J. M. Guerrero, "Microgrid transactive energy: Review, architectures, distributed ledger technologies, and market analysis," *IEEE Access*, vol. 8, pp. 19410–19432, 2020.

[16] S. Haghifam, H. Laaksonen, and M. Shafie-Khah, "Modeling a local electricity market for transactive energy trading of multi-aggregators," *IEEE Access*, vol. 10, pp. 68792–68806, 2022.

[17] S. Bhattacharya, T. Ramachandran, A. Somani, and D. J. Hammerstrom, "Impacts of energy flexibility in transactive energy systems with large-scale renewable generation," *IEEE Access*, vol. 10, pp. 14870–14879, 2022.

[18] T. Gokcek, I. Sengor, and O. Erdinc, "A novel multi-hierarchical bidding strategy for peer-to-peer energy trading among communities," *IEEE Access*, vol. 10, pp. 23798–23807, 2022.

[19] M. I. Azim, W. Tushar, and T. K. Saha, "Coalition graph game-based P2P energy trading with local voltage management," *IEEE Trans. Smart Grid*, vol. 12, no. 5, pp. 4389–4402, Sep. 2021.

[20] H. Wang and J. Huang, "Incentivizing energy trading for interconnected microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2647–2657, Jul. 2018.

[21] M. K. AlAshery, Z. Yi, D. Shi, X. Lu, C. Xu, Z. Wang, and W. Qiao, "A blockchain-enabled multi-settlement quasi-ideal peer-to-peer trading framework," *IEEE Trans. Smart Grid*, vol. 12, no. 1, pp. 885–896, Jan. 2021.

[22] Z. Guo, B. Qin, Z. Guan, Y. Wang, H. Zheng, and Q. Wu, "A high-efficiency and incentive-compatible peer-to-peer energy trading mechanism," *IEEE Trans. Smart Grid*, early access, Apr. 13, 2023, doi: 10.1109/TSG.2023.3266809.

[23] L. Exizidis, J. Kazempour, A. Papakonstantinou, P. Pinson, Z. De Grève, and F. Vallée, "Incentive-compatibility in a two-stage stochastic electricity market with high wind power penetration," *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 2846–2858, Jul. 2019.

[24] T. Baroche, P. Pinson, R. L. G. Latimier, and H. B. Ahmed, "Exogenous cost allocation in peer-to-peer electricity markets," *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 2553–2564, Jul. 2019.

[25] H. R. Bokkisam, R. M. Acharya, and M. Selvan, "Framework of transactive energy market pool for community energy trading and demand response management using an auction-theoretic approach," *Int. J. Electr. Power Energy Syst.*, vol. 137, May 2022, Art. no. 107719.

[26] S. L. Arun, K. Bingi, R. V. Priya, I. J. Raglend, and B. H. Rao, "Novel architecture for transactive energy management systems with various market clearing strategies," *Math. Problems Eng.*, vol. 2023, pp. 1–15, Apr. 2023.

[27] W. Tushar, C. Yuen, T. K. Saha, T. Morstyn, A. C. Chapman, M. J. E. Alam, S. Hanif, and H. V. Poor, "Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116131.

[28] J. Yang, A. Paudel, and H. B. Gooi, "Blockchain framework for peer-to-peer energy trading with credit rating," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2019, pp. 1–5.

[29] B. A. Bhatti and R. Broadwater, "Energy trading in the distribution system using a non-model based game theoretic approach," *Appl. Energy*, vol. 253, Nov. 2019, Art. no. 113532.

[30] M. Khorasany, A. Dorri, R. Razzaghi, and R. Jurdak, "Lightweight blockchain framework for location-aware peer-to-peer energy trading," *Int. J. Electr. Power Energy Syst.*, vol. 127, May 2021, Art. no. 106610.

[31] K. N. Khaqqi, J. J. Sikorski, K. Hadinoto, and M. Kraft, "Incorporating seller/buyer reputation-based system in blockchain-enabled emission trading application," *Appl. Energy*, vol. 209, pp. 8–19, Jan. 2018.

[32] T. Wang, J. Guo, S. Ai, and J. Cao, "RBT: A distributed reputation system for blockchain-based peer-to-peer energy trading with fairness consideration," *Appl. Energy*, vol. 295, Aug. 2021, Art. no. 117056.

[33] X. Zhang, S. Zhu, J. He, B. Yang, and X. Guan, "Credit rating based real-time energy trading in microgrids," *Appl. Energy*, vol. 236, pp. 985–996, Feb. 2019.

[34] Y. Xia, Q. Xu, H. Qian, and L. Cai, "Peer-to-peer energy trading considering the output uncertainty of distributed energy resources," *Energy Rep.*, vol. 8, pp. 567–574, Apr. 2022.

[35] V. F. Yu, T. H. A. Le, and J. N. D. Gupta, "Sustainable microgrid design with multiple demand areas and peer-to-peer energy trading involving seasonal factors and uncertainties," *Renew. Sustain. Energy Rev.*, vol. 161, Jun. 2022, Art. no. 112342.

[36] Z. Zhang, R. Li, and F. Li, "A novel peer-to-peer local electricity market for joint trading of energy and uncertainty," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1205–1215, Mar. 2020.

[37] F. Frei, A. Loder, and C. R. Bening, "Liquidity in green power markets—An international review," *Renew. Sustain. Energy Rev.*, vol. 93, pp. 674–690, Oct. 2018.

[38] S. Kuno, K. Tanaka, and Y. Yamada, "Effectiveness and feasibility of market makers for P2P electricity trading," *Energies*, vol. 15, no. 12, p. 4218, Jun. 2022.

[39] B. H. Rao, S. L. Arun, and M. P. Selvan, "Framework of locality electricity trading system for profitable peer-to-peer power transaction in locality electricity market," *IET Smart Grid*, vol. 3, no. 3, pp. 318–330, Jun. 2020.

[40] S. L. Arun and M. P. Selvan, "Intelligent residential energy management system for dynamic demand response in smart buildings," *IEEE Syst. J.*, vol. 12, no. 2, pp. 1329–1340, Jun. 2018.

[41] W.-R. Heilmann, "Decision theoretic foundations of credibility theory," *Insurance: Math. Econ.*, vol. 8, no. 1, pp. 77–95, Mar. 1989.

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