DeMCRP-ET: Decentralized Multi-Criteria Ranked Prosumers Energy Trading using Distributed Ledger Technology

N Nandini Devi[1], Surmila Thokchom[1†], Gautam Srivastava[2,4,5*], Rutvij H. Jhaveri[3], Diptendu Sinha Roy[1†]

[1]Department of Computer Science & Engineering, National Institute of Technology Meghalaya, Laitumkhrah, Shillong, 793003, Meghalay, India.
[2*]Department of Mathematics & Computer Science, Brandon University , Brandon, R7A 6A9, , Canada.
[3]Department of Computer Science and Engineering, School of Technology, Pandit Deendayal Energy University, Gandhinagar, 382007, Gujarat, India.
[4]Department of Computer Science & Math, Lebanese American University, Beirut, 1102, Lebanon.
[5]Research Centre for Interneural Computing, China Medical University, Taichung, 40402, Taiwan.

*Corresponding author(s). E-mail(s): srivastavag@brandonu.ca; Contributing authors: nandinidevi@nitm.ac.in; surmila.thokchom@nitm.ac.in; rutvij.jhaveri@sot.pdpu.ac.in; diptendu.sr@nitm.ac.in;
[†]These authors contributed equally to this work.

Abstract

Due to global warming and climate change, power generation from renewable resources, such as solar, wind, fuel cells, and others, is becoming increasingly important. The smart grid's incorporation of renewable energy resources makes Peer-to-Peer (P2P) energy trading through the local energy market possible. Due to its distributed nature, it faces many challenges regarding security and privacy in the energy trading procedure. Most existing works do not consider data privacy among the participants. A P2P energy trading model with Decentralized Multi-Criteria Ranked Prosumers called DeMCRP is introduced to address these privacy and security challenges in smart grid energy trading. The proposed DeMCRP trading model uses Corda-distributed ledgers, consensus, and smart contracts for energy trading between energy buyers and sellers, also termed prosumers. In the DeMCRP model, the mapping procedure between prosumers is done based on priority values for such prosumers determined using a multi-criteria decision-making method, namely the Preference Ranking for Organization Method for Enrichment Evaluation II (PROMETHEE II). Further, an energy-trading smart contract performs energy trading between buyers and sellers. The transactions' validation, verification, and uniqueness process through the consensus of the distributed ledger by the notaries. The Distributed Service Operator (DSO) selects 51% of sellers as notaries according to the rank of the sellers. The rank of the sellers is determined using a multi-criteria decision-making method called PROMETHEE II by considering various parameters such as energy surplus, trust factor, and number of times the seller is selected as notary. Further, the performance analysis of the proposed scheme has been carried out in terms of network deployment time and memory utilization. The proposed DeMCRP technique works in polynomial time if the number of participants increases. Furthermore, the security analysis has been carried out for various security features like data sharing privacy, users' privacy, non-repudiation, integrity, and preventing double-spending. The proposed method protects the privacy of the participants' data and stops double spending, which isn't taken into account by many existing methods.

Keywords: Smart Grid, Energy Trading, Distributed Energy Resources, Prosumers, PROMETHEE, Peer-to-Peer (P2P) trading.

1 Introduction

Renewable energy sources have evolved in recent years, opening opportunities for peer-to-peer trading between communities, distributed energy producers, and prosumers. The energy penetration rate of rooftop photovoltaic (PV) panels and other distributed energy resources, such as electric vehicles, battery energy storage systems, and heat pumps, is increasing tremendously. This increases the number of prosumers, improves end-user flexibility, and creates new market opportunities for various energy system stakeholders [1]. The existing traditional energy trading system is based on a centralized system. The conventional approach is ineffective for integrating prosumers and distributed energy resources in the energy trading paradigm [2–4]. Different Countries use techniques like Feed-in Tariffs and net metering to let prosumers sell their energy to the grid. These techniques are more beneficial for the grid. A few decades back, decentralized ledger systems and distributed computing concepts were introduced. Recently these concepts have been used in the energy sector.

The advancement in information and communication technologies enables the new noble market design, which leads to an alternative emerging technology for prosumers to trade energy directly with each other locally. These end-user-centered new market designs are typically known as local energy markets [5]. Peer-to-peer energy trading is one of the solutions for this form of energy trading [6–9]. This technology allows prosumers to sell their access energy to buyers or the main grid. This method offers numerous social, economic, and environmental benefits. The main challenges of this trading framework are security and privacy issues. Prosumers always hesitate to accept new technologies lacking adequate security and privacy features. Therefore, the most critical aspect of creating peer-to-peer financial models is creating an effective process that addresses security and privacy concerns.

The existing decentralized system for constructing a peer-to-peer energy trading model suffers from many security, privacy, and performance issues. New technologies such as blockchain and distributed ledgers have lately garnered the attention of industries and academia to achieve improved security and privacy issues without sacrificing the model's performance in energy transactions and price settlement processes. Few studies have suggested an energy trading strategy based on Ethereum's public blockchain [10, 11]. Such a model can have high energy consumption and poor performance by executing proof of work. Concerning security, privacy, and performance, numerous blockchain-based methodologies and techniques have been developed [12]. Inferences can be drawn from these analyses that distributed ledger technology can be used effectively to provide security and privacy features for prosumers without sacrificing the performance of the proposed model. The major contributions of the proposed work include:

- Proposes a P2P energy trading architecture that provides data privacy among participants using the Corda distributed ledger.
- Presents a methodology for ranking the prosumers based on multiple criteria.
- Proposes novel schemes for notary selection and transaction verification based on a multi-parameter preference setting for sellers.
- Comprehensive security analyses have been carried out for the proposed model taking into account users' privacy and data privacy in terms of non-reputability, message integrity, double spending, and phishing security.

The proposed article is organized as follows: In Section 2, the overview of the existing literature is carried out. The proposed architecture and overall procedure of the proposed trading model ***DeMCRP*** is presented in Section 3. Further, the results and the discussions of the proposed trading model have been carried out in Section 4. Finally, the proposed article is concluded in Section 5.

2 Related Works

In this section, the contributions of various researchers around the globe on smart grid energy trading and energy management are presented. Most researchers focus on the security and privacy of the participants in the energy trading process. Recently, distributed ledger technology, such as blockchain technology, has inspired academics and industries to provide secure energy trading and transactions. Various works on peer-to-peer energy trading in the smart grid use blockchain to achieve energy and information exchange security.

The trustworthy and incentivized energy trading framework is introduced in [13]. The requirements for consumers and prosumers to participate in the energy trading process are things like transparency, non-repudiation, no single point of failure, prosumers' privacy, truthful bidding, a trustworthy distributed environment, etc., which are achieved through the use of distributed ledger technology, precisely the Ethereum blockchain platform with the proof-of-stack consensus mechanism and smart contracts. Alzahrani *et al.* [14] proposed a model for charging/discharging and scheduling process for electric vehicles by considering various factors such as energy cost, their needs, and quality of service. The proposed model also provides real-time energy optimization for load, storage, and comfort without analyzing the historical data. Alzahrani *et al.* [15] developed a multi-objective optimization model by deploying a non-dominated genetic sorting algorithm to optimize objectives of pollution emission, operation cost and loss of load expectation by considering renewable energy resources. The authors in [16] have investigated the application of IOTA's Directed Acyclic Graph-based block-free distributed ledger, one of the distributed ledger technologies, for an energy trading platform. This method eliminates the scalability and latency issues that plague blockchain-based solutions. The process of peer-to-peer energy trading is accomplished by ranking buyers and sellers depending on their various parameters. Groß *et al.* [17] proposed enerDAG, a flexible and robust local energy trading platform. Through smart contracts, the trading process is conducted. The proposed platform offers buyers a financial advantage by providing cheaper energy prices. A flexible permissioned ascription scheme with an Ethereum-based Hyperledger Besu blockchain framework for P2P energy trading is designed in [18]. This framework guarantees security and privacy without compromising performance. Jogunola *et al.* [19] explored the usage of various distributed ledger technologies in P2P energy trading. A P2P energy trading platform is implemented on the IBM Hyperledger Fabric platform, where a smart contract is deployed to manage trust and transactions. The authors in [20] devised a distributed algorithm that protects users' privacy and enables them to regulate their energy consumption optimally in parallel via smart contracts on the blockchain. This work establishes a blockchain system for IoT devices, and a smart contract is created to support a holistic transactive energy management system. The researchers of [21] designed a blockchain-based framework for transactive energy for prosumers. This paradigm increases individual profit, ensures socially optimal performance, and incentivizes prosumers to participate in the transactive energy platform. The authors of [22] developed a community-based P2P energy trading market using blockchain technology and smart contracts. This market has two processing modes: on-chain mode for updating smart contracts and off-chain mode for confirming the outcome on-chain. A blockchain-based P2P energy trading framework incorporating multi-settlement to handle the diverse trading preferences for different electric sources and demands is proposed in [23]. This framework achieves security aspects like preventing collusion attacks between different sets of market participants. Ali *et al.* [24] developed a blockchain-assisted P2P energy trading model called SynergyChain to improve the scalability and decentralization of prosumers. This model integrates the reinforcement learning module to improve the system's overall performance. On the basis of an end-user marginal price, a comprehensive framework for a transactive energy market is provided, along with a blockchain and power system layer [25]. This new slot-ahead electricity market model is built through modified blockchain integration. The financial resources are managed evenly using blockchain. Therefore, the wallet billing rates between customers, utilities, and distributed generator owners correspond to the broadcast data from the smart meters. The authors of [26] propose a blockchain-based novel P2P energy trading architecture that integrates negotiation based on an auction and pricing mechanisms in the local market. The pricing mechanism and auction process are modeled as a cooperative game. The authors in [27] proposed a cooperative game-theoretical approach for P2P energy trading that increases the satisfactory factor in terms of energy bills and revenue of consumers and producers, respectively. Zhou *et al.* [28] proposed the secure multiparty computation based secure quadratic programming algorithm for network-constrained peer-to-peer energy trading market which guaranteed bidirectional privacy. Gao *et al.* [29] designed a secure energy trading platform based on blockchain technology. The proposed method protects consumers' privacy, authenticity, and data integrity. The authors of [30] developed a peer-to-peer energy trading framework to reduce the uncertain influence of renewable energy generators on a distributed network operation with optimal energy management decisions. Wang *et al.* [31] proposed a centralized residential peer-to-peer energy trading market using the supply function method where the market clearing price is co-decided by all participants, which ensures fairness and transparency. Toubeau *et al.* [32] used distributed learning scheme known as federated learning wherein data of individuals are stored in a decentralized form. The proposed method is framed based on cross-series learning which allows smooth integration of new clients who joined in the community without causing data scarcity. Guo *et al.* [33] proposed a negotiable energy trading model by combining the consensus alternating direction method of multipliers and power transfer distribution factor. The proposed method ensures the property of optimality and decentralization. Liu *et al.* [34] proposed a privacy-preserved approach based on hybrid secure computation for fully distributed P2P energy trading. The proposed method ensures privacy preservation and computational efficiency by employing the CRT-Paillier encryption method and designing additional random encryption coefficients. Ping *et al.* [35] demonstrates the effect on participants' interest when the energy trading market coordinator is an untrusted party. The authors proposed a blockchain-based privacy-preserving energy trading model to optimize energy trading, which resists the dishonesty of delegates and preserves individual privacy.

In Table 1, the contributions and the limitations of some of the existing models are discussed in detail. Providing a secure platform for energy trading without compromising performance is one of the main concerns with smart grid energy trading. Some existing energy trading frameworks do not consider data privacy among trading partners. The current blockchain-based energy trading model has problems with scalability and privacy because all the peers share the same data. A framework for trading energy based on a distributed ledger is proposed here. In the work that is being proposed, data privacy is preserved while different security needs are met. Moreover, the proposed model is lightweight and does not face scalability problems. This proposed trading model also considered various parameters like surplus energy, trust factor, and frequency of peer to be selected as a notary to calculate the rank value for selecting the notary. The mapping procedure is performed based on parameters like surplus energy, selling price, buying price, type of energy, and local distance between them.

Table 2 compares the trading model features to some existing literature. Therefore, the proposed trading model provides scalability while security and privacy are preserved.

Table 1: Summary of some existing works.

Papers	**Contributions**	**Limitations**
Saha *et al.* [36]	Proposed blockchain-based approach which ensures security in the internet of energy and electric vehicle interfaces.	1. The blockchain platform used is not mention. 2. Data privacy among the participants are not taken into account.
Zhou *et al.* [28]	Proposed a secure multiparty computation based secure quadratic programming algorithm for network-constrained peer-to-peer energy trading market	1. Multi-time step is not considered. 2. Shared information privacy is not considered.
Guo *et al.* [33]	Introduced a P2P energy trading mechanism which supports direct energy exchange between prosumers.	Preserved privacy of the consumers' and prosumers' but data privacy among the participants are not taken into account.
Toubeau *et al.* [32]	Proposed a method to store participants data in a distributed manner using federated learning.	Not discussed about potential information leakage among the participants.
Wang *et al.* [31]	Proposed a centralised residential peer-to-peer energy trading market using the supply function method where the market clearing price is co-decided by all participants.	1. The uncertainty of energy demand and the production is not considered. 2. Information sharing privacy is not considered.

3 Proposed Trading Architecture

The section presents the proposed trading model architecture. The detailed structure and functionalities of the proposed model are presented in Figure 1. The proposed trading model is made up of two parts: a stage for categorization and mapping and a stage for transaction and settlement. We have considered the N number of trading participants in this proposed work. Furthermore, a detailed discussion of the stages is presented here in this section.

3.1 Categorization and Mapping

In this stage categorization and Mapping process for the proposed trading framework is done.

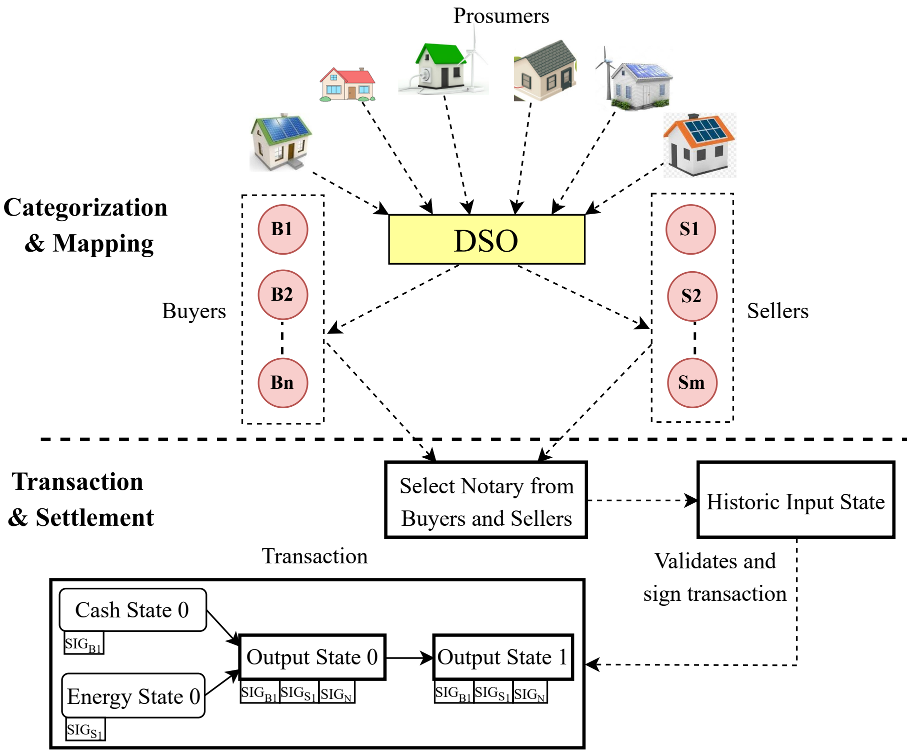


Fig. 1: Architecture of proposed trading model

3.1.1 Categorization

At this stage, the trading participants are labeled as either buyers or sellers based on their energy demand (ED) and surplus (ES), respectively. Figure 2 presents the overall process of labeling prosumers as sellers and buyers. In this, prosumers advertise to the Distributed Service Operator (DSO) various parameters such as the amount of energy generated, the amount of energy required for their use, the price bid, the type of generated energy, the location, etc. The DSO then determines how much energy prosumers need and how much they have left over for a particular duration. For a time, the DSO classified prosumers as buyers and sellers if their energy demand exceeded the corresponding threshold values (ω_b and ω_s), which differed depending on the type of participating entity (smart homes, industries, PV farms, wind energy generating firms, and so on). The overall procedure for the categorization process is described in Algorithm 1. This process is done once for every duration of trading, which is considered as 1 hour. In this, the overall time taken for the categorization process is considered deployment time for further analysis of the proposed method.

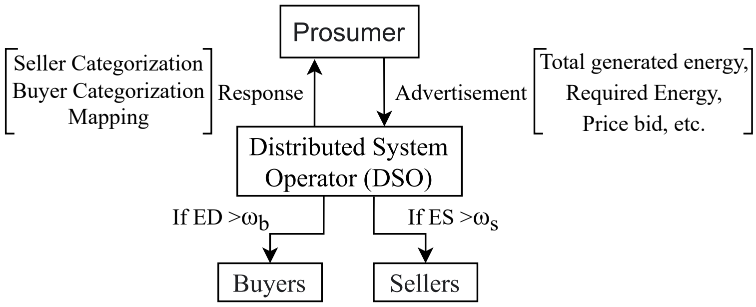


Fig. 2: Categorization procedure of prosumers as sellers and buyers

Algorithm 1 Algorithm for Prosumer Categorization

Input: Energy Demand (ω) and Energy Surplus (σ) of Prosumers
Output: Categorize Prosumers as Seller and Buyer

for $i = 1$ to $\mathcal{P}$ **do** // $\mathcal{P} \rightarrow$ Number of Prosumers
  if $\omega_i > \omega_b$ **then** // $\omega_b \rightarrow$ minimum energy demand threshold
    Categorize Prosumer i as Buyer
  end if
  if $\sigma_i > \omega_s$ **then** // $\omega_s \rightarrow$ minimum energy surplus threshold
    Categorize Prosumer i as Seller
  end if
end for

3.1.2 Mapping

The DSO performed the mapping process using the priority value of sellers and buyers to realize energy trading between them. The priority value for all buyers and sellers is evaluated using the multi-criteria decision-making method called PROMETHEE II [37–39]. In this process, various parameters like the amount of energy surplus (σ), the amount of energy demand (ω), the price bid by the buyer(β) and the seller (ρ), the type of generator (τ), and the distance (λ) are considered. The steps for formulating the priority values of sellers are illustrated as follows.

1. Evaluation matrix (EM)

$$EM = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_N \end{array} \begin{array}{c} \begin{array}{cccc} \sigma & \rho & \tau & \lambda \end{array} \\ \begin{pmatrix} \sigma_1 & \rho_1 & \tau_1 & \lambda_1 \\ \sigma_2 & \rho_2 & \tau_2 & \lambda_2 \\ \vdots & \vdots & \vdots & \vdots \\ \sigma_N & \rho_N & \tau_N & \lambda_N \end{pmatrix} \end{array} \tag{1}$$

2. Choose the maximum (max) and minimum (min) value of each criterion.

3. Normalization of EM is done to make further calculations simpler. For this, we have to categorize the criteria as beneficial and non-beneficial. The categorization process and normalization of criteria are carried out as shown below.
   (a) Beneficial criteria: The criteria whose higher value is desired are known as beneficial criteria. The parameters σ and τ are beneficial criteria in the case of our proposed work. For these parameters, the normalization is done as follows.

$$\sigma_i = \frac{[\sigma_i - min(\sigma)]}{[max(\sigma) - min(\sigma)]} \tag{2}$$

$$\tau_i = \frac{[\tau_i - min(\tau)]}{[max(\tau) - min(\tau)]} \tag{3}$$

   where $i = 1, 2, \ldots, N$.
   (b) Non-beneficial criteria: The criteria whose lower value is desired are known as non-beneficial criteria. Two parameters, ρ and λ are non-beneficial criteria. The normalization of these parameters is done as follows.

$$\rho_i = \frac{[max(\rho) - \rho_i]}{[max(\rho) - min(\rho)]} \tag{4}$$

$$\lambda_i = \frac{[max(\lambda) - \lambda_i]}{[max(\lambda) - min(\lambda)]} \tag{5}$$

   where $i = 1, 2, \ldots, N$.
4. Calculate the evaluative differences of i^{th} alternative with respect to other alternative as follows. Evaluative differences $D_{criteria}(S_i, S_j)$, $\forall\ i = 1, 2, \ldots, N$ for each criteria is evaluated as:

$$D_\sigma(S_i, S_j) = \sigma_i - \sigma_j \quad \forall j = 1, 2, \ldots, N. \tag{6}$$

$$D_\rho(S_i, S_j) = \rho_i - \rho_j \quad \forall j = 1, 2, \ldots, N. \tag{7}$$

$$D_\tau(S_i, S_j) = \tau_i - \tau_j \quad \forall j = 1, 2, \ldots, N. \tag{8}$$

$$D_\lambda(S_i, S_j) = \lambda_i - \lambda_j \quad \forall j = 1, 2, \ldots, N. \tag{9}$$

   Here, we calculate all $D_{criteria}(S_i, S_j)$ if $i \neq j$. Using the above evaluative differences values and a number of criteria (4), matrix D of size $k \times 4$ is generated. Here, $k = N \times (N - 1)$ as the evaluative differences between the same alternatives are not considered.

5. Calculate the preference values $P(k,l)$ as follows:

$$P(k,l) = \begin{Bmatrix} 0 & if & (D(k,l) \leq 0) \\ D(k,l) & & else \end{Bmatrix} \tag{10}$$

   where $l = 1, \ldots, 4$.
6. Calculate the aggregated preference value as follows:

$$\pi(k) = \sum_{l=1}^{4} P(k,l) \tag{11}$$

7. Then matrix F of size $N \times N$ is form using the values of $\pi(k)$. In this, for the same alternatives, the value will not be assigned.

$$F = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_N \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \ldots & S_N \end{array} \\ \begin{pmatrix} - & \pi(S_1,S_2) & \ldots & \pi(S_1,S_N) \\ \pi(S_2,S_1) & - & \ldots & \pi(S_2,S_N) \\ \vdots & \vdots & \vdots & \vdots \\ \pi(S_N,S_1) & \pi(S_N,S_2) & \ldots & - \end{pmatrix} \end{array} \tag{12}$$

8. Next, the leaving and entering outranking flows are calculated as follows:
   Leaving (positive) flow for S_i^{th} alternatives,

$$\varphi(S_i)^+ = \frac{1}{N-1} \sum_{a=1}^{N} F(S_i, S_a) \tag{13}$$

   Entering (negative) flow for S_i^{th} alternatives,

$$\varphi(S_i)^- = \frac{1}{N-1} \sum_{a=1}^{N} F(S_a, S_i) \tag{14}$$

9. Further, the net outranking flow $(\varphi(S_i))$ for each alternative is determined as follows:

$$\varphi(S_i) = \varphi(S_i)^+ - \varphi(S_i)^- \tag{15}$$

10. Then, the priority of all the considered alternatives (sellers) is determined according to the descending order of their $\varphi(S_i)$ values.

The above-discussed steps also calculate the buyers' priority values ($\varphi(B_j)$, $j = 1$ to m) according to the buyers' parameters, such as ω, β, τ, and λ.

According to the above-calculated priority values of buyers and sellers, the DSO proceeds with the mapping procedure between sellers and buyers. The buyer with

Algorithm 2 Algorithm for Mapping between Sellers and Buyers

Input:
Sellers paramters: Energy surplus (σ_j), price bid (ρ_j), type of generator (τ) and distance from DSO (λ), $\forall\ j = 1, ..., n$
Buyers paramters: Energy demand (ω_k), price bid (β_k), and distance from DSO (λ), $\forall k = 1, ..., m$

Output: Map between Seller S_j with Buyer B_k

Determined priority values $\varphi(S_j)$ and $\varphi(B_k)$ of S_j and B_k using PROMETHEE II, $\forall\ j = 1, ..., n,\ k = 1, ..., m$
Sort S_j as per the decreasing order of their $\varphi(S_j)$, $\forall j = 1, ..., n$
Sort B_k as per the decreasing order of their $\varphi(B_k)$, $\forall k = 1, ..., m$
for $j = 0$ *to* n **do**
  for $k = 0$ *to* m **do**
    if $\sigma_j > 0$ && $\omega_k > 0$ **then**
      Map S_j **with** B_k // Mapping between sellers and buyers
      if $\sigma_j < \omega_k$ **then**
        $\omega_k = \omega_k - \sigma_j$
        $\sigma_j = 0$
      else if $\sigma_j > \omega_k$ **then**
        $\sigma_j = \sigma_j - \omega_k$
        $\omega_k = 0$
      else
        $\sigma_j = 0$
        $\omega_k = 0$
      end if
    end if
  end for
end for

the higher priority will get a chance to trade with the higher priority seller for that trading instance. The overall mapping procedure of the proposed work is presented in Algorithm 2.

3.2 Transaction settlement

In this stage, the details of network formation, transaction, and trading settlement of the proposed model are done. Figure 3 presents the overall structure of this stage. Further, we will discuss the procedures involved in this stage in detail.

3.2.1 Notary Selection

The DSO selects the notaries from the n number of sellers according to their ranking value. The ranking value of every participant is determined using the multi-criteria decision-making method,PROMETHEE II [37–39]. Various parameters, such as the amount of surplus energy (σ), trust factor (γ), and the number of times the seller is selected as a notary (μ) are considered in determining the ranking value of the sellers. The sellers are sorted based on their rank. Further, the first $\varkappa$% from the sorted list are selected as notaries for verification. The steps involved in the ranking procedure are discussed below.

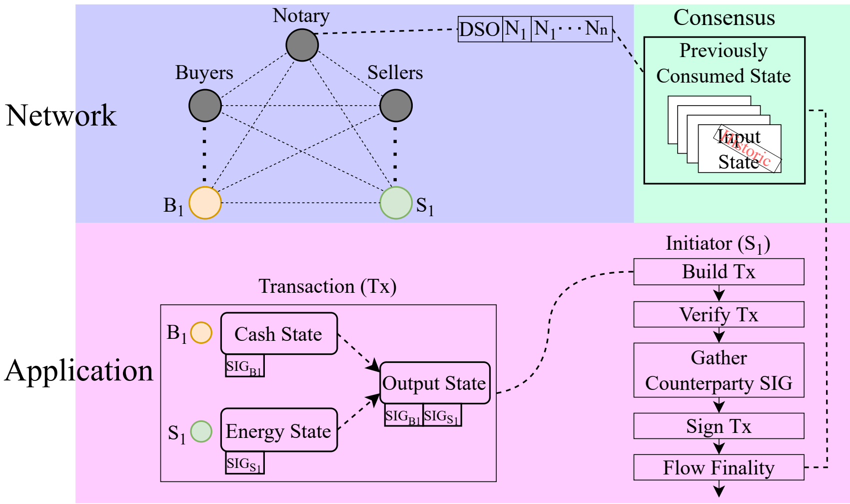


Fig. 3: Transaction settlement procedure among prosumers in proposed method

1. First, the decision matrix (DM) is created based on the sellers' parameters.

$$DM = \begin{array}{c c} & \begin{array}{ccc} \sigma & \gamma & \mu \end{array} \\ \begin{array}{c} S_1 \\ S_2 \\ \vdots \\ S_n \end{array} & \begin{pmatrix} \sigma_1 & \gamma_1 & \mu_1 \\ \sigma_2 & \gamma_2 & \mu_2 \\ \vdots & \vdots & \vdots \\ \sigma_n & \gamma_n & \mu_n \end{pmatrix} \end{array} \tag{16}$$

2. The maximum (max) and minimum (min) value of each criteria are selected.
3. Next normalized the DM to simplifies the further calculation. In this approach, the matrix normalization is done as follows.
   - For beneficial criteria (σ and γ) the matrix normalization is done as follows:

$$\sigma_i = \frac{[\sigma_i - min(\sigma)]}{[max(\sigma) - min(\sigma)]} \tag{17}$$

and

$$\gamma_i = \frac{[\gamma_i - min(\gamma)]}{[max(\gamma) - min(\gamma)]} \tag{18}$$

where $i = 1, 2, \ldots, n$.

- For non-beneficial criteria (μ), the normalization is done using the following equation.

$$\mu_i = \frac{[max(\mu) - \mu_i]}{[max(\mu) - min(\mu)]} \tag{19}$$

where $i = 1, 2, \dots, n$.

4. For each criterion, the evaluative difference ($D_{criteria}$) of i^{th} alternative from other alternatives is calculated using the following equations.

$$D_\sigma(S_i, S_j) = \sigma_i - \sigma_j \quad \forall j = 1, 2, \dots, n. \tag{20}$$

$$D_\gamma(S_i, S_j) = \gamma_i - \gamma_j \quad \forall j = 1, 2, \dots, n. \tag{21}$$

$$D_\mu(S_i, S_j) = \mu_i - \mu_j \quad \forall j = 1, 2, \dots, n. \tag{22}$$

where $i \neq j$ and $i = 1, 2, \dots, n$. Using the above calculated evaluative difference ($D_{criteria}$) and the number of criterion (3), a matrix D of size $k \times 3$ is generated. As the evaluative difference between the same alternatives is not considered, the value of k is $n \times (n-1)$.

5. Next, the preference value $P(k, l)$ is calculated as follows:

$$P(k,l) = \left\{ \begin{array}{ll} 0, & if \quad (D(k,l) \leq 0) \\ D(k,l), & else \end{array} \right\} \tag{23}$$

where $l = 1, 2, 3$.

6. From this, the aggregated preference value is calculated using the equation given below.

$$\pi(k) = \sum_{l=1}^{3} P(k,l) \tag{24}$$

7. Then, the matrix F of size $n \times n$ for all alternatives is generated using the above calculated aggregated preference values ($\pi(k)$). In this, no value is assigned in the field of the same alternatives.

$$F = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_n \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \dots & S_n \end{array} \\ \begin{pmatrix} - & \pi(S_1, S_2) & \dots & \pi(S_1, S_n) \\ \pi(S_2, S_1) & - & \dots & \pi(S_2, S_n) \\ \vdots & \vdots & \vdots & \vdots \\ \pi(S_n, S_1) & \pi(S_n, S_2) & \dots & - \end{pmatrix} \end{array} \tag{25}$$

8. The leaving (positive) and the entering (negative) outranking flows are calculated as follows: Leaving (positive) flow for S_i^{th} alternatives,

$$\phi(S_i)^+ = \frac{1}{n-1}\sum_{a=1}^{n} F(S_i, S_a) \tag{26}$$

Entering (negative) flow for S_i^{th} alternatives,

$$\phi(S_i)^- = \frac{1}{n-1}\sum_{a=1}^{n} F(S_a, S_i) \tag{27}$$

9. Then, the net outranking of each alternative is calculated using the equation below.

$$\phi(S_i) = \phi(S_i)^+ - \phi(S_i)^- \tag{28}$$

The rank of sellers is determined according to the descending order of their $\phi(S_i)$ values. From this, the DSO selects the notaries. Algorithm 3 describes the details procedure for the notaries selection process.

Algorithm 3 Algorithm for Notary Selection

Input: Energy Surplus (σ), trust factor (γ) of seller and the number of times the seller is selected as a notary (μ)

Output: Select $\varkappa$% Sellers as Notary

1: Construct decision matrix (DM) based on the value of σ, γ and μ of sellers.
2: Calculate net outranking value ($\phi(S_i)$) of all sellers S_i. // $i = 1$ to n.
3: Rank all the Sellers according to the descending order of their $\phi(S_i)$.
4: Select first $\varkappa$% Sellers as Notary

3.2.2 Transaction procedure

The transaction settlement of energy and money between buyers and sellers is done through Corda distributed ledger. This ledger provides information privacy among the participants. In Corda, the data is shared among the parties in private. Figure 4 presents sharing facts among the participants in the Corda ledger. In this, the fact 1 is shared between participant A and F, which is not shared with other participants. The fact 4 is shared among participants A, B, and C, which is not shared with other participants. In this way, the information privacy of participants is preserved in the Corda ledger.

The proposed technique used the Corda network for transaction procedures between buyers and sellers. The seller creates the energy state as shown in Figure 5a and initiates the energy transfer flow. Then, the seller signs the transaction through the trading contract. Conversely, the buyer creates the Cash State as shown in Figure 5b and initiates the Cash Transfer flow. Then, the buyer signs the transaction, which

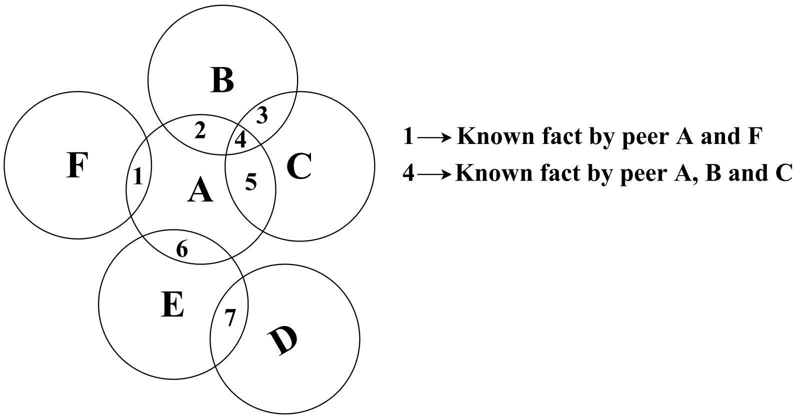
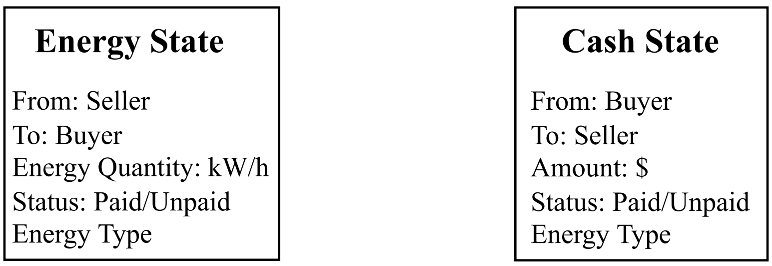


Fig. 4: Information sharing among participants in Corda ledger

contains the cash state. The proposed technique used the Corda network for transaction procedures between buyers and sellers. The seller creates the energy state as shown in Figure 5a and initiates the energy transfer flow. Then, the seller signs the transaction through the trading contract. Conversely, the buyer creates the Cash State as shown in Figure 5b and initiates the Cash Transfer flow. Then, the buyer signs the transaction, which contains the cash state. Further, the new energy state is formed where the owner of the energy state will be the buyer, and the new cash state is formed where the new owner of the cash state is the seller. Then, the transaction is signed by both buyer and the seller. Finally, the transaction is confirmed and signed by the previously selected notaries if the input states are unconsumed (previously not used) and also by checking the signature of both the seller and the buyer. Further, the notaries add the consumed states to the ledger maintained by notaries for further verification. Figure 6 shows the overall transaction and settlement between the buyer and seller.



(a) Energy state details

(b) Cash state details

Fig. 5: Detailed structure of (a) Energy state and (b) Cash state

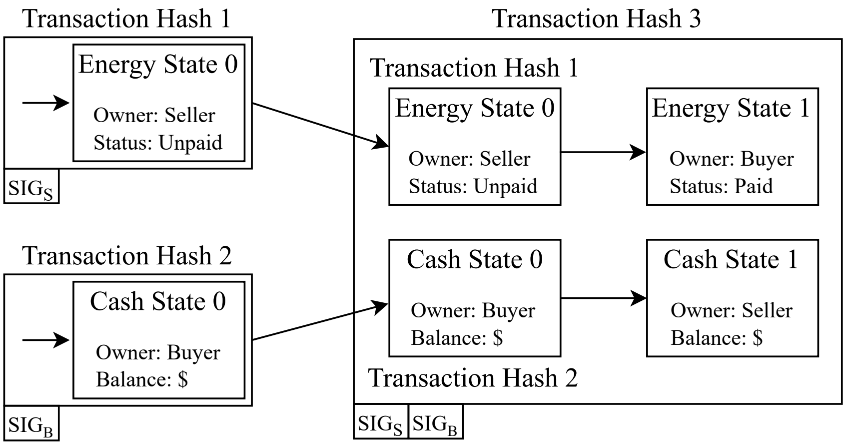


Fig. 6: Transaction between prosumers

The overall flow of the proposed model is presented in Figure 7. First, trading participants are registered with the DSO. Then, the DSO authenticates and categorizes them according to their energy demand and surplus energy. Further, the DSO performed the mapping process according to their priority value which is determined using their respective parameters. Then, the transaction procedure is done between the mapped seller and buyer through a trading contract. For the transaction verification, notaries have been selected from the sellers based on the rank value discussed above. These notaries maintain a ledger containing all the unconsumed states used for the verification procedure. Then, the seller creates the energy state and signs the transaction, and the buyer creates the cash state and signs the transaction. Further, an output state is produced from the cash and energy state that contains both seller and buyer signed. Next, the notaries check for usage of any consumed state. If it contains only unconsumed states, the notaries verify and sign the transaction. Finally, notaries mark the used unconsumed state as consumed and put the hash of these states in the ledger for verification purposes.

4 Results and Discussions

This section contains the analyses of the proposed model. The proposed model has been analyzed in terms of performance, security, and privacy aspects.

4.1 Expermental setup

The experiment analysis has been carried out on systems Intel i5-9300H, 2.40 GHz, 4 cores, 8 GB RAM, Window 11 (System1) and Intel i5-10300H, 2.50 GHz, 4 cores, 16 GB RAM, Window 11 (System2). The proposed method used the Corda-distributed ledger for transactions between prosumers.

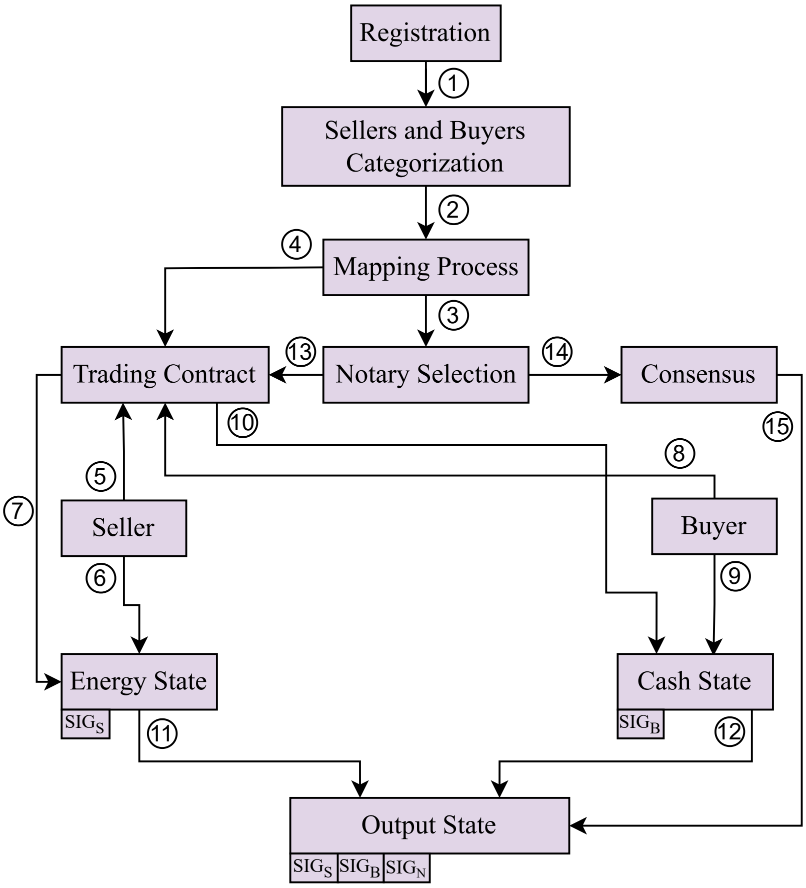


Fig. 7: Overall workflow of proposed trading model

4.2 Experiments

Experiments are carried out by considering various aspects. In this, 10 buyers are considered, and determine the weightage value of each buyer is according to the parameters such as energy demand, buyer price, and trust factor. The scaling of the parameters is done for better understanding and simplification. Similarly, 10 sellers are considered, and weightage values are evaluated based on parameters of sellers such as energy surplus, sellers' price bid, energy type, and trust factor of the seller. For the consensus mechanism, 51% of the sellers are selected as notaries based on the weightage value of the sellers, which is evaluated considering parameters such as energy surplus, trust factor, and notary selection frequency.

4.3 Results and observations

4.3.1 Results

The analysis of the experimental result has been carried out. In Figure 8, the weightage of the sellers is evaluated using the equations 1 to 15 by taking parameters such as energy demand, buyer price, and trust factor as inputs. Then, the ranking of the sellers is done by considering the weighatge value. Similarly, Figure 9 shows the evaluated weightage value of the buyers by taking parameters like energy demand, buyer price, and trust factor of the buyer as inputs, and the ranking process of buyers is performed based on the evaluated weightage value. The mapping procedure of the buyers and sellers is performed according to the proposed mapping algorithm Algorithm 2 according to the rank of buyers and sellers.

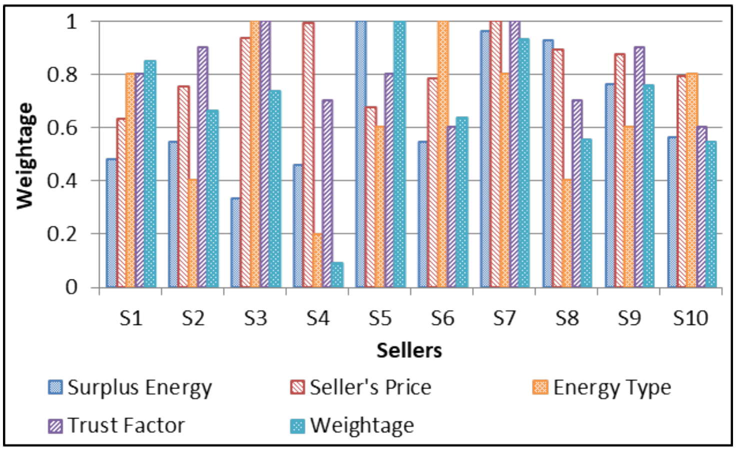


Fig. 8: Evaluating weightage value of sellers based on input parameters.

The notaries performed the consensus mechanism for verification of the transactions. Notaries are selected from the sellers. The notaries are selected based on the preference value, which is determined based on various factors of sellers such as energy surplus, trust factor, and notary selection frequency using equations 16 to 28. Figure 10 shows the preference value of each seller with their factors, such as energy surplus, trust factor, and notary selection frequency. Then, the sellers are sorted according to their preference values in descending order, and the first 51% is selected as the notaries. These sellers and DSO verifies the transactions made between buyers and sellers.

The nodes' deployment times and memory utilization of the proposed method has been analyzed in both test System 1 and test System 2. Figure 11 presents the time taken while deploying a different number of nodes in both systems. Figure 12 shows the memory usage analysis in both systems.

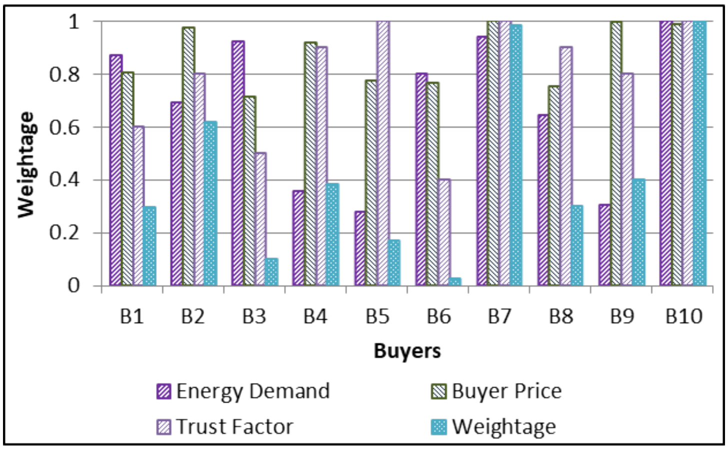


Fig. 9: Evaluating weightage value of buyers based on input parameters.

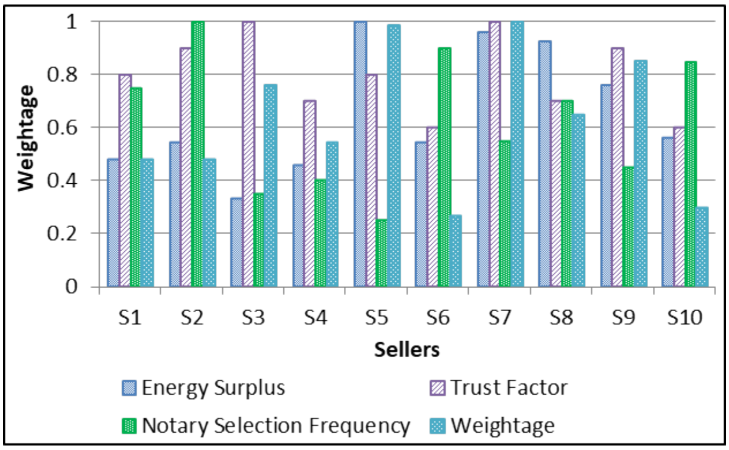


Fig. 10: Evaluating Preference value of sellers for notary selection based on input parameters

4.3.2 Observations and future scope

From the above analysis, it is observed that the seller S5 in Figure 8 and buyer B10 in Figure 9 have the highest weightage value; therefore, get the highest rank. The proposed mapping algorithm gives a higher opportunity to the buyer and seller who have got the highest rank value. For the verification and consensus mechanism, 51% of the sellers are selected as notaries according to their preference value. This prevents various attacks as the attacker needs to attack more than half of the sellers which is almost impossible. The proposed method also prevents from single point failure as the verification is not done only by the DSO. For the network deployment time and memory usage, it is observed that the proposed method consumed time and memory

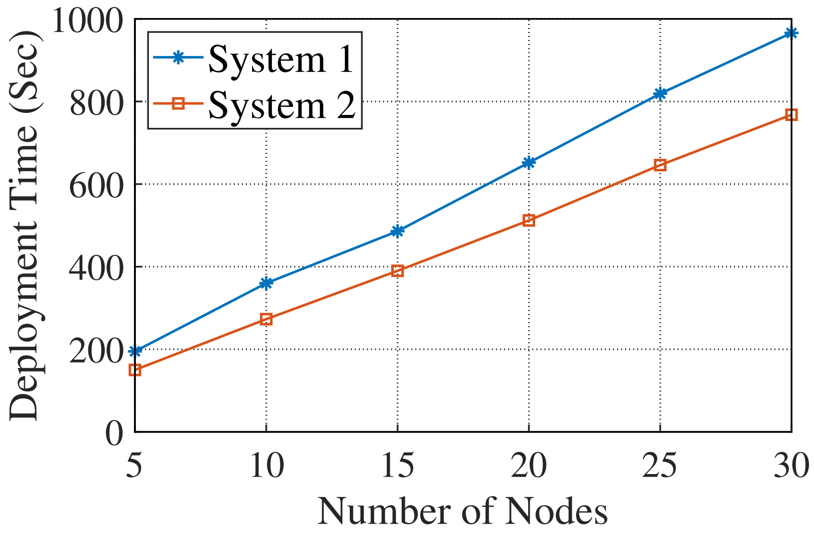


Fig. 11: Deployment time of nodes in test system 1 and test system 2

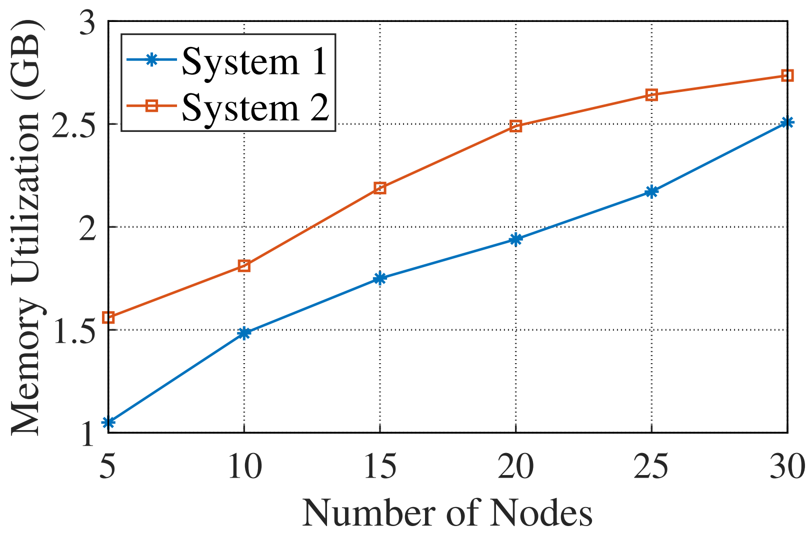


Fig. 12: Memory utilization of the proposed model with different numbers of nodes in test system 1 and test system 2

linearly as the number of prosumers increases and works in polynomial time. Therefore, the proposed way is scalable.

The proposed work considered the statistical data for the categorization process of prosumers as buyers and sellers for a period of time. This may induce a problem when the number of prosumers are increased. Therefore, in future, this data can the predicted using various machine learning and deep learning approach using real-time data.

4.4 Security Analyses

The security analysis of the proposed model has been made on various security aspects. Table 2 presents the security features comparison with various existing works. Further, the details of the security aspects that are taken into account are discussed.

Table 2: Comparative study of security features with previous existing works

Security features	Saha *et al.* [36]	Kaur *et al.* [40]	Aggarwal *et al.* [41]	Kumar *et al.* [42]	Muzumdar *et al.* [13]	**DeMCRP-ET model**
Data Privacy	×	×	×	×	×	✓
Non Repudiability	✓	×	✓	✓	✓	✓
Phishing Security	✓	×	×	✓	×	✓
Message Integrity	✓	✓	✓	✓	×	✓
Identity Privacy	✓	✓	✓	✓	✓	✓
Double Spend	×	×	×	×	×	✓

4.4.1 Data Privacy

The proposed model shared the transactions with only those participants who are involved in the transaction. The proposed model does not share information regarding the transactions of energy and money between buyer and seller with the other buyers and sellers. This approach makes preservation of information privacy among the trading participants and prevents the prediction of users' energy uses patterns. The information privacy preservation of the proposed model in energy and cash transaction is shown in Figure 13 and Figure 14. In this, Buyer1 and Seller1 are transferring energy and money between them. Here, the transactions done between them are not shared with other sellers and buyers. From Figure 13 and 14 it is clear that the energy and cash transaction information is shared between Seller1 and Buyer1 but not shared with Seller2 and Buyer2.

4.4.2 Non-Repudiability

In the proposed technique, each transaction between buyers and sellers in the energy trading process is signed by both parties.Next, the notaries check for the signatures of the participants who are involved in the transaction. After that, the notaries signed the transaction if the required signature exits in the transaction and commit the transaction. The notaries also check for the presence of already consumed states from the ledger of the hash value of consumed states. This ensures the non-repudiation of every transaction with their signature.

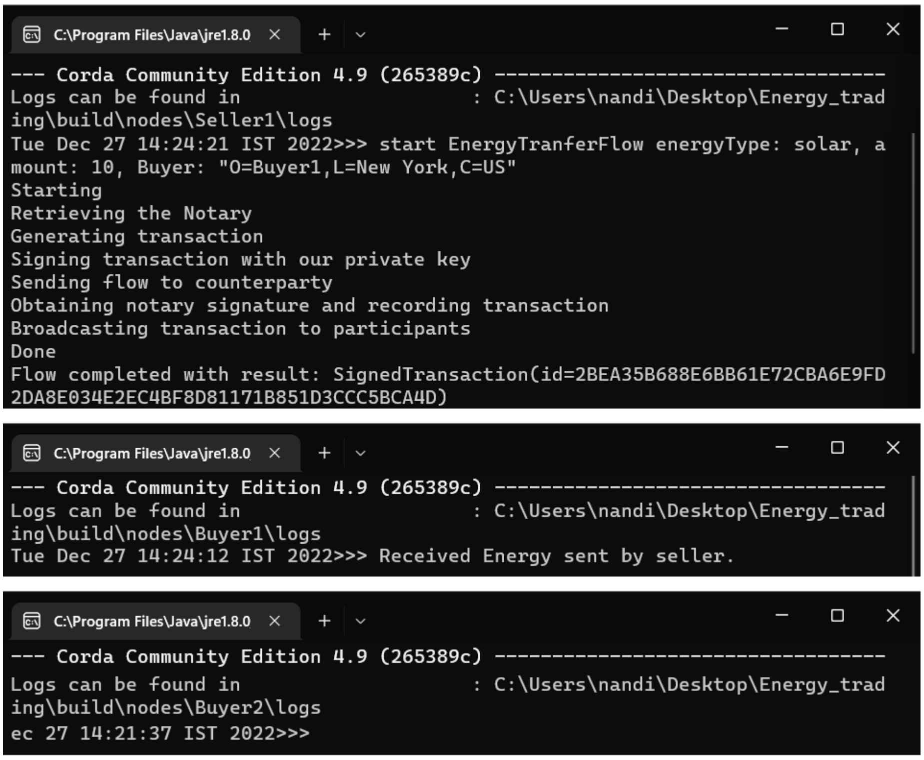


Fig. 13: Privacy preservation while energy flow is done

4.4.3 Message Integrity

The proposed method used the Corda ledger. In this, a transactions ledger with a time-stamp is maintained that connects the current state of a contract to its previous states. This chain guarantees the integrity and provenance of data over time. Moreover, an irreversible hash function (SHA256) is used for integrity checking in Corda ledger. In the proposed method, the notaries also provide integrity by using the consensus maintained in the distributed ledger. The records are stored on a decentralized and immutable ledger, which offers tamper-proof, transparent auditing and traceability.

4.4.4 Identity Privacy

The proposed approach incorporated the Corda distributed ledger; hence, the information of the participants is shared only with those who need to know it and is kept private from others. This approach offers privacy to the participants of the proposed trading model.

4.4.5 Double Spend

Double spending occurs when a participant attempts to send the same state to two separate recipients simultaneously or in rapid succession, resulting in two conflicting

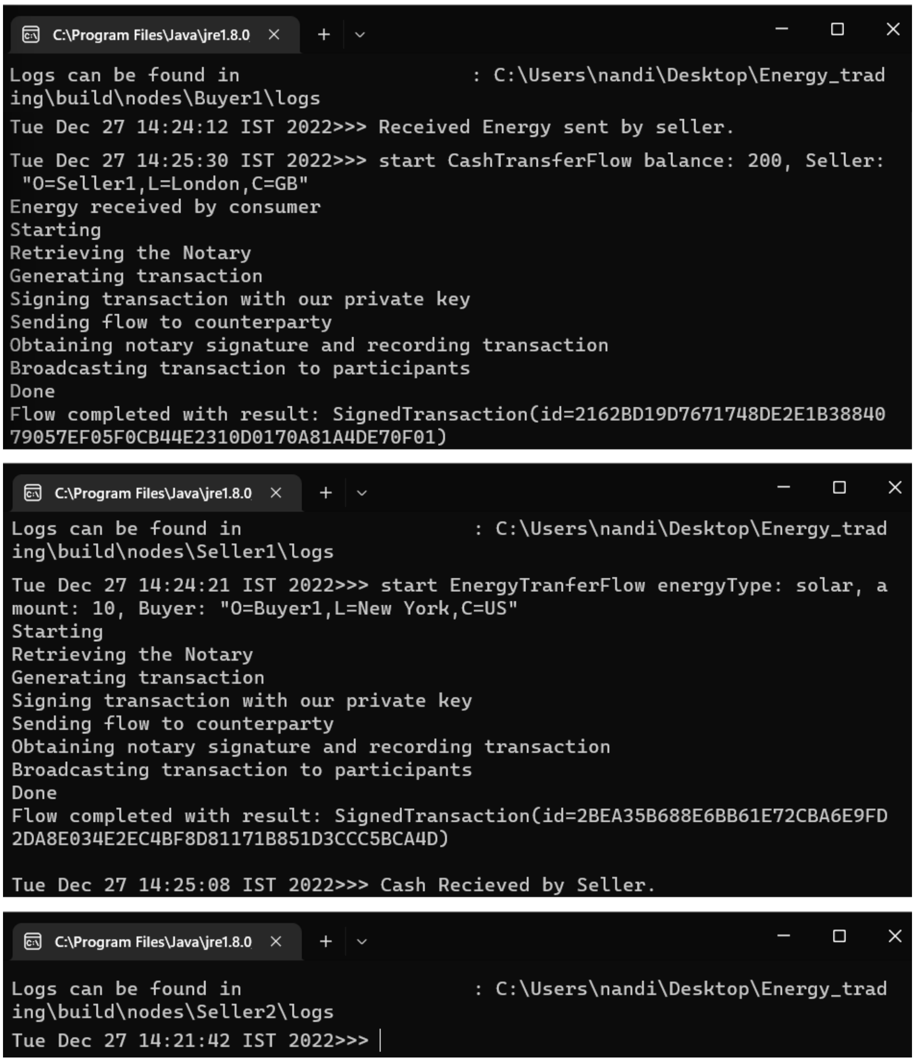


Fig. 14: Privacy preservation while cash flow is done

transactions. In the proposed work, the notaries are used for the consensus procedure of the transactions between buyers and sellers. Notaries maintain the hash of the consumed states in the proposed method for further verification. Also, notaries check for the signature of the seller and buyer whenever transactions are made between them. The notaries also check for the presence of any consumed (or used) states in the transaction made between buyers and sellers using the ledger of consumed states maintained by them. Therefore, this method prevents the double spending of both the buyer and sellers.

4.4.6 Phishing Security

In the proposed method, all participants of the trading model participate in consensus and smart contracts. To secure the transactions, more than 50% of the participants' consensus is required. However, if all the participants' consensus is considered for performing the transaction, it may degrade the performance of the proposed system. Therefore, the proposed method considered 51% of the prosumers as notaries for the verification and validation process of transactions without compromising the overall performance. This features makes it difficult for phishing attacks as it needs at least 51% of the sellers to be controlled by the attackers to agree with the consensus.

5 Conclusion

Smart grids improve the energy demand and supply process by allowing prosumers to sell or purchase energy based on their needs rather than relying on net metering and fixed rate policies. However, the existing method for energy trading in the smart grid faces many security and privacy challenges, such as data sharing privacy, users' privacy, non-repudiation, integrity, and preventing double-spending. This article designed a Corda distributed ledger-based energy trading model to provide secure and private transactions between buyers and sellers.This scheme selects 51% of the sellers as notaries for ensuring security aspects without compromising the system performance. These notaries verify, validate, and check for the uniqueness of transactions between sellers and buyers. The notaries are selected according to the ranking value of sellers. The ranking process is done based on various factors using a multiple-criteria decision-making technique called PROMETHEE II. Further, to perform energy trading between buyers and sellers, this article proposed a method for mapping between buyer and seller by considering various buyer and seller parameters. The performance analysis of the proposed scheme has been carried out in terms of network deployment time and memory utilization. The proposed method also provides various security features like data sharing privacy, users' privacy, non-repudiation, integrity, and preventing double-spending.

Declarations

Ethics Approval

This research did not contain any studies involving animal or human participants, nor did it take place on any private or protected areas. No specific permissions were required for corresponding locations.

Conflict of Interest

The authors have no conflicts of interest to declare.

Data Availability

All data is available upon request of the authors

Author Contributions

Conceptualization: N Nandini Devi and Surmila Thokchom; Methodology: Rutvij H. Jhaveri; Formal analysis: Gautam Srivastava and Mohamed Baza; Original Draft: N Nandini Devi and Surmila Thokchom and Diptendu Roy; Review & Editing: Gautam Srivastava, and Rutvij H. Jhaveri

Funding

No funding was obtained for this study

Consent to Publish

Not Applicable

References

[1] Alshehri, K., Ndrio, M., Bose, S., Başar, T.: Quantifying market efficiency impacts of aggregated distributed energy resources. IEEE Transactions on Power Systems **35**(5), 4067–4077 (2020) https://doi.org/10.1109/TPWRS.2020.2979997

[2] Facchini, A.: Distributed energy resources: Planning for the future. Nature Energy **2**(8), 1–2 (2017)

[3] Fares, R.L., Webber, M.E.: The impacts of storing solar energy in the home to reduce reliance on the utility. Nature Energy **2**(2), 1–10 (2017)

[4] Abbas, A.O., Chowdhury, B.H.: Using customer-side resources for market-based transmission and distribution level grid services–a review. International Journal of Electrical Power & Energy Systems **125**, 106480 (2021)

[5] Parag, Y., Sovacool, B.K.: Electricity market design for the prosumer era. Nature energy **1**(4), 1–6 (2016)

[6] Amin, U., Hossain, M.J., Tushar, W., Mahmud, K.: Energy trading in local electricity market with renewables—a contract theoretic approach. IEEE Transactions on Industrial Informatics **17**(6), 3717–3730 (2020)

[7] Ali, F.S., Aloqaily, M., Alfandi, O., Ozkasap, O.: Cyberphysical blockchain-enabled peer-to-peer energy trading. Computer **53**(9), 56–65 (2020)

[8] Devi, N.N., Thokchom, S.: Multi-attribute based prosumers prioritization for energy trading in smart grid. In: 2021 IEEE 18th India Council International Conference (INDICON), pp. 1–6 (2021). IEEE

[9] Devi, N.N., Panda, G., Thokchom, S.: Optimal ranking-based charging station selection for electric vehicles. International Journal of Emerging Electric Power Systems (0) (2023)

[10] Afzal, M., Huang, Q., Amin, W., Umer, K., Raza, A., Naeem, M.: Blockchain enabled distributed demand side management in community energy system with smart homes. IEEE Access **8**, 37428–37439 (2020)

[11] Aggarwal, S., Kumar, N., Gope, P.: An efficient blockchain-based authentication scheme for energy-trading in v2g networks. IEEE Transactions on Industrial Informatics **17**(10), 6971–6980 (2020)

[12] Aggarwal, S., Chaudhary, R., Aujla, G.S., Kumar, N., Choo, K.-K.R., Zomaya, A.Y.: Blockchain for smart communities: Applications, challenges and opportunities. Journal of Network and Computer Applications **144**, 13–48 (2019)

[13] Muzumdar, A., Modi, C., Madhu, G., Vyjayanthi, C.: A trustworthy and incentivized smart grid energy trading framework using distributed ledger and smart contracts. Journal of Network and Computer Applications **183**, 103074 (2021)

[14] Alzahrani, A., Sajjad, K., Hafeez, G., Murawwat, S., Khan, S., Khan, F.A.: Real-time energy optimization and scheduling of buildings integrated with renewable microgrid. Applied Energy **335**, 120640 (2023)

[15] Alzahrani, A., Rahman, M.U., Hafeez, G., Rukh, G., Ali, S., Murawwat, S., Iftikhar, F., Haider, S.I., Khan, M.I., Abed, A.M.: A strategy for multi-objective energy optimization in smart grid considering renewable energy and batteries energy storage system. IEEE Access **11**, 33872–33886 (2023)

[16] Park, J., Chitchyan, R., Angelopoulou, A., Murkin, J.: A block-free distributed ledger for p2p energy trading: Case with iota? In: International Conference on Advanced Information Systems Engineering, pp. 111–125 (2019). Springer

[17] Groß, C., Schwed, M., Mueller, S., Bringmann, O.: enerdag–towards a dlt-based local energy trading platform. In: 2020 International Conference on Omni-layer Intelligent Systems (COINS), pp. 1–8 (2020). IEEE

[18] Pradhan, N.R., Singh, A.P., Kumar, N., Hassan, M.M., Roy, D.S.: A flexible permission ascription (fpa)-based blockchain framework for peer-to-peer energy trading with performance evaluation. IEEE Transactions on Industrial Informatics **18**(4), 2465–2475 (2021)

[19] Jogunola, O., Hammoudeh, M., Anoh, K., Adebisi, B.: Distributed ledger technologies for peer-to-peer energy trading. In: 2020 IEEE Electric Power and Energy Conference (EPEC), pp. 1–6 (2020). IEEE

[20] Yang, Q., Wang, H.: Privacy-preserving transactive energy management for iot-aided smart homes via blockchain. IEEE Internet of Things Journal **8**(14), 11463–11475 (2021)

[21] Yang, Q., Wang, H.: Blockchain-empowered socially optimal transactive energy

system: Framework and implementation. IEEE Transactions on Industrial Informatics **17**(5), 3122–3132 (2020)

[22] Zhang, M., Eliassen, F., Taherkordi, A., Jacobsen, H.-A., Chung, H.-M., Zhang, Y.: Demand–response games for peer-to-peer energy trading with the hyperledger blockchain. IEEE Transactions on Systems, Man, and Cybernetics: Systems **52**(1), 19–31 (2021)

[23] AlAshery, M.K., Yi, Z., Shi, D., Lu, X., Xu, C., Wang, Z., Qiao, W.: A blockchain-enabled multi-settlement quasi-ideal peer-to-peer trading framework. IEEE Transactions on Smart Grid **12**(1), 885–896 (2020)

[24] Ali, F.S., Bouachir, O., Özkasap, Ö., Aloqaily, M.: Synergychain: Blockchain-assisted adaptive cyber-physical p2p energy trading. IEEE Transactions on Industrial Informatics **17**(8), 5769–5778 (2020)

[25] Hamouda, M.R., Nassar, M.E., Salama, M.: A novel energy trading framework using adapted blockchain technology. IEEE Transactions on Smart Grid **12**(3), 2165–2175 (2020)

[26] Hua, W., Zhou, Y., Qadrdan, M., Wu, J., Jenkins, N.: Blockchain enabled decentralized local electricity markets with flexibility from heating sources. IEEE Transactions on Smart Grid (2022)

[27] Devi, N.N., Thokchom, S., Singh, T.D., Panda, G., Naayagi, R.T.: Multi-stage bargaining of smart grid energy trading based on cooperative game theory. Energies **16**(11), 4278 (2023)

[28] Zhou, X., Wang, B., Guo, Q., Sun, H., Pan, Z., Tian, N.: Bidirectional privacy-preserving network-constrained peer-to-peer energy trading based on secure multiparty computation and blockchain. IEEE Transactions on Power Systems (2023)

[29] Gao, J., Asamoah, K.O., Xia, Q., Sifah, E.B., Amankona, O.I., Xia, H.: A blockchain peer-to-peer energy trading system for microgrids. IEEE Transactions on Smart Grid (2023)

[30] Jia, Y., Wan, C., Cui, W., Song, Y., Ju, P.: Peer-to-peer energy trading using prediction intervals of renewable energy generation. IEEE Transactions on Smart Grid **14**(2), 1454–1465 (2022)

[31] Wang, J., Zhang, J., Li, L., Lin, Y.: Peer-to-peer energy trading for residential prosumers with photovoltaic and battery storage systems. IEEE Systems Journal **17**(1), 154–163 (2022)

[32] Toubeau, J.-F., Teng, F., Morstyn, T., Von Krannichfeldt, L., Wang, Y.: Privacy-preserving probabilistic voltage forecasting in local energy communities. IEEE

Transactions on Smart Grid **14**(1), 798–809 (2022)

[33] Guo, Z., Qin, B., Guan, Z., Wang, Y., Zheng, H., Wu, Q.: A high-efficiency and incentive-compatible peer-to-peer energy trading mechanism. IEEE Transactions on Smart Grid (2023)

[34] Liu, J., Long, Q., Liu, R.-P., Liu, W., Cui, X., Hou, Y.: Privacy-preserving peer-to-peer energy trading via hybrid secure computations. IEEE Transactions on Smart Grid, 1–1 (2023) https://doi.org/10.1109/TSG.2023.3293549

[35] Ping, J., Yan, Z., Chen, S.: A privacy-preserving blockchain-based method to optimize energy trading. IEEE Transactions on Smart Grid **14**(2), 1148–1157 (2022)

[36] Saha, R., Kumar, G., Geetha, G., Alazab, M., Thomas, R., Rai, M.K., Rodrigues, J.J., *et al.*: The blockchain solution for the security of internet of energy and electric vehicle interface. IEEE Transactions on Vehicular Technology **70**(8), 7495–7508 (2021)

[37] Figueira, J., Greco, S., Ehrgott, M.: Multiple criteria decision analysis: state of the art surveys (2005)

[38] Brans, J., Vincke, P.: A preference ranking organisation method: The promethee method formcdm. Management Science **31**(6), 647656 (1985)

[39] Behzadian, M., Kazemzadeh, R.B., Albadvi, A., Aghdasi, M.: Promethee: A comprehensive literature review on methodologies and applications. European journal of Operational research **200**(1), 198–215 (2010)

[40] Kaur, K., Kaddoum, G., Zeadally, S.: Blockchain-based cyber-physical security for electrical vehicle aided smart grid ecosystem. IEEE Transactions on Intelligent Transportation Systems **22**(8), 5178–5189 (2021)

[41] Aggarwal, S., Kumar, N.: A consortium blockchain-based energy trading for demand response management in vehicle-to-grid. IEEE Transactions on Vehicular Technology **70**(9), 9480–9494 (2021)

[42] Kumar, G., Saha, R., Rai, M.K., Buchanan, W.J., Thomas, R., Geetha, G., Hoon-Kim, T., Rodrigues, J.J.: A privacy-preserving secure framework for electric vehicles in iot using matching market and signcryption. IEEE Transactions on Vehicular Technology **69**(7), 7707–7722 (2020)