AMERICAN UNIVERSITY OF BEIRUT

ENHANCING POWER QUALITY AND ENERGY TRADING IN DISTRIBUTION NETWORK ENABLED WITH BLOCKCHAIN

by
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ABSTRACT
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This thesis aims to develop a methodology for optimizing energy flow in a distributed network characterized by a distributed system operator (DSO), energy management gateway (EMG), renewable energy (RE) sources and grid. The users of different buses will play a major role in optimizing the power flow, in addition to supplying the needed demand. Based on the location and size of renewables and stored energy, it is expected to reach the least power losses, cost, and voltage deviations possible in the network. The network is supported by blockchain to ensure secure and transparent transactions in addition to facilitating trading between peers. The network is subjected to time domain power flow (TDPF), Prophet forecast, and peer-to-peer (P2P) trading connected to a blockchain to reach optimal configuration.

Keywords — renewables, distributed system operator, energy management gateway, blockchain.

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ABBREVIATIONS

Abbreviation	**Explanation**
PV	Photovoltaic
RES	Renewable Energy Source
BESS	Battery Energy Storage systems
P2P	Peer-to-Peer
DSO	Distribution System Operators
EMG	Energy Management Gate
GA	Genetic Algorithm
ESS	Energy Storage System
DER	Distributed Energy Resources
DG	Distributed Generators
MV	Medium Voltage
SOC	State of Charge
STC	Standard Test Condition
NOCT	Nominal Operating Cell Temperature
Voc,STC	PV module open circuit voltage under STC
Isc,STC	PV module short circuit current under STC
Vmppt,STC	PV module voltage at maximum power point under STC
Imppt,STC	PV module current at maximum power point under STC
Kv	Voltage-temperature coefficient
Ki	Current-temperature coefficient

CHAPTER 1

INTRODUCTION

With the increasing presence of RE sources in microgrids, the energy market is gradually changing from centralized to decentralized with the possibility for P2P energy trading. However, the RE-generating units in the network may affect the power quality of the system. Therefore, users with RE sources and grid need to be connected to a controller, and linked to a compatible server to achieve optimal power quality and flow. The blockchain, on the other hand, provides the necessary management among peers, allowing the trading of energy among the users themselves or between the users and energy sources.

1.1. Impact of RE and BESS on Power Quality in Networks

The integration of RE sources, such as solar and wind, alongside BESS, is driving a paradigm shift in power grids. While these technologies are pivotal for sustainable energy generation, their deployment presents challenges to maintaining grid stability and power quality. A key concern is the impact of RE sources on **active and reactive power flows**, which are critical to efficient grid operation.

The intermittent nature of RE generation leads to fluctuations in **active power**, resulting in frequency deviations and supply-demand imbalances. For instance, during periods of high RE generation, excess active power may cause overloading of transmission lines, increasing resistive losses and reducing system efficiency. Conversely, during low-generation periods, insufficient active power can destabilize the grid and necessitate reliance on backup generation systems.

In addition to active power challenges, RE integration significantly affects **reactive power** dynamics, which are essential for maintaining voltage levels within permissible limits. Many RE systems, especially those connected via inverters, do not inherently generate or absorb reactive power as conventional synchronous generators do. This limitation can lead to voltage instability, increased reactive losses in transmission and distribution networks, and degradation of power factor. Moreover, poor reactive power management may result in higher currents in the network, further exacerbating power losses and reducing the lifespan of grid components.

To mitigate these issues, BESS play a pivotal role in stabilizing both active and reactive power flows. BESS can absorb excess active power during peak RE generation, reducing resistive losses and preventing overloading. They also contribute to reactive power compensation, supporting voltage regulation and enhancing grid stability. Advanced control systems are essential to coordinate RE sources, BESS, and the grid, enabling real-time monitoring and optimization of energy generation, consumption, and storage. These systems must also address reactive power requirements and harmonic mitigation to ensure seamless energy flow and maintain power quality.

1.2. P2P Trading

P2P trading between users and energy storage systems, without the need for central authorities, allows for efficient energy distribution and enhances the overall resilience of the power network by enabling users to trade energy directly and optimize their usage of renewable and stored power.

Energy-sharing models form the backbone of decentralized energy systems by outlining how prosumers (those who both produce and consume energy) exchange and trade energy within a network. These models are crucial for enabling effective energy distribution in projects where multiple entities are involved in energy generation and consumption. They can be divided into three distinct designs:

1. **Centralized Authority Model**: In this model, a single centralized entity, such as a utility company or grid operator, oversees the distribution and trading of energy. The centralized authority controls the entire energy-sharing process, regulating how much energy is traded between prosumers and ensuring the stability of the system. While this model is traditionally used in large-scale energy markets, it has limited flexibility and often lacks the responsiveness needed for decentralized or community-driven grids.
2. **Operator-Driven Model (Price Maker and Price Takers)**: This design involves an intermediary or operator (the price maker) who sets the energy prices and facilitates the exchange between users (price takers). The operator determines the pricing based on supply and demand, and users can trade energy based on those prices. This model provides more flexibility than a fully centralized system but still relies on an external authority for pricing and coordination.
3. **P2P Energy-Sharing Model**: In the P2P model, prosumers directly trade energy with each other without the need for a central authority or intermediary. Prosumers with excess energy can sell it to others in the network who need it, creating a decentralized and dynamic market. This model mirrors P2P networks commonly used in computer science for resource sharing, where each "peer" in the network acts as either a supplier or a consumer. P2P energy sharing is particularly effective in community microgrids, where prosumers nearby and can exchange energy locally, maximizing the use of distributed energy resources (DERs) such as solar panels and wind turbines.

In the context of **community microgrids**, which consist of prosumers generating their energy through small-scale DERs, P2P energy sharing offers significant benefits. It allows for the local exchange of excess energy, reducing dependence on the main grid and increasing energy self-sufficiency. This decentralized model improves the efficiency and resilience of energy distribution by optimizing the flow of energy between users in real-time, while also reducing transmission losses associated with long-distance energy transport.

P2P energy-sharing models provide a more flexible and scalable approach to energy management, particularly as more RE sources are integrated into the grid. By allowing prosumers to trade energy directly, these models encourage a more balanced and efficient distribution of energy resources, making them ideal for the evolving landscape of decentralized energy systems.

1.3. Blockchain

Blockchain is a revolutionary decentralized technology designed to securely and transparently manage transactions across a distributed network. Unlike traditional systems that rely on a central authority, blockchain operates on a P2P basis, where every transaction is recorded in a shared, immutable ledger. In the energy sector, particularly within microgrids, blockchain plays a crucial role by enabling direct energy trading between users (prosumers/consumers) and energy sources without intermediaries. This system enhances trust and transparency, as all transactions are verified by the network participants and stored permanently, reducing the risks of fraud or disputes. Blockchain also facilitates the efficient management of energy supply and demand, optimizing power flow while maintaining grid stability. Automating transactions through smart contracts, allows energy to be exchanged seamlessly and fairly, creating a more resilient and flexible energy market in decentralized networks.

CHAPTER 2

LITERATURE REVIEW

In this literature review, two key topics essential to the development of this thesis to be covered: the optimization of power flow in distributed networks and the integration of blockchain technology with energy trading, particularly P2P trading. The first section will explore methodologies for optimizing energy flow in a network comprising DSO, EMG, RE sources, and the grid, aiming to minimize power losses, costs, and voltage deviations. The second section will focus on how blockchain technology ensures secure and transparent transactions while facilitating energy trading among peers, contributing to a decentralized and efficient energy market.

2.1. Literature on Power Flow Optimization Methods

Li et al. [2] introduced inherent and maximum renewable energy indices to assess the accommodation capacity within microgrids, using a Monte Carlo-based algorithm for reactive power optimization. Most scenarios showed improvements in these indices following optimization, except when the adjustable range was minimal. The rise of microgrids and renewable energy sources has shifted energy trading from centralized to P2P, resulting in voltage fluctuations in transmission and distribution systems. Roy et al. [7] proposed a sequential optimization strategy for active and reactive power allocation within a droop-controlled island AC microgrid. Their fuzzy-embedded multi-objective particle swarm technique led to a 12% decrease in total power loss and an 18% improvement in voltage deviation.

Chedid et al. [8] employed genetic algorithm (GA) for multi-objective optimization to determine the optimal sizing and allocation of photovoltaic (PV) and BESS in distribution networks, reducing power losses and improving voltage profiles. Alramlawi et al. [9] introduced an economic model predictive controller for microgrid power management, comparing PV inverters with battery inverters for reactive power generation. This study demonstrated that PV inverters were more cost-effective for reactive power generation. Additionally, a study [10] emphasized the importance of BESS in reducing microgrid operational costs. By using nonlinear programming and artificial neural network (ANN) short-term forecasting, a 2.5% reduction in costs was observed, enhancing the prediction of future power demands.

In [19], the author developed decentralized methods for computing optimal power setpoints for residential PV inverters, addressing limitations in traditional controllers by introducing optimal power flow (OPF) techniques. A novel ADMM-based framework enabled decentralized resolution of OPF problems, improving scalability for large networks. Aense E et al. [20] proposed an optimal inverter dispatch (OID) framework for low-voltage distribution systems with high PV penetration, focusing on minimizing overvoltage risk and balancing power reserves. This approach applied conditional value-at-risk to manage forecast inaccuracies, addressing the uncertainty from solar irradiance.

As the complexity of active distribution networks increases, challenges like high power loss and voltage deviation have been addressed using data-driven methods [21]. One promising approach uses 1D convolutional neural networks (1D-CNNs) to optimize power flow, which has proven effective in reducing power loss and voltage deviation in modified IEEE33 node systems. Huazhi et al. [22] explored reactive power optimization to stabilize voltage in systems with high integration of wind and PV generation. Their enhanced particle swarm optimization algorithm demonstrated greater computational efficiency and improved voltage stability, particularly in high-renewable scenarios.

Zacharia et al. [23] emphasized the role of microgrids in smart grid systems, proposing optimization algorithms for both grid-connected and islanded modes. Their approach optimized performance by controlling load shedding, PV generation, and Energy Storage System (ESS) operations, with real-time simulations confirming its effectiveness. Chaoauchi et al. [24] combined AI techniques and multi-objective optimization to reduce operational costs and environmental impacts in microgrids. Their system forecasts renewable energy availability and load demand, improving the accuracy of energy management and reducing costs and emissions.

In [25], Maulik presented an optimization method for droop settings in islanded microgrids to minimize costs and emissions, using a stochastic approach and fuzzified particle swarm optimization. This method showed effectiveness in a 33-bus system. P. Li et al. [26] introduced a fuzzy multi-objective optimization model to minimize economic costs and network losses in microgrids, using chaotic binary particle swarm optimization (CBPSO) to enhance the search capability of traditional methods. Benchmark tests confirmed the accuracy and performance of CBPSO in comparison with traditional methods.

J. J. et al. [27] presented a methodology for the optimal operation of islanded microgrids, balancing economic, emission, and load ability objectives. Using the multi-objective antlion optimizer, their results highlighted the importance of considering load ability in microgrid planning and operation. The authors in [28] developed a multi-agent system (MAS)-based control model for reactive power sharing in islanded microgrids, addressing issues like feeder impedance mismatches. Their approach, validated by simulations, showed effective reactive power sharing and plug-and-play capability.

The challenge of optimal placement and sizing of distributed generation (DG) in distribution systems was addressed by the authors in [29], who used a multi-objective optimization approach with GA to minimize power losses and costs. Their method, tested on solar and wind DGs, demonstrated effectiveness in IEEE 33-bus and 69-bus systems. Atia et al. [30] introduced an optimization scheme for sizing distributed renewable generation (DRG) and energy storage systems (DESS) using a novel energy management system (EMS), validated through a case study on an IEEE 34-bus microgrid, emphasizing its effectiveness in investment and operational strategies.

Babacan et al. [31] addressed the allocation of BESS to mitigate voltage fluctuations from high solar PV penetration. Their GA-based bi-level optimization method, validated on the IEEE 8500-Node test feeder, demonstrated effectiveness in minimizing daily peak demand and improving global optimality. For a foundational understanding of power systems, two key references were utilized: Power System Analysis by Hadi Saadat [32] and Power System Analysis & Design by Glover, Samra, and Overbye [33].

These resources provided essential concepts and methodologies for the research presented in this thesis.

2.2. Literature on Blockchain and P2P Energy Trading

The integration of blockchain technology into energy trading has been a subject of significant research, with numerous studies examining its potential to address various challenges in energy markets, including scalability, security, and decentralization.

Di Silvestre et al. [1] explored technical challenges in energy transactions, such as power loss fluctuations and the amplified injection of reactive power for voltage support at P-V nodes. Their work demonstrated blockchain's capability to make technical decisions beyond purely economic considerations. Specifically, they studied a 9-bus Medium Voltage (MV) microgrid with two scenarios involving three energy transactions, where consumers acted as negotiators and distributors calculated losses. The research highlighted the efficiency of blockchain in managing these complex interactions within microgrids.

Auxiliary services and energy storage systems were explored by the authors in [3], who proposed a blockchain-based grid-side shared energy storage market aimed at promoting clean energy consumption and reducing costs. By ensuring that storage systems cover peak modulation loads under market policies, this study demonstrated how blockchain could streamline operations while enhancing system performance.

Otola et al. [4] took a different approach by incorporating a self-balanced differential evolution algorithm to optimize reactive power flow, coordinated by a distribution system operator. Blockchain was instrumental in analyzing reactive power losses and ensuring cost-efficient price allocation for various market cases. Their research demonstrated that blockchain can significantly reduce production costs related to reactive power, underscoring its potential to optimize power system operations while maintaining security and transparency.

Building upon the foundational work by Di Silvestre, another study [5] employed a glow-worn optimization method to limit energy flow and maintain voltages within nominal ranges at PV nodes. Blockchain was integrated to facilitate remuneration within a residential 9-bus microgrid, leading to reduced power losses and zero reactive power loss, ensuring a more reliable power supply.

The European Union directive EU 2-19/944 introduced a dynamic procurement system for flexible and adaptable reactive power flow [6], which leveraged a two-layer blockchain topology. This system accounted for transaction time and scales and integrated a decentralized oracle network for external data input. Smart contractors validated transactions, with the system capable of processing thousands of transactions within 10 seconds, demonstrating blockchain's scalability in real-time energy markets.

The integration of traditional centralized databases with blockchain was explored by Mu et al. [11], who designed a hybrid energy blockchain system. This system combined a blockchain layer, smart contracts, a database layer, and a client layer, creating a more feasible energy trading platform that enhanced security and efficiency. This approach underscored the growing trend toward decentralized energy markets and blockchain's role in facilitating transparent, efficient, and secure P2P energy trading.

Niloy et al. [13] proposed a blockchain-based peer-to-peer power trading system that enabled a smart microgrid to seamlessly transition between the national grid and localized grid conditions. Smart contracts were written in Solidity to facilitate multiple trades on the Binance blockchain platform, ensuring the system's security and reliability. Their study highlighted blockchain's role in enabling self-sufficiency and robust trading systems while reducing the reliance on centralized authorities.

In addition to these studies, Chen et al. [15] focused on the customers' risk preferences in energy trading, employing a double-side mechanism for energy transactions. Ethereum and Remix development environments were used to create a secure and optimal platform, showcasing how blockchain technology could be tailored to meet specific market conditions and customer needs. This research emphasized the flexibility of blockchain in creating customized, efficient energy trading solutions.

Further enhancing blockchain applications, a study in [16] integrated distributed generators and battery storage systems with smart meters to improve the performance of a microgrid. Jamil et al. [17] proposed a predictive energy trading platform that leveraged blockchain for real-time support and generation scheduling of distributed energy resources. By incorporating smart contracts and predictive analytics based on historical data, this system improved short-term energy consumption forecasting and helped optimize energy trading. Hyperledger Caliper was used to evaluate blockchain performance, confirming the system's potential for improving service quality and optimizing energy resource management.

Park et al. [18] explored the use of Hyperledger Fabric for peer-to-peer energy trading in South Korea, where blockchain performance was evaluated using Hyperledger Caliper. The study showed how blockchain technology could facilitate decentralized energy trading, enabling fairer electricity tariffs and reducing reliance on centralized energy operators.

Further advancements in decentralized energy markets were explored by Kang et al. [34], who proposed a localized P2P electricity trading model for plug-in hybrid electric vehicles (PHEVs). This approach utilized consortium blockchain technology to ensure security and privacy, optimizing electricity pricing and trading volumes through a double auction mechanism. The PETCON method enhanced social welfare while addressing transaction security and privacy concerns, demonstrating blockchain's role in optimizing P2P trading systems for electric vehicles in smart grids.

In [35], another study explored blockchain's potential in peer-to-peer energy markets, using smart contracts to ensure fair payment and decentralized coordination. The introduction of decentralized optimization techniques, such as the Alternating Direction Method of Multipliers (ADMM), further improved system performance by enabling local optimization of DERs.

Peck et al. [36] examined the potential for open energy markets where excess solar energy could be traded using blockchain, creating more flexibility and responsiveness in energy markets. By enabling transparent, immutable energy transactions, blockchain could disrupt traditional energy trading models, allowing residential producers to sell excess energy back to the grid during peak hours.

Khalid et al. [38] proposed a decentralized hybrid P2P energy trading system that utilized smart contracts to reduce energy costs, emissions, and improve grid resilience. By eliminating the need for a centralized manager, this blockchain-based system reduced operational costs and improved efficiency.

The shift from traditional hierarchical energy systems to decentralized models was further explored in [39], where P2P energy sharing was presented as a viable solution for future energy markets. The study reviewed global pilot projects and identified key challenges for the widespread adoption of P2P systems, emphasizing blockchain’s role in facilitating transparent and secure energy trading platforms.

The use of blockchain in solar energy markets was explored in [40], where a P2P trading system enabled decentralized energy transactions. By using ERC20 tokens for payments and integrating ESS, this study highlighted blockchain’s potential in creating efficient, market-driven energy trading systems.

Jamil et al. [41] further developed blockchain-based systems by integrating predictive analytics with energy trading platforms. The research highlighted the importance of using historical energy data to forecast consumption patterns and optimize energy trading, providing a model for improving service quality through secure and efficient transaction mechanisms.

The decentralized market clearing mechanism for P2P energy trading proposed in [42] addressed issues of privacy, power losses, and network utilization fees. By incorporating an electrical distance approach, this study demonstrated the effectiveness of decentralized market clearing in ensuring cost-effective and efficient transactions in P2P energy markets.

Tushar et al. [43] reviewed P2P energy trading and highlighted its benefits, such as reducing peak demand, lowering reserve requirements, and minimizing network losses. By providing a comprehensive overview of the state-of-the-art research, this study outlined future research directions and underscored blockchain’s potential in optimizing energy trading systems.

In [44], blockchain technologies were explored alongside auction mechanisms for facilitating P2P energy trading within microgrids. Using Ethereum's smart contracts, this study introduced new frameworks for energy trading, emphasizing how blockchain could enable transparent, decentralized transactions within local energy markets.

Seven et al. [45] proposed a novel P2P energy trading mechanism for Virtual Power Plants (VPPs) using Ethereum-based smart contracts. By integrating blockchain with cost optimization strategies, this study addressed the financial aspects of P2P trading, further highlighting blockchain’s potential in transforming energy markets.

Through these studies, blockchain technology is clearly emerging as a transformative force in the energy sector. Its ability to facilitate decentralized, transparent, and secure energy trading systems has the potential to revolutionize how energy is produced, traded, and consumed, paving the way for more efficient, cost-effective, and sustainable energy markets.

This thesis introduces an approach for optimizing energy flow within a distributed network that involves the coordination of DSO, EMG, and various energy sources. While previous research often concentrates on either optimization methods or P2P energy trading separately, this study seeks to address both aspects simultaneously.

The research proposes a hybrid framework that combines multiple advanced techniques, including a TDPF model, forecasting mechanisms, and blockchain technology. These elements work in synergy to optimize energy management in a distributed system by not only ensuring that power flow is efficiently distributed but also enhancing the operational reliability and economic efficiency of the network.

A key component of this approach is to minimize power losses, optimize voltage profiles, and ensure the reliable delivery of energy throughout the system. This approach addresses a critical challenge in traditional power grids, where optimizing power flow is typically limited to centralized systems without considering local distribution conditions or the integration of renewable energy sources.

Forecasting plays a crucial role in enhancing the accuracy of the energy management process. The research employs the Prophet forecasting model to predict energy consumption patterns, generation profiles from renewable sources, and demand fluctuations. These forecasts enable more proactive and informed decisions, allowing for optimized energy dispatch and a reduction in the reliance on expensive peak-load power generation. The ability to predict and manage fluctuations in energy demand and supply is critical for maintaining grid stability and optimizing resource allocation.

Furthermore, the integration of blockchain technology provides a secure, transparent, and decentralized platform for P2P energy trading. By leveraging blockchain, the system can ensure that energy transactions between prosumers (energy producers and consumers) are executed in a trustless environment, where smart contracts automatically enforce the terms of the energy trade. This decentralization reduces the need for intermediaries, enhances market participation, and ensures that transactions are both secure and transparent.

The combined use of optimization techniques with P2P energy trading creates a dynamic and flexible solution for energy management. The optimization methods improve the overall performance of the energy network by reducing operational costs, minimizing energy losses, and improving the voltage stability. Meanwhile, the P2P trading system offers economic benefits by enabling local energy transactions, allowing participants to buy and sell energy directly. This reduces the need for centralized energy procurement, further driving down costs and improving system efficiency.

By combining these elements—TDPF optimization, forecasting, and blockchain-based P2P trading—the thesis presents a more dynamic and integrated approach to energy management. This comprehensive framework not only optimizes energy flow within the network but also provides a scalable and secure solution for future energy systems, especially in environments where decentralized, renewable energy sources play a significant role. The approach outlined in this research offers a more holistic solution that balances technical efficiency with market flexibility, paving the way for more sustainable and cost-effective energy systems.

CHAPTER 3

SYSTEM MODELLING

3.1. Problem Definition

The system under consideration is shown in Figure 1. As can be seen, the power generation sources include the electric utility, PV systems and BESS. Users will be categorized into two groups. The first group consists of prosumers, who have RE sources and can both produce and consume energy, contributing to the prosumer society.

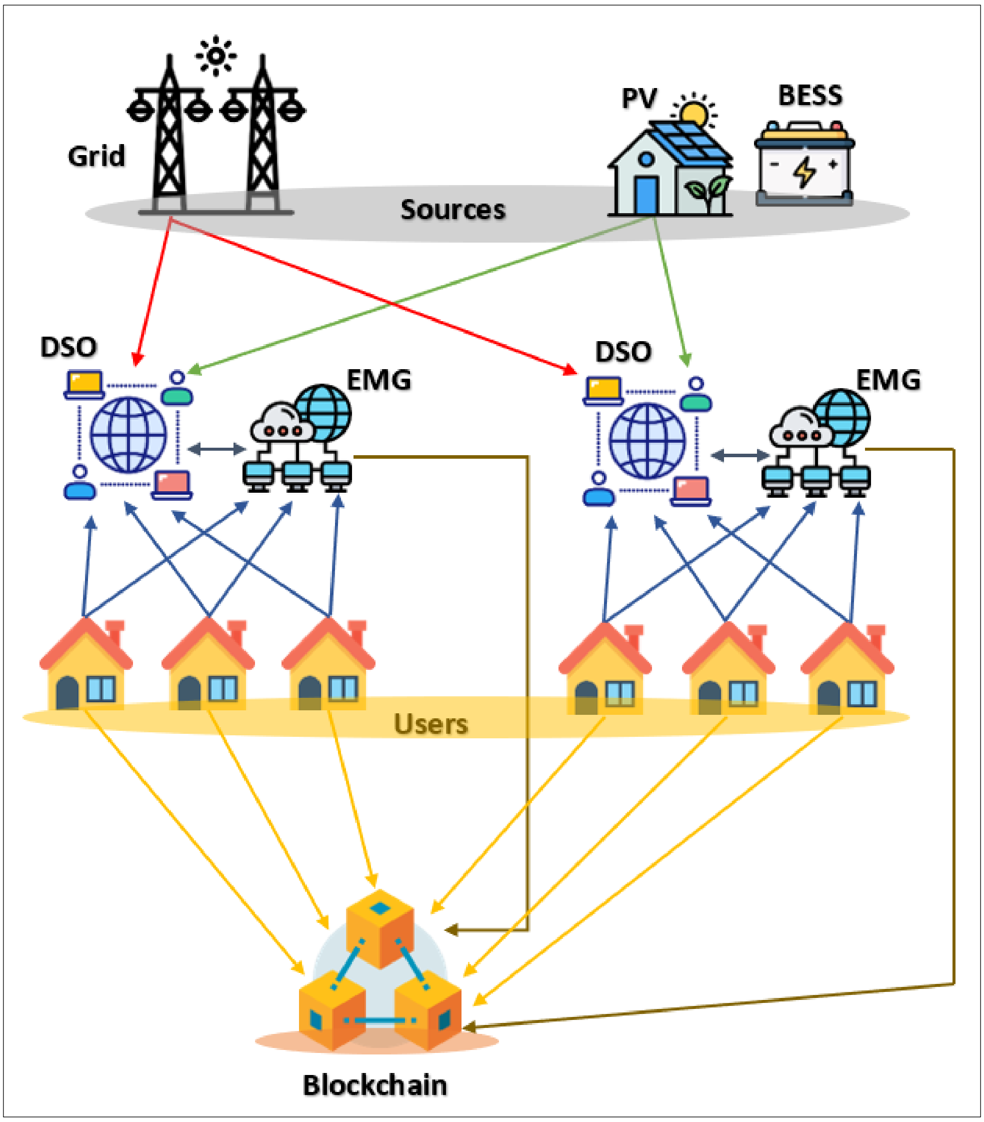


Figure 1 General Architecture of the Proposed Method Using Blockchain

Additionally, they will be connected to the DSO immediately to record their BESS's state of charge (SOC). The second group consists of consumers, who only consume energy and do not have PV or BESS installed at their homes or buses. In terms of transaction processing, the EMG facilitates interactions between consumers and prosumers using smart contracts, initiating functions on the blockchain to update balances and settle transactions. Moreover, the EMG manages notifications and messaging between users, which includes informing consumers about energy offers, notifying consumers about sales, or updates regarding energy transactions. Finally, the blockchain ensures the security and accuracy of energy trading transactions.

In this thesis, the problem of PV and BESS sizing and energy trading is formulated as a multi-objective optimization problem as follows:

$$\begin{cases} minCost = CE_{grid} \, . \, E_{grid} + CE_{PV} \, . \, E_{PV} + \; CE_{BESS} \, . E_{BESS} + \; C_{Blcochain} \\ min \sum_{i=1}^{n} VD_i = min \sum_{i=1}^{n} |1 - V_i| \\ minS_{loss}(grid, PV, BESS) \end{cases} \tag{1}$$

Where 'Cost' represents the total cost of energy generation, 'CE_{grid}' represents the cost of energy generated by the grid, 'CE_{pv}' represents the cost of energy generated by the PV, 'CE_{BESS}' represents the cost of energy generated by the BESS, and '$C_{Blockchain}$' represents the cost of energy generated by the blockchain. 'VD' denotes voltage deviation from the slack bus bar and 'S_{loss}' is the system's apparent power losses.

This problem formulation aims to optimally size and allocate PV and BESS units in terms of size and location. It is well known that maximum power losses, maximum cost, and maximum voltage deviations are observed during peak demand hours, and since the objective of the optimization is to minimize these parameters, then the optimization will be performed during peak load hour. After finding the optimal configuration TDPF is performed in order to determine the voltage profile on each bus and power losses during each hour of a year.

The load flow equations are depicted in equality constraints as follows:

$$P_{g_i} - P_{d_i} - V_i\, B_{ij}G_{ij} = 0 \tag{2}$$

$$P_{g_i} - P_{d_i} - V_i \sum V_i(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}) = 0 \tag{3}$$

$$Q_{g_i} - Q_{d_i} - V_j \sum V_j(G_{ij}cos\delta_{ij} + B_{ij}sin\delta_{ij}) = 0 \tag{4}$$

In these equations, 'P_{g_i}' and 'Q_{g_i}' represent the active and reactive power generation, and the 'P_{d_i}' and 'Q_{d_i}' represent the active and reactive power load demands for the "i-th" bus, respectively. 'G_{ij}' and 'B_{ij}' represent the conductance and susceptance between the "i-th" and "j-th" buses, respectively.

Operating Constraints:

$$V_{min}L_i \leq VL_i \leq V_{max}L_i \qquad \text{i = 1.......N (PQ)} \tag{5}$$

$$SL_i \leq S_{max}L_i \qquad \text{i = 1.......N (L)} \tag{6}$$

Where N(PQ) represents the total number of load buses, $S_{max}L_i$ is the maximum apparent power flow at the ith bus and SL_i is the apparent power at the branch. VL_i is the magnitude of the voltage at the ith load bus and $V_{min}L_i$ and $V_{max}L_i$ are its minimum and maximum limits.

PV-inverter capacity limits:

$$30\%\ of\ peak\ capacity < P_{inverter} < peak\ capacity \tag{7}$$

Power Factor limits: $0.92 < PF < 1$ (8)

Voltage limits: $0.9 < V(i) < 1\ (p.u)$ (9)

Power Balance Constraints:

$$PGrid(t) = PD(t) + PLoss(t) \tag{10}$$

$$QGrid(t) = QD(t) + QLoss(t) \tag{11}$$

Where '$PGrid(t)$' is the real active power of the grid, '$PD(t)$' is the active power demand and '$PLoss(t)$' is the active power loss within the branches. Similarly, '$QGrid(t)$', '$QD(t)$' and '$QLoss(t)$' represent reactive power components.

3.2. PV Modeling

The output power of the PV module used can be calculated using the Equations and Figure described in [8].

The Specification of PV module used is as follows:

Table 1 Specifications of the PV module used [8]

LG365QIC-A5	
Voc,STC (V)	42.8
Isc,STC (A)	10.8
Vmppt, STC (V)	36.7
Imppt, STC (A)	9.95
NOCT (◦C)	44
Kv (V/◦C)	-0.10272
Ki (A/◦C)	4.00E-03
Dimensions (mm3)	1700 x 1016 x 40
Module efficiency (%)	21.1

3.3. BESS Modelling

The BESS is a Lithium-Ion Power Back Battery System manufactured by Tesla Company. The characteristics of the BESS used in this study are illustrated in Table 2:

Table 2 Specifications of Battery Module [8]

Tesla Power Pack	
AC Voltage (V)	380
Maximum Charging Power (Kw)	50
Maximum Discharging Power (Kw)	50
Depth of Discharge (%)	100
AC Efficiency (%)	89
AC Energy Capacity (KWh)	210

In this study, we will focus on minimizing both active and reactive power losses, which is a key difference from the approach taken in [8], where only active power loss was addressed. Hence, it is essential to mention that modeling the dispatch of the batteries and PV generations will accurately account for reactive power and power factor in the TDPF analysis.

CHAPTER 4

METHODOLOGY

4.1. Methodology Work Flow

Figure 2 illustrates the workflow of the methodology adopted in this thesis:

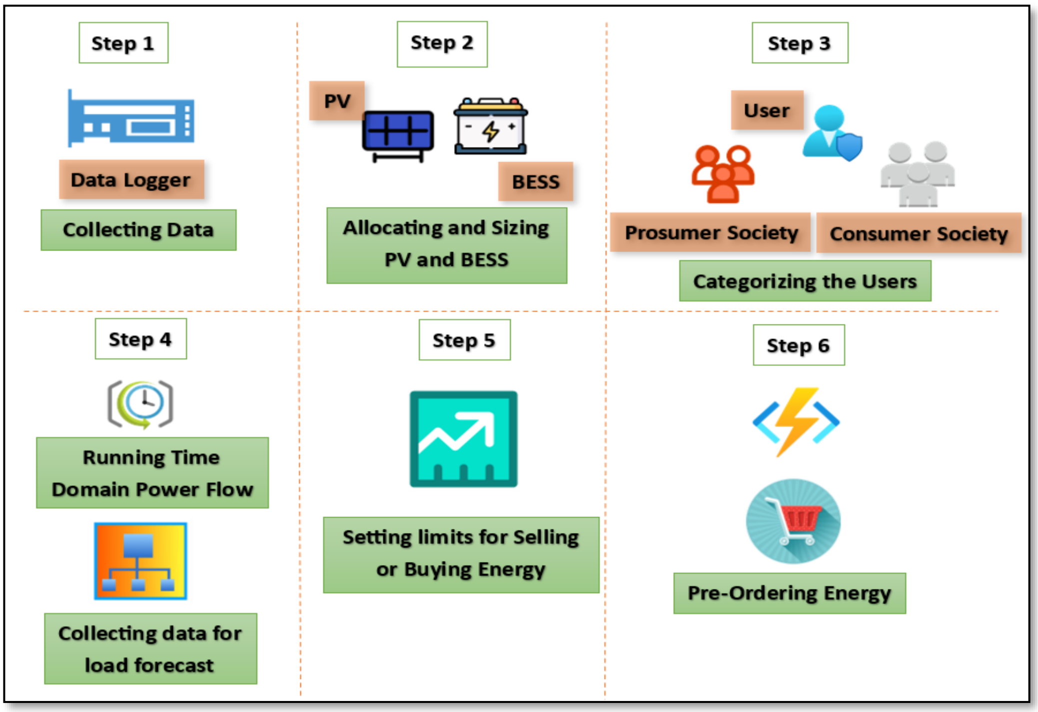


Figure 2 Methodology Work Flow

First, data loggers will be strategically deployed at load terminals, facilitating the continuous monitoring and logging of energy flow patterns over a minimum duration of one month. By capturing data from both energy sources and load terminals, this initiative aims to meticulously examine the fluctuations in energy production and consumption. Through the systematic analysis of this extensive dataset, insights into the temporal variations and underlying trends in energy dynamics will be garnered, allowing for a deeper comprehension of the intricate interplay between energy sources and end-user demand.

Second, an optimal approach is implemented to the network to find the optimal size and placement of renewable energy sources and BESS, thereby, leading to the lowest loss, cost and voltage deviations. To do so, GA plays a role in running the multi-objective approach. GA is a heuristic search method used in artificial intelligence and computing, as referenced in [8]. This tool with a Pareto optimal set of solutions would help in sizing the PV and BESS, as well as pressing a control of the minimum power factor at each bus. Subsequently, through power flow analysis, we select the configuration that produces an annual voltage profile with acceptable limits as the optimal solution using 'MATLAB'.

Third, after the sizing and allocation of the PV and BESS systems, users will be categorized as prosumers and consumers. Prosumers are the users capable of both selling and buying energy, and they'll be added to the prosumer's society. On the other hand, consumers are the users that solely consume electricity and they'll be added to the consumer's society.

Fourth, TDPF analysis will be conducted within the network, accompanied by systematic data collection.

Fifth, the efficacy of prediction, whether about energy consumption or production, is directly proportional to the volume and granularity of collected data. As data acquisition increases, the precision of predictions improves, facilitating more informed decision-making processes. This heightened predictive accuracy streamlines operational efficiency by reducing time overhead.

In the final Step, the expeditious processing of blockchain operations in subsequent transactions is bolstered, as the availability of robust predictive models enhances transaction speed and reliability, thereby fostering a more responsive and agile energy trading ecosystem.

4.2. Energy Management

To facilitate the energy transactions, the algorithm governing the sale and purchase of energy is outlined in Figure 3. As seen from the flowchart, the DSO distinguishes between the prosumer's society and responds to the EMG's requests regarding whether to provide the data of the consumer or prosumer to fulfill a specific request or transaction. It also quantifies the amount of active and reactive power required to regulate voltage profiles at different buses, ensuring optimal network operation. Consequently, the total power loss can be estimated a crucial role in validating and verifying data from meters, prosumers, and consumers before it is recorded on the blockchain, ensuring the authenticity and accuracy of energy production and consumption.

In terms of transaction processing, the EMG facilitates interactions between consumers and prosumers using smart contracts, initiating functions on the blockchain to update balances and settle transactions. Moreover, the EMG manages notifications and messaging between users, which includes informing consumers about energy offers, notifying prosumers about sales, and sending alerts or updates regarding energy transactions. The EMG keeps these balances current using data from the blockchain, and information retrieved from meters. The implementation of security measures is imperative to safeguard user data while ensuring only authorized individuals can access the system.

Additionally, authentication processes will be thoroughly examined, with data encryption playing a central role. Therefore, blockchain technology holds significant promise for the energy sector, particularly when applied to electrical networks.

The DSO will establish a connection with the EMG, utilizing data obtained through time domain power flow and interconnected language between blockchain and MATLAB, such as Python, Raspberry Pi, or other platforms.

Conversely, prosumers may be requested to sell stored energy when their BESS is fully charged. The DSO will instantly transmit each prosumer’s data to the EMG, as previously mentioned. GA optimization will determine whether there is minimal apparent power loss in the network. However, in cases of urgent load, the demand must be classified as an exception, and the demand must be supplied from sufficient stored energy. If the load is urgent, the same criteria apply to prioritizing electricity supply, but this time, power injection must occur before the urgent load. Subsequently, the EMG will instruct the prosumer to sign and deploy a transaction status. The same procedure applies when a prosumer requests to sell stored energy. Afterward, a notification will inform the prosumer whether the transaction is approved or denied. If the user has specified a percentage at which no more energy will be provided by the BESS, the notification will appear at the specified percentage, unless it exceeds the minimum SOC of batteries. It’s important to note that after running GA, the DSO may ask various prosumers to provide the deficiency in power injections, even if their batteries aren’t fully charged yet, provided the deficiency exceeds the two thresholds mentioned above. Figure 3 illustrates the algorithm that will manage the whole system operation described. Inaugurating a groundbreaking phase, the implementation of time-domain power flow analysis marks a pivotal juncture in our system, initiating the systematic collection of load data. This foundational dataset serves as the bedrock for subsequent load forecasting endeavors, pivotal in anticipating energy requirements across various temporal scales-ranging from daily to seasonal or annual projections. With energy predictions elucidating forthcoming demands, well secured, transparent, fast and scalable transactions might take place. In scenarios of energy deficit, prioritization is accorded to essential services, while surplus energy is proactively directed toward prosumers for battery charging, fostering an ecosystem of collaborative energy exchange.

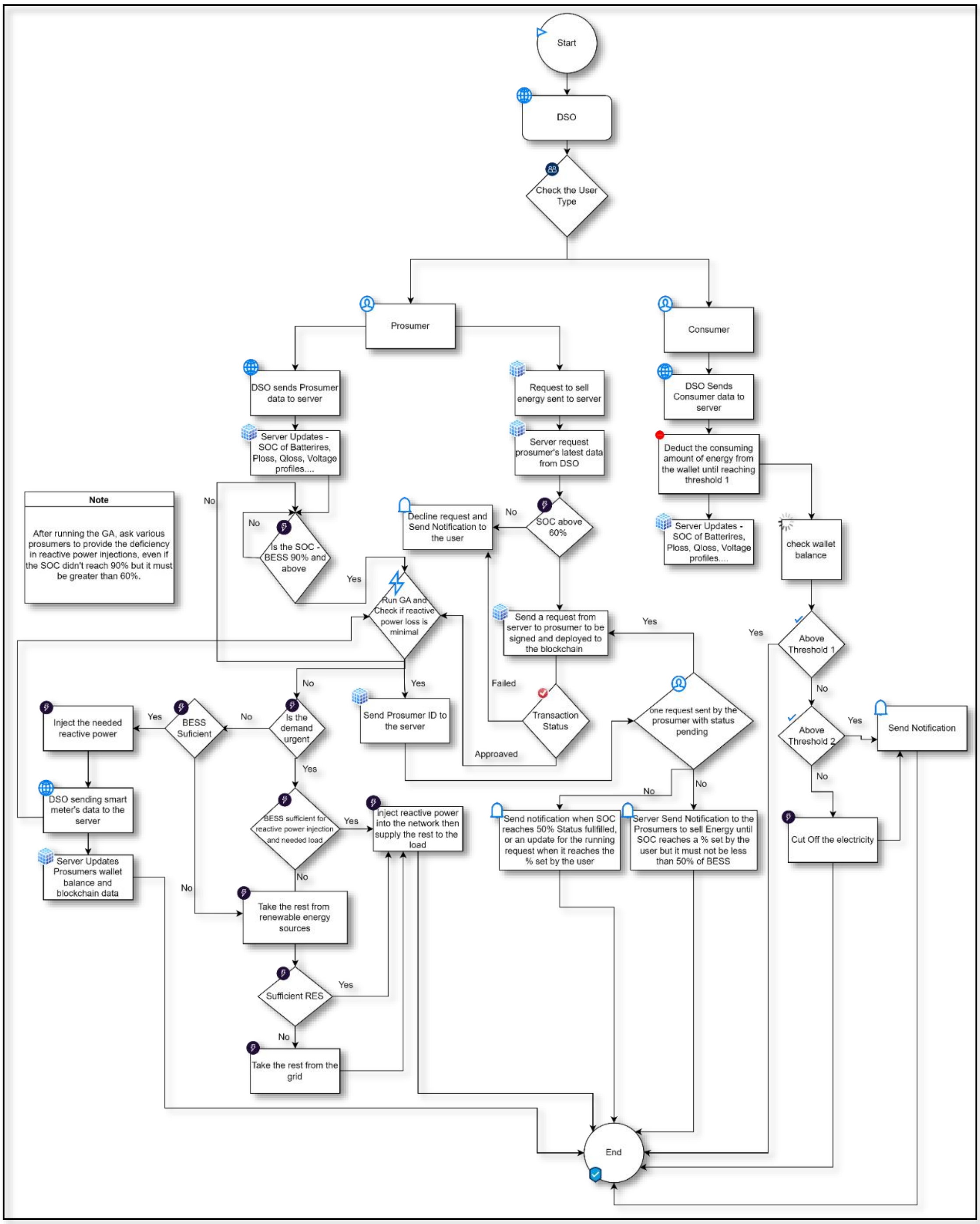


Figure 3 Energy Flowchart in a Network with DSO, Server and Blockchain

4.3. Blockchain Layers

Table 3 highlights the blockchain architecture across multiple layers, each with a distinct role. The **Application Layer** includes features that directly interact with end users, such as account settings, history tracking, and other user-focused functionalities, facilitating smooth interaction with the blockchain platform. The **Technology Layer** forms the core of blockchain operations, encompassing cryptographic algorithms for data security, consensus mechanisms to validate transactions, and integration with platforms like Binance, which contribute to the system's operational framework. The **Network Layer** represents the decentralized structure of the blockchain, consisting of nodes (from Node 1 to Node N) that verify transactions and propagate blocks, maintaining the integrity of the distributed network. The **Data Layer** manages the storage of validated transactions in blocks (from Block 1 to Block N), ensuring an immutable and linked chain of records. Finally, the **API** serves as the interface, allowing external systems to interact with the blockchain by querying data, sending transactions, and integrating other applications seamlessly. To understand its intricate workings, the DSO will establish a connection with the EMG, utilizing data obtained through TDPF and interconnected language between blockchain and MATLAB, such as Python, Raspberry Pi or other platforms.

Table 3 Application and Blockchain Layers

Application Layer	Account Setting/ History Tracking ….
Technology Layer	Encryption Algorithm/ Consensus Mechanism/ Binance …
Network Layer	Node 1 Node 2 ….. Node n
Data Layer	Block 1 Block 2 … Block n
API	

4.4. Peer to Peer Energy Trading

In the context of transactions within the blockchain, Figure 4 illustrates P2P energy trading system. Both prosumers and consumers are connected to the blockchain via their individual wallets. Every transaction is securely recorded in a smart contract and subsequently stored in a block on the blockchain. A smart meter measures the flow of energy for prosumers, accommodating bidirectional energy flow, while supporting unidirectional energy flow for consumers. The energy consumption or deduction from each user's total energy will be sent to the DSO instantly, with the data then transmitted to the EMG for recording. Simultaneously, for every KWH consumed or produced, a certain amount of USDT dollars will be added or deducted from the user's wallet. As previously mentioned, consumers aim to purchase the most cost-effective energy available in sequence. Two thresholds will trigger alerts to consumers when their wallet balance reaches a minimum amount. At this point, the EMG will update the SOC of the batteries, Ql_{oss}, P_{loss}, total power loss and voltage profiles through the DSO. Furthermore, prosumers will sign a transaction and deploy it to the blockchain, monitoring the transaction status. If a prosumer's BESS is insufficient compared to the demand, the consumer may be asked to purchase the remainder from RE sources if available. Otherwise, to avoid power cutoff, the consumer will be compelled to purchase it from the grid.

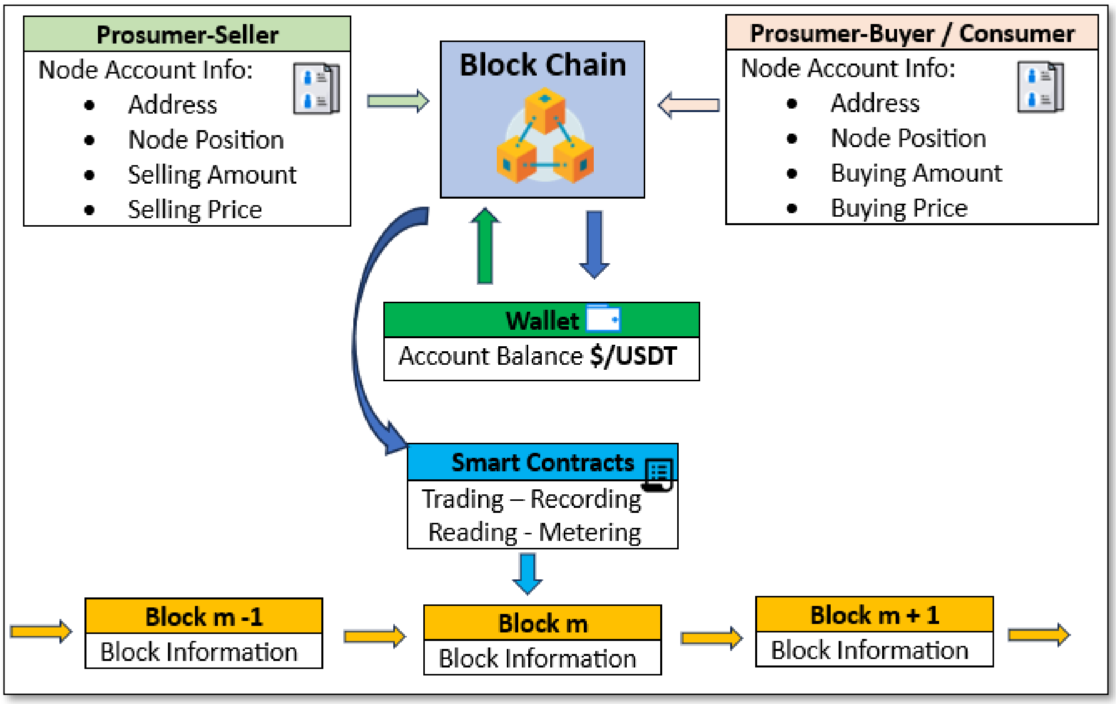


Figure 4 Peer to Peer Energy Trading

Building on the energy trading process illustrated in Figure 4, the blockchain ensures secure, transparent, and efficient transactions between prosumers and consumers. Each user interacts with the system through their personalized wallet, which is directly linked to the blockchain and managed via the EMG. Once a transaction is initiated, smart meters play a pivotal role by accurately measuring the energy exchanged, whether it is delivered to or received from a consumer. These real-time measurements are immediately transmitted to the DSO, allowing the system to update key network parameters such as power flows and voltage levels.

The blockchain not only records the transaction but also facilitates fair and automated energy pricing through smart contracts, which execute predefined rules for cost calculations and fund transfers. For consumers, wallet balances are critical; automated alerts ensure they are informed well before their balance is insufficient to complete further transactions. Prosumers benefit by tracking the energy they have sold and the corresponding earnings, all of which are recorded immutably. Additionally, the EMG's integration provides continuous updates on network performance, such as battery SOC, system losses, and voltage profiles, enabling the DSO to optimize energy allocation dynamically.

In cases where demand exceeds local supply, the system offers alternatives. Consumers are notified to purchase the shortfall from other available RESs or, if necessary, from the grid. This hierarchical approach prioritizes renewable sources, supporting sustainable energy utilization while maintaining grid stability. The entire process is designed to maximize user satisfaction, network reliability, and environmental benefits.

CHAPTER 5

IMPLEMENTATION

5.1. Network and Parameters

The IEEE 13-Bus network, depicted in Figure 5, is the network under study for the analysis conducted in this paper. A detailed summary of the network's operating parameters is presented in Table 4. Additionally, the load category and peak demand associated with each bus are comprehensively listed in Table 5. For a deeper understanding of the network, the transmission parameters, including line impedances and configurations, are thoroughly illustrated in Table 6.

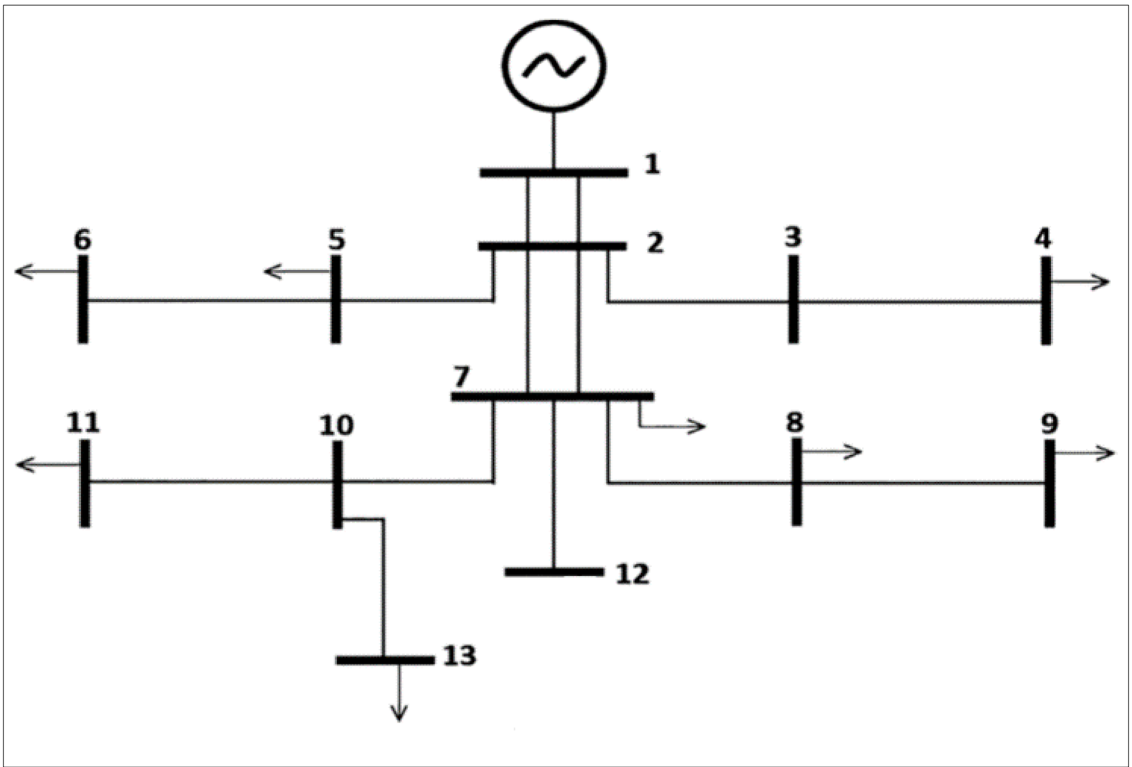


Figure 5 IEEE -13 Bus Network

Table 4 Network Operating Parameters

Base Voltage (KV)	4.22
Base Power (KVA)	490
Base Current (A)	123.2
Base impedance (Ω)	34.51
Base siemens (μs)	28,902.4

Table 5 Load Category and Peak Demand of Each Bus

Bus no.	**Load Category**	**Peak Demand (KW + jKVAr)**
4	Commercial	411 + j288
5	Residential	172 + j122
6	Residential	233 + j135
7	Commercial	1158 + j662
8	Residential	181 + j155
9	Industrial	842 + j461
11	Residential	191 + j83
13	Residential	127 + j85

Table 6 Network Transmission Parameters [8]

From	**To**	**R(pu)**	**X(pu)**	**B(pu)**
1	2	0.015	0.015	6.12E-05
2	3	0.004	0.004	1.53E-05
3	4	0.004	0.004	1.53E-05
2	5	0.004	0.004	1.53E-05
5	6	0.002	0.002	9.17E-06
2	7	0.015	0.015	6.12E-05
7	8	0.002	0.002	9.17E-06
8	9	0.004	0.004	1.53E-05
7	10	0.002	0.002	9.17E-06
10	11	0.002	0.002	9.17E-06
10	13	0.006	0.006	2.45E-05
7	12	0.007	0007	3.06E-05

5.2. Prophet Forecast

5.2.1. Introduction to Prophet Forecasting

Prophet is an open-source forecasting tool developed by Facebook that is widely used for time-series data prediction. It is designed to handle various forecasting challenges, particularly in the case of data with strong seasonal trends and missing values, making it suitable for a wide range of applications, from energy demand forecasting to business trend predictions. Prophet is a statistical model built on a generalized additive model (GAM) framework, which is designed to forecast time series data that exhibit seasonality and trend changes.

It incorporates three key components into the forecasting process:

- **Trend:** The underlying growth or decline in the data over time.
- **Seasonality:** The periodic fluctuations that repeat at fixed intervals (e.g., daily, weekly, yearly).
- **Holiday Effects:** Special events or holidays that may affect the data at irregular intervals.

Prophet is designed to make it easy for non-experts to generate forecasts without deep statistical knowledge while still providing robust, customizable, and highly accurate results. It is especially useful for time series that have multiple seasonality (e.g., yearly and weekly) and varying levels of noise, making it more flexible than traditional forecasting models like ARIMA.

5.2.2. Key Uses of Prophet Forecasting

- **Energy Demand Prediction:** Prophet is frequently used in the energy sector to forecast energy consumption patterns, particularly in distributed energy systems where demand can be highly variable and affected by seasonal factors. Forecasting future demand allows for better grid management, efficient energy storage, and optimized generation dispatch.

- **Financial Market Prediction:** Prophet is applied to financial data such as stock prices, sales figures, and market trends, helping analysts predict future movements and prepare for market fluctuations.
- **Supply Chain and Inventory Forecasting:** Companies use Prophet to predict future demand for products, which helps them plan production schedules, manage inventories, and reduce stockouts or overstocking.
- **Load Forecasting in Power Grids:** By using Prophet, utilities can forecast electricity load with high accuracy, assisting in energy production planning and grid balancing. This can be especially important for integrating renewable energy sources that have variable outputs.
- **Decomposition of Time Series:** Prophet splits the time series data into trends, seasonal components, and holidays. This allows for more detailed analysis and a better understanding of how each factor influences the data.
- **Seasonality Detection:** Prophet automatically detects the seasonality within the data, including daily, weekly, and yearly seasonality. It is also flexible enough to handle custom seasonal patterns, such as business cycles or weather-related variations.
- **Handling Missing Data and Outliers:** One of Prophet's strengths is its ability to handle missing data points, gaps in data, and outliers without requiring complex preprocessing. The model automatically adjusts for these irregularities, making it robust for real-world data.

- **Automatic Changepoint Detection:** Prophet automatically detects and models changepoints—points where the underlying trend of the data shifts. This is particularly useful in forecasting scenarios where trends may not be linear and can change abruptly.

Forecasting with Uncertainty Intervals: Unlike many traditional forecasting methods, Prophet generates forecasts with uncertainty intervals, providing a range of potential outcomes. This feature helps decision-makers assess risks and make more informed decisions.

5.2.3. Roles of Prophet Forecasting in Distributed Energy Systems

In distributed energy systems, Prophet plays a crucial role in enhancing grid stability and improving operational efficiency. Here are some of the specific roles it fulfills:

- **Optimizing Energy Flow:** By accurately predicting future energy demand and supply, Prophet helps system operators optimize the energy flow within the grid. This ensures that the right amount of energy is produced and delivered at the right time, minimizing waste and reducing costs.
- **Integrating Renewable Energy Sources:** Prophet's ability to forecast fluctuating energy patterns from renewable sources, such as solar and wind, is vital for integrating these sources into the grid. By predicting periods of high and low energy production, Prophet helps balance the supply with demand, reducing reliance on non-renewable backup sources.
- **Peer-to-Peer Energy Trading:** In P2P energy trading models, where consumers exchange energy directly, Prophet's forecasting capabilities can predict future

energy availability and demand. This allows participants in a P2P network to make informed decisions about when to buy or sell energy, optimizing market transactions and ensuring a fair pricing mechanism.

- **Reducing Power Losses and Ensuring Grid Stability:** By forecasting energy demand and supply fluctuations, Prophet enables better management of power losses in distribution networks. The ability to predict and manage the flow of energy efficiently contributes to a more stable and resilient grid, especially in complex, decentralized energy systems.

Prophet forecasting is a powerful tool that provides flexibility and accuracy in predicting time series data, making it ideal for applications in distributed energy systems. Its capabilities to model trends, seasonal variations, and uncertainties make it an invaluable asset for energy management, grid optimization, and peer-to-peer energy trading. By integrating Prophet forecasting into these systems, utilities, and energy producers can better anticipate demand, reduce costs, and improve overall system efficiency. Through its adaptability and user-friendly interface, Prophet is revolutionizing how forecasting is applied to energy systems, helping to enable smarter, more sustainable energy practices.

5.2.4. Implementation of Prophet Forecasting in our System

Regarding energy consumption forecasting; we use real-life data of users who have already installed PV or PV and BESS systems.

The forecasting stages are described as follows:

- **Data Collection:** We gather data on each user's energy consumption over a specific period. The goal is to refine predictions until the difference between actual and forecasted consumption is less than 5%.This step was facilitated by Deye inverters in conjunction with the SOLARMAN Smart platform, which enabled the efficient collection of the data as outlined below:

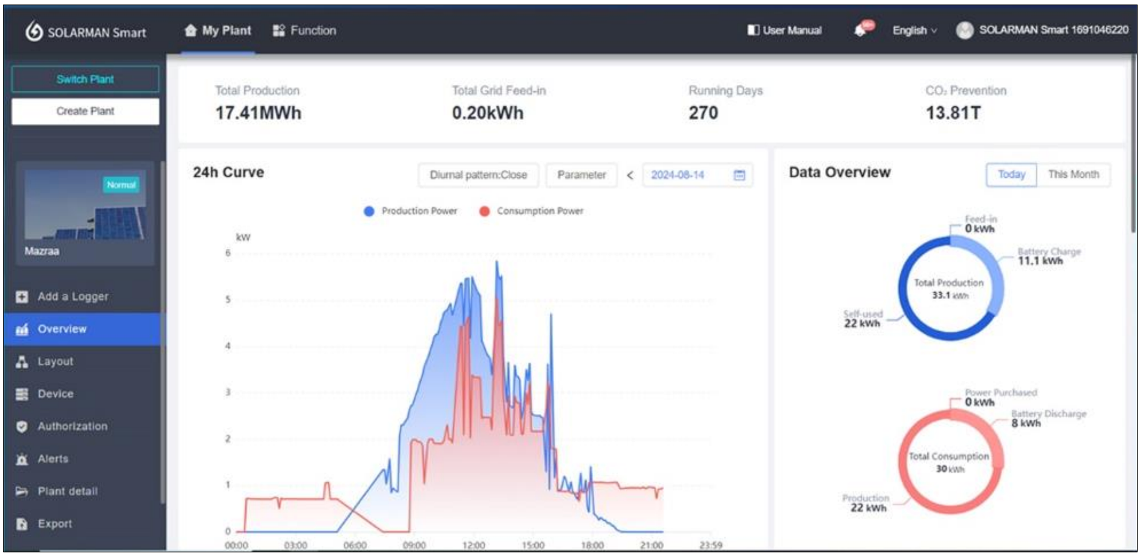


Figure 6 Home Page of SOLARMAN Smart Platform

- **Forecast Accuracy Validation:** For example, after collecting consumption data for May, we predict the energy usage for June 1. The data from May consists of weekdays, and since June 1 is also a weekday, we specifically selected data from the same season and workdays to ensure similar conditions as much as possible for accurate prediction. If the prediction is over 95% accurate when compared to actual usage on June 1, the May data is deemed accurate for forecasting. If not, we continue collecting data through June or until the forecast accuracy reaches the 95% target. In our case, one month of data collection sufficed to meet this goal.
- **Setting Consumption Ranges:** Once forecasting accuracy is established, predictions are made within a specified range, bounded by a lower and upper limit.

For instance, if User 4 on June 1st has a peak demand of 15 kW and actual consumption of 8 kWh, their forecasted consumption might be 7.5 kWh, with a range of 5 kWh (lower limit) to 10 kWh (upper limit).

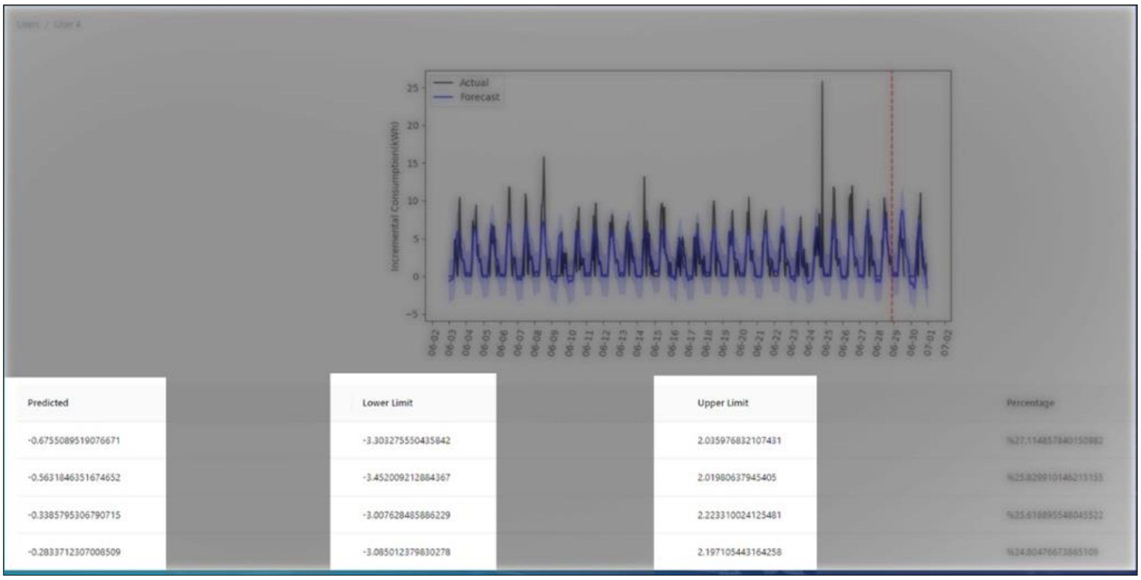


Figure 7 Forecasted Values with Upper and Lower Confidence Limits

- **Applying the Worst-Case Scenario:** We then take the upper limit (10 kWh) as the forecasted consumption, assuming the user may reach this maximum level. The percentage difference between the peak demand (15 kW) and the upper limit (10 kWh) is 33%. This difference is projected across the network to estimate demands, so if User 4's peak demand is 400 kW, they are forecasted to consume 268 kWh.

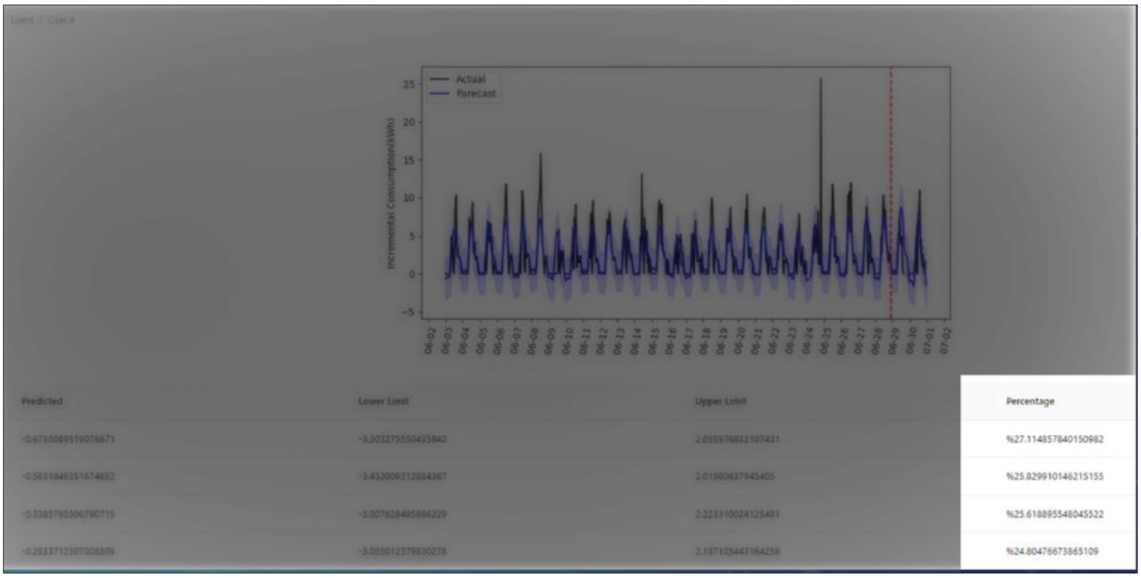


Figure 8 Percentage of Load Consumption Projected to the Actual Values in the Network

- **Risk Management and Trading Flexibility:** To encourage trading, we could consider using lower or predicted values, but taking the worst-case scenario ensures safety.

A list of available sellers will then be provided to the consumers. Prosumers can sell energy from PV or BESS, ensuring they do not exceed the allowed power for sale. PV is the primary energy source, followed by BESS. If the requested power exceeds the seller's available power, the buyer will be prompted to purchase energy from another seller. If no other options are available, the buyer will be directed to purchase energy from the grid which is available 24/7. Once a transaction occurs, it will be recorded as a block in the blockchain, documenting the amount of USDT transferred from the buyer to the seller and the amount of energy purchased. Each user will have a wallet with a wallet address connected to the blockchain. If consumer requests power within the allowed limits but lacks sufficient funds in their wallet, they will be prompted to recharge their wallets.

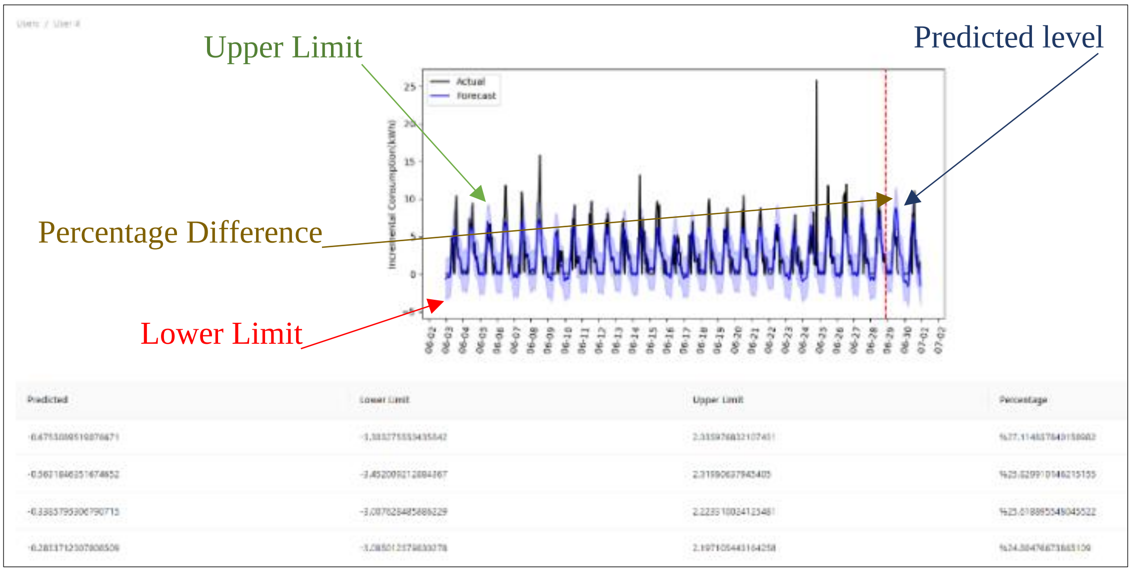


Figure 9 Example on Forecasting Results (User 4)

5.3. Determining Initial System Parameters Using TDPF

Before proceeding with the optimization process using GA, we perform an initial analysis by running TDPF simulations. TDPF provides a detailed assessment of the power system's performance under dynamic operating conditions, enabling the determination of critical initial parameters required before optimization.

The TDPF simulation calculates key parameters of the system prior to optimization, including:

- **Active Power Losses**: Quantifying the energy lost in the network due to resistive elements of the transmission and distribution lines.
- **Reactive Power Losses**: Measuring the losses associated with reactive power flow, which can impact voltage stability and power factor.
- **Voltage Profiles**: Analyzing the voltage levels across the network to identify any deviations from acceptable limits and regions prone to instability.

- **Total Cost of Losses**: Calculating the economic impact of both active and reactive power losses on the system's operational costs.

By using TDPF, we consider real-time variations in load and generation to capture a comprehensive picture of network behavior under unoptimized conditions. These results establish the baseline initial parameters necessary for evaluating the improvements achieved through the GA-based optimization.

For more detailed insights into the methodology and application of TDPF, refer to [8], [21], [22], [32] and [37].

5.4. Genetic Algorithm (GA)

5.4.1. Introduction to GA

GAs are a class of optimization algorithms inspired by the principles of natural selection and genetics. They are part of a larger family of evolutionary algorithms (EAs), which use mechanisms such as selection, crossover (recombination), and mutation to solve optimization and search problems. GA is particularly effective for solving complex, nonlinear problems where traditional methods may not work or are computationally expensive. A GA is a heuristic search and optimization technique based on the concept of natural evolution. It starts with a population of candidate solutions, which are encoded as chromosomes (typically as strings of bits, numbers, or characters). The algorithm then applies evolutionary operators such as:

- **Selection:** Individuals are selected based on their fitness scores, representing how well they solve the problem.
- **Crossover (Recombination):** Pairs of individuals are combined to produce offspring, allowing the exchange of information between them.

- **Mutation:** Random changes are applied to some individuals to introduce diversity and prevent the algorithm from converging too early.
- **Fitness Evaluation:** The fitness function evaluates how good a solution is by assigning it a fitness score.

Through these iterative steps, the algorithm "evolves" the population towards better solutions.

5.4.2. Key Uses of Genetic Algorithm

- **Optimization Problems:** GAs are widely used to find the best solution to optimization problems that involve large, complex, and poorly understood solution spaces. Examples include optimization of energy distribution, scheduling, and resource allocation.
- **Machine Learning:** GAs are applied to feature selection, hyperparameter tuning, and neural network training, where they search for the best configuration of models to improve performance.
- **Engineering Design:** In fields like civil, mechanical, and electrical engineering, GAs are used for design optimization, where the objective is to find the most efficient design given various constraints.
- **Game Strategy:** GAs are used to evolve strategies in games, especially in situations where players face a variety of unknowns or where optimal strategies emerge over time.
- **Energy Systems Optimization:** In distributed energy systems, GAs are applied to optimize energy flow, power generation, and distribution, ensuring efficient operation and minimizing energy losses.

- **Global Search Capability:** One of the key strengths of GAs is their ability to explore the entire solution space and avoid getting trapped in local optima. They are ideal for solving complex optimization problems with many variables and constraints.
- **Adaptation to Changing Environments:** GAs can adapt to dynamic environments by evolving solutions over time. This makes them particularly useful for problems where the conditions or constraints change over time.
- **Handling Nonlinear and Discrete Problems:** GAs are robust in handling nonlinear, non-differentiable, and discrete problems, which are often difficult for traditional optimization methods to tackle.
- **Parallelism and Efficiency:** GAs can be parallelized, allowing for faster convergence when solving large-scale optimization problems by processing multiple solutions simultaneously.
- **Multi-Objective Optimization:** GAs are capable of solving multi-objective optimization problems, where multiple conflicting objectives must be optimized simultaneously. This is often the case in energy systems, where cost, efficiency, and environmental impact need to be balanced.

5.4.3. Roles of Genetic Algorithm in Distributed Energy Systems

In the context of distributed energy systems, Genetic Algorithms play a crucial role in improving system efficiency, reducing costs, and ensuring reliable energy distribution. Below are some of the key roles GAs play in such systems:

- **Energy Flow Optimization:** GAs are used to optimize the flow of energy in distributed systems by determining the most efficient routing of energy from various generation sources to consumers, minimizing energy losses, and maximizing system efficiency.

- **Renewable Energy Integration:** GAs help optimize the integration of renewable energy sources, such as solar and wind, by determining the optimal mix of renewable and non-renewable resources to meet energy demand. This includes minimizing costs, reducing carbon footprints, and ensuring stability within the grid.
- **Load Balancing:** GAs are applied to balance the load across different components of the energy network, ensuring that no part of the grid is overburdened. This helps in maintaining grid stability, reducing the risk of outages, and improving overall system performance.
- **Optimal Sizing of Energy Storage:** In distributed energy systems, GAs are used to optimize the sizing and placement of energy storage systems, ensuring that they are adequately sized to store excess energy from renewable sources and discharge when needed. This improves system flexibility and reliability.
- **Cost Minimization:** Genetic algorithms help minimize operational costs in distributed energy networks by finding the optimal allocation of resources. This includes optimizing the usage of energy storage, generation sources, and minimizing transmission losses.
- **Energy Trading Optimization:** In peer-to-peer (P2P) energy trading systems, GAs are applied to optimize trading strategies between consumers and producers. The algorithm finds the best trade deals based on factors such as demand, availability, and cost, ensuring efficient energy exchanges in the marketplace.

Genetic Algorithms are powerful optimization tools that can be applied to a wide range of complex problems, particularly those with large search spaces and nonlinear constraints. In the context of distributed energy systems, GAs play an essential role in optimizing energy flow, integrating renewable sources, balancing loads, and minimizing costs. Their ability to adapt to changing conditions, handle multi-objective optimization, and explore large solution spaces makes them a valuable tool for improving the efficiency and sustainability of energy systems. Through the use of GAs, distributed energy systems can achieve better coordination, higher efficiency, and more reliable operation, paving the way for a smarter and more sustainable energy future.

5.4.4. GA Implementation

To optimally allocate and size the PV systems and BESS within our network, the GA is employed to run a multi-objective optimization approach, as outlined in [8]. This method generates a Pareto-optimal set of solutions, assisting in determining the appropriate sizing for both the PV and BESS, while also ensuring precise control over the minimum power factor at each bus. Following this, TDPF analysis is utilized to select the configuration that yields the optimal solution. This configuration is evaluated based on its ability to produce acceptable voltage profiles, maintain an optimal power factor, and minimize power losses within acceptable limits, using the 'MATLAB' environment.

The modeling and specification of the PV and BESS, along with the associated equality and inequality constraints, are derived from the work presented in [8]. To avoid redundancy, this paper will not reiterate those details but will focus specifically on minimizing both active and reactive power losses, which distinguishes our approach from that in [8], where only active power loss was considered. Incorporating these additional equations and constraints for reactive power and power factor in the TDPF analysis is critical for an accurate and comprehensive optimization process.

5.4.4.1. Algorithm

Function GAfnct(x)

Input: Vector x representing the number of batteries and PV Panels installed at each bus

Output: result containing apparent power losses and total cost

1. **Initialization**

   Set constants:

   E_{Grid}, E_{PV}, E_{Batt}, SOC_{min}, SOC_{max}, 30% inverter capacity, Peak inverter capacity, C_{Grid}, C_{PV}, C_{Batt}, PF_{min}, PF_{max}, S_{max}

   Define active power output (p2 to p13) and reactive power output (q2 to q13) equations for each bus.

2. **PV Panel Allocation**

   For each bus (i from 2 to 13):

   Allocate PV panels based on:

   Panel efficiency.

   Maximum allowable capacity at the bus.

   Compute real (P_{PV}) and reactive (Q_{PV}) power contributions for each bus, ensuring that:

   Total installed capacity does not exceed the limits.

   Operating conditions (power factor, voltage profiles) are respected.

   Update p2 to p13 and q2 to q13 based on PV contributions.

3. **Battery Dispatching**

   For each bus:

Compute battery apparent power (S_{Batt}) considering efficiency and discharge limits.

Calculate real (P_{Batt}) and reactive (Q_{Batt}) power contributions from the battery.

Update the state of charge (SOC).

4. **Power Generation at Each Bus**

   Add PV and Battery contributions (P_{PV}, P_{Batt} and Q_{PV}, Q_{Batt}) to the corresponding bus power generation (p and q).

5. **Y-Bus Matrix Construction**

   Initialize ybus matrix.

   For each line in the system:

   Update diagonal and off-diagonal elements of ybus using line impedance and admittance data.

6. **Gauss-Seidel Power Flow Analysis**

   Initialize bus voltage, power, and other parameters.

   While maximum error > tolerance:

   For each bus:

   If PV bus: Update voltage magnitude and angle.

   If PQ bus: Update complex voltage using current injections and neighbor bus voltages.

   Recalculate power and errors.

7. **Power Flow Fitness Function**

   Compute current flows (I_{ij}) and line power flows (S_{ij}) for each line.

   Calculate total apparent power losses and total cost:

   result(1): Total apparent power losses across the network.

   result(2): Total cost of power from the grid and battery systems.

8. Print Results

Output:

Total reactive power losses.

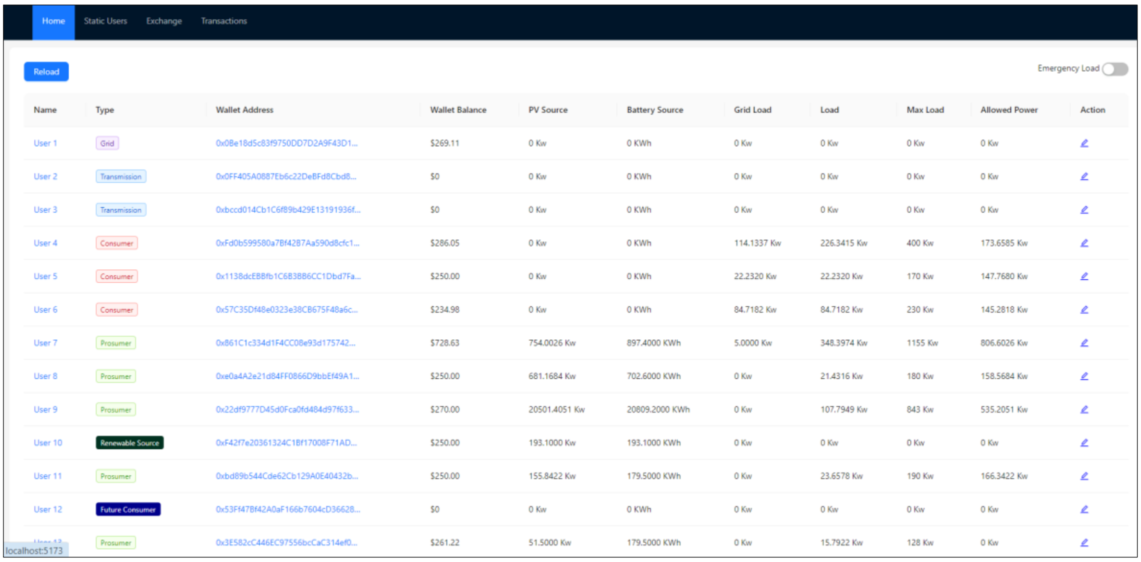
Total system cost.

CHAPTER 6

APPLICATION “P2P TRADING”

An application for energy trading was developed using JavaScript to facilitate seamless peer-to-peer energy exchanges. After the allocation of PV and BESS within the network, users are categorized as either prosumers, who generate surplus energy, or consumers, who require additional energy. This application enables users to trade energy with each other or purchase it directly from the grid, which remains available 24/7. Consumers or porsumers, while consuming energy, are presented with a list of prosumers offering energy, along with details about the energy source—whether from PV, BESS, or the grid—the associated costs, and the amount of USDT required for the transaction. To ensure transparency and fairness, the app deducts the required amount from the consumer’s wallet upon purchase.

The system is designed to prevent users from exceeding allowed limits, ensuring that neither the buyer nor the seller violates the constraints necessary for TDPF. This mechanism maintains voltage levels and power factors within permissible ranges, effectively minimizing power losses and preserving the stability of the distribution network.



Home Static Users Exchange Transactions

Reload

Emergency Load

Name	Type	Wallet Address	Wallet Balance	PV Source	Battery Source	Grid Load	Load	Max Load	Allowed Power	Action
User 1	Grid	0x0Be18d5c83f9750DD7D2A9F43D1...	$269.11	0 Kw	0 KWh	0 Kw	0 Kw	0 Kw	0 Kw	
User 2	Transmission	0x0FF405A0887Eb6c22DeBFd8Cbd8...	$0	0 Kw	0 KWh	0 Kw	0 Kw	0 Kw	0 Kw	
User 3	Transmission	0xbccd014Cb1C6f89b429E13191936f...	$0	0 Kw	0 KWh	0 Kw	0 Kw	0 Kw	0 Kw	
User 4	Consumer	0xFd0b599580a7Bf42B7Aa590d8cfc1...	$286.05	0 Kw	0 KWh	114.1337 Kw	226.3415 Kw	400 Kw	173.6585 Kw	
User 5	Consumer	0x1138dcEB8fb1C6B3B86CC1Dbd7Fa...	$250.00	0 Kw	0 KWh	22.2320 Kw	22.2320 Kw	170 Kw	147.7680 Kw	
User 6	Consumer	0x57C35Df48e0323e38CB675F48a6c...	$234.98	0 Kw	0 KWh	84.7182 Kw	84.7182 Kw	230 Kw	145.2818 Kw	
User 7	Prosumer	0x861C1c334d1F4CC08e93d175742...	$728.63	754.0026 Kw	897.4000 KWh	5.0000 Kw	348.3974 Kw	1155 Kw	806.6026 Kw	
User 8	Prosumer	0xe0a4A2e21d84FF0866D9bbEf49A1...	$250.00	681.1684 Kw	702.6000 KWh	0 Kw	21.4316 Kw	180 Kw	158.5684 Kw	
User 9	Prosumer	0x22df9777D45d0Fca0fd484d97f633...	$270.00	20501.4051 Kw	20809.2000 KWh	0 Kw	107.7949 Kw	843 Kw	535.2051 Kw	
User 10	Renewable Source	0xF42f7e20361324C1Bf17008F71AD...	$250.00	193.1000 Kw	193.1000 KWh	0 Kw	0 Kw	0 Kw	0 Kw	
User 11	Prosumer	0xbd89b544Cde62Cb129A0E40432b...	$250.00	155.8422 Kw	179.5000 KWh	0 Kw	23.6578 Kw	190 Kw	166.3422 Kw	
User 12	Future Consumer	0x53Ff47Bf42A0aF166b7604cD36628...	$0	0 Kw	0 KWh	0 Kw	0 Kw	0 Kw	0 Kw	
[illegible]	Prosumer	0x3E582cC446EC97556bcCaC314ef0...	$261.22	51.5000 Kw	179.5000 KWh	0 Kw	15.7922 Kw	128 Kw	0 Kw	

localhost:5173

Figure 10 Application Home Page

As seen from the figure in the application, users are classified into different types based on their roles and energy needs. **User 1** represents the grid, which only sells energy to other users. **Users 2 and 3** are transmission buses, acting as passive nodes in the system that neither buy nor sell energy. **Users 4, 5, and 6** are consumers who exclusively buy energy. **Users 7, 8, 9, 11, and 13** are prosumers equipped with PV or BESS systems, capable of both selling and buying energy. **User 10**, known as the renewable bus, only has renewable resources without any load, meaning they can only sell energy. **User 12** represents a future consumer, illustrating that new users can easily be integrated into the network. In our specific case, this is modeled as a transmission bus. Each user has a unique wallet address with a hash linked to the blockchain, ensuring that every transaction, wallet charging, and discharging event is securely recorded. This process is linked to the user's hash, creating a transparent and traceable record of all activities. Users who are eligible to buy or sell energy maintain a wallet balance in USDT, which is charged, deducted, or added for every kilowatt-hour (kWh) bought, sold, or if a user decides to charge their wallet. The system also displays the amount of PV and BESS capacity at each bus, the forecasted load consumption, peak load (as specified in Table 5), and the maximum allowable power to be bought or sold in order to maintain network constraints. Additionally, an **emergency load button** is available for consumers, ensuring that energy purchases cannot proceed unless the emergency load is supplied and that the total energy transactions do not exceed the specified power limits.

6.1. Trading Using the App

In the application, the buyer is required to specify the amount of energy they wish to purchase from the network. If the requested amount exceeds the allowed power limit, the user will be denied from making the purchase, and a warning message will appear prompting them to re-enter the amount. The message will suggest the amount should be below the allowed limit to ensure system stability. If the desired energy amount is within the allowable limits, a list of available prosumers will be displayed, showing each one’s maximum energy offering capacity. For example, if the consumer wants to purchase 100 kW of energy, but Prosumer 1 can only offer 70 kW, the consumer will be guided to either buy from multiple prosumers in the list to meet the required 100 kW, or if needed, purchase the remaining energy from the grid. This ensures that the network's power constraints are adhered to while facilitating smooth transactions between peers and the grid.

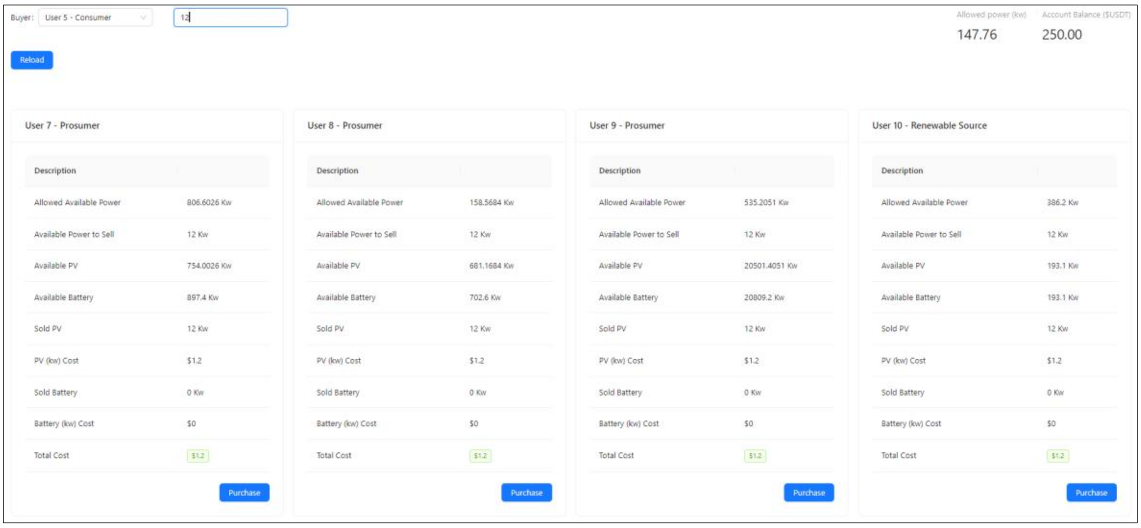


Figure 11 Energy Trading Work Flow Through the App

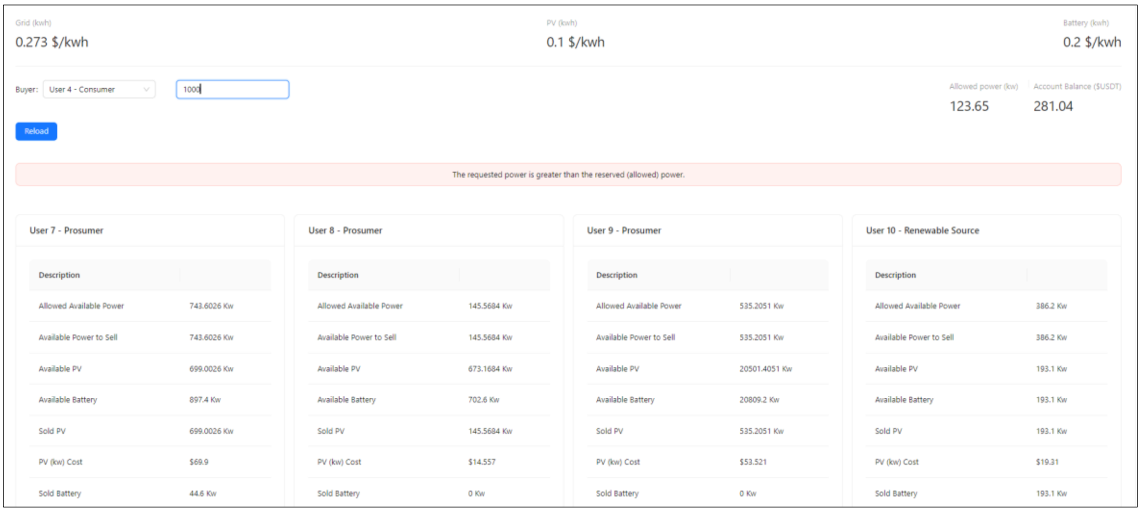


Figure 12 Transaction Alert

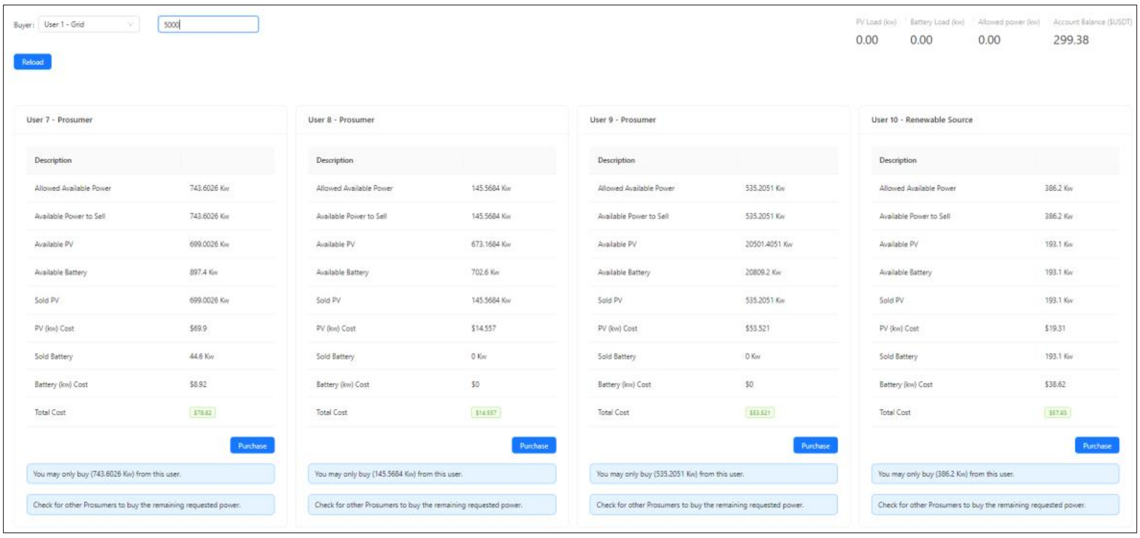


Figure 13 Maximum Energy Offering Capacity for Each Prosumer

Once the transaction is completed, a notification will appear confirming the success of the transaction. Simultaneously, the details of the transaction are securely stored in a block on the blockchain. This transaction is then added to a comprehensive transaction list that displays the following information:

- **Transaction Hash (Hx):** A unique identifier for the transaction.
- **Amount of USDT:** The exact amount deducted from the buyer's wallet.
- **Sender's Wallet Address and Hash:** The wallet and its corresponding hash from which the energy was sold.
- **Receiver's Wallet Address and Hash:** The wallet and its corresponding hash to which the energy was delivered.
- **Energy Source:** Whether the power was supplied from PV, BESS, or both.
- **Total Power Received:** The total energy received by the buyer, specifying any additional energy sourced from the grid if the requested amount exceeded what prosumers could provide.

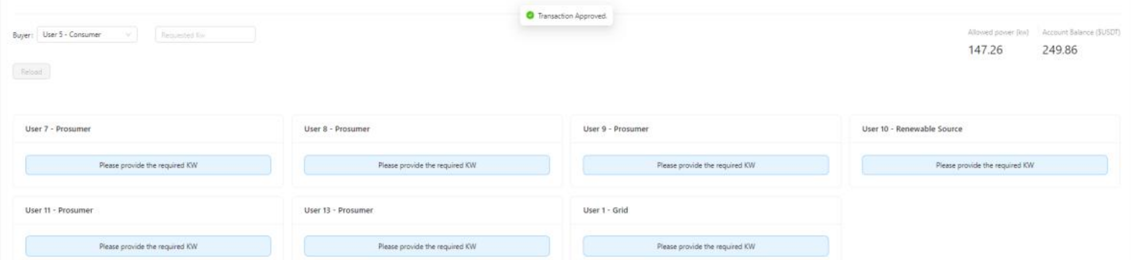
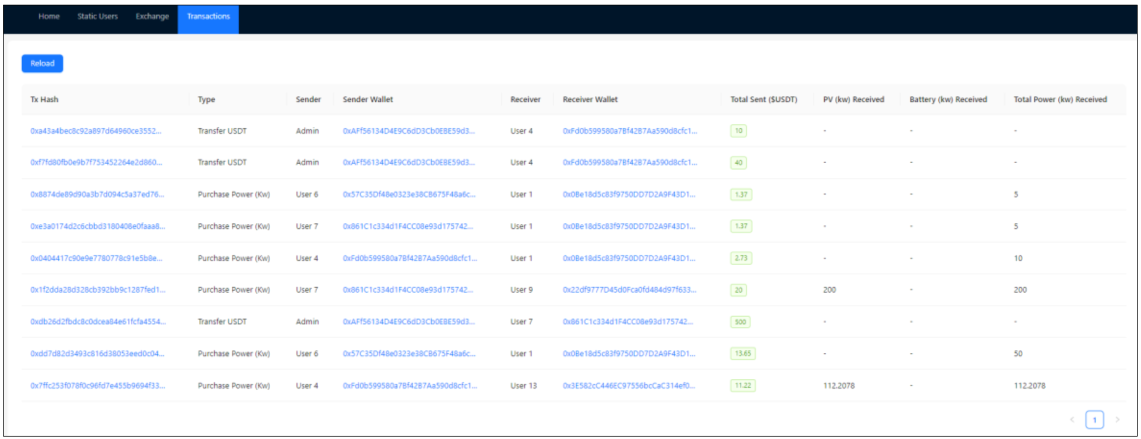


Figure 14 Transaction Approved



Tx Hash	Type	Sender	Sender Wallet	Receiver	Receiver Wallet	Total Sent ($USDT)	PV (kw) Received	Battery (kw) Received	Total Power (kw) Received
0xa43a4bec8c92a897d64960ce3552...	Transfer USDT	Admin	0xAFf56134D4E9C6dD3Cb0EBE59d3...	User 4	0xFd0b599580a7Bf42B7Aa590d8cfc1...	10	-	-	-
0xf7fd80fb0e9b7f753452264e2d860...	Transfer USDT	Admin	0xAFf56134D4E9C6dD3Cb0EBE59d3...	User 4	0xFd0b599580a7Bf42B7Aa590d8cfc1...	40	-	-	-
0x8874de89d90a3b7d094c5a37ed76...	Purchase Power (Kw)	User 6	0x57C35Df48e0323e38CB675F48a6c...	User 1	0x0Be18d5c83f9750DD7D2A9F43D1...	1.37	-	-	5
0xe3a0174d2c6cbbd3180408e0faaa8...	Purchase Power (Kw)	User 7	0x861C1c334d1F4CC08e93d175742...	User 1	0x0Be18d5c83f9750DD7D2A9F43D1...	1.37	-	-	5
0x0404417c90e9e7780778c91e5b8e...	Purchase Power (Kw)	User 4	0xFd0b599580a7Bf42B7Aa590d8cfc1...	User 1	0x0Be18d5c83f9750DD7D2A9F43D1...	2.73	-	-	10
0x1f2dda28d328cb392bb9c1287fed1...	Purchase Power (Kw)	User 7	0x861C1c334d1F4CC08e93d175742...	User 9	0x22df9777D45d0Fca0fd484d97f633...	20	200	-	200
0xdb26d2fbdc8c0dcea84e61fcfa4554...	Transfer USDT	Admin	0xAFf56134D4E9C6dD3Cb0EBE59d3...	User 7	0x861C1c334d1F4CC08e93d175742...	500	-	-	-
0xdd7d82d3493c816d38053eed0c04...	Purchase Power (Kw)	User 6	0x57C35Df48e0323e38CB675F48a6c...	User 1	0x0Be18d5c83f9750DD7D2A9F43D1...	13.65	-	-	50
0x7ffc253f078f0c96fd7e455b9694f33...	Purchase Power (Kw)	User 4	0xFd0b599580a7Bf42B7Aa590d8cfc1...	User 13	0x3E582cC446EC97556bcCaC314ef0...	11.22	112.2078	-	112.2078

Figure 15 Transaction List

If any user charges their wallet, a unique transaction hash will be generated and displayed in the transaction list, as shown in the figure. This hash serves as a secure identifier for the wallet-charging process, ensuring transparency and traceability. The transaction list will also record the wallet address of the user, the corresponding hash, the amount of USDT added to the wallet, and the timestamp of the transaction.

Each successful transaction within the energy trading network is meticulously recorded in a block on the blockchain, ensuring both transparency and security for all users. This block contains all essential transaction details, such as the unique hash ID for the transaction, the amount of USDT exchanged, the wallet address and corresponding hash of both the sender and the receiver, the source of the energy (whether from PV, BESS, or the grid), and the total power delivered. By leveraging blockchain technology, the system guarantees that every transaction is immutable and verifiable, creating a trusted environment where users can confidently trade energy.

CHAPTER 7

RESULTS AND DISCUSSION

Once the PV and BESS are perfectly allocated between the nodes to ensure minimum losses and efficient energy distribution in the network, P2P energy trading will take place. The allocation and sizing of the PV and BESS systems installed at each bus to meet the specified conditions and constraints are detailed in Table 7. After optimization, the DSO will record the installed capacities of PV and BESS at each bus to maintain an updated network profile.

Table 7 Allocation of PV and BESS

Bus No.	PV Installed (Kw)	BESS Installed (Kwh)
7	755.003	897.4655
8	683.169	702.026
9	20703.406	2810.2
10	193.2	192.1
11	154.843	180.4731
13	164.708	180.4731

Note that buses not mentioned in Table 7 do not have PV or BESS installations. After the convergence to an optimal BESS-PV-Grid configuration, testing the networks' performance is conducted using TDPF.

The results of active and reactive power losses before and after the allocation and sizing of PV and BESS are presented in Table 8, highlighting the impact of the optimization process.

Table 8 Losses Before & After the Allocation of PV & BESS

Power Losses	**Before**	**After**
P_{loss} (KW)	121.5	65
Q_{loss} (KVAr)	53	-2.1

As shown in Table 8, the average active power losses dropped significantly from 121.5 kW to 65 kW, whereas approximately zero reactive power loss is observed. Furthermore, controlling the power factor would reduce the reactive power dramatically, which leads to a lower S_{loss}. Additionally, it results in a predicted voltage drop at the buses, which requires the intervention of adding more power injection to maintain stability. This adjustment helps enhance the overall system efficiency and reliability under varying load conditions. Such measures not only improve voltage regulation but also contribute to the long-term sustainability of the network. It is taken into consideration that the voltages on all buses must not violate the lower and upper boundaries; the same conditions are applied to the power factor. Consequently, reducing the reactive power transmitted helps to minimize power losses during peak hours. The optimal power factors in this configuration have decreased the voltages on each bus within the network. Upon optimizing the network with the addition of more BESS and PV panels, improvement has been observed in the voltages of each bus, as shown in Table 9. The results align with expectations, as energy source dispatch was strategically timed during peak demand hours to mitigate significant voltage drops.

Table 9 Voltage Profiles Before & After the Allocation of PV & BESS

Bus No	Voltage (pu)	Voltage* (pu) after optimization
1	1	1
2	0.8993	0.9634
3	0.8953	0.9528
4	0.8914	0.9356
5	0.8934	0.9464
6	0.8917	0.9452
7	0.8355	1.0041
8	0.8322	0.965
9	0.8268	1.0012
10	0.8341	0.9293
11	0.8331	0.9261
12	0.8335	0.9258
13	0.8320	0.9579

Table 10 Annual Energy Profile

	Original Configuration	Optimized Configuration
Load Energy (MWh)	9903.75	10,425.476
Losses (MWh)	550.15	238.66
PV Energy (MWh)	-	3549.15
Battery Output Energy (Mwh)	-	321.15

As shown in Table 10, PV and BESS will partially supply the demand instead of the grid, resulting in a reduction in annual losses. To calculate the cost of operation with and without PV and BESS, the following energy unit costs have been considered: Grid tariff of 0.273$/Kwh, PV cost of energy of 0.08$/Kwh, 0.16$/Kwh to be augmented by charging costs for BESS, and a blockchain’s transaction fee of 0.00013 $/Kwh. The optimization process successfully reduced the cost of losses in the network from $150,190.95 to $65,154.18, demonstrating a significant improvement in overall system efficiency. The overall energy cost dropped from 2,703,723.75$ to 2,202,879.048$ considering that this network may process 60,000,000 transactions per year. However, it remains relatively high due to the requirement for additional BESS installations to satisfy both the growing demand and reduce the network’s reactive power losses.

Consequently, blockchain technology plays a pivotal role in improving the efficiency, security, and transparency of the energy trading process within the network. Each successful transaction in the energy trading system is securely recorded as a block on the blockchain, which ensures an immutable, verifiable, and tamper-proof record of activities.

By leveraging blockchain, the system achieves unparalleled transparency, allowing users to confidently trade energy in a trusted environment. This not only prevents unauthorized alterations but also ensures real-time verification of transactions, thus fostering user trust and operational reliability.

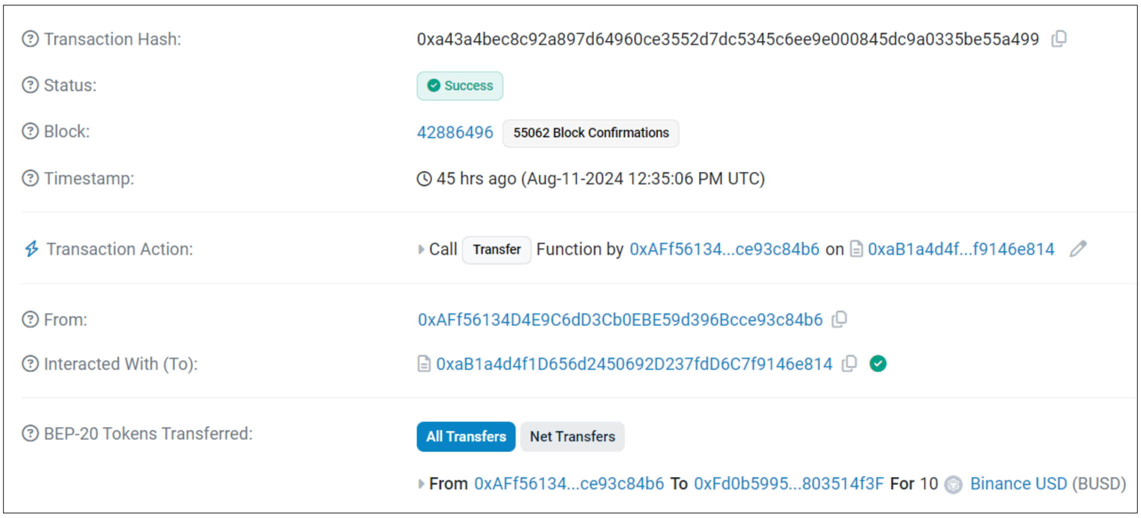


Figure 16 Blockchain Transaction Record

The integration of blockchain technology in the energy trading significantly enhances overall network performance:

1. Improved Transaction Efficiency: Blockchain simplifies and automates the transaction process, reducing administrative overhead and minimizing delays.

2. Reduced Power Losses: By facilitating local P2P energy trading, the system decreases reliance on centralized grids, reducing transmission losses and enhancing energy distribution efficiency.
3. Enhanced Voltage Stability: Decentralized energy trading encourages localized energy exchanges, which help stabilize voltage levels by utilizing the optimized power flow resulting from the optimization process.
4. Economic Sustainability: The platform empowers prosumers to monetize surplus RE while enabling consumers to access energy at competitive rates, driving economic efficiency.
5. Incentivizing Renewables: The transparent and secure nature of blockchain motivates participants to adopt RESs, fostering environmental sustainability and reducing carbon footprints.

In addition to the cost savings and enhanced operational efficiency, this approach fosters a more sustainable and resilient energy network, capable of adapting to future challenges. By utilizing advanced forecasting methods like the Prophet tool, the network can anticipate fluctuations in energy demand and generation, enabling proactive adjustments and reducing the risk of resource overcommitment or underutilization. This not only streamlines the integration of new users but also supports long-term energy planning. Furthermore, the P2P trading mechanism empowers communities by promoting energy independence and reducing reliance on centralized grids, which can be vulnerable to outages or inefficiencies. This decentralized approach contributes to energy equity, ensuring access to affordable, clean energy for all participants, while also supporting global efforts to combat climate change through the adoption of renewable energy technologies.

By prioritizing the use of RE, the trading directly contributes to creating an eco-friendly energy landscape. Prosumers are incentivized to generate clean energy, and consumers are encouraged to buy this sustainable energy rather than relying on fossil fuel-based sources. This shift helps decrease carbon emissions and supports environmental goals, making it an excellent tool for promoting green energy adoption.

Furthermore, the transparent and secure blockchain technology underpinning the application ensures accountability, tracking every transaction to prevent disputes and build trust among users. In the context of our country, this P2P trading could play a pivotal role in addressing the current challenges of energy shortages and unreliable grid systems. Initially, it could be implemented in small communities or neighborhoods where solar PV systems and BESS installations are feasible. Users in these communities could trade energy among themselves, reducing dependence on imported fuel and costly electricity. Additionally, this trading encourages economic growth by allowing users to monetize their renewable energy investments. It also reduces electricity costs for consumers by offering access to locally generated power at competitive prices. The system's built-in flexibility and scalability ensure that as renewable energy production grows, the network remains efficient and reliable. This innovative approach not only addresses immediate energy challenges but also sets the foundation for a sustainable and self-sufficient energy future.

CHAPTER 8

CONCLUSION

This thesis has described a modified multi-objective optimization approach using GA to size and site PVs and BESS with the least power loss in a distribution network, all controlled by DSO. In addition, EMG server was introduced and known as the link between the DSO and Blockchain, where all users with their descriptions are identified using JavaScript. To ensure better scalability and less complexity load consumption forecasting took place, using the prophet tool. Last, the transactions and trading among the peers will take place and be stored in the blockchain.

The optimal PV-BESS-Q grid-connected configuration significantly reduced losses and costs while improving power factor and voltage profiles across all buses. Upgrading the optimized configuration by increasing the PV and BESS capacity further reduced energy losses. A notable decrease in total cost was observed following the integration of renewable energy sources, alongside additional improvements in voltage profiles. The power factor at the buses also improved, minimizing reactive power losses (Q_{loss}) and enhancing the network's efficiency in utilizing apparent power. These outcomes were applied to the specified application, enabling transparent and secure transactions among peers. Users benefited from access to lower-cost energy sources such as PV and BESS, with emergency loads receiving prioritized support when necessary. To address complexity and scalability, load consumption forecasting was introduced to predict individual user consumption, determining the transferable power within the network.

Finally, all actions—ranging from wallet charging and adding new members to energy exchanges and USDT transactions—were recorded in blocks. These blocks were securely linked in a blockchain, ensuring the integrity and transparency of the entire process.

This study holds significant potential benefits for society and the world by addressing critical challenges in energy management, sustainability, and technological integration. By optimizing the placement and sizing of PV panels and BESS, the study promotes the efficient use of renewable energy resources, reducing dependence on fossil fuels and lowering greenhouse gas emissions. The integration of blockchain technology ensures secure and transparent energy transactions, fostering trust in decentralized energy markets and encouraging the adoption of clean energy solutions. The inclusion of load consumption forecasting enhances scalability and precision in energy allocation, paving the way for smarter, more adaptable energy networks. These advancements collectively contribute to more reliable and cost-effective energy distribution, empowering communities with access to affordable, sustainable energy sources. On a broader scale, this study supports global efforts to combat climate change, improve energy equity, and transition towards a resilient and sustainable energy future.

CHAPTER 9

FUTURE WORK

In our study, the data is gathered for one month to predict the load consumption and forecast for each user one day ahead. To enhance the process, an automated system might be introduced to record the data instantly, reducing the need for manual data entry and enabling real-time updates. Additionally, the EMG server may be further developed to study the TDPF autonomously, potentially superseding the role of the DSO. This evolution would streamline the system, minimizing complexity and making energy management more efficient.

In our current approach, we link to an existing blockchain to ensure the transparency and security of transactions. However, a more integrated solution could involve constructing a dedicated blockchain where the DSO, EMG, TDPF, and all associated tools are embedded as part of a unified blockchain ecosystem. This approach would enable seamless interaction between all components, providing a decentralized and efficient platform for managing the entire energy trading and optimization process. Developing such a comprehensive blockchain-based system will be the focus of my next research topic, Inshallah.

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