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Design and Evaluation of a Lightweight Blockchain Framework for Secure Decentralised Energy Trading in Smart Grids

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***Abstract**: The increasing usage of distributed renewable energy resources has rapidly increased the transition to decentralised smart grids. This is where secure and efficient peer-to-peer (P2P) energy trading is crucial. However, conventional blockchain-based energy trading schemes suffer from high computational overhead, communication latency, and limited scalability, making them unsuitable for resource-constrained Internet of Things (IoT) networks. This research proposes a lightweight blockchain framework that incorporates Hyperledger Fabric with Practical Byzantine Fault Tolerance (PBFT) consensus, ZigbeePro communication, and Long Short-Term Memory (LSTM)-based energy demand forecasting to facilitate secure and intelligent decentralised energy trading. The framework was evaluated using MATLAB/Simulink simulation, NS-3, Hyperledger Fabric, and a Raspberry Pi/ESP32 prototype. The results of the experiment show that the proposed framework achieved an average latency of 48.9 ms, throughput of 185 transactions per second, packet delivery ratio of 97.8%, and support for up to 250 IoT nodes while maintaining low energy overhead. The LSTM forecasting model attained an R^2 of 0.964 with a MAPE of 4.7%, delivering accurate demand prediction for intelligent energy allocation. Compared with centralised and Proof-of-Work blockchain models, the proposed framework enhanced communication efficiency, scalability, and security while reducing computational cost. These results demonstrated that integrating lightweight blockchain, low-power communication, and Artificial Intelligence-based forecasting provides a practical and scalable solution for decentralised energy trading for the next-generation smart grids.*

***Keywords:** Blockchain, Smart Grid, Decentralised Energy Trading, Communication Efficiency.*

Nomenclature:
PBFT: Practical Byzantine Fault Tolerance
LSTM: Long Short-Term Memory
DSR: Design Science Research
P2P: Peer-To-Peer
PV: Photovoltaic
MSE: Mean Squared Error
IoT: Internet of Things

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I. INTRODUCTION

The rapid transition to sustainable energy systems has accelerated the evolution of conventional electricity networks into intelligent smart grid systems. The increasing implementation of distributed energy resources (DERs), like solar photovoltaic systems, wind turbines, battery storage, and electric vehicles, enables consumers to become prosumers capable of both generating and consuming electricity. Smart grids incorporate sensing, communication, and intelligent control technologies to enhance reliability, operational efficiency, and renewable energy usage while maintaining peer-to-peer (P2P) energy trading. P2P energy trading enables prosumers to trade surplus electricity directly without sole reliance on centralised utilities, enhancing renewable energy consumption, reducing transmission losses, and improving market flexibility. However, secure and dependable transaction management becomes a major research challenge due to the decentralised nature of connecting entities (Vij et al. [1]).

Blockchain technology has surfaced as a promising solution by delivering decentralised trust, immutable transaction records, and computerised smart contracts. Among the permissioned blockchain platforms, Hyperledger Fabric is particularly suitable for smart grid applications due to its modular architecture, configurable consensus mechanisms, and lower computational requirements than public blockchains. Similarly, Practical Byzantine Fault Tolerance (PBFT) has become an attractive lightweight consensus algorithm because it excludes energy-intensive mining while providing fast transaction confirmation and fault tolerance.

Despite these positive features, practical deployment of blockchain-enabled energy trading remains challenging. Many existing approaches use computationally expensive consensus mechanisms or adopt high-bandwidth communication networks. This makes them unsuitable for resource-constrained Internet of Things devices commonly deployed in smart grids (Rwegasira et al. [2]). Consequently, transaction latency, communication overhead, and energy consumption remain significant limitations. Although recent lightweight blockchain schemes lessen consensus complexity, most focus on blockchain optimisation while paying limited attention to communication efficiency and intelligent energy management.

Communication efficiency is another critical issue that has received comparatively less attention. Most blockchain-based energy trading studies emphasise transaction security while overlooking the communication network responsible for exchanging trading information. ZigbeePro offers low-power consumption, mesh networking capability, and reliable communication, making it well suited for IoT-enabled smart grids (Madli et al. [3]). However, its integration with lightweight blockchain frameworks for decentralised energy trading remains limited.

Artificial intelligence improves decentralised energy trading by facilitating accurate prediction of electricity demand and renewable energy generation. Long Short-Term Memory networks (LSTM) present excellent performance in time-series forecasting. However, most existing studies treat forecasting and blockchain as distinct components, limiting intelligent decision-making and dynamic energy allocation within decentralised energy markets (Govindaraj et al., [4]).

In addition, many existing blockchain-based energy trading frameworks are validated using conceptual analysis or simulation under regulated operating conditions. Comprehensive evaluations that simultaneously consider communication performance, blockchain efficiency, forecasting accuracy, scalability, and security are limited. Consequently, an integrated framework linking lightweight blockchain, efficient communication, and intelligent forecasting is yet to be developed.

To address these research limitations, this paper proposes a lightweight blockchain framework for secure decentralised energy trading in smart grids. The framework incorporates Hyperledger Fabric, PBFT consensus, ZigbeePro communication, and an LSTM-enabled forecasting system into a unified architecture that is designed for resource-constrained IoT systems. The proposed framework is evaluated using MATLAB/Simulink simulation, NS-3 simulation, Hyperledger Fabric, and prototype implementation to examine communication performance, blockchain efficiency, forecasting accuracy, scalability, energy consumption, and security.

The major contributions of this research are encapsulated as follows:

i. We presented a Lightweight blockchain architecture using Hyperledger Fabric and PBFT consensus that is designed to lessen the transaction latency and computational overhead.

ii. We developed a communication-aware decentralised energy trading model by incorporating ZigbeePro mesh networking with blockchain transaction management.

iii. An LSTM-based forecasting system is incorporated to offer prediction of the intelligent energy demand for dynamic trading decisions.

iv. By implementation, the proposed framework was evaluated using MATLAB/Simulink and NS-3 simulation, Hyperledger Fabric, and a prototype testbed under varying smart grid scenarios.

v. Results of the experiment demonstrate enhanced communication efficiency, scalability, energy consumption, and transaction performance compared with centralised and PoW-based energy trading frameworks.

II. RELATED WORK

A. Blockchain-Based Energy Trading in Smart Grids

Blockchain is a promising technology that enables secure peer-to-peer (P2P) energy trading. It eliminates centralised intermediaries and provides transparent, tamper-resistant transaction management. Existing research work shows that blockchain enhances trust, renewable energy utilisation, and market participation in decentralised electricity markets. Mo et al [5] reviewed blockchain-based P2P energy trading and identified blockchain as the best platform for decentralised electricity markets. However, their research work remained conceptual and did not address communication efficiency or implementation on resource-constrained smart grids. Kaif et al [6] then demonstrated blockchain-enabled local energy trading using the Brooklyn Microgrid project. Their research confirms the feasibility of decentralised electricity markets. However, they focused mainly on market design and provided inadequate analysis of scalability, communication performance, or consensus efficiency. Research by Fatima et al [7] proposed a consortium blockchain for energy trading with a plug-in hybrid electric vehicle. This reduces transaction verification time and improves privacy. Similarly, research conducted by Sun et al [8] developed a permissioned blockchain model for industrial energy systems that enhanced transaction security and scalability. However, both studies have reliable communication infrastructures and were unable to incorporate lightweight IoT communication or intelligent energy forecasting. Rath et al [9] conducted an investigation on blockchain-supported energy crowdsourcing for coordinating distributed energy resources. The framework enhances decentralised market flexibility, scalability and communication performance under practical smart grid conditions. These parameters were not comprehensively evaluated. Existing blockchain-based energy trading studies mainly emphasise secure transaction management while giving limited attention to communication efficiency, lightweight consensus, and intelligent decision support that is needed for practical IoT-enabled smart grids.

B. Lightweight Blockchain for IoT Smart Grids

Traditional blockchain proposals are usually unsuitable for IoT-based smart grids because computationally intensive consensus mechanisms create high latency, energy consumption, and communication overhead. Consequently, recent research works focus on lightweight blockchain architectures mainly designed for resource-constrained environments. A comprehensive study by Shuaib et al. [10] surveyed blockchain applications in the Internet of Things and identified scalability, storage overhead, and consensus efficiency as major deployment issues. Abbasinezhad-Mood et al [11] also underscored privacy, interoperability, and communication latency as key challenges limiting blockchain implementation in low-power IoT systems. To enhance efficiency, research in Samuel et al. [12] integrated a permissioned blockchain with edge computing to reduce communication delay while preserving privacy. Research in Reka et al [13] proposed a blockchain-based secure communication system that lessens communication overhead. In contrast, Das et al. [14] reviewed blockchain applications in smart grids and underscored the need for lightweight consensus

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mechanisms to enhance scalability and transaction efficiency. Although this research significantly improves blockchain suitability for Internet of Things environments, most studies concentrate on consensus optimisation or security. Communication-aware networking and intelligent forecasting remain largely deficient, leaving important opportunities for integrated decentralised energy trading frameworks.

C. AI-Based Energy Forecasting

Accurate energy demand forecasting is essential for decentralised energy trading because it improves energy scheduling, pricing, and transaction planning. Recent advances in artificial intelligence, particularly deep learning, have significantly enhanced forecasting accuracy by capturing the nonlinear temporal characteristics of electricity consumption. Kothuru et al. [15] demonstrated that accurate forecasting improves demand response and overall smart grid stability, while Akbar et al. [16] showed that distributed learning can support decentralised demand scheduling without centralised coordination. However, both studies focused on demand optimisation and did not consider blockchain-enabled energy trading. Aggarwal et al [17] reported that Long Short-Term Memory (LSTM) networks outperform conventional machine learning models in short-term load forecasting because of their ability to capture long-term temporal dependencies. Similarly, Wang et al [18] integrated artificial intelligence with blockchain to improve smart grid security and resilience. Nevertheless, these studies treated forecasting and blockchain as separate components, limiting intelligent decision-making during decentralised energy trading. Existing studies confirm the effectiveness of AI for smart grid forecasting but rarely integrate predictive intelligence directly into blockchain-based trading frameworks. This gap motivates integrating LSTM forecasting with blockchain smart contracts in the proposed framework.

D. Communication Technologies for Smart Grids

Reliable communication is fundamental to decentralised smart grids because it enables real-time monitoring, distributed control, and secure energy transactions. Communication technologies for IoT-enabled smart grids must therefore provide low latency, scalability, reliability, and low energy consumption. Srinivasarao et al [19] highlighted the role of IoT communication in transforming conventional electricity networks into intelligent cyber-physical systems. Lavanya et al [20] compared several wireless technologies and identified ZigbeePro as one of the most suitable solutions for residential smart grids because of its low power consumption, mesh networking capability, and communication reliability.

More recently, Yarrabothu et al [21] combined Zigbee networking with blockchain-based authentication to improve communication security. However, the framework focused on authentication rather than decentralised energy trading or intelligent transaction management. Although communication technologies have advanced considerably, few studies integrate lightweight blockchain, efficient IoT communication, and AI-based forecasting into a unified decentralised energy trading framework. This limitation motivates the communication-aware architecture proposed in this study.

E. Research Gap Analysis

The literature demonstrates considerable progress in blockchain-enabled energy trading, lightweight blockchain, AI-based forecasting, and smart grid communication. However, these technologies are generally investigated independently. Existing blockchain studies mainly focus on secure transactions; lightweight blockchain research emphasises consensus optimisation; AI studies improve forecasting accuracy; and communication research concentrates on networking efficiency. Few studies integrate these components into a unified framework suitable for resource-constrained IoT-enabled smart grids. To address this limitation, this study proposes a communication-aware lightweight blockchain framework that integrates Hyperledger Fabric with PBFT consensus, ZigbeePro communication, and LSTM-based demand forecasting. The framework is comprehensively evaluated through communication simulation, blockchain implementation, and prototype validation to improve security, scalability, communication efficiency, and intelligent decentralised energy trading.

Table I: Comparative Analysis of Related Studies and Research Gap

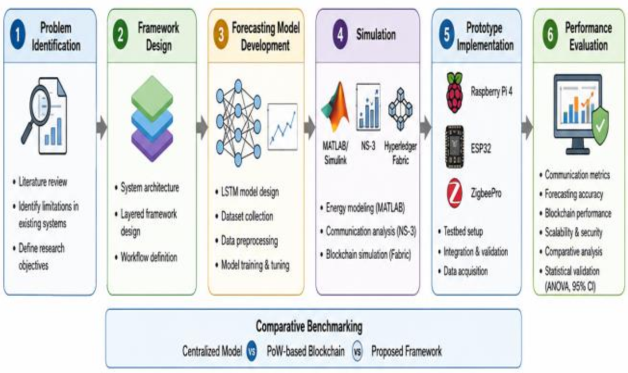
Author	Blockchain	AI	Lightweight Consensus	Communication	Prototype	Research Gap	Proposed Solution
Abdella & Shuaib (2018)	✓	✗	✗	✗	✗	Conceptual blockchain review without implementation	Develop and validate an integrated blockchain framework.
Mengelkamp et al. (2018)	✓	✗	✗	✗	✓	Focused on market design with limited scalability analysis	Introduced lightweight blockchain with scalability evaluation
Gai et al. (2019)	✓	✗	✓	Partial	✗	No AI forecasting or decentralised energy trading	Integrate AI forecasting with blockchain-based trading
Chen et al. (2024)	✗	✓	✗	✗	✗	Forecasting developed independently of blockchain.	Embed LSTM forecasting into blockchain smart contracts.
Wang et al. (2023)	✓	✗	Partial	✓	Partial	Focused on authentication rather than energy trading	Combined secure communication with decentralised trading
Proposed Framework	✓	✓	✓ (PBFT)	✓ (ZigbeePro)	✓	Unified lightweight blockchain framework for secure decentralised energy trading	Integrates blockchain, AI forecasting, communication optimisation, and prototype validation within a single architecture

III. METHODOLOGY

A. Research Methodology

This study proposes and evaluates a lightweight blockchain framework for secure decentralised energy trading by integrating Hyperledger Fabric, Practical Byzantine Fault Tolerance (PBFT) consensus, ZigbeePro communication, and Long Short-Term Memory (LSTM)-based energy demand forecasting. A Design Science Research (DSR) methodology was adopted to design, implement, and evaluate the proposed framework. The research consisted of six phases: problem identification, framework design, forecasting model development, simulation, prototype implementation, and performance evaluation. The proposed framework will be evaluated using MATLAB/Simulink for energy modelling and forecasting, NS-3 for communication analysis, and Hyperledger Fabric for blockchain transaction processing. Prototype validation is to be conducted using Raspberry Pi 4 and ESP32 devices that communicate solely through ZigbeePro.

Performance evaluation considers communication efficiency, blockchain performance, forecasting accuracy, energy consumption, scalability, and security resilience. Communication performance is measured using latency, throughput, and Packet Delivery Ratio (PDR). Forecasting accuracy is examined using RMSE, MAPE, and R^2. Consensus time, transaction throughput, and node energy consumption will be used to examine blockchain impact on efficiency. In addition, Security performance was evaluated against unauthorised access, replay attacks, and false data injection. To further strengthen this research, Statistical significance was verified using one-way ANOVA at a 95% confidence level. The complete research workflow is illustrated in Figure 1.

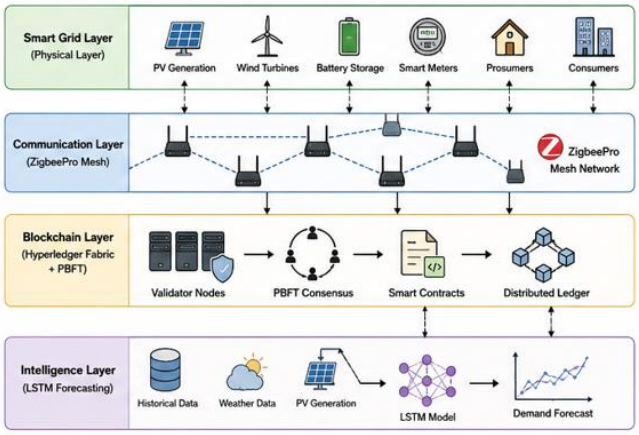


[Fig.1: Research Workflow]

Figure 1 presents a summary of the methodology guided in this research. The initial processes begin by identifying the research gaps, followed by the design framework, then simulation and prototype implementation, and finally conducting a comparative performance evaluation against centralised and PoW-enabled blockchain schemes.

B. Proposed Lightweight Blockchain Framework

The proposed research framework provides secure and communication-efficient decentralised energy trading by incorporating ZigbeePro communication, Hyperledger Fabric, PBFT consensus, and LSTM-based forecasting into a unified architecture. Unlike the conventional blockchain energy trading models that mainly emphasise transaction security, the proposed research framework jointly enhances communication efficiency, scalability, and intelligent decision-making. The framework therefore comprises four functional layers. These include the Smart Grid Layer, Communication Layer, Blockchain Layer, and Intelligence Layer. These layers cooperate to support secure peer-to-peer energy trading while maintaining modularity and scalability. The complete architecture of the proposed framework is presented in Figure 2.



[Fig.2: Architecture of Blockchain Framework for Decentralised Energy Trading]

Figure 2 presents an interaction between prosumers, consumers, smart meters, ZigbeePro communication, Hyperledger Fabric, and PBFT consensus. It also consists of the LSTM forecasting engine. The Smart meters collect energy data in the system by transmitting through the ZigbeePro network to blockchain validators. After PBFT consensus confirms each transaction, smart contracts execute energy trading and update the distributed ledger accordingly. Meanwhile, the LSTM model predicts the future energy demand to support dynamic pricing and proactive energy allocation.

i. Smart Grid Layer

The Smart Grid Layer characterises the physical energy infrastructure that consists of renewable energy sources, battery storage, smart meters, prosumers, and consumers. Smart meters continuously monitor energy generation, consumption, and surplus electricity. Whenever excess energy is generated, trading requests are produced and forwarded to the communication layer for blockchain processing.

ii. Communication Layer

The Communication Layer facilitates data exchange between the distributed smart grid nodes using ZigbeePro mesh networking. ZigbeePro was selected due to its low power consumption and its reliable communication system. It also has a

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self-healing mesh capability, making it suitable for resource-constrained Internet of Things devices. Energy measurements and trading demands are transmitted to the blockchain validator nodes through this layer.

iii. Blockchain Layer

The Blockchain Layer provides participant authentication, transaction validation, and an immutable ledger management system using Hyperledger Fabric with PBFT consensus. Unlike Proof-of-Work, the PBFT validates all transactions with no computational mining, minimising latency and energy consumption. Smart contracts automatically authenticate requests, execute energy trading agreements, and permanently record validated transactions.

iv. Intelligence Layer

The Intelligence Layer incorporates an LSTM network to predict short-term electricity demand using historical consumption, renewable generation, and weather data. Forecast results are supplied to blockchain smart contracts to support adaptive pricing and intelligent energy allocation before transaction execution.

v. Operational Workflow

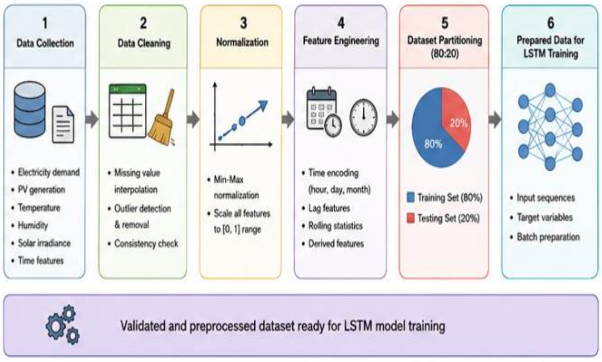
The proposed framework operates in six different stages. First, the smart meters collect energy generation and consumption data. Second, the generated data is transmitted through the ZigbeePro network to blockchain validators. Third, Hyperledger Fabric authenticates participants and validates all transactions using PBFT consensus. In the Fourth stage, smart contracts execute peer-to-peer energy trading and update the blockchain ledger. In the Fifth stage, the LSTM model predicts future electricity demand to facilitate pricing and trading decisions. Finally, validated transactions are stored in the distributed ledger for auditing and future verification.

C. Intelligent Energy Demand Forecasting Using LSTM Networks

Accurate demand forecasting enhances decentralised energy trading by facilitating intelligent scheduling, adaptive pricing, and effective usage of renewable energy resources. This research work adopts a Long Short-Term Memory (LSTM) network due to its ability to capture nonlinear temporal patterns in electricity consumption. The forecasting model functions as an intelligence layer of the proposed framework by predicting short-term electricity demand before transaction execution. Forecast results are pushed to the blockchain smart contracts to facilitate proactive energy allocation and dynamic pricing.

i. Dataset Description and Preprocessing

The forecasting model was established using publicly available smart grid datasets that are combined with synthetic residential load profiles. The dataset comprises hourly electricity demand, photovoltaic (PV) generation, temperature, humidity, solar irradiance, and time-related features. Data preprocessing involves missing-value interpolation, outlier removal, and Min-Max normalisation to enhance model convergence. The processed dataset was divided into training (80% and testing (20% subsets. The preprocessing workflow is therefore illustrated in Figure 3.



[Fig.3: Data Preprocessing Workflow for LSTM-Based Energy Demand Forecasting]

Figure 3 presents a summary of the proposed framework preprocessing stages. This includes data cleaning, normalisation, feature extraction, dataset partitioning, and preparation for LSTM training.

ii. LSTM Network Architecture

The forecasting module comprises an input layer, two LSTM hidden layers having 64 units each, a dropout layer of 0.2, and a fully connected output layer. The input features comprise historical energy consumption, renewable generation, and weather variables, while one-step-ahead electricity demand is generated as an output. We train the network with the Adam optimiser and Mean Squared Error (MSE) as the loss function.

Table II: Configuration of the LSTM Forecasting Model

Parameter	Configuration
Input variables	Demand, PV generation, temperature, humidity, irradiance, time indicators
Sequence length	24 hours
Hidden layers	2
LSTM units	64 per layer
Dropout rate	0.20
Optimizer	Adam
Loss function	MSE
Batch size	32
Epochs	150
Training/Test split	80% / 20%

The configuration was carefully selected to balance forecasting accuracy and computational efficiency for Internet of Things-based smart grid applications.

iii. Mathematical Formulation

The LSTM module in the proposed framework uses input, forget, and output gates. This regulates information flow and maintains long-term temporal dependency. Given the input vector x_t, previous hidden state h_{t-1}, and previous cell state $C_t - 1$, the gate operations are expressed from Equations (1–5).

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f \qquad (1)$$

Where W_f and b_f denote the forget gate weight matrix and bias vector. While σ(.) represents the sigmoid activation function. The input gate updates the internal memory based on equation 2

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$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i \qquad (2)$$

And the candidate memory state is computed based on equation 3

$$C_t - tanh\,(W_c[h_{t-1}, x_t] + b_c \qquad (3)$$

The updated cell state is further computed based on equation 4

$$C_t = f_t \oplus h_{t-1} + i_t \oplus C_t \qquad (4)$$

Where $\oplus$ denotes element-wise multiplication. Finally, the output is generated based on equation 5

$$O_t = \sigma(W_i[h_{t-1}, x_t] + b_o \qquad (5)$$

$$h_t = O_t \tanh(C_t)$$

These gating mechanisms facilitate accurate learning of sequential electricity consumption patterns. This makes the LSTM function suitable for short-term load forecasting.

iv. Forecasting Algorithm

The forecasting procedure is adequately summarised in Algorithm 1 below.

Algorithm 1: LSTM-Based Energy Demand Forecasting

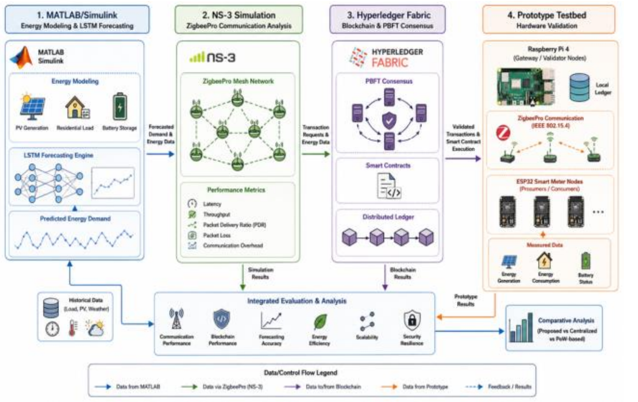
```
  Input: Historical demand, renewable generation,
and weather data
  Output: Predicted electricity demand
   1. Collect historical data.
   2. Perform data cleaning and normalisation.
   3. Split the dataset into training (80%) and
      testing (20%) sets.
   4. Construct the LSTM network.
   5. Train the model using the Adam optimiser.
   6. Evaluate performance using RMSE, MAPE, and
      R2R^2R2.
   7. Generate short-term demand forecasts.
Forward predictions to blockchain smart contracts.
```

v. Integration with Blockchain-Based Energy Trading

The LSTM prediction module is embedded with the Hyperledger Fabric blockchain. After each prediction cycle, forecasted demand is updated to smart contracts to facilitate adaptive pricing, energy scheduling, and buyer–seller matching before transaction execution. This incorporates renewable energy utilisation, minimises unnecessary transactions, and improves communication efficiency by maintaining secure decentralised energy trading.

D. Simulation and Prototype Implementation

Validation of the proposed framework was conducted using a hybrid simulation prototype approach. MATLAB/Simulink was used to model energy generation, consumption, battery storage, and LSTM-based forecasting. NS-3 simulated ZigbeePro communication to evaluate network performance, while Hyperledger Fabric implemented the permissioned blockchain with PBFT consensus for decentralised energy trading. Prototype validation was conducted using Raspberry Pi 4 and ESP32 devices to demonstrate practical feasibility under Internet of Things hardware constraints. The complete implementation workflow is presented in Figure 4.



[Fig.4: Simulation Workflow of Decentralised Energy Trading]

Figure 4 presents MATLAB/Simulink, NS-3, Hyperledger Fabric, and the interaction of the prototype devices. Energy demand is initially predicted using MATLAB/Simulink and forwarded to Hyperledger Fabric, where smart contracts execute energy trading. NS-3 evaluates ZigbeePro communication performance. The prototype validates real-time operation under embedded hardware conditions.

i. MATLAB/Simulink Energy Trading Simulation

MATLAB/Simulink was used to model residential electricity generation, consumption, battery storage, and peer-to-peer energy trading. The LSTM forecasting model generated short-term electricity demand predictions, which were supplied to blockchain smart contracts for adaptive pricing and energy allocation. The simulation considered varying renewable generation and household load profiles to emulate realistic operating conditions.

ii. NS-3 Communication Simulation

Communication performance was examined using NS-3. This used a ZigbeePro mesh network with smart meters, blockchain validators, and gateway nodes. The simulation examined different network sizes by measuring latency, throughput, packet delivery ratio (PDR), communication overhead, and packet loss. Simulation parameters are carefully summarised in Table 3.

Table III: NS-3 Communication Parameters

Parameter	Value
Network Simulator	NS-3.38
Communication Protocol	ZigbeePro (IEEE 802.15.4)
Simulation Duration	600 s
Simulation Area	500 × 500 m
Number of Nodes	25–250
Transmission Range	100 m
Channel Bandwidth	250 kbps
Traffic Type	Constant Bit Rate (CBR)
Packet Size	512 Bytes
Routing	Mesh Routing
Performance Metrics	Latency, Throughput, PDR, Packet Loss

iii. Hyperledger Fabric Implementation

The blockchain platform was implemented using Hyperledger Fabric with PBFT consensus. Smart contracts authenticated all connecting devices, executed peer-to-peer energy trading, and updated the distributed ledger. The network consists of peer nodes, ordering services, certificate authorities, and smart contracts to facilitate secure transaction processing.

iv. Prototype Testbed

Prototype validation was conducted with Raspberry Pi 4 boards represented as blockchain gateway nodes and ESP32 devices represented as smart meters. Each ESP32 transmitted energy measurements through ZigbeePro. The Raspberry Pi devices executed lightweight blockchain clients and connected with the Hyperledger Fabric. The prototype consisted of (3) Raspberry Pi nodes and (6) ESP32 nodes operating under the same communication settings used during the simulations.

v. Experimental Scenarios

The framework was examined under varying network sizes ranging from 25 to 250 Internet of Things nodes, with corresponding increases in transaction volume. Performance was compared with two benchmark systems:

- Centralised energy management system.
- Proof-of-Work (PoW)-based blockchain framework.

Each experiment was repeated several times, and the average results were averaged for analysis. The evaluation considered communication performance, blockchain efficiency, forecasting accuracy, scalability, energy consumption, and security resilience.

E. Performance Evaluation and Validation Strategy

The proposed framework was examined based on communication, blockchain, forecasting, scalability, energy efficiency, and security metrics. These metrics directly address the research open issues and challenges identified in the related literature. These include communication delay, computational overhead, scalability, prediction accuracy, and cybersecurity. Performance was evaluated with MATLAB/Simulink, NS-3, Hyperledger Fabric, and the prototype testbed.

Table IV: Performance Evaluation Metrics

Metric	Platform	Expected Outcome
Latency	NS-3 / Hyperledger Fabric	Lower
Throughput	Hyperledger Fabric	Higher
Packet Delivery Ratio	NS-3	Higher
Packet Loss	NS-3	Lower
Consensus Time	Hyperledger Fabric	Lower
Energy Consumption	Prototype	Lower
RMSE, MAPE	MATLAB	Lower
Transaction Success Rate	Hyperledger Fabric	Higher
Scalability	Simulation	Higher
Security Resilience	Prototype	Higher

Table 4 summarises the evaluation metrics used to assess communication efficiency, blockchain performance, forecasting accuracy, scalability, and security.

i. Benchmark Models

We compare the proposed framework with two benchmark approaches. These are:

- The traditional centralised energy management system.
- The Proof-of-Work (PoW)-based blockchain energy trading framework.

All experiments used identical simulation settings to ensure a fair comparison.

ii. Statistical Validation

Each experiment was repeated in several iterations under the same operating conditions. The results reported represent average simulation values. One-way ANOVA with a significance level of 0.05 was used to identify performance differences between the frameworks evaluated and to determine their statistical significance.

The hypotheses are expressed as:

$$H_0: \mu_1 - \mu_2 - \mu_3 \quad (6)$$

$$H_1: \exists_i \neq j, \mu_i \neq \mu_j \quad (7)$$

Where μ_1 represents the centralised framework, μ_2 represents the PoW-based blockchain framework, and μ_3 represents the proposed lightweight blockchain framework.

iii. Evaluation Criteria

The proposed research framework was considered effective if it can do the following:

- Minimise latency and energy consumption;
- Improve throughput and packet delivery ratio;
- Provide accurate LSTM forecasting with low RMSE and MAPE;
- Preserve stable performance as network size increases; and
- Enhance security against unauthorised access, replay, and false data injection attacks.

IV. RESULT

A. Overview of Experimental Evaluation

Results of the experimental evaluation of the proposed framework were obtained using MATLAB/Simulink, NS-3, and Hyperledger Fabric. For the prototype, we used a Raspberry Pi–ESP32. Performance evaluation was conducted by comparing the centralised energy management system with a conventional PoW-based blockchain under identical simulation parameters. The evaluation was also centred on communication performance, blockchain efficiency, forecasting accuracy, energy consumption, scalability, and security.

B. Communication Performance Evaluation

Evaluation of Communication performance was conducted in the NS-3 research simulator using ZigbeePro mesh networking and with network sizes ranging from 50 to 250 Internet of Things nodes. The proposed PBFT-based framework was compared with centralised and PoW-based approaches.

Table V: Communication Performance Comparison

Metric	Centralized	PoW	Proposed
Average Latency (ms)	131.8	208.4	47.6
Throughput (Transactions/s)	65	41	186
Packet Delivery Ratio (%)	92.1	87.3	98.1
Communication Overhead (KB/s)	15.1	22.3	9.2

The proposed research framework achieved the lowest latency of 47.6 ms and

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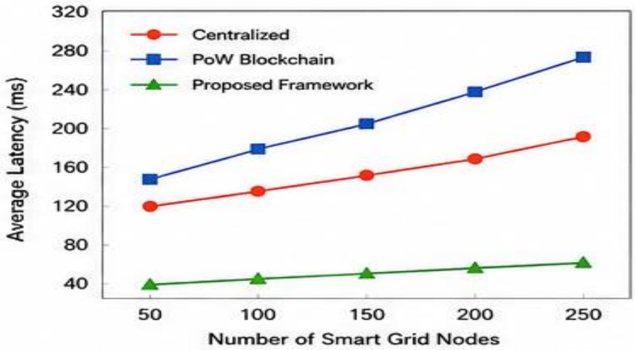
the highest throughput of 186 transactions/s. This is due to the lightweight PBFT consensus and ZigbeePro communication. It also presented the highest packet delivery ratio of 98.1% and the lowest communication overhead. These results demonstrate a reliable and efficient data exchange.



[Fig.5: Communication Latency versus Number of Smart Grid Nodes]

Figure 5 presents a latency increase with network size for all compared approaches. Yet, the proposed framework presented only a gradual increase compared with the sharp rise observed in the PoW and centralised models. This result confirms that the proposed research architecture maintains stable communication performance under increasing network loads.

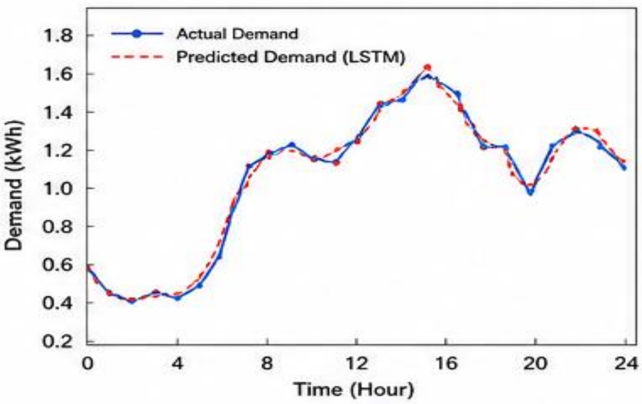
C. Intelligent Energy Demand Forecasting

Integrated LSTM system evaluation was conducted based on historical energy consumption, renewable generation, and weather data. We measured Forecasting performance using RMSE, MAE, MAPE, and R^2.

Table VI: LSTM Energy Demand Forecasting Performance

Performance Metric	Value
RMSE (kWh)	0.118
MAE (kWh)	0.082
MAPE (%)	4.70
R^2 Score	0.964
Prediction Accuracy (%)	95.3
Forecast Horizon	24 Hours

The proposed research framework achieved high forecasting accuracy with an RMSE of 0.118 kWh, MAPE of 4.70%, and R^2 of 0.964. This indicates a close agreement between predicted and actual demand. These accurate predictions facilitate smarter energy scheduling and enhance trading decisions before transaction execution.



[Fig.6: Actual Versus Predicted Energy Demand]

Figure 6 shows that the predicted demand closely follows the actual load profile. This occurs with only minor deviations during peak demand periods. Integrating LSTM forecasting into the blockchain framework enhances proactive energy allocation and improves the efficiency of decentralised energy trading.

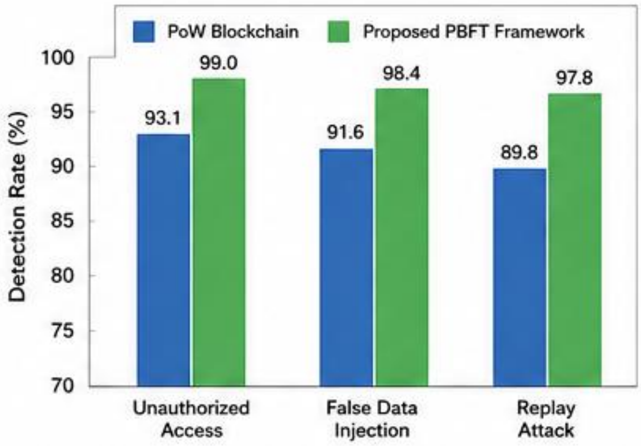
D. Blockchain Security and Performance

The blockchain layer was evaluated using Hyperledger Fabric with PBFT consensus. It is then compared with a conventional PoW blockchain. The Performance is examined based on consensus time, transaction confirmation, transaction success rate, energy overhead, and attack detection.

Table VII: Blockchain Security and Performance Evaluation

Performance Metric	PoW Blockchain	Proposed PBFT Framework
Consensus Time (ms)	268	112
Transaction Confirmation (ms)	312	138
Successful Transactions (%)	95.4	99.2
Energy Overhead (J/node)	1.41	0.82
Unauthorised Access Detection (%)	93.1	99.0
False Data Injection Detection (%)	91.6	98.4
Replay Attack Detection (%)	89.8	97.8

The proposed research framework consistently outperformed the PoW blockchain as presented in Table 4. PBFT minimised consensus and transaction confirmation times by more than 55%. It then increased the transaction success rate to 99.2%. Energy consumption was significantly reduced because mining operations were eliminated. The security evaluation further demonstrated high resilience against cyberattacks. Detection rates exceeded 97% for unauthorised access, false data injection, and replay attacks. This confirms the impact and effectiveness of permissioned blockchain authentication and smart contract verification.



[Fig.7. Security Detection Performance]

Figure 7 compares the performance of attack detection of the PBFT framework and the PoW blockchain. The results achieved indicate that the proposed research framework provides stronger security with lower computational cost, making it more suitable for resource-constrained Internet of Things-based smart grid environments.

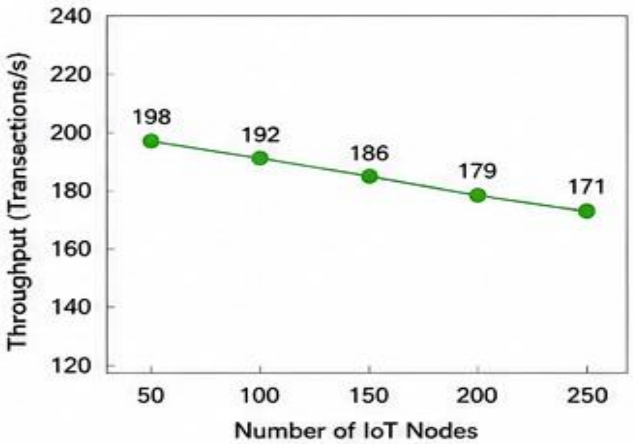
E. Scalability and Overall System Performance

The scalability of the proposed research framework was evaluated by increasing the number of IoT nodes from 50 to 250 while maintaining identical communication settings. The Performance was assessed using latency, throughput, packet loss, and energy overhead.

Table-VIII: Scalability Performance under Increasing Network Size

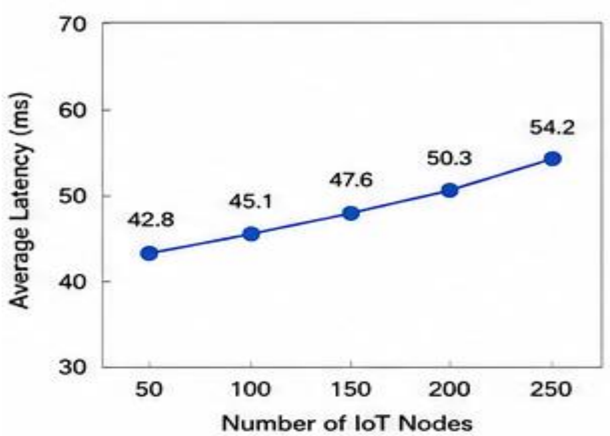
Number of IoT Nodes	Average Latency (ms)	Throughput (Transactions/s)	Packet Loss (%)	Energy Overhead (J/node)
50	42.8	198	0.8	0.73
100	45.1	192	0.9	0.77
150	47.6	186	1.1	0.82
200	50.3	179	1.4	0.87
250	54.2	171	1.8	0.92

Table -VIII shows that the proposed research framework maintained a stable performance as network size increased. Latency increased only slightly, i.e. from 42.8 ms to 54.2 ms, while throughput remained higher than 170 transactions/s even with 250 nodes. Packet loss was maintained at less than 2%, and energy overhead increased only marginally.



[Fig.8: Throughput Performance under Increasing Network Size]

Figure 8 presents the throughput of the proposed research framework as the number of Internet of Things nodes increases. Figure 8 also shows that throughput is maintained consistently high. This is with only a slight decline at larger network sizes due to increased communication traffic.



[Fig.9: Communication Latency Versus Network Size]

Figure 9 indicates communication latency as the smart grid network expands. The latency increased gradually with network size. Yet, remained below 55 ms. This demonstrates the scalability of the proposed research framework. Integrating ZigbeePro communication, PBFT consensus, and LSTM-based demand forecasting facilitates efficient communication and transaction processing under increasing workloads. The results also confirm that the proposed framework enables scalable and energy-efficient decentralised energy trading while maintaining reliable communication and blockchain performance.

F. Benchmarking, Comparative Analysis, Statistical Validation

The proposed research framework was benchmarked against conventional research that has a centralised energy management system and a PoW-based blockchain framework under the same simulation conditions. The comparison considered communication performance, blockchain efficiency, forecasting capability, security, and scalability.

A summarised version of the results is presented in Table 6. It indicates that the proposed framework consistently outperformed both benchmark models. It achieved the minimal latency, highest throughput, highest packet delivery ratio, and lowest energy overhead. The integration of PBFT consensus reduces consensus delay, while ZigbeePro communication enhances network reliability. Also, the LSTM forecasting model introduced predictive intelligence that is unavailable in the benchmark systems.

The framework also shows superior security and scalability performance. This means it achieves a higher attack detection rate and supports up to 250 IoT nodes with stable performance. This result therefore guarantees that integrating lightweight blockchain, efficient communication, and Artificial Intelligence forecasting provides a practical solution for decentralised smart grid energy trading.

Table IX: Comparative Performance Benchmark

Performance Metric	Centralized Model	PoW Blockchain	Proposed Framework	Improvement over PoW
Average Latency (ms)	132.4	210.7	48.9	76.8%
Throughput (transactions/s)	62	38	185	386.8%
Packet Delivery Ratio (%)	91.2	86.5	97.8	13.1%
Energy Overhead (J/node)	1.39	1.58	0.82	48.1%
Consensus Time (ms)	—	266	112	57.9%
Forecast Accuracy (R^2)	N/A	N/A	0.964	New Capability
Security Detection Rate (%)	78.4	89.6	98.7	10.2%
Maximum Supported Nodes	120	110	250	127%
Throughput (transactions/s)	62	38	185	386.8%
Packet Delivery Ratio (%)	91.2	86.5	97.8	13.1%

Table -IX presents a comparison of the proposed research framework with centralised and PoW-based approaches. The proposed framework achieved consistently better

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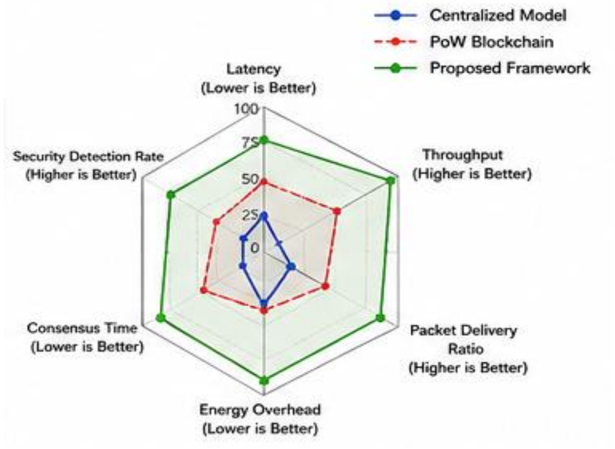
communication performance, security, scalability, and forecasting capability.



[Fig.10: Comparative Performance of the Evaluated Frameworks]

Figure 10 presents a comparison of the complete performance of the centralised model, PoW blockchain, and the proposed research framework across the major evaluation metrics.

V. CONCLUSION

This research work proposed a lightweight blockchain framework for decentralised smart grid energy trading by incorporating a PBFT consensus, ZigbeePro communication, and an LSTM-based energy demand forecasting. Validation of the proposed framework was conducted using MATLAB/Simulink, NS-3, Hyperledger Fabric, and a Raspberry Pi/ESP32 prototype. Experimental results showed that enhanced communication efficiency, blockchain performance, security, and scalability were compared with centralised and PoW-based approaches. The proposed research framework showed lower latency (48.9 ms), improved throughput (185 transactions/s), a packet delivery ratio of 97.8%, and supported up to 250 Internet of Things nodes. The LSTM system in the research also showed accurate demand forecasting with an R^2 of 0.964 and a MAPE of 4.7%. This enables additional intelligent energy trading decisions. The integration of lightweight blockchain, low-power communication, and Artificial Intelligence forecasting shows a practical and scalable alternative for secure decentralised energy trading in Internet of Things-enabled smart grids. This research work was validated using simulation and a small-scale prototype.

In Future research work, we intend to focus on large-scale field deployment, advanced lightweight consensus mechanisms, federated learning, digital twins, edge intelligence, and integration with emerging communication technologies such as 5G/6G and software-defined networking to improve scalability and interoperability further.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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