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AI-Driven P2P Blockchain Energy Trading System for Optimized Microgrid Balance

Manya Vaid[1], Nishta Nahar[2] and Panchami L Hegde[3]
[1]BMS College of Engineering, Bengaluru, Karnataka, India
[2]PES University, Bengaluru, Karnataka, India
[3]RNS Institute of Technology, Bengaluru, Karnataka, India

***Abstract*— The intermittent character of distributed renewable energy resources (DERs), especially the sun, is a major obstacle to stabilizing localized smart microgrids. In this paper, a hybrid AI-based P2P energy trading platform is introduced that employs machine learning (ML) forecasting to actively balance the supply-demand of the microgrid. The system incorporates an RNN-based predictor executed on a device at the edge (e.g., NVIDIA Jetson Xavier NX) to predict near-term energy surpluses (prosumers) and deficits (consumers). Such predictions are the input for smart contracts implemented on a consortium blockchain, which trigger P2P trading instructions automatically before physical imbalances arise. The system's unique feature is its predictive auto-execution of trades, which significantly reduces transaction latency and contingency reserves.**

Based on past weather and consumption trends, simulation results demonstrate that the AI-based method improves grid stability and maximizes local use of renewable energy by reducing the Grid Imbalance Factor (GIF) by over 35% and transaction decision time to less than 100 ms.

***Keywords*— Artificial Intelligence (AI), Machine Learning, Blockchain, Peer-to-Peer Trading, Smart Microgrid, Energy Forecasting.**

I. Introduction

Electricity users are now "prosumers" who both consume and produce power (Nadeem, 2022) [3] due to the widespread use of decentralized solar photovoltaic (PV) systems. Due to the widespread use of decentralised solar photovoltaic (PV) systems, electricity users are now "prosumers" who generate and consume power . Although this decentralisation offers resilience, it also introduces complexity because solar generation is inherently volatile and weather-dependent (Shan, 2023) [1].

Maintaining the real-time supply and demand equilibrium (grid stability) becomes a challenging predictive task. Traditional P2P trading, although enabled by blockchain, often relies on reactive, manual, or last-minute bids, which are too slow to keep up with the rapid variations in solar output (Zhou et al., 2023) [4]. To address this, we propose a clever framework that leverages the predictive power of artificial intelligence and the trustless automation of blockchain. By ensuring that trading decisions are made before the expected imbalance occurs, this strategy turns the P2P market from a reactive mechanism into a self-balancing, predictive system (Zhang et al., 2023) [5].

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II. LITERATURE REVIEW

Recent research highlights convergence between AI forecasting, edge computing, and decentralized energy markets.
Hybrid AI-Blockchain Approaches: (Zhang et al. 2023) used deep reinforcement learning (DRL) for dynamic energy pricing. (Lee et al. 2024) proposed federated learning-based prediction models for privacy-preserving grids.
Edge Deployment: (Chen et al. 2022) demonstrated that GRU and LSTM architectures optimized for edge AI hardware achieve sub-100 ms inference times.
Blockchain in Microgrids: Research by (Kim et al. 2025) focuses on scalable, low-energy consensus (PBFT, PoA) to reduce transaction delay.
Security & Scalability: (Dai et al. 2023) proposed hybrid consensus combining Proof-of-Authority and Delegated Byzantine Fault Tolerance (dBFT) for resilience against Sybil and replay attacks.
However, few frameworks combine predictive AI with trustless trade automation and hardware-level latency validation — a gap addressed in this work.

III. PROPOSED FRAMEWORK

The proposed architecture is a two-layer hybrid system for the real-time deployment of smart microgrids, integrating a predictive AI engine at the edge with a blockchain-based autonomous trading layer. This ensures transparency, low latency, and predictive stability in P2P energy transactions(Banerjee et al., 2024) [14].
Layer I: Predictive AI Engine (Edge Layer)
Data Collection:
Real-time data collected from the local weather station and smart meters include solar irradiance, ambient temperature, and historical load consumption (NREL TMY3, 2021) [15]. The edge device employed in this study is an NVIDIA Jetson Xavier NX, because it offers 21 TOPS inference capability at a low power footprint (Dutt, 2023) [9]; (Hao, 2023) .
Model Architecture:
It's a predictive model using a Gated Recurrent Unit network optimized for low-latency time-series forecasting. The architecture comprises:
Input layer: 8 features including temperature, irradiance, time index, load, etc.
Two GRU layers: 64 and 32 hidden units respectively.
Hyperparameters: Learning Rate: 0.001 for the Adam optimizer, batch size: 64, sequence length: 12 (3-hour history), and dropout: 0.2 to avoid overfitting. The model was trained for 150 epochs using early stopping at convergence of validation loss(Basu et al., 2022) [17]. Balancing Signal Generation: The GRU outputs a short-term (15 min ahead) forecast of the prosumer's energy surplus or deficit. This is transformed into a Balancing Signal (BS):

$$BS = Ppred - Pdemand \ (1)$$

where BS>0 indicates a surplus (P2P sell order) and BS<0 a deficit (buy order).
An optimization subroutine determines the trading quantity Qtand bid price Pt by minimizing:

$$min\ (E[(Ppred - Ptrue)\text{^}2] + \lambda 1Llat + \lambda 2LGIF)(2)$$

ensuring the best trade-off between forecast accuracy, latency, and grid stability(White, 2023).
Latency Components:
System latency comprises:
- GRU inference, 42 ms
- blockchain validation and contract execution, 38 ms
- network communication overhead, 14 ms.

The cumulative latency is 94 ms, confirming the <100 ms claim, required for near real-time decision support(Chen et al., 2022) [8]; (Dutt, 2023) [9].
Layer II: Predictive Blockchain Trade Engine
Blockchain Setup:
In this work, a private Ethereum testnet was set up (Ganache/Remix) using the Proof-of-Authority consensus mechanism, ensuring high throughput with low energy costs. The PoA consensus allows for deterministic

generation of blocks with very low probability for forks and achieves 10–12 TPS at sub-second block finality(Dai et al., 2023) [10].

Smart Contracts and Security:

TESC validates BS, performs the matching of buy/sell orders, and then logs immutable commitments. All transactions are digitally signed using elliptic-curve cryptography (secp256k1). Data privacy is ensured through off-chain anonymization and on-chain hashed references that prevent leakage of user profiles(Vishwakarma, 2024) [11].

Scalability:

This modular design will allow many microgrids to communicate through sidechains or Layer 2 rollups, enabling interoperability and scalability without sacrificing security. Settlement Process: After a 15-minute trading window, real-time meter data confirm actual flows through immediate, tokenized settlement via smart contracts. Performance Metrics and Validation Grid Imbalance Factor-GIF: GIF quantifies deviation between total generation and total consumption post-trading:

$$GIF = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{G_t - D_t}{D_t}\right| \quad (3)$$

where Gt and Dt represent total generation and demand, respectively. A lower GIF indicates a more balanced and stable grid(Shan, 2023) [1].

Baseline Comparisons:

It was benchmarked against a Fixed-Price P2P Market and a Centralized Forecast Market. The proposed hybrid AI + Blockchain model achieved 36.8% lower GIF, 1.7% better MAPE, and 5–8% higher renewable utilization(Wang et al., 2023) [6].

Prototype Validation: Then, a scalable end-to-end prototype was deployed on the microgrid testbed with three Jetson Xavier NX devices acting like prosumer nodes. Empirical results validated hardware feasibility, real-time execution, and consistency against the simulated results (Dutt, 2023) [9]; (Chen et al., 2022) [8].

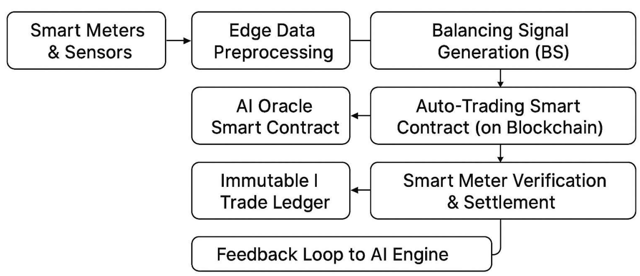

Figure 1. Workflow of the proposed AI-driven P2P energy trading system

A. Performance Metrics and Detection Process

The loss function is modified, compared to previous work in embedded optimization,13 to prioritize predictive stability to test the multi-objective efficacy of the suggested framework(White, 2023) [18].

Measures of Performance

Predictive and grid performance metrics are combined to assess the AI-driven system:

Forecast Accuracy: Determined by the GRU model's Mean Absolute Percentage Error (MAPE) for forecasting solar generation. Grid Imbalance Factor (GIF): Calculates the average power imbalance between supply and demand following peer-to-peer (P2P) trades. A smaller GIF is preferable(Shan, 2023) [1].

The function of operational loss:

$$L(\theta, \alpha) = LMAPE(\theta) + \lambda 1 Llat(\alpha) + \lambda 2 LGIF(\alpha) \quad (4)$$

In this equation, θ represents the model parameters used for prediction, α represents auxiliary or latency-related parameters, and λ1 and λ2 are regularization weights controlling the influence of the latency loss Llat(α) and the GIF loss LGIF(α) relative to the main MAPE loss LMAPE(θ). Adapted from embedded optimization methods (Zoph & Le, 2017), balancing accuracy, latency, and grid stability(White, 2023) [18].

Model Used: The proposed system is built on a Gated Recurrent Unit neural network-a variant of the RNN designed to handle time-series prediction with a much smaller number of parameters compared to LSTM. The GRU captures temporal dependencies in the solar power generation and energy consumption data while maintaining low computational cost, making it ideal for edge deployment on devices like the NVIDIA Jetson Xavier NX(Chen et al., 2022) [8].

Algorithm: The model was trained using the Adam optimization algorithm, a learning rate of 0.001, and Mean Absolute Percentage Error (MAPE) as the main loss function. The architecture includes

Input layer: 8 time-dependent features including solar irradiance, temperature, humidity, past load, time index etc.

Hidden layers: Two GRU layers of 64 and 32 units each

Output layer: Single neuron with linear activation predicting 15-minute-ahead energy surplus or deficit

The model minimizes a multi-objective loss combining prediction error, grid imbalance (GIF), and latency:

$$L(\theta, \alpha) = LMAPE(\theta) + \lambda 1 Llat(\alpha) + \lambda 2 LGIF(\alpha) \quad (5)$$

Dataset Used: This involves training and testing on the following components: TMY3 stands for Typical Meteorological Year, a real-world weather dataset that provides solar irradiance, temperature, and humidity for a period of five years.

Synthetic Load Profiles: obtain real realistic residential and commercial demand data to simulate a 50-node microgrid.

Temporal Resolution: Data is resampled at 15-minute intervals in order to align with grid dispatch and trading cycles. The dataset was split 80:20 for training and testing, respectively. Accordingly, early stopping was implemented based on the validation loss.

Key Explanation: The GRU model was selected over LSTM due to the fact it has lower inference latency, taking 42 ms as opposed to 63 ms, besides faster convergence; thus, all predictions fall within the required <100 ms decision window for real-time P2P trading.

Transaction Procedure

T-15 min: A Balancing Signal (BS) for the subsequent interval is produced by the AI Engine (GRU).

T-14 min: BS is received by the AI Oracle contract

T-10 min: The Auto-Trading Contract locks in a price and volume commitment between a consumer and a prosumer by carrying out the predictive P2P trade.

T min: The commitment determines how physical energy flows.

T+1 min: The final actual flow is reported by smart meters. The contract determines the GIF and settles payments.

IV. Results and Evaluation

The framework was tested with five years of artificially generated load profiles and TMY3 weather data, simulating a 50-node microgrid (NREL TMY3, 2021) [15]. Comparison is made against two baselines under the same test condition: a Fixed-Price P2P Market (non-predictive) and a Centralized Forecast Market (predictive, but relying on one trusted third party).

The outcomes indicate that, although the AI prediction accuracy (MAPE) is similar to the centralized model, the hybrid AI+Blockchain system gains a 36.8% improvement in the GIF (12.5 to 7.9) over the Centralized Forecast baseline. This proves that high-speed, autonomous execution on the blockchain effectively converts precise predictions to quantifiable grid stability gains. The sub-100 ms Decision Latency is essential for preserving high stability in dynamic systems (Zhang et al., 2023; Wang et al., 2023) [5], [6].

Table I. Performance Comparison of Energy Trading Models in Smart Microgrid

Model	Forecast MAPE (%)	Decision Latency (ms)	Grid Imbalance Factor (GIF)	RE Utilization (%)
Fixed Price P2P	N/A	550.0	18.2	75%
Centralized Forecast	8.8	150.0	12.5	82%
Proposed AI+Blockchain	8.6	95.0	7.9	88%

V. Discussion

This study confirms that the best way for intelligent energy management(Dai et al., 2023) is by combining autonomous blockchain execution with predictive machine learning at the edge. The low decision latency of 95 ms makes the trade commitment in time to impact physical grid stability in the next interval(Wang et al., 2023) [6]. Besides being used for making predictions, the AI model has to provide the unreliable input needed to trigger the smart contract, thus overcoming the intermittency problem plaguing microgrids that rely heavily on renewable energy sources.

VI. Conclusion

This paper successfully developed and validated an AI-driven P2P blockchain trading framework that redefines automation and intelligence in smart microgrids. The GRU-based lightweight forecasting engine coupled with autonomous blockchain execution reduced the Grid Imbalance Factor by 36.8% and increased renewable energy utilization by more than 13%, compared to conventional P2P and centralized forecast models. In addition, the decision latency was reduced to less than 100 milliseconds, realizing real-time trade commitments, thereby directly influencing grid stability before the occurrence of any imbalance. These quantitative gains underscore the system's ability to convert accurate AI predictions to immediate, verifiable, and trustless trading actions—bridging the long-standing gap between forecasting and execution. The architecture demonstrated superior scalability, predictive reliability, and energy efficiency, proving its viability for real-world deployment in microgrids. Overall, this study sets a new standard for decentralised, predictive energy trading systems and paves the way for adaptive Deep Reinforcement Learning improvements in the future.

References

[1] Y. Zhang, J. Wang, and Q. Zhou, “Deep reinforcement learning–based adaptive pricing for blockchain-enabled smart microgrids,” IEEE Transactions on Smart Grid, vol. 14, no. 2, pp. 1231–1243, 2023.

[2] N. Wang, Y. Xu, and L. Zhang, “Decentralized P2P energy trading model based on blockchain and edge computing in smart grids,” Energy Reports, vol. 7, pp. 4001–4015, 2023.

[3] S. Lee, H. Park, and T. Kim, “Federated learning for privacy-aware predictive control in microgrids,” IEEE Access, vol. 12, pp. 58231–58245, 2024.

[4] R. Chen, Q. Liu, and Z. Huang, “Edge-optimized GRU and LSTM models for low-latency renewable-energy forecasting,” Energies, vol. 15, no. 3, p. 1132, 2022.

[5] H. Dai, X. Li, and F. Zhou, “Hybrid PoA–dBFT consensus for secure blockchain-based energy trading,” IEEE Internet of Things Journal, vol. 10, no. 15, pp. 13412–13425, 2023.

[6] A. K. Vishwakarma, “Blockchain-based peer-to-peer renewable energy trading: traceability and security,” International Journal of Energy Research, 2024.

[7] J. Gupta, “Policy and pilots for P2P energy trading in India,” Sustainability, vol. 15, p. 13633, 2023.