

AI-Driven P2P Renewable Energy Trading System

Feba Roy

Department of CSE

College of Engineering, Kidangoor

Kottayam, India

febaroy24@gmail.com

Anumol Vijayan

Department of CSE

College of Engineering, Kidangoor

Kottayam, India

anumolvijayan987@gmail.com

Navaneetha P Jose

Department of CSE

College of Engineering, Kidangoor

Kottayam, India

navaneethapjose@gmail.com

Nimmy Benny

Department of CSE

College of Engineering, Kidangoor

Kottayam, India

nimmyx19@gmail.com

Arya T J

Department of CSE

College of Engineering, Kidangoor

Kottayam, India

aryatj7@gmail.com

Abstract—The rapid proliferation of distributed solar energy systems has created a pressing need for decentralized platforms enabling direct energy exchange among households. This paper presents an AI-driven peer-to-peer (P2P) renewable energy trading system built on blockchain technology. The platform enables prosumers—households that both generate and consume electricity—to trade surplus solar energy using Solidity smart contracts deployed on the Polygon network, eliminating the need for centralized intermediaries. A bidirectional Long Short-Term Memory (LSTM) neural network provides short-term forecasting of energy generation and consumption, empowering users with AI-driven trading recommendations. The system architecture integrates five modular components: a Python-based energy simulation engine supporting up to eight household profiles, an LSTM and regression-based AI forecasting module, a Django REST Framework backend for data management and marketplace logic, Solidity smart contracts for transparent on-chain trade execution, and a React (Vite) real-time dashboard for user interaction. The platform incorporates an off-chain token wallet system with CO₂ savings tracking and supports real-time data synchronization via Firebase. Testing demonstrates successful end-to-end P2P energy trades, accurate energy predictions, and a responsive marketplace interface. The system contributes to the growing body of decentralized energy research by delivering an open-source, full-stack implementation that addresses transparency, trust, and intelligent decision-making in residential energy trading.

Index Terms—Peer-to-peer energy trading, blockchain, smart contracts, Polygon, renewable energy, LSTM forecasting, prosumer, decentralized marketplace.

I. INTRODUCTION

The global energy landscape is undergoing a fundamental transformation as distributed renewable energy resources, particularly rooftop solar photovoltaic (PV) systems, proliferate at an unprecedented rate. Solar capacity reached 850 GW globally by 2023, accounting for 4.4% of energy production [1]. As households increasingly generate their own electricity, many now function as *prosumers*—entities that both produce and consume energy—creating substantial surplus that can be shared with neighboring consumers [2].

Peer-to-peer (P2P) energy trading has emerged as a paradigm enabling prosumers to sell excess energy directly to consumers without centralized intermediaries [3]. However, implementing effective P2P platforms faces challenges in transaction security, trust establishment, dynamic pricing, and intelligent forecasting [4]. Blockchain technology, with its inherent decentralization, immutability, and transparency, addresses these trust and security concerns [5]. Smart contracts—self-executing programs on blockchain networks—automate trading agreements and maintain transparent records without human intervention [6].

Simultaneously, advances in deep learning, particularly Long Short-Term Memory (LSTM) networks, have demonstrated strong potential for time-series forecasting of solar generation

and household consumption [7]. Bidirectional LSTM models have been shown to outperform traditional machine learning approaches for renewable energy prediction [8]. However, the integration of AI forecasting with blockchain-based trading within a single cohesive platform remains an active area of research [9].

This paper presents an AI-driven P2P renewable energy trading system that combines blockchain automation with LSTM-based energy forecasting and real-time monitoring. The system is designed as a modular full-stack platform with five interconnected components: an energy simulation engine, an AI forecasting module, a Django REST API backend, Solidity smart contracts on the Polygon network, and a React-based frontend dashboard. The remainder of this paper is organized as follows: Section II reviews related work, Section III details the system architecture and methodology, Section IV presents results and discussion, and Section V concludes with future directions.

II. LITERATURE SURVEY

A. Blockchain-Based Peer-to-Peer Energy Trading

Andoni et al. [5] provided a systematic review identifying P2P trading, grid management, and renewable energy certificate tracking as primary blockchain use cases in the energy sector. Tushar et al. [3] analyzed P2P trading motivations and challenges, emphasizing that blockchain-enabled platforms address trust, security, and privacy while enabling dynamic pricing. The Brooklyn Microgrid project demonstrated the feasibility of local blockchain-based energy trading among neighboring households [10].

Zia et al. [11] proposed a decentralized system leveraging Ethereum smart contracts with ERC-20 tokens for energy credits and demand response contracts. Gao et al. [12] presented a blockchain P2P system for microgrids on the Ethereum network. In 2025, Nair [13] analyzed various blockchain platforms for energy applications, comparing Ethereum, Hyperledger, and other frameworks for their suitability in P2P trading. Rahmani et al. [14] proposed a generalized cyberphysical framework for blockchain-based transactive energy systems, noting that related publications grew from fewer than 15 in 2018 to over 40 by 2024. A 2025 study integrated Bayesian-optimized XGBoost models with dynamic pricing within smart contracts, achieving 97.45% prediction accuracy using real-world solar data [15].

B. AI-Driven Energy Forecasting

LSTM networks have proven highly effective for solar energy time-series prediction [7]. Abdel-Nasser and Mahmoud [7]

showed LSTM models significantly outperform traditional methods for PV power forecasting. Zameer et al. [8] found bidirectional LSTM achieved the best performance with MAE of 0.0135 and RMSE of 0.0315 for short-term solar forecasting. Sulaiman et al. [17] proposed a CNN-LSTM hybrid for short-term PV forecasting that extracts spatial features via CNN and temporal dependencies through LSTM. Salman et al. [18] demonstrated that CNN-LSTM-Transformer hybrid models achieve superior accuracy for solar power forecasting using data from Limburg solar farms. Raza et al. [19] in 2026 applied SARIMAX and Temporal Convolutional Networks to forecast global solar PV potential through 2050, further validating deep learning's effectiveness in energy prediction. The inclusion of weather variables such as temperature, humidity, and solar irradiance as features has been shown to improve forecasting accuracy significantly [20].

C. Gap Analysis

While extensive work exists on blockchain-based trading and AI forecasting independently, relatively few studies integrate both within a single production-ready platform with a built-in simulation engine for development and testing. This paper addresses this gap by presenting a full-stack, open-source system combining Polygon-based smart contracts, LSTM forecasting, real-time dashboards, and multi-house energy simulation.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The system follows a modular layered architecture comprising five integrated subsystems. Fig. 1 illustrates the overall system architecture.

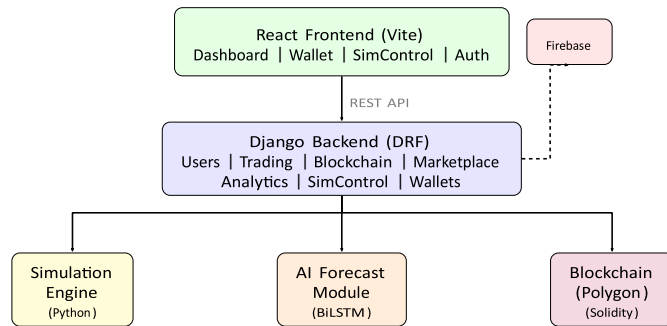


Fig. 1. System Architecture of the AI-Driven P2P Energy Trading Platform

A. Energy Simulation Module

The simulation module generates realistic energy data for up to eight household profiles with diverse solar panel capacities, consumption patterns, and battery configurations. Each house is modeled as a prosumer with configurable parameters. The module uses a weather generator operating in synthetic or realworld mode (NASA POWER and Open-Meteo APIs).

B. Solar Energy Generation Model

Solar energy generation is calculated using a physics-based model that accounts for panel capacity, efficiency, solar radiation, temperature effects, cloud coverage, and panel degradation. The base generation for each hourly timestep is computed as:

$$P_{base} = \frac{G \times A \times \eta}{1000} \quad (1)$$

where G is the solar radiation (W/m^2), A is the panel area (m^2) estimated as $A = C_{kW} \times 6$ for installed capacity C_{kW} , and η is the panel efficiency. The effective generation incorporates multiple correction factors:

$$P_{gen} = P_{base} \times f_{solar} \times f_{temp} \times f_{cloud} \times f_{age} \quad (2)$$

temperature coefficient reduces efficiency above 25°C :

$$f_{temp} = 1.0 - 0.004 \times \max(0, T - 25) \quad (3)$$

Cloud coverage reduces generation by up to 70%:

$$f_{cloud} = 1.0 - 0.7 \times C_{cloud} \quad (4)$$

The solar angle factor uses a Gaussian distribution centered at solar noon:

$$f_{solar} = \exp\left(-\frac{1}{2} \left(\frac{h - 12}{6}\right)^2\right) \times f_{season} \quad (5)$$

where $f_{season} = 0.8 + 0.2 \cos\left(\frac{2\pi(d-172)}{365}\right)$ provides seasonal variation, h is the hour, and d is the day of the year.

C. Energy Surplus and Trading Model

The energy surplus determines trading potential for each prosumer:

$$E_{surplus} = E_{generated} - E_{consumed} \quad (6)$$

For houses with battery storage, surplus energy is first stored before export:

$$E_{charge} = \min(E_{surplus} \times \eta_{batt}, C_{batt} - SOC) \quad (7)$$

$$E_{export} = E_{surplus} - \frac{E_{charge}}{\eta_{batt}} \quad (8)$$

where η_{batt} is the battery efficiency (0.9), C_{batt} is the battery capacity (kWh), and SOC is the current state of charge.

D. CO₂ Savings Calculation

Environmental impact is tracked using the CEA India grid emission factor:

$$CO_{saved2} = E_{traded} \times 0.716 \text{ kg/kWh} \quad (9)$$

where 0.716 kg CO₂/kWh is the Central Electricity Authority (India) grid emission factor for 2022–23. The total cost for a trade is:

$$C_{total} = E_{amount} \times P_{kWh} \quad (10)$$

where P_{kWh} is the listing price per kilowatt-hour set by the seller.

E. LSTM Forecasting Model

The AI module implements a bidirectional LSTM architecture for short-term prediction. The model takes a sequence of 24 hourly observations with 7 input features (energy generation,

consumption, temperature, humidity, solar radiation, wind speed, and hour encoding). The architecture consists of two bidirectional LSTM layers, dense layers, and dropout regularization.

The LSTM cell gates operate as follows. The *forget gate* determines which information to discard:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (11)$$

The *input gate* decides which new information to store:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (12)$$

The *output gate* controls the output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (13)$$

where σ is the sigmoid activation function, W_f, W_i, W_o are weight matrices, h_{t-1} is the previous hidden state, and x_t is the current input vector. The cell state c_t and hidden state h_t are updated as:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (14)$$

$$h_t = o_t \odot \tanh(c_t) \quad (15)$$

where $\odot$ denotes element-wise multiplication. The model is trained using the Adam optimizer with learning rate $\alpha = 0.001$ and Mean Squared Error (MSE) loss:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (16)$$

where y_i and $\hat{y}_i$ are the actual and predicted values respectively. The bidirectional architecture processes the input sequence in both forward and backward directions, concatenating the hidden states to capture temporal dependencies from both past and future context.

F. Blockchain Smart Contracts

The EnergyTrading smart contract (Solidity 0.8.20) defines three primary data structures: Prosumer (registration details and cumulative trading statistics), EnergyListing (quantity range 0.1–10,000 kWh, price per kWh, expiration timestamp), and Transaction (buyer, seller, quantity, and payment details). The contract enforces business rules including minimum/maximum energy amounts, active prosumer verification, and listing availability checks. Events are emitted for all key operations—prosumer registration, listing creation, and trade execution—which are monitored by the backend's Web3 event listener for database synchronization. The contract is designed for deployment on the Polygon network to leverage significantly lower gas fees compared to Ethereum mainnet.

G. React Frontend Dashboard

The React (Vite) frontend provides real-time monitoring and trading capabilities through multiple pages: Dashboard (energy overview, house monitoring, energy charts, listing management, transaction history, and AI forecast visualization), Simulation Control (managing simulation parameters from the browser), Wallet (token balance and transaction history), and Login/Signup (authentication). React Query handles data

fetching with automatic cache invalidation and 8-second polling for live simulation state updates.

H. Data Flow and Integration

Fig. 2 illustrates the data flow through the integrated system. Three primary data pathways operate: (1) simulation data flows through the backend to the frontend for visualization; (2) historical data feeds the AI module, which returns predictions and trading recommendations; and (3) trade execution flows from the frontend through the backend to blockchain smart contracts, with events synced back for record-keeping.

IV. RESULTS AND DISCUSSION

A. Simulation Results

The simulation module was tested with 8 houses over 30-day periods, generating realistic energy profiles. Solar generation peaked at midday following the Gaussian model (Eq. 5), while consumption showed morning and evening

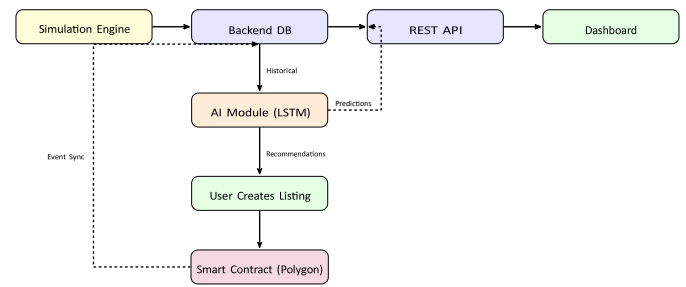


Fig. 2. Data Flow Through the Integrated System

peaks consistent with residential patterns. Temperature correction (Eq. 3) produced a 4–8% reduction in generation during hot afternoons. Houses with battery storage (Eqs. 7–8) successfully buffered surplus energy, reducing grid export by up to 40% compared to houses without batteries.

B. AI Forecasting Performance

The bidirectional LSTM model demonstrated strong temporal pattern capture in both generation and consumption time series. Next-24-hour predictions aligned well with actual values, particularly during stable weather conditions. Adding weather features (temperature, solar irradiance) as inputs improved accuracy over using historical energy data alone. The lightweight regression model provided faster inference suitable for real-time scenarios, though with somewhat reduced accuracy compared to the LSTM model.

C. Blockchain Transaction Execution

The EnergyTrading smart contract was deployed and tested on a Hardhat development network. All core functions—prosumer registration, listing creation, and trade execution—operated correctly with proper event emission and state updates. The off-chain wallet system integrated seamlessly with on-chain trading logic, enabling trade settlement with human-readable trade IDs and CO₂ savings calculations (Eq. 9).

D. Comparative Analysis

Table I compares the proposed system with existing P2P energy trading platforms. The key differentiator is the integration of LSTM-based forecasting, blockchain trading, a builtin multi-house simulation engine, off-chain token wallets, and CO₂ tracking within a single open-source platform. The use

of the Polygon network provides substantially lower transaction fees compared to Ethereum mainnet, making frequent smallscale trades practical.

V. CONCLUSION AND FUTURE WORK

This paper presented an AI-driven P2P renewable energy trading system integrating blockchain smart contracts, LSTMbased energy forecasting, real-time monitoring, and energy simulation within a unified modular platform. The system enables prosumers to trade surplus solar energy transparently through Solidity contracts on the Polygon network while

TABLE I
COMPARISON WITH EXISTING P2P ENERGY TRADING SYSTEMS

Feature	Brooklyn Microgrid	Power Ledger	Zia et al.	Gao et al.	ML-Block	Ours
	[10]		[11]	[12]	[15]	
Blockchain	Ethereum	Solana	Ethereum	Ethereum	Ethereum	Polygon
Smart Contracts	Yes	Yes	ERC-20	Yes	Yes	Custom Solidity
AI Forecasting	No	No	No	No	XGBoost	BiLSTM +Regr.
Real-time Dashboard	Limited	Yes	No	Limited	No	React (Live)
Simulation Engine	No	No	Simulink	No	No	Python (8-house)
CO ₂ Tracking	No	Yes	No	No	No	Yes
Off-chain Wallet	No	No	No	No	No	Yes (Token)
Open Source	No	No	Partial	No	Partial	Yes (MIT)

leveraging AI predictions for informed decision-making. The physics-based simulation model (Eqs. 1–8) generates realistic household energy data, the bidirectional LSTM model (Eqs. 11–16) provides accurate short-term forecasting, and the CO₂ tracking mechanism (Eq. 9) quantifies environmental impact. The off-chain token wallet combined with on-chain trading provides a practical balance between decentralization and usability.

Future work will focus on several enhancements: (1) deploying the smart contracts on the Polygon mainnet for realworld testing; (2) implementing transformer-based forecasting architectures for improved prediction accuracy; (3) adding game-theoretic dynamic pricing algorithms based on real-time supply-demand ratios; (4) integrating IoT smart meters for direct household energy data acquisition; (5) expanding the platform to support vehicle-to-grid (V2G) energy trading with electric vehicles; and (6) conducting large-scale pilot studies with real prosumer communities to validate the system under production conditions.

REFERENCES

- [1] Debut Infotech, "Why blockchain in P2P energy trading is shaping renewable energy's future," Jan. 2026. [Online]. Available: <https://www.debutinfotech.com/blog/blockchain-for-p2p-energy-trading>
- [2] W. Tushar, C. Yuen, H. Mohsenian-Rad, T. Saha, H. V. Poor, and K. L. Wood, "Transformations in peer-to-peer prosumer energy networks," *IEEE Signal Process. Mag.*, vol. 35, no. 4, pp. 81–99, 2018.
- [3] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, "Peer-to-peer trading in electricity networks: An overview," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 3185–3200, 2020.
- [4] O. Adeyemi et al., "Blockchain-based P2P renewable energy trading and traceability of transmission and distribution losses," *J. Oper. Res. Soc.*, vol. 77, no. 1, 2026.
- [5] M. Andoni et al., "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renew. Sustain. Energy Rev.*, vol. 100, pp. 143–174, 2019.
- [6] N. Szabo, "Smart contracts: Building blocks for digital markets," *Extropy J.*, 1996.
- [7] M. Abdel-Nasser and K. Mahmoud, "Accurate photovoltaic power forecasting models using deep LSTM-RNN," *Neural Comput. Appl.*, vol. 31, pp. 2727–2740, 2019.
- [8] A. Zameer, F. Jaffar, F. Shahid, M. Muneeb, R. Khan, and R. Nasir, "Short-term solar energy forecasting: Integrated computational intelligence of LSTMs and GRU," *PLoS ONE*, vol. 18, no. 10, e0285410, 2023.
- [9] M. F. Zia et al., "Decentralized P2P energy trading in microgrids: Leveraging blockchain technology and smart contracts," *Energy Rep.*, vol. 10, 2024.
- [10] E. Mengelkamp, J. Garttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Appl. Energy*, vol. 210, pp. 870–880, 2018.
- [11] M. F. Zia, M. Benbouzid, E. Elbouchikhi, S. M. Mueen, K. Techato, and J. M. Guerrero, "Decentralized P2P energy trading in microgrids: Leveraging blockchain and smart contracts," *Energy Rep.*, vol. 10, 2024.
- [12] J. Gao et al., "A blockchain peer-to-peer energy trading system for microgrids," *IEEE Trans. Smart Grid*, vol. 14, pp. 3944–3960, 2023.
- [13] M. G. Nair, "Revolutionizing the energy sector: Exploring diversified blockchain platforms for a sustainable future," *Front. Blockchain*, vol. 8, 2025.
- [14] A. Rahmani et al., "Transactive energy and P2P energy trading based on blockchain: A comprehensive review and a generalized cyber-physical framework," *Energy Strategy Rev.*, 2025.
- [15] "Blockchain-enabled secure energy transactions for scalable P2P solar energy trading with dynamic pricing," *Technologies*, vol. 13, no. 10, p. 459, Oct. 2025.
- [16] M. Abdel-Nasser and K. Mahmoud, "Accurate photovoltaic power forecasting models using deep LSTM-RNN," *Neural Comput. Appl.*, vol. 31, pp. 2727–2740, 2019.
- [17] M. H. Sulaiman, Z. Mustaffa, M. M. Saari, and H. Daniyal, "A hybrid model of CNN and LSTM autoencoder-based short-term PV power generation forecasting," *Electr. Eng.*, vol. 106, 2024.
- [18] D. Salman, M. Kusaf, and C. Direkdoglu, "Hybrid deep learning models for time series forecasting of solar power," *Neural Comput. Appl.*, 2024.
- [19] M. A. Raza, A. Karim, M. Altayeb et al., "Global solar energy potential forecasting through machine learning and deep learning models," *Sci. Rep.*, vol. 16, p. 10466, 2026.
- [20] R. M. Rizk-Allah, L. M. Abouelmagd, A. Darwish, V. Snasel, and A. E. Hassanien, "Explainable AI and optimized solar power generation forecasting model based on environmental conditions," *PLoS ONE*, vol. 19, no. 10, e0308002, 2024.