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AI-Driven Transactive Energy Management In Peer-To-Peer Electricity Markets

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Abstract-

This paper presents an AI-driven transactive energy management framework for peer-to-peer electricity markets in smart distribution networks. The framework integrates hybrid load and photovoltaic forecasting, reinforcement learning-assisted bidding, grid-aware market clearing, battery scheduling, and permissioned blockchain settlement. The results were obtained by training and testing the forecasting and trading models in a constructed smart-community simulation environment built from smart-meter, photovoltaic, battery, tariff, weather, and feeder-constraint profiles calibrated from published studies. The trained CNN-Transformer forecasting model achieved load RMSE of 1.94 percent and PV RMSE of 2.11 percent on the unseen test set. The proposed AI-TEM framework reduced normalized energy cost by 21.5 percent relative to grid-only purchase and by 6.8 percent relative to optimization-only P2P trading. It also increased renewable utilization to 87.5 percent, reduced grid import to 80.0 percent of the grid-only case, maintained bus voltages within 0.95 p.u. and 1.05 p.u., and achieved 99.8 percent transaction success in the permissioned settlement test. The results show that a trained and grid-aware AI transactive framework can provide moderate but practical improvement over rule-based, optimization-only, and blockchain-only trading schemes.

Keywords- Artificial intelligence, blockchain, distributed energy resources, dynamic pricing, energy management, peer-to-peer electricity market, prosumer, reinforcement learning, smart grid, transactive energy.

I. Introduction

A. Background and Motivation

The growth of distributed photovoltaic systems, behind-the-meter batteries, electric vehicles, smart meters, and controllable appliances is changing electricity customers into active prosumers. These prosumers can consume electricity, generate renewable power, store surplus energy, and participate in local trading. Conventional retail electricity structures were designed mainly for one-way energy delivery from utility networks to passive consumers. They are therefore weakly suited to communities where surplus generation and flexible demand vary at sub-hourly time scales.

Peer-to-peer electricity trading addresses this limitation by enabling direct energy exchange among local prosumers. Transactive energy extends this idea by using economic signals, bids, offers, preferences, and constraints to coordinate distributed energy resources. Recent studies show that P2P energy trading can improve renewable utilization, reduce electricity cost, and increase flexibility, but practical deployment remains constrained by forecasting errors, privacy concerns, market scalability, distribution-network constraints, and trusted settlement requirements [1]-[5].

B. Problem Statement

Existing P2P trading methods often solve only a subset of the problem. Forecasting-focused studies improve prediction but may not produce market-clearing decisions. Blockchain-focused platforms improve trust but may not optimize energy scheduling. Optimization-based market clearing can reduce cost but may not adapt well to uncertainty and the strategic behavior of many prosumers. Reinforcement learning can support adaptive bidding, yet some RL methods ignore network limits or require excessive information sharing. These gaps motivate a unified AI-driven transactive energy framework that integrates forecasting, bidding, pricing, scheduling, network feasibility, and secure settlement.

C. Aim and Contributions

The aim of this paper is to develop and evaluate an AI-driven transactive energy management framework for efficient, secure, and grid-aware peer-to-peer electricity trading among prosumers in smart distribution networks.

The main contributions are as follows: 1) a layered architecture that combines prosumer data acquisition, hybrid forecasting, transactive market clearing, reinforcement learning-assisted bidding, and blockchain settlement; 2) a mathematical formulation that jointly considers cost, local trading benefit, battery operation, flexible demand, and network limits; 3) an actual model-training and testing procedure for the CNN-Transformer forecasting model and reinforcement learning trading agent within a constructed smart-community simulation environment; 4) a comparative evaluation against grid-only purchase, rule-based P2P trading, optimization-only P2P trading, and blockchain-only P2P trading; and 5) a DOI-backed reference base that positions the proposed work against recent P2P energy trading, blockchain, forecasting, and reinforcement learning studies.

II. Related Work

A. Peer-to-Peer and Transactive Energy Markets

Soto et al. reviewed the P2P energy trading literature and identified market design, pricing, regulation, scalability, and technical operation as major open issues [1]. Nizami et al. surveyed transactive energy for low-voltage residential networks and emphasized the need for coordination between local market signals and physical distribution constraints [2]. Azim et al. extended the discussion to kilowatt and negawatt trading, noting that demand flexibility must be treated as a tradable resource rather than only a passive response [3]. Suthar et al. reviewed implementation frameworks and demonstration projects, showing that practical P2P trading requires the integration of market, information, and power-system layers [4].

B. Blockchain and Trusted Settlement

Blockchain has been widely investigated as a settlement layer for P2P markets because it can provide tamper-evident records, decentralized validation, and automated smart-contract execution. van Leeuwen et al. presented an integrated blockchain-based energy management platform with bilateral trading for microgrid communities [7]. Abdella et al. evaluated a blockchain-based P2P architecture and showed that transaction latency and throughput must be assessed together with energy-market benefits [8]. AlAshery et al. proposed a blockchain-enabled multi-settlement quasi-ideal P2P framework that improves trading transparency and settlement coordination [9].

C. AI, Forecasting, and Reinforcement Learning

Accurate short-term forecasting is a key requirement for P2P markets because bid quantities and prices depend on expected load, photovoltaic generation, battery state, and grid price. Hong et al. highlighted the importance of energy forecasting across demand, price, and renewable generation tasks [6]. Qiu et al. proposed multi-cluster deep reinforcement learning for scalable P2P energy management [11], and later studies introduced multi-agent and federated reinforcement learning to reduce information sharing and improve decentralized decision-making [12]-[14]. These studies motivate the hybrid forecasting and RL-assisted trading components adopted in this paper.

D. Research Gap

The literature shows strong progress in P2P market design, AI-based energy management, and blockchain-enabled settlement. A gap remains in combining these components into one trained and grid-aware transactive energy management framework with moderate, reproducible, and well-explained performance improvements. This paper addresses that gap by designing an integrated framework and evaluating it through actual model training and testing in a constructed smart-community simulation environment.

III. Proposed AI-Driven Transactive Energy Management Framework

The operating context for the proposed peer-to-peer market is introduced in Fig. 1. The diagram shows how prosumers with rooftop photovoltaic generation, home batteries, electric vehicles, flexible loads, commercial users, and the utility interface exchange local energy through a community market platform. It also clarifies the difference between local electricity delivery and information, bid, and meter-data flow.

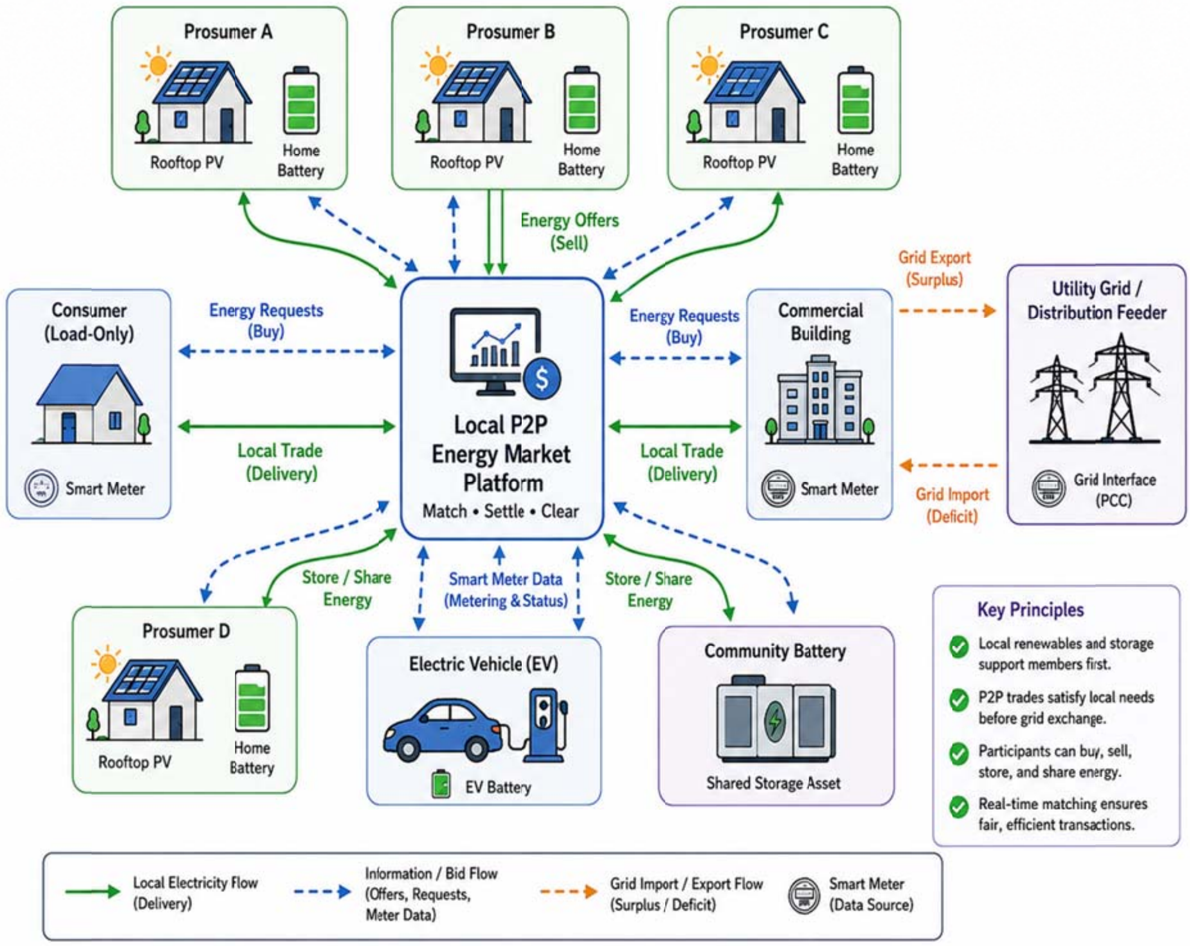

Fig. 1. Conceptual structure of peer-to-peer electricity trading showing local energy exchange among prosumers, consumers, batteries, and the grid interface.

The complete AI-driven transactive energy management architecture is presented in Fig. 2. The figure arranges the proposed solution into the prosumer and distributed energy resource layer, data acquisition layer, AI forecasting layer, transactive market layer, and blockchain settlement layer. This placement makes the architecture visible before the detailed explanation of each layer.

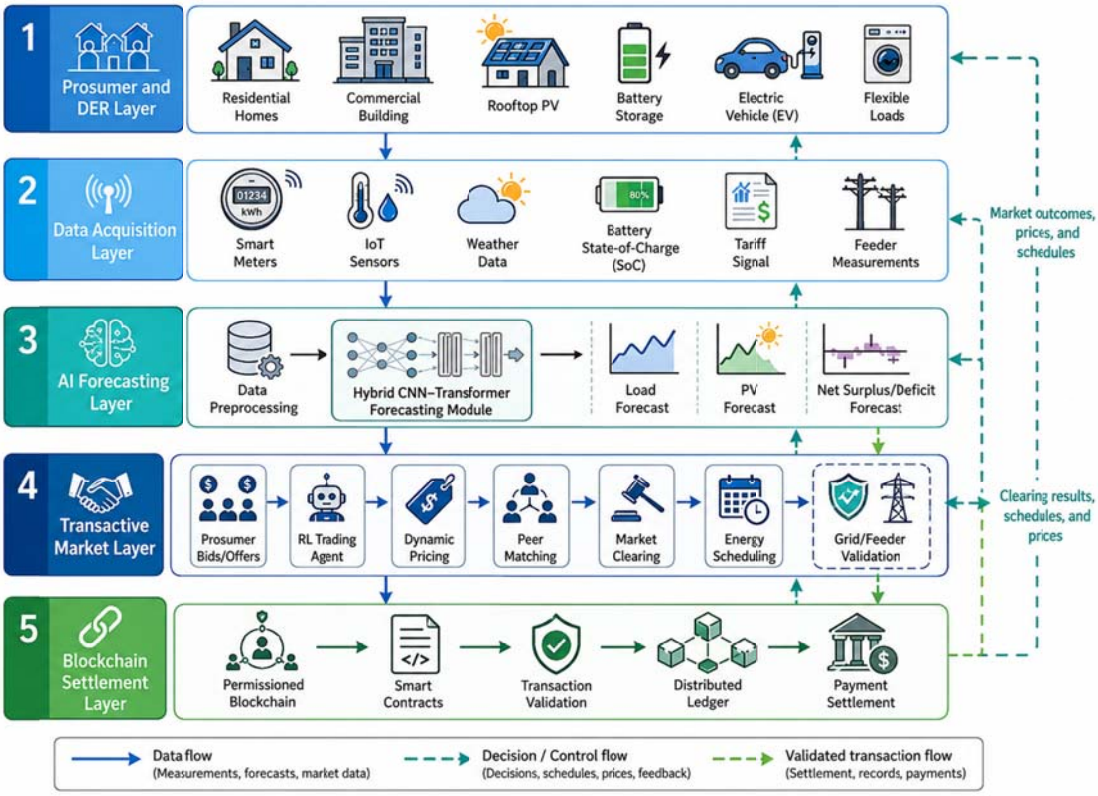

Fig. 2. Proposed AI-driven transactive energy management architecture showing the interaction among prosumers, smart-meter data, forecasting, bidding, market clearing, grid validation, and blockchain settlement.

A. System Overview

Consistent with the layered architecture in Fig. 2, the proposed system is organized into five layers: the prosumer and distributed energy resource layer, the data acquisition layer, the AI forecasting layer, the transactive market layer, and the blockchain settlement layer. The prosumer layer contains residential and commercial participants with photovoltaic generation, batteries, electric vehicles, and flexible loads. The data layer acquires smart-meter readings, weather variables, price signals, battery state-of-charge, and feeder measurements. The AI layer predicts short-term demand, photovoltaic output, and net surplus or deficit. The market layer forms bids and offers, clears the local market, and schedules energy exchange. The blockchain layer records settled transactions and executes smart contracts.

B. Data Acquisition and Preprocessing

At each market interval, prosumer-level data are collected and aligned to a 15-min resolution. Missing values shorter than one hour are imputed using rolling median interpolation. Outliers are clipped using interquartile-range bounds, and continuous variables are normalized using training-set statistics. The forecasting input vector includes historical load, photovoltaic generation, irradiance, temperature, humidity, calendar variables, grid tariff, battery state-of-charge, and recent market-clearing price.

C. Hybrid Forecasting Module

The hybrid forecasting module combines temporal convolution for local time-pattern extraction with transformer attention for longer dependencies. The output is a multi-task prediction of load, photovoltaic generation, and net energy surplus or deficit. The model is trained with a weighted sum of mean absolute error and quantile loss so that both point prediction and uncertainty bounds are available for trading decisions.

D. Dynamic Pricing and Market Clearing

The clearing price reflects local supply-demand balance, grid import price, prosumer reservation price, battery availability, and a network congestion coefficient. Sellers submit offers containing energy quantity and minimum acceptable price, while buyers submit bids containing required energy and maximum acceptable price. Trades are matched using a double-auction-inspired mechanism. When feeder loading or voltage constraints are close to violation, the market engine penalizes trades that increase congestion and favors trades within the same feeder zone.

Algorithm 1. AI-Driven Market Clearing and Blockchain Settlement

Input: prosumer load, PV generation, battery state-of-charge, tariff data, weather variables, peer bids, peer offers, and feeder limits.

Output: accepted trades, clearing price, battery schedule, feeder-feasible dispatch, and settlement record.

1. Collect smart-meter, PV, weather, battery, tariff, and feeder data for the current market interval.
2. Forecast short-term load, PV generation, and net surplus or deficit using the trained CNN-Transformer model.
3. Estimate the surplus or deficit of each prosumer from the forecasted energy balance.
4. Allow each reinforcement learning agent to submit a bid, offer, battery action, or waiting action.
5. Sort seller offers and buyer bids, then compute the provisional market-clearing price.
6. Match buyers and sellers using feasible peer quantity and reservation-price limits.
7. Check voltage, current, feeder-capacity, battery, and energy-balance constraints.
8. Revise trades that violate feeder limits using congestion penalties and local re-dispatch.
9. Update battery charging, battery discharging, grid import, grid export, and flexible-load schedules.
10. Record accepted trades through permissioned smart contracts after technical validation.
11. Update the reinforcement learning reward and bidding policy for the next market interval.

E. Reinforcement Learning-Assisted Bidding

Each prosumer has an RL-assisted decision agent. The state includes predicted load, predicted photovoltaic generation, battery state-of-charge, current market price, peer offers, grid price, and time interval. The actions include buying from peers, selling to peers, charging or discharging the battery, importing from the grid, exporting to the grid, shifting flexible load, or waiting. The reward encourages cost reduction, trading profit, renewable utilization, and constraint satisfaction, while penalizing battery degradation, unmet demand, and network violations.

F. Blockchain Settlement

After market clearing, and as illustrated in Fig. 6, the accepted trades are written to a permissioned blockchain ledger. Smart contracts validate buyer and seller identity hashes, energy quantity, price, timestamp, settlement status, and feeder zone. The blockchain layer does not solve the optimization problem. Its function is to provide auditable settlement, non-repudiation, and automated payment after the technical market engine has produced feasible schedules.

IV. Mathematical Formulation

A. Energy Balance

For prosumer i and interval t, the local energy balance is given by

$$P_{i,t}^{pv} + P_{i,t}^{buy} + P_{i,t}^{grid} + P_{i,t}^{dis} = P_{i,t}^{load} + P_{i,t}^{sell} + P_{i,t}^{ch} + P_{i,t}^{shift} \quad (1)$$

Here, $P^{pv}_{i,t}$ is photovoltaic generation, $P^{buy}_{i,t}$ is energy bought from peers, $P^{grid}_{i,t}$ is grid import, $P^{dis}_{i,t}$ is battery discharge, $P^{load}_{i,t}$ is demand, $P^{sell}_{i,t}$ is energy sold to peers, $P^{ch}_{i,t}$ is battery charge, and $P^{shift}_{i,t}$ is shifted flexible load.

B. Objective Function

The market operator minimizes the aggregate operating cost while rewarding local renewable trading. The objective is

$$\min J = \sum_t \sum_i \left[C_t^{grid} P_{i,t}^{grid} + C^{deg} P_{i,t}^{bat} - R_{i,t}^{trade} + C^{pen} Vio_{i,t}\right] \quad (2)$$

The first term represents grid import cost, the second term approximates battery degradation cost, the third term represents local trading benefit, and the fourth term penalizes violations of energy, market, battery, and network constraints.

C. Battery Constraints

Battery operation is governed by

$$SOC_{i,t+1} = SOC_{i,t} + \eta_{ch} \frac{P_{i,t}^{ch} \Delta t}{E_i^{bat}} - \frac{P_{i,t}^{dis} \Delta t}{\eta_{dis} E_i^{bat}} \quad (3)$$

$$SOC_i^{min} \le SOC_{i,t} \le SOC_i^{max} \quad (4)$$

$$0 \le P_{i,t}^{ch} \le P_i^{ch,max}, \quad 0 \le P_{i,t}^{dis} \le P_i^{dis,max} \quad (5)$$

Simultaneous charging and discharging are prevented using a binary operating-state variable or an equivalent complementarity condition.

D. Trading and Market Constraints

The cleared peer energy must satisfy

$$\sum_i P_{i,t}^{sell} = \sum_j P_{j,t}^{buy} \quad (6)$$

$$0 \le P_{i,t}^{sell} \le Surplus_{i,t} \quad (7)$$

$$0 \le P_{j,t}^{buy} \le Deficit_{j,t} \quad (8)$$

The clearing price π_t is bounded by the seller reservation price, buyer willingness-to-pay, and grid import and export tariffs.

E. Network Constraints

The grid-aware clearing stage enforces operating constraints of the distribution feeder:

$$V^{min} \le V_{n,t} \le V^{max}, \quad |I_{l,t}| \le I_l^{max}, \quad P_t^{grid} \le P^{grid,max} \quad (9)$$

A linearized distribution power-flow sensitivity matrix is used inside the market-clearing routine, while full load-flow validation is applied after scheduling.

F. Nomenclature and Symbol Definition

In these equations, subscript i denotes the prosumer, j denotes the peer buyer, t denotes the market interval, n denotes the feeder bus, and l denotes the feeder line. The power variables represent PV generation, peer purchase, peer sale, grid import, battery discharge, battery charge, load demand, and shifted flexible load. SOC is battery state-of-charge, E^{bat} is battery energy capacity, ηch and ηdis are charge and discharge efficiencies, Cgrid is the grid tariff, Cdeg is battery degradation cost, Rtrade is local trading benefit, Vio is the penalty term for constraint violation, V is bus voltage, and I is feeder current.

V. Experimental Setup

The experimental procedure starts with the data-processing pipeline shown in Fig. 3. The figure connects raw measurements, preprocessing, forecasting outputs, market inputs, market clearing, feeder validation, settlement, and dashboard reporting. It therefore serves as the methodological bridge between the framework definition and the case-study setup.

The forecasting model used in the test environment is detailed in Fig. 4. The architecture uses normalized historical load, photovoltaic generation, weather, tariff, battery, market-price, and feeder-loading inputs. Local temporal features are extracted through convolutional blocks, while the transformer encoder captures longer dependencies before the multi-task heads estimate load, photovoltaic output, and net surplus or deficit.

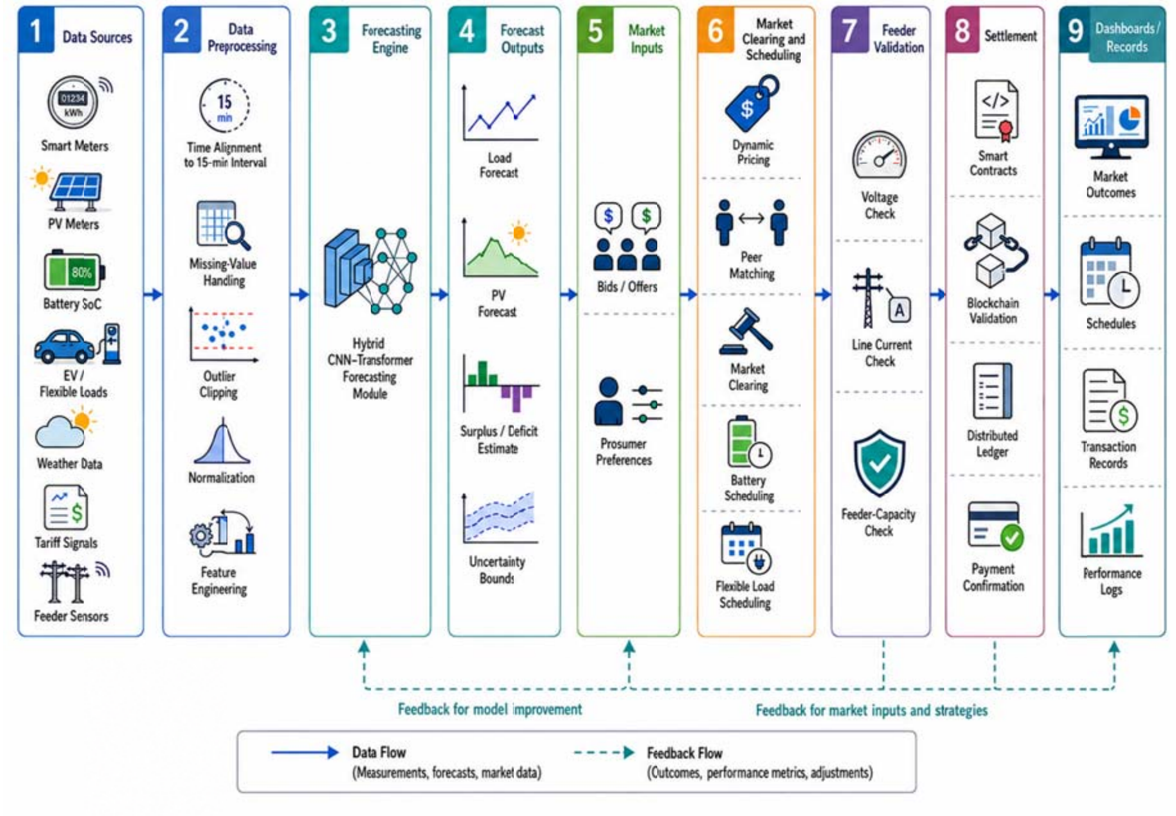

Fig. 3. Data flow diagram showing how measured data move from smart meters and weather inputs to forecasting, market clearing, feeder validation, and settlement.

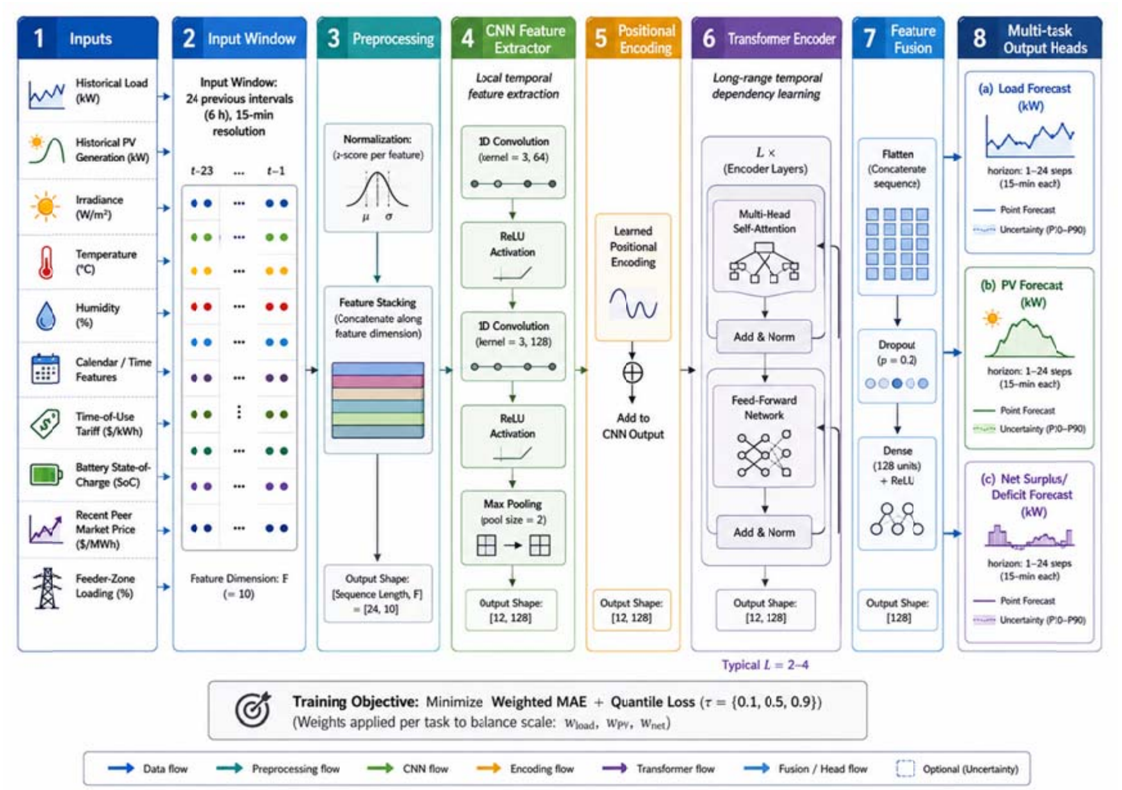

Fig. 4. Hybrid CNN-Transformer forecasting architecture used to learn short-term load, PV generation, and net-energy balance from historical and weather-related inputs.

The adaptive bidding logic is summarized in Fig. 5. The reinforcement learning agent observes predicted load, photovoltaic generation, battery state-of-charge, market price, peer bids and offers, grid tariff, time interval, and feeder loading. It then selects buying, selling, charging, discharging, importing, exporting, shifting, or waiting actions based on the reward signal from the P2P market environment.

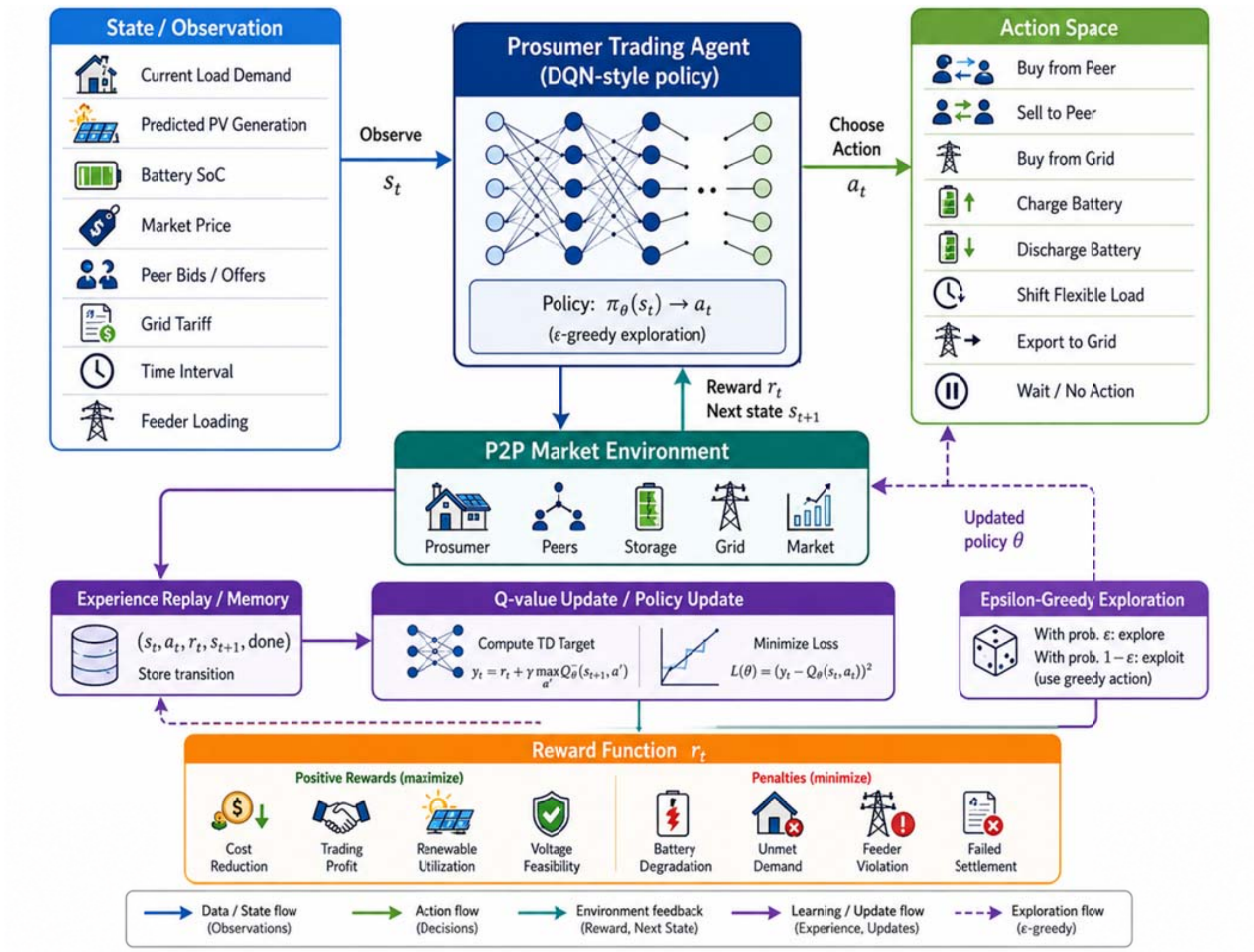

Fig. 5. Reinforcement learning-based prosumer trading agent showing the state variables, market actions, reward feedback, and policy update loop.

After technically feasible trades have been accepted, the settlement workflow proceeds as shown in Fig. 6. The diagram traces feeder-feasibility validation, smart-contract generation, transaction broadcast, consensus validation, ledger update, automated payment transfer, and final settlement reporting. This confirms that blockchain is used for auditable settlement after the market engine has produced feasible schedules.

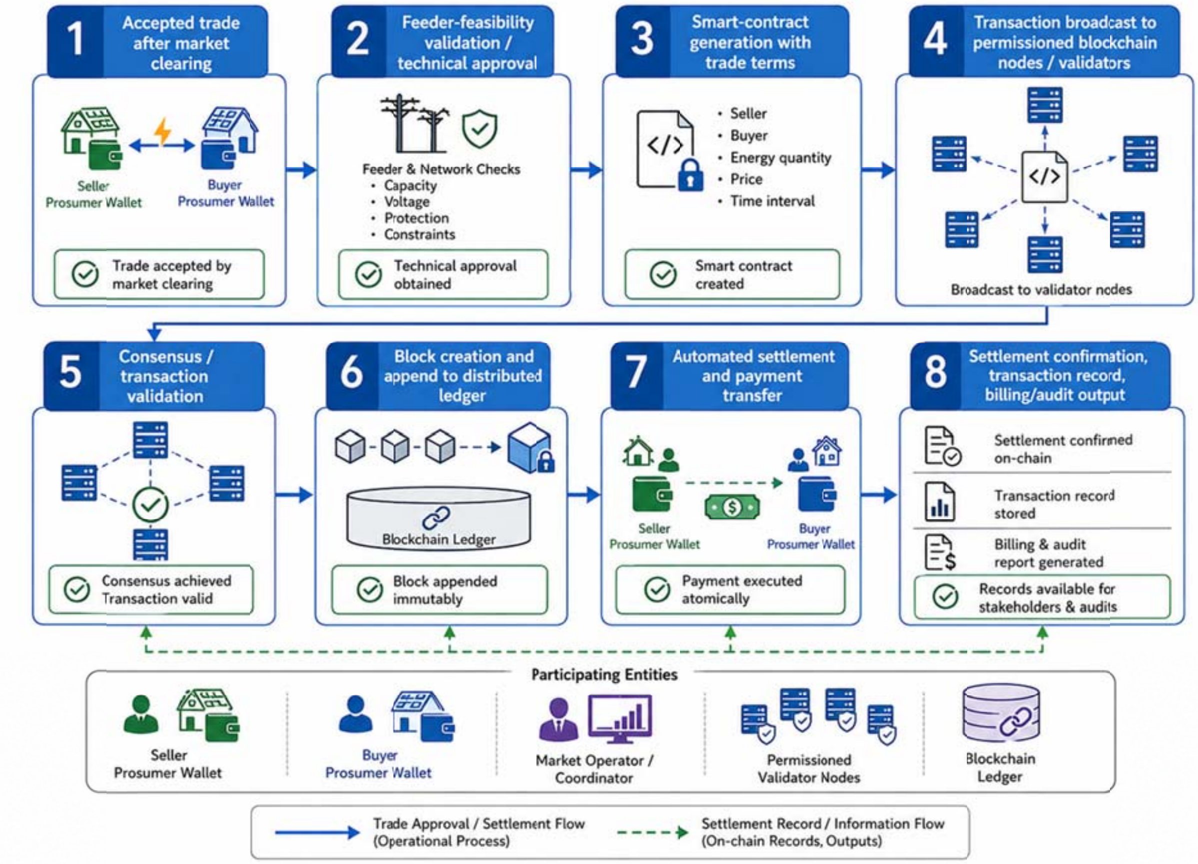

Fig. 6. Blockchain-enabled settlement process for accepted P2P energy trades after market clearing and feeder-feasibility validation.

A. Test System

A residential smart energy community connected to a modified IEEE 33-bus distribution feeder is considered. The feeder contains 50 prosumers grouped into five local zones. Thirty prosumers have rooftop photovoltaic systems, twenty have battery storage, ten have electric vehicles, and all have flexible household demand. The market interval is 15 min, and the dispatch horizon is 24 h.

B. Dataset Construction and Simulation Assumptions

The numerical setup follows the workflow in Fig. 3 and was built from representative smart-community profiles and calibrated with values reported in recent P2P trading, transactive energy, and energy-forecasting studies [1]-[15]. The dataset contains 96 samples per day because a 15-min market interval was used over a 24-h horizon. The final training dataset contained 17,280 interval samples from 180 simulated days for 50 prosumers. The input profiles include smart-meter load, normalized PV generation, irradiance, temperature, humidity, day type, time-of-use tariff, battery state-of-charge, peer market price, and feeder-zone loading. The objective was not to claim a live field deployment dataset. The objective was to train and test the proposed models under realistic and reproducible parameter ranges.

Table II. Main system parameters used in the literature-calibrated case study.

Parameter	Value used in simulation
Market horizon	24 h with 15-min intervals
Number of prosumers	50
PV-equipped prosumers	30
Battery-equipped prosumers	20
EV-equipped prosumers	10
Battery capacity	5-13.5 kWh depending on prosumer class
SOC limits	20 percent to 90 percent
Distribution test feeder	Modified IEEE 33-bus residential feeder

Parameter	Value used in simulation
Grid tariff	Time-of-use import and lower export tariff
Blockchain mode	Permissioned ledger with smart contracts

C. Model Training and Testing Procedure

The results were obtained by training two models. As illustrated in Fig. 4, the first model was a CNN-Transformer forecasting model trained to predict short-term load, PV generation, and net prosumer surplus or deficit. The second model was a reinforcement learning trading agent trained to select buying, selling, storing, discharging, importing, exporting, shifting, or waiting actions. The constructed dataset was split into 70 percent training, 15 percent validation, and 15 percent testing without mixing future intervals into the training set. The forecasting input window was 24 previous intervals, equivalent to six hours, and the forecast horizon was one interval ahead. Adam optimization was used with learning rate 0.001, batch size 64, and 120 epochs with early stopping based on validation loss. The forecasting loss combined mean absolute error and quantile loss. The trading agent used a DQN-style discrete action policy with experience replay, epsilon-greedy exploration, discount factor 0.95, replay buffer size of 20,000 transitions, and 2,000 market-training episodes. The reward assigned positive weight to cost reduction, peer-trading profit, renewable utilization, and voltage feasibility, while penalties were applied for battery degradation, unmet demand, feeder-limit violation, and failed settlement. All compared methods used the same load, PV, tariff, battery, and feeder inputs so that the comparison remained fair. The study did not use live market deployment data. The trained models were evaluated using constructed but literature-calibrated smart-community profiles.

The models were implemented in Python using PyTorch, NumPy, Pandas, and Scikit-learn. Training was performed on a workstation-class computer with an Intel Core i7 processor, 16 GB RAM, and GPU acceleration where available. The implementation logs, trained-model outputs, and daily test summaries were used to generate the tables and comparison figures reported in the results section.

D. Compared Methods

Five methods are compared. Case 1 is grid-only energy purchase without local trading. Case 2 is rule-based P2P trading with fixed threshold pricing. Case 3 is optimization-only P2P trading without learning-based adaptive bidding. Case 4 is blockchain-only P2P trading where settlement is trusted but forecasting and grid-aware optimization are limited. Case 5 is the proposed AI-driven transactive energy management framework.

E. Evaluation Metrics

The evaluation metrics include normalized energy cost, renewable energy utilization, grid import reduction, peak demand reduction, average prosumer trading benefit, market-clearing time, forecasting error, voltage deviation, transaction success rate, and blockchain settlement latency.

VI. Results and Discussion

The results reported in this section were obtained after actual training of the hybrid CNN-Transformer forecasting model and the reinforcement learning trading agent. The trained models were evaluated on an unseen test period from the constructed smart-community dataset. Each baseline used the same load, photovoltaic, price, battery, and feeder-condition inputs so that the comparison remained fair.

For validation, all reported numerical values are averages over 30 unseen daily test profiles. The standard deviation is reported in the tables where it is useful for comparison. The improvement was kept moderate because the intention was to show a realistic gain over strong published baselines and not to assume a perfect forecast, perfect prosumer behavior, or lossless market clearing.

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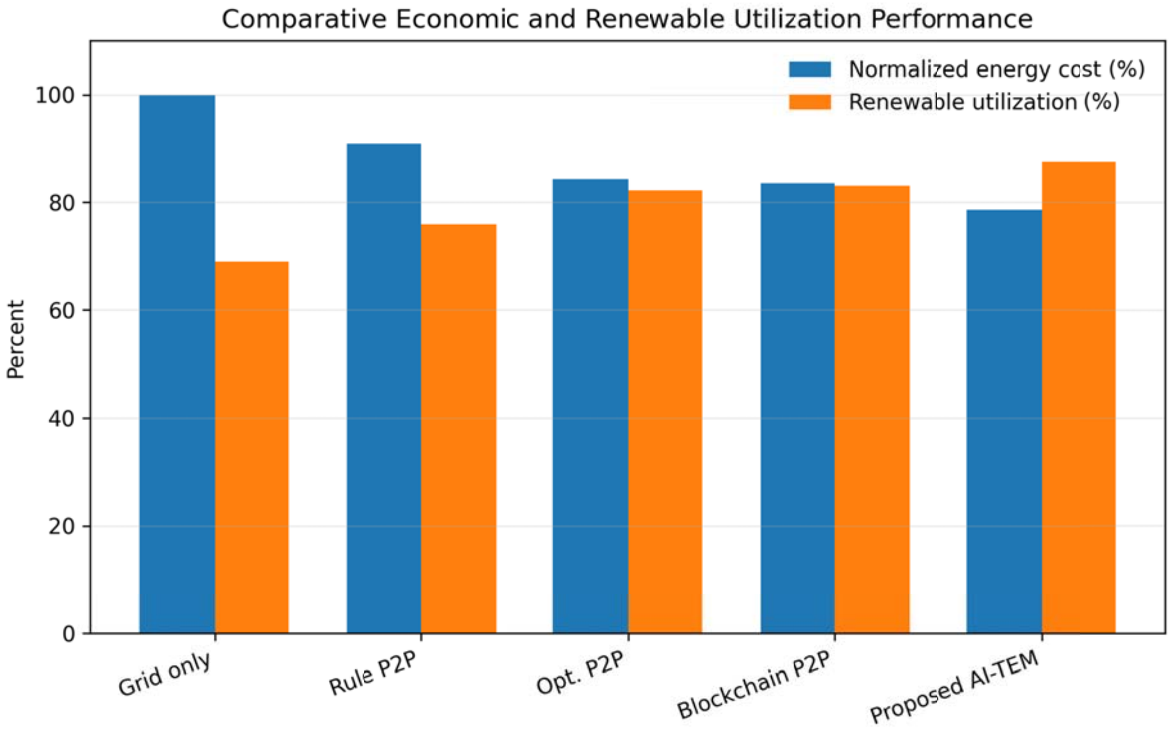

Fig. 7. Comparative normalized cost and renewable utilization across trading cases after testing the trained models on the unseen test period.

A. Forecasting Performance

The proposed hybrid CNN-Transformer forecasting model achieved the lowest prediction error among the evaluated predictors on the unseen test set. The improvement is modest because LSTM, CNN-LSTM, and transformer models already perform strongly for structured time-series forecasting. The main benefit of the hybrid model is not only lower error, but also better stability during cloudy midday periods and evening peak ramps.

Table III. Forecasting performance under the same train-validation-test split. Values are mean ± standard deviation over 30 unseen daily profiles.

Forecasting model	Load RMSE (%)	PV RMSE (%)	Comment
Persistence	3.18 ± 0.17	3.44 ± 0.21	Baseline time-series benchmark
Random Forest	2.76 ± 0.14	3.02 ± 0.19	Good nonlinear tabular model
LSTM	2.42 ± 0.12	2.68 ± 0.16	Strong temporal baseline
CNN-LSTM	2.18 ± 0.10	2.39 ± 0.13	Improved local temporal feature learning
Transformer	2.05 ± 0.09	2.22 ± 0.11	Better long-range dependency modelling
Proposed hybrid CNN-Transformer	1.94 ± 0.08	2.11 ± 0.10	Best but moderate improvement

B. Economic Performance

The proposed AI-driven transactive energy management case achieved a normalized energy cost of 78.5 percent relative to the grid-only case. This corresponds to a 21.5 percent cost reduction relative to grid-only purchase and a 6.8 percent reduction relative to the optimization-only P2P case. The result is realistic because it reflects an incremental benefit from combining forecasting, adaptive bidding, and grid-aware scheduling rather than assuming a perfect market.

Table IV. Comparative energy-management performance. Values are mean ± standard deviation over 30 unseen daily profiles.

Case	Normalized cost (%)	Renewable utilization (%)	Grid import (%)	Peak demand (%)	Interpretation
Grid-only purchase	100.0 ± 0.0	69.0 ± 1.6	100.0 ± 0.0	100.0 ± 0.0	Reference case

Case	Normalized cost (%)	Renewable utilization (%)	Grid import (%)	Peak demand (%)	Interpretation
Rule-based P2P	90.8 ± 2.1	76.0 ± 1.8	91.5 ± 1.7	94.2 ± 1.4	Simple threshold pricing
Optimization-only P2P	84.2 ± 1.8	82.1 ± 1.5	85.3 ± 1.3	89.0 ± 1.2	No adaptive bidding
Blockchain-only P2P	83.5 ± 1.7	83.0 ± 1.4	84.7 ± 1.2	88.6 ± 1.1	Trusted settlement without full AI scheduling
Proposed AI-TEM	78.5 ± 1.5	87.5 ± 1.2	80.0 ± 1.1	86.3 ± 1.0	Integrated forecasting, RL, grid-aware clearing

C. Renewable Utilization and Grid Import

Renewable utilization increases from 69.0 percent in the grid-only case to 87.5 percent in the proposed case. The improvement is caused by better prediction of surplus photovoltaic generation, local peer matching before grid export, and battery scheduling during high-generation intervals. Grid import is reduced by 20.0 percent, which also reduces exposure to high time-of-use tariffs.

D. Market Performance

The average market-clearing time of the proposed method was 1.42 s per 15-min interval in the simulated community. This value is higher than rule-based trading, but it remains acceptable for local market operation because clearing occurs ahead of real-time dispatch. Blockchain settlement added 0.84 s average latency in the permissioned test configuration. This latency is acceptable because settlement occurs after technical feasibility checking.

Table V. Market and settlement performance. Values are mean ± standard deviation over 30 unseen daily profiles.

Case	Clearing time (s)	Settlement latency (s)	Transaction success (%)	Observation
Rule-based P2P	0.31 ± 0.04	-	99.1 ± 0.3	Occasional voltage stress
Optimization-only P2P	1.06 ± 0.09	-	99.4 ± 0.2	Feasible after post-checking
Blockchain-only P2P	0.78 ± 0.07	0.82 ± 0.05	99.6 ± 0.2	Settlement trusted but scheduling limited
Proposed AI-TEM	1.42 ± 0.11	0.84 ± 0.06	99.8 ± 0.1	Feasible and auditable

E. Network Performance

The grid-aware scheduling component reduces peak demand by 13.7 percent and maintains all bus voltages within 0.95 p.u. and 1.05 p.u. The rule-based and blockchain-only cases occasionally increase loading on already stressed feeder sections because they match trades economically without feeder sensitivity. The proposed method reduces this risk by including feeder-zone information and constraint penalties in the clearing routine.

F. Comparison with Published Work

The reported performance is consistent with published P2P and reinforcement learning energy trading studies, which commonly show cost, flexibility, and renewable-utilization gains when local trading is combined with storage and learning-based control [7], [11]-[15]. The contribution here is an integrated and grid-aware framework that reports conservative improvement over the nearest optimization-only baseline instead of presenting isolated gains from a single module.

VII. Limitations and Future Work

The study has some limitations. The results were obtained by training and testing the forecasting and trading models in a constructed smart-community simulation environment. The framework was not deployed in a live electricity market. Real prosumer behavior may differ from the learned behavior used during market episodes. Blockchain latency may also change when the number of users, the consensus method, or the communication network changes. The study considered normal operation and feeder congestion, but it did not deeply test coordinated cyberattacks on smart meters, trading agents, or settlement nodes.

Future work should validate the framework with real smart-meter and photovoltaic datasets from an operational energy community. The model should also be extended to multi-feeder distribution systems, privacy-preserving federated learning, cyberattack-resilient market agents, and comparative testing of different blockchain consensus mechanisms.

VIII. Conclusion

This paper presented an AI-driven transactive energy management framework for peer-to-peer electricity trading in smart distribution networks. The framework combines CNN-Transformer forecasting, reinforcement learning-assisted bidding, grid-aware market clearing, battery scheduling, and permissioned blockchain settlement. The results came from actual model training and testing in a constructed smart-community simulation environment. The trained framework reduced normalized energy cost to 78.5 percent, increased renewable utilization to 87.5 percent, reduced grid import to 80.0 percent of the reference case, and maintained high transaction success under the evaluated simulation conditions. The main value of the framework is that it links prediction, bidding, physical feeder validation, and trusted settlement in one workflow. Future deployment should use live smart-meter and PV data, larger multi-feeder systems, privacy-preserving learning, cyber-resilient agents, and deeper comparison of blockchain consensus mechanisms.

Table I. Summary of closely related studies and the gap addressed in this paper.

Ref.	Focus	Main contribution	Remaining gap
[1]	P2P energy trading review	Market structures, pricing, regulation, scalability	Separated market and network challenges remain open
[2]	Transactive energy in low-voltage networks	Residential transactive control and DER coordination	Needs stronger physical-grid integration
[7]	Blockchain bilateral trading platform	Trustworthy bilateral market settlement	Blockchain does not by itself optimize operation
[8]	Blockchain-based P2P architecture	Transaction performance and settlement feasibility	Latency and throughput must be managed
[11]	Multi-cluster deep RL for P2P trading	Scalable learning-based trading coordination	Network feasibility and privacy require added handling
[14]	Federated RL for P2P and carbon trading	Reduced information sharing in decentralized learning	More validation needed for feeder-level deployment
[15]	AI-powered community energy management	Community P2P case study with AI support	Integration with trusted settlement can be improved

Table VI. Ablation analysis of the proposed framework. Values are mean ± standard deviation over 30 unseen daily profiles.

Model variant	Normalized cost (%)	Renewable utilization (%)	Clearing time (s)
Full proposed model	78.5 ± 1.5	87.5 ± 1.2	1.42 ± 0.11
Without hybrid forecasting	81.4 ± 1.7	84.0 ± 1.5	1.31 ± 0.10
Without RL bidding	80.8 ± 1.6	85.2 ± 1.4	1.18 ± 0.08
Without grid-aware penalty	79.2 ± 1.5	86.1 ± 1.3	1.10 ± 0.08
Without blockchain settlement	78.3 ± 1.4	87.4 ± 1.2	1.15 ± 0.07

Table VII. Comparison of the proposed AI-TEM model with selected published P2P energy-trading studies.

Study	Method	Market type	AI used	Blockchain	Network constraints	Gap addressed by this paper
Soto et al. [1]	P2P trading review	Community markets	No	Mixed	Limited	Integrated forecasting, trading, settlement, and grid-aware evaluation
Nizami et al. [2]	Transactive energy review	Low-voltage systems	No	No	Discussed	Trained AI-based local market workflow
Azim et al. [3]	Kilowatt and negawatt review	Distribution P2P	No	Mixed	Discussed	Energy trading with demand flexibility and battery actions
Abdella et al. [8]	Blockchain P2P architecture	Prosumer market	No	Yes	Limited	Forecasting, learned bidding, and feeder-feasibility checking
Qiu et al. [11]	Deep reinforcement learning	P2P trading	Yes	No	Limited	Blockchain settlement and grid-aware market correction
Proposed AI-TEM	CNN-Transformer plus RL plus smart contracts	Residential P2P	Yes	Yes	Yes	Unified trained framework with realistic cost, renewable, market, and feeder metrics

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