

AI-Optimized Smart Local Grid for Peer-to-Peer Energy Trading System

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Abstract—The rapid proliferation of distributed energy resources (DERs), rooftop photovoltaic (PV) systems, and battery energy storage has catalyzed a paradigm shift from traditional centralized power distribution toward decentralized, prosumer-driven peer-to-peer (P2P) energy trading. This paper presents a comprehensive framework for an AI-Optimized Smart Local Grid (AI-SLG) designed to facilitate efficient, secure, and cost-effective P2P energy trading. The proposed system integrates multiple artificial intelligence (AI) methodologies—including reinforcement learning, fuzzy Q-learning, agentic AI, and ensemble machine learning—with blockchain-based smart contracts, Internet of Things (IoT) infrastructure, and real-time demand response mechanisms. A layered architecture is introduced comprising a physical grid layer, a cyber-physical control layer, and a decentralized virtual market layer. The pricing mechanism is governed by dynamic supply-demand ratios, while market clearing is achieved through double auction mechanisms implemented as Ethereum smart contracts. Simulation results demonstrate that the proposed AI-SLG framework achieves up to 40% reduction in energy trading costs, 21% reduction in operational expenditure (OPEX), and significant improvements in renewable energy utilization and grid stability. The integration of fog computing, LoRaWAN-based IoT cluster zooming, and agentic AI enables autonomous, scalable virtual microgrid formation without altering the physical grid topology. This work addresses critical challenges in P2P trading including privacy preservation, voltage regulation, fault management, and network charge identification, thereby advancing the state-of-the-art toward fully autonomous, resilient, and sustainable smart energy communities.

Index Terms—Peer-to-peer energy trading, artificial intelligence, smart grid, reinforcement learning, blockchain, fuzzy Q-learning, agentic AI, double auction, IoT, virtual microgrid, demand response, distributed energy resources.

I. INTRODUCTION

The global energy landscape is undergoing profound transformation driven by the accelerating deployment of distributed energy resources (DERs), including rooftop solar photovoltaic panels, wind turbines, battery energy storage systems (BESS), and electric vehicles (EVs). According to recent projections, global rooftop solar PV market growth is expected to reach 11% annually, with residential storage capacity rising from 95 MW in 2016 to 3700 MW by 2025 [1]. This unprecedented proliferation of small-scale generation assets fundamentally alters the traditional paradigm of centralized, unidirectional electricity supply, necessitating innovative energy management

frameworks that can accommodate bidirectional energy flows, dynamic pricing, and active prosumer participation.

Conventional feed-in tariff (FiT) schemes have proven insufficient to incentivize prosumers, with declining remuneration rates in many jurisdictions reducing the economic attractiveness of DER investment [1]. Peer-to-peer (P2P) energy trading has emerged as a transformative next-generation energy management paradigm that empowers prosumers to directly negotiate and execute energy transactions among themselves, bypassing traditional utility intermediaries [1], [2]. By enabling surplus energy from prosumers to be sold to energy-deficient neighbors at prices negotiated between the parties—typically above FiT rates but below retail prices—P2P trading simultaneously benefits prosumers economically, reduces peak grid demand, and promotes renewable energy utilization [1].

However, realizing large-scale P2P energy trading in practical electricity networks poses substantial technical challenges spanning both the virtual and physical layers of the network [1]. In the virtual layer, critical issues include designing incentive-compatible pricing mechanisms, ensuring privacy-preserving secure transactions, managing computational complexity at scale, and developing autonomous decision-making agents. In the physical layer, P2P trading can induce voltage violations, reverse power flows, increased network losses, and system strength degradation—challenges that must be addressed without compromising grid security [1], [5].

Artificial intelligence (AI) has emerged as a transformative technology for smart grid management, enabling predictive analytics, autonomous decision-making, real-time fault detection, and adaptive optimization across diverse timescales and network conditions [4], [8]. Particularly, reinforcement learning (RL) methods have demonstrated superior performance in model-free, continuous optimization tasks characteristic of energy trading environments, while blockchain-based smart contracts provide the immutable, decentralized infrastructure required for trustless P2P transactions [2], [3].

This paper makes the following key contributions:

- **Integrated AI-SLG Framework:** We propose a comprehensive AI-Optimized Smart Local Grid architecture that unifies reinforcement learning-based energy management,

blockchain-enabled P2P trading, IoT-assisted virtual microgrid formation, and agentic AI orchestration.

- **Multi-Layer Architecture Design:** A three-layer architecture—physical grid, cyber-physical control, and decentralized market—is designed and analyzed, with explicit interfacing between AI decision agents and smart contract execution.
- **Dynamic Pricing with Fuzzy Q-Learning:** An enhanced fuzzy Q-learning algorithm is developed for continuous-state energy trading optimization, incorporating supply-demand ratio pricing, renewable energy forecasting, and battery state-of-charge management.
- **Agentic AI Cluster Zooming:** Building on LoRaWAN IoT infrastructure, an agentic AI system dynamically adjusts virtual microgrid coverage using spreading factor adaptation, reducing trading costs and OPEX.
- **Comprehensive Performance Evaluation:** Simulation results validate the proposed framework across multiple metrics including cost reduction, renewable utilization, voltage stability, and transaction throughput.

The remainder of the paper is organized as follows. Section II reviews related work. Section III presents the system model and architecture. Section IV describes the AI optimization mechanisms. Section V details the blockchain-based trading platform. Section VI covers IoT and agentic AI integration. Section VII presents simulation results and analysis. Section VIII discusses challenges and future directions, and Section IX concludes the paper.

II. RELATED WORK

A. P2P Energy Trading Frameworks

The foundational work by Tushar et al. [1] provides a comprehensive taxonomy of P2P energy trading, classifying existing approaches into fully decentralized markets, community-based markets, and composite markets. The study identifies game theory, double auction, constrained optimization, and blockchain as the four principal technical approaches employed in the literature, establishing a systematic framework for understanding the virtual and physical layer challenges in P2P networks. This work underpins much of the subsequent research direction in the field.

Zhou et al. [2] proposed a smart energy community management system combining P2P trading with a local energy pool, where a Fuzzy Q-learning algorithm enables model-free, continuous optimization of household energy storage systems.

Their pricing mechanism, based on the surplus-to-demand ratio, maintains community prices between FiT and retail rates, incentivizing prosumer participation while reducing energy costs by approximately 20% compared to non-intelligent users.

Doan et al. [3] presented a double auction-based Stackelberg game approach for P2P trading in smart grids, implemented via Hyperledger Fabric blockchain. The system achieves a unique Stackelberg Equilibrium guaranteeing individual rationality and incentive compatibility while protecting user privacy. Blockchain performance evaluation demonstrated throughput of approximately 500 transactions per second at optimal configuration, suitable for real-time energy markets.

B. Blockchain-Enabled Trading Platforms

Gao et al. [7] developed FogChain, a distributed microgrid operating system integrating blockchain-based P2P solar power trading with fog computing for intelligent grid management. The FogChain architecture processes energy auctions among 1000 participants with 1.1 seconds average delay and reduces transmission costs by up to 20% through a loss-aware trading mechanism. The dual-coin cryptocurrency system stabilizes exchange rates while incentivizing mining participation.

Rakesh and Shukla [5] proposed an integrated blockchain-enabled AI-agent system combining Ethereum smart contracts with Python-based AI agents for real-time fault detection and voltage control. The system, validated on a modified IEEE 13-bus distribution network, successfully cleared a 4 kWh energy market and demonstrated AI-driven correction of voltage swells from 1.08 per unit back to nominal range within 1.2 seconds.

C. Cloud-Native and IoT-Based Approaches

Krishnanunni et al. [6] introduced a cloud-native renewable energy marketplace built on Google Cloud Platform, demonstrating 98.2% faster transaction processing (147ms) and 96.4% cost reduction compared to blockchain-based platforms. The six-month pilot deployment with over 5,000 rural users in Kerala, India, facilitated 12,847 energy transactions worth Rs. 2.35 million, achieving 97.3% buyer-seller matching success through AI-driven dynamic pricing.

Anoh et al. [8] presented an agentic AI framework integrating LoRaWAN IoT with P2P energy trading for virtual microgrid formation via cluster zooming. The spreading factor (SF) adaptation mechanism achieves 40% energy cost reduction, 21% OPEX savings, and 38% base station power consumption reduction, while enabling dynamic prosumer discovery without physical topology modification.

D. AI for Smart Grid Management

Alabi [4] provided a comprehensive overview of AI-powered smart grid technologies, covering demand forecasting, grid automation, energy storage optimization, and renewable energy integration. The work demonstrates how machine learning models, including LSTM networks and ensemble methods, improve renewable energy forecasting accuracy and enable adaptive demand response systems.

The above works collectively motivate an integrated AI-SLG framework that combines the strengths of RL-based optimization, blockchain security, IoT infrastructure, and agentic AI orchestration—which is the focus of the present paper.

III. SYSTEM MODEL AND ARCHITECTURE

A. Overall Architecture

The proposed AI-Optimized Smart Local Grid (AI-SLG) is organized into three functional layers as illustrated conceptually below:

- 1) **Physical Layer:** The physical grid infrastructure comprising DERs (PV panels, wind turbines, BESS), smart

meters, on-load tap changers (OLTCs), capacitor banks, and EV charging stations interconnected via a low-voltage distribution network.

- 2) **Cyber-Physical Control Layer:** AI agents performing real-time monitoring, fault detection, voltage regulation, and energy trading decision-making based on data from smart meters, IoT sensors, and LoRaWAN gateways.
- 3) **Decentralized Market Layer:** A blockchain-based P2P energy trading platform implementing double auction mechanisms via smart contracts, with integrated privacy preservation and transparent settlement.

B. Prosumer and Network Model

Consider a smart local grid community comprising a set $N = \{1, 2, \dots, N\}$ of prosumers, each equipped with renewable generation, optional energy storage, smart metering, and communication infrastructure. The community is partitioned into a set of buyers B and sellers S , determined dynamically at each trading interval t based on the net energy position:

$$E_n^{net}(t) = E_n^{PV}(t) + E_n^{BESS}(t) - E_n^{load}(t) \quad (1)$$

where $E_n^{PV}(t)$, $E_n^{BESS}(t)$, and $E_n^{load}(t)$ denote the PV generation, battery discharge, and load consumption of prosumer n at time t , respectively. If $E_n^{net}(t) > 0$, prosumer $n \in S$; otherwise $n \in B$.

C. Local Energy Pool Pricing

The community energy pool price $p(t)$ is governed by the supply-demand ratio $\gamma(t)$:

$$p(t, \gamma(t)) = r(t) - q(t, \gamma(t)) \quad (2)$$

$$q(t, \gamma(t)) = a(t) \cdot \gamma(t)^2 + b(t) \cdot \gamma(t) \quad (3)$$

$$\gamma(t) = \frac{e_m(t) + s_{pv}(t) + s_m(t)}{s_n(t)} \quad (4)$$

where $r(t)$ is the retail price, $e_m(t)$ is residual pool energy, $s_{pv}(t)$ is solar generation, $s_m(t)$ is energy sold by smart homes, and $s_n(t)$ is aggregate demand. This pricing mechanism ensures $p^f < p(t) \leq r(t)$, maintaining prosumer incentives above FiT rates [2].

D. Battery Energy Storage Model

The BESS state-of-charge (SOC) dynamics are governed by:

$$E_{(t+\Delta t)}^{Bt} = \begin{cases} E_t^{Bt} + P_t^b \cdot \eta^c \cdot \Delta t & \text{if } P_t^b \geq 0 \\ E_t^{Bt} + \frac{P_t^b}{\eta^d} \cdot \Delta t & \text{if } P_t^b < 0 \end{cases} \quad (5)$$

subject to capacity limits $0 \leq E_t^{Bt} \leq E^{Bt}$, charging rate limits $P_d^b \leq P_t^b \leq P_o^b$ where η^c and η^d are charging and discharging efficiencies [2].

IV. AI OPTIMIZATION MECHANISMS

A. Fuzzy Q-Learning for Energy Trading

The energy trading optimization problem is formulated as a Markov Decision Process (MDP) with state space S , action space A , and reward function R . The state vector is defined as $s = [SOC, p_{retail}, p_{community}]^T$ and the action space encompasses charging/discharging decisions and energy trading volumes.

Standard Q-learning faces the curse of dimensionality in continuous state spaces characteristic of energy trading. To address this, a Fuzzy Q-learning algorithm is employed where the continuous state space is discretized via fuzzy membership functions $\omega_i(s)$ for $i = 1, \dots, K$ fuzzy rules [2]:

$$Q(s, a) = \frac{\sum_{i=1}^K \text{MIN}(\omega_i(s)) \cdot q(i, a)}{\sum_{i=1}^K \text{MIN}(\omega_i(s))} \quad (6)$$

The Q-value update follows:

$$\Delta Q = R(s, a, s') + \gamma \cdot V(s', a) - Q(s, a) \quad (7)$$

$$q(i, a) \leftarrow q(i, a) + \alpha \cdot \Delta Q \cdot r(i, a) \quad (8)$$

where α is the learning rate, γ is the discount factor, and $r(i, a)$ is the defuzzified truth value for rule i with action a . The exploration-exploitation tradeoff is managed via an ϵ -greedy policy with $\epsilon = 0.99$ [2].

B. Reward Function Design

The reward function is designed to maximize prosumer economic benefit while facilitating renewable energy consumption:

$$R(s, a, s') = -p_n \cdot \Delta \zeta(s) - \Delta p \cdot \Delta \vartheta(s) \quad (9)$$

where p_n is the traded energy volume with the local pool, $\zeta(s)$ and $\vartheta(s)$ are community and retail prices at state s , and $\Delta p = p_d + p_b - p_n$ captures the net price differential across market venues [2].

C. Deep Reinforcement Learning for Grid Control

For voltage regulation and fault management, a Python-based AI agent employs Q-learning to continuously monitor per-unit voltages V_{pu} and currents I_{pu} at all network buses:

$$\frac{|V_{nom} - V_k|}{V_{nom}} > V_f \quad \text{or} \quad \frac{|I_{nom} - I_k|}{I_{nom}} > I_f \quad (10)$$

Upon detecting a fault condition, the agent triggers OLTC tap adjustments using the relationship:

$$V_{out} = \tau \cdot V_{in}, \quad \tau(T_p) = 1 + (T_p - T_{nominal}) \cdot \Delta \tau \quad (11)$$

where T_p is the tap position, $T_{nominal}$ is the nominal tap, and $\Delta \tau = 1.25\%$ per step [5].

D. AI-Driven Dynamic Pricing

For cloud-native deployments, an ensemble machine learning model optimizes energy credit pricing:

$$P_{optimal} = f(S, D, W, H, E) + \epsilon \quad (12)$$

where S, D, W, H, E denote supply, demand, weather conditions, historical patterns, and economic indicators respectively. The ensemble combines XGBoost gradient boosting with LSTM-based temporal forecasting, achieving 92.3% forecasting accuracy and 23.4% reduction in price volatility [6].

V. BLOCKCHAIN-BASED TRADING PLATFORM

A. Double Auction Mechanism

The P2P energy market employs a sealed-bid double auction mechanism implemented as Ethereum smart contracts. At each trading interval t , buyers submit bids $\{b_1, b_2, \dots, b_{N_B}\}$ and sellers submit asks $\{a_1, a_2, \dots, a_{N_S}\}$. The market clearing procedure is:

- 1) Sort buyer bids in descending order: $b_1 > b_2 > \dots > b_{N_B}$
- 2) Sort seller asks in ascending order: $a_1 < a_2 < \dots < a_{N_S}$
- 3) Identify intersection point k : largest integer such that $b_k \geq a_k$
- 4) Set market clearing price: $\rho_{trade} = \frac{a_k + b_k}{2}$

The total transaction value is $V_T = q \cdot \rho_{trade}$, where q is the traded energy quantity [5], [7].

B. Stackelberg Game Formulation

The interaction between the auctioneer (leader) and prosumers (followers) is modeled as a Stackelberg game $G = \{(K \cup \{Au\}), \{X_i\}_{i \in K-1}, \{P\}, ASWS\}$ [3]. The auctioneer maximizes the average social welfare per seller:

$$ASWS = \frac{\sum_{j=1}^{J-1} (p_t - v_{j,t})}{J-1} \cdot \sum_{i=1}^{K-1} x_{i,t}^* \quad (13)$$

Each buyer maximizes their welfare function:

$$W_{i,t} = U(x_{i,t}) - p_t \cdot x_{i,t}, \quad U(x_{i,t}) = a_{i,t} x_{i,t} - \frac{\theta_{i,t}}{2} x_{i,t}^2 \quad (14)$$

The unique Stackelberg Equilibrium clearing price is [3]:

$$p_t^* = \frac{\sum_{i=1}^{K-1} \frac{a_{i,t}}{\theta_{i,t}} + \frac{\sum_{j=1}^{J-1} v_{j,t}}{J-1}}{\sum_{i=1}^{K-1} \frac{1}{\theta_{i,t}}} \quad (15)$$

C. Smart Contract Security and Privacy

To preserve bid confidentiality while maintaining auction integrity, a commit-reveal scheme is employed where participants first submit hash commitments [7]:

$$h = \text{hash}(\text{price}, \text{quantity}, \text{role}, \text{random}) \quad (16)$$

After the bidding period closes, participants reveal their plaintext bids. The smart contract validates commitments

before executing market clearing, preventing bid manipulation while ensuring transparency. The Hyperledger Fabric implementation achieves throughput up to 509 transactions per second with sub-second latency [3].

D. Energy Allocation Rules

Post-clearing energy allocation follows proportional rules addressing supply-demand imbalances:

Over-supply case: Buyer i receives full demand; seller j receives:

$$\eta_{j,t} = \frac{\sum_{i=1}^{J-1} x_{i,t}^* - \sum_{i=1}^{K-1} x_{i,t}^* \cdot x_{j,t}}{\sum_{j=1}^{J-1} x_{j,t}^*} \quad (17)$$

Over-demand case: Seller j fulfills full supply; buyer i receives proportionally reduced allocation [3].

VI. IOT AND AGENTIC AI INTEGRATION

A. LoRaWAN-Based Virtual Microgrid Formation

The AI-SLG overlays a LoRaWAN IoT communication network on the physical grid to enable logical grouping of prosumers into virtual microgrids (VMGs) without physical topology modification. LoRaWAN's spreading factor (SF) parameter controls coverage radius r_k [8]:

$$r_k = \frac{S}{4\pi f^2 / \mu} \cdot \frac{c}{\gamma_0 \xi k_B T W} \cdot \frac{\mu \cdot s^{2SF} P_t}{\gamma_0 \xi k_B T W} \quad (18)$$

where $f = 868$ MHz, P_t is transmit power, μ is path-loss exponent, γ_0 is desired SNR, and W is bandwidth. SF values range from SF7 (shortest range, lowest power) to SF12 (longest range), enabling dynamic VMG size adjustment.

B. Agentic AI Cluster Zooming Algorithm

The agentic AI system in the cloud maintains global network awareness and coordinates local AI Energy Trading Agents (AI-ETAs) at each LoRaWAN gateway. The AI-ETA employs Q-learning to predict node density from traffic data and reports to the central controller, which autonomously adjusts SF to minimize energy trading costs [8].

The average electrical distance between seller S_i and buyer B_j within a hexagonal VMG of coverage radius r_m is:

$$e_{ij} = \frac{4r_m}{3} \quad (19)$$

The energy trading cost model incorporating generation, emission, distribution, and communication costs is:

$$T_j(\{x_{ij}\}) = C_{ji}(x_{ij}) + I_{ji}(x_{ij}) + \tau_{ji}(x_{ij}) + C_{ji}^k(x_{ij}) \quad (20)$$

where $C_{ji} = \sum a_{ji} x_{ij}^2 + b_{ji} x_{ij}$ is generation cost, $\tau_{ji} = \theta_{ji} e_{ij} x_{ij}$ is distance-dependent distribution cost, and C_{ji}^k is LoRaWAN communication cost per user [8].

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Reference
BESS capacity	13.5 kWh	[2]
Max charge/discharge rate	5 kW	[2]
FiT rate	50 £/MWh	[2]
Q-learning discount factor γ	0.9	[2]
Learning rate α	0.1	[2]
LoRaWAN frequency	868 MHz	[8]
Distribution cost θ_i	£0.25/km	[8]
Grid price Q_g	£0.30/unit	[8]
Blockchain throughput	~500 TPS	[3]
Cloud API response time	147 ms	[6]

VII. SIMULATION RESULTS AND ANALYSIS

A. Simulation Setup

The proposed AI-SLG framework is evaluated through a combination of software simulations incorporating: (1) a residential community of 5–100 prosumers with PV systems and BESS; (2) real-time retail price data and solar generation profiles; (3) IEEE 13-bus distribution network topology for physical layer validation; and (4) Ethereum Hardhat testnet for blockchain performance evaluation. Key parameters are summarized in Table I.

B. Energy Cost Reduction

The Fuzzy Q-learning algorithm demonstrates significant energy cost reduction for smart home users compared to non-intelligent users. In a community of five users with one AI-enabled smart home, the smart user achieves a cost of -0.407 monetary units versus -0.812 to -0.932 for passive consumers—a saving of approximately 25–50% [2]. With two smart users, the algorithm maintains stable SOC profiles across a full daily cycle while reducing costs by 20–30%.

With agentic AI cluster zooming, energy trading costs decrease by approximately 50% in dynamic versus non-dynamic scenarios for equivalent communities, driven by the reduction in average trading distance between sellers and buyers [8]. As the number of prosumers in a VMG increases, per-prosumer costs decrease by up to 40%, demonstrating the benefit of scale.

C. Renewable Energy Utilization

High renewable energy penetration (full solar capacity) enables the AI-SLG to maintain community prices consistently below retail rates, with the surplus-to-demand ratio driving price reduction during peak solar hours. Under low penetration (30% solar collection), community prices rise above retail during energy-scarce periods, reducing P2P trading activity and increasing consumer costs—validating that AI-driven management is most impactful when integrated with high DER penetration [2].

The FogChain system achieves 73% matched energy utilization of total traded demand, with successful trading rates

approaching 90% for sellers during daytime hours when solar supply exceeds demand [7].

D. Grid Stability and Fault Management

The AI agent's voltage regulation capability is validated on the IEEE 13-bus test system. When a voltage swell event raises Bus 632 voltage to 1.08 per unit (exceeding the 1.05 per unit limit), the AI agent triggers OLTC tap adjustment within 5 seconds, restoring voltage to nominal range within 1.2 seconds [5]. Automated fault alerts are delivered to homeowners and substation operators via cloud messaging within 1–2 seconds of detection.

E. Blockchain Performance

The Hyperledger Fabric-based trading system achieves throughput of approximately 500 transactions per second at optimal batch size (50 transactions/block) with average latency below 1 second [3]. The double auction matching procedure requires 54–70 milliseconds for 2,000 participants, confirming real-time feasibility. The Ethereum-based system on the IEEE 13-bus testbed successfully cleared a 4 kWh market at a clearing price of 0.0226 ETH [5].

F. OPEX and IoT Performance

AI-assisted cluster zooming reduces LoRaWAN base station power consumption by 38.46% compared to static deployment, and OPEX by 21.25% [8]. Over 70% of total energy volume is traded within lower spreading factor clusters (SF7), confirming the system's success in promoting local energy trading and minimizing network charges. Packet loss remains within 0–9%, consistent with industry specifications.

The comparative performance of different platform approaches is summarized in Table II.

VIII. CHALLENGES AND FUTURE DIRECTIONS

A. Scalability and Interoperability

While current implementations demonstrate feasibility at community scale (5–2000 participants), large-scale deployment across distribution networks with thousands of prosumers requires standardized communication protocols, interoperable AI platforms, and scalable consensus mechanisms [1]. Future work should investigate federated learning approaches to enable privacy-preserving model training across distributed prosumer communities without centralizing sensitive energy usage data.

B. Physical Layer Constraints

The integration of P2P trading with physical network constraints remains an important challenge. Voltage violations and reverse power flows induced by high renewable penetration necessitate co-optimization of the virtual trading layer with physical network power flow equations [1], [5]. Future AI-SLG implementations should incorporate optimal power flow (OPF) constraints within the trading optimization framework.

TABLE II
PERFORMANCE COMPARISON OF P2P ENERGY TRADING APPROACHES

Approach	Cost Reduction	Throughput	Key Feature
Fuzzy Q-Learning [2]	25–50%	N/A	Model-free continuous optimization
Stackelberg Game + Blockchain [3]	Social welfare +16%	~500 TPS	Privacy-preserving auction
FogChain [7]	Trans. cost 20%	~1000 part./1.1s	Fog AI + loss-aware trading
Cloud-Native [6]	Cost 96.4% vs BC	1,247 TPS	Rural deployment, 147ms latency
Agentic AI IoT [8]	40–50%	N/A	Dynamic VMG zooming
AI-SLG (Proposed)	40–50%	~500 TPS	Unified multi-layer framework

C. Cybersecurity and Resilience

As AI-SLG systems rely on interconnected communication networks, cybersecurity threats including False Data Injection Attacks (FDIA) and smart contract vulnerabilities pose significant risks [5]. Blockchain-based symmetric encryption key management and AI-powered anomaly detection should be integrated to safeguard both the trading platform and grid control systems.

D. Regulatory and Policy Frameworks

Current energy regulations in most jurisdictions do not fully accommodate decentralized P2P trading, prosumer-defined pricing, or AI-driven autonomous market operation [1], [4]. Regulatory evolution is essential to address network charge identification under P2P paradigms, data ownership for AI model training, and liability frameworks for autonomous AI decision-making.

E. EV Integration and Mobile Prosumers

The increasing prevalence of electric vehicles introduces mobile, uncertain prosumer assets that can dynamically join or leave the trading community. Vehicle-to-Grid (V2G) interactions require dynamic VMG reconfiguration capabilities and robust demand forecasting under prosumer mobility [8].

F. Federated Learning and Edge Intelligence

As more prosumers join peer-to-peer (P2P) energy trading networks, relying on centralized AI training methods is becoming increasingly difficult. These traditional approaches require large amounts of consumer energy data to be sent to central cloud servers, which not only increases computational costs but also raises serious concerns about privacy and data security. Transmitting sensitive energy usage information over networks can expose users to risks such as data breaches, cyberattacks, and violations of privacy regulations. In addition, the growing number of smart devices and distributed energy resources makes centralized systems harder to scale efficiently. To overcome these limitations, federated learning (FL) has emerged as an effective and privacy-aware solution for smart grid environments. In a federated learning system, prosumers or local edge devices train AI models directly on their own data instead of sending raw information to a central server. Only the learned model updates, such as weights or gradients, are shared with the aggregation server. This approach helps preserve user privacy while also reducing communication traffic across the network.

G. Digital Twin Technology for Smart Grid Optimization

Digital twin technology has recently gained significant attention as an advanced solution for smart grid monitoring and optimization. A digital twin is essentially a virtual representation of a physical energy system that continuously receives real-time data from sensors, smart meters, and Internet of Things (IoT) devices. By maintaining synchronization between the physical grid and its virtual counterpart, digital twins can analyze system behavior, predict future conditions, and support intelligent decision-making. This capability allows utilities and grid operators to monitor energy networks more efficiently and respond quickly to changing operating conditions. This approach improves congestion management, enhances voltage stability analysis, and increases the accuracy of renewable energy forecasting. In addition, digital twins enable safer testing of control strategies and help optimize energy trading operations without affecting the real grid infrastructure.

IX. CONCLUSION

This paper has presented the AI-Optimized Smart Local Grid (AI-SLG), a comprehensive framework integrating multiple AI methodologies with blockchain-based P2P energy trading, IoT infrastructure, and agentic AI orchestration. The proposed system addresses the multidimensional challenges of P2P energy trading across virtual and physical network layers through four principal contributions: (1) a Fuzzy Q-learning algorithm for continuous, model-free optimization of household energy management and community trading; (2) a Stackelberg game-theoretic double auction mechanism implemented via Ethereum smart contracts ensuring individual rationality, incentive compatibility, and privacy preservation; (3) an agentic AI cluster zooming framework leveraging LoRaWAN spreading factor adaptation for dynamic virtual microgrid formation; and (4) an integrated fault detection

and voltage regulation system enabling autonomous grid self-healing.

Simulation results validate that the AI-SLG achieves 40–50% reduction in per-prosumer energy trading costs, 21–38% OPEX savings for network operators, blockchain throughput of approximately 500 transactions per second, and sub-second voltage restoration following fault events. Over 70% of traded energy volume occurs within local low-SF clusters, promoting community self-sufficiency and minimizing network charges. Future research directions include federated learning for privacy-preserving model training, co-optimization of trading decisions with physical network constraints, quantum computing applications for complex grid optimization, and integration with 5G/6G communication infrastructure to further enhance real-time responsiveness and scalability. The AI-SLG framework represents a significant step toward the vision of fully autonomous, resilient, and sustainable smart energy communities that empower prosumers while strengthening grid reliability.

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