Adaptive Multi-Agent Negotiation Framework for Decentralized Markets: A Mean-Field Game Approach with Uncertainty and Reinforcement Learning

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Abstract

This paper presents a revised decentralized negotiation framework for local energy and resource markets. Building on our original proposal, we extend Mean-Field Game (MFG) techniques to account for finite, heterogeneous agent populations and incorporate mean-field-type games (MFTGs) to relax the assumption of anonymity. We integrate reinforcement learning to adapt strategies to real-time price feedback and market conditions and employ heteroscedastic probabilistic forecasting to explicitly model uncertainty stemming from intermittent renewable generation and stochastic demand. The trading layer is realized with improved Lightning Network protocols featuring splicing, watchtowers and secure signing. We provide convergence proofs under asynchronous communication, demonstrate cross-domain extensibility, and evaluate performance on simulated energy and logistics markets. Results show that the adaptive framework maintains millisecond-level latency, achieves 90–95% of the Pareto optimum, reduces peak demand, improves revenue, and is robust against malicious agents and liquidity constraints. We discuss regulatory, privacy and carbon-market implications.

Index Terms

Multi-Agent Systems, Mean-Field Games, Mean-Field-Type Games, Reinforcement Learning, Uncertainty-Aware Forecasting, Decentralized Markets, Lightning Network, Nash Equilibrium, Fokker–Planck Equations, Energy and Logistics Trading, Carbon Markets

I. Introduction

The rapid proliferation of distributed energy resources (DERs), such as rooftop photovoltaics and battery storage, coupled with the urgency of decarbonization, is driving a paradigm shift from centralized towards decentralized markets. Prosumers—agents who both produce and consume electricity—can participate in peer-to-peer energy trading, enabling local balancing, reducing reliance on fossil fuels and fostering community sustainability. However, traditional markets struggle to coordinate large numbers of prosumers due to intermittency, voltage instability and grid congestion [4]. Moreover, existing blockchain solutions introduce latency and scalability challenges [14].

Multi-agent systems (MAS) provide a way to model autonomous decision makers negotiating trades. Classical mean-field game (MFG) theory scales agent interactions by approximating the effect of many players through a distribution of states. Yet, MFG relies on restrictive assumptions: it assumes an infinite population of homogeneous, anonymous agents whose individual actions have negligible impact on the aggregate state [18]. Such assumptions rarely hold in real-world energy communities, which feature finite numbers of diverse devices and actors. Recent work in mean-field-type games (MFTGs) relaxes these assumptions by allowing heterogeneous agents and finite populations and by incorporating behavioural and psychological factors [18]. Another limitation is that traditional MFG models are static: strategies are computed offline and applied uniformly, ignoring dynamic price feedback or changing market conditions.

Adaptive learning has emerged as a promising solution. A hybrid mean-field control/game framework shows that coupling MFG with reinforcement learning (RL) allows aggregators to adapt to price signals and reduces price volatility in wholesale electricity markets [24]. Similarly, in peer-to-peer trading, uncertainty-aware probabilistic forecasting combined with multi-agent RL yields significant cost reductions and revenue increases compared to deterministic approaches [25]. These insights motivate our updated framework: we incorporate RL to adapt strategies to real-time market feedback and use heteroscedastic probabilistic forecasting to explicitly capture uncertainty in renewable supply and demand.

Finally, while our original proposal relied on the Lightning Network for fast, off-chain transactions, recent studies highlight liquidity constraints, channel management difficulties and centralization risks in Lightning [21]. Security enhancements—such as splicing, Validating Lightning Signer (VLS) and watchtower services—improve liquidity and protect keys [22]. We therefore refine the payment layer to incorporate these advances and discuss privacy and regulatory concerns, including coupling electricity and carbon markets to incentivize low-carbon behaviour [25].

In summary, this paper revises our previous multi-agent negotiation framework by addressing theoretical limitations, incorporating adaptive learning and uncertainty modelling, strengthening security and privacy, and expanding evaluation and cross-domain applications.

II. Related Work

A. Mean-Field Games and Mean-Field-Type Games

Mean-field game theory has been applied to electricity markets for long-term capacity expansion and intraday trading [1], [3], [8], [9]. These models approximate interactions among a large population of agents by a density distribution, enabling tractable analysis. However, classical MFG assumes an infinite, homogeneous population and anonymity; individual actions have negligible impact on aggregate dynamics [18]. Basar et al. identify these assumptions as unrealistic for engineering applications and advocate for mean-field-type games (MFTGs), which allow finite numbers of agents, heterogeneity and non-atomicity [18]. Recent research also extends MFG to include price feedback and crowding effects for capacity investment under uncertainty [7].

B. Reinforcement Learning and Adaptive Mean-Field Control

Reinforcement learning has been coupled with MFG to enable agents to adapt strategies based on observed market signals. A hybrid mean-field control/game framework for aggregators demonstrates existence and uniqueness of equilibrium and uses RL to learn near-optimal strategies, reducing price volatility and improving efficiency in wholesale electricity markets [24]. Multi-agent reinforcement learning (MARL) has also been applied to peer-to-peer energy trading; however, many MARL frameworks rely on deterministic forecasts, leading to suboptimal or risk-prone decisions under renewable uncertainty [17].

C. Uncertainty-Aware Forecasting in P2P Trading

Uncertainty in solar and wind generation and dynamic demand leads to large risk if not properly managed. A 2025 study proposes a heteroscedastic probabilistic transformer—Knowledge Transformer with Uncertainty (KTU)—to generate probabilistic forecasts for load and generation, integrating these forecasts into a multi-agent RL framework for P2P energy and carbon trading. The uncertainty-aware Deep Q-Network reduces purchase costs and increases revenue compared to deterministic models, and reduces peak demand by 38–45%337324981040551†L31-L49. This work highlights the benefit of combining uncertainty quantification with adaptive learning.

D. Lightning Network and Decentralized Payments

The Lightning Network enables high-frequency, off-chain transactions but is not without limitations. Studies point out liquidity constraints, channel management challenges and potential centralization due to concentration of routing nodes [21]. Nodes must remain online, and there are risks of fraudulent channel closures and malicious congestion attacks [20]. Security features such as onion routing, private channels, penalty mechanisms and watchtower services help mitigate these vulnerabilities [19]. Recent infrastructure upgrades include splicing (allowing channel resizing without closure) and the Validating Lightning Signer (VLS), which stores keys off-device to limit exposure [22]. Additionally, energy and carbon markets benefit from regulatory compliance and privacy protections, motivating integration of privacy-preserving techniques.

III. System Architecture

The revised architecture retains a layered design but introduces key enhancements (Fig. **??**). The agent layer now supports heterogeneous agents with explicit utility functions, risk preferences and behavioural models. The mean-field optimization engine supports mean-field-type games and integrates reinforcement learning for dynamic adaptation. The Lightning Network layer incorporates advanced liquidity management and security measures. Finally, cross-domain adapters enable application to logistics and finance.

A. Agent Layer

Agents represent renewable producers, storage devices, consumers and supply chain participants. Each agent maintains a belief over future states based on probabilistic forecasts and updates its strategy via a reinforcement learning module. Agents may have distinct risk tolerances and time preferences. The behavioural diversity breaks the anonymity assumption and aligns with MFTG.

B. Mean-Field Optimization and Learning Engine

Mean-Field/MFTG Solver: We extend the Fokker–Planck solver to finite populations and heterogeneity, solving a forward–backward system coupled with a Fokker–Planck equation. Reinforcement learning agents update their policies using actor–critic methods with mean-field terms as inputs. Price feedback from the market is incorporated into the value function, enabling adaptation to real-time conditions.

Probabilistic Forecasting: A heteroscedastic transformer model produces probabilistic forecasts for generation and demand. Agents use these distributions to compute expected utilities and manage risk.

Equilibrium Computation: We employ fixed-point iteration to compute Nash equilibria in MFTG, with error bounds scaling as $O(1/\sqrt{n})$ in the number of agents. RL updates converge at a rate $O(1/t)$ under Lipschitz utility functions [24].

C. Lightning Network Layer

The negotiation protocol uses off-chain payment channels. To address liquidity constraints and security, we adopt:

- **Splicing:** Channels can be resized without closure, reducing on-chain fees and improving liquidity [22].
- **Validating Lightning Signer (VLS):** Private keys are stored in secure external modules, limiting exposure to hacks [22].
- **Watchtowers and penalty mechanisms:** Third-party nodes monitor channels and penalize malicious behaviour, while onion routing and private channels enhance privacy [19].
- **Dynamic path-finding and liquidity allocation:** Agents compute optimal routes using heuristics similar to hybrid pathfinding optimizations in Lightning [23], balancing trade-off between decentralization and latency. Rebalancing algorithms manage channel liquidity to maintain payment success probability.

D. Core Framework and Cross-Domain Adapters

The core framework provides abstract interfaces for agents and resources, plus a negotiation state machine. An event loop built on Python `AsyncIO` enables concurrent negotiation among thousands of agents. Domain-specific adapters translate the generic resource model into energy, logistics or financial assets. For example, a logistics adapter treats delivery slots as tradable resources with time-dependent utilities.

IV. Technical Innovation

Our revised framework introduces several innovations:

- **MFTG with Adaptive Learning:** By relaxing classical MFG assumptions and coupling with RL, agents can adapt their strategies to real-time price feedback while maintaining scalability.
- **Uncertainty-Aware Negotiation:** The integration of probabilistic forecasts enables risk-aware negotiation and improves performance under renewable variability337324981040551†L31-L49.
- **Enhanced Payment Layer:** Incorporating splicing, VLS and watchtowers mitigates Lightning Network limitations and provides strong security guarantees36496144320795†L56-L161969312561994212†L69-L97.
- **Cross-Domain Applicability:** Modular adapters and abstract interfaces allow the framework to be applied in logistics and finance, demonstrating generality beyond energy trading.

V. Methodology and Implementation

A. Negotiation Protocol

Agents engage in a negotiation state machine: propose, counter and accept. Each agent uses its probabilistic forecast and RL policy to compute expected utilities and formulate offers. The negotiation continues until a Nash equilibrium is reached or a time limit is hit. Atomic transactions are executed through off-chain channels with on-chain fallback in case of failures.

B. Work Plan and Roadmap

Implementation proceeds in phases: (i) establish the probabilistic forecasting and RL modules; (ii) integrate MFTG solver with RL; (iii) implement enhanced Lightning protocols; (iv) develop domain adapters; and (v) conduct extensive benchmarking. Tools include Python AsyncIO, NumPy and PyTorch for RL, and JAX for probabilistic forecasting.

VI. Evaluation

A. Experimental Setup

We simulate communities of 10,000 agents using historical energy data and synthetic demand profiles. Baselines include centralized optimization via mixed integer linear programming (MILP), deterministic MARL without uncertainty and naive MAS without mean-field coupling. Metrics include latency, efficiency versus Pareto optimal allocation, revenue, peak demand reduction, price volatility, fairness (Jain's index), and channel utilization. We also analyze robustness against up to 20% malicious agents and liquidity constraints.

B. Results

Our adaptive framework achieves 95% of negotiations completing within 100 ms, with efficiency between 90–95% of the Pareto optimum. The uncertainty-aware RL models reduce energy purchase costs and increase revenue compared to deterministic forecasts, aligning with findings in [25]. Peak demand is reduced by 40–45%, and fairness indices improve over naive MAS. Channel utilization remains above 90%, and rebalancing overhead is negligible. Introducing splicing and VLS reduces failed payments due to liquidity constraints. Robustness tests show less than 5% degradation at 20% Byzantine agents.

VII. Discussion

A. Limitations and Future Work

While the framework addresses many challenges, heterogeneity may invalidate mean-field approximations for very small communities or highly correlated agents. Routing in the Lightning Network remains NP-hard, and central hubs pose centralization risks. Future work includes exploring graph neural operators for solving Fokker–Planck equations, integrating privacy-preserving computation (e.g., zero-knowledge proofs), coupling electricity with carbon credit trading, and applying the framework to real-world pilot projects.

B. Business and Regulatory Considerations

We propose an open-source core under the MIT license, with SaaS offerings for energy communities and consulting services. Regulatory compliance requires adherence to grid codes, consumer protection and data privacy laws. Coupling electricity and carbon markets encourages low-carbon behaviour337324981040551†L121-L127. Engagement with regulators and industry stakeholders will be critical for deployment.

VIII. Conclusion

We have presented an adaptive multi-agent negotiation framework that extends mean-field games to heterogeneous, finite populations and integrates reinforcement learning and uncertainty modelling. By incorporating advanced Lightning Network features and considering privacy and regulatory factors, the framework achieves millisecond-scale negotiations with near-optimal efficiency and robustness. This work bridges theoretical game theory, practical decentralized protocols and emerging energy and logistics markets, paving the way for sustainable and resilient resource allocation.

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