EAI Endorsed Transactions
on Scalable Information Systems

Research Article EAI.EU

Decentralised Coordination for Demand-Side Solar-Storage and Its Electricity Market Participation

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Abstract

The rapid proliferation of rooftop photovoltaics and behind-the-meter battery storage is creating systemic risks in distribution networks. This includes local network constraint violations, insufficient outage resilience, and enlarged cybersecurity attack surfaces, leaving millions of demand-side distributed energy resources (DERs) to operate without coordinated oversight. Existing solutions (dynamic operating envelopes, virtual power plants, peer-to-peer trading, and single-household energy management systems) each address only partial aspects of this challenge. Based on multi-agent reinforcement learning, this paper proposes a Decentralised Coordination Framework (DCF) that organises the energy dispatch into a three-tier hierarchical architecture. Specifically, it has a user layer executing Proximal Policy Optimisation (PPO) for local dispatch, a feeder layer in which a dynamically elected $L1$ leader applies MADDPG to coordinate community flexibility via a Virtual Aggregation Unit (VAU); and a cross-feeder layer where an $L2$ leader manages inter-community balancing and market interfaces. It integrates a directed acyclic graph (DAG)-based verifiable execution ledger, Paillier homomorphic encryption, and LLM-based anomaly detection to enhance security. Potential market participation pathway and revenue distribution mechanism are proposed to align with the Australian National Electricity Market. The DCF provides a scalable, market-ready foundation for commercial demand-side DER deployment under high renewable penetration.

Received on 03 March 2026; accepted on 12 March 2026; published on 19 March 2026

Keywords: Distributed energy resources, Multi-agent reinforcement learning, Decentralised coordination, Electricity market participation

doi:10.4108/eetsis.12071

1. Introduction

1.1. Background and Motivation

The large-scale penetration of distributed energy resources (DERs) is fundamentally reshaping the operational paradigm of modern distribution systems. Demand-side (household-side) assets, typified by rooftop photovoltaics (RPV) and behind-the-meter battery storage (BTMS), are expanding towards the periphery of the electricity network at an unprecedented rate. In Australia, for example, national rooftop photovoltaic (PV) installed capacity reached 28.3 GW by the second half of 2025, covering approximately 43% of residential customers and accounting for roughly 14.2% of total national electricity generation, and more than 183,000 new residential storage systems were installed in the second half of 2025 alone [1]. Besides, the federal government has set a target of 2 million home battery installations by 2030 with the Cheaper Home Batteries Program, implying an additional distributed storage capacity of approximately 40 GWh [2]. Similar growth trends are observed in China, Japan, Europe, the UK, and the USA. The large-scale penetration of DERs has become a common structural challenge confronting distribution systems worldwide.

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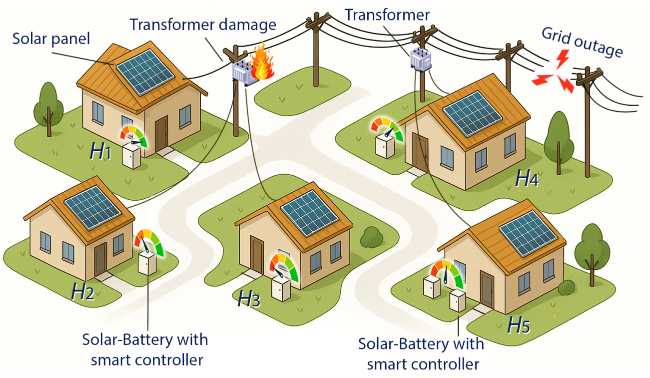

Figure 1. Exemplary Energy Coordination Scenario

However, the rapid growth of DERs does not automatically translate into system-level synergistic benefits. In the absence of a unified coordination mechanism, millions of demand-side solar and storage devices operate independently according to their own local conditions, thereby generating significant systemic risks across three dimensions. Fig. 1 depicts the issues.

First, local network constraint conflicts. When neighbouring user nodes, e.g., users in households H_1, H_2, and H_3, simultaneously feed surplus electricity into the public grid during peak photovoltaic generation periods, or simultaneously charge from the grid during off-peak tariff periods, the transformer thermal loading and feeder voltage at the Point of Common Coupling (PCC) will exceed safe operating boundaries, potentially causing equipment damage or localised outages [3].

Second, insufficient outage resilience. During grid outage events triggered by natural disasters (e.g., bushfires, flooding), users with more pre-stored energy can only maintain their own supply, whilst neighbouring users with less storage lose their power supply guarantees [3]. For example, people in H_2 cannot access the energy stored in the battery at H_1, even though there is surplus energy in H_1.

Third, an enlarged cyber-security attack surface. The large number of internet-connected energy devices constitutes a broad attack surface; compromised devices can be exploited to execute coordinated, synchronised charge/discharge attacks, causing transformer overloads and potentially cascading damage to grid infrastructure [4]. For example, by controlling smart controllers installed in H_1 to H_5, an attacker can launch a DDoS attack.

The root cause of these three categories of risk lies in the inherent characteristic of demand-side small-scale solar and storage resources: they are "observable but unorganisable". Specifically, they are individually small in capacity, stochastic and discrete in behaviour, and lacking a proxy agent capable of assuming scheduling responsibility. This leaves them in a "dormant" state that is unpredictable and undispatchable from the grid's perspective. Therefore, the core challenge is not the physical existence of resources per se, but whether the vast number of dispersed demand-side solar and storage resources can be organised into equivalent flexible resources that are *planning-credible*, *execution-verifiable*, and *market-deliverable*.

1.2. Recent Solutions

To coordinate and manage demand-side DERs, academia and industry have proposed several categories of solutions, principally: Dynamic Operating Envelopes (DOEs), Virtual Power Plants (VPPs), Peer-to-Peer energy trading (P2P), and single-household Home Energy Management Systems (HEMS). However, each of these approaches exhibits structural limitations in addressing the systemic challenges described above, as summarised in Table 1.

Dynamic Operating Envelopes (DOEs) are deployed top-down by Distribution Network Service Providers (DNSPs) and suppress feeder overloads and voltage violations by setting time-varying import/export power limits $[\underline{P}_i(t), \overline{P}_i(t)]$ for each connection point [5]. However, the DOE mechanism is fundamentally a constraint-imposition tool rather than a behaviour-optimisation tool: it specifies the power boundary for user node u_i at time t but provides no optimisation guidance for charge/discharge behaviour within that boundary. Research has shown that even within the bounds permitted by DOEs, arbitrary energy-sharing and grid-feed-in behaviour can still cause localised voltage problems and low resource utilisation [6]. Furthermore, the DOE mechanism has no outage response capability and provides no cross-user cooperative dispatch interface.

Virtual Power Plants (VPPs) aggregate distributed storage resources through a centralised dispatch platform to participate in grid ancillary services and spot markets as a unified entity [7]. However, centralised architectures face scalability bottlenecks as they scale: when the number of managed nodes N grows substantially, the communication overhead and computational complexity of the central dispatcher grow at no better than linear rates, and the risk of single-point failure increases accordingly. More critically, existing VPP schemes execute only centralised output dispatch across assets and do not optimise the physical energy-sharing pathways between neighbouring users, making community-level local balancing unachievable [8].

Peer-to-Peer Energy Trading Platforms (P2P) allow users to trade electrical energy directly with each other, achieving local optimisation of user revenue at the economic level [9]. However, P2P platforms typically operate only at the financial settlement layer

Table 1. Capability Comparison: Existing Approaches vs. Proposed DCF

Capability Dimension	DOE	VPP	P2P	HEMS	DCF (Ours)
User behaviour optimisation (within envelope)	×	Partial	Partial	✓	✓
Decentralised scalable coordination	×	×	Partial	×	✓
Community-level autonomous outage response	×	×	×	×	✓
Planning credibility & execution verifiability	×	Partial	×	×	✓
Spot-market-deliverable productisation	×	Partial	Partial	×	✓
Privacy protection & security auditing	×	×	×	×	✓

and do not coordinate the actual charge/discharge schedule of the user node [10]. They therefore cannot physically prevent network congestion. This means that when multiple users act synchronously in response to price signals, overload events can still be triggered at the physical network layer. Furthermore, existing P2P schemes possess no autonomous cooperative capability under outage scenarios.

Single-household HEMS and solar-storage optimisation schemes perform locally optimal dispatch of photovoltaic generation, load demand, and storage state for a single user node u_i [11], achieving notable results in improving self-consumption ratios and reducing electricity costs [11–15]. However, single-node optimisation strategies may induce divergence between individual and collective optima at the system level: when the majority of nodes in the set $\mathcal{U}$ simultaneously execute locally optimal charging or discharging strategies, their superimposed effect will produce unpredictable power surges at common network nodes [16].

However, existing solutions address individual aspects but lack the systematic approach needed for the three challenges listed above.

1.3. Contributions of This Paper

This paper proposes a decentralised coordination framework for demand-side solar-storage dispatch and market participation (hereafter **DCF**). Key innovations and contributions of this paper are as follows.

- **A formally described three-tier hierarchical coordination architecture.** The user layer employs proximal policy optimisation (PPO) as its core algorithm to achieve local autonomous dispatch; the feeder layer uses a dynamically elected $L1$ leader node implementing multi-agent deep deterministic policy gradient (MADDPG) to achieve cooperative optimisation within the virtual aggregation unit (VAU); and the cross-feeder layer has an $L2$ leader node executing system-wide surplus/deficit coordination under an extended observation space. This architecture achieves near-global-optimal system-level objectives through a cascaded optimisation structure whilst preserving decentralised robustness, effectively circumventing the scalability bottleneck of centralised VPPs.
- **A community-level autonomous microgrid formation mechanism for outage resilience.** It proposes a local communication scheme based on power line communication (PLC) and ultra-narrowband radio (UNB) that supports autonomous discovery of surviving node sets $\mathcal{U}_s$ and dynamic committee formation under backbone communication failure conditions. Energy-sharing scheduling under islanded operation is achieved through a distributed consensus mechanism, significantly enhancing community energy supply resilience during extreme weather events [17, 18].
- **An integrated privacy protection and security auditing mechanism.** This paper combines partial homomorphic encryption (PHE) based on the Paillier scheme [19] with large language model (LLM)-based proposal anomaly detection. This simultaneously protects the privacy of user energy consumption data and performs real-time auditing of the dispatch proposals $s_i(t)$ submitted by node u_i, automatically identifying and isolating nodes with malicious behavioural signatures, thereby ensuring the cooperative dispatch process is robust to Byzantine Failures [20, 21].

The remainder of this paper is organised as follows. Section 3 establishes the system model. Section 2 summarises recent research advances. Section 4 details the hierarchical decentralised coordination mechanism. Section 5 introduces the multi-timescale rolling planning strategies. Section 6 describes the security and privacy protection mechanisms. Section 7 discusses the electricity market participation pathways and investment governance structures. Section 8 summarises the paper and points out future work.

2. Related Work

Substantial research has been devoted to grid stability [16], renewable energy utilisation [22], and demand prediction [23]. In grid stability, Gorman et al. studied the feasibility of using batteries to mitigate long-duration power interruption in the USA and identified influencing factors [3]. In renewable energy sharing, Qiu et al. optimised renewable energy usage in single households by considering long-term and short-term energy storage [22]. Li et al. optimised a single solar-storage device to achieve better revenue in electricity trade [10]. Research has addressed centralised and hierarchical multi-microgrid management [16], but these approaches typically assume dedicated microgrid infrastructure and centralised controllers, rather than ad-hoc formation from existing household devices without pre-installed microgrid hardware. In energy prediction, conventional ML methods (random forests, gradient boosting), deep learning architectures (LSTM, CNN-LSTM, Transformers, TimeGPT [24]), and LLM have achieved strong performance in short-term grid load prediction [25], long-term total power load [26], and price forecasting [27].

Effective energy coordination requires advanced algorithms to balance diverse benefits under various constraints, especially when considering the dynamic nature of energy generation and consumption. Potentially useful algorithms include set function optimisation (SFO) used for quasistatic scenarios [28], Lyapunov optimisation [29] and multi-armed bandit [30, 31] for dynamic scenarios [32–34], and multi-agent reinforcement learning (MARL) for more complex, dynamic, and large-scale environments [35, 36].

Energy coordination and device collaboration need strong security assurance to avoid attacks on the household devices and/or grid. In addition, energy data should be captured, stored and shared securely to fulfil government requirements for auditability, traceability, and privacy preservation ability [7]. This requires fundamental innovation in data integrity assurance [37, 38] and privacy-preserving [39–42]. Moreover, malicious detection [43, 44] and defence [45] are also critical for the system security, especially in distributed systems. For example, Xie and Zheng proposed an approach based on a distributed hash table (DHT)-based for data deduplication and efficient retrieval in blockchain systems, which can be employed for storing a large volume of energy coordination and trading data [46].

3. System Model and Problem Formulation

3.1. System Architecture Overview

Fundamental Design Principles. The DCF framework is designed according to three fundamental principles. (1) **Decentralised robustness**, the system maintains basic coordination functionality under any single-node or local sub-network failure condition, without relying on a globally reachable central controller. (2) **Hierarchical scalability**, coordination complexity grows at a sub-linear rate as the node population N increases, supporting large-scale DER integration. (3) **Planning deliverability**, the framework presents itself externally as a dispatchable object with well-defined power boundaries and temporal resolution, satisfying the admission requirements of distribution system operators (DSOs) and electricity markets.

Please note that the DCF is designed as an architectural foundation. It defines the coordination structure, inter-layer interfaces, useful algorithm assignments, and market participation pathways for demand-side DER deployment. As such, the framework is analysed at the design level rather than through simulation or field trials, which are reserved for the subsequent studies described in Section 8.

Three-Tier Hierarchical Architecture. The DCF framework comprises three functional tiers, as illustrated in Fig. 2. Let the system contain N user nodes, denoted by the set $\mathcal{U} = \{u_1, u_2, \dots, u_N\}$. Based on the physical topology of distribution feeder zones (DFZs), $\mathcal{U}$ is partitioned into M communities (feeders), denoted $\mathcal{C} = \{\mathcal{C}_1, \mathcal{C}_2, \dots, \mathcal{C}_M\}$, where a community $\mathcal{C}_m$ contains several user nodes, e.g., 100 to 200 in Australia.

Layer 1 User Layer. The individual user node u_i is the basic operational unit. A rooftop PV system, user load, battery energy storage system (BESS), and edge intelligent controller (EIC, a.k.a. smart controller) together constitute a minimum autonomous unit (MAU), responsible for local sensing, forecasting, and dispatch decisions.

Layer 2 Feeder Layer. Community $\mathcal{C}_m$ serves as the coordination unit. A dynamically elected $L1$ leader node integrates the flexible capacity of all MAUs within the community and outputs the equivalent power curve $P^{\mathrm{eq}}_{\mathcal{C}_m}(t)$ of the virtual aggregation unit (VAU) as a single dispatchable interface for the DSO and market.

Layer 3 Grid and Market Layer. Composed of the $L2$ leader node and external DSO/market interfaces, this layer is responsible for cross-feeder surplus/deficit coordination and encapsulates VAU curves into market-deliverable products for the spot market.

Interface Relationship with DSO. The DCF framework complies with the DOE specification [5]. The DSO issues time-varying import/export power limits for each connection point u_i as hard constraints:

$$\underline{P}_i(t) \le P_i^{\mathrm{net}}(t) \le \overline{P}_i(t), \quad \forall\, u_i \in \mathcal{U},\ t \in \mathcal{T} \tag{1}$$

DOE constraints are embedded into the user-layer decision process. Within these boundaries, the DCF framework actively optimises user behaviour, compensating for the inherent inability of the DOE mechanism to guide behaviour. The information flows across all

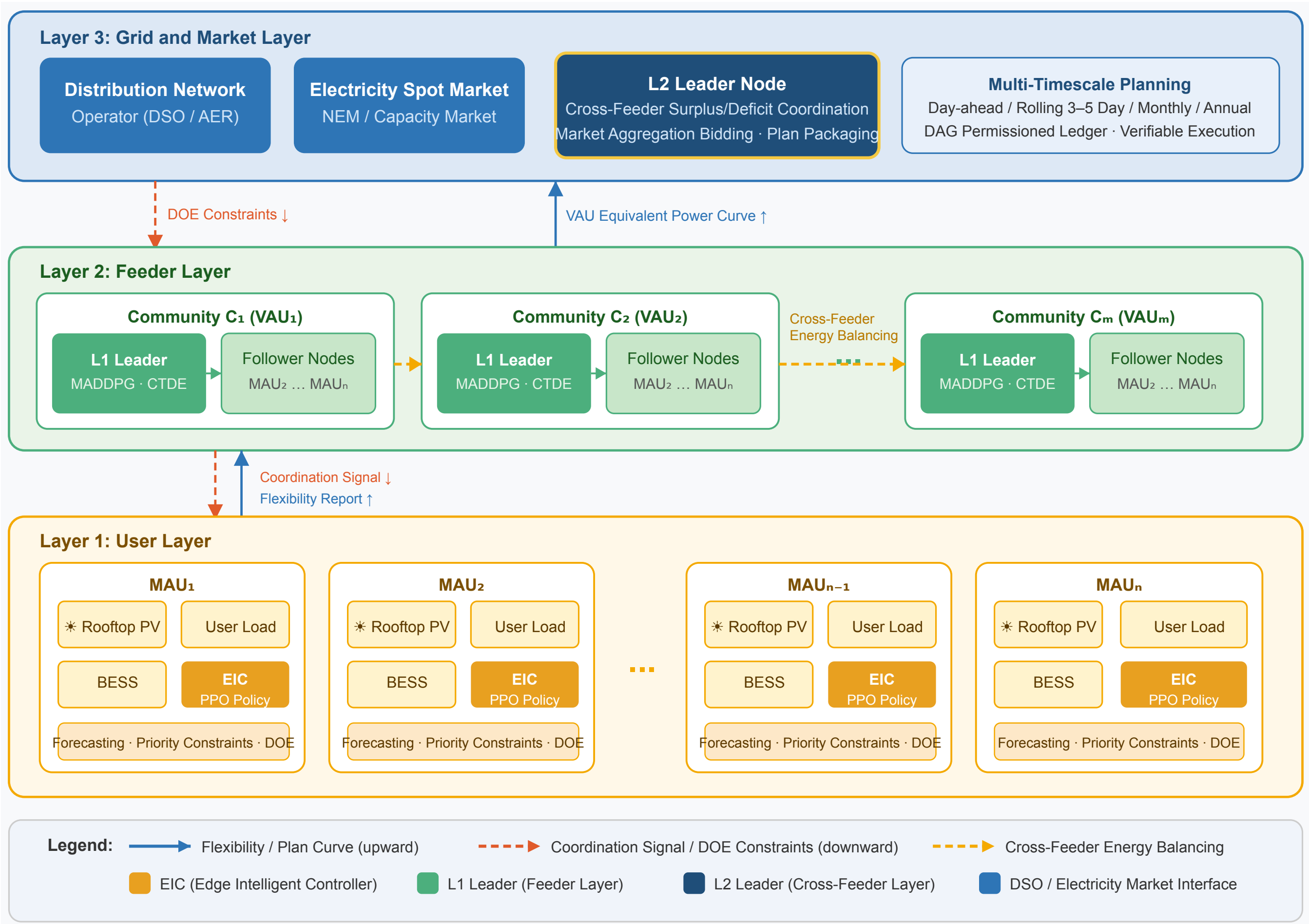

Figure 2. DCF Decentralised Hierarchical Coordination Framework.

three layers are processed through edge-side encryption; detailed security mechanisms are described in Section 6.

3.2. Minimum Autonomous Unit Modelling

The MAU is the basic physical and decision-making unit of the DCF framework. For node u_i, its operational state is jointly described by the photovoltaic output $P_i^{\text{pv}}(t)$, user load $P_i^{\text{load}}(t)$, storage state-of-charge $E_i^{\text{soc}}(t)$, and the node net exchange power $P_i^{\text{net}}(t)$.

The output of the PV sub-system is subject to irradiance and temperature, and satisfies non-negativity and rated power upper-bound constraints. The state-of-charge of the storage sub-system evolves according to a charging/discharging-efficiency-driven dynamic equation and is jointly constrained by three conditions: a SOC safety domain, upper bounds on charge/discharge power, and charge/discharge mutual exclusivity. These constraints ensure that the storage device responds to dispatch instructions within its safe operating envelope. Detailed parameterisation is provided in subsequent research.

At any time step t, the nodal power balance equation is:

$$P_i^{\text{net}}(t) = P_i^{\text{load}}(t) + P_i^{\text{chg}}(t) - P_i^{\text{pv}}(t) - P_i^{\text{dis}}(t) - P_i^{\text{share,out}}(t) + P_i^{\text{share,in}}(t) \tag{2}$$

where $P_i^{\text{share,out}}(t)$ and $P_i^{\text{share,in}}(t)$ denote the shared power output from and received by node i to/from the community, respectively. This equation organically links single-node local balancing with community-layer energy sharing.

User load priority is governed by a rigid three-tier mechanism. *Priority 1* essential residential or core business loads receive absolute protection; no external dispatch instruction may disrupt their supply. *Priority 2* encompasses flexible loads within the self-consumption optimisation range. *Priority 3* comprises dispatchable loads eligible for scheduling and market arbitrage. This mechanism is a foundational design element enabling the DCF framework to gain user trust and achieve large-scale deployment.

Based on this priority definition, the *dormant flexible resources* of node u_i are defined as the sum of load capacity and storage capacity that is currently not participating in dispatch, not earning market revenue, but possesses adjustable capability subject to priority constraints. Their availability is characterised by three indicators: the adjustable power interval $\Delta P_i^{\text{flex}}(t)$, the adjustable duration $\tau_i^{\text{flex}}(t)$, and the availability factor $\rho_i(t) \in [0, 1]$, which together constitute the standardised flexibility capacity declaration interface that the MAU reports to the feeder layer.

Regarding storage technology selection, this paper adopts the electrochemical storage pathway whilst remaining agnostic to specific battery chemistries. Lithium-ion batteries are suited to temperate climates where high response speed is required; sodium-ion batteries offer advantages in low-temperature performance and safety; lead-acid batteries are appropriate for cost-sensitive scenarios with low regulation frequency requirements. In practice, a configurable technology selection scheme should be formulated according to climate conditions, installation space, and regulation objectives [20].

3.3. Optimisation Objective Formulation

The optimisation objective of the DCF framework is to simultaneously achieve three system goals under the joint action of user load priority constraints and grid operational constraints: economic efficiency, grid stability, and distributional fairness. These three objectives are partially competing in nature and can be unified into a weighted multi-objective reward function:

$$\begin{aligned} R_i(t) &= w_1 \cdot r_i^{\text{eco}}(t) - w_2 \cdot r_i^{\text{grid}}(t) - w_3 \cdot r_i^{\text{fair}}(t), \\ &\text{s.t.} \quad w_1 + w_2 + w_3 = 1 \end{aligned} \tag{3}$$

The economic revenue term $r_i^{\text{eco}}(t)$ comprises three components: grid feed-in revenue, electricity purchase cost, and intra-community P2P trading revenue. An internal trading incentive is formed through the ordering constraint between the feed-in tariff, retail tariff, and P2P price:

$$\lambda^{\text{fit}}(t) \le \lambda^{\text{p2p}}(t) \le \lambda^{\text{retail}}(t), \quad \forall\, t \in \mathcal{T} \tag{4}$$

The grid stability penalty term $r_i^{\text{grid}}(t)$ applies a quadratic penalty function to feeder voltage violations and transformer thermal overloads, with a non-linear amplification penalty for severe violations, thereby forming a progressive constraint on safety boundaries during optimisation [22].

The fairness penalty term $r_i^{\text{fair}}(t)$ employs a Gini-coefficient-based metric, amortising the distributional inequality of cumulative revenue across community nodes into each time step, ensuring that the fairness signal exerts a continuous regulatory effect during MARL training [47].

The complete constraint set governing the above three-objective structure comprises: SOC evolution constraints, power balance constraints, DOE constraints, SOC safety domain constraints, charge/discharge mutual exclusivity constraints, and user priority constraints. Because this problem involves the joint decision-making of N heterogeneous agents in a partially observable stochastic environment, it is hard be solved in real time by a centralised solver [13]. The hierarchical MARL architecture described in Section 4 is designed specifically as a decomposition solution to this challenge.

4. Hierarchical Decentralised Coordination

4.1. User Layer: PPO-Based Local Autonomous Dispatch

The core task of the user layer is to enable each MAU to achieve autonomous optimal scheduling of local solar and storage resources subject to user load priority constraints and DOE hard constraints. Because the demand-side context features a continuous action space, a non-stationary stochastic environment (due to PV output and load uncertainty), and requires no explicit modelling of environment dynamics, this paper employs proximal policy optimisation (PPO) [48] as the decision-making algorithm for user-layer agents.

Each MAU's EIC operates as an independent PPO agent, taking locally observable information as input, and outputting charge/discharge power commands and community shared power declarations. The input consists of the current state of charge (SOC), short-term PV and load forecast sequences, real-time price signals, and coordination signals issued by the feeder layer. DOE constraints are embedded as hard constraints into the decision process, ensuring all output actions strictly satisfy the DSO's network operational requirements. The EIC simultaneously integrates a local short-term forecasting module to provide necessary forward-looking information for decision-making.

The PPO algorithm possesses significant advantages in stability and sample efficiency in continuous action spaces and requires no sharing of policy parameters between agents, naturally accommodating the privacy-protection requirements of distributed deployment. The optimisation objectives and reward function design of the user layer follow the objective defined in Section 3.3 (i.e., equation (3)).

4.2. Feeder Layer: MADDPG-Based Virtual Aggregation Unit Coordination

The core task of the feeder layer is to integrate the discrete adjustable capabilities of multiple heterogeneous MAUs within community $\mathcal{C}_m$ into externally deliverable equivalent flexible resources, i.e., the virtual aggregation unit (VAU). The principal challenge at the feeder layer is that load profiles, PV configurations, and storage capacities of users within the community differ significantly; relying solely on user-layer local autonomy cannot eliminate the divergence between individual optima and system optima.

This paper introduces a dynamic $L1$ leader mechanism at the feeder layer. A leader node $u_{l_1}^{(m)}$ is dynamically elected within the community through distributed reputation voting [18]. It aggregates the flexibility capacity declarations reported by all MAUs in the community and generates a community-level cooperative dispatch strategy, using the multi-agent deep deterministic policy gradient (MADDPG) algorithm [49]. MADDPG adopts the centralised training with decentralised execution paradigm. Specifically, during training, the $L1$ leader is permitted to access global state information within the community to improve strategy quality; during execution, each follower node acts independently based only on local observations and the coordination signal broadcast by the $L1$ leader, thereby achieving a balance between coordination effectiveness and communication overhead [28].

The optimisation results of the feeder layer are issued as coordination signals to each user-layer agent, and simultaneously output the VAU equivalent net-load boundary curve $P_{\mathcal{C}_m}^{\mathrm{eq}}(t)$ to the upper layer as the dispatchable interface for the grid and market layer. Detailed algorithm design, convergence analysis, and communication protocols for the feeder layer will be further elaborated in subsequent research.

4.3. Cross-Feeder Layer: $L2$ Leader and System-Wide Surplus/Deficit Coordination

The core task of the cross-feeder layer is to coordinate system-wide energy surpluses and deficits across multiple VAUs, further improving the overall renewable energy utilisation rate of the system and reducing the impact on the upstream network. When a persistent supply-demand imbalance occurs within a single community, or when there is a pronounced spatio-temporal complementarity between adjacent communities, cross-feeder energy balancing can effectively smooth the system-wide net-load curve.

This paper introduces a dynamic $L2$ leader mechanism at the cross-feeder layer. The $L2$ leader is produced through hierarchical election by the $L1$ leaders of each community and is responsible for formulating cross-community energy transfer strategies under an extended observation space. Such a space comprises the cross-zone line capacity matrix $\mathbf{Y}$ and the system-wide net-load surplus/deficit distribution vector $\delta(t)$. Cross-feeder energy sharing is only activated when significant supply-demand mismatches exist between communities, to reduce unnecessary cross-zone power transmission losses. The $L2$ leader also employs the MADDPG framework, with an observation space and action space extended relative to those of the $L1$ leader to reflect cross-zone line constraints and loss factors.

> The three-layer optimisation structure is coupled in a cascaded manner. Specifically, user-layer actions provide boundary conditions for feeder-layer decisions, feeder-layer outputs provide surplus/deficit information to the cross-feeder layer, and the coordination results of the cross-feeder layer are fed back to the feeder layer as updated coordination signals, forming a closed-loop iteration. This cascaded structure decomposes the originally $\mathcal{O}(N)$-scale centralised joint optimisation problem layer by layer, significantly reducing solution complexity whilst maintaining proximity to global objectives through leader-guided optimisation.

Let us briefly examine the scaling properties of the three-tier decomposition compared to a centralised baseline. Given the same joint optimisation problem, the centralised dispatcher manages all N user nodes. The complexity of this problem increases significantly. For example, the communication overheads between those agents are $\mathrm{O}(N^2)$, which creates a scalability bottleneck as the number of nodes N grows. In contrast, the hierarchical decomposition of the DCF reduces this. When the community leader ($L1$ leader) is elected, the feeder-layer communication overheads for intra-community optimisation are $\mathrm{O}(K)$, where $K = N/M$ represents the community size (typically 100 to 200). Then, the cross-feeder level optimisation only involves those $L1$ leaders and is coordinated by the $L2$ leader. There are M $L1$ leaders in total. Thus, the cross-feeder coordination problem incurs $\mathrm{O}(M)$ communication overheads. Accordingly, the entire overheads are $\mathrm{O}(k) \times \mathrm{O}(M) = \mathrm{O}(N)$.

4.4. Dynamic Leader Election Mechanism

Leader nodes play a critical coordination and information aggregation role in the three-tier architecture; their reliability and integrity directly affect overall system performance. To avoid the single-point-of-failure risk and potential strategy manipulation associated with fixed leaders, this paper adopts a *reputation-based dynamic election mechanism* [37] at both the $L1$ and $L2$ layers.

The core logic of the election mechanism is shown in Fig. 3. Each candidate node maintains a historical reputation score that comprehensively reflects its device uptime, historical plan adherence rate, and communication reliability. At each election cycle, nodes meeting a minimum reputation threshold participate in

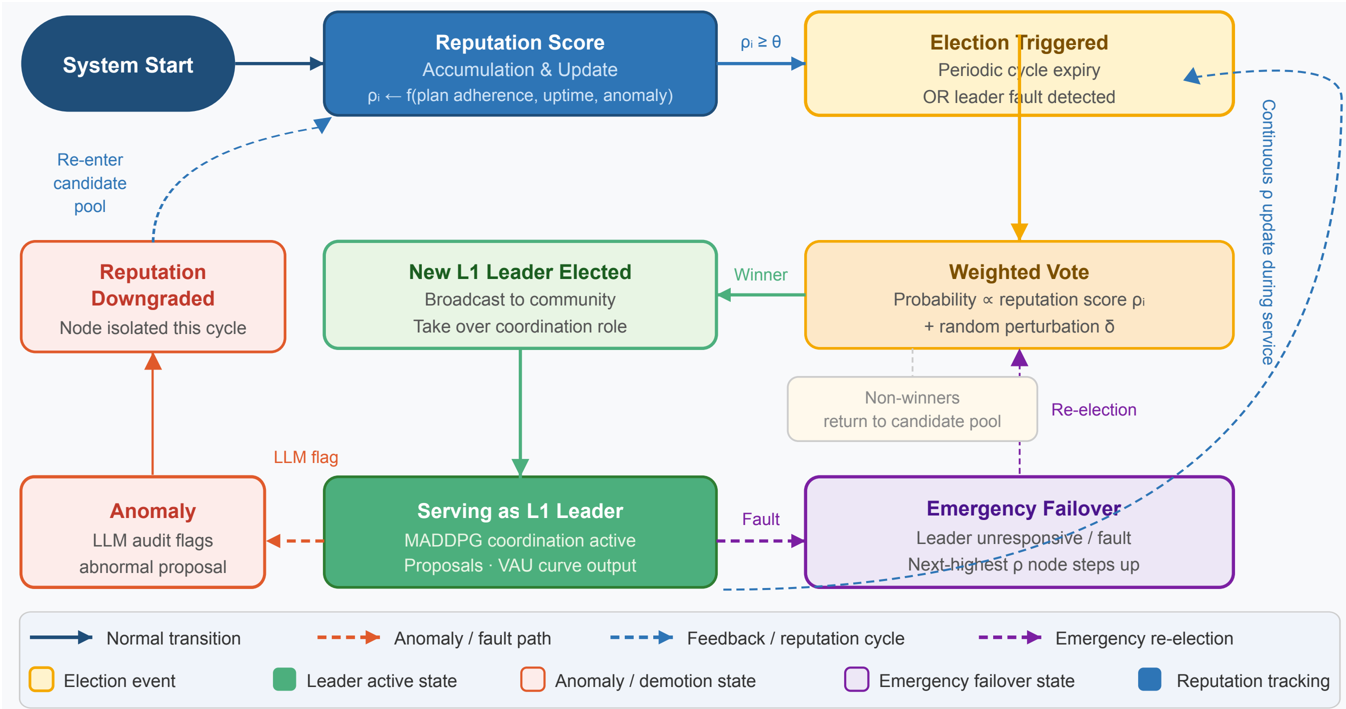

Figure 3. DCF Dynamic Leader Election Mechanism.

the election; the ultimately elected node is determined by reputation-weighted voting combined with random perturbation, to prevent any fixed node from monopolising the leader position over the long term. When the elected leader experiences a communication failure or device disconnection, a backup node can automatically assume its role, guaranteeing the continuous operation of the coordination mechanism under localised failure conditions.

The dynamic election mechanism simultaneously constitutes an important component of the security framework. By linking leadership status to historical behavioural reputation, malicious nodes are unable to accumulate sufficient reputation in the short term to be elected as leader. Thus, this effectively suppresses Byzantine attacks targeting the leader tier, the same as the security assurance strategies adopted in [18].

5. Multi-Timescale Rolling Planning

5.1. Multi-Timescale Rolling Planning Framework

Two factors collectively determine if the distributed solar and storage resources can enter the electricity dispatch and market system. First, whether credible planning commitments can be delivered to the grid and market. Second, whether compliance with those commitments can be sustained. Single-timescale optimisation schemes are unable to simultaneously satisfy the dual requirements of real-time power balancing and medium-to-long-term market contracts. Therefore, this paper constructs a rolling planning framework spanning multiple timescales to organically link discrete MAU decisions with external market productisation pathways. This paper divides the planning horizon into five tiers.

Real-time Layer. The time frame spans from seconds to minutes. The EIC executes the PPO policy locally, generating charge/discharge commands based on real-time SOC, PV output, and load status to respond to sudden power fluctuations and maintain instantaneous nodal power balance. The core objective of this layer is to ensure real-time compliance with DOE constraints and continuous enforcement of user load priorities.

Intraday Layer. The time frame spans from 15 minutes to 1 hour. The feeder-layer $L1$ leader updates the community-level cooperative dispatch strategy using a rolling forecast window and an 8-step horizon at 15-minute resolution, correcting plan deviations caused by accumulated forecast errors and issuing updated coordination signals to each MAU. The rolling power schedule curve output by this layer is the primary delivery interface between the feeder VAU and the DSO.

Day Rolling Layer. The time frame spans from one day to 3-5 days according to practical requirements. The $L2$ leader aggregates the forecast capability declarations of each community's VAU to generate day-ahead and rolling 3–5 day aggregate power plans, serving as the bidding basis for participation in the electricity spot market's day-ahead market and capacity market. The planning quality of this layer directly determines market admission capability and deviation settlement costs.

Monthly Settlement Layer. The planning execution status and actual energy consumption data of each node are consolidated on a calendar-month cycle to generate verifiable compliance evidence reports for market settlement and revenue distribution, supporting the investment governance and revenue allocation mechanism described in Section 7.

Long-term Resource Allocation Layer. Historical execution data is used to assess the overall flexible resource potential of the system, providing long-cycle decision support for storage capacity expansion, PV configuration optimisation, and market strategy adjustment.

The above five-tier planning framework is mutually coupled through a rolling correction mechanism: upper-tier plans provide constraint boundaries for lower tiers; lower-tier execution results feed back to correct upper-tier forecast models through deviation attribution, forming an adaptive closed-loop planning–execution–correction cycle.

5.2. Planning Credibility Mechanism

Planning credibility requires MAUs to generate power forecast curves with statistical reliability and translate them into externally committable flexibility capacity declarations. The planning credibility mechanism goes through three phases.

Forecast Support Phase. The EIC integrates a local short-term forecasting module to perform rolling forecasts of PV output and user load within the future dispatch window. The forecasting model may adopt an attention-enhanced deep learning architecture designated for time-series forecasting [23, 24]. Forecast outputs take the form of confidence intervals, providing uncertainty quantification for plan generation.

Plan Generation Phase. Based on forecast results, the EIC generates a power plan curve $\hat{P}_i(t)$ for the future dispatch window subject to DOE constraints and user priority constraints. After the feeder-layer $L1$ leader aggregates the plan curves of all MAUs in the community, it generates the VAU equivalent plan curve $P^{\text{eq}}_{\mathcal{C}_m}(t)$ through MADDPG cooperative optimisation, together with the adjustable margin $\Delta P^{\text{flex}}_{\mathcal{C}_m}(t)$ as the plan credibility boundary, and submits a committable power envelope to the upper layer.

Plan Credibility Scoring Phase. To reduce the risk of market deviation penalties, a plan credibility scoring mechanism is employed. It comprehensively considers the historical distribution of forecast errors, device uptime, and SOC margin. Then, a credibility score $\xi_{\mathcal{C}_m}(t) \in [0, 1]$ is assigned to each plan declaration. The credibility score serves both as supplementary information for market bidding and as a priority basis for intra-feeder-layer resource allocation, ensuring that high-credibility plans receive preferential resource guarantees.

6. Security and Privacy Protection Mechanisms

As introduced in Section 1, the decentralised coordination mode, whilst improving inter-house collaboration and system scalability, introduces new security exposure surfaces. For example, leader nodes may be attacked, malicious nodes may submit falsified dispatch proposals, and energy consumption data may be disclosed during transmission and storage. To tackle this challenge, security and privacy protection mechanisms are designed across three dimensions, addressing the core requirements of leader security [50, 51], data privacy [52, 53], and regulatory compliance, respectively. Please note that the security mechanisms are to provide a trustworthy coordination foundation for the entire framework without increasing the computational burden on edge devices.

6.1. LLM-Based Anomaly Detection and Malicious Node Isolation

In the decentralised coordination architecture, the primary attack vector of malicious nodes is the submission of falsified dispatch proposals. For example, a compromised node u_i may declare an excessively large discharge plan, inducing multiple neighbouring nodes to discharge simultaneously, ultimately causing transformer overloads and grid load collapse. To more precisely identify this threat, this paper introduces an LLM-based proposal auditing mechanism at the $L1$ leader layer.

Upon receiving the dispatch proposals $s_i(t)$ from all follower nodes within the community, the $L1$ leader does not incorporate them directly into the cooperative optimisation; instead, it first passes all proposals through the LLM audit module for real-time anomaly detection. The LLM audit module simultaneously captures both long-term behavioural patterns of nodes (e.g., historical charge/discharge patterns, contextual tariff response characteristics) and short-term abrupt changes (e.g., a single proposal's power significantly deviating from the historical distribution), enabling prediction-based anomaly judgement. Nodes identified as anomalous are suspended with an anomaly flag; their proposals are automatically isolated in the current dispatch cycle, and a reputation downgrade process is triggered. This mechanism effectively defends against internal attacks disrupting cooperative dispatch whilst avoiding excessive security restrictions caused by false alarms [54].

The above auditing mechanism, combined with the dynamic leader election mechanism described in Section 4.4, constitutes a two-layer defence. First, the election mechanism limits the probability of malicious nodes being elected as leaders at the access level. Second, the auditing mechanism provides coordinated interception of malicious behaviour that attempts to progressively accumulate influence through multiple small anomalous proposals. The two mechanisms are mutually complementary.

6.2. Homomorphic Encryption-Based Privacy-Preserving Data Sharing

User energy consumption data is highly sensitive: charge/discharge behavioural patterns can reveal household routines; load curves can expose trade secrets; and electricity usage behaviour can reflect individual health conditions. Therefore, how to protect user privacy whilst enabling the data sharing required for cooperative dispatch is a critical compliance requirement of the DCF framework in relation to third-party platforms and operators.

This paper adopts partial homomorphic encryption (PHE) [19] as the core privacy protection means, specifically the Paillier scheme. PHE permits additive operations to be performed directly on ciphertexts, which means the feeder-layer $L1$ leader can directly aggregate the encrypted power data reported by nodes within the community and complete plan summary verification without decrypting any node's raw data. This design ensures two properties. First, individual nodes' energy consumption data is invisible to any entity outside its authorised scope. Second, in-scope auditors (e.g., regulators) can obtain the minimum necessary information required for auditing through a selective disclosure mechanism without infringing on user privacy.

Regarding communication security, all data exchanges between nodes employ end-to-end encrypted channels. Under localised islanding scenarios (e.g., outage emergencies), encrypted communication schemes based on PLC are required to maintain the continuity of intra-community encrypted communication when backbone network connectivity is lost. Detailed implementation solutions and encryption overhead analysis will be elaborated in subsequent research.

6.3. Compliance Support and Auditing Mechanisms

Beyond internal security protection, the DCF framework must also satisfy the compliance requirements of external regulators, including DER visibility standards from market operators, data protection and privacy regulations, and post-incident reporting requirements. For example, the Australian Energy Market Operator (AEMO) applies the AESCSF framework [55]. This paper supports compliance demonstration capability through three categories of mechanisms.

Selective disclosure mechanism: Each node locally encrypts and protects the personal energy consumption data in its directed acyclic graph (DAG) ledger. Even where regulators hold audit authorisation, they can only access the minimum necessary information directly relevant to the audit task (e.g., community-level aggregate power, deviation statistics, anomalous event records) and cannot infer the energy consumption pathway of any individual user, thereby achieving a balance between compliance guidance and privacy protection [56].

Fine-grained access control: The system adopts a role-based access control model, clearly partitioning the access permissions of market operators, DSOs, authorised auditors, and individual users. Only the user themselves has full read access to their complete energy history; all other parties may only access aggregated or anonymised data within their assigned permission scope. This design is consistent with the data minimisation principle of data protection law/frameworks, including AESCSF in Australia [55].

Immutable transaction ledger: All plan execution snapshots are written to the DAG permissioned ledger. This ledger provides an immutable historical record complying with the DER visibility standards of market operators, supporting transaction traceability, incident investigation, and flexible regulatory compliance auditing without requiring a centralised data warehouse [17].

The security mechanisms described in this section, together with the dynamic leader election in Section 4, collectively constitute the trust foundation of the DCF framework.

7. Market Participation and Productisation

The ultimate objective of the DCF framework is not only to achieve energy coordination within the community, but also to connect the aggregated distributed solar and storage resources to the electricity spot market and ancillary services market in the form of market-deliverable products, realising sustainable revenue for users and investors. This section describes the productisation design of the DCF framework across three dimensions: market participation pathway, revenue distribution mechanism, and investment governance structure.

7.1. Electricity Spot Market Participation Pathway

The electricity spot market requires participants to possess clearly defined planning credibility and the capacity to bear deviation responsibility. For individual MAUs whose scale is relatively small, direct participation in the wholesale market entails high bidding costs and deviation penalty risks. This paper therefore adopts a tiered aggregation, progressive productisation participation pathway.

At the **user level**, individual MAUs primarily achieve electricity bill optimisation through demand management and flexible arbitrage within DOE constraints, without needing to engage the wholesale market directly. At the **feeder level**, the community VAU acts as a unified entity providing load flexibility services (e.g., VREG voltage support) to the DSO, earning network support payments. At the **cross-feeder level**, the $L2$ leader aggregates the available capacity of multiple VAUs into an entity approaching a single dispatchable object, participating in day-ahead market power bidding and automatic frequency regulation reserve (AFRR) bidding in the electricity spot market as a third-party aggregator. At the **system level**, long-term capacity credibility indicators support participation in capacity markets and quarterly resource allocation contracts.

The above four-tier pathway corresponds directly to the multi-timescale planning framework in Section 5.1. Specifically, the real-time layer supports user-side arbitrage; the intra-day layer supports VAU flexibility services to the DSO; the day-ahead and rolling planning layers support spot market bidding; and the monthly and annual layers support capacity contract compliance. It should be noted, however, that realising this participation pathway is subject to a number of regulatory prerequisites that involve non-trivial compliance costs and procedural timelines. Taking Australia as an example, at minimum, the $L2$ leader entity would need to be registered as a third-party aggregator under the NEM rules, satisfy AEMO's DER integration requirements. Deviation penalty exposure under the spot market settlement rules also represents a financial risk that must be managed through appropriate contractual arrangements between the platform operator and participating households. Furthermore, the NEM regulatory framework governing DER aggregation is itself subject to ongoing reform, reflecting the pace of rooftop PV and storage uptake across Australia. The modular architecture of the DCF, and specifically the configurability of the reward function weights in Eq. (3) and the adjustable planning horizon parameters across the five-tier framework in Section 5.1, are designed to allow the system to accommodate rule changes without requiring fundamental architectural redesign.

7.2. Revenue Distribution Mechanism

Fair distribution of market revenue is the core incentive for users to continue participating in cooperative dispatch. This paper adopts a contribution-weighted distribution model. After deducting feeder operational costs and necessary platform service fees, the remaining revenue is distributed to each node in proportion to its actual contribution to the community's collective objectives. Contribution is assessed across three dimensions. First, the energy actually provided by the node during the settlement cycle. Second, the plan compliance rate. Third, the device uptime. This design directly links revenue to contribution quality, incentivising users to improve plan compliance and device availability rather than merely pursuing installed capacity.

For nodes that provide islanded power supply services to neighbouring non-storage nodes during outage emergency scenarios, an additional resilience subsidy may be received to compensate for the additional equipment wear they may sustain under emergency conditions. Monthly revenue settlement is executed automatically by a smart contract based on the compliance evidence reports generated in Section 5, without requiring human intervention, ensuring transparency and auditability of the distribution process.

7.3. Investment Governance Structure

The formation mode of residential storage assets directly affects user participation willingness and the framework's deployment capacity. Three principal investment governance models can be adopted in the DCF framework, while maintaining transparent compatibility.

User-owned Mode. The user purchases storage equipment independently and subscribes to the DCF platform's EIC software and coordination services. The user retains all asset appreciation returns and market arbitrage profit shares, suitable for user cohorts with a clear preference for asset ownership.

Operator Co-investment Mode. The DCF operator or a special purpose vehicle (SPV) co-invests in purchasing storage equipment or provides storage equipment to users on a lease basis, with the operator responsible for full-lifecycle operations and maintenance. The user pays a fixed monthly fee and shares market revenue at an agreed ratio after rental settlement. This model significantly reduces the user's initial investment threshold and is suitable for those who wish to benefit from storage but are unwilling to bear asset holding risks.

Community Co-investment Mode. Multiple users within the community jointly contribute capital to establish a shared storage asset pool, managed uniformly by the DCF operator, with revenue distributed in proportion to contributions. This model helps reduce the packaging cost of individual assets and forms a larger VAU resource pool, enhancing market competitiveness.

8. Conclusions and Future Work

This paper has proposed a decentralised coordination framework (DCF) for high-penetration distributed solar and storage resources. It employs a three-tier multi-agent reinforcement learning architecture, consisting of a user-layer PPO, a feeder-layer MADDPG, and a cross-feeder-layer coordination, decomposing the centralised joint optimisation problem into a scalable hierarchical coordination problem. It proposes a reputation-based dynamic leader election mechanism, a five-timescale rolling planning, and a security and privacy mechanism integration. It also discusses the market participation pathway and revenue distribution mechanisms. To summarise, this paper provides an architecturally self-consistent and clearly market-interface-defined framework foundation for a subsequent series of studies. However, as this is the first time to propose such a comprehensive framework for hierarchical energy coordination, this paper does not include too many technical details that can be translated transparently into implementation. This is a limitation of the current progressive research. However, this paper builds up a solid foundation for future improvement. In the future, research will advance along the following four directions.

Algorithm Implementation and Simulation Validation. A simulation environment will be constructed based on real power networks feeder data; the three-tier MARL architecture will be fully implemented; and systematic hyperparameter optimisation, convergence analysis, and comparative experiments will be conducted.

Security Mechanism Prototype Testing. The Paillier encryption module and DAG ledger node prototype will be implemented on edge controller hardware platforms; the encryption computation overhead and the feasibility of lightweight deployment of the LLM audit module will be evaluated.

Multi-Region Adaptation and Large-Scale Extension: Framework adaptation research will be conducted in the Chinese distribution network context; the influence of different market rules and network topologies on framework performance will be analysed; and computational scalability solutions for node populations scaling to hundreds or thousands of nodes will be investigated.

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