Multi-Agent Reinforcement Learning for Real-Time Frequency Regulation in Power Grids

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ES 158: Sequential Decision Making in Dynamic Environments

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1 Relevance to the Course

This project addresses distributed optimal control in power grid frequency regulation, formulated as a **Multi-Agent Markov Decision Process (MA-MDP)**:

Decision-makers: $N = 20$ controllable units (batteries, gas generators, demand response) coordinating to maintain 60 Hz frequency.

Dynamics: Grid frequency evolves via swing equations with coupled electromechanical dynamics:

$$\frac{df}{dt} = \frac{P_{\text{gen}} - P_{\text{load}} - P_{\text{losses}}}{2H \cdot S_{\text{base}}} \tag{1}$$

where each agent's action ΔP^i affects total P_{gen}.

Sequential nature: Control decisions require multi-step lookahead due to renewable forecasts, load fluctuations, and other agents' actions. Incorrect responses cause cascading deviations requiring minutes to correct.

The problem exhibits core RL challenges: continuous state/action spaces, partial observability (local measurements with delays), stochastic disturbances (renewable intermittency), and safety constraints (frequency within ± 0.5 Hz). Multi-agent coordination introduces non-stationarity, credit assignment, and scalability challenges beyond single-agent RL.

2 Motivation and Related Work

Motivation: Renewable energy integration (>30% generation) disrupts grid operations due to lack of inertia, causing faster frequency dynamics, doubled rate-of-change-of-frequency [5], and \$10B+ annual regulation costs. Recent blackouts (Texas 2021, South Australia 2016) linked to inadequate frequency response. Multi-agent RL offers coordinated, adaptive control potentially reducing costs 20-40% [8].

Prior Work: Classical AGC uses PI controllers [3] but cannot optimize multi-step costs. MPC effective but requires accurate models [7]. Single-agent RL applied to dispatch [9, 1] but doesn't scale. MARL foundations include independent learners [6], CTDE methods (MADDPG [4], QMIX), and communication protocols [2].

Gap: No systematic evaluation of modern MARL algorithms on realistic frequency regulation with safety constraints and renewable integration. We compare CTDE vs. communication vs. independent learning with constraint-aware training on validated power system models.

3 Problem Definition

Agent/Environment: $N = 20$ agents (5 batteries, 8 gas plants, 7 demand response) in IEEE 68-bus transmission system with stochastic renewables.

Formal MA-MDP: $\mathcal{M} = (\mathcal{S}, \{\mathcal{A}^i\}, P, R, \gamma, N)$

State space $\mathcal{S} \subseteq \mathbb{R}^{140}$: Bus frequencies $f_k \in [59.5, 60.5]$ Hz, generator outputs P_g^j, renewable generation, load $\in [2000, 5000]$ MW, time features.

Local observations $O^i \subseteq \mathbb{R}^{15}$: Local frequency, own output/capacity, system frequency deviation $\Delta f_{\text{sys}} = \frac{1}{68}\sum_k (f_k - 60)$, renewable forecasts.

Actions $\mathcal{A}^i$: Power change $\Delta P^i \in [-\Delta P^i_{\max}, \Delta P^i_{\max}]$ MW/min with constraints:

- Capacity: $P^i + \Delta P^i \in [P^i_{\min}, P^i_{\max}]$
- Ramp rates: $|\Delta P^i| \leq R^i_{\max}$ (batteries: 50, gas: 10, DR: 5 MW/min)

Dynamics: Swing equation $2H\frac{df_k}{dt} = P_{\text{gen},k} - P_{\text{load},k} - \sum_l \frac{D_{kl}(f_k - f_l)}{X_l}$ plus stochastic load/renewables and N-1 contingencies (probability 0.001/step). Dynamics **unknown** to agents.

Shared reward:

$$R(s,a) = -1000\sum_k (f_k - 60)^2 - \sum_i C_i|\Delta P^i| - 0.1\sum_i W_i(|\Delta P^i|) - 10^4 \cdot \mathbf{1}[\text{violations}] \tag{2}$$

Objective: Maximize $J = \mathbb{E}[\sum_t \gamma^t R_t]$ subject to safety: $\Pr[|f_k - 60| > 0.5] < 0.01$.

Assumptions: Cooperative agents, partial observability, 2-sec communication delays, unknown grid model, historical data for validation.

Data/Infrastructure: 6 months ERCOT SCADA data, Pandapower simulator with IEEE 68-bus, PyMARL2 framework, 4x A100 GPUs.

4 Proposed Method and Goals

Candidate Methods:

1. **MADDPG** [4]: Centralized critic $Q(s, a^1, \ldots, a^N)$, decentralized actors $\pi^i(o^i)$ during execution. Addresses non-stationarity via CTDE.
2. **QMIX**: Value factorization $Q_{\text{tot}} = g(Q^1, \ldots, Q^N)$ with monotonic mixing. Adapted to continuous actions via NAF.
3. **TarMAC** [2]: Learned communication with attention mechanism. Agents exchange messages $m^i = \text{signature}(o^i, h^i)$ for coordination.
4. **IDDPG**: Independent learners baseline to quantify coordination benefits.

All methods incorporate **safety layers**: action projection onto constraint sets, safety critic predicting violation probability, and Lagrangian relaxation for soft constraints.

Method Justification: MADDPG proven for continuous multi-agent control; QMIX tests value vs. policy methods; TarMAC evaluates communication vs. CTDE; IDDPG provides coordination baseline.

Goals and Success Criteria:

- **Primary**: Frequency stability $|f - 60| < 0.2$ Hz for 99% of time (vs. 95% baseline), $\geq$25% cost reduction, zero critical violations
- **Coordination**: MADDPG/QMIX outperform IDDPG by $\geq$15% reward
- **Metrics**: Area Control Error, regulation cost $\sum_t \sum_i C_i|\Delta P^i_t|$, constraint violations, sample efficiency

Evaluation Plan:

- **Baselines**: PI-AGC (industry standard), centralized MPC (oracle), behavioral cloning on ERCOT data
- **Training**: 5M steps, 32 parallel envs, curriculum learning (normal $\rightarrow$ N-1 outages $\rightarrow$ extreme scenarios)
- **Scenarios**: Normal operation (100 episodes), N-1 contingencies (50), renewable ramps (30), distribution shift (50)

- **Ablations**: Coordination mechanisms, observation spaces, safety layers, reward weights

Feasibility: Pandapower validated, PyMARL2 tested, IEEE cases available, compute accessible. **Risks**: Training instability (mitigation: gradient clipping, target networks), insufficient exploration (importance sampling, safe exploration), scalability (GNNs if needed).

Timeline: Weeks 1-2: Environment setup; 3-4: IDDPG baseline; 5-7: MADDPG/QMIX; 8: TarMAC; 9-10: Evaluation; 11: Analysis; 12: Report.

Expected Impact: First systematic MARL comparison for power grid frequency regulation. Demonstrates coordination benefits, constraint handling, and path toward 25% cost reduction enabling higher renewable penetration.

References

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