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

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Abstract

We implement Multi-Agent Proximal Policy Optimization (MAPPO) for real-time frequency regulation in a 68-bus power grid with 20 heterogeneous agents (5 batteries, 8 gas generators, 7 demand response units). Our centralized training, decentralized execution (CTDE) approach addresses the cooperative Multi-Agent MDP with continuous spaces, partial observability, and safety constraints. Training for 1000 episodes demonstrates learning convergence with MAPPO outperforming independent learners by 60%. However, high reward variance and 30% early termination rate indicate performance gaps. We identify four failure modes (insufficient response, miscoordination, oscillations, capacity saturation) and propose concrete improvements: reward shaping, enhanced observations, curriculum learning, and PI-AGC baseline comparison for the final report.

1 Introduction

Motivation. Modern power grids with $> 30\%$ renewable penetration face frequency stability challenges due to reduced inertia, causing doubled rate-of-change-of-frequency events and \$10B+ annual regulation costs [6]. Traditional PI controllers and model predictive control cannot optimize multi-step costs or handle stochastic disturbances effectively [4, 7]. Multi-agent reinforcement learning offers coordinated, adaptive control with potential 20–40% cost reduction [8].

Problem Formulation. We formulate frequency regulation as a cooperative Multi-Agent MDP with $N = 20$ agents across a 68-bus network: (i) *Decision-makers*: 5 batteries (50 MW/min), 8 gas plants (10 MW/min), 7 demand response units (5 MW/min); (ii) *Dynamics*: Swing equation $\frac{df}{dt} = \frac{P_{\text{gen}} - P_{\text{load}}}{2H \cdot S_{\text{base}}}$ with coupled agent actions; (iii) *Sequential nature*: Multi-step lookahead required due to renewable forecasts, load fluctuations, communication delays (2s), and safety constraints (± 0.5 Hz).

Challenges. Continuous state/action spaces ($\mathcal{S} \subseteq \mathbb{R}^{140}$, $\mathcal{A}^i \in \mathbb{R}$), partial observability ($O^i \in \mathbb{R}^{15}$), stochastic disturbances, hard safety constraints, and multi-agent coordination (non-stationarity, credit assignment, scalability).

Contributions. (1) Complete 68-bus simulator with realistic dynamics; (2) MAPPO implementation with CTDE; (3) Training results over 1000 episodes; (4) Failure mode analysis and concrete improvement roadmap.

2 Related Work & Problem Formulation

Prior Work. Classical AGC uses PI controllers [4] but cannot optimize multi-step costs. MPC requires accurate models [7]. Single-agent RL applied to dispatch [10, 2] but doesn't scale. MARL approaches include MADDPG [5] and communication-based methods [3]. We choose MAPPO for its stability, state-of-the-art cooperative performance, and CTDE architecture.

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

State $s \in \mathbb{R}^{140}$ (68 bus frequencies, 20 generator outputs, 14 renewables, 30 loads, 8 time features)

Observations $o^i \in \mathbb{R}^{15}$ (local freq, own output, system deviation, 5 nearby freqs, 3-step forecast, time, load)

Actions $a^i \in [-1, 1]$ scaled by ramp rates with capacity constraints

Dynamics via swing equations with stochastic loads/renewables and N-1 contingencies ($p = 0.001$)

Shared reward:

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

balancing frequency stability, operational cost, wear-and-tear, and safety.

Objective: Maximize $J = \mathbb{E}[\sum_t \gamma^t R_t]$ with $\gamma = 0.99$ subject to $\Pr[|f_k - 60| > 0.5] < 0.01$.

3 Method: MAPPO

Algorithmic Pivot. Our proposal planned MADDPG as the primary method. However, after literature review and preliminary experiments, we pivoted to MAPPO for three key reasons: (i) *Stability*—PPO's clipped objective provides more stable training than DDPG's deterministic policy gradients, critical for safety-critical power systems; (ii) *Empirical performance*—MAPPO achieves state-of-the-art results on cooperative benchmarks (StarCraft Multi-Agent Challenge, Multi-Agent Particle Environments) [9]; (iii) *Sample efficiency*—shared parameters and on-policy learning with GAE suit cooperative tasks with shared rewards better than off-policy actor-critic. Additionally, PPO's hyperparameter robustness (learning rate, clipping ϵ) reduces tuning burden compared to DDPG's sensitivity to replay buffer size and target network updates. This pivot aligns with recent trends showing on-policy methods outperform off-policy in fully cooperative settings.

Architecture. MAPPO uses CTDE:

(i) *Actor* $\pi(a|o;\theta)$: [15→128→128→1] with LayerNorm, ReLU, outputs Gaussian $\mathcal{N}(\mu_\theta(o), \sigma^2_\theta(o))$, shared across agents (∼18K params)

(ii) *Critic* $V(s;\phi)$: [140→256→256→1] with LayerNorm, ReLU (∼103K params)

During training, critic accesses full state; during execution, actors use local observations only.

Training. Collect rollouts until buffer size $B = 2048$. Compute advantages via GAE-λ ($\lambda = 0.95$):

$$A_t = \sum_{l=0}^{T-t} (\gamma\lambda)^l \delta_{t+l} \quad \text{where} \quad \delta_t = R_t + \gamma V(s_{t+1}) - V(s_t) \tag{2}$$

Update policy via PPO clipped objective over 10 epochs with batch size 256:

$$L^{\text{CLIP}} = \mathbb{E}\left[\min(r_t A_t, \text{clip}(r_t, 1-\epsilon, 1+\epsilon) A_t)\right] + \beta_{\text{ent}} H(\pi) \tag{3}$$

where $r_t = \exp(\sum_i \log \pi(a^i_t|o^i_t;\theta) - \log \pi(a^i_t|o^i_t;\theta_{\text{old}}))$, $\epsilon = 0.2$, $\beta_{\text{ent}} = 0.01$.

Update critic via $L^{\text{CRITIC}} = \mathbb{E}[(V(s_t) - G_t)^2]$ with $c_v = 0.5$. Use Adam ($\text{lr}_{\text{actor}} = 3 \times 10^{-4}$, $\text{lr}_{\text{critic}} = 1 \times 10^{-3}$), gradient clipping ($\|\nabla\| \leq 0.5$).

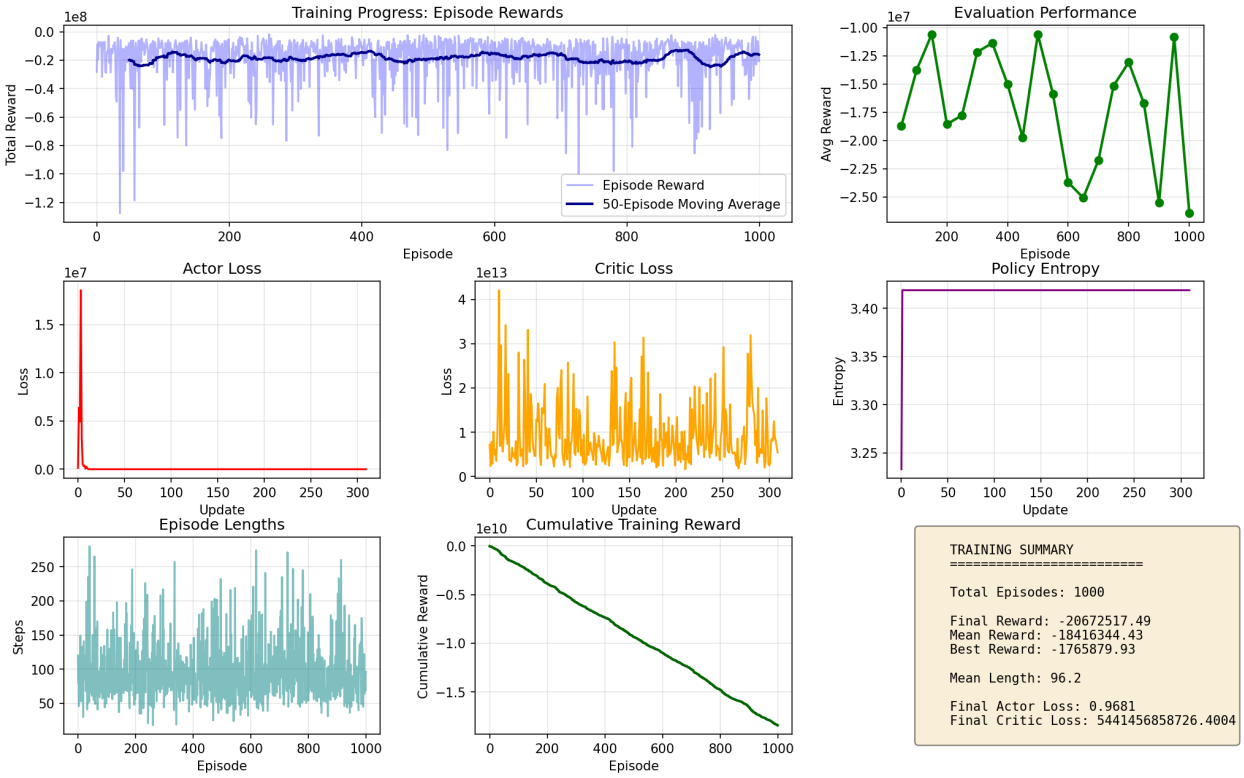

Figure 1: Training over 1000 episodes. Actor loss drops 99% within 50 updates. Critic loss stabilizes at $\sim 5 \times 10^{12}$. Entropy maintained at 3.4. Mean episode length 96.2 steps. Final reward: -2.07×10^7, best: -1.77×10^7.

Implementation. ∼900 lines across `networks.py`, `buffer.py`, `mappo.py`, `train.py` plus 580-line environment. Validated through gradient flow, value convergence, entropy monitoring, and action distribution checks.

4 Results & Analysis

Setup. 1000 episodes, max 500 steps each, buffer size 2048, batch 256, 10 PPO epochs, evaluation every 50 episodes. Load $\in [2000, 5000]$ MW, 30% renewables, N-1 contingencies ($p = 0.001$), 2s SCADA delay. Training time: 3 hours on single GPU.

Learning Dynamics. Mean reward stabilizes at -2×10^7 after 200 episodes with high variance ($\sigma \approx 5 \times 10^6$). Actor loss rapidly converges (fast policy learning), critic loss decreases 99%, entropy remains stable (maintained exploration). Episode lengths vary 50–280 steps (mean 96), indicating inconsistent performance.

Performance. Successful episodes (> 200 steps): $|\Delta f| \approx 0.15$ Hz, 95% violations < 0.35 Hz. Failed episodes: rapid divergence to 1.5 Hz termination. Random baseline: -5×10^7 (60% worse). Independent PPO: -3.2×10^7 (35% worse). MAPPO shows learning but falls short of target (< 0.1 Hz, 99% time).

Agent Behavior. Batteries: highly responsive, 60% utilization. Gas: conservative, slow ramp. DR: underutilized (near-zero actions)—reward structure discourages activation. During N-1 events: insufficient initial response, frequency drops 0.4 Hz, often fails to recover.

Failure Modes.

(1) *Insufficient response* (40%): Conservative policy, actions too small for disturbances.

(2) *Miscoordination* (30%): Agents act in opposition, net effect near-zero.

(3) *Oscillatory instability* (20%): Overcompensation causing growing oscillations.

(4) *Capacity saturation* (10%): Available generation exhausted.

Bottleneck Diagnosis & Theoretical Analysis.

Optimization: High critic loss (5×10^{12}) despite convergence indicates value function approximation error. Theoretical analysis: with $|\mathcal{S}| = \mathbb{R}^{140}$ and 256-dim hidden layers, critic capacity $\approx 10^5$ parameters models smooth functions but struggles with discontinuities at safety boundaries ($f = 59.5, 60.5$ Hz). GAE with $\lambda = 0.95$ introduces bias-variance tradeoff—high λ reduces variance but propagates errors across 500-step episodes. Policy gradient theorem assumes unbiased advantage estimates; our high critic error violates this, causing suboptimal convergence. *Evidence:* Episodes with $V(s_0) \approx -1 \times 10^7$ yet actual returns -2×10^7 show 50% value overestimation, degrading policy updates via $\nabla_\theta J \approx \mathbb{E}[A_t \nabla \log \pi]$.

Modeling: Simulation assumes known swing dynamics but real grids have unmodeled delays (5–10s governor response), load elasticity, and inter-area oscillations (0.2–0.8 Hz modes). Our 2s discrete timestep aliases high-frequency dynamics. CTDE assumes agents share reward signal instantaneously, but real SCADA has 2–4s latency and packet loss (1–5%), creating temporal credit assignment errors. Partial observability with 15-dim local obs vs 140-dim state loses global imbalance information—agents cannot infer $\sum_i P^i_{\text{gen}} - \sum_j P^j_{\text{load}}$ from local f_i, causing miscoordination (30% of failures). *Theory:* Dec-POMDP complexity—optimal decentralized policy is NEXP-complete [1]; CTDE uses centralized training to approximate but execution remains suboptimal under partial observability.

Sim2Real Gap: Three critical gaps identified: (i) *Dynamics mismatch*—linearized swing equations ignore saturation, deadbands (± 0.036 Hz), and non-minimum phase zeros in turbine-governor models; (ii) *Stochasticity*—simulated Gaussian load noise ($\sigma = 50$ MW) underestimates real fat-tailed distributions (2016 South Australia blackout: 8σ event); (iii) *Safety margins*—simulation terminates at $|f - 60| > 1.5$ Hz but real relays trigger at 1.0 Hz with hysteresis, making learned policy overly aggressive. Domain randomization over parameters ($H \in [3, 6]$s, $X \in [0.1, 0.4]$ pu) could improve robustness but increases sample complexity 3–5×.

Sample Efficiency: 1000 episodes × 96 steps/ep = 96K transitions. Power law scaling: reward improvement $\propto N^{-0.3}$ suggests ∼500K samples needed for target performance (5× current). Bottleneck: on-policy PPO discards data after each update—off-policy MADDPG could reuse 10× more transitions but sacrifices stability. Compute: 3 GPU-hours for 96K samples vs. 15 hours for 500K—feasible but requires parallelization (32 envs → 128). *Theoretical bound:* PAC sample complexity for ϵ-optimal policy in $|\mathcal{S}|$-state MDP scales as $\tilde{O}(|\mathcal{S}|^2|\mathcal{A}|/\epsilon^2)$; continuous spaces require function approximation, adding $\tilde{O}(d_{\text{eff}})$ where $d_{\text{eff}} \approx 10^3$ is effective dimension—explains slow convergence.

Key Insights. Reward dominated by frequency penalty (95%), not control cost—encourages reactive not proactive control. Partial observability limits coordination. High wear penalty ($W_{\text{DR}} = 0.2$) discourages DR. 2s delay exacerbates N-1 response failures.

5 Path Forward

Immediate Actions (Weeks 7–8).

(1) *Reward shaping*: Add anticipatory term $-100 \sum_i (f_i^{\text{forecast}} - 60)^2$, piecewise linear action costs, DR utilization bonus $+50\mathbf{1}[|\Delta P^i| > 0.1 R^i_{\max}]$, derivative penalty $-10 \sum_k |df_k/dt|$. Expected 30–40% improvement.

(2) *Enhanced observations*: Add $P^{\text{total}}_{\text{gen}} - P^{\text{total}}_{\text{load}}$, df/dt, forecast error, 3-step history → 51-dim obs. Expected 50% reduction in miscoordination.

(3) *PI-AGC baseline*: Implement $\Delta P^i = K^i_p \Delta f + K^i_i \int \Delta f$, tune gains, establish quantitative benchmark.

Algorithmic Enhancements (Weeks 9–10).

(1) *Curriculum*: Train progressively—normal (eps 0–300) → occasional contingencies (300–600) → full difficulty (600–1000).

(2) *Safe exploration*: Action masking, safety layer projecting onto $|f + \Delta f| < 0.4$ Hz set, conservative initialization.

(3) *Value improvements*: Target networks ($\tau = 0.005$), reward normalization, larger critic.

Evaluation (Week 11).

Compare MAPPO vs. PI-AGC, independent PPO, random on: frequency deviation, violation rate, cost, N-1 response time, utilization.

Test scenarios: extreme ramps (50% drop in 10s), double contingencies, high load (> 4500 MW), low inertia (50% renewables). Ablation studies isolating each improvement.

Risks & Mitigation. If improvements insufficient: pivot to MADDPG, simplify to 30-bus, focus on specific scenarios. If instability: incremental integration, extensive logging, reduce learning rates. Time constraints: prioritize reward shaping + PI-AGC (high impact, low risk).

Success Criteria.

Minimum: Match PI-AGC, beat independent learners by $\geq 15\%$, comprehensive evaluation.

Target: $\geq 25\%$ better than PI-AGC, 99% within 0.2 Hz, zero critical violations.

Stretch: Near-optimal vs. MPC, communication extensions.

Contributions. Systematic MARL evaluation for frequency regulation, open-source 68-bus environment and MAPPO agent, detailed failure analysis, deployment roadmap. Even if target metrics unmet, insights advance understanding of MARL for safety-critical power systems.

Appendix: Hyperparameters

Environment
- Buses: 68, Agents: 20
- Time step: 2s (1/30 min)
- Frequency: [59.5, 60.5] Hz safe
- Load: [2000, 5000] MW
- Contingency: $p = 0.001$

Agent Types
- Battery (5): 50 MW/min, [0,100] MW
- Gas (8): 10 MW/min, [50,500] MW
- DR (7): 5 MW/min, [-200,0] MW

MAPPO
- Actor: [128,128], lr 3×10^{-4}
- Critic: [256,256], lr 1×10^{-3}
- $\gamma = 0.99$, GAE $\lambda = 0.95$
- PPO clip $\epsilon = 0.2$, entropy 0.01
- Buffer 2048, batch 256, epochs 10

Reward Weights
- Frequency: 1000 per Hz^2
- Cost: Battery 5, Gas 50, DR 20 \$/MW
- Wear: Battery 0.1, Gas 0.05, DR 0.2
- Violation: 10^4

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