Autonomous Optimization in Decentralized Microgrids

Multi-Agent Reinforcement Learning for Dynamic Power Balancing

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1 Introduction

2 Methodology

3 Evaluation

4 Conclusion

- **Transition to Renewables**: Microgrids integrate distributed energy resources (DERs) like solar PV, wind turbines, and battery storage.

Introduction

Decentralized Microgrid Decarbonization

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- **High Volatility**: Renewable generation fluctuates rapidly due to weather conditions, challenging grid stability.
- **Scalability Limits**: Centralized control systems struggle to manage thousands of active endpoints in real-time.
- **Autonomous Optimization**: Shift toward localized, edge-computing intelligence using multi-agent architectures.

Key Challenges

Operational Hurdles in Modern Microgrids

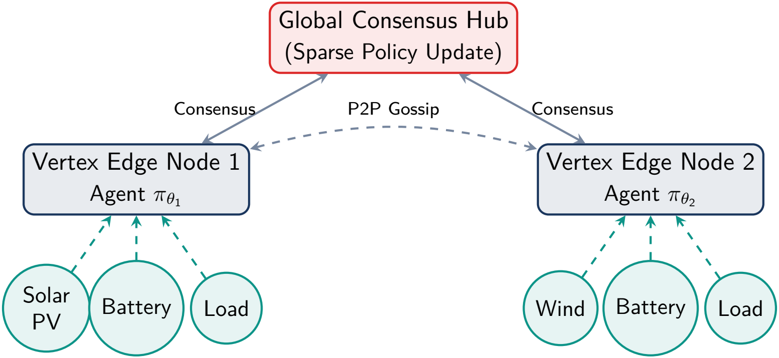
Problem Statement

Dynamic power balancing in microgrids requires real-time coordination under stochastic supply/demand profiles without exposing private local consumer data.

- **Dimensionality**: Large action spaces (battery charging/discharging, load shedding, grid import/export).
- **Communication Bottlenecks**: High latency prevents centralized optimization models from converging.
- **Data Privacy**: Consumers are unwilling to share high-resolution load profiles with a central entity.

Proposed Architecture

Decentralized Peer-to-Peer Control



Mathematical Formulation

Objective Function and Constraints

We formulate the microgrid optimization as a Decentralized Partially Observable Markov Decision Process (Dec-POMDP).

Objective Function

Minimize total operational cost across all nodes N over planning horizon T:

$$\min_{\boldsymbol{a}} \mathbb{E}\left[\sum_{t=1}^{T}\sum_{i=1}^{N}\left(C_i^{\text{grid}}(P_{i,t}^{\text{grid}}) + C_i^{\text{deg}}(P_{i,t}^{\text{bat}}) + \beta_i L_{i,t}^{\text{shed}}\right)\right]$$

Key Operational Constraints

$$\begin{aligned} P_{i,t}^{\text{gen}} + P_{i,t}^{\text{bat}} + P_{i,t}^{\text{grid}} = P_{i,t}^{\text{load}} - L_{i,t}^{\text{shed}} \qquad & \forall i, t \quad \text{(Power Balance)} \\ S_{i,t+1} = S_{i,t} + \eta_i P_{i,t}^{\text{bat}} \Delta t \qquad & \forall i, t \quad \text{(Battery SoC Dynamics)} \end{aligned}$$

Algorithmic Approach

Decentralized Actor, Centralized Critic

To solve the Dec-POMDP, we utilize a Multi-Agent Deep Deterministic Policy Gradient (MADDPG) variant:

- **Centralized Training**: Critics have access to the joint state $\boldsymbol{s} = (s_1, \ldots, s_N)$ and joint action $\boldsymbol{a} = (a_1, \ldots, a_N)$ during training.
- **Decentralized Execution**: During deployment, each agent π_{θ_i} acts using only its local observation o_i.
- **Policy Update**:

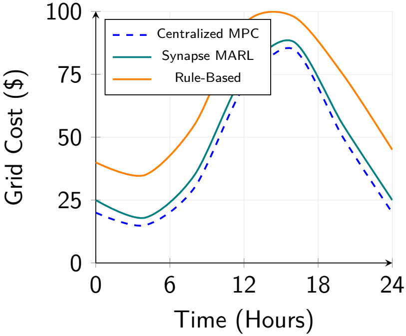
$$\nabla_{\theta_i} J(\theta_i) = \mathbb{E}_{\boldsymbol{s},\boldsymbol{a}\sim\mathcal{D}} \left[\nabla_{\theta_i} \pi_{\theta_i}(a_i|o_i) \nabla_{a_i} Q_i^{\psi}(\boldsymbol{s}, a_1, \ldots, a_N) \big|_{a_i=\pi_{\theta_i}(o_i)} \right]$$

Experimental Validation

Power Balancing Performance under Volatility

Simulation Setup:

- 10-node microgrid simulation.
- Fictional solar generation profiles from Nimbus database.
- Real-time pricing fluctuations.



Key Observations:

- Proposed Synapse method tracks optimal Centralized MPC closely.
- Significantly outperforms traditional Rule-Based

Performance Metrics

Quantitative System Evaluation

We evaluate the algorithms across 1,000 independent runs. Cost and carbon metrics are normalized.

Optimization Method	Time to Converge (s)	Daily Cost ($)	Carbon (kg)	Feasibility (%)
Centralized MPC	124.50	42.10	120.4	100.0
Rule-Based Heuristic	0.05	68.30	185.2	92.4
Decentralized Q-Learning	1.20	55.40	152.0	94.8
Synapse MARL (Ours)	**0.45**	**44.80**	**128.6**	**99.8**

System Capabilities
Standard Rochester Block Implementations

The Rochester theme provides distinctive colored blocks to structure different types of content:

Standard Block: Core System Features

Used for general statements, definitions, or standard descriptions of algorithm components.

Alert Block: Critical Operational Limits

Used to highlight critical constraints, safety violation thresholds, or convergence failure states.

Example Block: Localized Node Configuration

Used for case examples, specific physical parameters, or demonstration scenarios.

Case Study: Meridian Pilot

Field Implementation and Performance

To evaluate performance in production, we deployed the Synapse system at the Meridian Microgrid facility.

Deployment Profile

- **Location**: Apex Industrial Zone
- **Capacity**: 2.4 MW peak load
- **Renewables**: 1.2 MW solar PV, 800 kW battery storage
- **Duration**: 90-day trial period

Key Outcomes

- **Cost Savings**: 22.4% reduction in peak demand charges
- **Stability**: Zero power outages during high volatility
- **Efficiency**: 98.6% local solar consumption rate

- **Scalability to Microgrid Clusters**:

Future Directions

Scaling and Deployment Challenges

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- **Security and Robustness**:
  - Protecting edge models against malicious adversarial state injections.
  - Ensuring fail-safe rule-based logic is always active as a fallback.

Thank You!

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