Optimal Coordination of Distributed Energy Resources Using Deep Deterministic Policy Gradient

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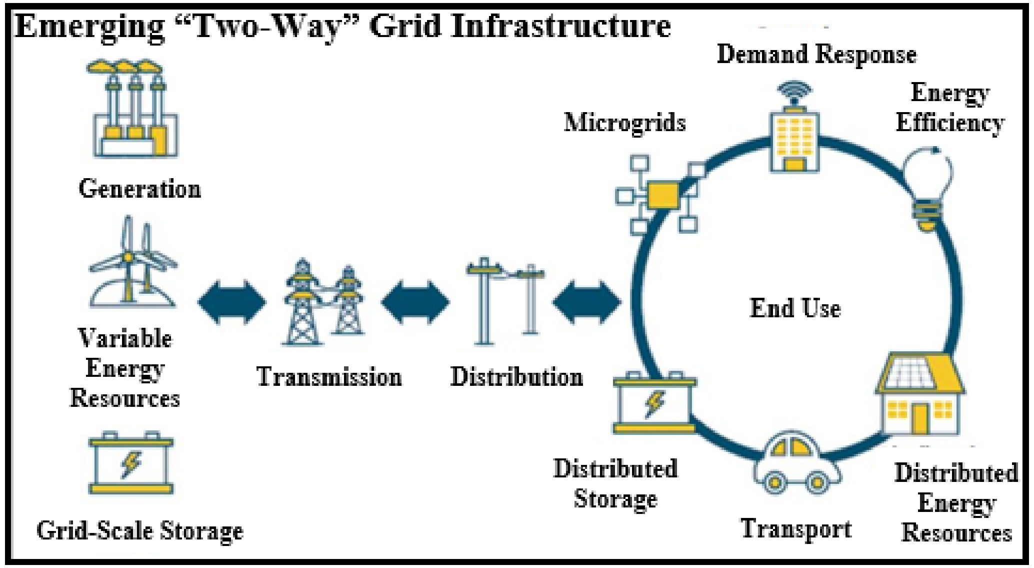
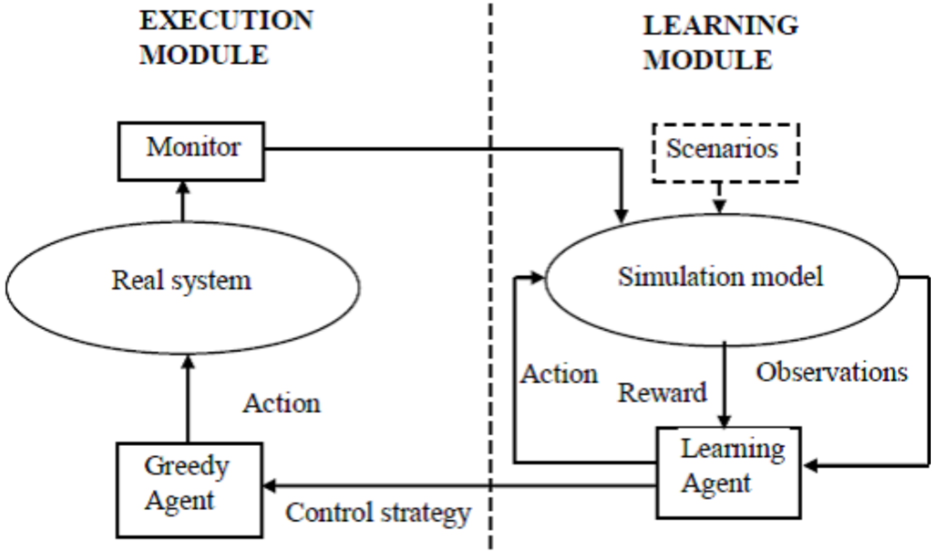
Outline

- Background
- Motivation and Contribution
- Microgrid System Model and Formulation
- Proposed Deep Deterministic Policy Gradient Approach
- Simulation Analysis
- Conclusion and Future Work

Background

- Distributed energy resource (DER) deployment in distribution systems has increased considerably
- Coordination of DERs amidst uncertainties is critical to harvesting their potential benefits
- Reinforcement learning (RL) is promising for power system applications, and has attracted surging attention due to its recent successes





Existing Methods

- Various RL methods have been proposed and investigated in recent years to tackle DER coordination challenges
  - Fitted-Q iteration algorithm to maximize self-consumption of renewable generation (RG) and minimize the electricity cost
  - A multiagent RL framework empowers autonomous agents of DERs and consumers for maximizing individual profit
  - Deep Q-learning method for coordination of battery energy storage systems (BESSs) considering microgrid system uncertainties
  - Deep RL approach to manage the optimal energy consumption of multiple smart homes with RG and BESS
  - Approximate dynamic programming with policy-based exploration for DER coordination in a remote microgrid
  - Deep deterministic policy gradient (DDPG) for optimal scheduling of DERs and service restoration

Motivation

- Shortcomings of existing methods:
  - Many of them are based on lookup table methods, which become inefficient when the problem size is large and infeasible when continuous states and actions are involved
  - BESS loss of life and degradation are not reasonably considered in the RL design

Contribution

- We propose an innovative DDPG-based RL for optimal DER dispatch with BESS loss of life explicitly modeled
  - Both calendrical and cyclical aging effects are taken into account when designing the dispatch policy

* A. Das and D. Wu. "Optimal Coordination of Distributed Energy Resources Using Deep Deterministic Policy Gradient." in *Proc. IEEE Power Energy Soc. Electr. Energy Stor. App. and Tech. Conf. (EESAT)*, Austin, TX, Nov. 2022, pp. 1-5.

Microgrid System Model

- Goal is to optimally dispatch DERs to minimize the cumulative operation cost
- DER includes
  - RG such as photovoltaic (PV) and wind
  - BESS assets
- Objective function consists of two components
  - BESS operation and maintenance (O&M) cost
  - Energy cost
- Component- and system-level constraints include
  - BESS power limit
  - BESS state of charge (SOC) transition and limit
  - Microgrid power balance

$$\min_{x} \sum_{t=1}^{T} (C_t^{\text{batt}} + C_t^{\text{ex}})$$

BESS O&M Cost

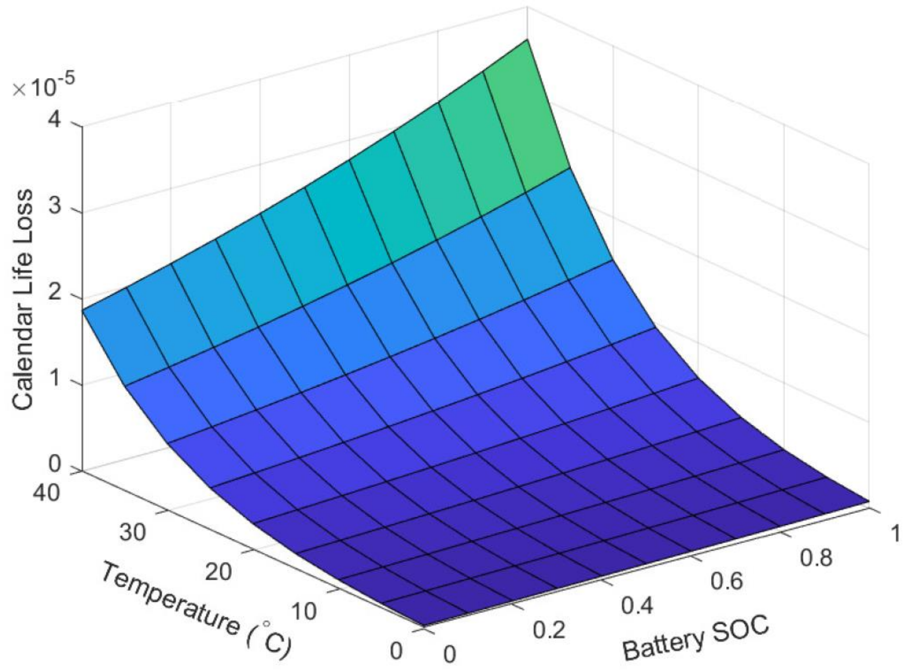
$$C_t^{\text{batt}} = \begin{cases} g p_t^{\text{batt}} \Delta t, if\, p_t^{\text{batt}} \geq 0 \; (discharging) \\ 0, \quad otherwise \; (charging) \end{cases}$$

Energy Cost

$$C_t^{\text{ex}} = \begin{cases} \dfrac{p_t^{\text{grid}} \lambda_t \Delta t}{\zeta}, if\, p_t^{\text{grid}} \geq 0 \\ p_t^{\text{grid}} \lambda_t \zeta \Delta t, if\, p_t^{\text{grid}} < 0 \end{cases}$$

BESS Life Loss

- This paper considers both cyclical and calendrical aging effects
- Cycle life loss is determined based on charging/discharging operation of BESS
  - Rainflow algorithm for determining the depth of discharge (DOD)
  - A cyclical aging model uses DOD to determine cycle life loss
- Calendar life loss is determined using a weighted modeling approach
  - Calendar life loss calculated due to staying at a certain SOC and temperature
  - Life loss is particularly prominent at high SOC
- Cumulative daily cycle life loss and calendar life loss are constrained to ensure the expect battery lifetime



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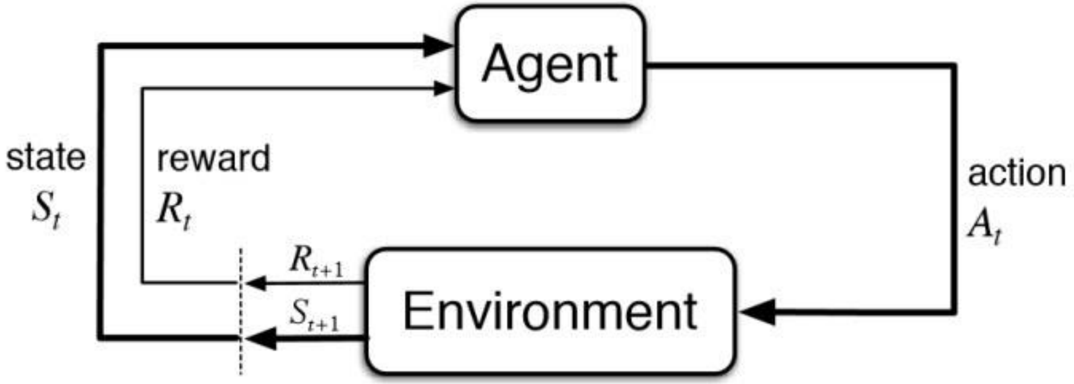
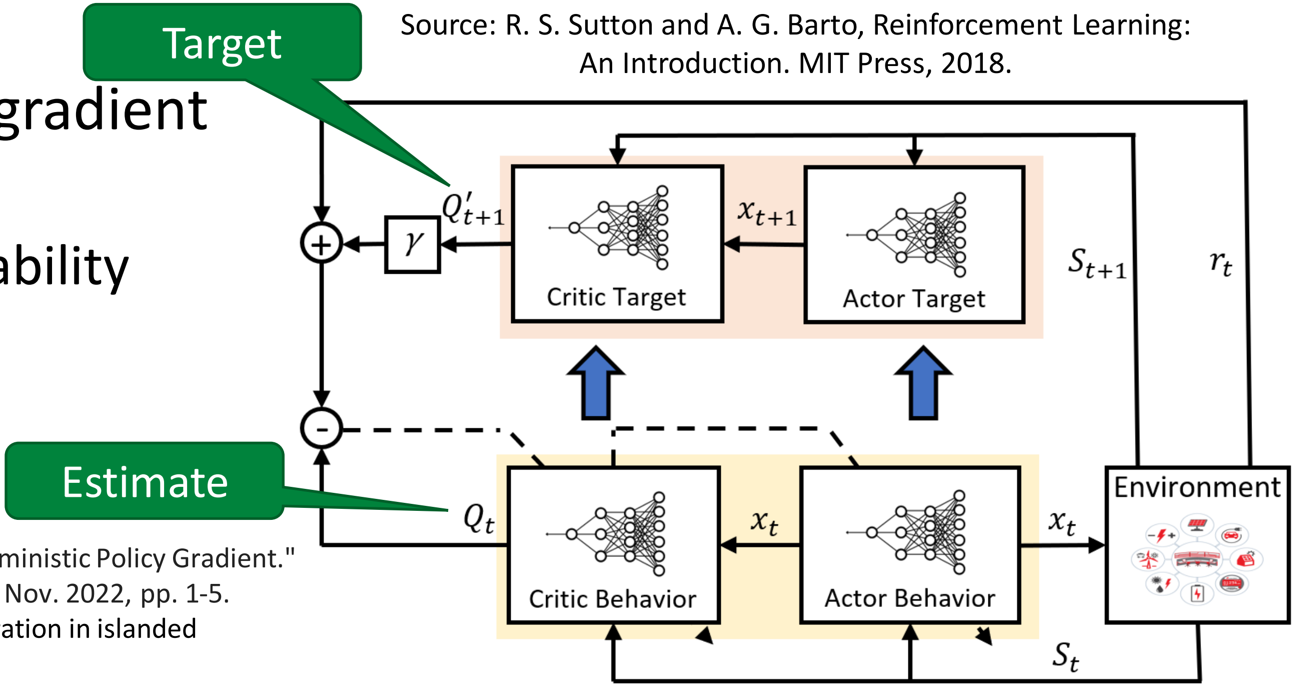
Problem Formulation and DDPG

- Sequential decision-making problem is formalized as a Markov decision process
  - State includes battery SOC, RG output, system load, retail price, and cumulative life losses
  - Action includes BESS charging/discharging power, and the power purchased from/sold back to the grid
- DDPG is an off-policy deterministic policy gradient method
  - An off-policy method improves learning stability and data usage efficiency
  - Safe exploration is ensured through action mapping, clipping, and reward shaping



Source: R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction. MIT Press, 2018.



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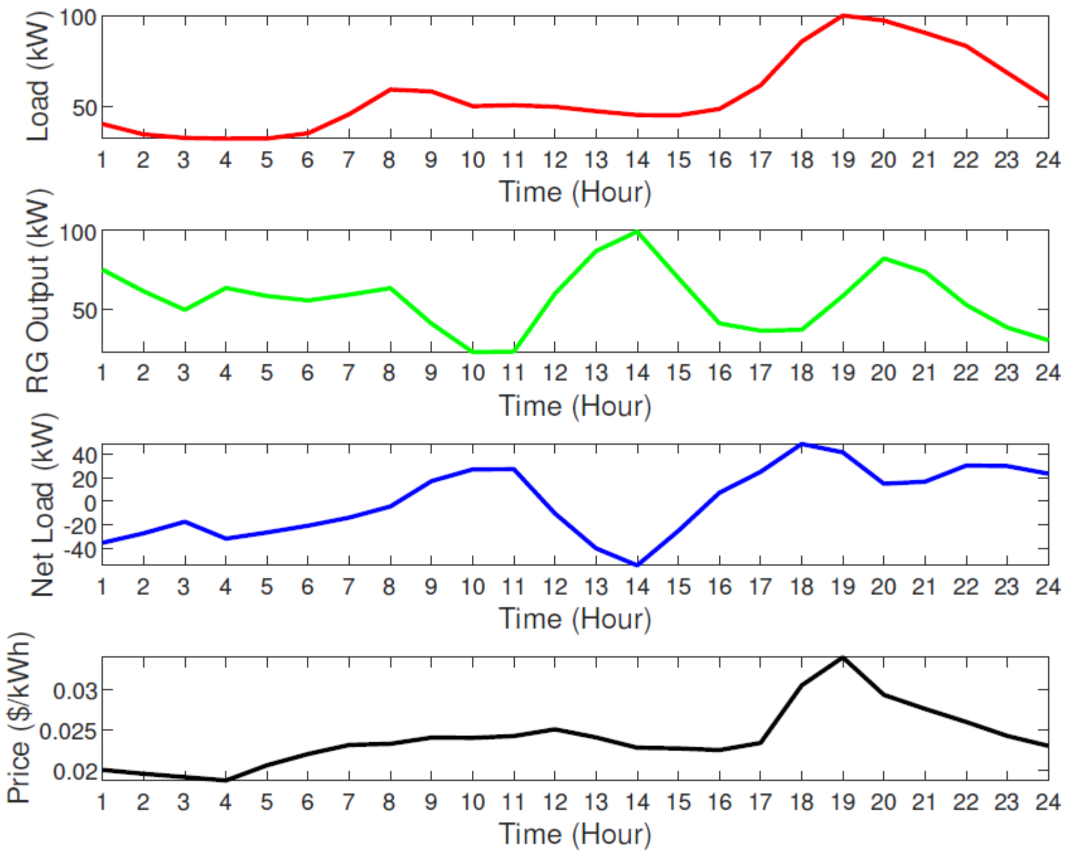
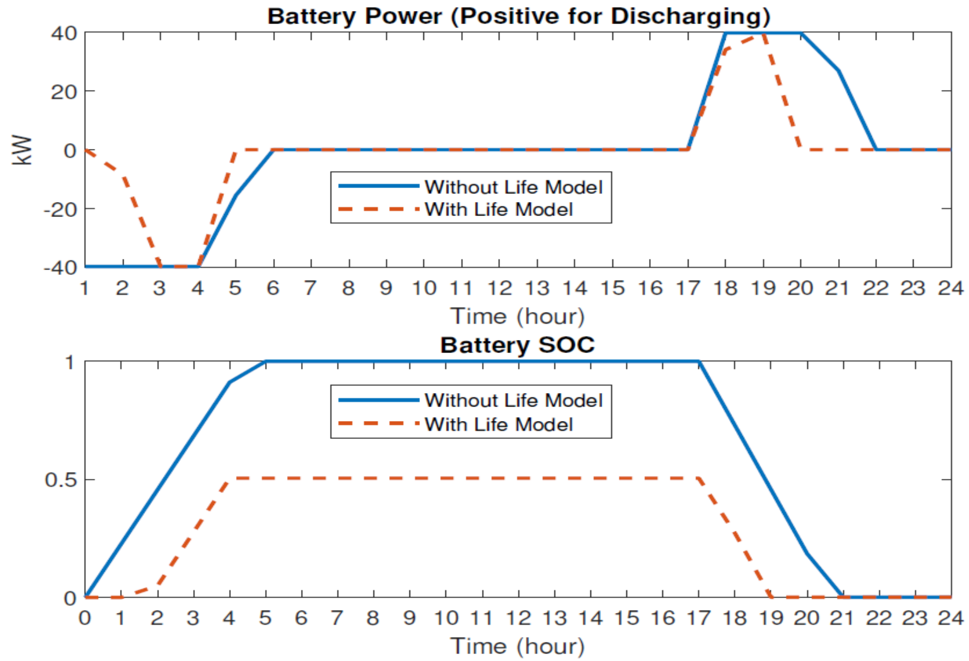
Simulation Setup

- Microgrid test system:
  - 100 kW wind and 50 kW PV
  - Lithium-ion BESS: 3 years of calendar life and 600 cycles
  - 160 kWh BESS energy capacity, 40 kW rated power, 83.7% round-trip efficiency
  - BESS SOC range: [0 1]
  - Residential load profiles with peak of 100 kW
- DDPG implemented using PyTorch
  - OpenAI gym for environment
  - Neural networks with two hidden layers and 64 neurons
  - ReLU and sigmoid activation functions



Case Study

- BESS dispatch results without the life loss model compared with the life loss model
  - BESS deep cycled when the life loss is not considered in control design, leading to reduced lifespan
  - Incorporating life-loss model into control design helps avoid deep cycling of BESS and expand its service life
- Different daily maximum life loss limits are also investigated
  - BESS expected lifetime is minimum when the life loss model ignored
  - With life loss model, BESS operation optimized to minimize cost and ensure expected lifetime
  - System with the life loss model considered offers 10% more savings over the calendar life



Model	$\bar{l}_t^{cyc}$ and $\bar{l}_t^{cal}$	Expected lifetime (years)
Without life loss	-	1.7
With life loss	1.1e-3	2.5
With life loss	9.1e-4	3

Conclusion and Future Work

- This work proposes an innovative DDPG-based RL approach for optimal DER dispatch, considering BESS calendrical and cyclical life loss models.
- Case studies were performed to show that the proposed approach can maximize benefits while ensuring the BESS lifespan requirement.
- One interesting future work is to develop an advanced RL approach based on the policy iteration strategy for DER coordination considering distribution power flow.
- Another interesting direction is to develop advanced multi-objective optimization to find a good balance between economic benefits and battery lifetime.

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* A. Das, D. Wu, and B.A. Bhatti, "Approximate Dynamic Programming with Enhanced Off-policy Learning for Coordinating Distributed Energy Resources," *IEEE Trans. Sustain. Energy*, Jul. 2023. (To Be Submitted)

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Thank You

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Backup Slide: DDPG Technique

- Critic network
  - Estimate the action-value function, and the network weights are updated to minimize the mean square error

Estimate

$$E_c = \frac{1}{M}\sum_{m=1}^{M}(e_c^m)^2$$

Target

$$e_c^m = Q\left(S_t^m, x_t^m \middle| \theta_Q\right) - \left(r_t^m + \gamma Q'\left(S_{t+1}^m, x_{t+1}^m \middle| \theta_Q'\right)\right)$$

$$\theta_Q = \theta_Q - \Phi_c \nabla_{\theta_Q} E_c;\ \theta_{Q'} = \tau\theta_Q - (1-\tau)\theta_{Q'}$$

Soft update

- Actor network
  - Learn a policy that minimizes the action-value function

$$\theta_v = \theta_v - \Phi_a \nabla_{\theta_v} J(\theta_v);\ \theta_{v'} = \tau\theta_v - (1-\tau)\theta_{v'}$$

$$\nabla_{\theta_v} J(\theta_v) = \frac{1}{M}\sum_{m=1}^{M}\nabla_{x_t^m} Q\left(S_t^m, x_t^m \middle| \theta_Q\right) \nabla_{\theta_v} v\left(S_t^m \middle| \theta_v\right)$$

- Safe exploration is ensured through action mapping, clipping, and reward shaping