A Hybrid Reinforcement Learning-MPC Approach for Distribution System Critical Load Restoration

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Motivation & Introduction

- Utilizing generation from variable and uncertain renewable energy resources could enhance distribution system resilience in the event of a transmission system outage
- The Critical Load Restoration Problem (CLRP) is that of scheduling available distribution system resources to maintain as much load as possible during transmission system outage
- Optimization-based Model Predictive Control (MPC) is a common approach for CLRP, while Reinforcement Learning (RL) is an emerging approach for this problem
- **We propose a hybrid RL-MPC approach through an operational energy reserve to characterize renewable generation uncertainty**

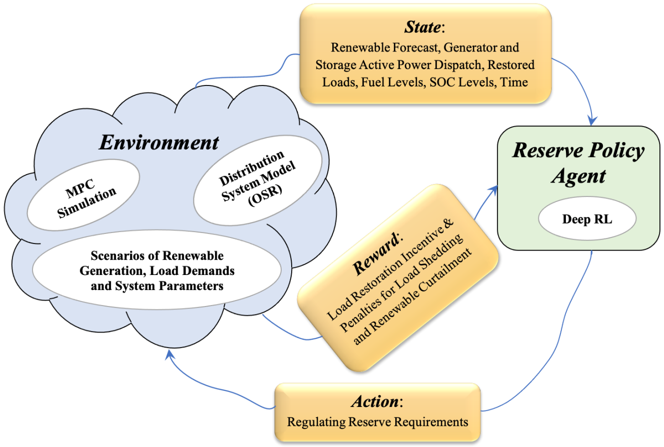

Fig 1. Hybrid RL-MPC controller learning framework

Hybrid Control Design

- RL determines an energy reserve policy: the amount of energy to have available at the end for the MPC time-horizon
  - State is determined by wind and solar forecasts, current power output, current restored load, and energy available as fuel and in batteries
  - The action is the final end-state battery energy and fuel energy available
  - Reward function is identical to MPC objective: **maximize restored load whilst not shedding previously restored load**
  - Maximize the cumulative expected reward utilizing Proximal Policy Optimization
- MPC-based Optimal Scheduling and Restoration (OSR), including
  - Prioritized Loads (real & reactive)
  - Linearized distribution power flow with voltage constraints
  - Microturbine dispatch (real & reactive) with fuel constraints
  - Battery charging/discharging with state-of-charge management
  - Renewable power generation/curtailment with limited reactive power dispatch
  - Enforcing RL-based reserve policy for end-state battery state-of-charge and fuel availability

Case Study

- Method is applied to a modified IEEE 13-bus distribution test system containing wind, solar, microturbine, and battery (see Figure 2)
- Performance of RL-MPC dynamic energy reserve policy (RP1) is compared against four MPC-based fixed energy reserve policies (RP2, RP3, RP4, & RP5) on 20 outage scenarios

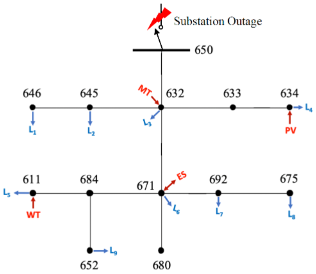

Fig 2. Modified IEEE 13-bus feeder

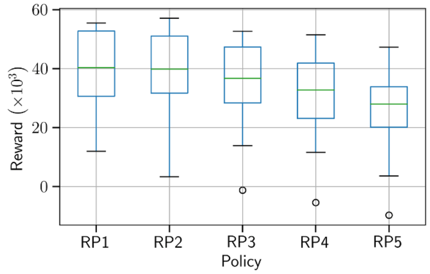

Fig 3. Total reward across 20 scenarios for RP1 – RP5

Simulation Results

- The RL-MPC approach (RP1) has several distinguishing characteristics over the fixed energy reserve policies – it has the highest median reward, best worst-case performance, and lowest sample variance, as shown in Figure 3
- As shown in the example in Figure 4, the RL-MPC controller manages the DERs interactively to monotonically increase the total restored load with a dynamic energy reserve policy

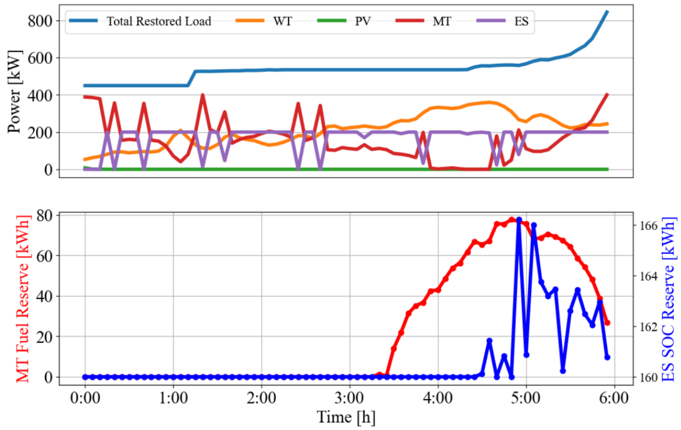

Fig 4. Single scenario example. Upper: sample power dispatch and restored load. Lower: RL-based dynamic energy reserve policy.

Conclusions

- The RL-MPC hybrid controller utilized RL to learn MPC parameters while the MPC included sophisticated operational constraints (e.g., voltage limits) which could be difficult to enforce with RL alone.
- This hybrid approach out-performed the MPC-based alternatives

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