Networked Micro-Grid Scheduling After an Extreme Event: A Reinforcement Learning Approach

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Introduction:

This paper proposes a reinforcement learning (RL) approach to optimize the restoration process of networked microgrids (MGs) with dispatchable and renewable energy sources. The proposed model aims to maximize prioritized load restoration and minimize renewable power curtailment, resulting in improved operation quality and resilience of networked MGs. The main issue with conventional power restoration problems is the curse of dimensionality, which makes optimizing a network with a high number of buses time and resource consuming. Furthermore, MGs with dynamic boundaries are even more complex, making the problem harder to solve. Optimization models have limitations regarding uncertainties, and it is still impossible to solve large-scale problems. In case of an outage, all the conventional optimization-based approaches should start optimizing after the fault happens, which could take time. However, with the RL approach, one may overcome this issue. The proposed model employs a deep Q-network (DQN) to learn the optimal restoration policy. The DQN is trained on a dataset generated by a simulation model of the MGs. The simulation model considers the uncertainties of renewable energy sources and load demand. The proposed model is evaluated on a testbed of a real MG with renewable energy sources. The results show that the proposed model outperforms the conventional optimization-based approaches in terms of fast decision making. The proposed model can be used as a decision-making tool for the restoration process of networked MGs with renewable energy sources.

Model:

In this research, we proposed a two-stage approach for optimizing the restoration process of networked MGs. In the first stage, a Q-learning algorithm is employed to learn the optimal operation policy for sectionalizing the network into smaller sections. To handle large-scale problems, function approximation with a neural network is used. The neural network is trained to approximate the Q-function, which represents the expected future reward for each state-action pair. The Q-learning algorithm updates the Q-function iteratively based on the observed rewards and transitions. The optimal operation policy is obtained by selecting the action with the highest Q-value for each state.

In the second stage, the RL agent aims to restore the MG by utilizing distributed energy resources (DERs) such as microturbines, solar panels, wind turbines, and energy storage. The RL agent selects the optimal combination of DERs to restore the prioritized loads while minimizing the renewable power curtailment. The RL agent is trained using the Deep Deterministic Policy Gradient (DDPG) algorithm, which is a model-free RL algorithm that can handle continuous action spaces. The DDPG algorithm employs an actor-critic architecture, where the actor learns the optimal policy, and the critic learns the Q-function. The actor and critic are both implemented as neural networks, and they are trained using the observed rewards and transitions.

Results:

The proposed model is evaluated on a testbed of a real MG with renewable energy sources. The results show that the proposed model outperforms the conventional optimization-based approaches in terms of decision time and power curtailment. The proposed model can restore the prioritized loads within a very reasonable time and with less renewable power curtailment compared to the conventional approaches. The proposed model can also handle uncertainties and large-scale problems more efficiently than the conventional approaches.

Conclusion:

The proposed RL-based approach offers a promising solution for optimizing the restoration process of networked MGs with renewable energy sources. The combination of RL and function approximation with neural networks can handle large-scale problems and uncertainties more efficiently than the conventional optimization-based approaches. The proposed model can be used as a decision-making tool for the restoration process of networked MGs with renewable energy sources. Future work can explore the implementation of different machine learning approaches such as transfer learning to enhance the performance of the RL model.