MSc Thesis Proposal

Graph Neural Network-Augmented Deep Reinforcement Learning Maintenance Optimization of Energy Infrastructure Networks

• Context of the research

In recent years, Deep Reinforcement Learning (DRL) algorithms have been increasingly used for operation and maintenance (O&M) optimization of energy infrastructure, owing to its ability to learn optimal decision policies through direct interaction with the environment, without explicit modeling of system dynamics or prior knowledge of the underlying environment dynamics or optimal strategies. By framing maintenance optimization as a sequential decision problem (SDP), DRL enables adaptive and data-driven maintenance optimization under uncertainty.

Despite these advantages, the application of DRL to maintenance optimization of energy infrastructure networks is faced with general challenges such as poor generalization, credit assignment, sparse rewards, partial observability and sample inefficiency, some of which may be attributed to the environment state representation being a flat vector of environment features. Such issues can be exacerbated in infrastructure networks with large number of components and complex operating conditions. Moreover, network infrastructures are often characterized by complex functional and topological interdependencies that cannot be efficiently captured by flat environment state vectors.

• Objective of the research

The goal of this research is to propose a DRL-based framework for the maintenance optimization of complex energy infrastructure networks, whose components are subject to dependent competing failures, while considering the underlaying uncertainties related to the operating conditions and their effects on network performance. The proposed methodology formulates the maintenance optimization problem as an SDP, solved using DRL. Graph theory is used to model network characteristics and interdependencies, while integrating the dynamics of the operating conditions. A Graph Neural Network (GNN) is developed to extract rich and topology-aware latent representations from the network (graph) that are subsequently used to augment the environment state vector provided to the DRL agent.

Furthermore, the research addresses the class imbalance problem in the agent's training data; a reward sparsity-related issue arising from the fact that the majority of agent-environment interactions occur during healthy network states characterized by the absence of component failures or network capacity reduction, whereas the scenarios of greatest relevance to agent's decision-making, involving severe degradation and (partial) failures, may significantly be underrepresented in the collected experience. To this end, a potential-based reward shaping strategy is adapted, leveraging component degradation states and GNN-derived metrics to provide dense, intermediate reward signals that guide the agent throughout the degradation phase. The research activities include:

- Familiarization with graph theory and sequential decision problems
- Literature review of DRL and GNN applications to O&M optimization of energy infrastructure
- Development and evaluation of a GNN model for network performance analysis, and a DRL-based maintenance optimization framework, integrating the developed GNN model
- Development of a potential-based reward shaping strategy to address reward sparsity during degradation evolution phase
- Application of the proposed DRL-based maintenance optimization framework to a case study and evaluating the optimized maintenance policy against the conventional and condition-based policies
- Analysis and interpretation of the obtained results.

• Required skills

- Interest in developing innovative algorithms to address real-world applications.
- Good knowledge of statistics/applied mathematics and AI/ML technologies and techniques.
- Good knowledge of Python and/or R programming languages, with a focus on DRL.

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