Risk-Aware Maintenance Optimization in Energy Components and Systems using Deep Reinforcement Learning and Graph Neural Networks

Context of the research

Energy components and systems operate in a continuously evolving environment due to factors such as fluctuating operational conditions, dynamic load demands, environmental variability, and component aging. Traditional maintenance approaches do not consider the evolving interactions between system components and their degradation processes, leading to suboptimal maintenance schedules, which can result in unexpected downtimes or increased operational costs, or even system-wide failures.

Graph Neural Networks (GNNs) offer a promising way to represent and analyse these realistic aspects of energy components and systems by modelling components as nodes and their interactions within the systems as edges. This graph-based abstraction allows capturing structural dependencies, obtaining health states which are not only intrinsic to the components, but also influenced by neighbouring components, operating environment and degradation evolution.

This research will focus on integrating GNNs and DRL into a unified framework to optimize maintenance schedules of energy components and systems, where failure can lead to costly downtime, safety hazards, or cascading effects across networks. Combining Deep Reinforcement Learning (DRL) with GNNs is expected to enable intelligent and adaptive maintenance strategies.

Objective of the research

This thesis aims to develop a framework combining GNNs and DRL to enable risk-aware and adaptive maintenance scheduling in energy components and systems. The GNN encodes the system state to dynamically represent the health and interdependencies of system components, and the DRL agent learns optimal policies for maintenance actions based on these graph-based representations.

The research activities include:

- Conducting a literature review on DRL, GNNs, and their applications in predictive/prescriptive maintenance and asset management.
- Modelling energy system assets as graphs.
- Designing and implementing a GNN encoder to capture system state and degradation patterns.
- Training a DRL agent to learn an optimal maintenance strategy.
- Benchmarking the proposed approach against classical and learning-based maintenance policies.
- Testing and validating the framework on real-world and synthetic case studies.
- Critically analysing the advantages and the limitations of the developed frameworks and defining future research directions.
- Writing of scientific papers as chapters of the thesis.

Case study

Electrical Power Transmission and Distribution

Power grids are inherently graph-structured systems where substations, transformers and transmission lines are interconnected and dynamically influenced by load, generation and environmental factors. The case study will consider a regional power grid consisting of high-voltage transmission lines, substations, and generation units, incorporating time-varying load demands, renewable generation variability (e.g., solar and wind), and weather-related contingencies.

Collaborations

The work will be performed in the Laboratory of Analysis of Systems for the Assessment of Reliability, Risk and Resilience (LASAR[3], www.lasar.polimi.it) of Politecnico di Milano.

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