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Transmission Expansion Planning Via Multi Objective Deep Reinforcement Learning

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In this study, we adopt a risk-informed approach to power Transmission Expansion Planning (TEP), treating it as a multi-objective optimization problem that aims at minimizing system risk and expansion cost and we investigate the potential of reinforcement learning. Specifically, we employ a modified version of Q-learning that enables the attainment of high rewards across multiple dimensions. The TEP reinforcement learning-based approach is tested on the IEEE 118-bus system, and comparisons are made to previous TEP expansion approaches.

Transmission system operators (TSOs) strive to enhance power grid performance by expanding infrastructure, through a decision-making process known as Transmission Expansion Planning (TEP). TEP aims to identify cost-effective network upgrades while enhancing system security, with a focus on the N-1 security criterion for grid robustness. Regulatory standards from the North American Electric Reliability Corporation (NERC) now mandate an analysis of system performance under simultaneous dual-element loss and an evaluation of cascading outage risks. Therefore, the TEP problem is multi-objective, driven by the need to strike a balance between capital expenditures and assurance of robust system security. Our study focuses on research from (Gjorgiev, 2022), utilizing an AC power flow-based cascading failure simulation model. In (Gjorgiev, 2022), TEP is framed as a multi-objective optimization task, and the NSGAII algorithm is used to find Pareto optimal solutions that balance expansion cost and the risk of cascading outages. Traditional metaheuristic algorithms are preferred for nonconvex and nonlinear optimization problems, yet they lack optimality guarantees and can be computationally intensive. This study develops an innovative approach, based on deep reinforcement learning (DRL) techniques (Sutton and Barto, 2018) to address the complexities of multi-objective, non-linear, and non-convex optimization problems. Recent advances in reinforcement learning (Mehta, 2022), demonstrate DRL's superior ability to efficiently explore decision variable spaces and cover the Pareto front. While DRL's application in power systems is limited, studies like (Wan, 2021) and (Pang, 2024) have explored DRL in TEP, focusing on minimizing costs and ensuring safe grid operation, albeit within the confines of N-1 or N-k reliability criteria and utilizing the DC power flow model. Notably, our study pioneers the application of Deep Reinforcement Learning (DRL) to TEP, incorporating an AC-PF cascading failure model.

We structure the TEP problem following the framework outlined in (Gjorgiev, 2022). Utilizing a meta-model of the AC Cascading failure model (Gjorgiev, 2022), developed in (Varbella, 2023), we employ the multi-objective Reinforcement Learning (RL) approach introduced in (Fan, 2023). The authors introduce a deep Q learning (DQN) method (Mihn, 2013) suitable for multi-objective decision-making. The problem is cast into a Markov decision process, where the agent sequentially incorporates new branches into the grid until reaching a maximum limit or identifying a Pareto optimal solution. At each step, the environment undergoes updates, yielding a vector-valued reward comprising the risk of cascading outages and the investment cost. The vector is scalarized using the Nash Social Welfare function, in Eq. (1), where v_i are the elements of the reward vector and n is the dimension of the reward vector.

$$NSW(v) = \left(\prod_{i=1}^{n} v_i\right)^{\frac{1}{n}} \quad (1)$$

In Figure 1, we show the DQN approach applied to TEP.

Fig. 1. Multi-Objective DQN for Transmission Expansion Planning.

We test the approach on the IEEE118-bus benchmark system, which has 186 branches and 118 nodes. In this case study, all 186 branches (lines and transformers) are candidates for the capacity expansion (i.e. via the construction of a parallel asset). The maximum allowable number of branches to be built is set to eight and the maximum number of new branches permitted per corridor is set to one. In Figure 2, we report the Pareto front of optimal solutions obtained by running our multi-objective DRL TEP method for 2000 episodes. The Pareto clearly shows the conflict between the cost of TEP and the improvement in risk, as observed in (Gjorgiev, 2022).

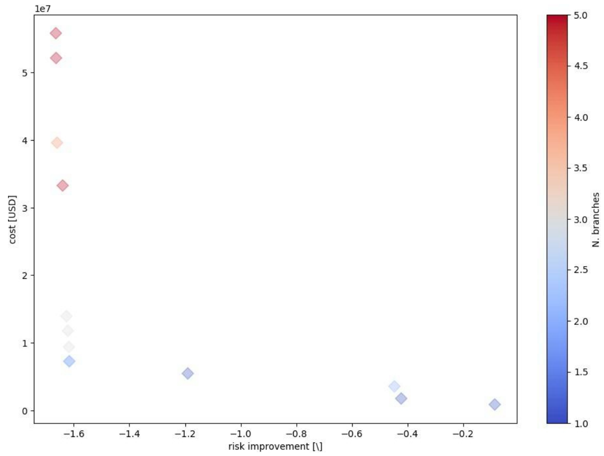

Fig. 2. Pareto Front with the Multi-objective DQN approach.

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