Engineering Risk Analysis Group
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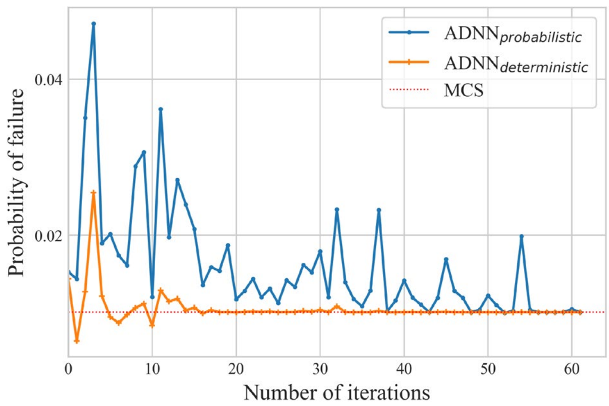
Master's thesis

Active learning of artificial neural networks for network reliability analysis

Nick Pfeiffer, July 2022

Background

In the modern society, lifeline networks play essential roles, which include transportation systems, utility distribution networks, and telecommunication networks. To effectively design and operate those systems, one can assess reliability of those networks. However, as it often requires a large number of network analyses, reliability evaluation becomes unaffordable as a network entails a large number of components or an expensive system function (e.g., traffic assignment and AC analysis of power networks). While surrogate models can be used to predict a network's performance (i.e., failure or survival) with a small number of training data, existing models show limitations with a large number of components and component events having discrete states, which are common characteristics of network problems.



The graph displays estimated probability of failure by the proposed ADNN-MCS method, plotted over the number of active learning iteration steps. The orange and blue curves show predictions when DNN's prediction is considered deterministic or probabilistic, respectively. Active learning is stopped if the DNNs' prediction reaches a predefined threshold of confidence; this often coincides with when the two predictions show a marginal difference.

Methodology

We propose using Deep Neural Networks (DNN) as a surrogate model to replace network analysis. Thereby, one can calculate a network's failure probability by evaluating a large number of Monte Carlo simulation (MCS) samples. DNN is particularly favorable for network problems as it can effectively handle high dimensionality and regression over discrete variables. Nevertheless, active learning of DNNs contains several distinctive challenges, such as hyperparameter tuning, selection of training data, and balance between exploration and exploitation. By developing a set of strategies to resolve these issues, we propose an algorithm named active-learning of DNN combined with MCS (ADNN-MCS).

Results

To demonstrate accuracy and efficiency of ADNN-MCS, we investigate connectivity analysis of various random graphs with different size and topology. The algorithm shows satisfactory and consistent accuracy over all example networks. Moreover, in all cases, ADNN-MCS requires a significantly lower number of network analyses than MCS. Such computational efficiency is underlined by analyzing the Sioux Falls benchmark network, which is assessed by (computationally expensive) traffic assignment optimization.

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