Increasing computational efficiency of seismic risk analysis for infrastructure networks

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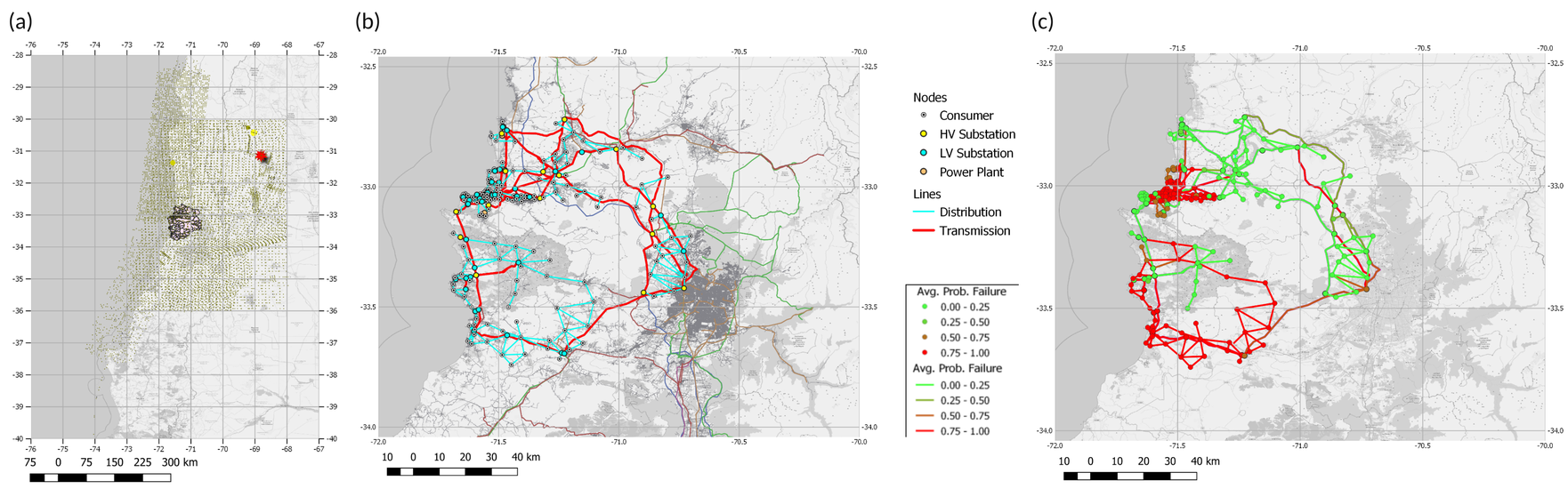
Introduction

Seismic risk assessment of spatially distributed infrastructure networks requires an enormous amount of simulations of earthquake scenarios, ground motion fields, damage states of infrastructure components and subsequent cascading failures. The simulation of ground motion fields and cascading failures in the network are the most demanding steps in the described workflow. Therefore, developing novel, computationally efficient methodologies for these tasks and applying them to a reasonable number of simulations is the most promising strategy on the way towards reliable evaluation of infrastructure network performance in the aftermath of an earthquake. With this poster contribution we aim to share our currently available simulation framework and a first idea of how to improve the efficiency of simulating cascading failures in infrastructure networks using graph neural networks.

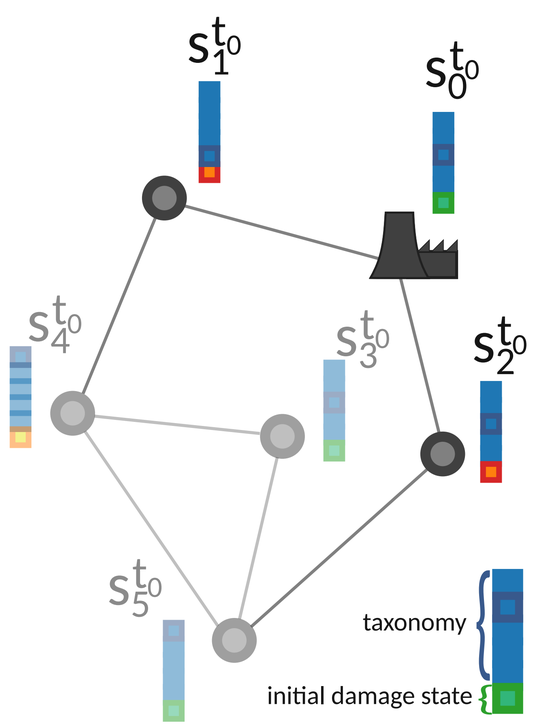
Seismic risk modeling framework

Based on a synthetic seismic catalogue, we select scenarios **(a)** and obtain random realizations of the ground motion intensity measure (e.g. the PGA). They are the input for evaluating the damage state of the infrastructure components with fragility functions[1]. Fragility functions provide the conditional probability of the damage state of the system, given an intensity measure of the ground motion. All experiments are conducted with synthetic data generated from graph-based modeling approaches, where we aim to represent a simplified version of the electrical power supply network of Valparaíso, Chile **(b)**. For each realization, we simulate random initial combinations of component damage states **(c)**. We also simulate cascading effects caused by the initial damages. There are cascading failure models based on graph efficiency for simulating the performance loss of the infrastructure network[2]. We measure the performance loss in terms of connectivity loss and affected population. In addition, we compute the probability of failure for each component due to cascading failures. The codes to perform the described simulations are available in an open GitHub repository [3].

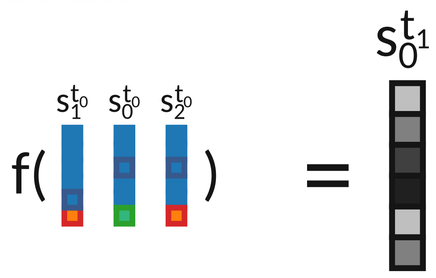


A graph neural network (GNN) surrogate model for failure cascades

Simulating cascading effects within a lifeline system is one of the most demanding steps in the risk analysis simulation chain and would therefore benefit strongest from the replacement by an efficient surrogate model. GNNs are deep learning based methods that operate on graph-like data and have evolved into a powerful graph analysis tool in recent years.[4] Due to their extreme efficiency and their natural ability to operate on graph-like data, GNNs pose a valuable opportunity to boost simulation efficiency in seismic risk assessment of lifeline infrastructure networks. The following example represents a potential setup for node-wise classification (operative, partially operative, not operative) of components in a power-supply network after a series of cascading failures. However, also graph-wise (instead of node-wise) classification and regression problems can be formulated within this framework in order to predict, for example, the connectivity loss of a lifeline system. While the gain in terms of efficiency (~ fraction of a second for the simulation of a cascade) compared to the graph-based simulation of cascading effects (~ few seconds per simulation of a cascade) is moderate, huge improvements are to be expected when training a surrogate model for physics based approaches, such as DC power flow analysis (~ hours per cascade simulation).



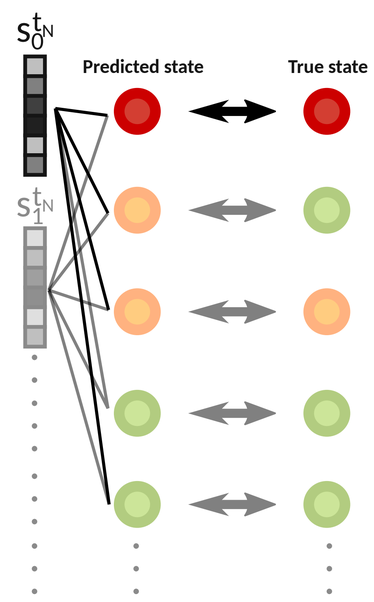
Message passing Information from neighbors are collected in order to learn about the role of a node within the graph. The function f is learned during training to provide meaningful feature vectors.



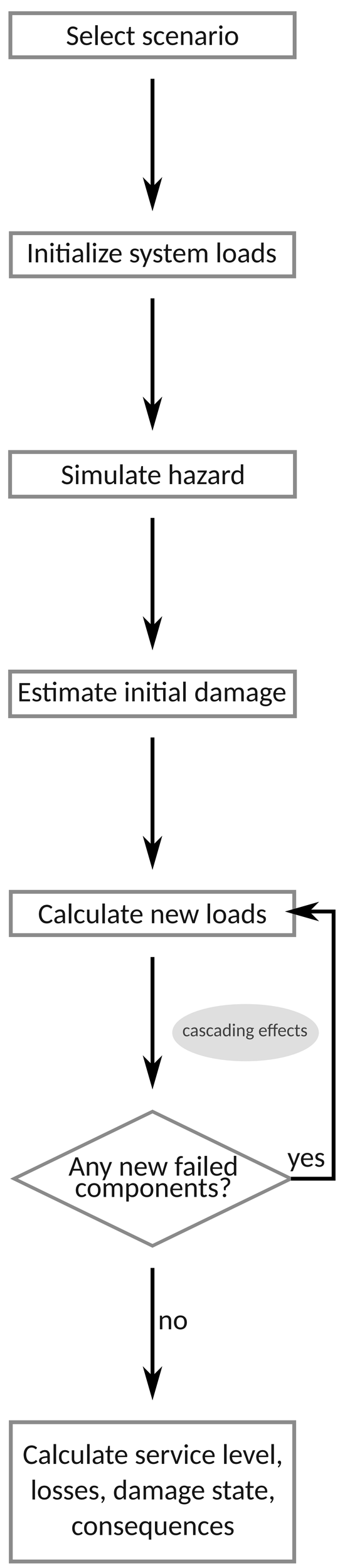
S_t - node feature vector at time t (taxonomy and initial damage state)

S_{t+1} - node feature vector at time t+1 (abstract vector including information about the node and its neighbors)

Evaluation against synthetic data The GNN output is evaluated against the results from graph-based simulations.



Simulation chain



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