Fast and Reliable $N - k$ Contingency Screening with Input-Convex Neural Networks

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ABSTRACT

We discuss preliminary work on accelerating contingency screening in power grids with machine learning while ensuring provable guarantees on reliability. Evaluating the feasibility of all possible $N - k$ contingencies in a power grid is computationally intractable for large k, requiring system operators to resort to contingency screening heuristics that sacrifice rigorous guarantees on reliability, i.e., that might predict an operating condition to be feasible and safe when it is in fact infeasible. In our work, we use input-convex neural networks (ICNNs) as feasibility classifiers for contingency analysis. In particular, we propose a training and postprocessing methodology for ICNNs leveraging tools from convex optimization that yield classifiers with good classification accuracy and provably zero false negative rate; that is, classifiers obtained through our approach will never classify an infeasible operating condition as feasible. We empirically validate our approach on an IEEE test network, showing that it yields substantial speedups in contingency screening runtime while maintaining good accuracy and zero false negative rate.