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Learning to Predict Security Constraints for Large-Scale Unit Commitment Problems

Rafael Sterzinger, Jan Poland, Max B. Paulus, Didier Chételat

ETH Zürich

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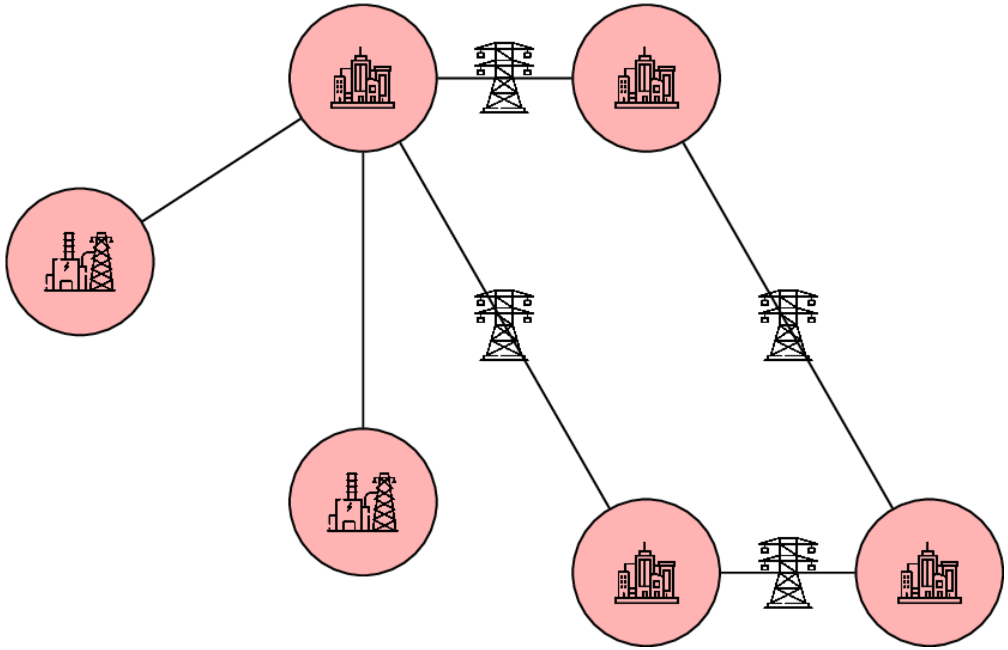
Unit Commitment

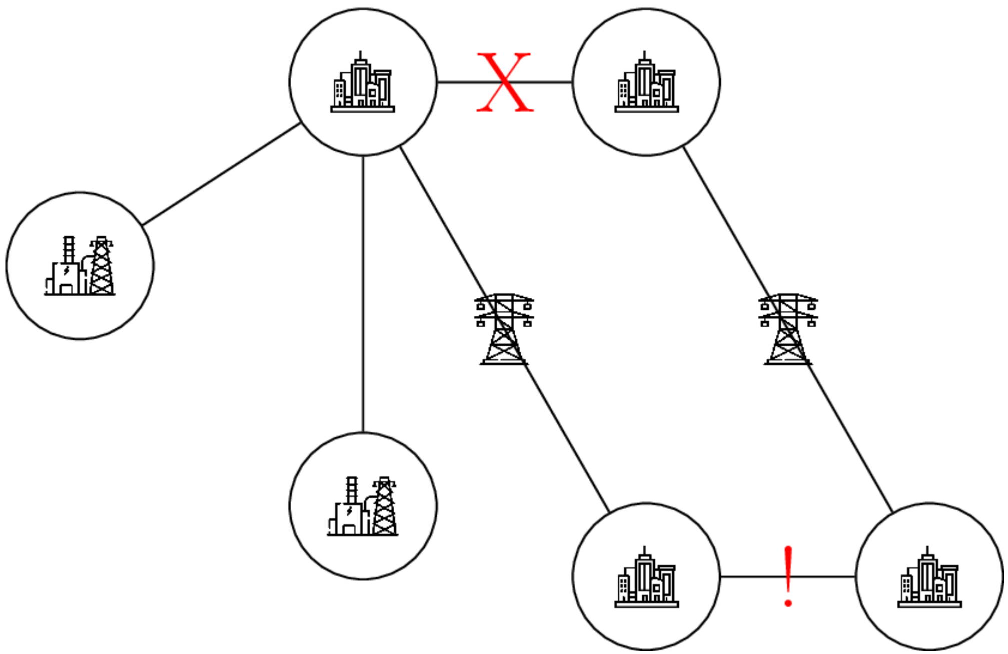
- Mission-Critical Task: cost-effective scheduling…



- …to meet demand at buses with sufficient supply.

Security Constrained Unit Commitment (N-1 Transmission Contingencies)

- On top, we have Security Constraints (SCs),…



- …which are quadratic w. r. t. transmission lines.

Standard Solving Approach

- SCUC problems are **formulated as Mixed-Integer Programs (MIPs) [1]**
- Solving time **influenced by problem size** (e.g. amount of constraints/variables)
- In SCUC typically several **100 million security constraints** (SCs) for a realistic power grid
- Fortunately, **small subset** of SCs **implies satisfaction of complement [2]**
- Solution: **Iterative Bottom-Up Solving [3]**

Why Machine Learning?

SCUC problems are **solved routinely** with only **small changes** which we can leverage to **predict SCs for a given instance** and provide them as hints to the solver...

$$\mathcal{C} = \mathrm{Model}(I)$$

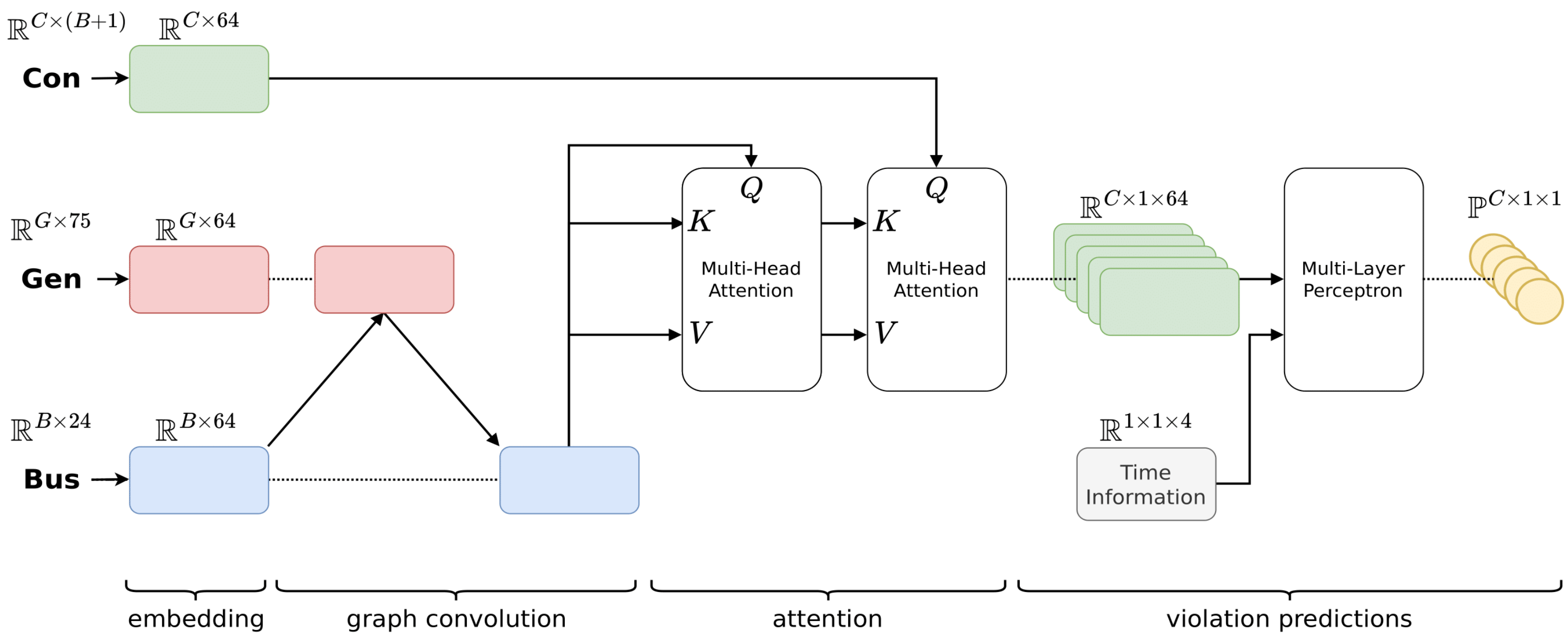
...such that we **circumvent expensive solves** and ideally obtain a safe optimal solution in a single iteration.

Data-Driven Baseline

- A step towards this, is the **K-Nearest Neighbors (KNN) predictor** by Xavier et al. (2021) [4]
- **Embed SC sets from iterative solving**
- KNN struggles in high-dimensional spaces due to **curse of dimensionality**
- In our setup, **bad predictive performance** (F1 Score <0.35) **for large grids** (>6000 buses)

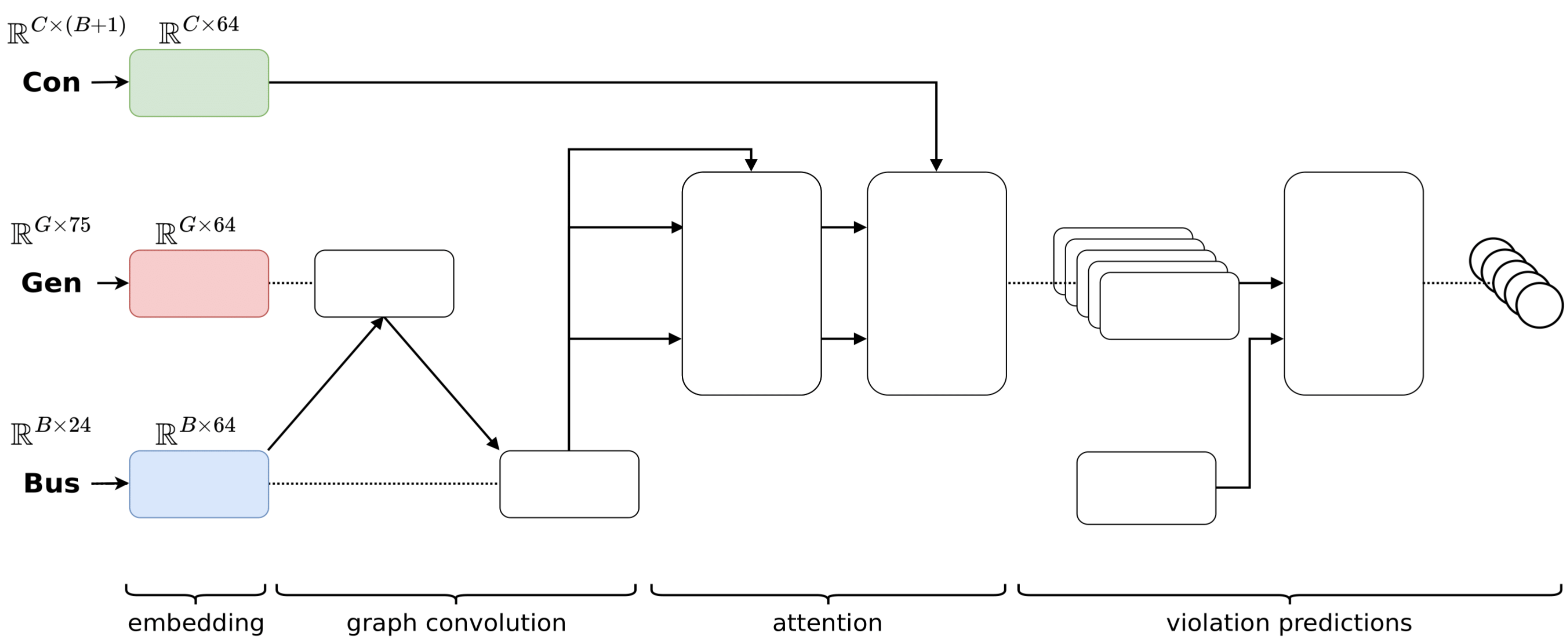
Contribution: Deep Security Constraint Prediction

Our architecture employs GNNs and Attention



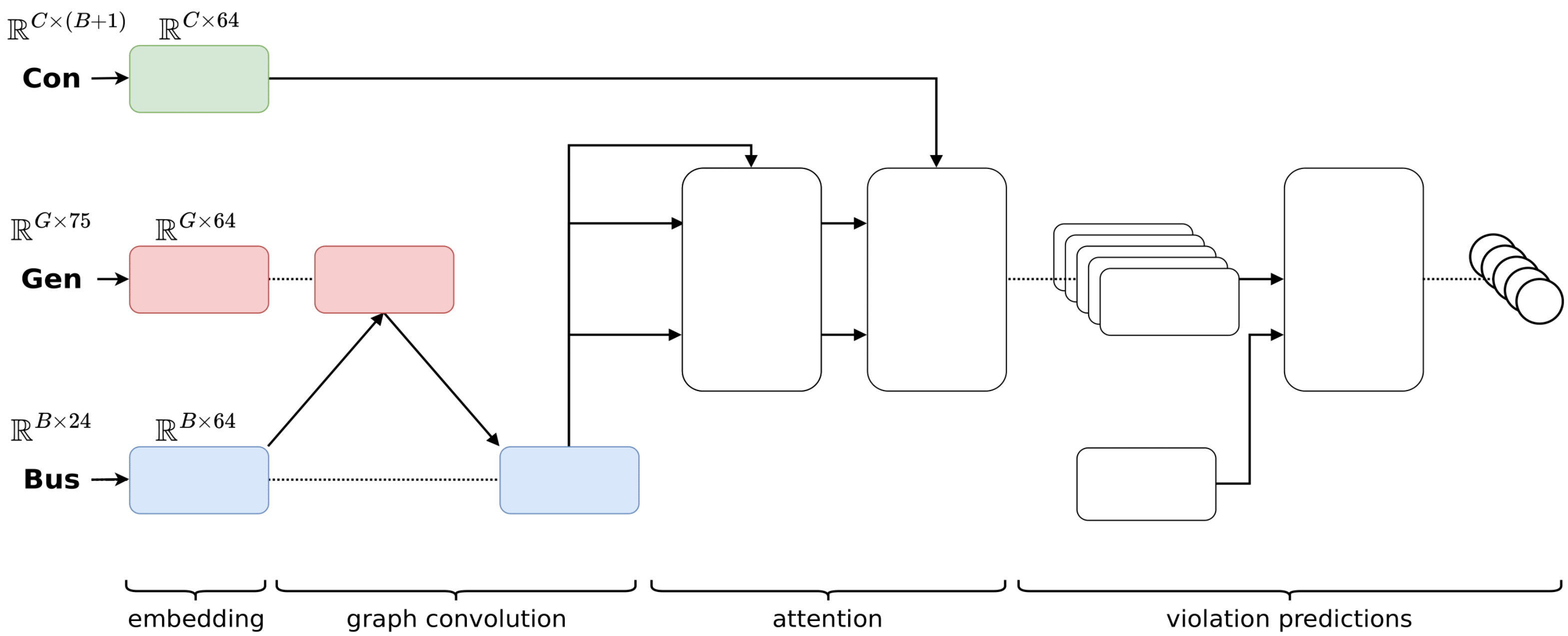
Contribution: Deep Security Constraint Prediction

Embedding Features to Common Dimension



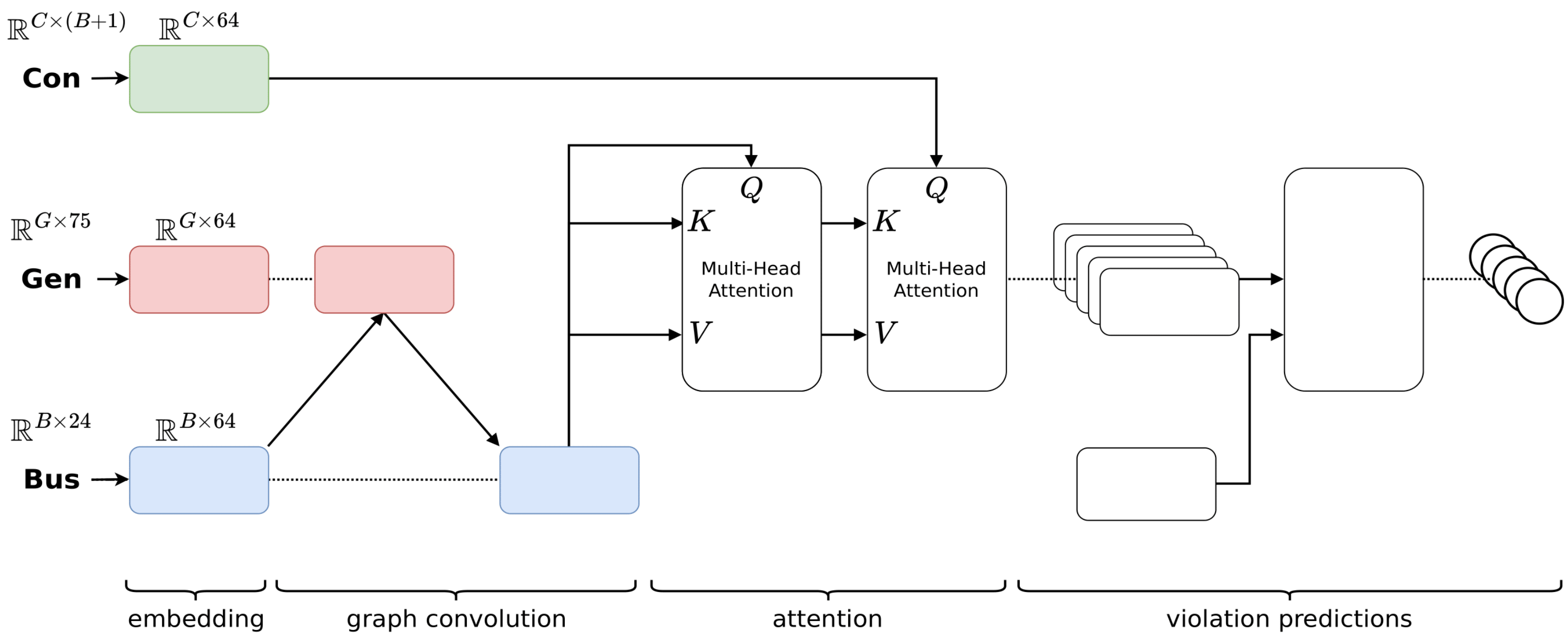
Contribution: Deep Security Constraint Prediction

Graph Convolution to combine Features



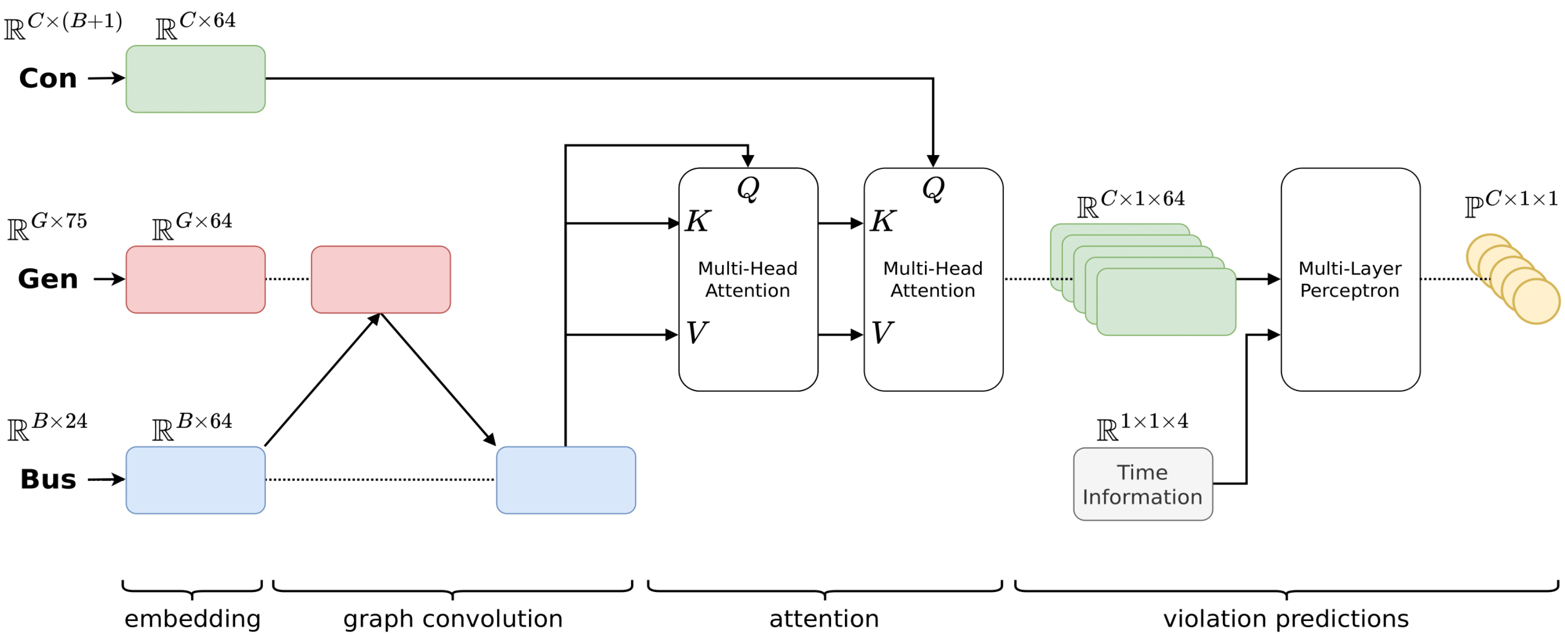
Contribution: Deep Security Constraint Prediction

- Self-Attention and Cross-Attention to map to SCs



Contribution: Deep Security Constraint Prediction

- MLP to predict Probability of SCs to retain



Optimization

Our Deep Security Constraint Predictor...

- ...is trained using the binary cross entropy loss:

$$L(\hat{y}) := -\frac{1}{|K|}\sum_{k\in K}[y_k \log(\hat{y_k}) + (1 - y_k)\log(1 - \hat{y_k})]$$

- ...and selects constraints depending on the predicted probability during test time.

Experimental Overview

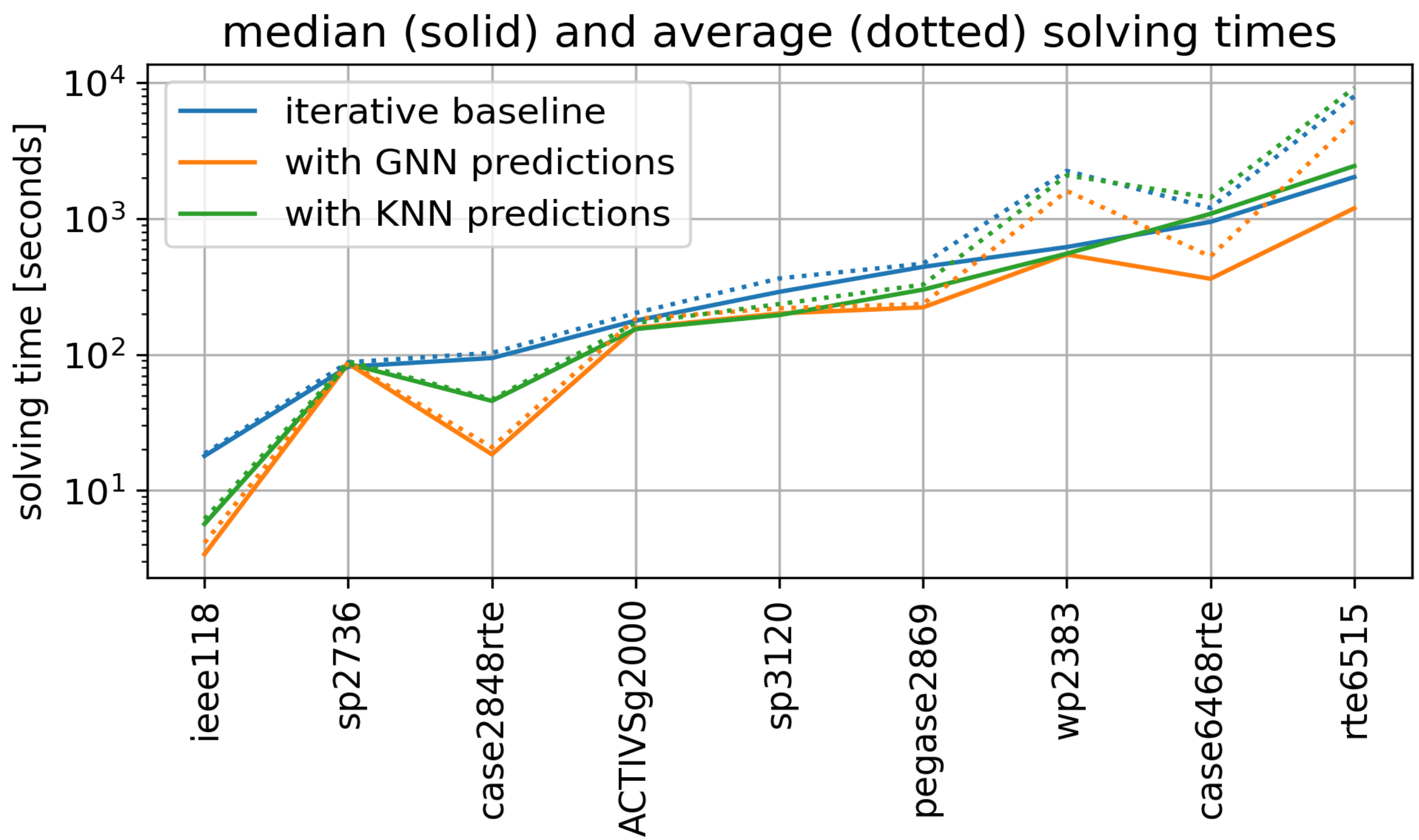
We evaluate our Deep Security Constraint Prediction:

- On a set of **nine power grids** composed of up to **6,500 buses** and **9,000 transmission lines**
- Against **two different baselines,** namely Iterative Solving, and K-Nearest Neighbors

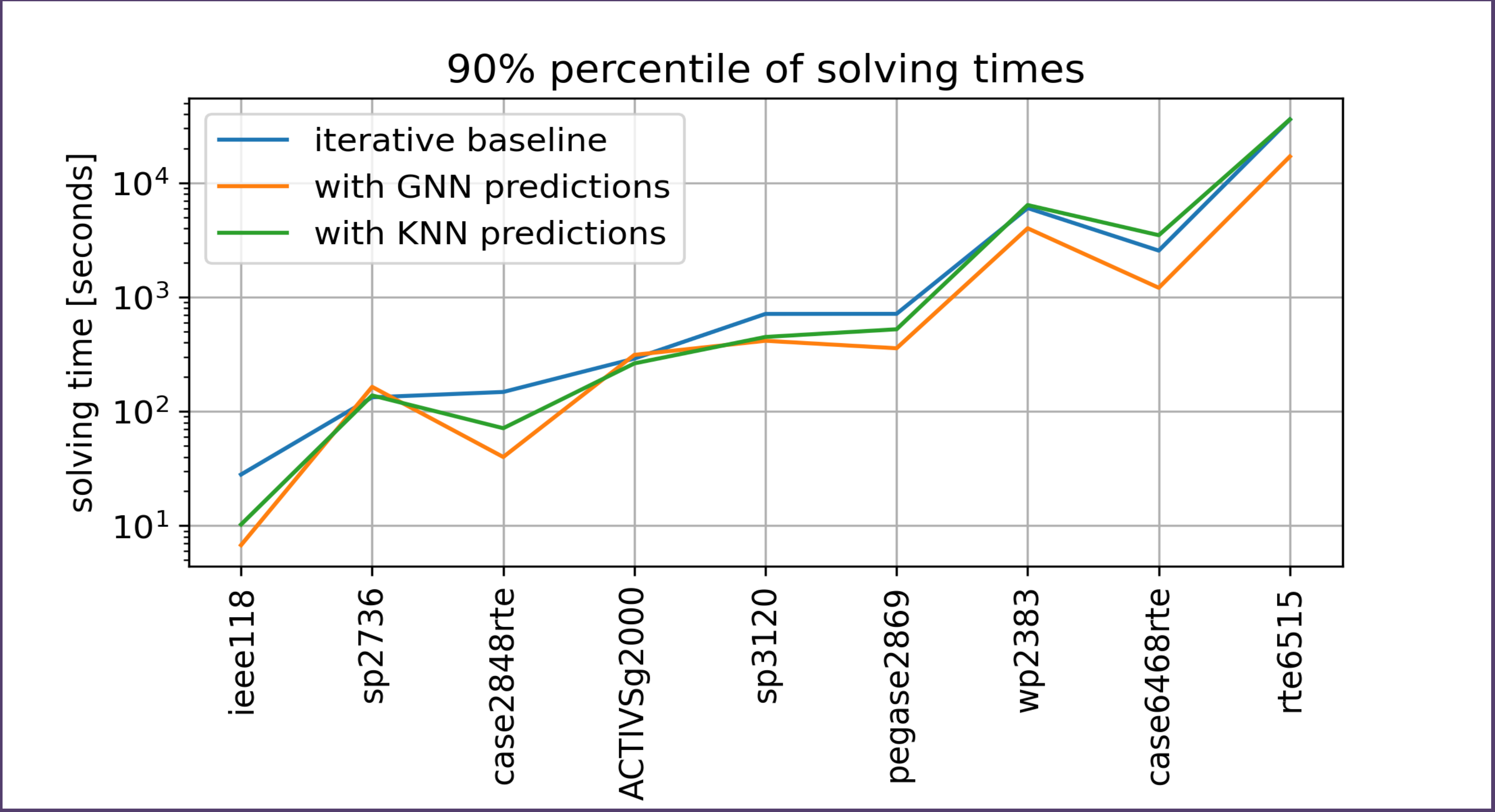
Predictive Performance of Learners

	Test F1 Score (higher is better)	
Power Grid	**GNN**	**KNN**
ieee118 (smallest)	**0.894**	0.887
sp2736	0.759	**0.811**
case2848rte	**0.951**	0.930
ACTIVSg200	0.743	**0.761**
sp3120	0.821	**0.835**
pegase2869	**0.858**	0.818
wp2383	0.711	**0.776**
case6468rte	**0.832**	0.334
rte6515 (largest)	**0.804**	0.298

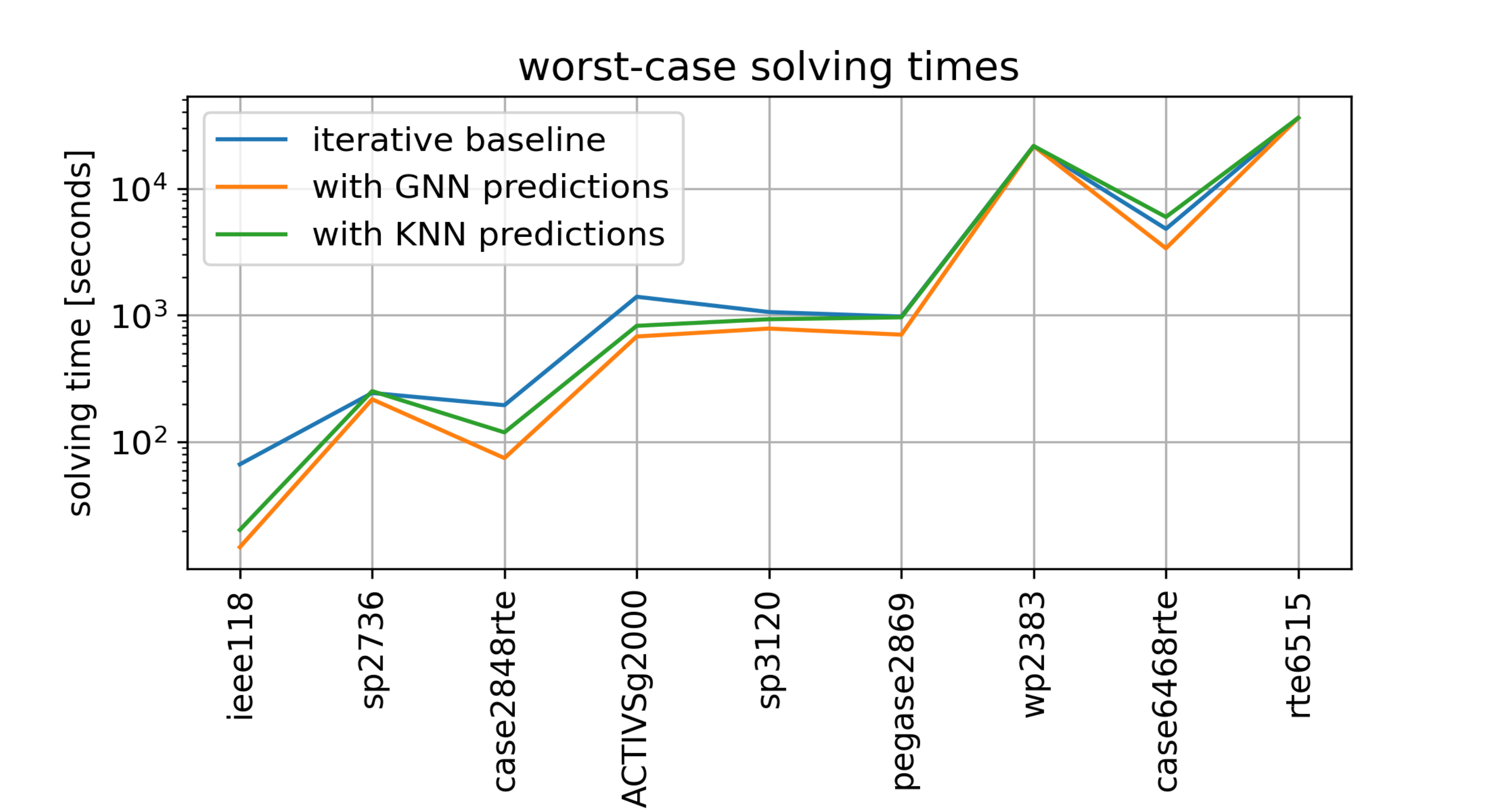
Results – Median/Average Performance



Results – Performance on Tough Instances



Results – Performance on Toughest Instances



Questions?

References

1. G. Morales-Espa˜na, C. Gentile, and A. Ramos, "Tight and Compact MILP Formulation for the Thermal Unit Commitment Problem," IEEE Transactions on Power Systems, vol. 28, no. 4, 2013.

2. F. Bouffard, F. D. Galiana, and J. M. Arroyo, "Umbrella Contingencies in Security-Constrained Optimal Power Flow," 15th Power systems computation conference, PSCC, vol. 5, 2005.

3. A. S. Xavier, F. Qiu, F. Wang, and P. R. Thimmapuram, "Transmission Constraint Filtering in Large-Scale Security-Constrained Unit Commitment," IEEE Transactions on Power Systems, vol. 34, May 2019.

4. A. S. Xavier, F. Qiu, and S. Ahmed, "Learning to Solve Large-Scale Security-Constrained Unit Commitment Problems," INFORMS Journal on Computing, vol. 33, May 2021.