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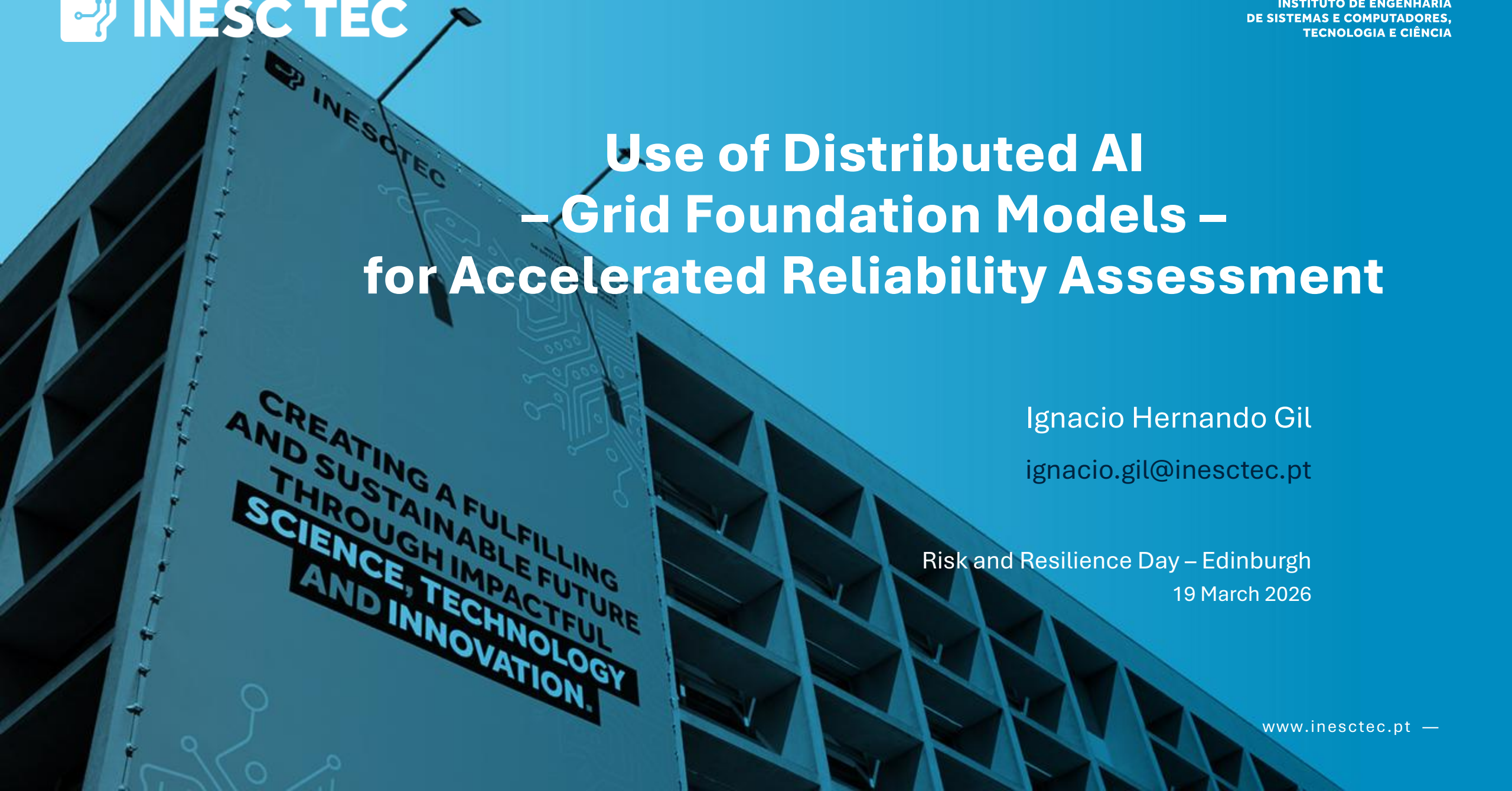

Use of Distributed AI – Grid Foundation Models – for Accelerated Reliability Assessment

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Risk and Resilience Day – Edinburgh

19 March 2026

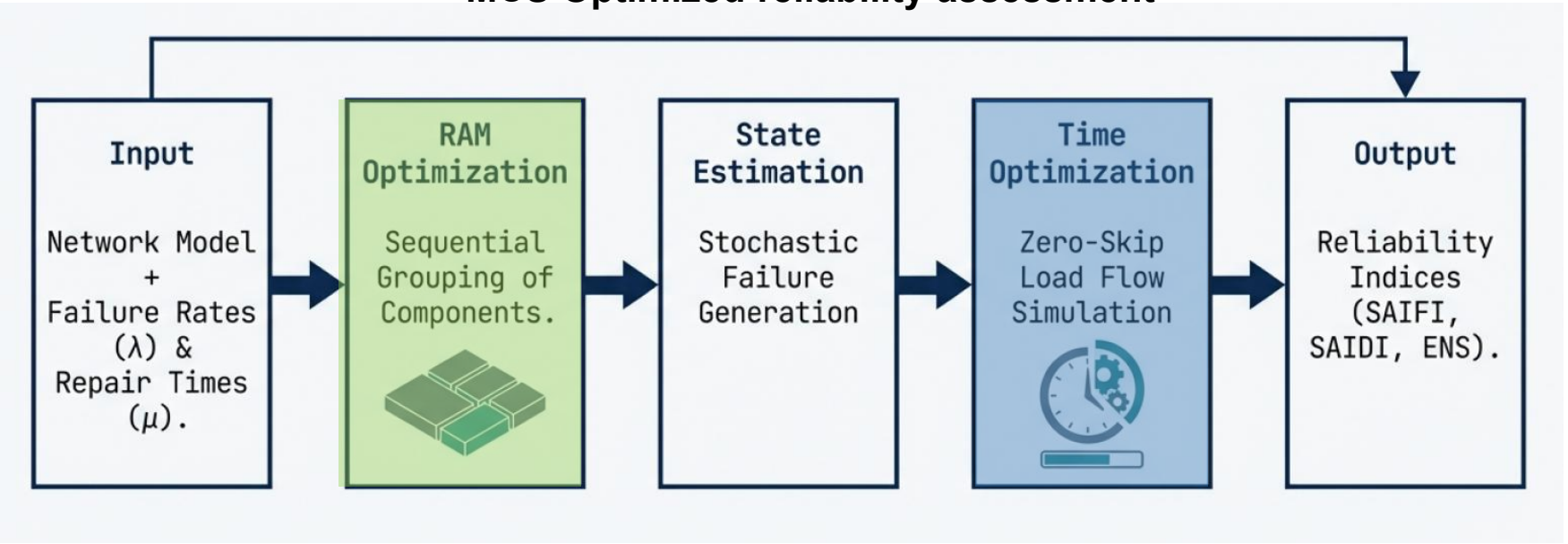
Stochastic reliability assessment of MV/LV networks

MOTIVATION: Quantify the **impact of planned network development on customer interruptions** due to failures in the MV/LV network using **probabilistic risk assessment**.

Monte Carlo simulation is well developed for reliability evaluation but has **limitations for large networks**

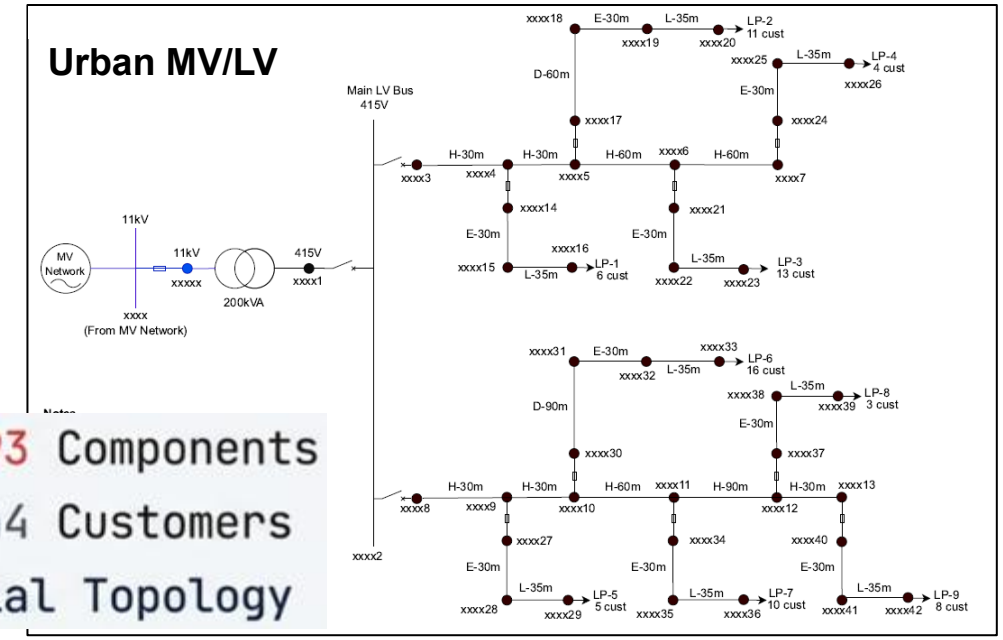
- ✗ High computing resources to **execute power flow simulations**
- ✗ Large memory requirements for the **failure state estimation**
- ✗ Long simulation times to **complete the power flow simulations**

MCS Optimized reliability assessment



Key roadblocks for larger network evaluation

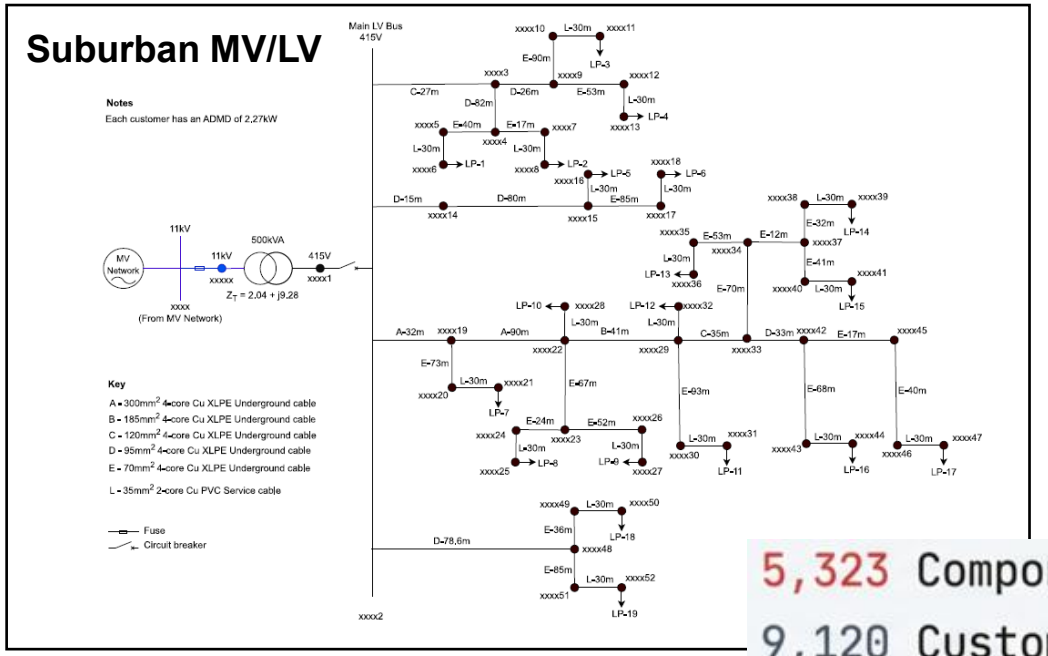
Urban MV/LV



3,993 Components
3,344 Customers
Radial Topology

Simulation time: 12.06 hours

Suburban MV/LV

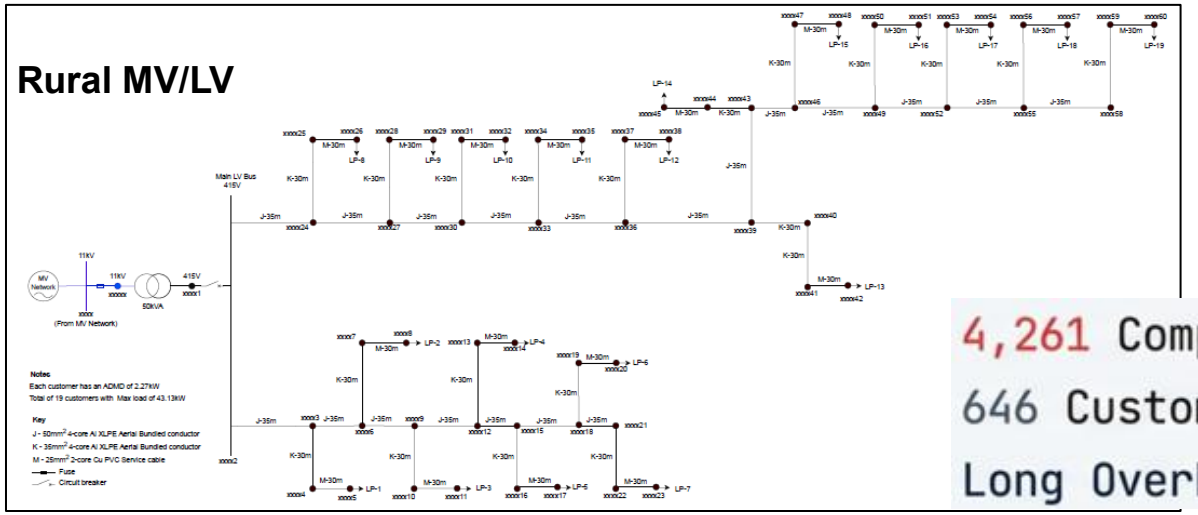


5,323 Components
9,120 Customers
Meshed Topology

Simulation time: 6.64 hours

pandapower

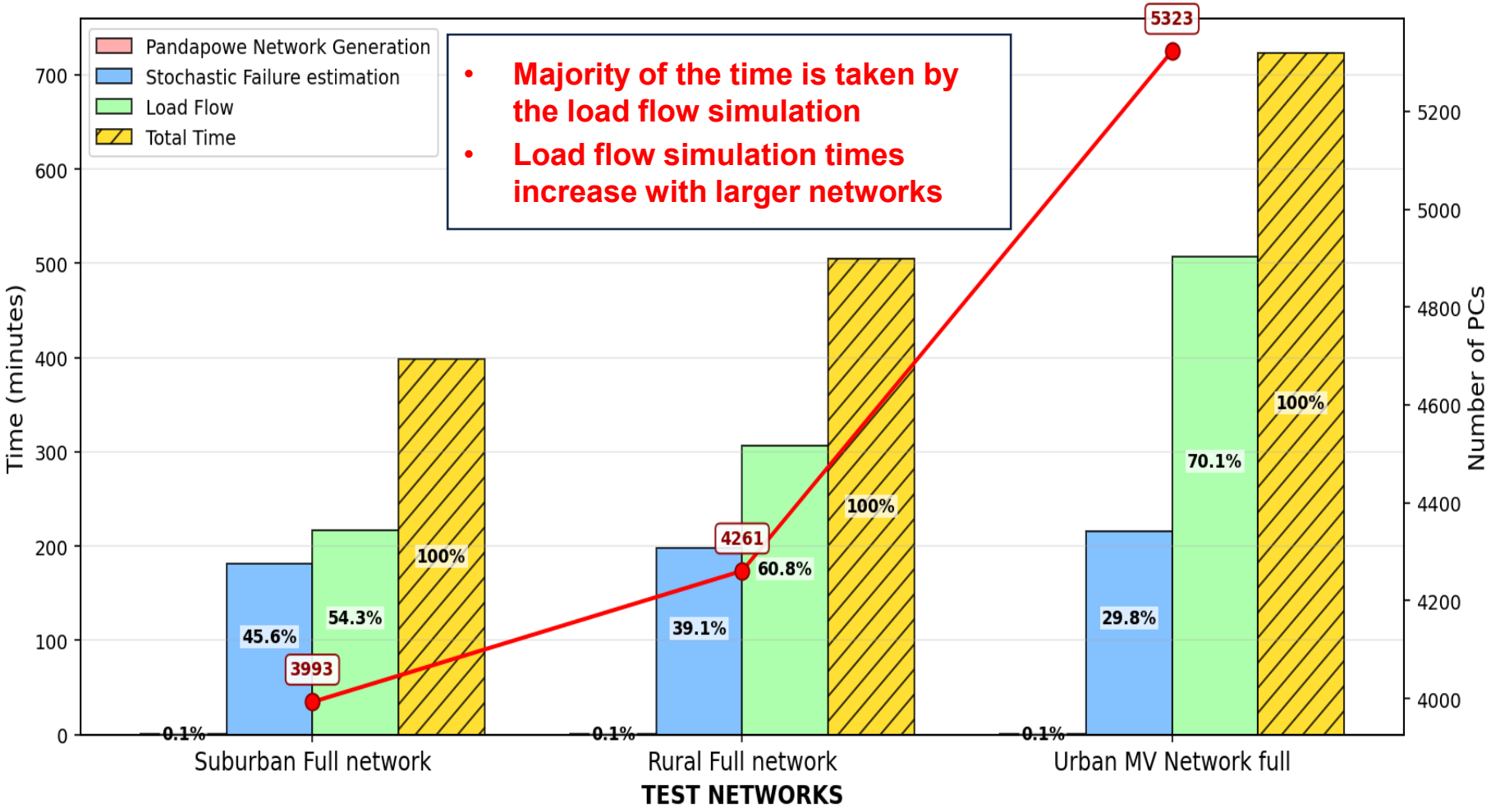
Rural MV/LV



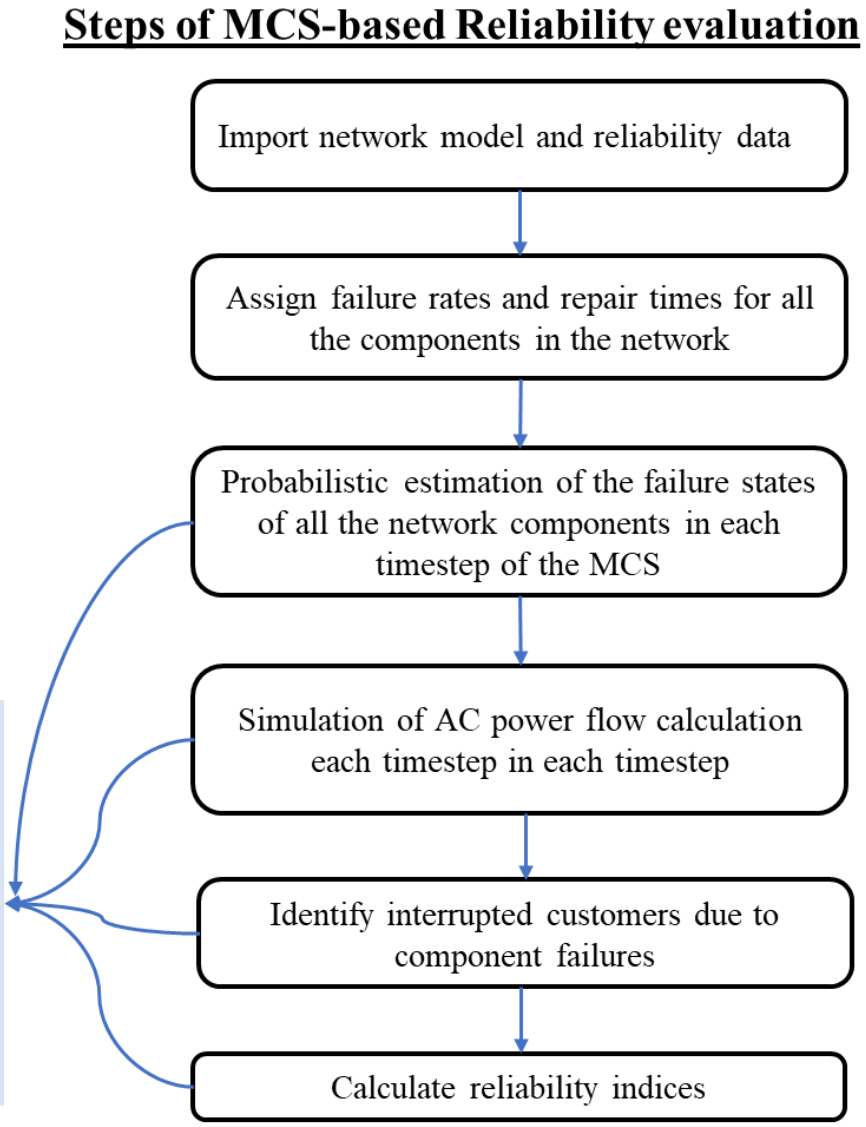
4,261 Components
646 Customers
Long Overhead Lines

Simulation time: 8.41 hours

Key roadblocks for larger network evaluation



Opportunity for GridFM



GridFMs to accelerate the load flow simulations in the order of X2 to X5

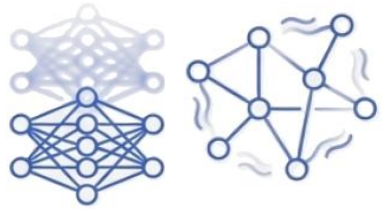
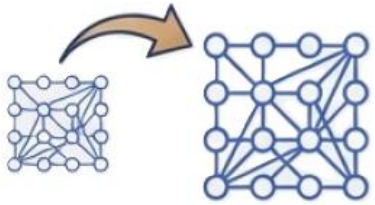
Fine tuning: Feature reconstruction of voltage at nodes to predict which customers are interrupted after a component failure

Potential benefits of the GridFM

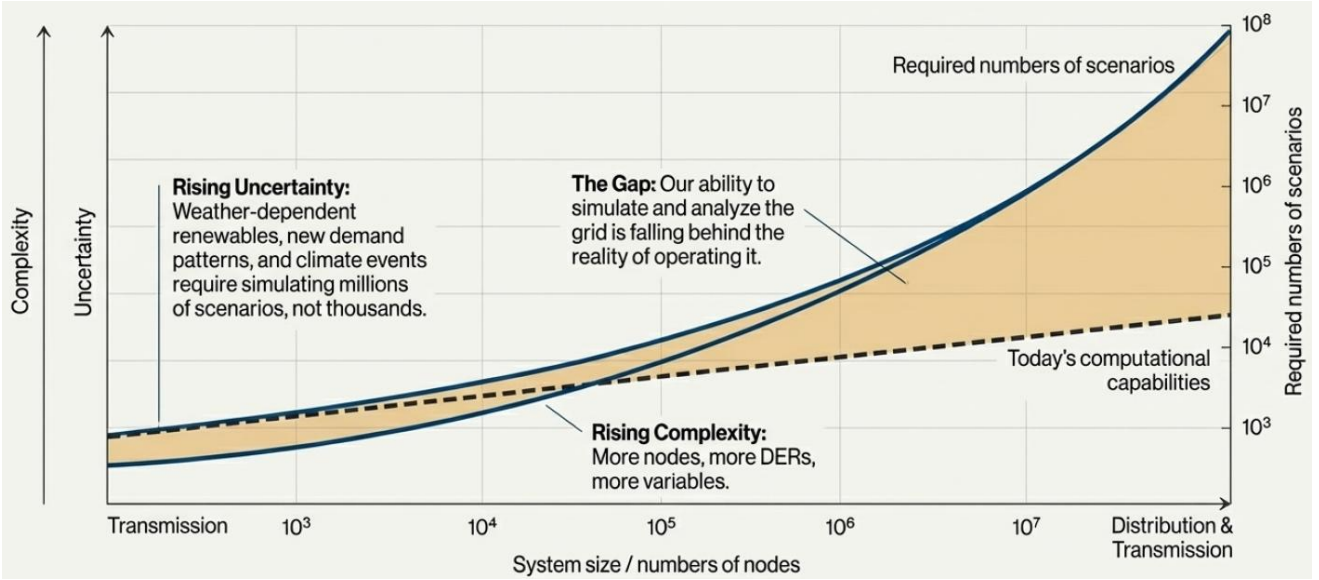
- GridFM can **predict the voltages at load buses during the power flow simulations** to identify interrupted customers following a grid failure
- Prediction-based approaches are faster and **require fewer computing resources** than computational methods that compute the power flow solution at each timestep.
- GridFM can provide **faster predictions** than AC power flow computations
- GridFM can **facilitate multi-level MCS** where higher resolution timesteps can be evaluated when failures occur.
- GridFM can enable **simulation of network reconfiguration** after failures to depict network operation.

Distributed AI for more resilient power grids

What is hindering wider adoption?

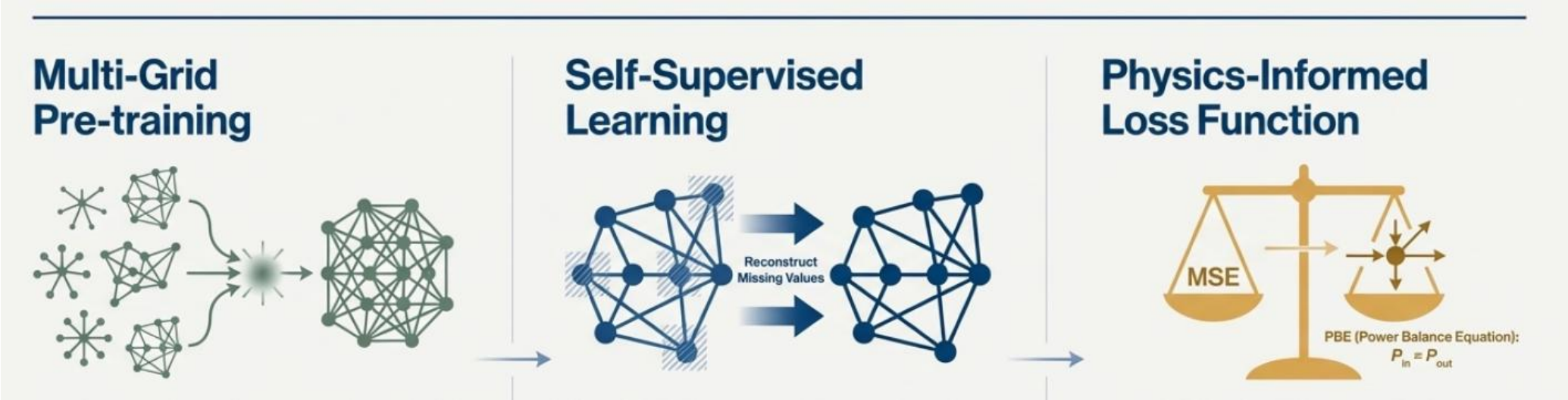
			
Designing deep graph structures with dynamic handling	**Transfer learning across graph structures**	**Limited interpretability**	**Large data requirements**

INCREASED COMPLEXITY ⟶



Introducing GridFM

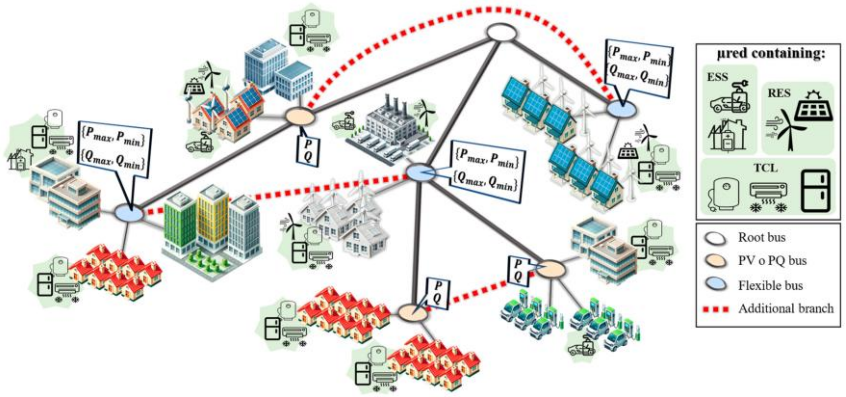
✓ Generalizable across multiple grid topologies ✓ Linear scaling ✓ Predictions consistent with Physics laws



LF ENERGY GridFM

GridFM community

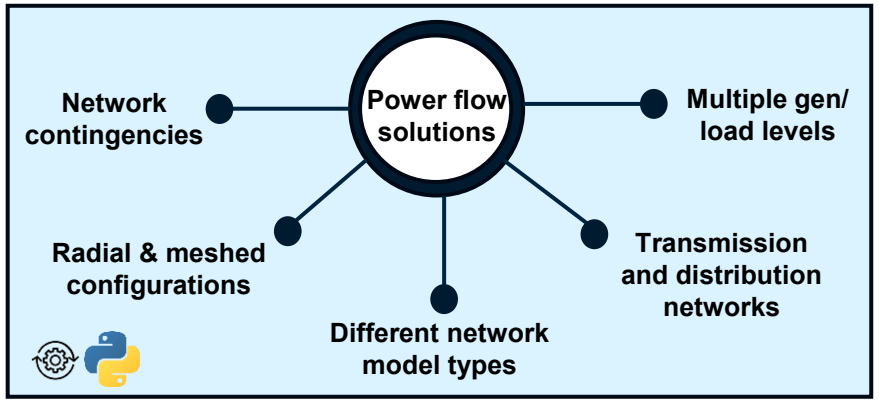
How GridFM works



✓ Multiple network configurations ✓ Hybrid AC/DC networks ✓ Poliferation of DERs

Pipeline of PF datastets

DATA GENERATION PACKAGE



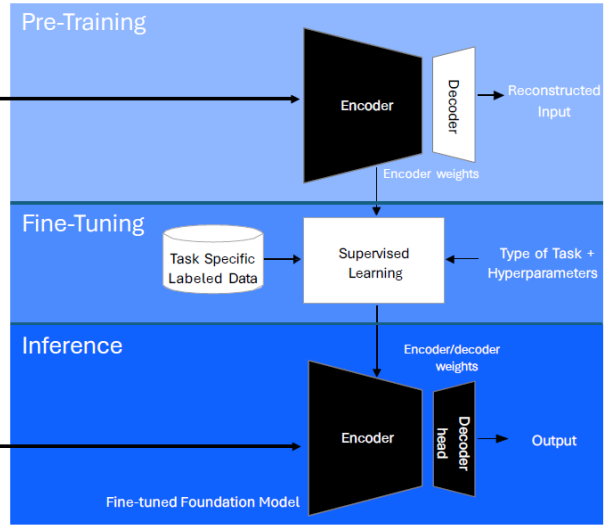
Data Source

FEATURE RECONSTRCUCTION PACKAGE

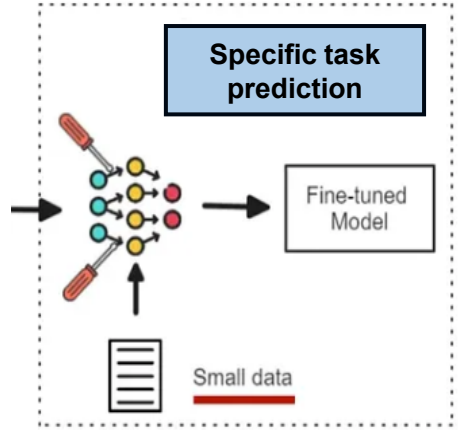
Nodal power flow predictions;
- **Voltage magnitude and angle**
- **Power generation**
- **Power demand**

Large Data

PyTorch



FINE TUNING PACKAGE

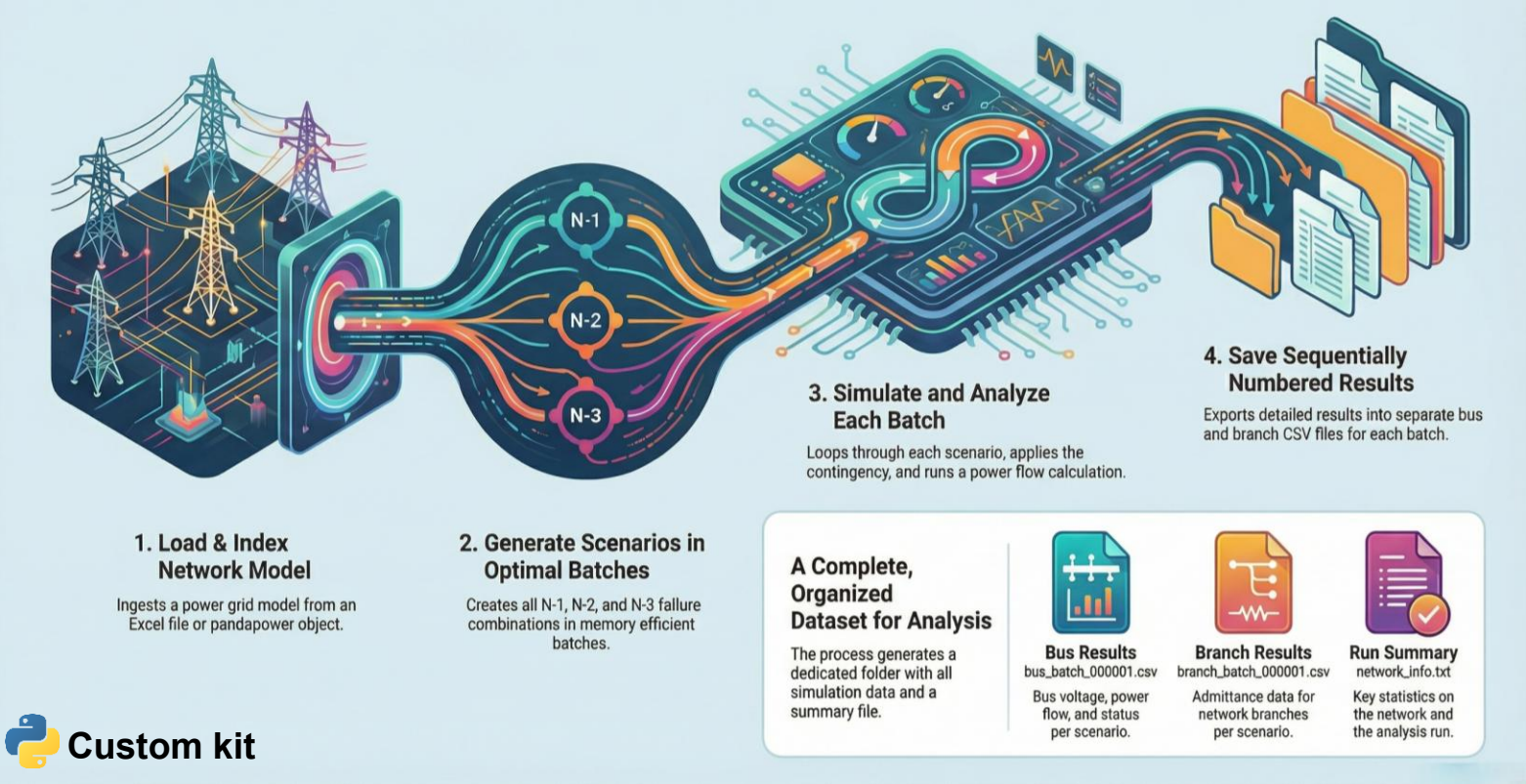


Downstream Applications

Regression	Classification	Forecasting
Power flow Contingency Analysis State estimation Grid expansion	Line limit violation Cascading failure Unit commitment Network overload	Load & generation forecasting

GridFM for accelerated reliability assessment

DATA GAPS → Contingency power flow – Training Data Generation



- ✓ Distribution networks (MV/LV)
- ✓ Contingency analysis (N-1, N-2, N-3)
- ✓ Memory optimised

23 networks with different MV/LV configurations

MATPOWER · DIgSILENT · PyPSA · PSS®E · pandapower · Excel

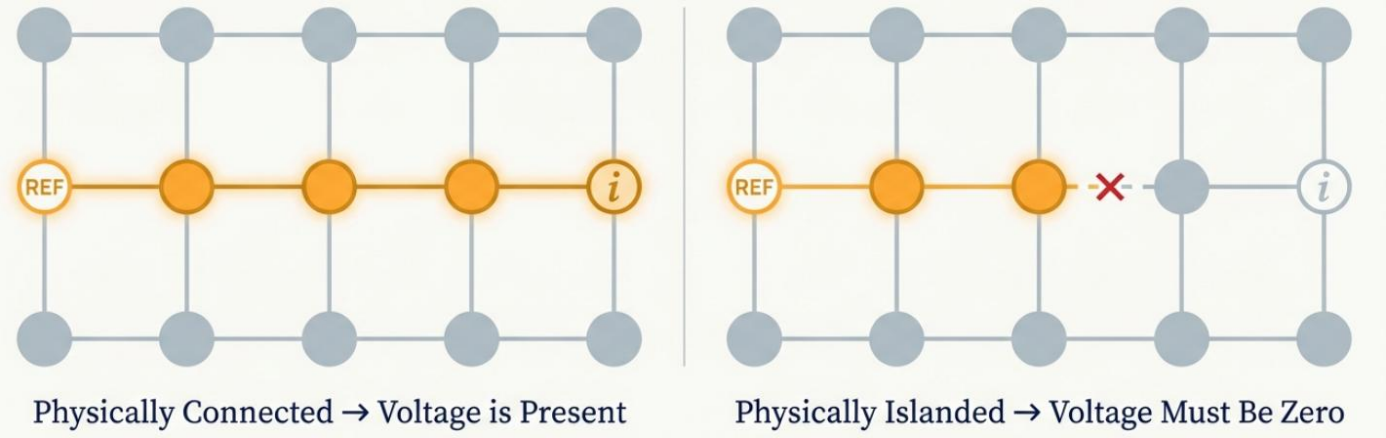
10%

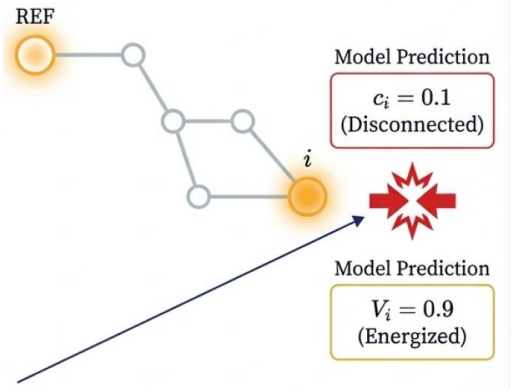
1.2 million scenarios generated
17.2 million in pipeline

LARGE STORAGE CAPACITY REQUIRED

SCENARIOS INCREASE QUADRATICALLY WITH NETWORK SIZE AND NUMBER OF CONTIGENCIES

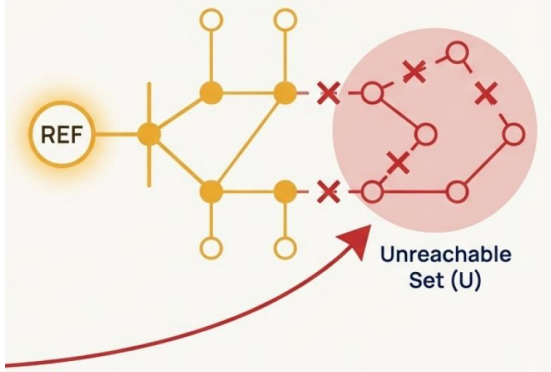
Loss function to predict voltage loss after network failure





If reachable, penalize for node voltage $V_i = 0$

$\mathcal{L}_{reach}$ penalizes voltage inconsistencies for reachable nodes



If unreachable, penalize for node voltage $V_i > 0$

$\mathcal{L}_{unreach}$ penalizes impossible voltages for unreachable nodes

$$L_{VDC} = \lambda(L_{reach} + L_{unreach})$$

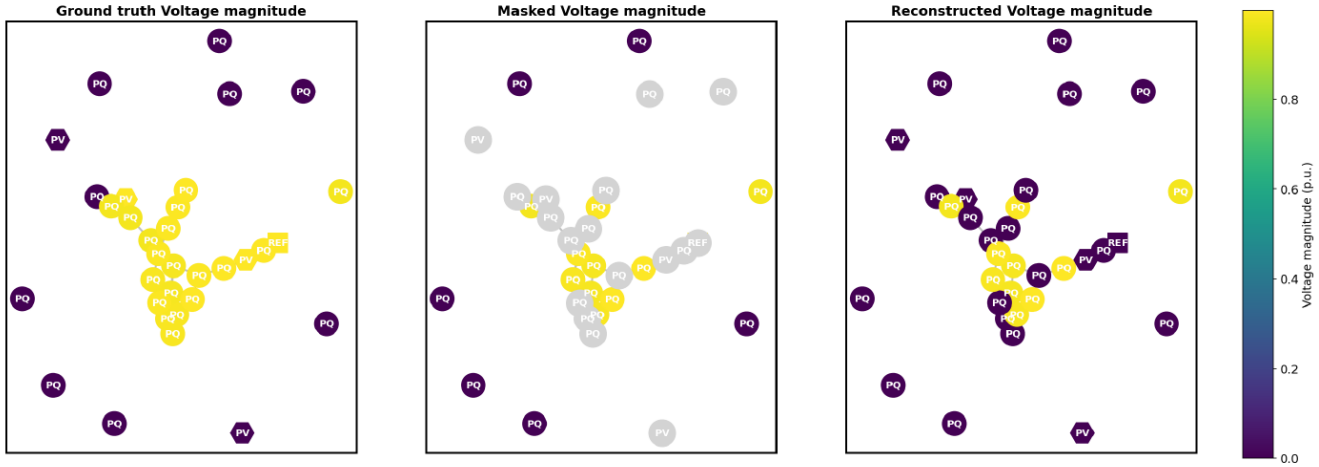
Predict node voltage based on connectivity to reference bus

Fully Differentiable Loss to predict disconnected nodes following a network failure

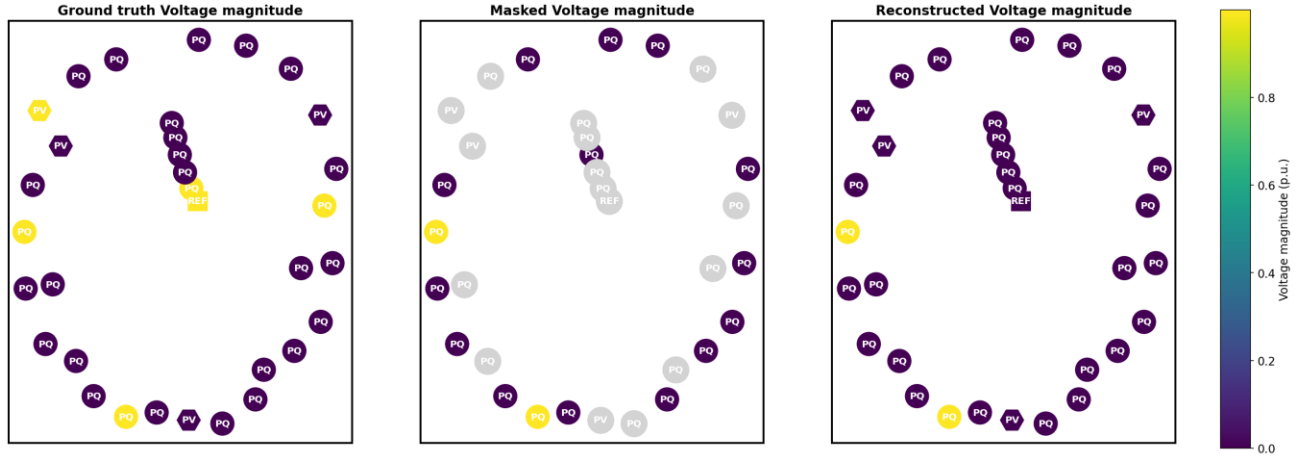
Accelerated load flow simulations in reliability assessment

Preliminary findings and way forward

➢ **Before training:**



➢ **After training:**



➢ **Key limitations:**

1. Memory requirement for graph propagation increases quadratically with the depth of the graph
2. Quadratic attention scaling for larger networks
3. High training costs due to preliminary computations of propagation depth and healthy graph for each forward step
4. Setting maximum propagation depth K_{max}

➢ **Next steps:**

1. Generation of training data sets
2. Training of the GridFM and performance evaluation
3. Fine tuning task to estimate reliability indices following prediction of interrupted customer following grid failure

Thanks for listening
Questions?

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