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AI-Based Static Voltage Stability Analysis of Power Grids

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Challenge:

- Electrical grids can experience various conditions causing instability, potentially leading to collapse.
- Identifying stable and unstable conditions allows for adjustments in feed/load at bus nodes to maintain stability (refer to Fig. 1).
- Calculating all conditions with conventional methods is computationally intensive, making it impractical for optimization tasks.

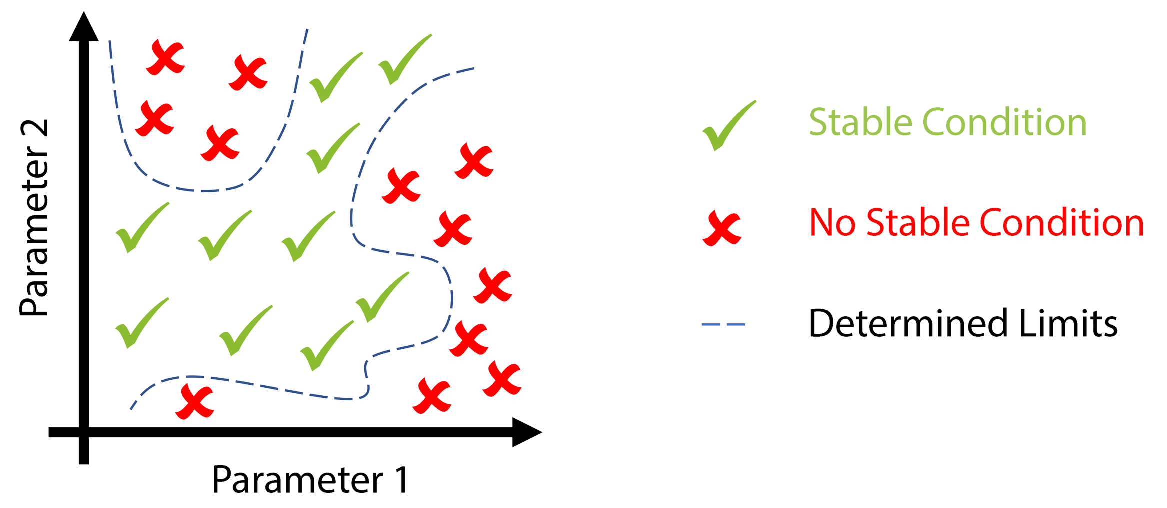

Fig. 1: Differentiation Between Stable and Unstable States on an Abstracted 2D Plane

Approach :

- Main research objective to develop AI approach for identifying static voltage stability in power grids
  -> improving computational time for optimization
- Utilized artificial neural networks (ANNs) with supervised and unsupervised training
- Generated training dataset with random cases for IEEE standard grids using load flow calculation and dV/dQ sensitivity analysis from PowerFactory (see Fig. 2)
- Considered different bus system types in load flow calculations
- Static voltage stability criteria: dV/dQ sensitivity must be positive at each bus node ([1], Eq. 1)

$$\frac{dV_i}{dQ_i} > 0 \quad \text{for } i = 1,2,\dots,n \qquad (1)$$

- Analyzed voltage contingencies and effects of data cleaning on stability thresholds (Eq. 2)

$$0.9\, V_\mathrm{n} < V < 1.1\, V_\mathrm{n} \qquad (2)$$

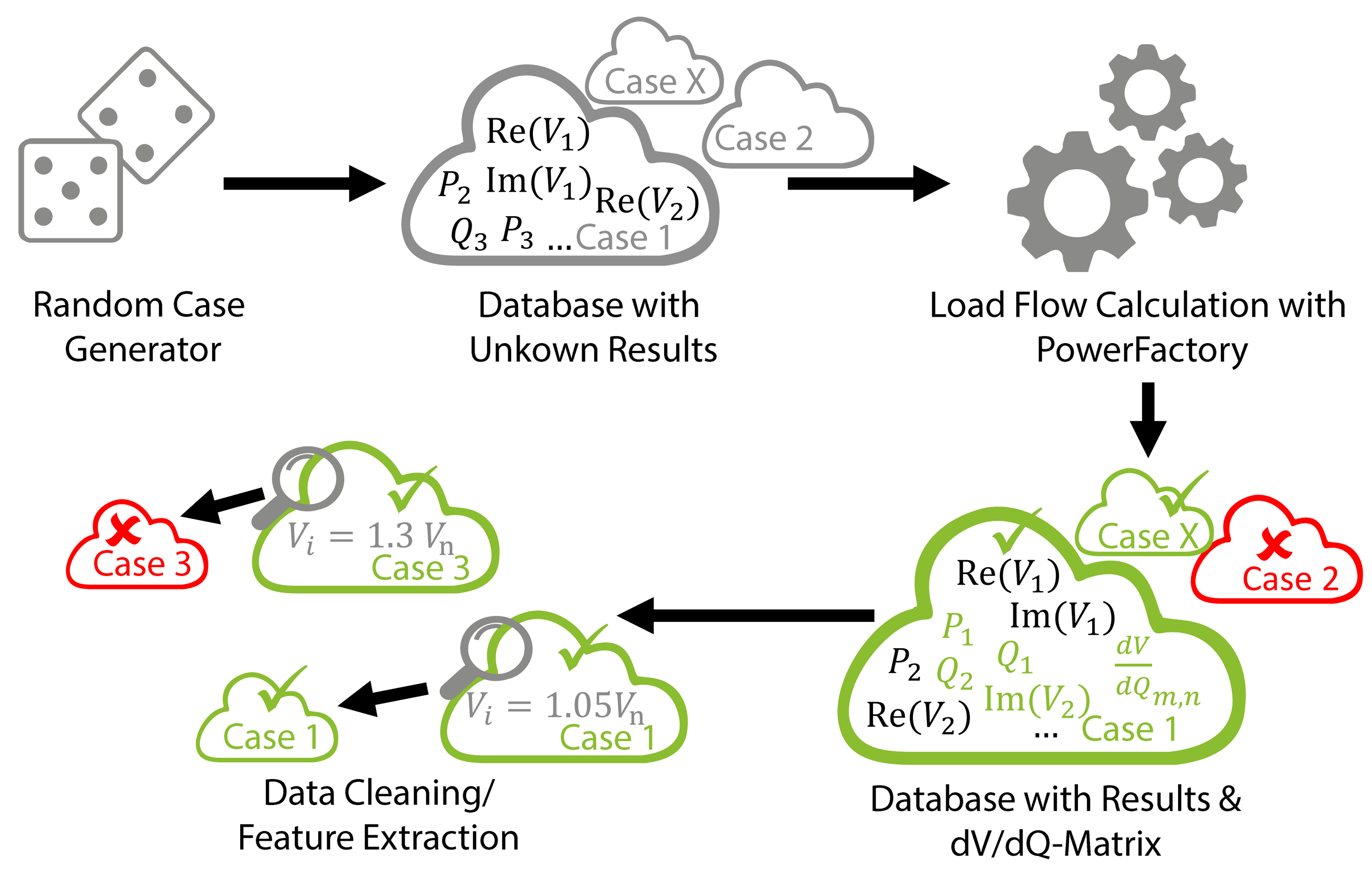

Fig. 2: Schematic Approach to Datageneration with PowerFactory

ANN Traning:

Supervised training methods used for a multilayer perceptron (MLP):

- Analyzed impact of data cleaning and feature reduction
- Due to unsuccessful hyperparameter optimization in Keras usage of the pruning function [3] from DataEngine to optimize MLP network architectures with various activation functions, learnings rates and numbers of hidden layers
- Achieved training accuracies up to 97% with DataEngine; similar accuracies attainable in Keras with optimized architecture using mean squared error loss and SGD optimizer with learning rate decay

Unsupervised training methods for a Kohonen network:

- Training outcomes with Kohonen network in DataEngine were unsatisfactory, leading to discontinuation of further investigation

Validation:

- High training accuracy achieved with MLP but low validation accuracy with an unknown data set (see Fig. 3), indicating poor generalization
- Analyzed extending the training dataset to improve generalization
- Found that extending the dataset was insufficient to enhance training accuracy with existing network architectures

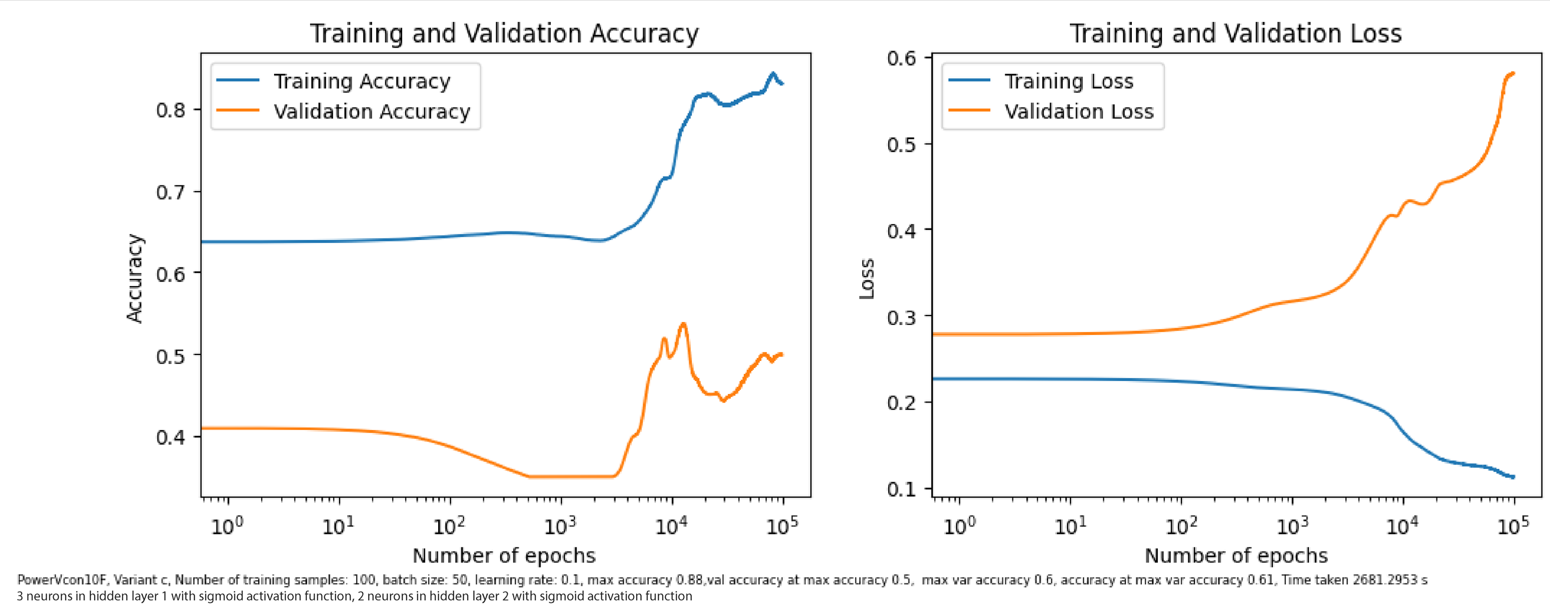

Fig. 3: Accuracy and Loss Curve of Keras Training of PowerVcon10F Variant c

Results:

- Demonstrated that the studied MLP network architectures lack generalizability and are unsuitable for deployment
- Generated dataset to be made available as open-access for further research
  -> applicable for testing with proposed variants, modern optimizers or different ANNs
- Secondary study outcome: examined a neural network that simulates a load flow calculation
  -> approximate missing values for the trained grid with high training and validation accuracy

Sources:

[1] Dr. Martin Schmieg. "P2021 Gutachten zur NEMO VIII, Los 1 - Stabilität (Kurzfassung)". In: DIgSILENT GmbH(2022)

[2] Rengin İdil Cabadağ. "Analysis of the Impact of Reactive Power Control on Voltage Stability in Transmission Power Grids". PhD thesis. TU Dresden, 2019.

[3] DataEngine, Tutorials und Grundlagen. MIT GmbH, 1998.

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