A Unified Machine Learning Approach for Data-driven Security Assessment of Power Grids

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GOTF Paper Session 2B: Machine Learning and Artificial Intelligence Applications to the Grid

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- Building up ML model for security assessment
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- Example I: ML for Transient stability assessment
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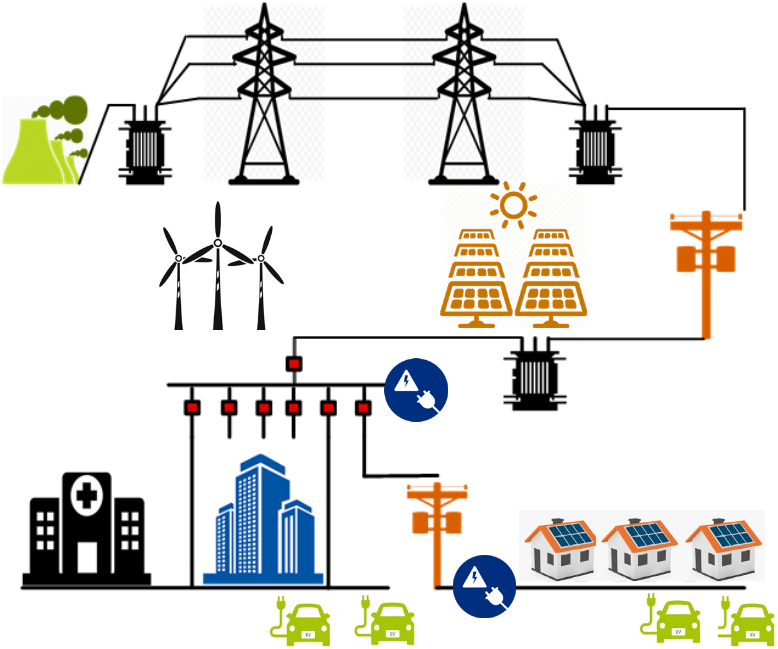
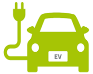
Background

Traditional power grid→ Future power grid



Uncertainty and variability



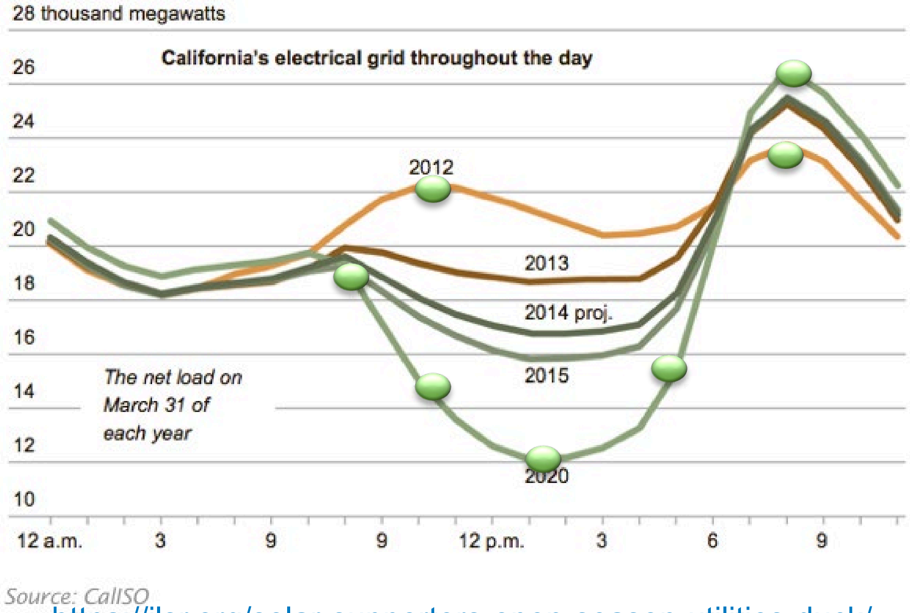
Stochastics

Vulnerability

Low inertia and weak grid

Challenge

The need for real-time dynamic security assessment and situational awareness for the future power grid with high renewable energy penetrations



https://ilsr.org/solar-supporters-open-season-utilities-duck/

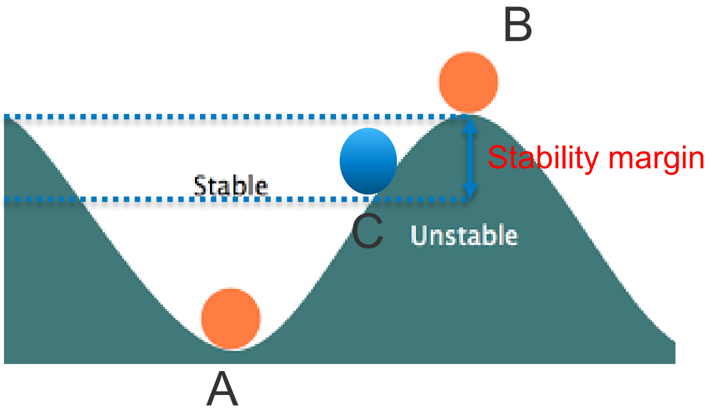
Key question: How do we solve the trade-off between computational accuracy and speed?

Steps of building up machine learning model for SA

Step 1: Representation

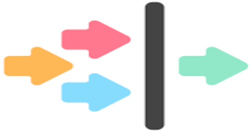
What to learn?

What's the input? What's the output?



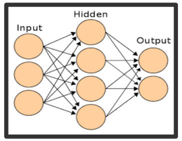
Step 2: Feature selection

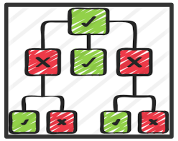
Pgen,
Inertia,
…

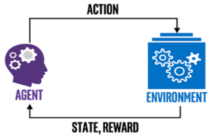


Useful features

Step3: Model selection

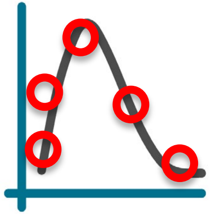






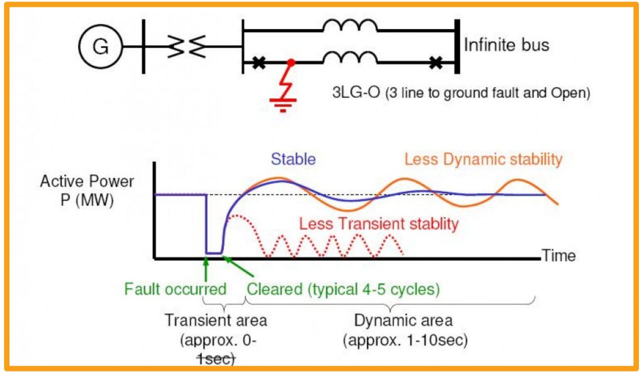
NN Decision Tree SVM Deep learning

Step4: Interpretation and validation

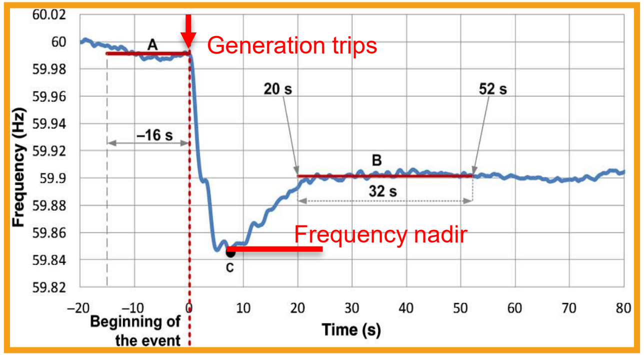


How do we define output security information?

- **Transient stability (CCT)**
  - The ability to maintain synchronism when subjected to a severe disturbance, such as a short circuit on a transmission line
- **Frequency stability (Frequency nadir)**
  - The ability of a power system to maintain steady frequency following a severe system upset resulting in a significant imbalance between generation and load.
- **Small-disturbance rotor angle stability (Damping ratio)**
  - The ability of the power system to maintain synchronism under small disturbances.



Transient stability[1]

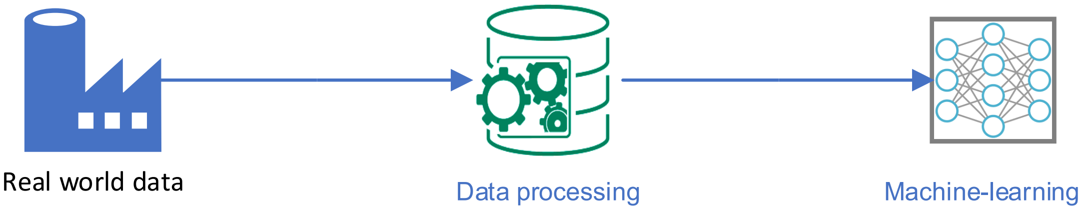


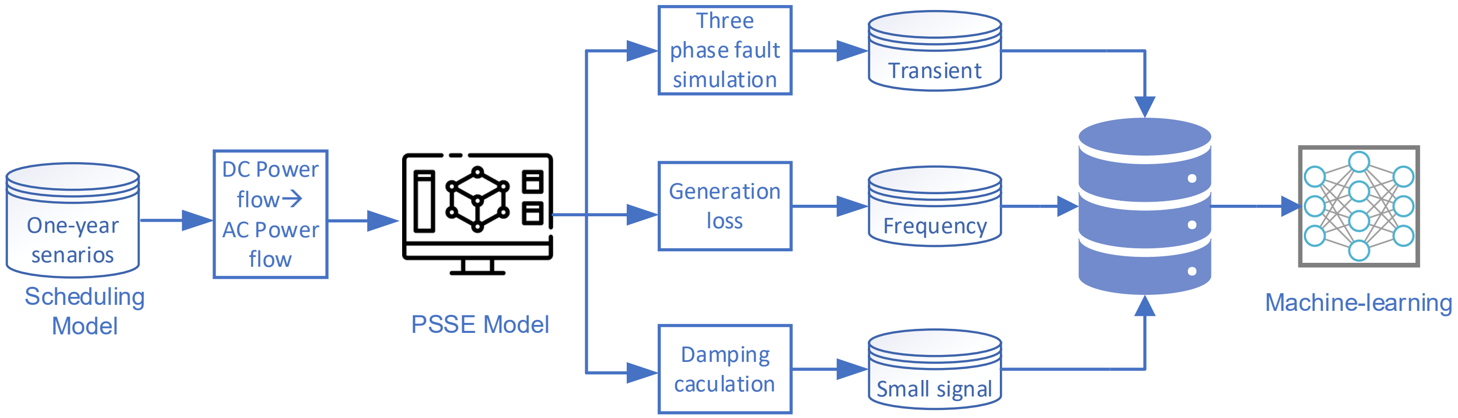
Frequency stability[2]

How could we generate a data base ?

Data base for security assessment

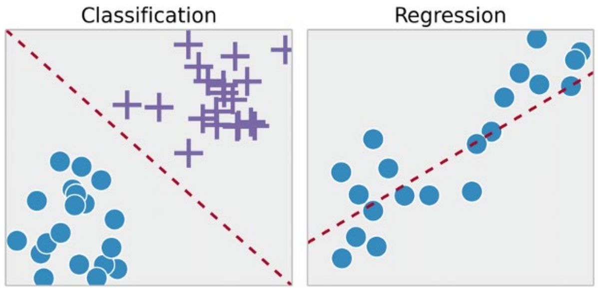
- Real operational data v.s. model-generated scenarios
- No-bias data base



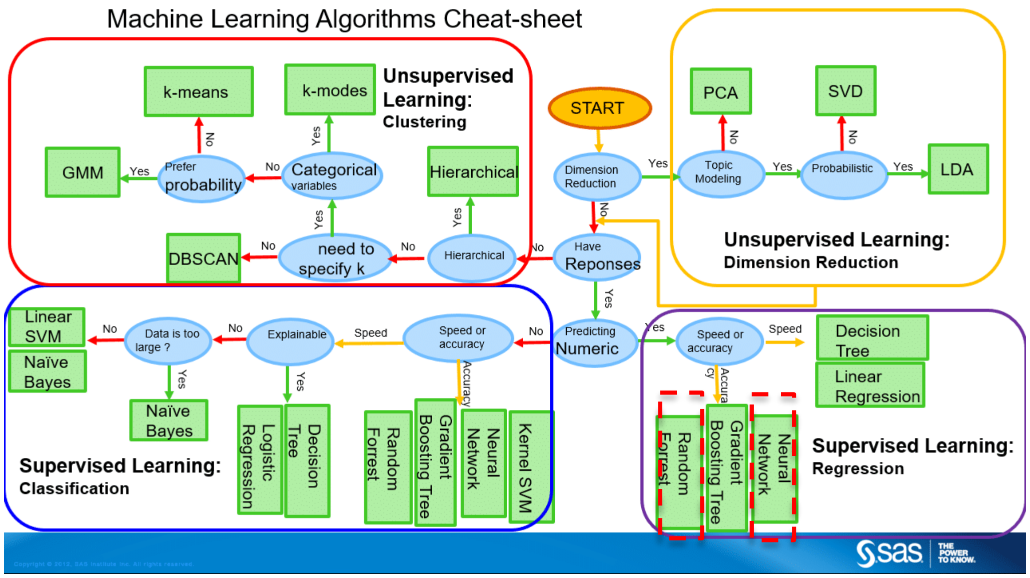


How do we select machine learning model?

- **Types of machine learning tasks**
  - Supervised learning
    - Regression
    - Classification
  - Unsupervised learning
  - Reinforcement learning

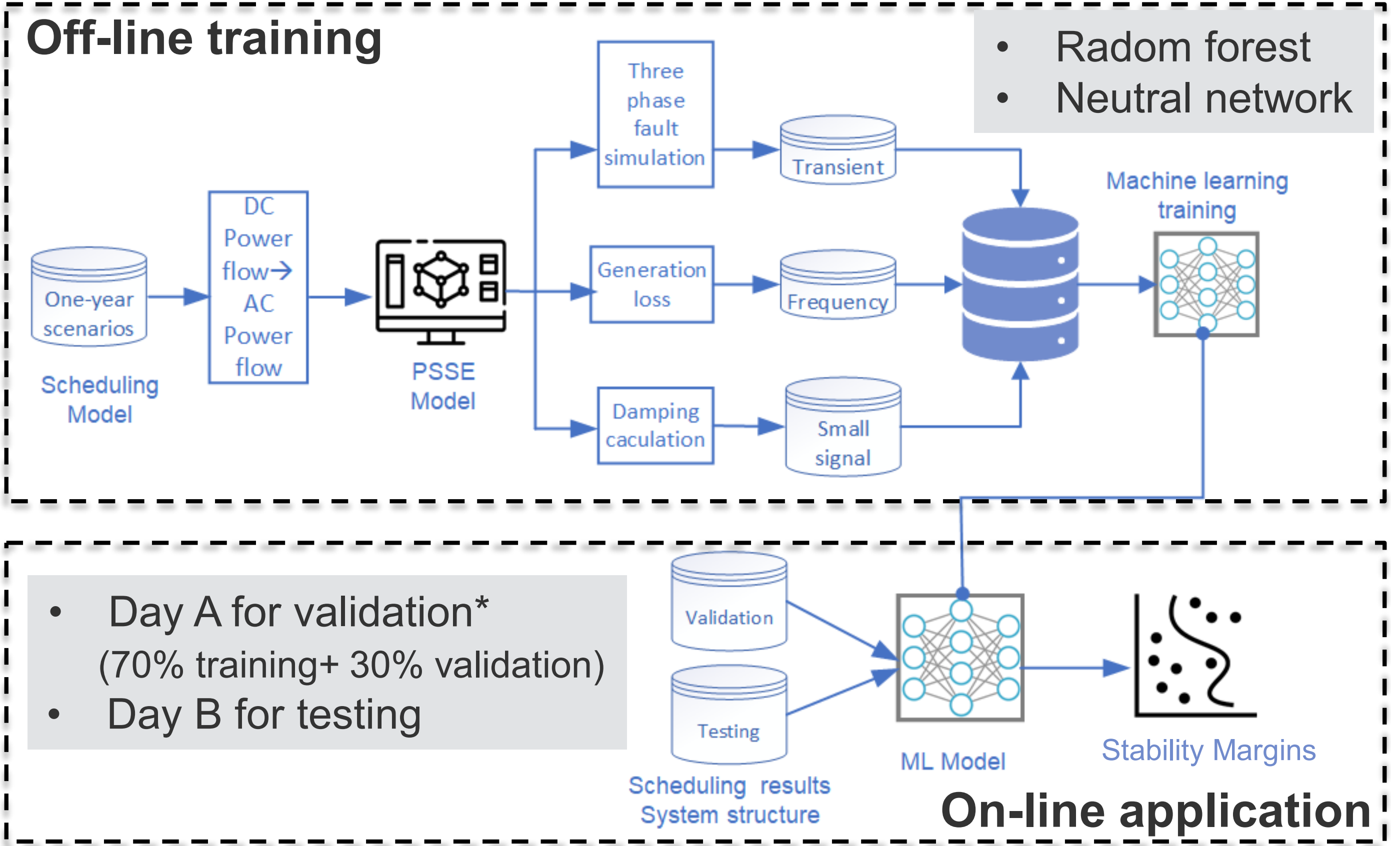


- **Machine learning model selection**



https://www.7wdata.be/big-data/which-machine-learning-algorithm-should-i-use/

Framework



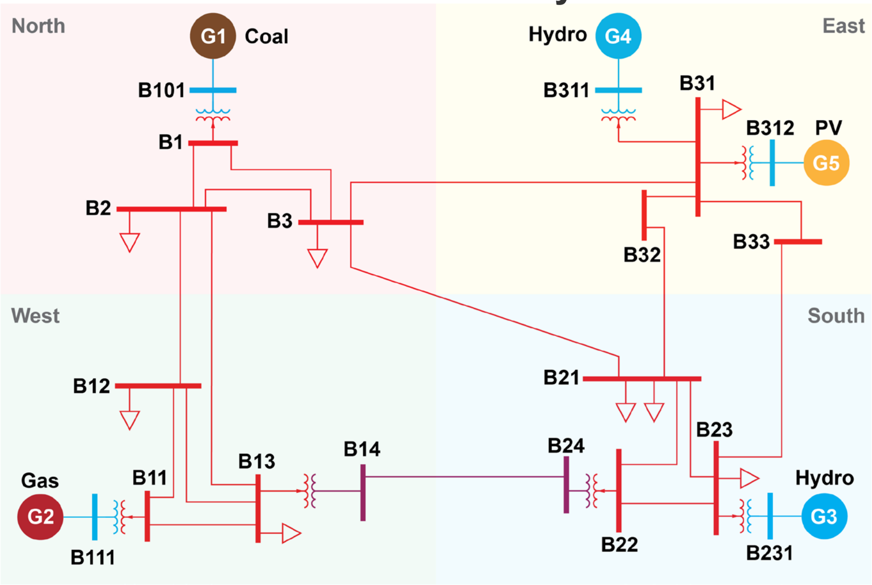
Stability Margins:

- Transient stability assessment (CCT<5 cycles, 0.0833s)
- Small-signal stability assessment (Critical damping ratio <5%)
- Frequency stability assessment (Frequency nadir<59.6 Hz)

* For preliminary testing, we only use one-day dispatch data for testing. (288 scenarios for one-day)

Small Test System

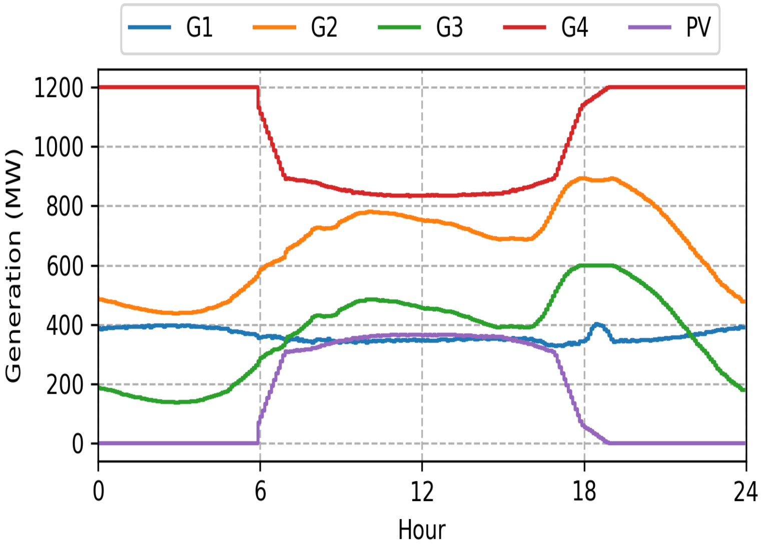
18-bus 4-area test system



Features

- Generator dispatch (real power and reactive power)
- Inertia of units
- Unit commitment…

One-day generator dispatch



Training dataset

Scheduling model→288 scenarios with 5 minutes step over 24 hours

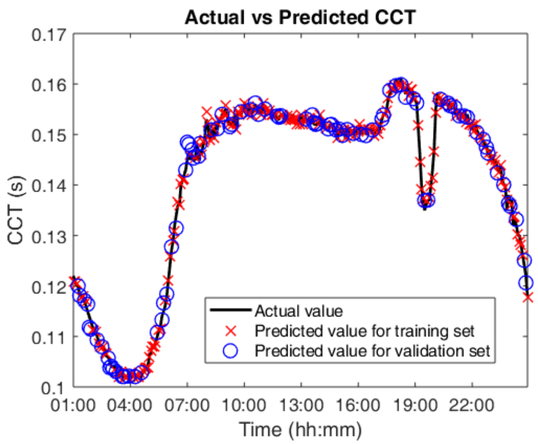
Machine learning for transient stability assessment

- **Input features:**
  - Real power of all generators.
- **Output:** critical clearing time (CCT)
- **Training data set**
  - PSS/E: time domain simulation on three-phase faults
- **Training algorithm**
  - Radom forests and neural network
- **Validation method**
  - Intra-day validation (70% for training, 30% for validation)
  - Inter-day testing (One day for training and validation, the other for testing)

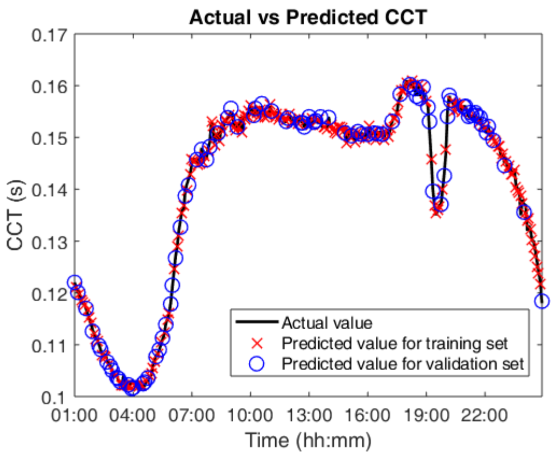
Machine learning for transient stability assessment

- Machine learning tool can accurately predict CCT
- Estimation error is less than 20 ms.

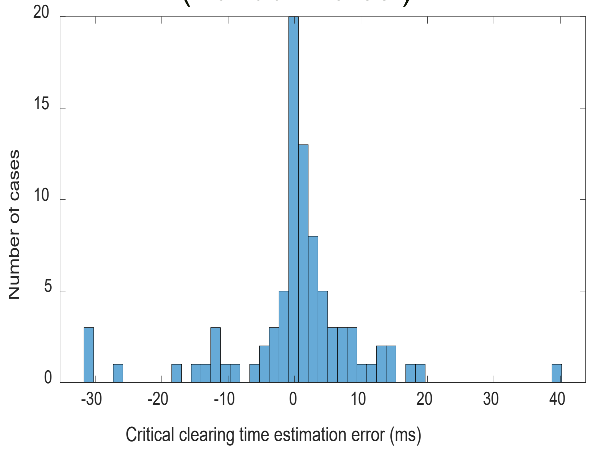
Random forest



Neural network

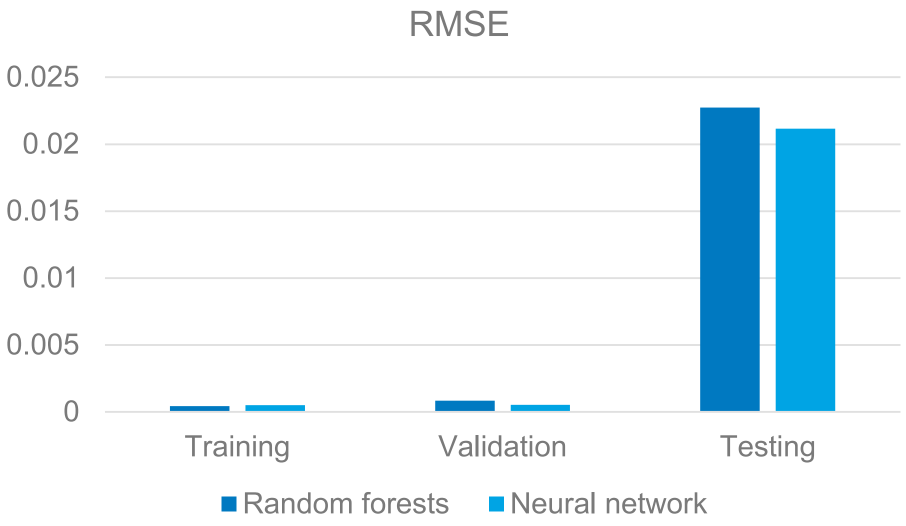


CCT estimation error distribution (Random forest)



Inter-day testing: predict CCT for the other day

- Intra-day validation: 70% of 288 dispatch scenarios in Day A were used for training and the remaining 30% were used for validation.
- Inter-day testing: The 288 scenarios in Day B were used in testing.

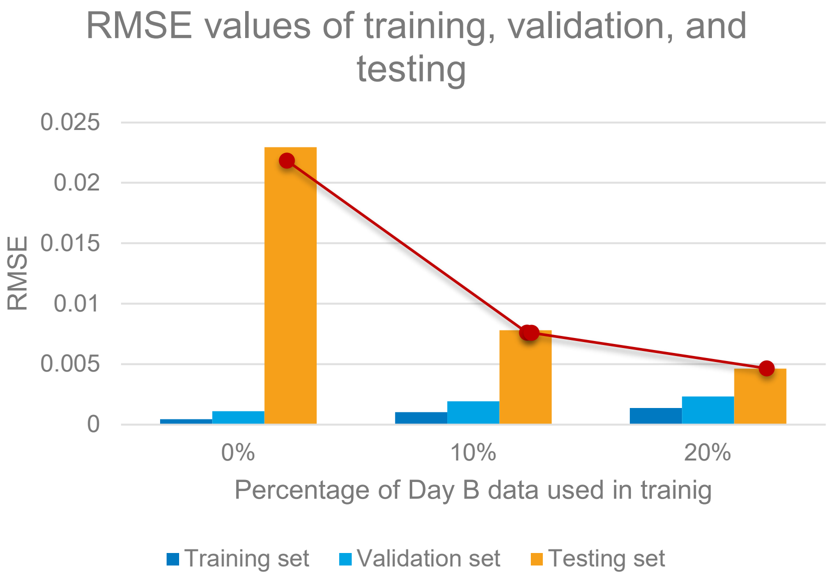


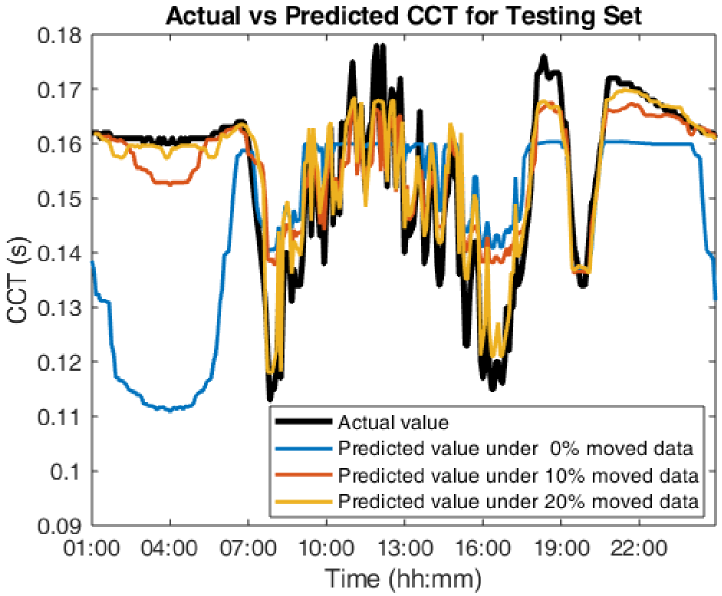
- The validation and training error levels are very close and small, while the testing error levels are large.

- This is most likely because the training data set may be insufficient and not diversified enough for the machine learning model to predict the transient stability in the dispatch scenarios in Day B.

Improvement of inter-day testing for CCT

- To support this hypothesis, a percentage of scenarios were randomly selected from Day B and added to the training dataset in Day A. (Random forests)

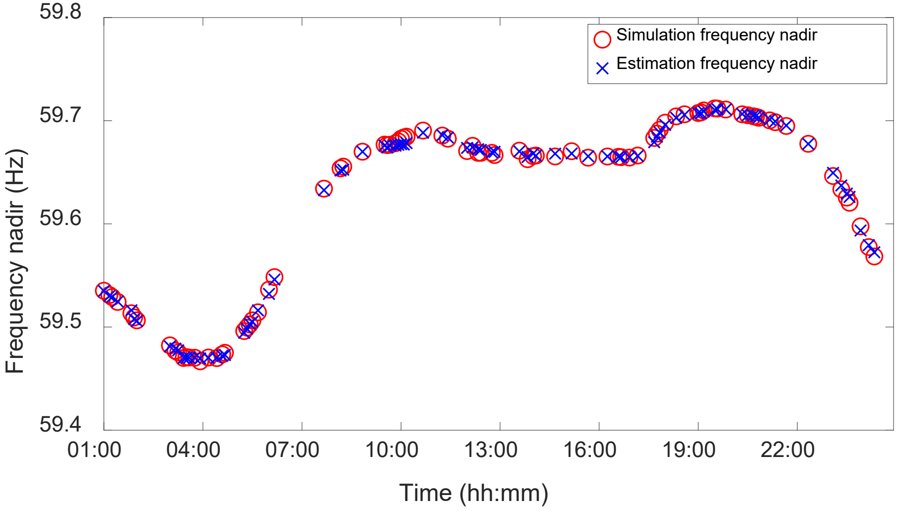




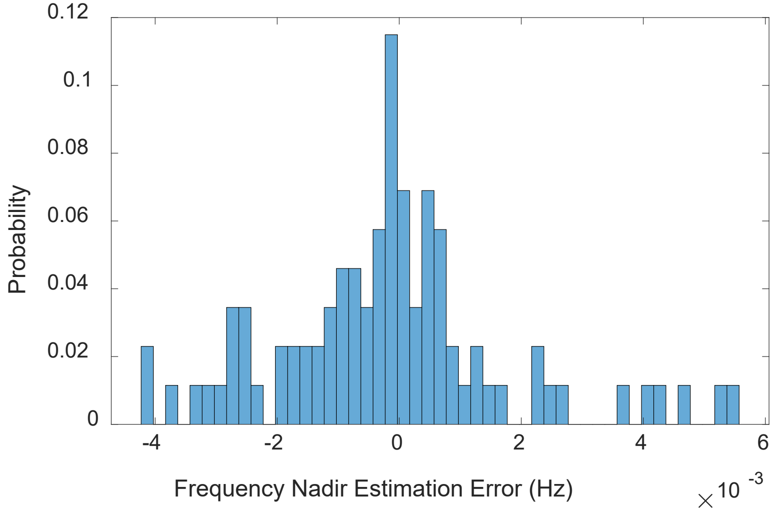
- With limited additional data, the accuracy can be highly improved.

Frequency stability assessment

- Machine learning tool can accurately predict frequency nadir
- Estimation error is less than 6 mHz.



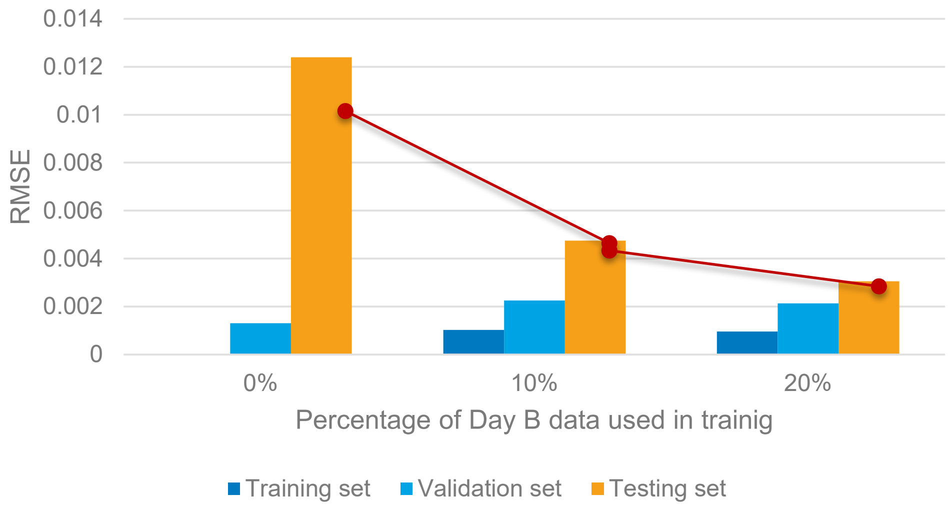
Simulation and estimation frequency nadir in testing dataset



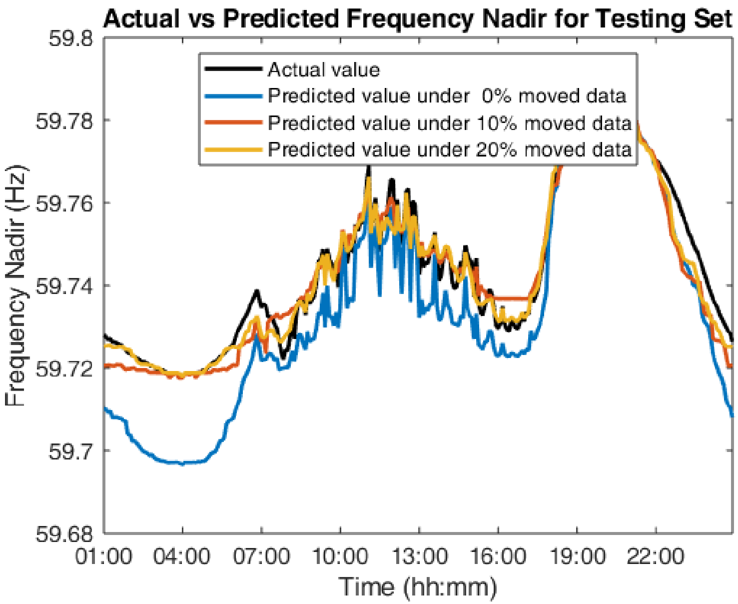
Frequency estimation errors distribution

Improvement of inter-day testing for frequency nadir

- **Inter-day testing- Random forest**

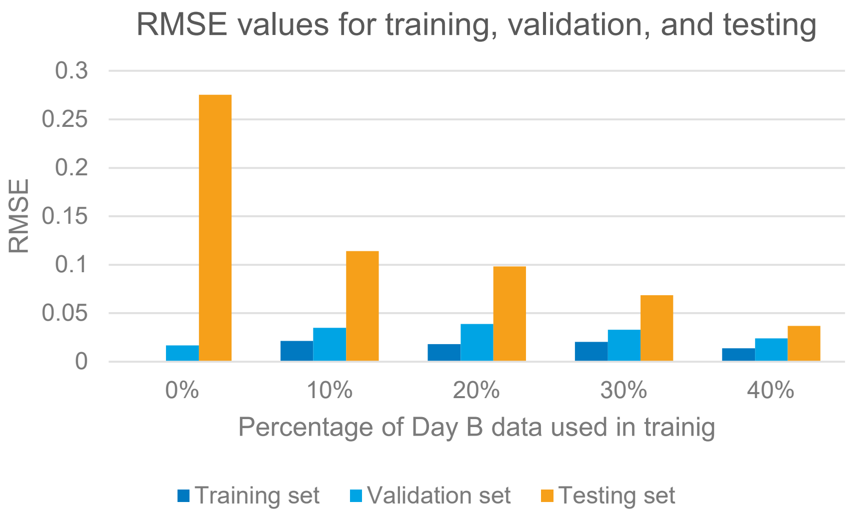


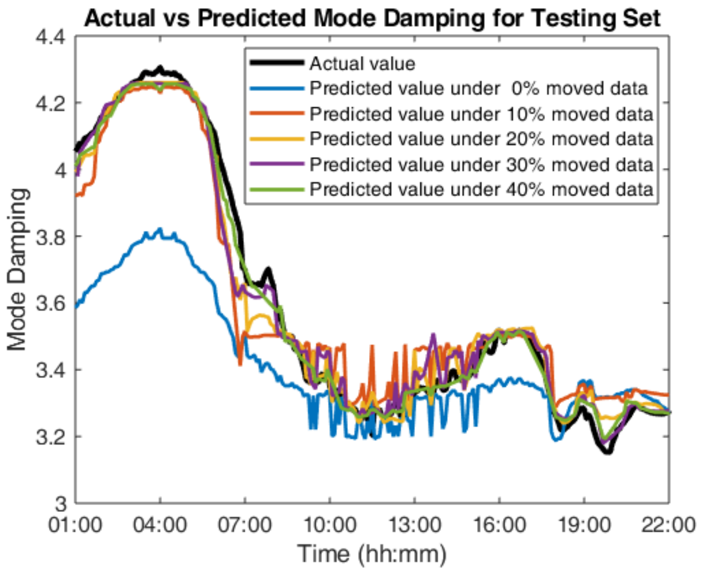
RMSE values for training, validation, and testing



Improvement of inter-day testing for small signal stability

- **Inter-day testing for mode damping (Random forests)**





Summary of stability assessment accuracy

Stability Problem	Input	Output	Estimation accuracy		
				Random forests	Neural network
Frequency	Generation dispatch results, inertia	Frequency nadir for the RCC contingency	Day A	98.30%	99.72%
			Day B (20% data in training)	94.91%	99.37%
Transient	Generation dispatch results, transmission network	Transient stability margin	Day A	98.44%	99.29%
			Day B (20% data in training)	93.39%	97.38%
Small-Signal	Generation dispatch results, transmission network	Small-signal stability margin	Day A	98.61%	98.59%
			Day B (20% data in training)	91.81%	98.70%

Comparison of assessment time

Stabilities	Time for stability assessment (86 scenarios)	
	Simulation	**Machine learning based**
Transient stability	~16 h	~0.18 ms (with trained model)
Frequency stability	~1 h	
Small signal stability	~1 h	

- The machine learning based tool can reduce stability assessment time significantly with minimal sacrifice on accuracy.

Potential applications

- **Potential applications**
  - Real-time security margin assessment
  - Short-term stability prediction and system adjustment
  - Stability-related resource procurement and stability validation in day-ahead markets
  - Accurate stability margin quantification of multiple power flow scenarios for long-term planning
- **Future**
  - Data-driven + model-driven

Summary

- The proposed machine learning tool is used to assess three stability metrics of the 18-bus test system:
  - Transient stability — critical clearing time
  - Frequency stability — frequency nadir
  - Small signal stability — damping ratio of oscillation mode

- The developed machine learning tool can be used to predict the system stability margins using load dispatch results.

- The proposed data-driven security assessment approach can reduce the computational burden of dynamic simulations, making it suitable for security stability assessment of high PV systems.

Question?

www.nrel.gov

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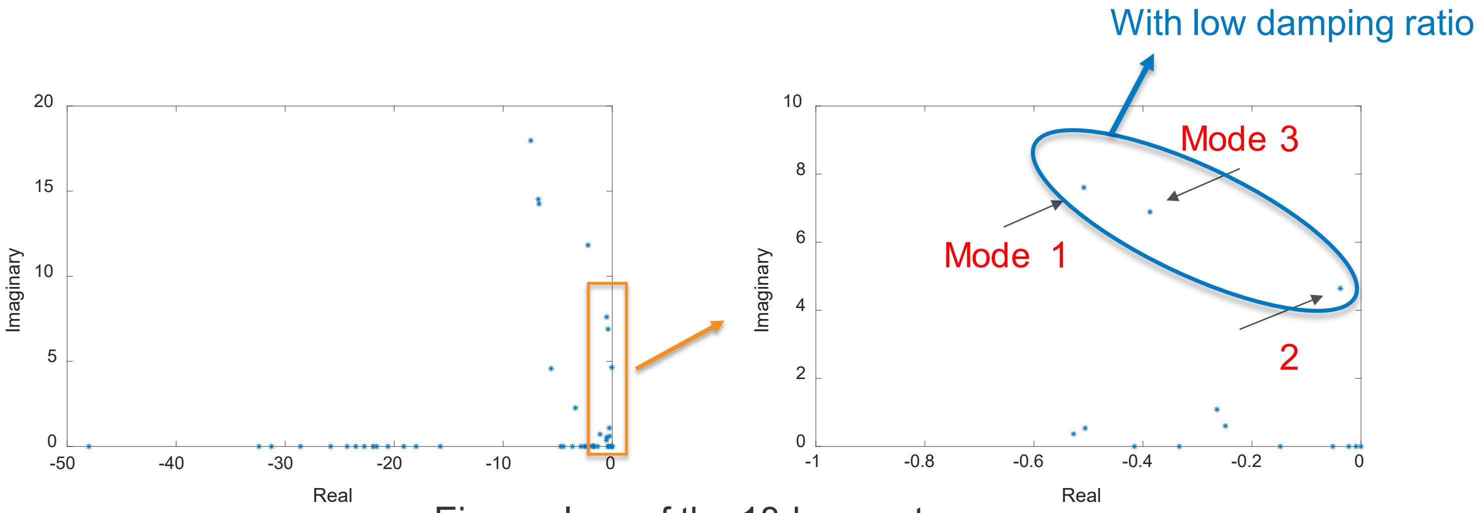
Small signal stability assessment

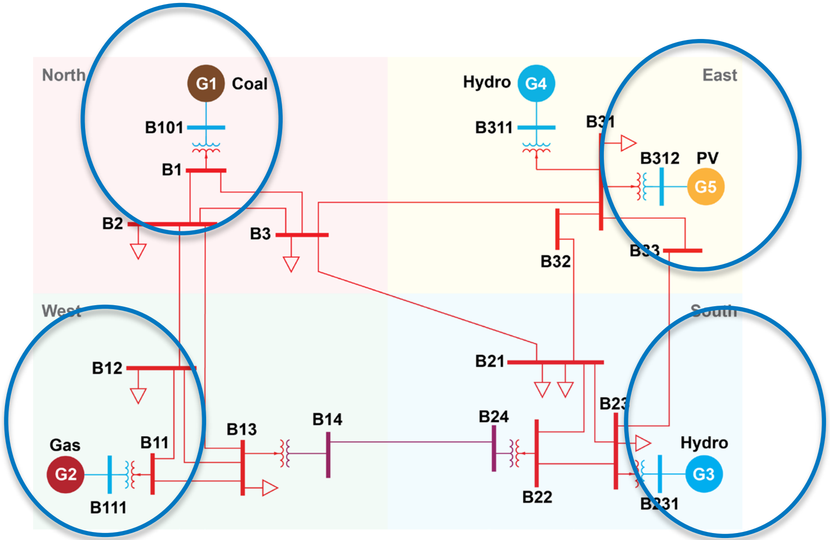
- Full eigenvalue analysis is performed for 18 bus model
- 47 eigenvalues in total: three have low damping ratio (below 10%)
- DSA tool predicts both mode damping ratio and frequency

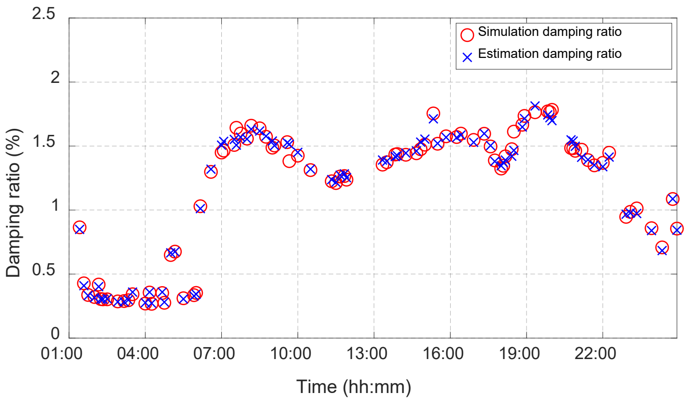


Eigenvalues of the 18-bus system

Small signal stability assessment: Mode 3

- Mode 3: frequency is 1.06 Hz and damping ratio is 5.83%
- All generators are involved in this mode





Actual and estimated damping ratio

- Machine learning tool can accurately predict the damping ratio
- Estimation error is less than 0.1%