NREL
Transforming ENERGY

Machine Learning-Based Security Assessment and Control for Bulk Electric System Operation

Haoyu "Harry" Yuan, Jin Tan, and Yingchen "YC" Zhang

National Renewable Energy Laboratory

ISGT 2020

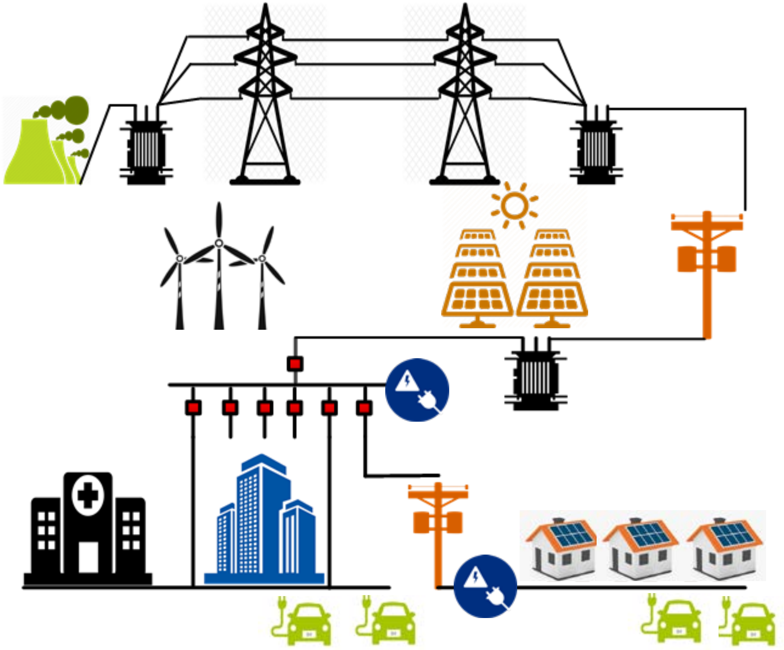
Washington, D.C.

February 20, 2020

Contents

Background

Traditional power grid → Future power grid



Uncertainty and variability

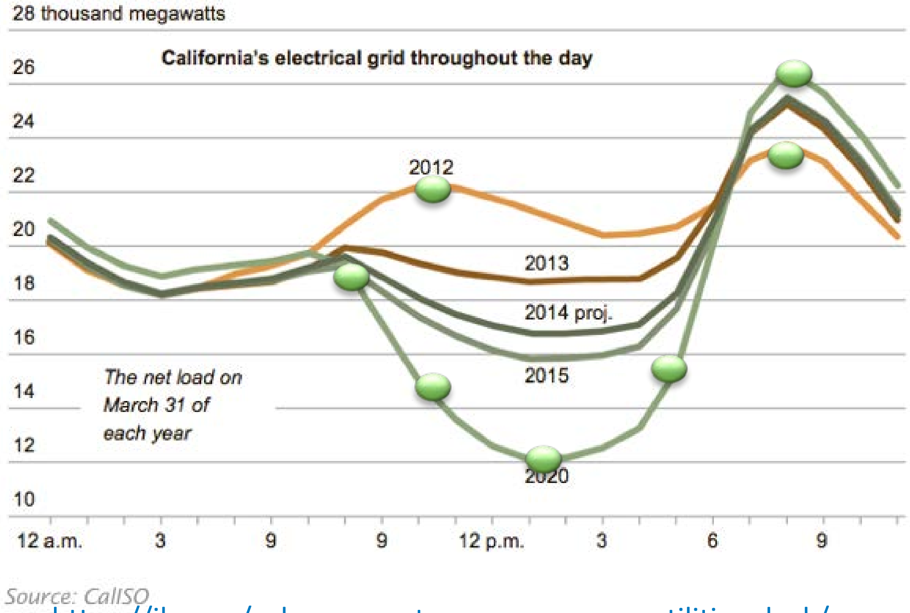
Stochastics

Vulnerability

Low inertia and weak grid

Challenges

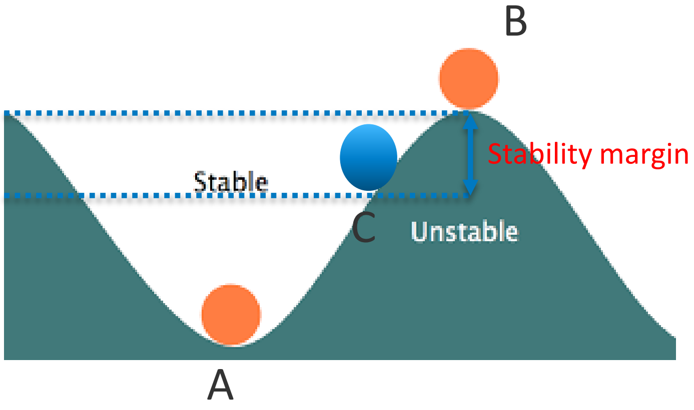
There is a need for real-time dynamic security assessment and situational awareness for the future power grid with high renewable energy penetrations.



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

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

Building the Machine Learning Model for Security Assessment

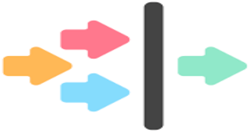


Step 1: Representation:

- What to learn?
- What's the input? What's the output?

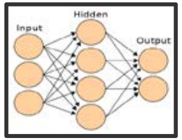
Step 2: Feature selection

Pgen,
inertia,
…

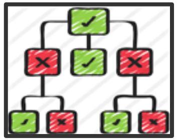


Useful features

Step3: Model selection



NN

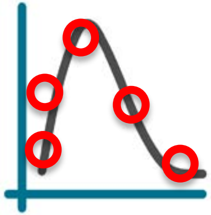


Decision tree

SVM

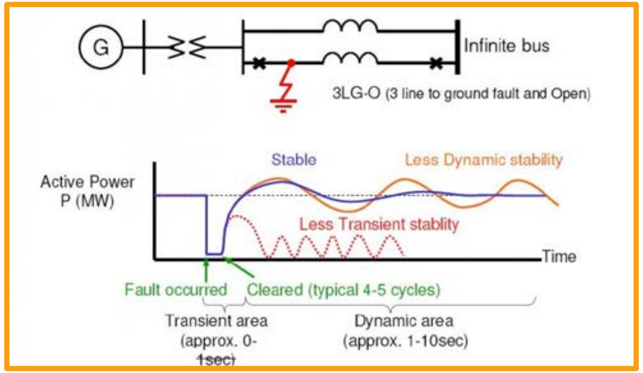
Deep learning

Step 4: Interpretation and validation

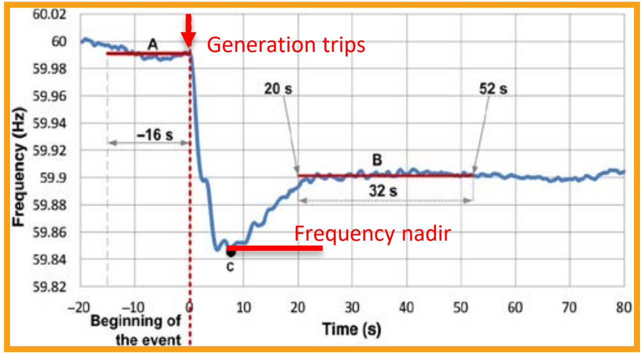


How Do We Define the Stability Margin?

- **Transient stability** **(critical clearing time [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.

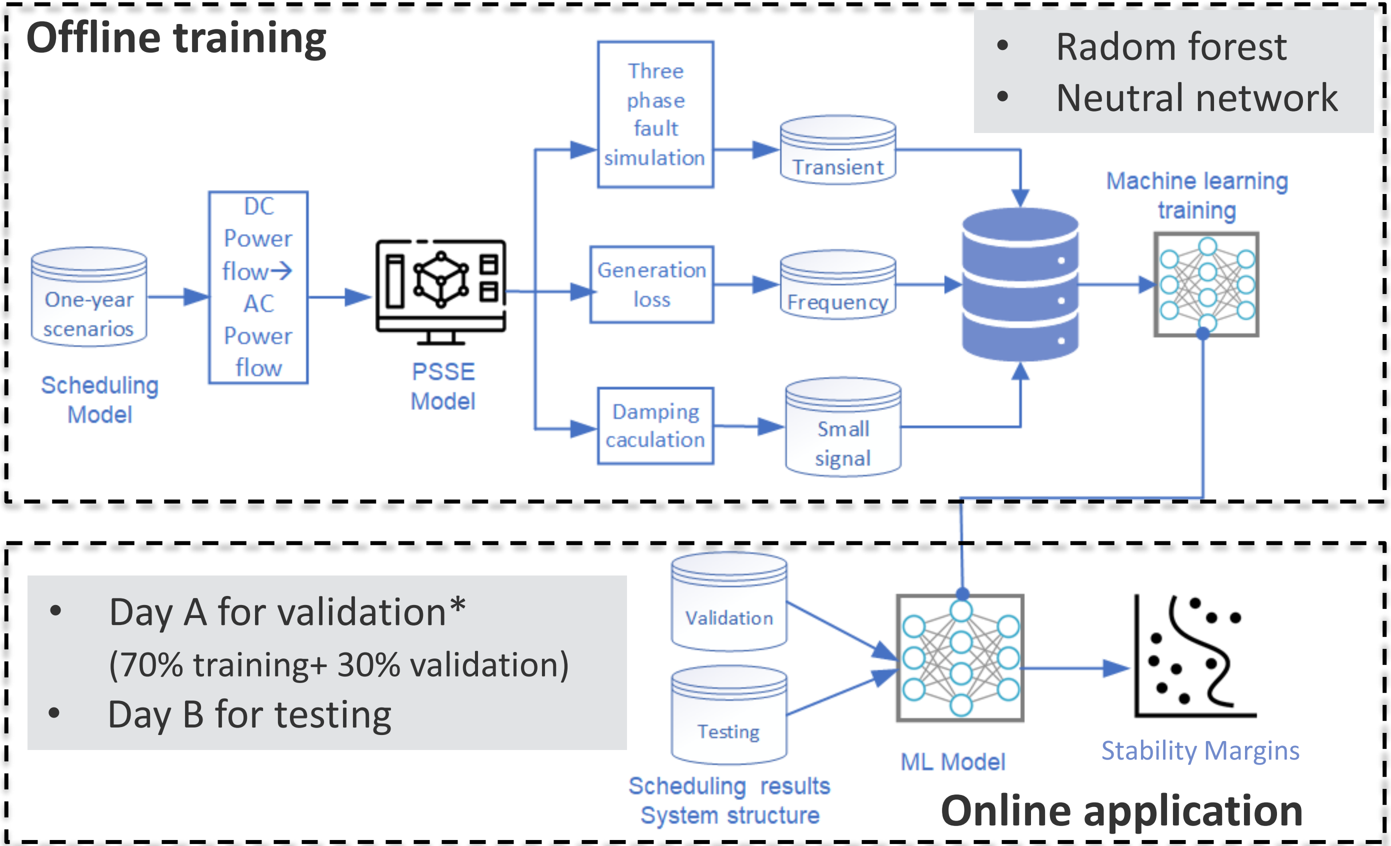


Transient stability



Frequency stability

Framework



- Radom forest
- Neutral network

- Day A for validation*
  (70% training+ 30% validation)
- Day B for testing

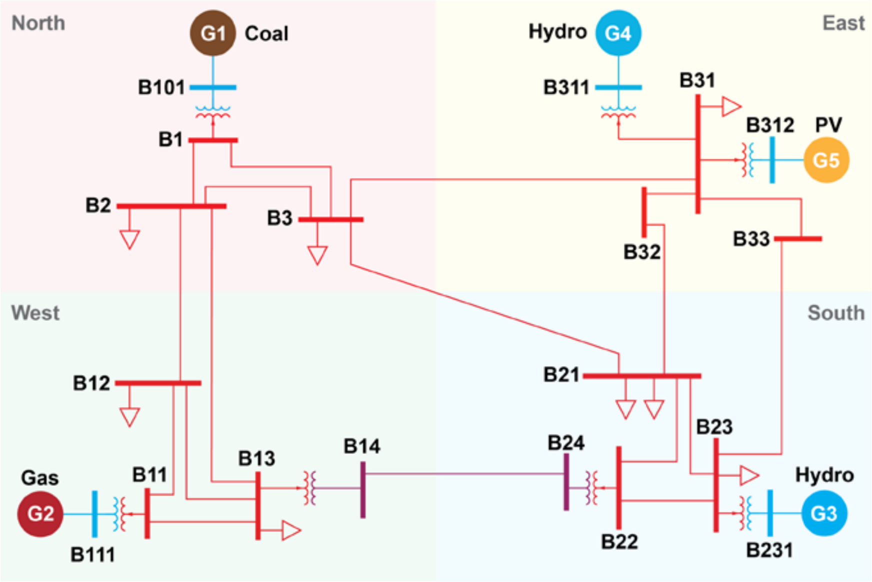
Stability margins:

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

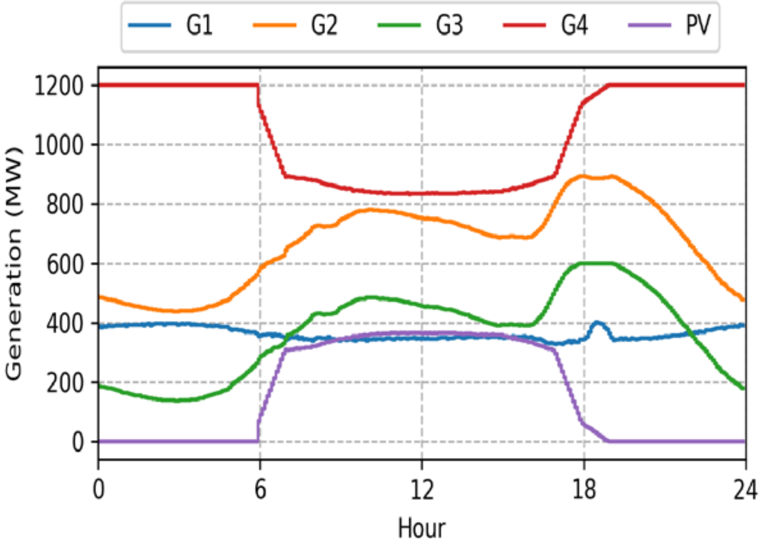
* For preliminary testing, we use only 1-day dispatch data (288 scenarios for 1 day).

Small Test System

18-bus, 4-area test system



1-day generator dispatch



Features:

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

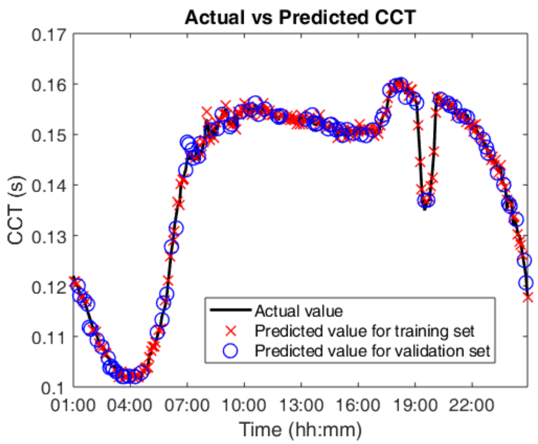
Training data set:

Scheduling model→288 scenarios with 5-min step over 24 h.

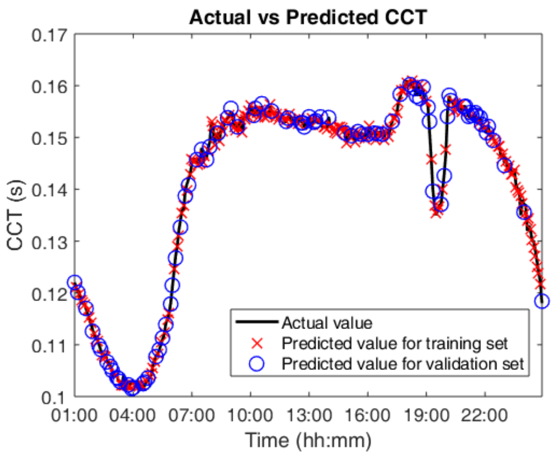
Machine Learning for Transient Stability Assessment

Input Features	Output	Training Data
Real power of all generators	CCT	Time domain simulation on three-phase faults

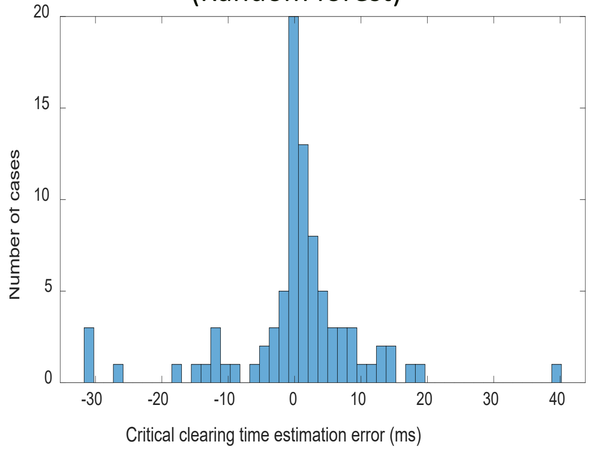
Random forest



Neural network



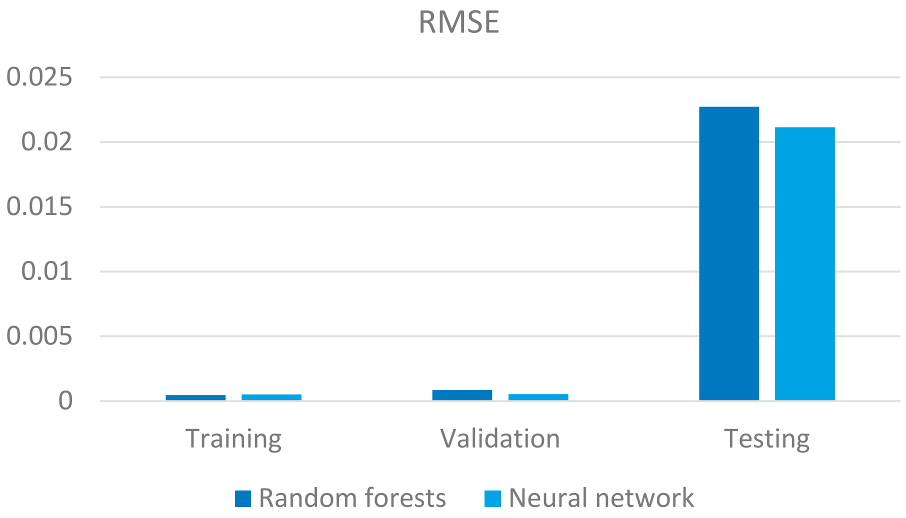
CCT estimation error distribution (Random forest)



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

Inter-Day Testing: Predict Critical Clearing Time for the Other Day

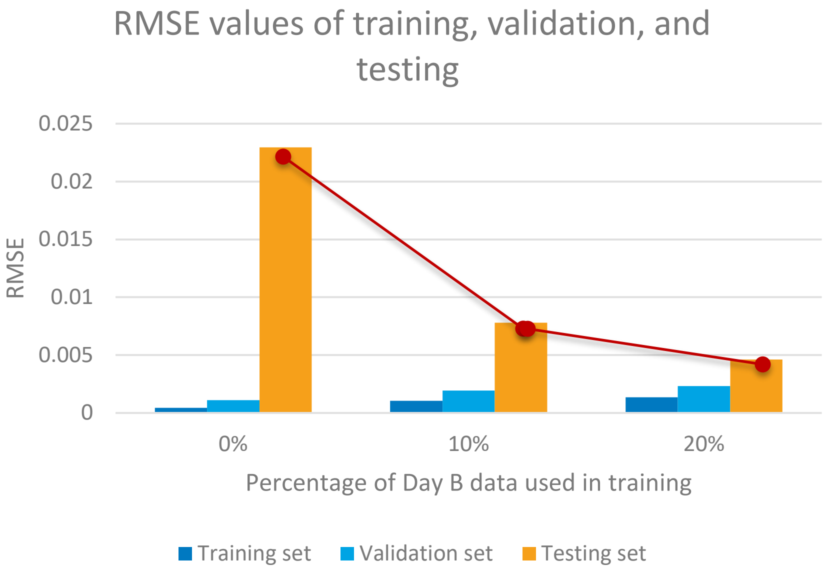
- Intraday validation: 70% of 288 dispatch scenarios in Day A were used for training, and the remaining 30% were used for validation.
- Inter-day testing: The 288 scenarios in Day B were used in testing.

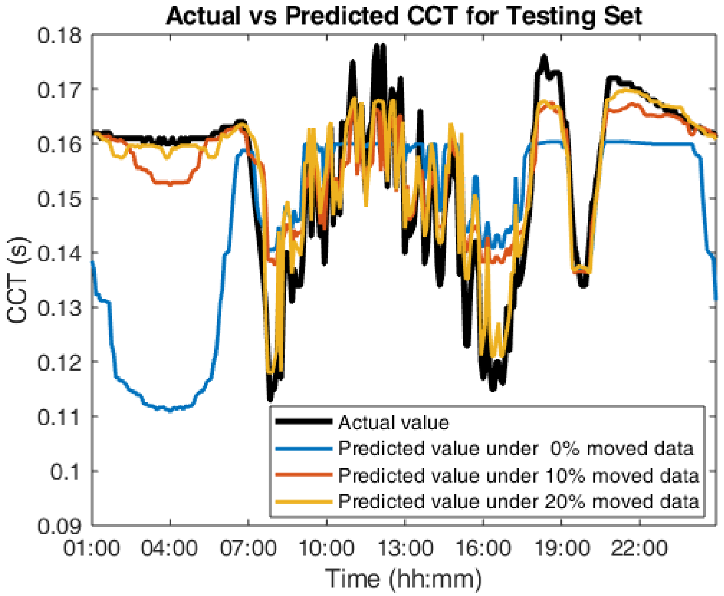


- The validation and training error levels are very close and small, whereas the testing error levels are large.
- This is most likely because the training data set might be insufficient and not diverse enough for the machine learning model to predict the transient stability in the dispatch scenarios in Day B.

Improvement of Inter-Day Testing for Critical Clearing Time

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





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

Summary of Three Security Assessments

- **Test system: 18-bus system**

Stability	Input	Output	Data Set		Estimation Accuracy	
			Training Data Set	Testing Data Set	Random Forests	Neural Network
Frequency	Generation dispatch results, inertia	Frequency nadir	70% data of Day A	The remaining 30% data of Day A	98.30%	99.72%
			100% data of Day A + 20% data of Day B	80% data of Day B	94.91%	99.37%
Transient	Generation dispatch results, transmission network	CCT	70% data of Day A	The remaining 30% data of Day A	98.44%	99.29%
			100% data of Day A + 20% data of Day B	80% data of Day B	93.39%	97.38%
Small-Signal	Generation dispatch results, transmission network	Damping ratio +Frequency	70% data of Day A	The remaining 30% data of Day A	98.61%	98.59%
			100% data of Day A + 20% data of Day B	80% data of Day B	91.81%	98.70%

Comparison of Assessment Time

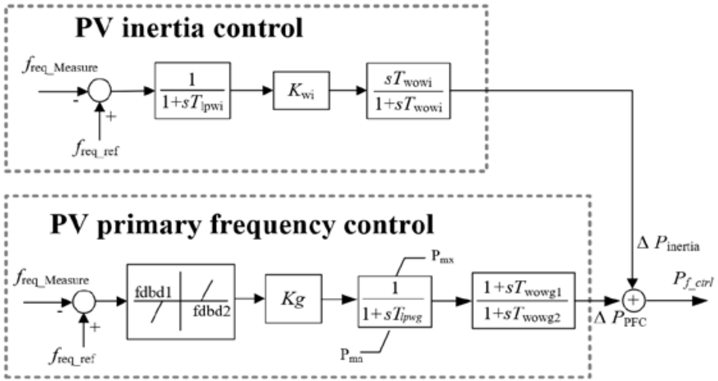
Stabilities	Time for Stability Assessment (86 Scenarios)	
	Simulation	Machine Learning-Based
Transient stability	~16 h	~0.18 ms (with trained model)
Frequency stability	~1 h	
Small-signal stability	~1 h	

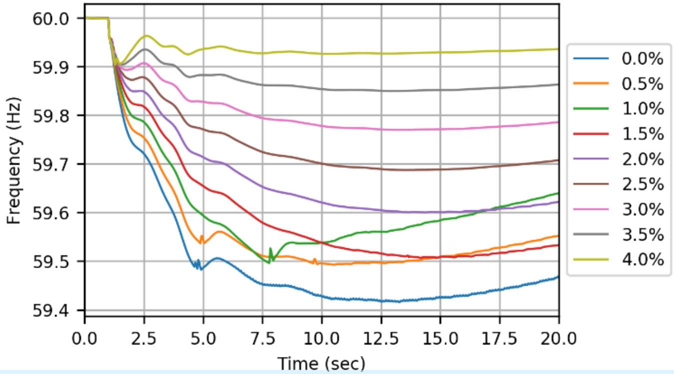
- The machine learning-based tool can significantly reduce stability assessment time with minimal sacrifice on accuracy.

Frequency Control of Photovoltaic Inverter

- Advanced inverter design can enable photovoltaics (PV) to provide **frequency control**.
- PV needs to be **curtailed** to provide upward response.
- Model-based approach to determine the optimal reserve requirement is **computationally intense**.

Frequency control block

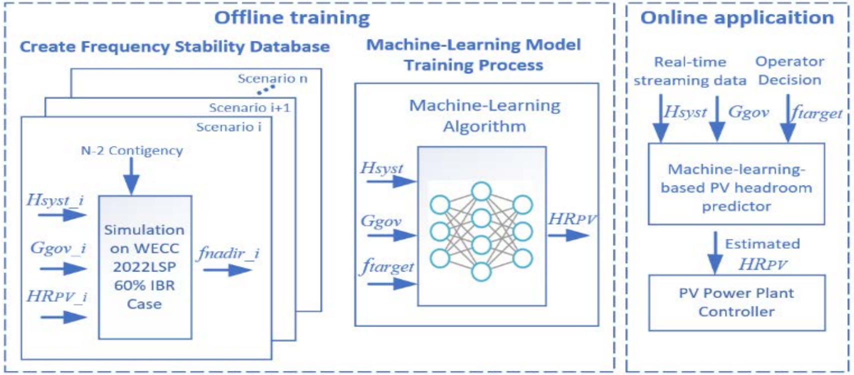




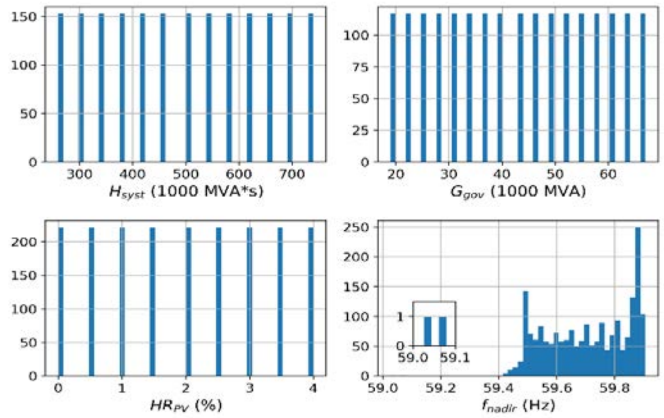
- More headroom leads to better frequency response but might not be economic.

Machine Learning Approach for Reserve Determination

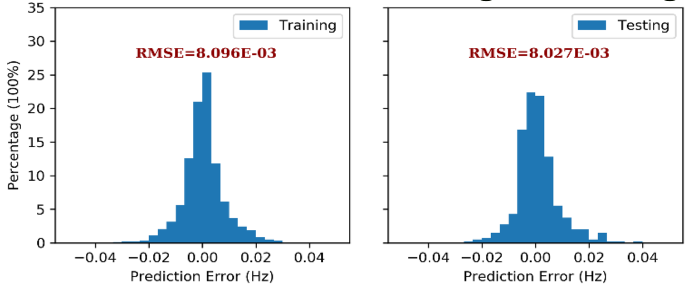
- Offline simulation of different operation conditions (approx. **2,000 cases**) of the 60% inverter-based resources Western Electricity Coordinating Council case (**10,000 + buses**).
- Inputs include system inertia, governor capacity, and targeted frequency nadir.
- Outputs the optimal PV reserve amount.



Histogram of features



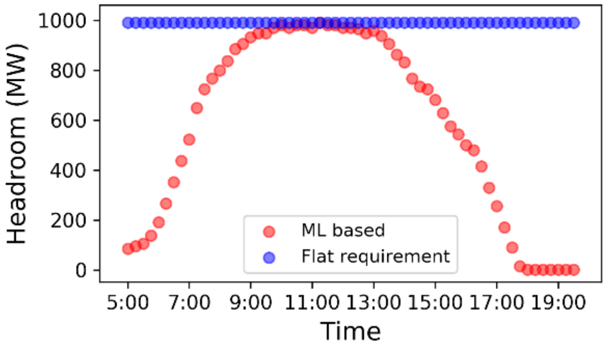
Prediction errors: training vs. testing



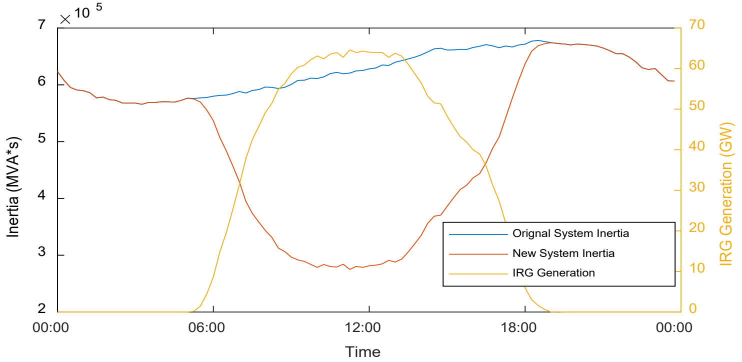
Validation on Unseen 1-Day Profile

- For each interval, the H_{syst} and G_{gov} as well as the 59.55-Hz target are input to the machine learning model to find the optimal headroom.
- For validation, the GE PSLF (positive-sequence load flow simulation) using the optimal headroom is performed, and the actual f_{nadir} is found.
- 40% headroom is saved compared with flat requirement.
- The prediction error is within 0.01 Hz.

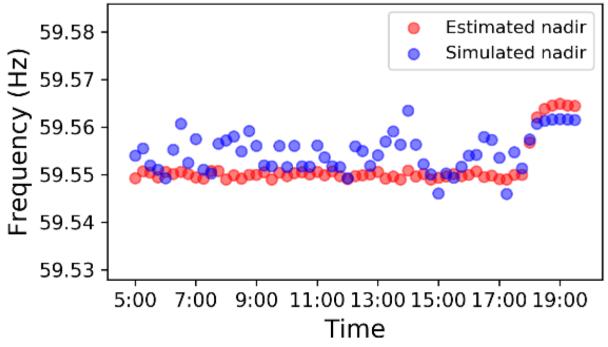
Optimal headroom reserve



1-day profile



Frequency nadir

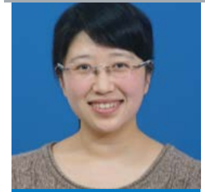


Conclusion

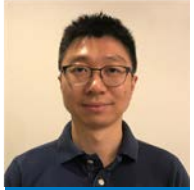
- The proposed machine learning tool is used to assess three stability metrics of the 18-bus test system using steady-state dispatch results.
  - Transient stability: CCT
  - Frequency stability: frequency nadir
  - Small-signal stability: damping ratio of oscillation mode.
- The proposed machine learning strategy can determine the optimal PV headroom reserve of an interconnection-level system for frequency control.
- It is demonstrated that machine learning-based tools can reduce the computational burden of dynamic simulations, making them suitable for online security assessment and stability control for systems with high penetrations of renewable generation.

Our Team

Dynamic Modeling Team


Jin Tan
PI


Yingchen(YC)
Co-PI


Harry


Vikas


Parag

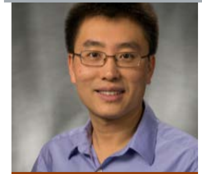

Himanshu

HIL Testing Team


Vahan

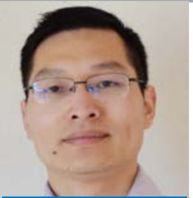

Przemyslaw

Scheduling Modeling Team


Jianhui
Technical Lead

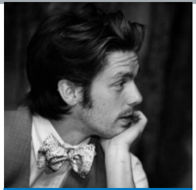

Shengfei


Erik
Technical Lead


Xin

EMT Modeling Team


Andy
Co-PI


Wallace

Project Management


David
Project Manager

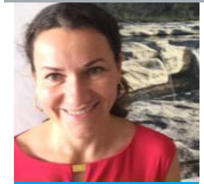
Data-driven Security Assessment


Yilu
Technical Lead


Steve


Summer

Technical Advisor


Julia


Clyde

EPRI
UTK
ERCOT
NREL
SMU

Questions?

www.nrel.gov

NREL/PR-5D00-76089

NREL Contact:
Jin Tan
jin.tan@nrel.gov

Presenter:
Haoyu "Harry" Yuan
haoyu.yuan@nrel.gov

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

NREL
Transforming ENERGY