A Machine Learning Framework for Bridging the Gap Between the Steady-State Scheduling and Dynamic Security Operation for Future Power Grids

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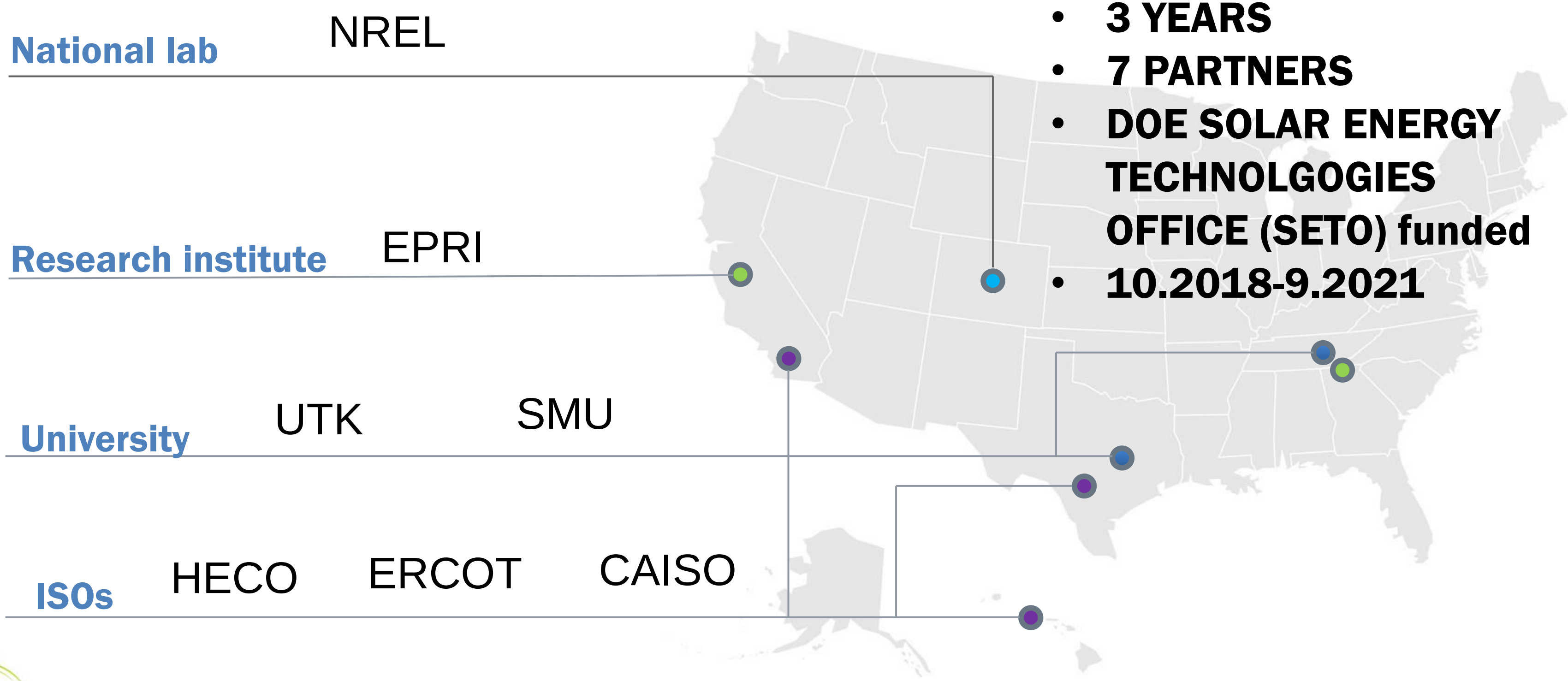
MIDAS Solar Project



- **3 YEARS**
- **7 PARTNERS**
- **DOE SOLAR ENERGY TECHNOLGOGIES OFFICE (SETO) funded**
- **10.2018-9.2021**

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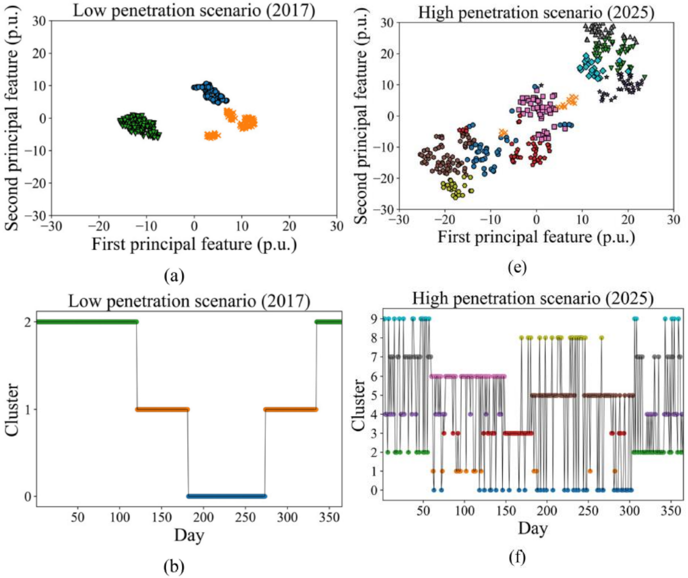
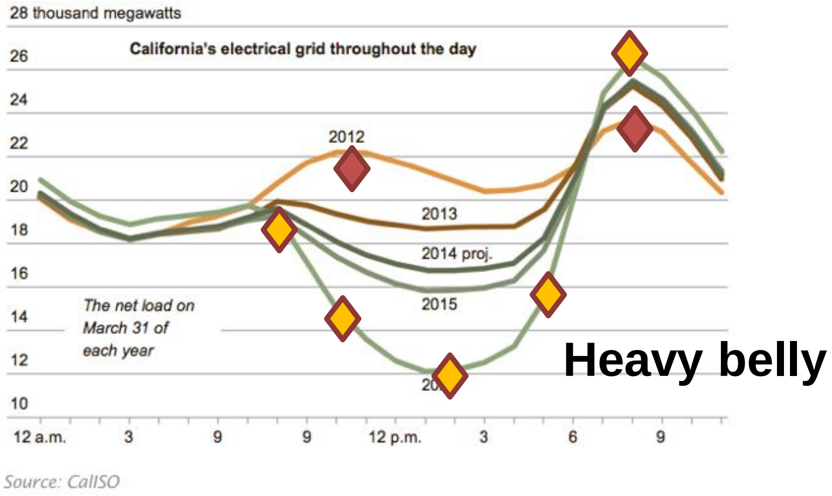
Background

Future power grid operational modes are diverse and uncertain.



Operation modes of Qinghai power system in China

Source: Hou, Q., et al. 2019. "Impact of High Renewable Penetration on the Power System Operation Mode: A Data-Driven Approach." *IEEE Transactions on Power Systems* 17, no. 35 (1): 731–41.



California Duck Curve

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

MIDAS

Challenges

Current

Electricity market
- Dispatch solution

Offline contingency analysis
- Select the typical scenarios.
- Through dynamic simulation.

Real-time dynamic security analysis
- Monitor

Day ahead

Hours

Seconds

Future

What if most dispatch solutions could not work properly without considering stability/ low-inertia issues?

What if there are no typical scenarios?

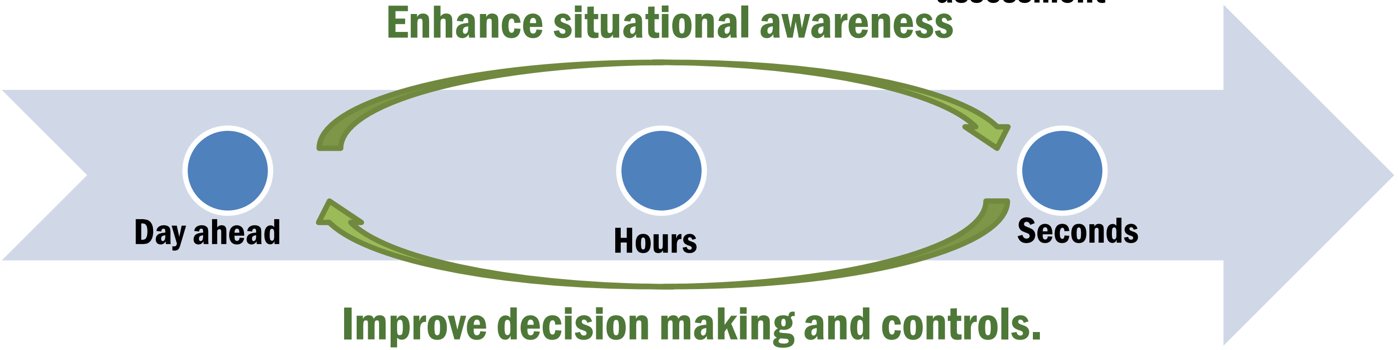
What if it is too late to alarm?

There is a need for improved situational awareness and decision making of **stability-related issue** for the future power grid with high renewable energy penetrations.

How Could Machine Learning Help?

Challenges

Electricity market | **Offline contingency analysis** | **Real-time dynamic security assessment**



Tools

Tool II: Security-constrained DC power flow:

- Consider the dynamic stability constraint in the scheduling model?
- How to form a constraint?

Tool I: Time-domain simulation:

Increasing the accuracy →
→ Increasing the computational burden
→ Hard to finish in real time.

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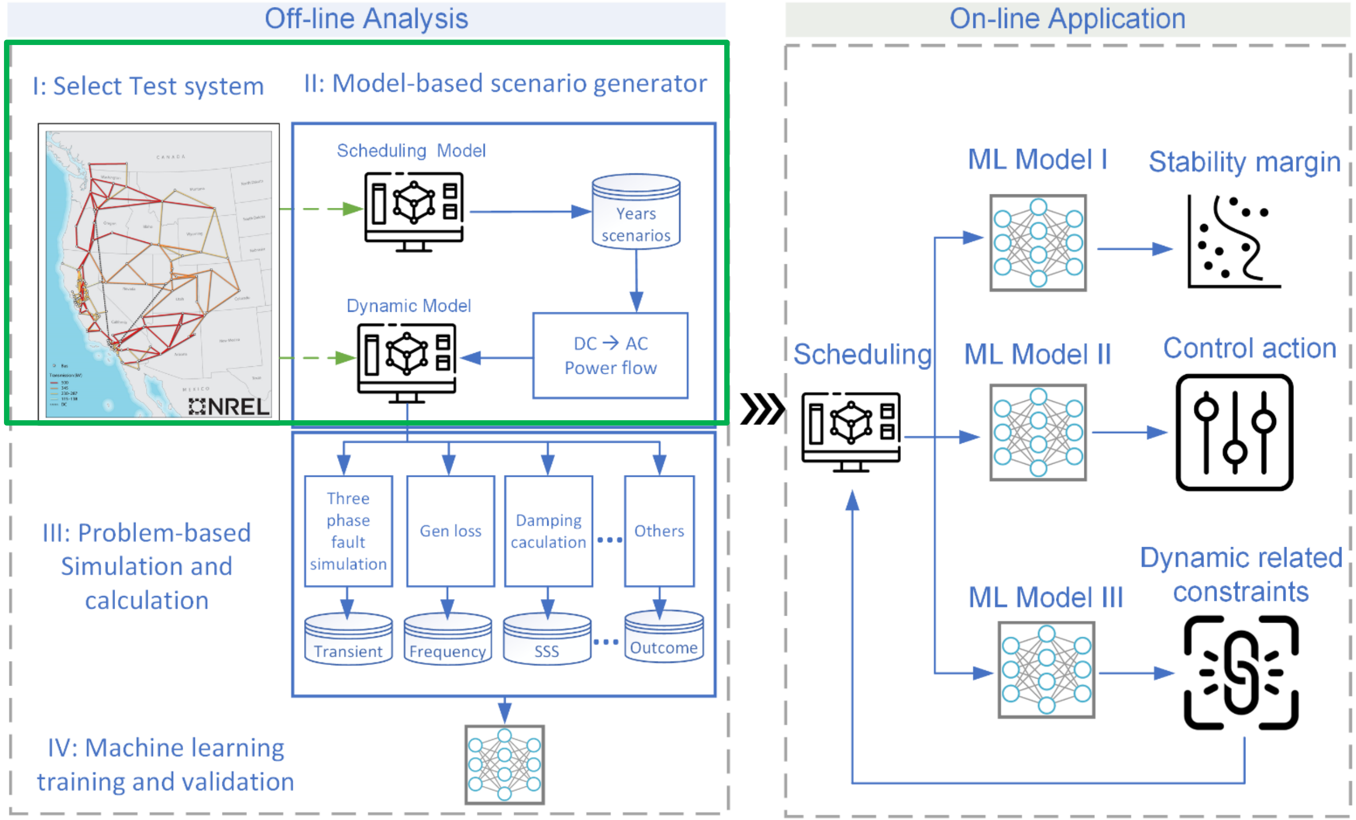
MIDAS – Machine Learning Framework

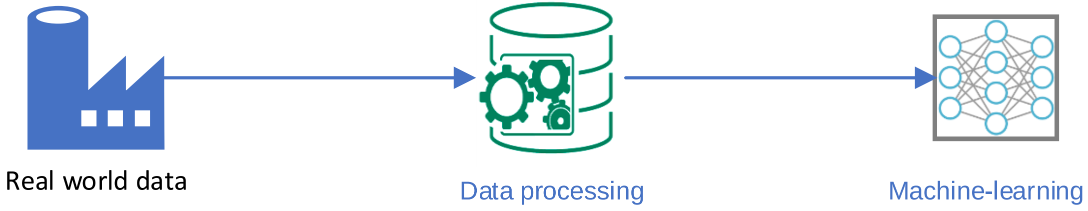


How Could We Generate a Training Data Set?

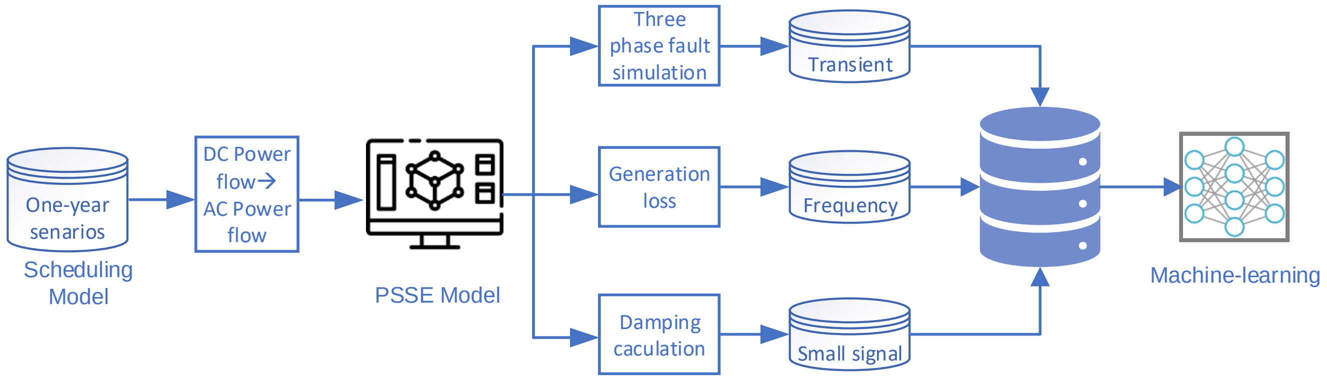
Database for security assessment

- No-bias database

Real operational data



Model-generated scenarios



240-Bus WECC Test System

Develop one-to-one scheduling and dynamic model of 240-bus Western Electricity Coordinating Council (WECC) test system for researchers and utilities to understand the challenges of grid operation with high photovoltaic (PV) penetrations.

Feature:

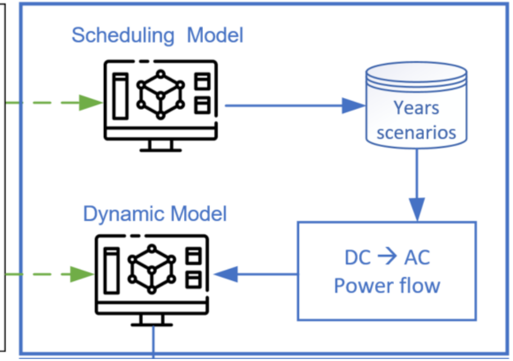
- An **open-source test system**
- Capture the main dynamic characteristics of WECC system, including **system frequency response and main inter-area oscillation modes**.
- Provide **temporal and spatial time-series data** of renewables and loads across WECC for 1 year.
- Renewable penetration cases: 20%, 40%, 60%, 80% (coming soon).

Base case we adopted:

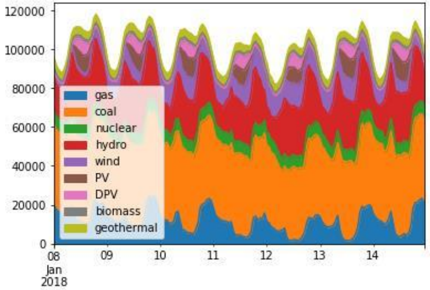
- Multi-Timescale Integrated Dynamics and Scheduling for Solar (MIDAS) tool generates 8,000+ power flow scenarios for 240-bus WECC.
- Renewable penetration is up to 49.2%.

I: Select Test system

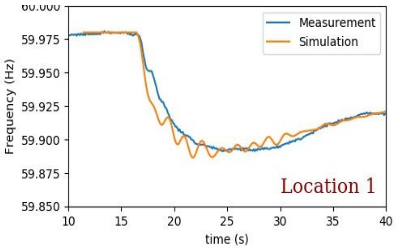
II: Model-based scenario generator



Example: 1-week dispatch



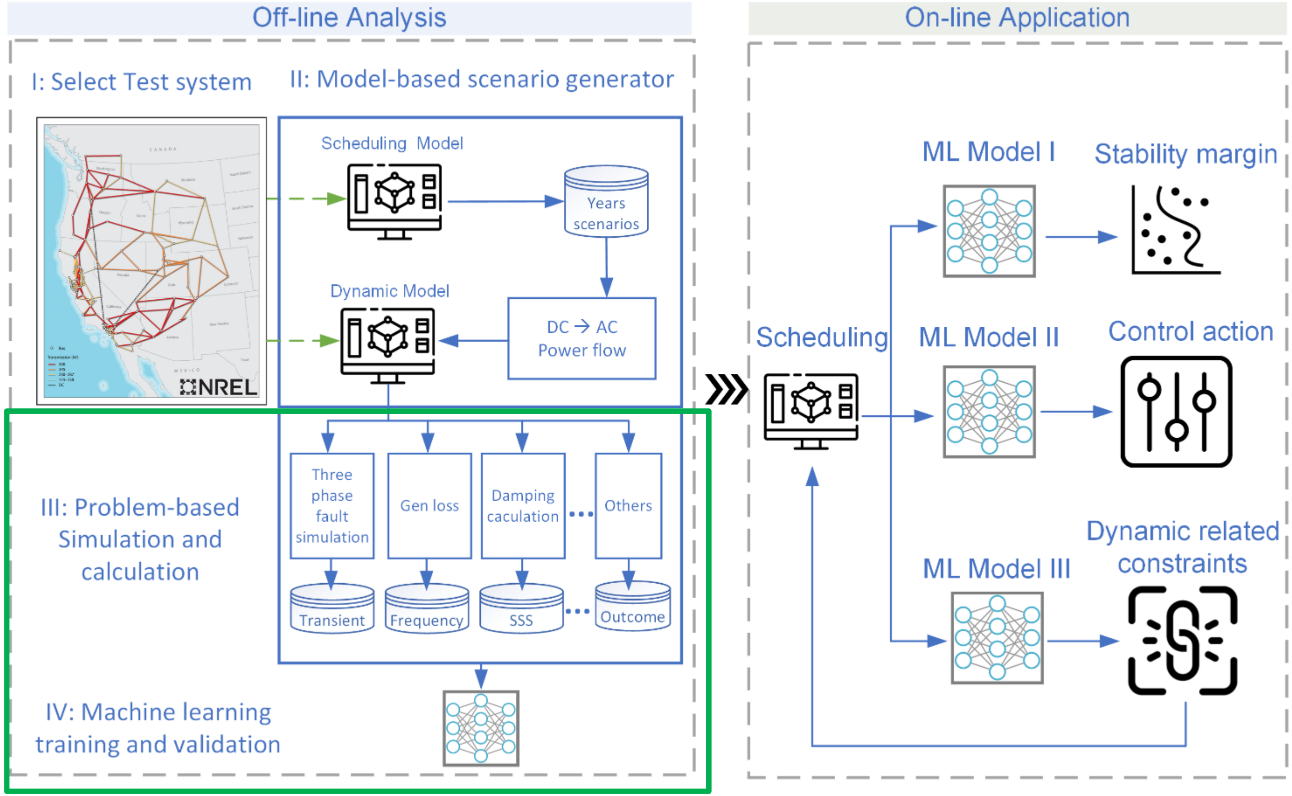
Frequency response with FNET validation in a real event



Test Case Repository for High Renewable Study: https://www.nrel.gov/grid/test-case-repository.html.

Source: Yuan, Haoyu, et al. 2020. "Developing a Reduced 240-Bus WECC Dynamic Model for Frequency Response Study of High Renewable Integration." *2020 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*: 1–5.

MIDAS – Machine learning Framework



Applications

Decision making

Smart PV reserve

Adaptive inertia requirement

Etc.

Situational awareness

Frequency stability

Small-signal stability

Transient stability

Minute-days

Minutes

Seconds

Control

Robust RAS design

Etc.

MIDAS

Example I: Frequency Stability Margin Assessment

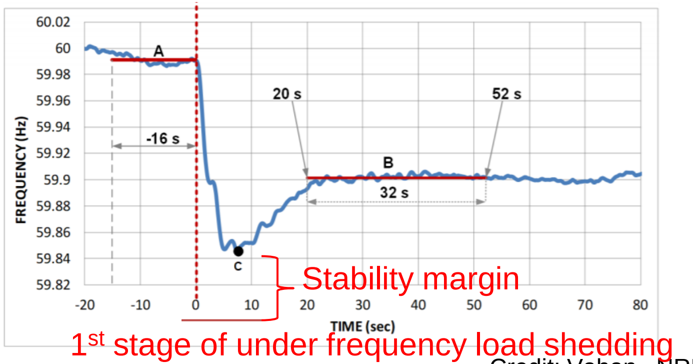
Swing equation of synchronous machine in per units:

$$2H\frac{d\omega}{dt} = P_{gen} - P_{load}$$

$$\mathrm{ROCOF} = \frac{d\omega}{dt} = (P_{gen} - P_{load} - P_{genloss})/2\underline{H}$$

effect **cause**

H is inertia constant.
ω is the rotor speed.
f= $\omega/2\pi$ is grid frequency.



Credit: Vahan , NREL

- Initial rate of decline of frequency—determined by inertia only
- Value of frequency nadir (Point C)—determined by inertia and primary frequency response (PFR)
- Value of settling frequency (Point B)—determined by PFR only.

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Physics-Based Feature Preprocessing

Feature selection

- $\boxed{\text{Active power dispatch}}$
- Dynamic parameters of generators
- $\boxed{\text{Inertia}}$
- Load amount
- Topological features
- Weather features
- Others.

Not the more, the better.

Feature normalization:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)}$$

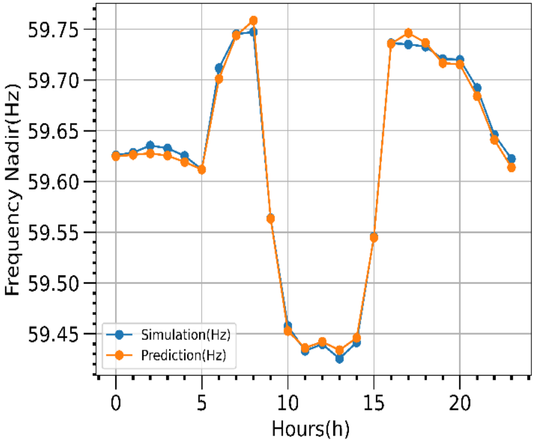
Goal:

- Weighted the inertia impact
- Weighted the large generator’s impact
- Minimize the impact of unseen cases in training data set.

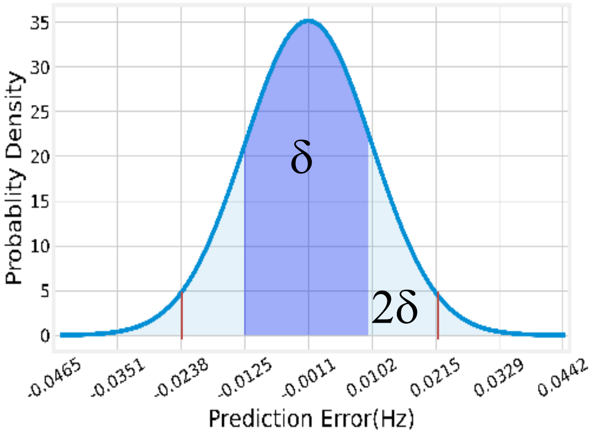
Frequency Stability Assessment

Deep neural network with 10% training data set

One-day example



Error distribution



Testing results

Training dataset Percentage	RMSE (Hz)	MAE (Hz)	R^2
2%	0.039212	0.029296	0.875427
4%	0.022400	0.017249	0.959396
6%	0.023165	0.016757	0.956427
8%	0.016522	0.012091	0.977915
10%	0.011392	0.008437	0.989487
20%	0.009903	0.007651	0.992038
30%	0.008478	0.005949	0.994147
40%	0.007238	0.005267	0.995762
50%	0.007175	0.005159	0.995825

Based on 10% training data set, with 96% probability, the absolute prediction error is smaller than 0.022 Hz.

Summary of Stability Margin Assessment

Stability Problem	Input	Output	Estimation Accuracy* (R^2)
Frequency	Generation dispatch results, inertia	Frequency nadir	99.72%
Transient	Generation dispatch results, transmission network	Min (CCT) Bus number	99.29%
Small-signal	Generation dispatch results, transmission network	Min (damping ratio) and mode frequency	98.59%

Stability Problem	Offline	Online
	Simulation for 8,780 scenarios	**Testing**
Frequency	12 hours	~0.18 ms
Transient	36 hours	
Small-signal	8 hours	

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

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*Deep neural network with 70% training data set

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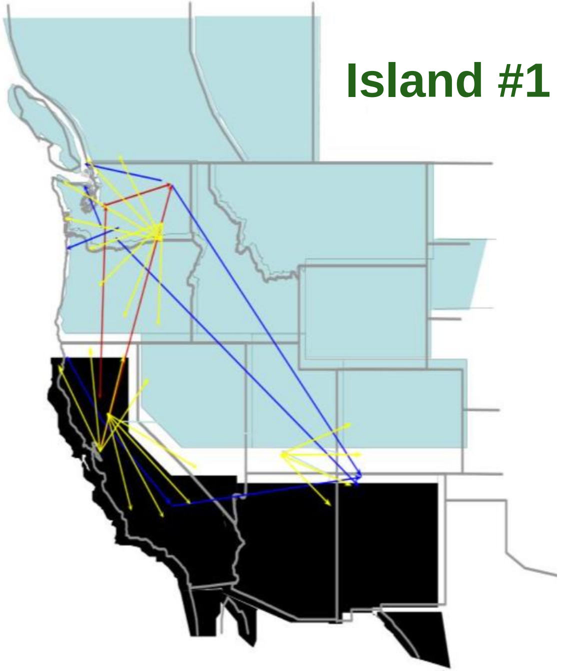
Etc.

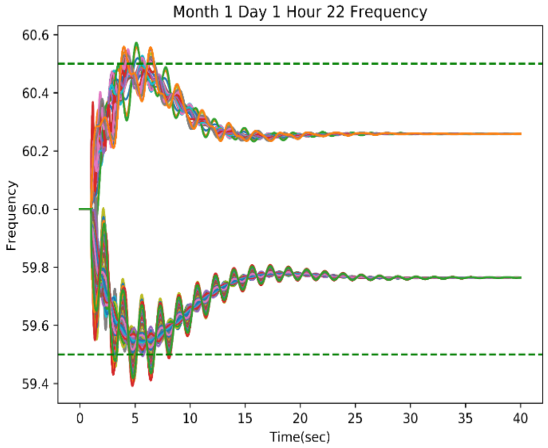
Example II: Robust Remedial Action Scheme

WECC-1remedial action scheme (RAS):

- Monitor 500-kV transmission system within California, Oregon, Washington, etc.
- A controlled separation of the WECC system into two islands
- Load shedding and generation trip are applied to each island to rebalance the system.



Proposed RAS



Apply robust load shedding and generation trip based on operational conditions.

Applications

Decision making

Smart PV reserve

Adaptive inertia requirement

Etc.

Situational awareness

Frequency stability

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Seconds

Control

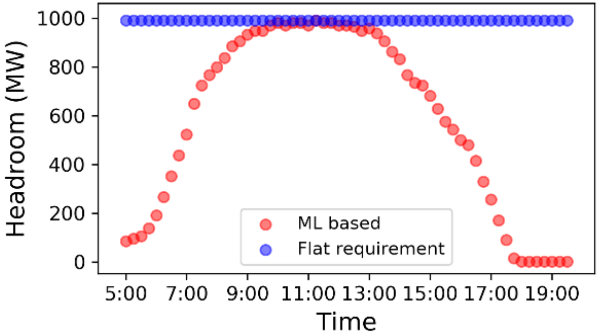
Robust RAS design

Etc.

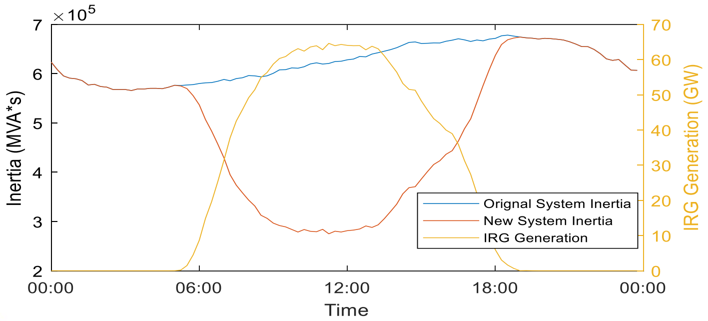
Example III: Smart Photovoltaic Reserve

Offline simulation of different operation conditions (approx. **2,000 cases**) of the 60% inverter-based resources WECC case (**10,000+ buses**).

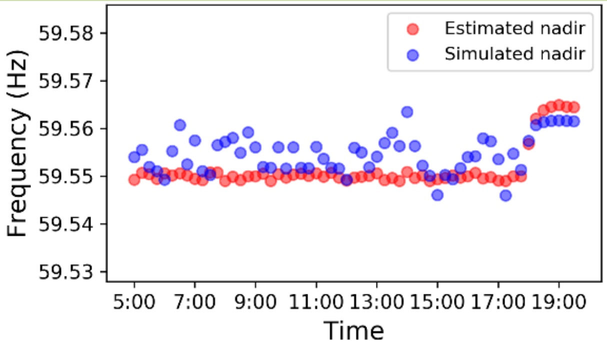
Optimal headroom reserve



1-day profile



Frequency nadir



Source: Yuan, H, J. Tan, Y.C. Zhang et al. 2020. "Machine Learning-Based PV Reserve Determination Strategy for Frequency Control on the WECC System." Presented at the 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference, Feb. 17, 2020 (1–5).

Summary

- The developed machine learning framework can used to

  (1) predict the system stability margins and increase the situational awareness by using dispatch data;

  (2) assist in a robust remedial action scheme (RAS) design;

  (3) help with decision making in real-time scheduling.

- It is demonstrated that machine learning-based tools can reduce the computational burden of dynamic simulations, making them suitable for online security assessment, stability control, and decision making for systems with high penetrations of renewable generation.

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
  - Cost-risk balance
  - Online deep learning.

Team

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The MIDAS machine learning framework bridges the gaps between studying power system dynamics and scheduling across different timescales.

Question?

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MIDAS website:
https://nrel-dev.nrel.gov/grid/midas.html

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