

## Abstract:

This paper proposes a machine learning based strategy, that is suitable for real-time operation, to determine the optimal **photovoltaic (PV) power plants reserve for frequency control**. The proposed machine learning algorithm is trained and tested on **1,987 offline simulations of a 60% renewable penetration** Western Electricity Coordinating Council (**WECC**) system. On a realistic 1-day operation profile of the WECC system, the ML model demonstrates a **savings of more than 40% PV headroom** compared to a conservative approach.

## PV Frequency Control

- Deteriorated frequency responses of main U.S. interconnections under ultra-high penetrations of IBR
- Advance inverter control will enable PV to provide frequency response.
- To provide upward response, PV headroom must be reserved

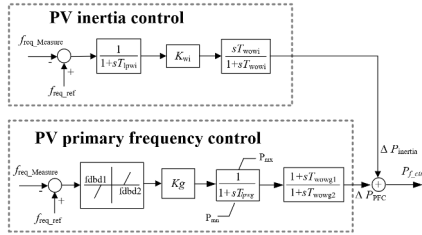


Fig. 1. Block of PV frequency control

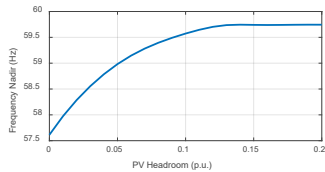


Fig. 2. Freq. response under different HR.

- Frequency response is highly related to reserve amount.
- There is tradeoff between stability and economics.
- Model-based approach to determine the reserve requirement is computational intense.

## Machine Learning-based Strategy

- A machine learning model that uses online system inertia,  $H_{\text{sys}}$ , online governor capacity  $G_{\text{gov}}$ , and targeted frequency nadir (i.e. lowest freq.),  $f_{\text{target}}$ , as input and determines the optimal PV headroom reserve amount,  $HR_{\text{PV}}$ .

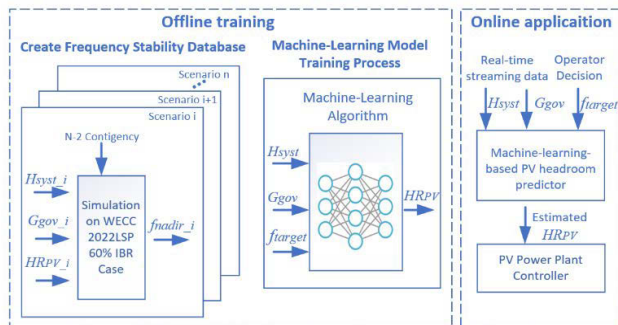


Fig. 3. Flow chart of the proposed strategy.

## Offline Training on the WECC system

- Offline simulation on the U.S. WECC system under different operation condition.
- 1,989 different operation conditions are simulated with different  $(H_{\text{sys}}, f_{\text{target}}, HR_{\text{PV}})$ .
- A Neural Network model is trained using TensorFlow backend.

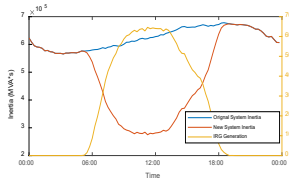


Fig. 4. One-day profile of the WECC system.

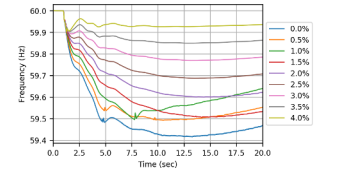


Fig. 5. Simulation results under different  $HR_{\text{PV}}$ .

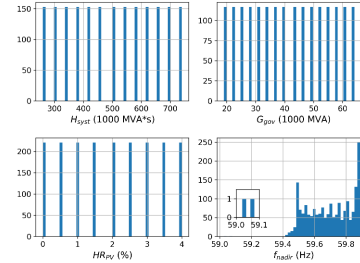


Fig. 6. Histograms of features.

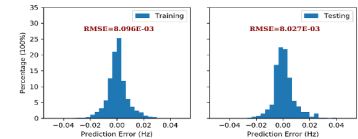


Fig. 7. Prediction errors.

- RMSE of predicted frequency nadir of training and testing set are both less than 0.01 Hz.

## Application on Unseen 1-day Profile

- ML model is further applied on unseen realistic 1-day profile (fig. 4).
- The PV reserve determined by ML model is 41% less than using flat requirement determined by worst case scenario.
- The frequency response is within 0.01Hz of the control target, 59.55 Hz.

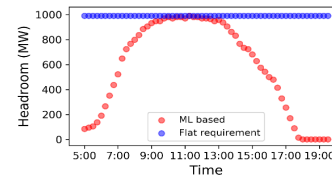


Fig. 8. Optimal HR vs. conservative HR.

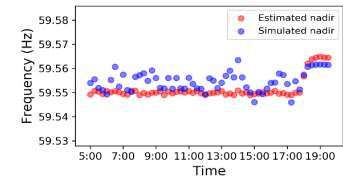


Fig. 9. Estimated vs simulated  $f_{\text{nadir}}$ .

## Conclusion

This paper proposed a machine learning based PV headroom determination strategy for frequency control. The proposed strategy was trained on 1,987 offline simulation cases of the WECC system and achieved prediction results less than 0.01 Hz. A demonstration of online application during a one-day period validated the effectiveness of the proposed strategy in terms of reserve saving and frequency response.