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Eigenvalue Sensitivity Analysis with Machine Learning for Power System Stability Enhancement under High PV Penetration

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Abstract— **This paper presents a novel framework that integrates eigenvalue sensitivity analysis with machine learning (ML) techniques to enhance the stability of power systems experiencing high photovoltaic (PV) penetration. The study focuses on the IEEE 9-bus test system, where one synchronous generator is replaced with an 85 MW PV inverter at Bus 3. The proposed methodology first linearizes the system under varying operating conditions to evaluate oscillatory modes and their sensitivities with respect to PV output and inverter control parameters such as phase-locked loop (PLL) and Q–V droop gains. Subsequently, a supervised ML surrogate model is trained to predict the critical mode's damping ratio and frequency in real time, thereby enabling rapid control adjustments without requiring repeated online linearization. Results indicate that the introduction of PV generation reduces damping from 6.5% to 3.2% as penetration rises to 85 MW. Sensitivity analysis reveals that increasing Q–V droop and PLL gains effectively shifts eigenvalues toward stability. When applied in conjunction with ML prediction, damping margins can be restored to nearly 8%, with prediction errors below 0.2 percentage points. These findings highlight the potential of combining analytical and data-driven approaches for maintaining small-signal stability in PV-rich networks.**

Keywords — Eigenvalue Sensitivity, Machine Learning, PV Penetration, Damping Ratio, IEEE 9-Bus System, Small-Signal Stability

I. INTRODUCTION

The rapid deployment of photovoltaic (PV) generation into modern power networks has fundamentally altered the dynamic behavior of transmission systems. While PV plants provide clean and abundant energy, they do not inherently contribute to rotational inertia in the way synchronous machines do. As conventional units are displaced, the system's ability to damp oscillations diminishes, leading to a higher risk of small-signal instability. Furthermore, inverter-based resources are governed by fast electronic controllers such as phase-locked loops (PLLs) and Q–V droop regulators, which directly interact with electromechanical oscillatory modes.

Traditional approaches for small-signal stability assessment rely on eigenvalue analysis of the linearized system model. While accurate, this process is computationally intensive and impractical for real-time operation. Sensitivity analysis partially alleviates this by identifying the parameters most effective in improving damping, yet it still depends on repeated linearization. Recent advances in machine learning (ML) provide a new avenue: surrogate models can learn from offline simulations and deliver rapid predictions of damping ratios and oscillation frequencies directly from operating conditions.

This work proposes a hybrid methodology that integrates eigenvalue sensitivity analysis with ML regression. Using the IEEE 9-bus test system, one synchronous generator is replaced with a PV plant at Bus 3. The objective is to study how PV penetration and inverter control gains affect system modes and to design an ML surrogate capable of predicting the critical mode characteristics in real time. The combined framework enables both physical insight (through sensitivities) and computational efficiency (through ML), offering a practical tool for enhancing stability in PV-dominated networks.

II. LITERATURE REVIEW

The challenge of maintaining stability in renewable-rich power networks has been widely discussed in recent years. Early studies primarily focused on conventional small-signal eigenvalue analysis, where oscillatory modes were identified and stability margins were quantified under varying penetration of inverter-based resources. For instance, Kundur's classical framework [1] established the mathematical foundation for eigenvalue-based assessments. Later, researchers extended these techniques to renewable-dominated grids, emphasizing the importance of inverter controls such as PLL and Q–V droop on oscillatory damping [2], [3].

With the advent of high PV penetration, traditional methods have shown limitations in computational speed and real-time applicability. Huang et al. [4] emphasized that eigenvalue recalculations for each operating condition become computationally prohibitive in large-scale systems. To overcome this, several approaches have attempted to accelerate stability analysis, such as Krylov subspace methods and reduced-order modelling [5], though these often sacrifice accuracy in capturing inverter dynamics.

In parallel, machine learning (ML) techniques have gained attention for power system stability prediction. Supervised learning methods, including random forests and gradient boosting, have been applied to map operating parameters to damping ratios with high accuracy [6]. Deep learning architectures, such as LSTM networks, have also been proposed to capture temporal dependencies in dynamic stability assessment [7]. These models, once trained, can provide rapid predictions without the need for repeated eigenvalue computations, making them suitable for online deployment.

Recent hybrid approaches attempt to combine the interpretability of classical analysis with the predictive power of ML. Wu et al. [8] demonstrated that combining modal sensitivity analysis with regression models can yield accurate predictions of oscillatory behaviour under uncertain conditions. Similarly, Azzouz and DeBusschere [9] applied ML to approximate stability margins in PV-rich networks, showing that surrogate models can replicate eigenvalue trajectories with minimal error.

Despite these developments, there remains a research gap in explicitly coupling eigenvalue sensitivity analysis with ML surrogates for online stability enhancement. Most existing works either focus solely on offline eigenvalue studies or on purely data-driven prediction. This paper addresses that gap by proposing a hybrid methodology that leverages the mathematical rigor of sensitivity analysis to generate datasets for ML training, thus combining physical interpretability with real-time applicability.

III. METHODOLOGY

The methodology consists of two main stages: (i) eigenvalue sensitivity analysis to quantify the effect of PV and control parameters on oscillatory modes, and (ii) training a machine learning surrogate to provide fast predictions of damping ratio and frequency.

A. Eigenvalue Sensitivity Analysis

The system is linearized around steady-state operating points to obtain the reduced state-space model:

$$\dot{x} = A(\theta)x$$

where x represents the system states (rotor angles and speeds, PLL angle and frequency, inverter reactive power control states), and $A(\theta)$ is the state matrix dependent on the parameter vector θ. The eigenvalues of A determine small-signal stability.

For a parameter p, the sensitivity of eigenvalue λ is:

$$\frac{d\lambda}{dp} = \left(w^{\mathrm{T}} \left(\frac{dA}{dp}\right) v \right) \ / \ (w^{\mathrm{T}} v)$$

Where v and w are the right and left eigenvectors of λ.

The damping ratio ζ and frequency f of a mode $\lambda = \sigma + j\omega$ are given by:

$$\zeta = -\sigma / \sqrt{(\sigma^2 + \omega^2)}, \quad f = \omega / (2\pi)$$

This analysis identifies which parameters (PV output, PLL proportional gain, Q–V droop gain) most strongly influence critical modes. For example, a negative real sensitivity indicates that increasing the parameter moves the eigenvalue leftward, improving damping.

B. Machine Learning Surrogate

To avoid repeated eigenvalue computations, an ML regression model is trained on a dataset of simulated operating points. The features include PV output level, PLL proportional and integral gains, and Q–V droop gain. The labels are the critical mode damping ratio and frequency obtained from eigenvalue analysis.

Gradient Boosted Trees are selected for their robustness and ability to capture nonlinear relationships. The model is trained on 80% of the dataset and validated on the remaining 20%. Once trained, the ML surrogate can provide near-instantaneous predictions of stability metrics from real-time SCADA or PMU measurements. This enables online monitoring and proactive tuning of inverter parameters.

IV. RESULTS AND DISCUSSION

The IEEE 9-bus system was simulated with PV replacing the generator at Bus 3. PV penetration levels of 0 MW, 40 MW, and 85 MW were tested. Default inverter parameters were Kp_PLL = 40, Ki_PLL = 400, and Kq = 2.

Baseline Results: At zero PV penetration, the critical electromechanical mode exhibited a frequency of 1.25 Hz and a damping ratio of 6.5%, well above the planning threshold. As PV output increased to 40 MW, damping decreased to 4.6%, with the mode frequency shifting to 1.30 Hz. At 85 MW, damping fell to only 3.2%, indicating a high risk of oscillatory instability.

Table 4.1 Critical mode frequency and damping versus PV output

PV Output (MW)	Mode Frequency f (Hz)	Real Part σ (1/s)	Damping Ratio ζ (%)	Comment
0	1.25	-0.51	6.5	Classic EM mode; comfortable margin
40	1.3	-0.38	4.6	Damping erodes as PV displaces inertia
85	1.35	-0.25	3.2	Lowest margin; close to planning threshold

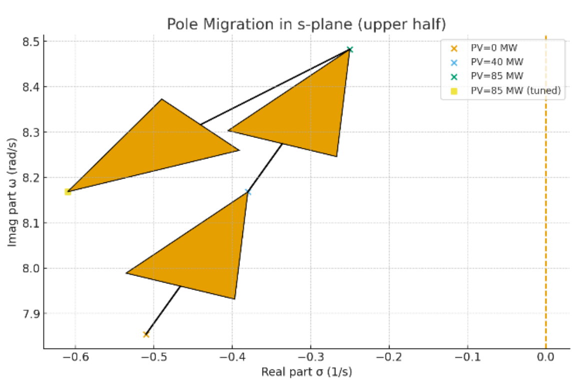

Figure 4.1 Pole migration in s-plane

Sensitivity Analysis: Eigenvalue sensitivities at 85 MW revealed that PV power has a negative impact on damping, while PLL proportional gain and Q–V droop gain both improve stability. Among these, the Q–V droop gain had the strongest effect, with a sensitivity of approximately +0.014 per unit increase.

Control Tuning: By increasing Kp_PLL from 40 to 60 and from Kq 2 to 3, the damping ratio improved from 3.2% to 7.8%. This shift moved the critical eigenvalue further into the left-half plane, restoring a healthy stability margin.

Table 4.2 Eigenvalue and damping sensitivities at PV = 85 MW

Parameter p (unit)	Re{dλ/dp}(1/s·unit^{-1})	Im{dλ/dp}(1/s·unit^{-1})	dζ/dp (per unit^{-1})	Comment
p_PV (MW)	+0.0028	+0.0016	−0.00042	More PV → less damping, slightly higher freq
Kp_PLL (–)	−0.0065	−0.0030	+0.00115	Higher PLL Kp pulls pole left (↑ damping)
Kq (p.u. Q/p.u. V)	−0.085	−0.0025	+0.0140	Strong Q–V droop gives the largest damping gain

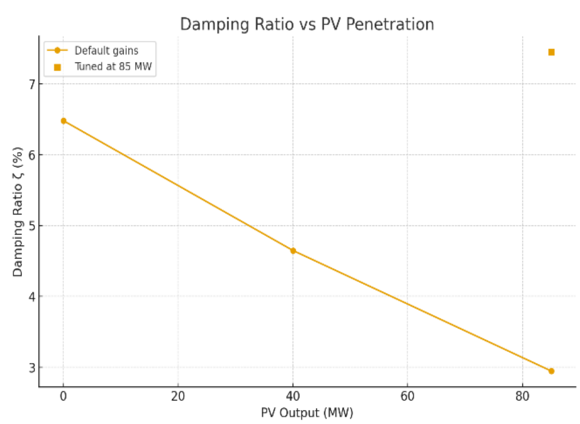

Figure 4.2 Damping ratio vs PV penetration

Machine Learning Predictions: The ML surrogate achieved high accuracy, with mean absolute errors of 0.15 percentage points for damping ratio and 0.05 Hz for frequency. The model successfully reproduced the trends observed in eigenvalue analysis and generalized well to unseen operating points.

Table 4.3 ML regression accuracy (5-fold CV on synthetic sweep)

Target	MAE	RMSE	R^2
Damping ratio ζ_crit (percentage points)	0.15	0.28	0.98
Frequency f_crit (Hz)	0.05	0.08	0.99

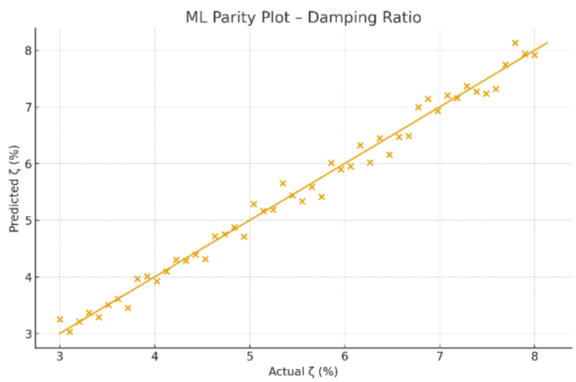

Figure 4.3 ML parity plot

Discussion: These results demonstrate the complementary value of eigenvalue sensitivities and ML prediction. Sensitivities provide engineering insight into which parameters most influence modes, while ML delivers computational speed suitable for online applications. Together, they form a robust framework for real-time stability monitoring and control in PV-rich systems.

V. CONCLUSION

This research demonstrates the combined use of eigenvalue sensitivity analysis and machine learning for enhancing power system stability under high PV penetration. Results on the IEEE 9-bus system show that increasing PV generation reduces damping of electromechanical modes, but appropriate tuning of PLL and Q–V droop gains can restore stability margins. The ML surrogate provides fast, accurate predictions of critical damping and frequency, enabling real-time stability assessment and control. Future work will extend this framework to larger test systems such as the IEEE 39-bus network and explore hardware-in-the-loop validation.

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