A Data-Efficient Method for Predicting Stability in Converter-Dominated Power Systems Under Various Operating Conditions

Md Pabel Sikder[1], Tomi Perttula[2], Janne Seppänen[3], Mahdi Pourakbari-Kasmaei[4]

Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland
[1]mdpabel.sikder@aalto.fi, [2]tomi.perttula@aalto.fi, [3]janne.seppanen@aalto.fi, [4]mahdi.pourakbari@aalto.fi

Abstract— **The transition from synchronous generators to converter-based renewable energy sources is changing the dynamic behavior of modern power systems. As this shift continues, maintaining small-signal stability is becoming more critical, particularly in weak grid conditions where the short-circuit ratio (SCR) is low. Existing methods for assessing stability often rely on detailed simulations across a wide range of power levels and grid strengths, which are not only computationally expensive but also time-consuming to implement in practice. This paper introduces a data-efficient method that enables rapid prediction of critical SCR limits that lead to instability by utilizing the amplitude difference between converter and grid impedances at their intersection frequency. The method extracts key coefficients through a semi-logarithmic linear regression model using amplitude margin (AM) and SCR data measured at any two distinct power levels. Once established, the model allows prediction of the critical SCR for any other power level without the need for further simulation. The method is validated using a standard Type-4 wind farm system, and the predicted results are compared against both frequency-domain and time-domain simulations. Accuracy is measured using standard error metrics, which confirms a strong correlation between the predicted and actual values. This approach offers a practical and computationally efficient solution for stability analysis in converter-dominated systems. It holds strong potential for application in future power grids integrating solar photovoltaics, battery storage, and other inverter-based technologies.**

Keywords— Stability prediction, Semi-log linear regression, Small-signal analysis, SCR, Type-4 wind farm.

I. Introduction

The rapid integration of converter-based renewable energy sources, such as wind, solar photovoltaics, and battery energy storage, is changing the dynamic characteristics of modern power systems [1]. As traditional synchronous machines are gradually replaced, the inherent inertia and voltage support they offered are notably reduced [2]. This transformation has raised new concerns about system stability, particularly in weak grid scenarios where SCRs are low. In such cases, small-signal instability may occur due to negative interactions between the voltage source converters (VSCs) and the grid impedance, which can often lead to poor performance or even system failure [3].

Impedance-based techniques are widely used for analyzing small-signal stability of converter-dominated power systems because they offer an intuitive physical understanding and work well with frequency-domain methods [4]. Specifically, the amplitude margin between the converter impedance and the grid impedance is used to evaluate how close the system is to instability. However, identifying the critical SCR and power level that causes instability typically requires extensive impedance measurements or frequency sweep simulations over various scenarios using traditional methods. This causes routine stability screening to be both time-consuming and computationally costly, particularly in grids with frequent operating condition changes or limited data access.

Over the years, different methods have been developed to address this limitation. Some researchers use analytical and sensitivity-based methods to assess system dynamics and identify stability margins [5, 6]. Others apply data-driven techniques to model complex, nonlinear behaviors in modern grids with high renewable integration [7, 8]. Although these methods have shown promising results, they often need large datasets for training, involve complex tuning, or produce black-box predictions that lack physical insight. Furthermore, many of these approaches lack a clear way to assess the reliability of their predictions or measure related errors, which limits their usefulness in real-world systems.

This paper aims to fill that gap by introducing a regression-based framework that uses amplitude margin characteristics derived from only two operating points. Unlike previous methods that depend on extensive simulations or unclear models, this approach provides a quick and physically relevant way to estimate the critical SCR values for any power level. The method directly links AM trends to grid strength and converter output, making stability prediction more straightforward without losing accuracy or insight. This makes the work particularly relevant in modern power systems planning and operation, where rapid assessment tools are vital due to increasing complexity and variability from renewable integration.

The proposed method is tested on a Type-4 wind farm model connected to a weak grid. Validation is carried out through both frequency-domain and time-domain simulations, and the predicted results are further evaluated using standard error metrics. The findings show that the method offers a practical and scalable solution for online stability assessment in power systems dominated by converter-based generation. In addition to wind power, the framework can also be adapted to other converter-connected technologies like solar photovoltaics and battery energy storage systems.

The paper is organized as follows: Section II outlines materials and methods, Section III describes the case study, Section IV presents and discusses the results, and Section V concludes with key findings and future research directions.

979-8-3315-8138-1

II. Materials and Method

A. Grid Strength, Damping, and Stability

The SCR is a fundamental metric used to quantify the grid strength at the point of connection to inverter-based resources (IBRs), and can be determined by (1). The grids with SCR ≥ 3 are considered strong, whereas SCR ≤ 3 denotes a weak grid, which increases the chance of instability and oscillations in converter-based systems [9].

$$\mathrm{SCR} = \frac{S_{\mathrm{Grid}}}{P_{\mathrm{IBR}}} \tag{1}$$

The damping ratio (ζ) quantifies the rate at which oscillations diminish. Values above 5% are generally considered well-damped, while those below 3% indicate weak damping [10]. It is calculated using (2), where the logarithmic decrement (δ) is defined in (3).

$$\zeta = \frac{1}{\sqrt{1+\left(\frac{2\pi}{\delta}\right)^2}} \times 100 \tag{2}$$

$$\delta = \frac{1}{n}\ln\left(\frac{x(t)}{x(1+nT)}\right) \tag{3}$$

where, n is the number of periods, $x(t)$ is the overshoot, and $x(1+nT)$ is the overshoot at the period n.

B. Linear Regression and Semi-Log Model

Linear regression is a widely used statistical method to model the relationship between a dependent variable and one or more independent variables [11]. The general form of a multiple linear regression model is shown in (4).

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \cdots + \varepsilon \tag{4}$$

where y is the dependent variable, x_1 and x_2 are the independent variables, β are the coefficients to be estimated, and ε is the error term.

However, the relationship between the AM, SCR, and the power level is not linear. AM varies logarithmically with SCR, while the dependence on power remains linear. To capture this, the generic linear regression was adapted into a semi-log linear regression model in (5). In matrix form, this can be expressed by (6).

$$AM = \beta_0 + \beta_1 \cdot \log(SCR) + \beta_2 \cdot P + \varepsilon \tag{5}$$

$$\boldsymbol{AM} = \boldsymbol{\beta} \cdot \boldsymbol{X} + \varepsilon \tag{6}$$

where the matrix ($\boldsymbol{X}$) includes SCR, power levels, and a column of ones for the intercept term. The observation vector ($\boldsymbol{AM}$) contains the corresponding amplitude margin values, which are calculated at the frequency where the converter and grid impedance amplitudes intersect, and the phase difference reaches or exceeds $-180°$, indicating the critical point of instability.

C. Coefficient Estimation

To estimate the regression coefficients, AM data corresponding to varying SCR values at two distinct power levels, P_1 and P_2 are obtained from the tested simulation model. The coefficients (β) are then computed using (7).

$$\boldsymbol{\beta} = (\boldsymbol{X}^{\mathrm{T}} \cdot \boldsymbol{X})^{-1} \cdot \boldsymbol{X}^{\mathrm{T}} \cdot \boldsymbol{AM} \tag{7}$$

For n observations, the matrix ($\boldsymbol{X}$) and the observation vector ($\boldsymbol{AM}$) are formulated as shown in (8).

$$\boldsymbol{AM} = \begin{bmatrix} AM_{1,P_1} \\ AM_{2,P_1} \\ \vdots \\ AM_{n,P_1} \\ AM_{1,P_2} \\ AM_{2,P_2} \\ \vdots \\ AM_{n,P_2} \end{bmatrix}; \quad \boldsymbol{X} = \begin{bmatrix} 1 & \log(\mathrm{SCR}_{1,\mathrm{P}_1}) & P_1 \\ 1 & \log(SCR_{2,P_1}) & P_1 \\ \vdots & \vdots & \vdots \\ 1 & \log(SCR_{n,P_1}) & P_1 \\ 1 & \log(SCR_{1,P_2}) & P_2 \\ 1 & \log(SCR_{2,P_2}) & P_2 \\ \vdots & \vdots & \vdots \\ 1 & \log(SCR_{n,P_2}) & P_2 \end{bmatrix} \tag{8}$$

D. Determination of Critical SCR

The critical SCR for a given power level is defined as the point where the amplitude margin reaches zero, marking the threshold between stable and unstable operation. By setting *AM = 0* in (5), the critical SCR expression is derived and presented in (10).

$$0 = \beta_0 + \beta_1 \cdot log(SCR) + \beta_2 \cdot P + \varepsilon \tag{9}$$

$$SCR_{\mathrm{critical}} = e^{-\left(\frac{\beta_0 + \beta_2 \cdot P + \varepsilon}{\beta_1}\right)} \tag{10}$$

This formula allows operators to quickly estimate the SCR limit for stability across any power level without additional simulations.

E. Error Metrics for Accuracy Checking

To evaluate the performance and accuracy of the proposed model, several standard statistical error metrics are used, such as mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2). This calculation is carried out using a set of established analytical formulas based on the methods described in [12]. Let AM_i^{actual} denote the measured amplitude margin at the i^{th} data point, $AM_i^{\mathrm{predicted}}$ the corresponding predicted value, and $\overline{AM}^{actual}$ the mean of the measured values. The total number of data points is n.

The MAE measures the average difference between the predicted and actual amplitude margin values. Lower MAE means better prediction. It is calculated using (11).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|AM_i^{\mathrm{actual}} - AM_i^{\mathrm{predicted}}\right| \tag{11}$$

The RMSE also measures the error, but it gives more weight to larger mistakes. A lower RMSE means the predictions are more consistent. It is given in (12).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(AM_i^{\mathrm{actual}} - AM_i^{\mathrm{predicted}}\right)^2} \tag{12}$$

The R^2 indicates the proportion of variance in the observed data that the model explains. Values of R^2 closer to 1 means better performance. It is calculated by (13).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(AM_i^{\mathrm{actual}} - AM_i^{\mathrm{predicted}}\right)^2}{\sum_{i=1}^{n}\left(AM_i^{\mathrm{actual}} - \overline{AM}^{\mathrm{actual}}\right)^2} \tag{13}$$

III. Case Study

A. Type-4 Wind Farm Model

A benchmark wind farm model from the PSCAD library is used for the simulation. This widely adopted model is applied without any structural modifications. It includes Type-4 wind turbines with permanent magnet synchronous generators, a full-scale back-to-back converter, DC link, filter, and a phase-locked loop for grid synchronization. Additional details can be found in [13, 14]. The system represents an 800 MW wind farm connected to a 118 kV, 50 Hz grid with an X/R ratio of 10. The single-line diagram is shown in Fig. 1.

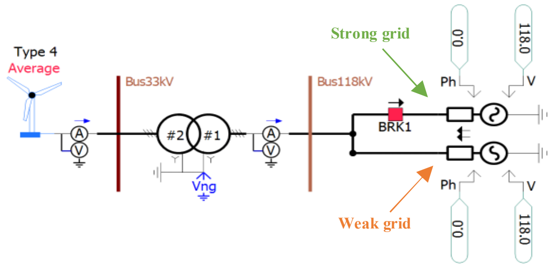


Fig. 1. Single-line diagram of the model.

A strong grid with SCR of 10 is added in parallel to the weak grid to ensure proper operation during the initial stages. After 3 seconds, a circuit breaker disconnects this strong grid, allowing the system to transition fully to the weak grid.

B. Impedance Analysis of Grid-Converter

An impedance measurement toolbox is used to extract converter admittance data across a frequency range of 35 Hz to 65 Hz; the toolbox details can be found in [15, 16]. The acquired data is used to calculate the converter impedance. This calculation is performed by a set of analytical formulas based on the methods detailed in [16, 17]. The transfer function of the closed-loop system is given in (14), where the closed-loop admittance matrix ($\underline{\boldsymbol{Y}}_{\text{close}}$) is defined by (15).

$$\frac{\boldsymbol{i}_{\text{ac}\alpha\beta}(s)}{\boldsymbol{v}_{\text{g}\alpha\beta}(s)} = \underline{\boldsymbol{Y}}_{\text{total}}(s) = \underline{\boldsymbol{Y}}_{\text{close}}(1,1) \tag{14}$$

$$\underline{\boldsymbol{Y}}_{\text{close}} = \frac{\underline{\boldsymbol{Y}}_c}{(\mathbf{I} + \underline{\boldsymbol{Y}}_c\,\underline{\boldsymbol{Z}}_g)} \tag{15}$$

The equivalent converter impedance matrix ($\underline{\boldsymbol{Z}}_c$) is then determined from the grid and total system impedances as outlined in (16).

$$\underline{\boldsymbol{Z}}_c = \frac{1}{\underline{\boldsymbol{Y}}_{\text{total}}} - \underline{\boldsymbol{Z}}_g \tag{16}$$

To evaluate grid impedance $(\boldsymbol{Z}_g)$ for various SCRs, their amplitude and phase angle are calculated using (17) and (18), respectively.

$$|\underline{\boldsymbol{Z}}_g| = \frac{V_g^2}{P_{\text{rated}} \cdot \text{SCR}} \tag{17}$$

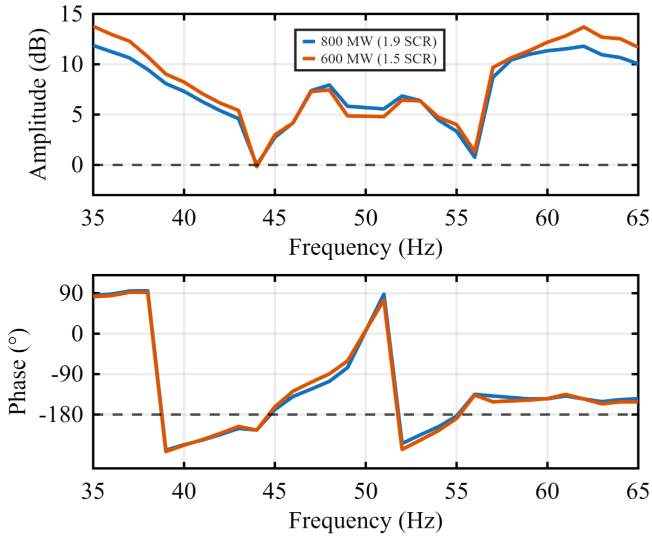
$$\theta = \tan^{-1}\left(\frac{X}{R}\right) \tag{18}$$

After obtaining the data, impedance-based Bode plots are used to assess stability by comparing the amplitude and phase differences between grid and converter impedances. The system is unstable if the amplitude difference is at or below 0 dB and the phase difference is at or below $-180°$ at the intersection frequency. The system is stable if it maintains a positive magnitude difference.

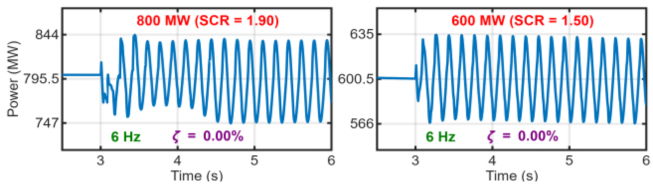
IV. Results and Discussion

A. Stability Analysis of Type-4 Wind Farm

The Impedance-based Bode plot and time-domain simulation in Fig. 2(a-b) show that the system becomes unstable at 44 Hz when the SCR is reduced to 1.9 and 1.5, corresponding to operating power levels of 100% (800 MW) and 75% (600 MW), respectively. At this 44 Hz intersection frequency, the AM is then calculated as a function of SCR over the range 0.1 to 10, using a small step size of 0.01 for each power level. These AM-SCR data are used for equation development and coefficient calculation.



(a)



(b)

Fig. 2. (a) Impedance-based Bode plot, (b) Time-domain simulation

B. Coefficient Calculation and Model Development

By replacing the obtained data of AM, SCR, and power level into (8), the coefficients (β) are estimated using (7). The resulting values are shown in (19).

$$\beta = \begin{bmatrix}\beta_0\\ \beta_1\\ \beta_2\end{bmatrix} = \begin{bmatrix}5.615\\ 13.412\\ -0.018\end{bmatrix} \tag{19}$$

Substituting the values of β into (5) and (10), the semi-log linear regression model and the expression for the critical SCR are derived as (20) and (21), respectively.

$$AM = 5.615 + 13.412 \cdot \log(SCR) - 0.018 \cdot P + \varepsilon \tag{20}$$

$$SCR_{\text{critical}} = e^{-\left(\frac{5.615\,-0.018\cdot P\,+\,\varepsilon}{13.412}\right)} \tag{21}$$

C. Comparison and Error Checking

To evaluate the performance of the proposed semi-logarithmic regression model, the AM predicted by equation (20) is compared with the actual data for operating power levels of 800 MW and 600 MW.

979-8-3315-8138-1

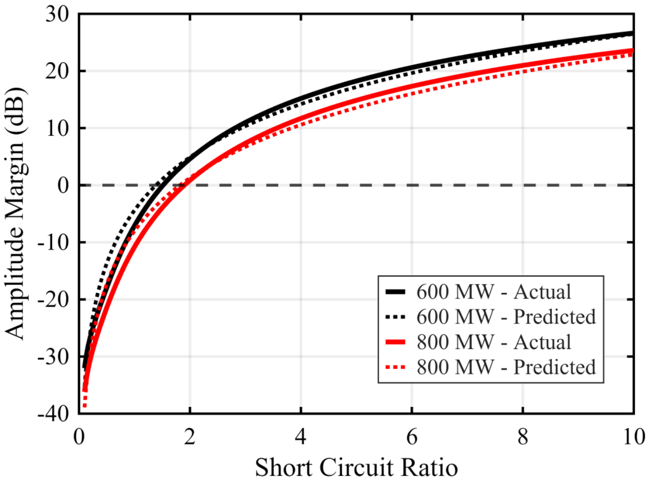


Fig. 3. Predicted vs. actual amplitude margin

TABLE I. SUMMARY OF ERROR METRICS RESULTS

Metric	Value	Interpretation
MAE	0.9721	Indicates high prediction accuracy as the mean error is only 0.97 dB
RMSE	1.1354	Confirms low overall error magnitude with minimal large deviations
R^2	0.9946	Excellent fit, explaining 99.46% of the variance in amplitude margin data

As shown in Fig. 3, the predicted curves closely follow the actual data across a wide range of SCR values. The model captures the expected smooth logarithmic relationship between AM and SCR while maintaining accuracy at both low- and high-power levels.

Quantitative validation was performed using standard error metrics, summarized in Table I. The MAE is found to be 0.9721 dB, indicating that the average prediction deviates less than 1 dB from the actual values. The RMSE is calculated as 1.1354 dB, confirming that the overall magnitude of error remains low. Additionally, the R^2 achieved a value of 0.9946, suggesting high predictive reliability. This high R^2 value demonstrates that the model explains more than 99% of the variance in the amplitude margin data. These results confirm that the regression-based model offers high accuracy with minimal computational complexity, making it a reliable tool for practical stability assessments under varying grid and operating conditions.

D. Stability Prediction and Validation

To demonstrate the applicability of the proposed semi-logarithmic regression model across a range of operating conditions, predicted amplitude margin curves are generated for multiple power levels ranging from 300 MW to 800 MW. These curves in Fig. 4(a) illustrate the relationship between AM and SCR over the full range from 0 to 10. A magnified view focusing on the critical region between SCR 0.5 and 3.5 is presented in Fig. 4(b) to highlight prediction accuracy around the instability threshold. For each power level, the critical SCR, defined as the point where the AM curve intersects zero (corresponding to the impedance-based instability condition in Fig. 2a), is extracted from the predicted data and compared to the actual critical SCR obtained through frequency-domain stability analysis.

Table II presents the predicted and actual critical SCR values for all power levels, along with the absolute deviation. The results show that the prediction error remains within a narrow band of ±0.04, which confirms the reliability of the regression-based approach.

To further verify the effectiveness of the proposed model, time-domain simulations are conducted for selected power levels (300 MW, 400 MW, 500 MW, and 700 MW). These power levels are not included in the original regression fitting process, thereby providing an unbiased test for generalization. For each case, simulations are performed at the predicted critical SCR and at a higher SCR level. As illustrated in Fig. 5, the system shows clear undamped oscillations at the critical SCR, indicating that the system becomes unstable. When the SCR is increased above this critical threshold, the system shows stable behavior with good damping characteristics.

This consistency between the predicted critical SCR values and the time-domain dynamic responses strengthens the validity of the model. The low absolute deviation across all power levels and the visual alignment of simulation results support the conclusion that the regression-based method can reliably estimate system stability boundaries under various operating conditions without the need for exhaustive simulations.

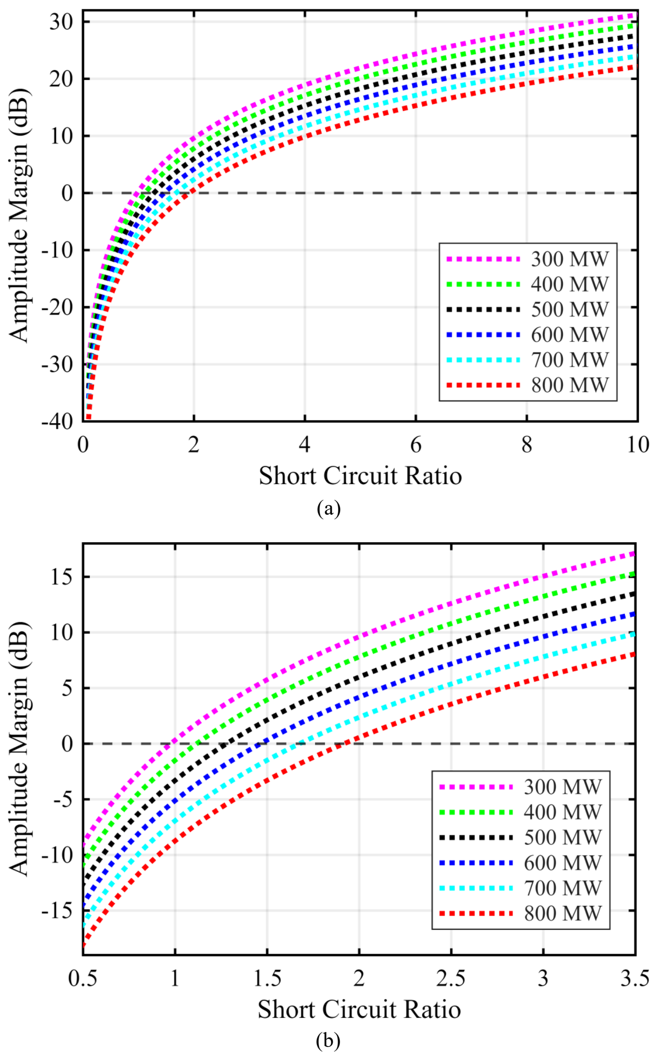


Fig. 4. (a-b). Predicted AM vs. SCR for various power levels

979-8-3315-8138-1

TABLE II. COMPARISON OF CRITICAL SCR ACROSS POWER LEVELS

Power (MW)	Capacity (%)	Predicted $SCR_{critical}$	Actual $SCR_{critical}$	Absolute Deviation
300	37.5	0.98	1.02	0.04
400	50	1.12	1.15	0.03
500	62.5	1.28	1.27	0.01
600	75	1.48	1.50	0.02
700	87.5	1.69	1.71	0.02
800	100	1.93	1.90	0.03

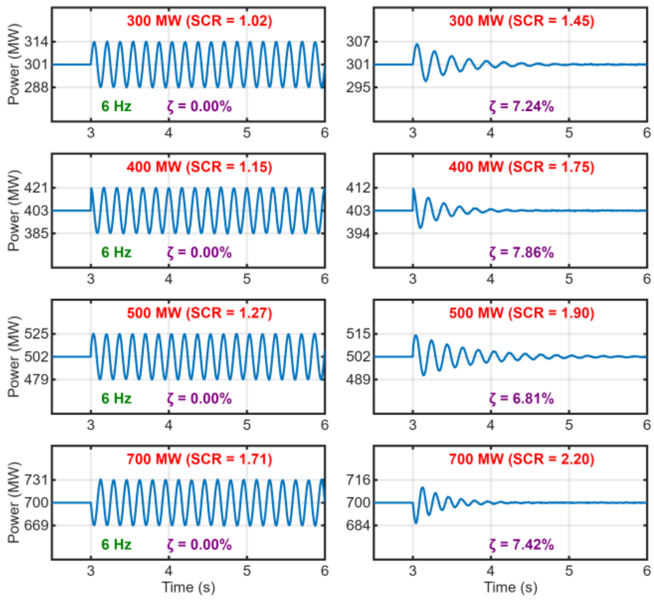


Fig. 5. Time-domain responses for validating stability prediction

V. CONCLUSION

This paper proposed a data-efficient approach for predicting the critical SCR based on amplitude margin characteristics of the converter and grid interaction in converter-dominated grids. By establishing a semi-logarithmic relationship between amplitude margin, SCR, and power levels, the model enables accurate estimation of small-signal instability thresholds using only two data points at distinct power levels. The methodology is tested on a Type-4 wind farm, and the predicted results showed strong alignment with the actual results across various operating conditions. Quantitative validation using error metrics, frequency-domain analysis, and time-domain simulations demonstrated minimal prediction error, which confirms the reliability and accuracy of the proposed method. The proposed approach reduces the computational effort required for stability screening by eliminating the need for detailed small-signal eigenvalue analysis or time-domain simulations at every operating point. This makes it particularly suitable for planning studies, real-time grid assessment, and system design under high converter penetration.

Future work will extend the approach to other converter types and control strategies. It will also integrate real-time measurement data for adaptive stability assessment. The effect of parameter uncertainty will be examined to improve accuracy in practical grid applications.

REFERENCES

[1] V. Geekiyanage and J. Seppänen, "Power System Stability Improvements Through Grid Forming Inverters for Systems with High Penetration of Grid Following Inverters," in *2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, Dubrovnik, Croatia: IEEE, Oct. 2024, pp. 1–5.

[2] J. Seppänen, M. Kuivaniemi, L. Haarla, and M. Lehtonen, "Relationship between power system inertia and inter-area mode natural frequency – Analysis and measurements," *Electric Power Systems Research*, vol. 241, p. 111366, Apr. 2025.

[3] W. Du, Q. Fu, X. Wang, and H. F. Wang, "Small-signal stability analysis of integrated VSC-based DC/AC power systems – A review," *International Journal of Electrical Power & Energy Systems*, vol. 103, pp. 545–552, Dec. 2018.

[4] M. Amin and M. Molinas, "Small-Signal Stability Assessment of Power Electronics Based Power Systems: A Discussion of Impedance- and Eigenvalue-Based Methods," *IEEE Transactions on Industry Applications*, vol. 53, no. 5, pp. 5014–5030, Sep. 2017.

[5] S. Li, Y. Tan, C. Li, Y. Cao, and L. Jiang, "A Fast Sensitivity-Based Preventive Control Selection Method for Online Voltage Stability Assessment," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 4189–4196, Jul. 2018.

[6] A. Karami, "Power system transient stability margin estimation using neural networks," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 4, pp. 983–991, May 2011.

[7] Q. Wang, F. Li, Y. Tang, and Y. Xu, "Integrating Model-Driven and Data-Driven Methods for Power System Frequency Stability Assessment and Control," *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4557–4568, Nov. 2019.

[8] Y. Zhou, Q. Guo, H. Sun, Z. Yu, J. Wu, and L. Hao, "A novel data-driven approach for transient stability prediction of power systems considering the operational variability," *International Journal of Electrical Power & Energy Systems*, vol. 107, pp. 379–394, May 2019.

[9] T. Perttula, M. P. Sikder, J. Seppänen, and M. P. Kasmaei, "Impact of Grid Characteristics on the Damping of Converter-Driven Subsynchronous Oscillation Modes," 2025 IEEE Kiel PowerTech, Kiel, Germany, 2025, pp. 1-5.

[10] J. Seppänen, J. Turunen, A.-J. Nikkilä, and L. Haarla, "Resonance of Forcing Oscillations and Inter-Area Modes in the Nordic Power System," *in 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Oct. 2018, pp. 1–6.

[11] Benoit, Kenneth. "Linear regression models with logarithmic transformations." London School of Economics, London 22, no. 1 (2011): 23-36.

[12] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression analysis evaluation," *PeerJ Comput. Sci.*, vol. 7, pp. 623, July 2021.

[13] Y. Wang, M. Wen, Y. Chen, "A simplified model of Type-4 wind turbine for short-circuit currents simulation analysis," *IET Gener. Transm. Distrib,* 16, 3036–3049 (2022).

[14] M. P. Sikder, T. Perttula, J. Seppänen, and M. Pourakbari-Kasmaei, "The Effect of Short-Circuit Ratio on Small Signal Stability of a Type-4 Wind Farm in Weak Grids," 2025 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe), Valletta, Malta, 20-23 Oct. 2025, pp. 1-5.

[15] D. Yang, X. Wang, M. Ndreko, W. Winter, R. Juhlin, and A. Krontiris, "Automation of impedance measurement for harmonic stability assessment of MMC-HVDC systems," *Proc. 18th Wind Integration Workshop,* 2019, pp. 1–6.

[16] H. Wu, X. Wang, Y. Liao, M. Ndreko, R. Dimitrovski, and W. Winter, "Development of the toolbox for AC/DC impedance matrix measurement of MTDC system," *Proc. 20th Wind Integration Workshop,* 2021, pp. 442–448.

[17] H. Wu and X. Wang, "Dynamic Impact of Zero-Sequence Circulating Current on Modular Multilevel Converters: Complex-Valued AC Impedance Modeling and Analysis," *IEEE Journal of Emerging and Selected Topics in Power Electronics,* vol. 8, no. 2, pp. 1947-1963, 2020.

979-8-3315-8138-1