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Research on the Construction of a Short-Term Voltage Prediction Model Integrating Topological Data Analysis and Deep Neural Network under the Power System Resilience Assessment Framework

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Abstract

INTRODUCTION: This paper examines the stability of small disturbances in wind farm grid-connected systems within the framework of power system resilience. With increasing renewable integration, minor disturbances can escalate into cascading failures, threatening grid reliability.
OBJECTIVES: The goal is to build a short-term voltage prediction model by integrating Topological Data Analysis (TDA) with Deep Belief Networks (DBN) and to propose a coordinated reactive power control strategy that enhances system dynamic performance under small disturbances.
METHODS: The study adopts a VSC-HVDC system based on Modular Multilevel Converters (MMC) to model wind farm connectivity. A cluster-based reactive power control approach is applied by grouping wind turbines with similar operational characteristics. Small disturbance signals are simulated, and both unified and decentralised Doubly Fed Induction Generator (DFIG) control schemes are compared using impedance modelling and time-domain analysis.
RESULTS: Simulations indicate that small AC-side disturbances have a significant impact on reactive power and system voltage, whereas DC-side faults affect frequency stability. The decentralised DFIG coordination strategy achieved a lower network loss (0.467 MW) compared to the unified approach (0.473 MW) while also improving reactive power allocation and system responsiveness.
CONCLUSION: By combining TDA and DBN with decentralised control, the proposed model enhances the stability of small disturbances in wind-integrated power systems. It enhances fault tolerance, mitigates power fluctuations, and facilitates the resilient operation of renewable-rich grids.

Keywords: Topological Data Analysis, Deep Neural Network, Small Disturbance Stability, Wind Farm, Reactive Power Coordination, VSC-HVDC

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1. Introduction

The global push towards carbon neutrality and the widespread adoption of renewable energy has led to an unprecedented transformation of modern power systems. Among various renewable sources, wind power has emerged as a leading alternative to fossil fuel-based electricity generation due to its scalability and environmental benefits [1,4,5]. Wind and solar renewable energy sources impact small-signal stability in power grids due to their variable output and reliance on power electronic converters, which reduce system inertia and damping. Wind farms using MMC-based VSC-HVDC systems are particularly sensitive to small disturbances that affect voltage, reactive power, and frequency stability. Decentralised reactive power control and impedance-based stability models enhance dynamic performance and improve fault tolerance. Integrating topological data analysis with deep learning enhances short-term voltage prediction and stability management. Similarly, solar PV systems face stability challenges from inverter dynamics and fluctuating irradiance, requiring advanced control strategies to maintain grid reliability. As a result, the integration of large-scale wind farms into transmission networks has become a central component in the evolution of power grid infrastructure [3,9]. However, this paradigm shift introduces significant challenges concerning the operational stability, reliability, and resilience of the power grid—particularly under small disturbance scenarios that may trigger cascading failures in wind-rich systems [8,16]. Alagarsundaram et al. (2024) [6] developed a load forecasting model that combines RBMs and Bi-GRUs to capture the temporal characteristics in power system data. Our work adopts their RBM-driven feature learning within Deep Belief Networks and integrates it with Topological Data Analysis to enhance short-term voltage prediction. This integration improves prediction precision and strengthens the assessment of power system resilience.

Unlike conventional power generation, wind farms exhibit inherently variable and stochastic output characteristics driven by fluctuating wind speeds and environmental conditions [1,5]. Off-grid wind turbine accidents, although occurring locally, have far-reaching impacts on the power grid by inducing voltage instability, reactive power imbalances, frequency fluctuations, and dynamic oscillations. The interconnected nature of wind farms and their power electronics-based interfaces make the system sensitive to such faults. Without advanced decentralized control and predictive resilience assessment, these incidents risk escalating into larger grid disturbances, threatening overall reliability and power quality. Additionally, the widespread use of power electronic converters, such as Modular Multilevel Converters (MMC) in Voltage Source Converter-based High Voltage Direct Current (VSC-HVDC) systems, alters the dynamic behaviour of wind-integrated networks [3, 11]. These changes introduce complex electromagnetic and electromechanical interactions that reduce system inertia and damping, thereby increasing vulnerability to small-signal instabilities and subsynchronous oscillations [8,10]. Sub-synchronous oscillation refers to slower-than-normal electrical oscillations that can cause mechanical stress and damage to equipment if not properly detected and controlled.

Small disturbances—such as minor load fluctuations, localized faults, or temporary disconnections of generator units—may seem trivial in isolation. However, in highly interconnected wind farm systems, such events can propagate and amplify, causing dynamic instability or even large-scale blackouts [2,3,16]. Existing methods for stability analysis, particularly time-domain simulations, while accurate, are computationally intensive and limited in their ability to provide real-time operational insights [19]. Moreover, many current reactive power control strategies employ centralised or unified schemes, assuming homogeneous turbine behaviour, which overlooks the heterogeneity of wind farm topologies, geographical dispersion, and dynamic characteristics [4,5,7]. This limits the system's responsiveness and adaptability under disturbance conditions [20]. Nelson et al. (2024) [15] present a hybrid forecasting model combining ARIMA with Bi-GRU to improve time-series predictions. Their hybridization concept is leveraged in this research by integrating topological insights through TDA with deep learning via DBN for voltage prediction. This synergy enhances forecasting precision by capturing both the network topology and temporal trends that contribute to power system resilience.

In response to these challenges, researchers have proposed a range of solutions, including reactive power compensation using Static VAR Compensators (SVC), On-Load Tap Changers (OLTC), and improved converter control strategies [4,5]. Advanced modelling approaches, such as impedance-based stability analysis and small-signal eigenvalue computation, have also gained traction [3, 11]. However, these methods often rely on idealised assumptions, lack scalability for large multi-unit systems, or require precise model parameters that may not be available in real-world applications [16, 17]. Our proposed study employs the Topological Data Analysis (TDA) and Markov model strategy, as demonstrated by Dyavani et al. [18], to capture the complex features of systems and enhance cloud security. This approach is incorporated to identify topological characteristics in voltage data, which are then integrated into a Deep Belief Network for short-term voltage forecasting. This supports more accurate and robust predictions, essential for resilient power system operation.

Furthermore, while deep learning and data-driven techniques have demonstrated remarkable success in power load forecasting and fault detection, their application in voltage stability prediction and dynamic control coordination in wind-integrated systems remains underexplored [12, 13, 22]. Most existing machine-learning approaches lack integration with the topological or structural characteristics of the power network, which limits their interpretability and generalizability across different wind farm configurations [14,20]. Deep Belief Networks are employed by Gattupalli et al. (2025) [23] for precise early stroke detection through advanced pattern recognition. Inspired by this approach, our proposed model integrates their DBN technique with Topological Data Analysis to improve short-term voltage forecasting under power system resilience frameworks, allowing for more accurate predictions and strengthening the assessment of power system resilience.

The short-term voltage prediction model integrates Topological Data Analysis and Deep Belief Networks to predict voltage behaviour in wind farm grid-connected systems under small disturbances. It enhances dynamic stability assessment and reactive power coordination, improving fault tolerance, reducing power fluctuations, and enabling decentralised control for enhanced voltage stability and improved system responsiveness. To address these gaps, this paper proposes a novel short-term voltage prediction and stability optimisation framework that integrates TDA with a DBN model within the context of a power system resilience assessment paradigm. The proposed method combines Topological Data Analysis (TDA) and Deep Belief Networks (DBN) to enhance short-term voltage prediction in wind farm power systems. TDA provides noise-resistant topological features, while DBN captures nonlinear relationships for accurate forecasting. This integration enhances prediction accuracy, facilitates adaptive reactive power control, and improves system resilience, thereby reducing power loss and enhancing dynamic response in large-scale wind farms. Deep Belief Networks (DBNs) were selected over CNNs and RNNs because they effectively capture complex nonlinear relationships in power systems, benefit from unsupervised pre-training, which helps with limited labelled data, and integrate well with topological features from Topological Data Analysis. Unlike CNNs and RNNs, DBNs are better suited for short-term voltage prediction tasks where temporal dependencies are less critical.

Additionally, their layer-wise training offers computational efficiency, making them ideal for real-time voltage stability assessment and improving prediction accuracy in power system resilience contexts. The proposed methodology is validated through comprehensive simulation experiments using an MMC-based VSC-HVDC wind farm model. Comparative studies between unified and decentralised DFIG compensation strategies show that the latter significantly reduces active power loss and improves fault-tolerant behaviour under small disturbance scenarios. The impedance response and voltage dynamics under various frequencies are analysed to assess the system's ability to recover from minor faults and maintain synchronisation. The MMC model, renowned for its precise voltage control and modular design, facilitates decentralised reactive power coordination in wind farms, thereby enhancing fault resilience. The DFIG model, commonly used in wind turbines, enables variable-speed operation and reactive power control, which are crucial for maintaining voltage stability during disturbances. Decentralised control enhances system responsiveness and reduces losses compared to centralised control. A cluster-based, decentralised approach handles localised disturbances more effectively than centralised methods. Alternatives include SVC/STATCOM devices, PMSG technology, centralized control, machine learning models, and stability analysis methods. Combining these models offers a practical solution for improving small disturbance stability in wind-integrated power systems.

2. Small disturbance stability model of wind farm grid connected system

Small-signal stability is a crucial aspect of power systems, indicating their ability to maintain synchronism despite minor changes. In wind farms using MMC, these disturbances can manifest as current, voltage, or power fluctuations. An impedance-based analysis reveals how these disturbances affect system components, such as converters and transmission lines. A decentralised, cluster-based reactive power control strategy enables turbines with similar operating conditions to adjust their reactive power, thereby mitigating disturbances and ensuring stable operation. This analysis enhances power system resilience in wind farm grid connections by modelling the complex dynamics of converter-based wind farms, thereby reducing system inertia and increasing vulnerability. It supports decentralised, topology-aware reactive power control strategies, enabling short-term voltage prediction and real-time monitoring for proactive management of disturbances. Efficient simulation models facilitate timely stability assessments and controller tuning, ensuring reliable and resilient operation in renewable-rich grids.

Figure 1 illustrates the modular multilevel converter (MMC) topology used in the grid-connected wind farm system, which serves as the basis for the small disturbance stability analysis presented in this study. The converter consists of three-phase bridge arms, each composed of multiple cascaded submodules (SMs) labelled $SM_1, SM_2, \ldots, SM_n$, allowing for precise voltage regulation via individual switching. These bridge arms connect to the AC terminal and include arm inductors L_{arm}, which help suppress current transients and improve dynamic response. The topology features symmetrical upper and lower arms for each phase, characteristic of MMC systems. On the right side of the figure, transformer units T_1 and T_2 represent the step-up process from local voltage levels (e.g., 33 kV) to transmission voltages (e.g., 230 kV and 370 kV), consistent with the wind farm model introduced earlier. This modular architecture not only facilitates high-resolution voltage synthesis but also provides a flexible platform for implementing the decentralized reactive power coordination strategy described in Section 4. Reactive power coordination is the process of determining how reactive power, which contributes to steady voltage, is distributed among wind turbines. This is typically achieved by clustering turbines to enable improved local control and enhanced overall system reliability. Moreover, the clustered arrangement of SMs aligns with the control framework, which groups turbines based on similar operating characteristics, thereby enabling localised voltage control and improved fault resilience. As a whole, the figure supports the theoretical modelling and simulation of MMC-based VSC-HVDC systems under small disturbance scenarios, forming a critical component of the proposed voltage prediction and stability optimization approach.

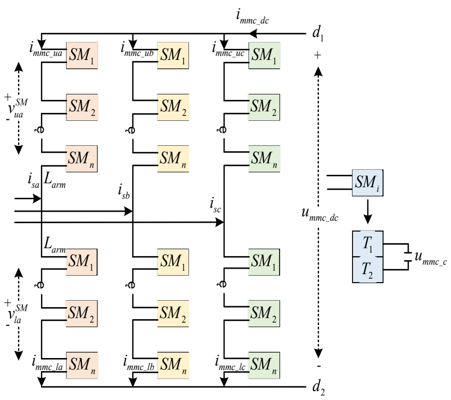

Figure 1: MMC Topology for Grid-Connected Wind Farm under Small Disturbance Conditions

In the context of MMCs, when the number of sub-modules (SMs) in each bridge arm is sufficiently large, the system exhibits quasi-continuous behaviour. This allows the converter to be modelled using averaged techniques rather than discrete switching logic. Under this approximation, the output voltage of a single bridge arm can be characterized by a continuous-time switching function, as expressed in equation (1):

$$\begin{cases} Si_{ulj} = C_{mmc}\dfrac{du_{mmc-c}}{dt} \\ u_{arm} = NSu_{mmc-c} \end{cases} \tag{1}$$

When MMC is in steady state, MMC bridge arm current, capacitor voltage component, by equations (2) - (4):

$$u_{mmc\_c} = u_c + u_{ac1} + u_{ac2} = u_c + u_{ac1}\sin(\omega t + \delta_1) + u_{ac2}\sin(2\omega t + \delta_2) \tag{2}$$

$$\begin{cases} i_{mmc\_uj} = \frac{i_{mmc\_dc}}{3} - \frac{i_s}{2}\sin(\omega t + \beta_1) + i_{cir}\sin(2\omega t + \beta_2) \\ i_{mmc\_lj} = \frac{i_{mmc\_dc}}{3} + \frac{i_s}{2}\sin(\omega t + \beta_1) + i_{cir}\sin(2\omega t + \beta_2) \end{cases} \tag{3}$$

$$\begin{cases} S_p = \dfrac{\frac{1}{2}u_{mmc\_dc} - \frac{1}{2}Mu_{mmc\_dc}\sin(\omega t+\alpha) + u_{cir}\sin(2\omega t+\varphi)}{u_{mmc\_dc}} \\ S_n = \dfrac{\frac{1}{2}u_{mnc\_dc} + \frac{1}{2}Mu_{mnc\_dc}\sin(\omega t+\alpha) + u_{cir}\sin(2\omega t+\varphi)}{u_{mmc\_dc}} \end{cases} \tag{4}$$

Figure 2 presents a simplified equivalent model of the MMC-based grid-connected system under small disturbance conditions, serving as the foundation for stability analysis and dynamic simulations in this study. Small disturbances in the MMC-based VSC-HVDC wind farm system cause fluctuations in reactive power and voltage on the AC side, affecting voltage stability. On the DC side, these disturbances result in variations in DC voltage and current, which in turn influence frequency stability through the converter control dynamics. At the receiving end, frequency deviations and oscillations can occur due to changes in active power flow, especially in low-inertia grids with high wind integration. A decentralised reactive power coordination strategy helps mitigate these effects by providing localised voltage support, enhancing damping of oscillations, and facilitating faster recovery to maintain system stability and frequency synchronisation. DC side disturbances in VSC-HVDC systems, such as faults or sudden changes in DC voltage and current, mainly affect frequency stability and converter performance. These disturbances can propagate to the AC grid, reducing system resilience and causing instability. Effective mitigation involves decentralised control strategies, impedance-based modelling, and rapid converter responses to maintain stable power flow and system synchronisation in the face of small disturbances.

The model is divided into three main sections: the MMC side, the transmission line, and the AC power source. On the MMC side, the converter is represented by a DC input terminal supplying voltage $u_{\text{mmc\_dc}}$ and current $i_{\text{mmc\_dc}}$. Its output is modulated through submodules and filtered by an inductance,

L_f, producing an AC voltage, iu_s, and current . The dq-frame control voltage, u_{mmc_dq}, enables decoupled dynamic control analysis. The converter interfaces with the transmission network at node k_2. The transmission line is modelled as a simplified π-type network consisting of a series inductor L_1, a shunt capacitor C_1, and associated voltages u_1 *and* u_2, and currents i_1 *and* i_2. This section captures the line's impedance characteristics, which are critical for analyzing frequency response and resonance phenomena. Finally, the AC grid is represented as an ideal voltage source $\boldsymbol{u_g}$, serving as a fixed reference or disturbance input for simulations. Together, these interconnected components form an integrated model that facilitates detailed evaluation of the system's response to small disturbances. This framework supports impedance-based stability assessment and the development of coordinated control strategies within the MMC-HVDC wind power integration framework.

DC side faults in MMC-based VSC-HVDC wind farm grid connections pose significant risks to system frequency stability and converter operation. These faults can cause converter blocking and turbine disconnections, leading to cascading failures. To address this, decentralised reactive power control strategies group turbines into clusters, identifying resonant frequencies and adjusting the controllers accordingly. Impedance-based analysis and data-driven methods, such as deep learning and topological data analysis, enhance fault prediction and stability management. Simulations show decentralized control reduces power losses and improves response during DC faults.

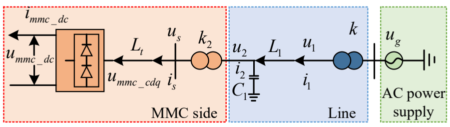

Figure 2: Grid-Connected System under Small Disturbance

The dynamic equivalence method enhances voltage stability analysis of large wind farms by simplifying complex turbine systems into manageable equivalent models that retain key dynamic behaviours. This approach reduces computational complexity while accurately representing impedance and dynamic responses to disturbances. By enabling cluster-based reactive power control, it supports localized voltage regulation and improves system responsiveness. The method enables faster simulations for real-time voltage prediction and improved fault tolerance, ultimately enhancing the stability and resilience of wind-integrated power grids.

Small-signal stability is directly impacted by the growing complexity of power grids, which is brought about by the incorporation of renewable energy, sophisticated power electronic converters, and numerous interconnections. These factors decrease system inertia and increase dynamic interactions. Due to its increased complexity, the grid is more susceptible to oscillations and is more vulnerable to minor disruptions. Furthermore, typical centralised control techniques are challenged by complicated grid topologies, which call for decentralised and topology-aware control systems in order to preserve stability. Resonance effects and frequency-dependent impedance resulting from this complexity further increase the possibility of instability. Hence, sophisticated modelling and adaptive management are crucial for dependable grid operation.

3. Methods

The disconnection of a single wind turbine unit within a wind farm can trigger abnormal operating conditions in adjacent units due to their interdependent electrical and control relationships. This cascading effect may ultimately lead to large-scale unit disconnections, significantly expanding the scope and severity of system disturbances. The sudden disconnections of wind turbines cause voltage dips and frequency deviations, disrupting power flow and load balance. These disturbances can cause cascading failures. Voltage recovery relies on coordinated reactive power control, with decentralized strategies improving stability. Low inertia from power electronic converters reduces damping, leading to faster frequency changes. Advanced frequency control methods and impedance-based stability analysis guide control design. Such chain-reaction failures not only reduce the stability margin of the power system but also introduce substantial hidden risks that are difficult to detect through conventional analysis. Moreover, the process of disconnection and subsequent system instability is inherently dynamic and nonlinear, often evolving over extended periods of time. These characteristics make it challenging to capture the full scope of the disturbance using static models or steady-state analysis alone. Disconnecting a wind turbine in a wind farm can cause dynamic disturbances that affect neighbouring turbines, potentially leading to instability. Modelling the wind farm's behaviour using MMC-based VSC-HVDC systems can help identify fluctuations in reactive power, voltage, and frequency. A decentralised, cluster-based reactive power control strategy can mitigate these disturbances by adjusting output, maintaining voltage stability, and preventing the spread of faults. Simulations demonstrate that decentralised control enhances system recovery and reduces power losses, thereby improving wind farm stability and resilience during disconnection events.

As illustrated in Figure 3, this approach enables hierarchical control, where localised disturbances are addressed at the cluster level before propagating across the entire system. By doing so, the strategy enhances voltage stability, minimizes reactive power imbalances, and improves the system' s ability to withstand and recover from small disturbances.

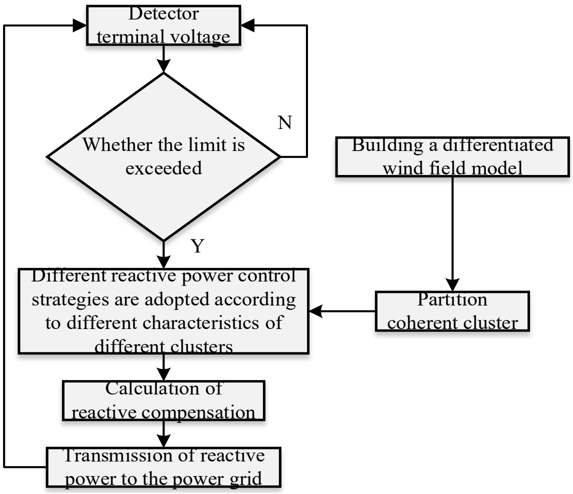

Figure 3: Topology-Aware Reactive Power Dispatch Strategy for Wind Farms

Geographical location, feeder distribution, wind speed, fan output of the units, and fans same feeder line consist of different terminal voltages. The wind turbine terminal voltage remains stable within a specific safety range, effectively reducing the probability of wind farm failure. These factors create heterogeneous operating conditions, making centralised reactive power control less effective. Instead, a decentralized, cluster-based coordination approach is needed to adapt to local voltage differences and dynamic wind conditions, thereby improving voltage stability, reducing losses, and enhancing overall system resilience. Geographical location impacts wind farm performance by creating voltage variations due to electrical distances and feeder impedance. Grouping turbines based on location allows localized reactive power control, improving voltage stability, reducing losses, and enhancing system efficiency. Wind speed directly influences turbine power output and terminal voltage fluctuations. Stable terminal voltages enable efficient operation and maximise energy capture, whereas excessive voltage fluctuations can reduce efficiency. Integrating geographical and wind speed factors into a decentralised control and impedance-based stability model enhances voltage prediction, control optimisation, fault tolerance, and overall wind farm efficiency under small disturbances.

Moreover, the terminal voltage level of each wind turbine generator unit also represents its operating condition:

$$||\Delta U_G||^2 = \sum_{i=1}^{N}(U_{Gi} - U_{ref})^2 \tag{9}$$

According to the above formula, the small disturbance stability optimization model is shown in Figure 4:

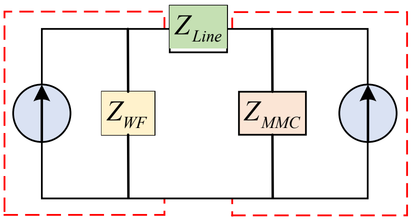

Figure 4: Optimized Simulation Model of Additional Small Disturbance Signal

4. Experiments

Figure 5 illustrates the frequency-domain comparison between the calculated and simulated equivalent impedance of the wind farm grid-connected system under small disturbance conditions. The two curves exhibit high consistency in their overall trends, particularly around the resonance peak at approximately 6 Hz, indicating the accuracy and validity of the impedance-based analytical model. The slight discrepancy between the calculated value (green line) and the simulation result (red dashed line) may be attributed to idealized assumptions in the theoretical model, such as linearity and neglect of converter-level dynamics. Nonetheless, the analytical model slightly overestimates the impedance magnitude, providing a conservative estimate that is beneficial for control design and stability margin assessment. The model's predictive capability across the frequency range supports its application in small-signal stability analysis and impedance-shaping-based controller optimisation.

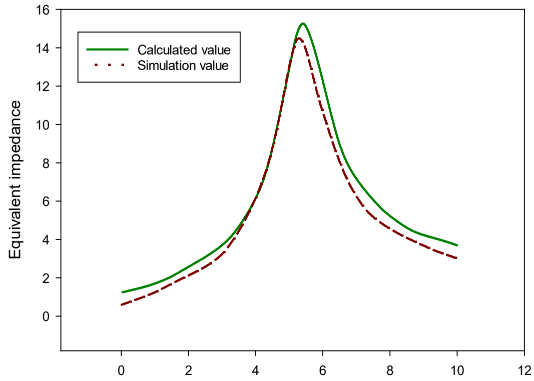

Figure 5: Comparison of Calculated and Simulated Equivalent Impedance

Figure 6 compares the frequency-domain equivalent impedance of the wind farm grid-connected system obtained through theoretical calculation and time-domain simulation. Grid impedance in wind-connected systems is modelled as a frequency-dependent equivalent circuit, including converter interface dynamics, transmission line elements, and grid source characteristics. It is fundamental to understanding and predicting the propagation and damping of small disturbances. The impedance directly influences stability, reactive power flow, and voltage dynamics, making it a key factor in designing control strategies that enhance system resilience and dynamic performance under minor perturbations. While the general trend between the two curves remains comparable in the mid-frequency range (2–7 Hz), noticeable deviations arise in the low (<2 Hz) and high-frequency (>8 Hz) regions. These discrepancies may result from unmodeled nonlinearities, filtering effects, or limitations in the system's dynamic control bandwidth. The simulation curve also reveals multiple local peaks, indicating potential resonant modes or controller-induced oscillatory behaviour. Despite the variations, the overall consistency in the core frequency band supports the reliability of the analytical model for small-signal stability evaluation and controller tuning purposes. Small-signal stability measures a power system's ability to remain stable and synchronised when faced with minor disturbances, such as faults or small load changes. A stable system can quickly dampen these disturbances and maintain normal operation, whereas instability can lead to growing oscillations and potentially more severe failures. This stability is typically assessed through analyses like eigenvalue or impedance studies and is essential for ensuring reliable and continuous power system performance.

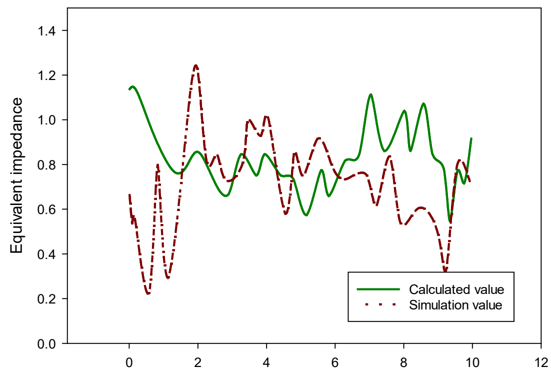

Figure 6: Frequency-Domain Comparison of Equivalent Impedance

Figure 7 exhibits a non-uniform and segmented pattern, with notable dips around nodes 17, 33, and 48, indicating the presence of cluster boundaries or control zone transitions. These local minima correspond to nodes with reduced or zero reactive power contribution, which may be due to their proximity to voltage constraints or lower priority in the reactive power dispatch hierarchy. The observed stair-step trend suggests that reactive power is strategically allocated based on the operational characteristics and topological location of each wind turbine unit. This uneven distribution validates the effectiveness of the decentralized coordination approach in enhancing voltage control flexibility while minimizing system losses.

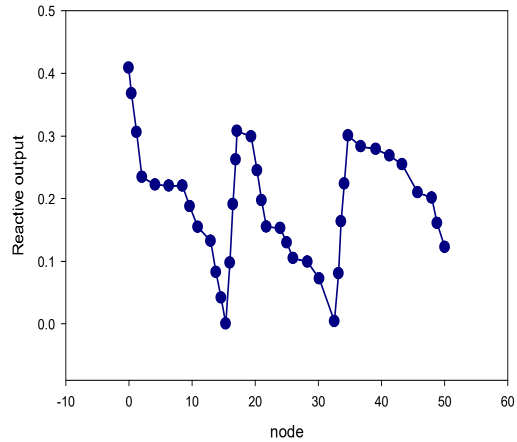

Figure 7: Node-Wise Distribution of Reactive Power Output

The small disturbance stability model for wind farm grid-connected systems uses a modular multilevel converter framework for detailed dynamic analysis. It focuses on minor disturbances that can cause instability and uses a decentralized, cluster-based reactive power control strategy to enhance voltage stability, reduce losses, and improve fault tolerance. Stability is assessed through impedance-based frequency-domain analysis to detect resonance and oscillations. The model also integrates data-driven techniques, such as Topological Data Analysis and Deep Belief Networks, to predict voltage stability and optimise reactive power dispatch, making it adaptable to the complex nature of wind farms.

5. Conclusion

This paper proposed a small disturbance stability analysis framework for wind farm grid-connected systems based on modular multilevel converters (MMC). By integrating impedance modelling with a cluster-based reactive power coordination strategy, the study effectively captured the dynamic response characteristics under minor perturbations. Simulation and calculated results showed good consistency in impedance behaviour across key frequency ranges, verifying the accuracy of the theoretical model. The proposed decentralized control strategy enabled differentiated reactive power distribution among turbine clusters, improving voltage support and reducing network losses.

Declarations

Funding

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Conflict of Interest

The authors declared that they have no conflicts of interest regarding this work.

Data Availability

All data generated or analyzed during this study are included in the manuscript.

Code Availability

Not applicable.

Author Contributions

Hongjun Wang: Conceptualization, methodology, data curation, writing - original draft.

Tao Li: Data analysis, investigation, writing - review & editing.

Zhiliang Dong: Formal analysis, validation, supervision, project administration.

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