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Review article: A review of dynamic response analysis methods for transmission tower-line systems under ice-wind hazards

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Abstract. Ice-wind hazards pose serious threats to transmission tower-line systems (TTLS), and dynamic response analysis is indispensable for elucidating the failure mechanisms of TTLS and guiding effective disaster mitigation strategies. This review elaborates on a series of dynamic response analysis methods for TTLS, covering analytical and mechanics-based methods, numerical simulation methods, stochastic and statistical methods, and methods based on artificial intelligence (AI) that show increasing potential to enhance predictive performance and computational efficiency. Detailed analyses are conducted on the fundamental assumptions, solution procedures, and uncertainty modeling of the various methods, as well as their respective methodological limitations. Finally, this review identifies key challenges associated with modeling, computation, and uncertainty quantification. Future research directions are proposed to advance intelligent and resilience-oriented strategies for the sustainable development of TTLS subjected to ice-wind loads.

Author keywords: Transmission tower-line systems (TTLS); Ice-wind hazards; Dynamic response; Resilience implications.

1 Introduction

1.1 Background of ice-wind hazards

Transmission tower-line systems (TTLS) form the backbone of modern society, ensuring the reliable delivery of electricity across regions (Jamal et al., 2025; Cheng et al., 2024; Wang et al., 2024b). However, these systems are increasingly vulnerable to more frequent and severe extreme weather events. Among meteorological stressors, icing and strong winds pose significant challenges to TTLS, especially within complex urban infrastructures (Zhang et al., 2023a; Nyangon, 2024; Mohanty et al., 2024). Ice accretion on conductors and towers not only increases structural self-weight but also alters aerodynamic characteristics, thereby enhancing wind-induced vibrations, local stress concentrations, and overall dynamic response (Wu and Chen, 2023). When these two phenomena act concurrently, the resulting coupled ice–wind loading can induce pronounced nonlinear dynamic effects that frequently exceed the assumptions prescribed in conventional design standards, posing substantial risks to the reliability and safety of TTLS (Ma et al., 2022; Song and Li, 2023).

The formation of ice on overhead transmission lines (OHTLs) generally results from in-cloud icing, freezing rain, or wet snow accretion, all of which are governed by ambient temperature, humidity, droplet size, and wind velocity (Zhang et al., 2023a; Zhu et al., 2019; Huang et al., 2025). Once deposited, the ice modifies the conductor's cross-sectional geometry,

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producing irregular aerodynamic profiles that increase both drag and lift coefficients. When exposed to strong winds, these ice-laden conductors can experience complex aeroelastic instabilities, most notably galloping and coupled multi-degree-of-freedom motions (Liu et al., 2025). These dynamic motions may propagate along adjacent spans, leading to large-amplitude displacements, excessive bending moments at tower joints, and cascading line failures.

Historical events have demonstrated the destructive potential of ice–wind hazards. The 1998 North American ice storm and the 2008 southern China ice disaster, for example, caused the collapse of thousands of towers and widespread power outages affecting millions of residents (Cholette et al., 2020; Ding et al., 2008). Numerous documented cases across different regions and climatic zones highlight the spatial distribution and magnitude of such disasters. Moreover, climate change may alter the frequency and spatial distribution of meteorological conditions associated with icing and strong winds. Despite advances in meteorological forecasting and anti-icing technologies, accurately predicting the combined effects of these hazards remains challenging due to their stochastic and interdependent nature. Consequently, a comprehensive understanding of coupled dynamic behavior is essential not only for robust risk assessment but also for enhancing the resilience and reliability of future TTLS (Pani and Samal, 2025; Dwivedi et al., 2024).

1.2 Importance of dynamic response analysis

The mechanical behavior of TTLS under ice–wind hazards exhibits highly nonlinear and time-dependent characteristics (Wu and Chen, 2023; Dikshit and Alipour, 2025). Ice accretion not only increases structural mass and surface roughness but also alters aerodynamic coefficients and natural frequencies, thereby intensifying the sensitivity of the system to fluctuating wind loads. Under such coupled excitations, transient vibration, resonance, and load redistribution may occur, leading to local over-stress, fatigue damage, or even progressive failure (Song and Li, 2023; Mahmoudi et al., 2021; Meng et al., 2025; Ma et al., 2020; Li et al., 2024). Conventional quasi-static or uncoupled analyses fail to capture these dynamic interactions, resulting in potential underestimation of structural vulnerability and serviceability degradation in extreme cold regions.

Dynamic response analysis is essential for understanding the mechanical behavior of TTLS under ice–wind hazards (Gao et al., 2020). By integrating stochastic wind fields, time-varying ice accretion, and nonlinear structural behavior, it reveals critical vibration modes, amplification mechanisms, and damage evolution processes that govern system reliability (Xiao et al., 2024; Li et al., 2025, 2023a; Peng et al., 2025). Moreover, it provides a foundation for resilience-based design and early-warning systems by linking dynamic responses with monitoring data and performance criteria. Thus, a rigorous dynamic analysis framework is indispensable for accurately assessing and mitigating risks associated with coupled ice-wind effects in modern transmission networks.

1.3 Related literature analysis

A bibliometric search was conducted in the Web of Science Core Collection using combinations of the topic terms “ice,” “wind,” “dynamic response,” “transmission tower,” and “overhead line” for publications from 1990 to 2025. Records focused solely on meteorological modeling or static ice-load estimation without relevance to tower-line dynamic response were excluded, leaving 4,680 records for bibliometric analysis. Fig. 1 illustrates the main research subjects and hotspots related to

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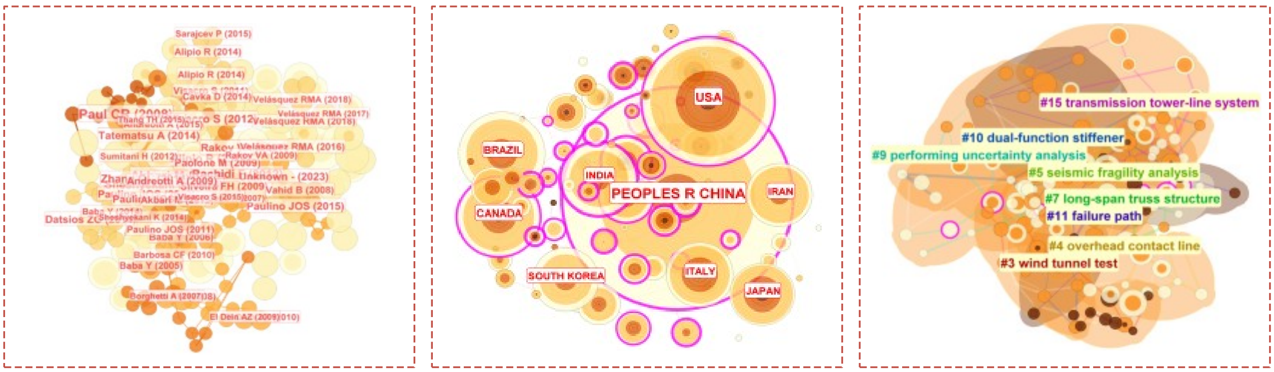
ice–wind hazards affecting TTLS. CiteSpace was employed for network visualization and co-citation and keyword-cluster analyses; node size reflects the relative prominence of the corresponding items in each network. As shown in Fig. 2, research activity was limited before 2001 and increased substantially after 2009. Publication output has grown particularly rapidly in recent years, highlighting sustained interest in dynamic response analysis under coupled ice–wind conditions and an increasing emphasis on resilience-oriented assessment and integrated hazard simulation for TTLS.



(a) (b) (c)

Figure 1. The mapping knowledge domain of ice-wind hazards based on TTLS. (a) Co-citation analysis; (b) Country and institution analysis; (c) Cluster analysis of keywords.

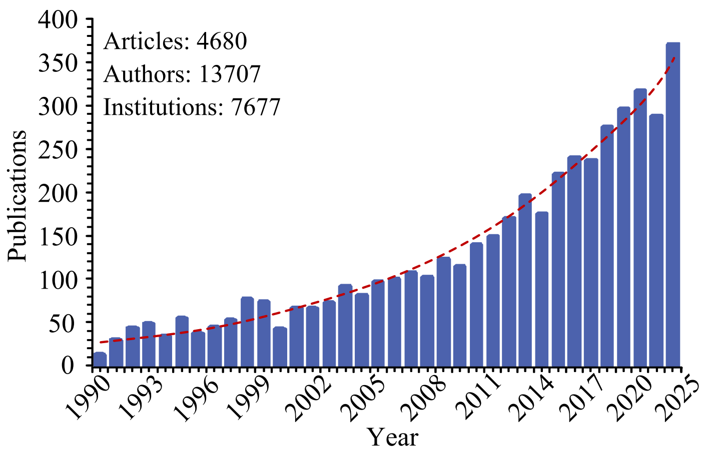


Figure 2. The number of papers varies with the year.

1.3.1 Research subjects of ice-wind hazards

As shown in Fig. 1(a), major contributors to the study of ice-wind hazards on TTLS include Farzaneh M., Diana G., Wang Y., Lu P., and Zhang Z. According to Fig. 1(b), the United States, China, and Canada dominate research in this field, followed by Japan, Norway, and Finland. Institutions such as Hydro-Québec Research Institute (IREQ), Harbin Institute of Technology,

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and the Chinese Academy of Sciences have made significant advances in ice-load modeling, structural response analysis, and risk mitigation for TTLS under combined environmental loads.

1.3.2 Research hotspots of ice-wind hazards

As illustrated in Fig. 1(c), research on ice–wind hazards is highly interdisciplinary, linking atmospheric meteorology, structural dynamics, and system reliability. Current hotspots include ice accretion modeling, aerodynamic load simulation, dynamic response of transmission towers and conductors, and resilience assessment. Recent studies emphasize high-fidelity simulation and multi-hazard coupling, reflecting growing attention to the safety and resilience of modern TTLS under extreme ice-wind conditions.

1.4 Organization of the paper

This paper is structured as follows. Section 1 introduces the background, significance, and research progress of ice–wind hazards on TTLS. Section 2 presents linear analytical and nonlinear mechanics-based formulations for dynamic response analysis. Section 3 discusses numerical simulation methods based on the finite element method (FEM), finite difference method (FDM), and finite volume method (FVM). Section 4 summarizes stochastic and statistical methods, such as Monte Carlo simulation (MCS), random field modeling (RFM), spectral analysis method (SAM), response surface method (RSM), and time series method (TSM). Section 5 reviews artificial intelligence (AI)-based methods, including machine learning (ML), deep learning (DL), and physics-informed machine learning (PIML), for dynamic response analysis. Section 6 provides a synthesis of existing methods, discusses their implications for tower-line system resilience, and outlines future research perspectives. Section 7 concludes the paper.

2 Analytical and mechanics-based methods

Analytical and mechanics-based methods provide simplified representations of the dynamic behavior of TTLS while retaining the principal physical mechanisms. They range from linearized vibration formulations that permit tractable analytical solutions to nonlinear formulations that account for geometric and material nonlinearities, aerodynamic coupling, and ice-induced parameter variations.

2.1 Linear analytical method

Linear analytical methods, such as modal superposition (MS), equivalent linearization (EL), and frequency-domain analysis (FDA), are suitable for simple structural configurations and small deformation ranges, where the governing equations can be linearized with minimal loss of accuracy. Early investigations modeled TTLS, including towers, conductors, and insulator strings, as elastic beam or truss systems with constant stiffness and damping. This formulation enabled the use of classical vibration theory and modal superposition to obtain closed-form or semi-analytical solutions. Building on these foundations, analytical and reduced-order treatments have been used to characterize the dynamic behavior of iced transmission systems

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under wind excitation. Brown et al. (2007) analyzed ice-event loads derived from structural response, while Veerakumar et al. (2020) examined the effects of dynamic ice accretion on the aerodynamic drag of a power transmission cable. More general studies in aeroelasticity and structural dynamics, including reduced-order aeroelastic modeling (Hesse and Palacios, 2014), laminar-separation flutter (Barnes and Visbal, 2019), and high-frequency unsteady-lift formulations (Taha and Rezaei, 2020), provide methodological foundations for simplified wind-induced response analysis. For transmission-line systems, simplified dynamic representations have also been developed for icing-related system response and wind-induced swing of heavily iced lines (Chen et al., 2022; Lou et al., 2023), while studies of viscoelastic damping and frequency-dependent modal behavior provide complementary tools for representing structural dynamics (Wang et al., 2022a; Bae and Cho, 2023). Such reduced formulations can lower computational demand, but they generally cannot capture localized shedding, asymmetric accretion, or strongly non-stationary turbulence with the same fidelity as high-resolution nonlinear simulations. Consequently, linear analytical frameworks remain best suited to mechanism interpretation and preliminary response estimation within their assumed linear range.

2.2 Nonlinear mechanics-based methods

Unlike linear analytical formulations, nonlinear mechanics-based methods consider material nonlinearity, large deformations, and complex interactions. These formulations are typically implemented numerically; here they are grouped according to their mechanical representation, whereas Sect. 3 focuses on the underlying numerical discretization strategies. (1) Nonlinear finite element analysis (NFEA) is widely used to model both material and geometric nonlinearities, capturing large displacements and irreversible deformations. Recent advances, such as adaptive meshing and parallel processing, have improved the computational efficiency of NFEA and enabled large-scale simulations (Beisiegel et al., 2021; Badia et al., 2018). (2) Plasticity models (PMs), including von Mises and Drucker–Prager yield criteria (Lagioia and Panteghini, 2016), are crucial for predicting irreversible deformation in TTLS under extreme loading conditions. These models provide a more realistic representation of failure mechanisms, such as tower buckling and cable rupture, which linear models cannot capture (Tian et al., 2019; Wang et al., 2023). (3) Nonlinear time-history analysis (NTHA) offers insights into the dynamic response of TTLS subjected to time-varying loads. By accounting for the nonstationary nature of ice and wind forces, NTHA facilitates the evaluation of dynamic effects such as resonant frequencies and damping, which are critical for infrastructure safety (Hadianfard, 2012; Langlois and Legeron, 2014). However, its high computational cost limits its applicability to smaller models or simplified scenarios. (4) Hysteresis models (HMs) (Laudani et al., 2014; Peng et al., 2018; Kim and Lee, 2019), such as the Bouc–Wen and Masing models, simulate energy dissipation during cyclic loading, a common phenomenon in systems subjected to repeated ice–wind cycles. These models improve predictions related to material degradation and long-term performance (Ding et al., 2019; Maleki et al., 2023). Despite their effectiveness, nonlinear methods face challenges, particularly computational demands and uncertainties in material models and loading conditions.

To provide a clear overview, Table 1 summarizes the main categories, underlying assumptions, and key applications of the linear analytical and nonlinear mechanics-based methods discussed above.

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Table 1. Summary of analytical and mechanics-based methods for TTLS dynamic response under ice–wind hazards.

Method	Sub-method	Main assumptions	Representative applications
Linear analytical methods	MS (Brown, 2007; Han et al., 2019)	a. Linear behavior; b. Small deformation; c. Proportional damping; d. Independent ice-wind loads.	a. Preliminary dynamic analysis; b. Modal decomposition; c. Efficient response estimation.
	EL (Chen et al., 2022; Bae and Cho, 2023)	a. Equivalent stiffness/damping; b. Steady state.	a. Simplified nonlinear response; b. Moderate ice–wind coupling.
	FDA (Hesse and Palacios, 2014; Wang et al., 2022a; Lou et al., 2023)	a. Stationary Gaussian excitation; b. Steady state.	a. Frequency response; b. Random vibration analysis.
Nonlinear mechanics-based methods	NFEA (Beisiegel et al., 2021; Badia et al., 2018)	a. Geometric/material nonlinearities; b. Large deformation; c. Ice–wind interaction.	a. Full structural response; b. Transient, large-deformation effects.
	PM (Lagioia and Panteghini, 2016; Tian et al., 2019; Wang et al., 2023)	a. Material yielding; b. Irreversible deformation.	a. Yielding and buckling analysis; b. Collapse prediction.
	NTHA (Hadianfard, 2012; Langlois and Legeron, 2014)	a. Time-dependent excitation; b. Non-steady state.	a. Transient dynamics; b. Resonance analysis; c. Damping evaluation.
	HM (Laudani et al., 2014; Peng et al., 2018; Kim and Lee, 2019; Ding et al., 2019; Maleki et al., 2023)	a. Cyclic loading; b. Hysteretic energy dissipation; c. Stiffness degradation.	a. Energy dissipation; b. Cyclic degradation assessment.

3 Numerical simulation methods

The dynamic response of TTLS under ice–wind hazards is governed by three fundamental physical processes: the geometrically nonlinear dynamics of multi-span conductors (Wu and Chen, 2023; Huang et al., 2021; Fu and Sivaselvan, 2023; Lou et al., 2024), the stochastic and spatially correlated characteristics of turbulent wind fields (Liu et al., 2023b, a; Yan et al., 2024), and the ice-induced variations in mass distribution and aerodynamic properties (Dehkordi et al., 2013; Cai et al., 2019a, b; Chen et al., 2024). These interacting mechanisms collectively give rise to nonlinear, stochastic, and time-dependent structural behaviors that cannot be adequately represented by analytical formulations alone. To capture these effects, this section reviews three classical numerical discretization methods. FEM is employed to model nonlinear structural dynamics, FDM is used to discretize governing equations and perform time-domain simulations of conductor dynamics, and FVM is applied to resolve

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the flow around iced conductor cross-sections and extract the corresponding aerodynamic coefficients. Fully coupled fracture, contact, and impact processes associated with ice shedding are beyond the scope of this review. Representative numerical modeling examples associated with structural and aerodynamic simulations are presented together in Fig. 3 (Cai et al., 2025; Alminhana et al., 2018; Zhou et al., 2025b).

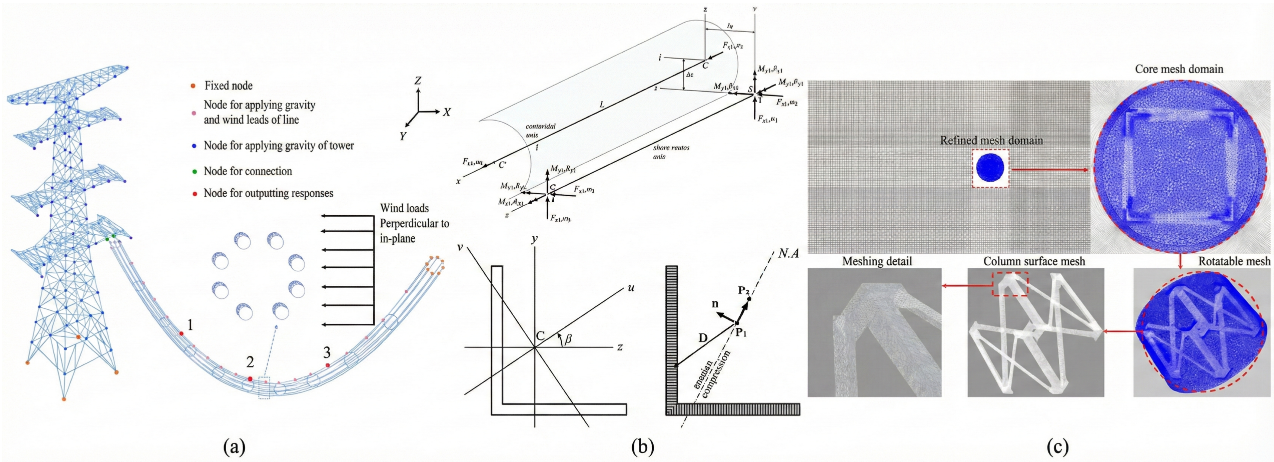

Figure 3. Relevant numerical simulation results. (a) Finite element model of eight-bundle TTLS (reprinted from Cai et al., 2025, copyright 2025 Elsevier publishing); (b) Beam-column element end forces and displacements, and idealised angle cross section (reprinted from Alminhana et al., 2018, copyright 2018 Elsevier publishing); (c) Meshing details (reprinted from Zhou et al., 2025b, copyright 2025 Elsevier publishing).

3.1 FEM-based numerical simulation

FEM provides the primary structural analysis framework for understanding the dynamic behavior of TTLS under coupled ice–wind conditions. Studies have shown that ice accretion substantially modifies conductor mass distribution, effective stiffness, and aerodynamic characteristics (Dong et al., 2024; Veerakumar et al., 2020; Cai et al., 2019a), thereby producing notable shifts in natural frequencies and amplifying large-displacement responses under turbulent winds (Yang et al., 2025a; Fu et al., 2023). Considerable attention has been devoted to the nonlinear dynamics of multi-span conductor systems, where sag-tension coupling (Warminski et al., 2016; Han et al., 2019; Zurru, 2025), follower forces (Fu and Sivaselvan, 2023; Zhang et al., 2024b), and geometric stiffening effects (Wu and Chen, 2023; Desai et al., 1995; Rawlins, 2001) must be represented using cable-specific finite elements and iterative large-deformation solvers. Such approaches have been demonstrated to be essential for accurately representing tension redistribution and multi-span interaction effects during heavy icing events. In parallel, studies on tower–conductor coupling have highlighted that conductor motion can substantially influence tower base forces, joint rotations, and member-level demands, particularly when asymmetric icing introduces spanwise differential loading (Song and Li, 2023; Yang et al., 2012; Zhang et al., 2013; Zhu et al., 2025). Related investigations have further revealed the sensitivity of lattice towers to combined ice weight and fluctuating wind moments, with nonlinear FEM analyses showing that

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local yielding, leg-buckling, and joint flexibility can govern overall system stability under severe icing scenarios (Farzaneh and Savadjiev, 2005; Makkonen et al., 2014; Cucuzza et al., 2022). Some studies have also incorporated refined material models and semi-rigid joint representations to better capture the progressive accumulation of damage under repeated wind excitation (Do and Filippou, 2018; Van den Nieuwenhof and Coyette, 2003; Zhang et al., 2023b). Despite substantial progress, challenges remain, including the treatment of localized nonlinearities, the numerical stability of highly flexible conductor-tower systems, and the representation of time-evolving ice geometry over long-duration storm conditions. Nevertheless, FEM remains the most comprehensive and rigorously validated structural solver for ice-wind-induced dynamic response analysis and continues to serve as the computational foundation for integrating advanced wind-field generation, aerodynamic characterization, and multi-physics coupling strategies.

3.2 FDM-based numerical simulation

FDM provides an efficient numerical framework for problems in which the governing cable equations can be discretized directly in space and time (Omurtag and Lytton, 2010; Adel et al., 2022). Compared with formulations that require element assembly and, in nonlinear cases, repeated iterations, finite-difference schemes can offer low per-step computational cost for long-duration simulations. High-order spatial discretization and explicit or implicit time-marching schemes provide flexible accuracy–efficiency tradeoffs. In particular, explicit schemes permit fine temporal resolution provided that the time step satisfies the corresponding stability condition (Majchrzak and Mochnacki, 2020; Wang et al., 2021). FDM is also well suited to wave-like transient processes associated with sudden ice shedding, where abrupt mass loss produces propagating tension waves and local dynamic interactions (Kollár and Farzaneh, 2008, 2013; Zhongbin et al., 2022; Zhang et al., 2024a). Central-difference formulations are widely used for transient dynamics because of their simple implementation and favorable computational efficiency, although their stability remains conditional on the selected time step (Souza et al., 2024; Georgette et al., 2025; Soares, 2019). Nevertheless, FDM is less convenient than FEM for localized geometric or material nonlinearities, complex tower geometry, and intricate boundary interactions. Consequently, it is most naturally used for conductor-dynamics subproblems or within hybrid numerical frameworks.

3.3 FVM-based numerical simulation

Ice accretion alters the aerodynamic geometry of conductors, leading to asymmetric force distributions that drive phenomena such as galloping and VIV (Yang et al., 2025a; Matsumiya et al., 2021). FVM-based simulations, particularly using Reynolds-averaged Navier–Stokes (RANS) and Detached Eddy Simulation (DES), effectively capture the nonlinear variations in aerodynamic coefficients associated with various ice shapes and wind attack angles, offering detailed insights into drag, lift, and moment coefficients that influence conductor oscillations (Mou et al., 2021; Liu et al., 2020b, a; Zhao et al., 2025a; Ding et al., 2022). These simulations provide a more accurate representation of aerodynamic behavior than traditional analytical or empirical models, which fail to account for the spatial variation of forces. FVM is also increasingly applied to characterize three-dimensional wind effects on tower structures. By resolving complex flow separation, wake interference, and turbulent aerodynamic loading, such simulations can provide detailed load information for subsequent structural-response analysis (Phan

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et al., 2025; Zhou et al., 2025b). Additionally, FVM's integration with structural solvers enhances the modeling of wind-ice interactions by applying time-dependent pressure distributions as spatially varying loads in finite element models. This approach improves accuracy over traditional uniform wind pressure models, offering a more realistic depiction of forces acting on iced OHTLs and towers during extreme weather events (van den Berg et al., 2018; Makarov et al., 2022). Thus, FVM plays a pivotal role in advancing the study of ice-wind interactions, providing essential insights into the dynamic behavior and safety of TTLS.

4 Stochastic and statistical methods

Stochastic and statistical methods are fundamental to capturing the uncertainties inherent in ice–wind hazards and their effects on the dynamic response of TTLS (Brown, 2007; Li, 2023). Unlike deterministic analyses that rely on fixed load and structural parameters, stochastic approaches explicitly account for the probabilistic nature of atmospheric icing, wind excitation, and the variability of material and geometric properties. This probabilistic representation enables the quantification of response variability, the assessment of low-probability and high-consequence events, and the evaluation of system reliability under compound hazard scenarios. A wide range of methods, including MCSs (Dikshit and Alipour, 2025; Sanabria and Cechet, 2010), RFMs (Mantelli et al., 2016; Wang et al., 2022b), SAMs (Zhao et al., 2025b; Lin et al., 2025), RSMs (Gao et al., 2023; Zhao et al., 2023), and TSMs (Wei et al., 2012; Yang et al., 2025b), have been developed to capture different aspects of uncertainty propagation and system response characteristics. The following subsections summarize these methodological developments, explain their theoretical foundations and computational features, and review their applications and limitations in the dynamic analysis of TTLS subjected to ice-wind hazards.

4.1 Monte Carlo simulation

MCS is a powerful probabilistic method used to quantify uncertainties in complex systems, particularly in scenarios involving highly variable or nonlinear behavior (Sengupta and Chakraborty, 2022; Ding et al., 2024). In the context of tower-line systems subjected to ice–wind hazards, it is employed to model the inherent uncertainty in both environmental loads, such as fluctuating wind speeds and ice accumulation (Hammer et al., 2024), and system properties, including material strengths and geometrical configurations. By generating random samples from predefined probability distributions for the key input variables, MCS provides a robust framework for estimating the distribution of system responses, including stress, displacement, and failure probabilities, across a range of possible hazard scenarios (Hu et al., 2022; Zhou et al., 2025a; Li et al., 2023b). This approach is particularly advantageous when addressing the combined and often unpredictable effects of ice and wind, which can interact in nonlinear ways that are difficult to capture through deterministic methods. In structural reliability analysis, MCS has proven effective for evaluating the performance of tower-line system components under extreme load conditions (Lannoye et al., 2012; Gupta and Verma, 2024). However, due to its computational intensity, especially for large-scale tower-line systems with numerous uncertain variables, MCS often requires the use of high-performance computing resources.

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4.2 Random field modeling

Modeling the spatial variability of environmental factors such as wind speed, ice accumulation, and temperature enables the characterization of how ice–wind hazards affect TTLS. RFMs such as Gaussian random fields (Berild and Fuglstad, 2023; Hörning and Bárdossy, 2025) and Markov random fields (Balram and Moura, 1993; Gioffrè and Gusella, 2002) are commonly used to represent spatial dependence and correlation. For extended tower-line corridors, such representations provide a natural framework for describing spatially varying environmental loads across multiple spans. Challenges arise from the computational demand associated with large systems and from the selection and calibration of stochastic processes. Advances in computational resources and statistical methods have improved the feasibility of RFM-based assessments in large-scale structural systems.

4.3 Spectral analysis method

SAMs generally include power spectral density (PSD), Fourier transform (FT), wavelet analysis, cross-spectral analysis, and frequency response function evaluation, all of which are used to characterize the frequency-domain properties of stochastic loads and structural responses. Comparing the frequency content of external loads with the system's natural frequencies helps identify potential resonance. For OHTLs, non-uniform ice accretion can alter structural dynamic characteristics (Ajder, 2022), while the joint action of ice shedding and wind can amplify transient responses (Lou et al., 2022). Although effective, spectral analysis is limited in handling strongly nonlinear behavior and rapidly time-varying loads, and hybrid approaches that combine spectral information with time-domain simulations or data-driven reliability analysis can improve assessment capability (Behrendt et al., 2022).

4.4 Response surface method

RSM constructs an empirical approximation of system responses using a limited set of experimental or simulation data and can therefore reduce the cost of repeated high-fidelity analyses. In TTLS applications, such a surrogate can be used for sensitivity analysis, parameter screening, and reliability-oriented calculations once a representative training design has been generated. Response-surface and related surrogate strategies have been widely developed for structural reliability and optimization (Gao et al., 2023; Zhao et al., 2023; Zhang et al., 2022b). However, the accuracy of RSM decreases when system behavior is highly nonlinear or exhibits discontinuities, in which case higher-fidelity surrogate or adaptive sampling strategies may be required.

4.5 Time series method

TSMs are used to model temporal evolution and to analyze historical observations for identifying patterns and forecasting environmental or structural variables (Dudek et al., 2025; Unlu and Peña, 2025). Classical statistical and hybrid forecasting models have been widely applied to wind-speed prediction; for example, Zhang et al. (2020) developed an adaptive hybrid model for short-term wind-speed forecasting. Stochastic time-series representations can also capture temporal dependence in environmental variables, as illustrated by spatio-temporal wind-speed models (Mao and Rychlik, 2018). Although data-driven

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methods offer advantages for complex nonlinear sequences, conventional TSMs remain valuable for long-term assessment and for applications with limited data. For irregular and non-stationary ice–wind processes, combining time-series analysis with stochastic simulation or spectral information provides a practical route to improve predictive robustness.

A systematic comparison of stochastic and statistical methods reviewed above is provided in Table 2. It summarizes their fundamental principles, typical applications in TTLS under ice–wind hazards, as well as their respective strengths and limitations. This synthesis highlights the complementary nature of these methods: while some methods are effective in capturing probabilistic variability across multiple sources of uncertainty, others excel in addressing spatial heterogeneity, frequency-domain characteristics, design optimization, or temporal dependencies.

Table 2. Summary of stochastic and statistical methods for TTLS dynamic response under ice-wind hazards.

Principle	Representative applications	Strengths	Limitations
MCS Random sampling to model uncertainty	a. Reliability of lines/substations; b. Ice-wind failure probability.	a. Handles uncertainties; b. Conceptually simple; c. Widely applicable.	a. High computation
RFM Models spatial variability and correlation	a. Large-scale spatial load analysis	a. Captures spatial heterogeneity; b. Regional-scale analysis.	a. Data-intensive; b. Computationally heavy.
SAM Frequency-domain analysis for resonance	a. Iced-conductor vibration; b. Wind-induced resonance.	a. Resonance identification; b. Clear physical interpretation.	a. Limited for nonlinear or non-stationary cases
RSM Surrogate modeling for sensitivity/optimization	a. Structural optimization; b. Key parameter identification.	a. Low computational cost; b. Multi-parameter optimization.	a. Lower accuracy for strong nonlinearity
TSM Models temporal evolution and dependence	a. Forecasting response trends	a. Captures time correlation; b. Supports long-term prediction.	a. Limited by nonlinearity or insufficient data

5 AI-based methods

Analytical, numerical, stochastic, and statistical methods have long formed the core tool for examining the dynamic response of TTLS under ice–wind hazards, offering physically interpretable descriptions of loading mechanisms and structural behavior. Despite their fundamental importance, these conventional approaches often face challenges in capturing pronounced nonlinearities, multi-factor coupling effects, and the rapidly increasing volume of monitoring and simulation data. Recent advances in AI provide a complementary data-driven paradigm capable of learning complex response patterns directly from high-dimensional datasets, thereby enabling efficient surrogate modeling (Peng et al., 2021a; Koutsoupakis and Giagopoulos, 2023; Birky et al.,

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2022), damage assessment (Mishra et al., 2020; Zhang et al., 2022a), and probabilistic prediction (Dong et al., 2021; Ye et al., 2021). Emerging applications in structural and wind engineering further demonstrate the potential of AI-based techniques to enhance the representation of ice accretion, wind-induced excitation, and their joint influence on system performance. This section reviews current developments in ML, DL, and PIML, with emphasis on their contributions to improving the analysis and prediction of dynamic responses under coupled hazards.

5.1 Machine learning method

ML methods are increasingly applied to construct surrogate models for predicting the nonlinear dynamic response of iced tower-line components subjected to variable wind and icing conditions. Regression-based methods, particularly support vector regression (SVR) and Gaussian process regression (GPR), have demonstrated strong capability in representing high-dimensional input-output relationships while offering probabilistic estimates useful for uncertainty propagation (Peng et al., 2021b; Gong et al., 2025; Yoshikawa and Iwata, 2023). Ensemble learning algorithms such as random forests (RFs) and gradient boosting (GB) are employed to infer ice accretion characteristics from meteorological variables, and consistently outperform traditional empirical formulations in recent studies of atmospheric icing and wind-structure interaction (Meehan et al., 2023; Rahman et al., 2024). Unsupervised learning approaches, including K-means and hierarchical clustering, support the identification of representative combined loading patterns from long-term monitoring datasets, facilitating reduced but physically meaningful hazard scenarios for dynamic analysis (Hao et al., 2019; Yang and Li, 2023). In parallel, classification and clustering tools can support scenario screening and condition evaluation when monitoring data are sparse or affected by operational noise. These advances highlight the growing role of ML in surrogate prediction, scenario extraction, and condition evaluation for ice-wind-structure interaction problems.

5.2 Deep learning method

Building on the capabilities of traditional ML models while addressing their limitations in capturing highly nonlinear spatial–temporal dependencies, DL methods provide a flexible framework for ice–wind-related prediction problems. Convolutional neural networks (CNNs) have been applied to transmission-line icing data (Li et al., 2022), enabling automatic extraction of hierarchical features without extensive manual feature engineering. Recurrent architectures such as long short-term memory (LSTM) networks and related sequence models have shown strong performance in modeling time-dependent icing evolution and sequential monitoring data (Chen et al., 2025b; Wang and Ma, 2025). Autoencoders and encoder–decoder networks are adopted for dimensionality reduction and surrogate modeling of large-scale simulation datasets, allowing efficient prediction across varying flow or loading states (Francés-Belda et al., 2024). Graph neural networks (GNNs) have also been explored for graph-structured reliability assessment in power systems (Park et al., 2024), suggesting a route for explicitly representing connectivity and load paths in future TTLS applications. Transfer learning has been investigated for transmission-line dynamic thermal rating (Paldino et al., 2024), indicating its potential when labeled field data are limited. These developments collectively highlight the advantages of DL in modeling multi-scale nonlinearities and spatial–temporal complexity, while direct applications to TTLS dynamic response under coupled ice–wind hazards remain comparatively limited.

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5.3 Preliminary exploration of PIML

PIML has emerged as a promising framework for enhancing the physical consistency of data-driven models, particularly in scenarios where limited observations, extrapolation requirements, or the need to enforce governing equations poses challenges for conventional ML and DL approaches. In structural and fluid dynamics research, physics-informed neural networks (PINNs) have demonstrated that incorporating equilibrium conditions, boundary constraints, and energy conservation principles into the learning objective can substantially improve predictive robustness under sparse-data conditions (Cai and Wang, 2024; Shukla et al., 2025; Koo and Rahnemoonfar, 2024).

Within the context of ice-wind-structure interaction, PIML can provide a systematic means for combining deterministic models of aerodynamic loading, icing accretion processes, and structural dynamic equations with field observations and high-fidelity simulations. Such hybridization narrows the hypothesis space of neural models, enhances the physical interpretability of predictions, and improves generalization across rarely observed or extreme loading combinations. Emerging developments in neural operators and graph-based learning further expand this capability by enabling the incorporation of discretized physics and structural topology into the model architecture, which is particularly advantageous for transmission towers and conductor systems whose dynamic responses depend strongly on connectivity and load-path characteristics. Evidence from wind-induced structural-response prediction suggests that embedding governing dynamics can improve physical consistency and prediction stability (Chen et al., 2025a). Although applications of PIML to TTLS remain preliminary, current findings indicate substantial potential for developing predictive models that achieve a more effective balance between data-driven flexibility and the enforcement of mechanical consistency.

To facilitate a clearer comparison among the AI-based methods discussed in Sections 5.1-5.3, Table 3 provides a concise summary of three major categories: ML, DL, and PIML. The table outlines representative techniques within each category along with their main advantages and limitations, offering a structured overview of how these methods contribute to dynamic response analysis under ice-wind hazards.

Abbreviations: PCA – principal component analysis; SVM – support vector machine; GRU – gated recurrent unit; RNN – recurrent neural network; GCN – graph convolutional network; FNO – Fourier neural operator; BEM – boundary element method.

6 Summary and implications

The methods reviewed in Sections 2 to 5 exhibit distinct advantages and inherent limitations in representing the dynamic response of TTLS under ice–wind hazards, reflecting the diverse modeling philosophies and levels of physical fidelity across analytical, numerical, stochastic and statistical, and AI-based methods. Section 6.1 provides an integrated summary of these methodological categories, while Section 6.2 discusses their implications for enhancing tower-line system resilience.

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Table 3. Summary of AI-based methods for TTLS dynamic response under ice-wind hazards.

Method	Category	Representative techniques	Strengths	Limitations
ML	Supervised regression	SVR, GPR, RF, GB	✓ Handles nonlinear regression ✓ GPR provides uncertainty quantification	✓ Limited ability to represent spatial–temporal patterns ✓ Requires feature engineering
	Unsupervised learning	K-means, Hierarchical clustering, PCA	✓ Facilitates scenario reduction and pattern characterization	✓ Lacks direct predictive ability ✓ Performance sensitive to input normalization and scaling assumptions
	Classical classifiers	SVM, Logistic regression, Ensemble classifiers	✓ Robust to small datasets ✓ Interpretable decision boundaries	✓ Requires manually crafted features ✓ Limited in high-dimensional dynamics
DL	Convolutional architectures	CNN, 2D/3D CNN, ResNet	✓ Strong in capturing spatial correlations ✓ Enables automatic hierarchical feature extraction	✓ Requires sizable datasets ✓ Limited physical interpretability
	Sequence models	LSTM, GRU, RNN	✓ Learns long-term temporal dependencies ✓ Effective for sequential monitoring data	✓ Struggles with long-sequence stability ✓ May overfit noisy data
	Autoencoder-based models	Autoencoder, Encoder–decoder architectures	✓ Compresses high-dimensional data ✓ Supports construction of reduced-order representations	✓ Latent space not necessarily physically meaningful
	Graph-based learning	GNN, GCN	✓ Incorporates structural connectivity and load paths explicitly	✓ Requires careful graph construction ✓ Limited by current benchmark datasets
PIML	PINNs	PINN, Variational PINN	✓ Maintains physical consistency with limited data	✓ Training instability ✓ Sensitive to PDE weighting
	Neural operators	DeepONet, FNO	✓ Learns operators rather than point-wise mappings ✓ Efficient for parametric sweeps	✓ Requires curated simulation datasets ✓ Interpretability still evolving
	Hybrid ML–physics	DL integrated with FEM/BEM, Surrogate-enhanced simulators	✓ Improves extrapolation and physical plausibility ✓ Reduces simulation cost	✓ Integration complexity ✓ Domain-specific tuning needed

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6.1 Summary of existing methods

To synthesize the method differences identified in the preceding sections, a comparative framework is established based on several evaluation dimensions, including physical interpretability, computational efficiency, applicability to nonlinear and multi-physics coupling, data requirements, and suitability for rare-event prediction. These dimensions provide a consistent basis for assessing the relative strengths and limitations of these methods. A consolidated comparison based on these criteria is presented in Table 4.

Table 4. Comparison of existing methods for TTLS dynamic response under ice-wind hazards.

Category	Core methods	Strengths	Limitations
Category 1	Linear analytical and nonlinear mechanics-based	✓ High physical interpretability ✓ Fast computation ✓ Suitable for mechanism exploration	✓ Applicable only to simplified geometries ✓ Limited capability for strong nonlinearity or multi-physics coupling
Category 2	FEM, FDM, FVM	✓ High-fidelity modeling of aerodynamics, ice accretion, and structural dynamics ✓ Applicable to complex configurations	✓ Computationally intensive, especially for long-duration time-history and probabilistic simulations ✓ Requires detailed parameters
Category 3	MCS, RFM, SAM, RSM, TSM	✓ Quantifies uncertainty in ice growth, wind variability, and structural response ✓ Supports probabilistic assessment	✓Accuracy depends on assumed distributions ✓ Limited physical interpretability
Category 4	ML, DL, PIML	✓ Efficient nonlinear surrogate modeling ✓ Hierarchical spatial–temporal learning and high-dimensional representation	✓ Require extensive data or feature engineering ✓ Limited physical interpretability ✓ Potential overfitting ✓ High training complexity and sensitivity to physics-based constraints in advanced AI models

A qualitative cobweb comparison is further adopted to extend Table 4 and visualize the relative profiles of the reviewed methods within a unified multi-dimensional framework. The model employs axes radiating from a common origin, each corresponding to one evaluation indicator, and each method is mapped onto these axes according to its relative performance level, forming a characteristic envelope that reflects its overall capability. For dynamic response analysis under ice–wind hazards, six indicators are selected: (1) physical interpretability; (2) nonlinear capability; (3) multi-physics coupling fidelity; (4) computational efficiency; (5) data requirements; and (6) rare-event suitability.

The indicator values are derived from qualitative judgments based on the methodological assessment in Sections 2–5 and normalized to a common ordinal scale for visualization. For the five performance-oriented axes, larger values indicate stronger capability; for the data-requirements axis, larger values indicate greater data demand. The diagram is therefore intended as a qualitative comparison rather than a quantitative ranking.

Fig. 4 presents the qualitative cobweb comparison of the four method categories examined in this review, namely analytical and mechanics-based methods (Category 1), numerical simulation methods (Category 2), stochastic and statistical methods (Category 3), and AI-based methods (Category 4). The radial axes correspond to six indicators relevant to TTLS dynamic

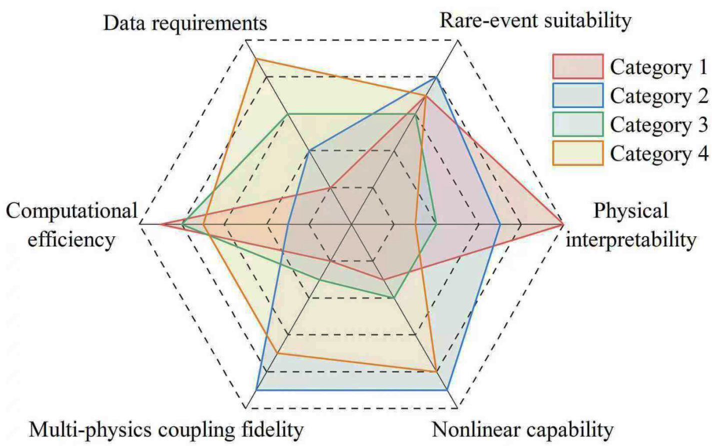

Figure 4. Qualitative cobweb comparison of four method categories for TTLS dynamic response analysis under ice-wind hazards.

response analysis under ice–wind hazards: physical interpretability, nonlinear capability, multi-physics coupling fidelity, computational efficiency, data requirements, and rare-event suitability. For the performance-oriented axes, larger radial values indicate stronger capability, whereas on the data-requirements axis a larger value denotes greater data demand. The diagram shows that Category 1 offers high interpretability and computational efficiency but is limited for strong nonlinear or multi-physics interactions. Numerical simulation methods offer high fidelity for nonlinear and coupled processes, although at considerable computational cost. Stochastic and statistical methods perform well in uncertainty quantification but depend strongly on assumed distributions and provide limited physical representation. AI-based methods show strong potential for nonlinear feature extraction and rapid surrogate prediction, although they require substantial data and offer limited physical transparency. Overall, the visual comparison clarifies the complementary strengths and weaknesses of the four categories and highlights the need to combine multiple methodological perspectives when analyzing TTLS response under ice-wind hazards.

6.2 Implications for transmission tower-line system resilience

The evolution of system functionality during an ice–wind hazard event, as illustrated in Fig. 5, provides a structured basis for examining how different method categories contribute to resilience assessment and enhancement. The characteristic trajectory comprises a preparation phase, a degradation phase driven by ice accretion and wind-induced damage, and a recovery phase that may culminate in full, degraded, or incomplete restoration. This functional evolution captures the essential dynamic features of TTLS subjected to compound environmental loading. The following subsection discusses the implications of the reviewed methods for advancing the understanding and improvement of TTLS resilience under such coupled hazards.

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6.2.1 Methodological implications for resilience assessment

The four method categories reviewed in this paper collectively advance the capacity to assess the resilience of TTLS under ice-wind hazards. Analytical and mechanics-based methods clarify the physical mechanisms that govern ice accretion, wind loading, and structural dynamics, offering transparent formulations that help identify key parameters driving fragility. Numerical simulation methods capture nonlinear behavior, aerodynamics, and the interaction between icing and high wind, enabling detailed scenario-specific evaluations that support resilience-oriented performance metrics such as residual capacity and failure progression pathways. Stochastic and statistical methods incorporate uncertainty in hazard evolution, material properties, and response variability, thereby supporting probabilistic resilience metrics including failure probability, expected functionality loss, and recovery trajectories. AI-based methods provide additional capabilities in surrogate modeling, high-dimensional pattern extraction, and data-driven inference, enabling rapid prediction of system behavior under evolving or compound loading conditions. Taken together, these methodological developments address different but mutually reinforcing aspects of hazard characterization (Panteli et al., 2017; Mujjuni et al., 2023), structural vulnerability assessment (Wei et al., 2019; Souto et al., 2024), and uncertainty quantification (Mahzarnia et al., 2020; Stankovic et al., 2023), which collectively form the foundation of resilience assessment.

6.2.2 Modeling implications under ice-wind hazards

The resilience trajectory illustrated in Fig. 5 clarifies how the four method categories contribute in complementary ways to understanding TTLS performance under ice-wind hazards. Analytical and mechanics-based methods are most effective in the preparation phase, where their mechanistic representations help identify conditions associated with the onset of degradation at t_0. Numerical simulation methods become essential in the degradation phase, capturing the nonlinear and coupled processes responsible for the sharp functionality decline between t_0 and t_1. Stochastic and statistical methods augment this analysis by quantifying the variability in degradation magnitude and timing, thereby characterizing the range of possible $q(t)$ trajectories.

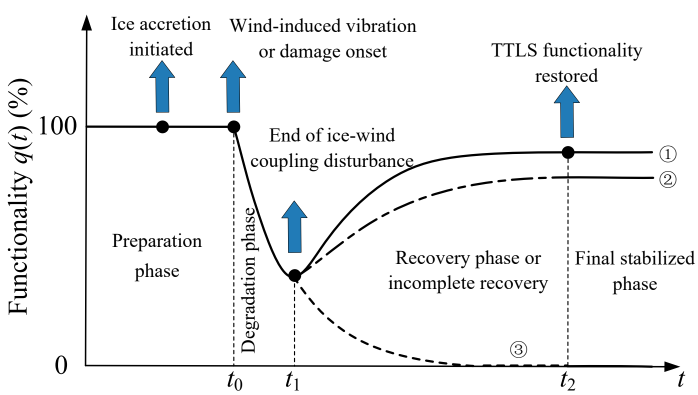

Figure 5. $q(t)$ of TTLS under ice–wind hazards, with representative recovery outcomes comprising full restoration ①, degraded restoration ②, and incomplete recovery ③.

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In the recovery phase beginning at t_2, AI-based methods provide rapid inference capabilities that support the estimation of recovery rates and the differentiation among the representative restoration paths depicted in Fig. 5, including full, degraded, and incomplete recovery. Viewed together, these methods offer complementary insights into the mechanisms, uncertainties, and temporal evolution of TTLS functionality, and their combined use provides a more comprehensive interpretation of the resilience curve than any individual method alone.

6.2.3 Strategic implications for resilience enhancement

The insights summarized above lead to several implications for enhancing the resilience of TTLS under ice-wind hazards. Analytical and stochastic models improve hazard characterization by identifying critical icing thresholds, wind excitation conditions, and joint occurrence probabilities, which are essential for defining design envelopes and operational preparedness. High-fidelity numerical simulations support both component-level and system-level resilience enhancement by revealing stress concentrations, vulnerable configurations, and structural or operational adjustments that can mitigate the rapid functionality degradation observed between t_0 and t_1. AI-based methods contribute significantly to the recovery process by enabling rapid fusion of multi-source monitoring data, accelerating damage detection, refining estimates of restoration time, and informing optimal allocation of repair resources. These capabilities directly influence the slope and duration of the recovery phase beginning at t_2, thereby improving system-wide restoration efficiency. In the longer term, hybrid modeling frameworks that integrate physics-based simulations with AI-driven inference and probabilistic modeling provide a basis for resilience enhancement. Such frameworks enable continuous updating of risk indicators and performance forecasts as new monitoring data and environmental information become available.

7 Conclusions and future work

This paper reviews the current research and development of dynamic response analysis methods for TTLS under ice-wind hazards. Analytical and mechanics-based, numerical, stochastic and statistical, and AI-based methods are summarized, and their main characteristics and research focuses are identified. Analytical and mechanics-based methods provide mechanism-based insight into structural dynamics and nonlinear behavior, while numerical simulations offer high-fidelity modeling of nonlinear and multi-physics processes. Stochastic and statistical methods play an important role in quantifying uncertainties in hazard evolution and structural responses. AI-based methods, an emerging research direction, show potential for surrogate modeling, pattern recognition, and rapid assessment, especially when combined with monitoring data.

The comparative analysis indicates that no single method can address the full complexity of ice-wind-structure interaction. Analytical and mechanics-based formulations offer physical interpretability, while high-fidelity numerical models require significant computational and modeling resources; stochastic and statistical methods additionally depend on assumptions regarding hazard and response variability. AI-based methods are expected to attract increasing interest as they can complement physics-based models and support fast prediction. Future research will likely move toward integrated modeling frameworks that combine the strengths of physical, statistical, and data-driven approaches. In addition, real-time monitoring, digital twin

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technologies, and intelligent decision-support systems are anticipated to become important trends for improving the resilience and operational reliability of TTLS under severe ice-wind conditions.

Data availability. No new experimental data, numerical models, or code were generated in this review.

Author contributions. BQ conceived the review and drafted the manuscript. YL contributed to literature investigation, methodological organization, and manuscript revision. MB supervised the work and critically revised the manuscript. All authors approved the final manuscript.

Competing interests. The authors declare that they have no conflict of interest.

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