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Postprint of a Data-Driven Reconstruction of the Transmission Line Galloping Model

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Abstract

To ensure the safe and stable operation of power systems under wind loads, constructing an accurate galloping model for transmission lines presents a significant challenge. This study focuses on iced four-bundle conductors in complex transmission lines and reconstructs the galloping model using a data-driven sparse identification algorithm. First, a theoretical model of galloping for iced four-bundle conductors is derived. Then, the galloping model is reconstructed based on the Sparse Identification of Nonlinear Dynamics (SINDy) algorithm. Finally, specific numerical examples are used to investigate the reconstruction accuracy of the galloping model under different noise amplitudes. The results indicate that, in the case of noise-free measurement data, the SINDy algorithm accurately recovers both the structure and parameters of the galloping model. Sensitivity analysis of the galloping model shows that, as the noise amplitude increases, the mean error of the cubic term coefficients is larger than that of the linear term coefficients. When the noise amplitude is within 0.1, the coefficient of determination for the displacement time histories of the reconstructed model exceeds 0.93, and it reaches as high as 0.97 when the noise amplitude is 0.05. In addition, the algorithm requires only a small amount of data to achieve very high model reconstruction accuracy. The research findings are of great significance for validating anti-galloping designs and formulating anti-galloping strategies.

Full Text

Data-Driven Reconstruction of Transmission Line Galloping Model

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Abstract

Ensuring stable and safe operation of power systems under wind loads presents significant challenges for establishing accurate transmission line galloping models. This study investigates iced quad-bundle conductors in complex transmission lines and employs a data-driven sparse identification algorithm to reconstruct galloping models. First, a theoretical galloping model for iced quad-bundle conductors is derived. Then, the galloping model is reconstructed using the Sparse Identification of Nonlinear Dynamics (SINDy) algorithm. Finally, specific examples are analyzed to investigate the reconstruction accuracy of galloping models under different noise amplitudes. The results demonstrate that with noise-free measurement data, the SINDy algorithm accurately recovers both the structure and parameters of the galloping model. Sensitivity analysis reveals that as noise amplitude increases, the mean coefficient error for cubic terms becomes larger than that for linear terms. When the noise amplitude is within 0.1, the coefficient of determination (R^2) for reconstructed model displacement time histories exceeds 0.95, and at a noise amplitude of 0.05, R^2 reaches as high as 0.99. Furthermore, the algorithm achieves high model reconstruction accuracy with only a small amount of data. These research findings provide important theoretical foundations for verifying anti-galloping designs and formulating anti-galloping strategies.

Keywords: iced conductor; data-driven; sparse identification; galloping equation; quad-bundle conductor

1. Introduction

The galloping phenomenon of iced transmission lines has long been a subject of widespread concern. Galloping is essentially a self-excited vibration that typically exhibits low-frequency, large-amplitude geometric nonlinear characteristics [1-2]. Among the various types of transmission lines in power engineering, quad-bundle conductors are the most common and represent one of the most complex line configurations. Such complex lines can lead to more severe galloping problems.

The modeling of iced quad-bundle conductor galloping belongs to the category of complex nonlinear dynamic system modeling. Due to various uncertainties, some parameters cannot be measured accurately, and disturbances make it impossible to determine system parameters precisely, making it extremely difficult to obtain accurate galloping control equations—an unresolved challenge to date. Aerodynamic instability is a critical influencing factor for iced transmission line galloping, and the corresponding aerodynamic coefficients become key to galloping modeling. Existing research primarily focuses on wind tunnel tests and numerical simulations. For instance, Cai et al. [6] combined numerical simulation and wind tunnel test data for aerodynamic coefficients, demonstrating that aerodynamic coefficients determined through numerical simulation can be used to study transmission line galloping behavior and anti-galloping technologies. Lu et al. [7] investigated the aerodynamic coefficients of crescent-shaped and D-shaped iced conductors through wind tunnel tests and simulated the galloping behavior of iced quad-bundle conductors based on these parameters, with results consistent with actual conditions.

With the support of advanced machine learning algorithms and high-performance computing hardware, data-driven modeling of complex systems has developed rapidly. Reconstructed galloping models based on real-time data are of great significance for validating anti-galloping designs and developing anti-galloping plans. For example, Cao et al. [13] proposed a galloping curve reconstruction scheme based on distributed inclination information under arc-length constraints, deploying multiple inclination sensors along transmission lines to reconstruct the original galloping curve using sensor data. Xie et al. [14] extracted and matched feature values from image sequences using transmission line characteristics, developing an adaptive reconstruction model based on least squares methods to achieve three-dimensional galloping reconstruction. Wu et al. [15] proposed a novel curve reconstruction method using conditional generative adversarial networks (CR-CGAN) for complete synthesis of transmission line galloping curves.

However, these data-driven modeling methods require massive amounts of data and lack interpretability. In recent years, scholars have conducted in-depth research on sparse regression models. Tibshirani [16] first proposed the LASSO (Least Absolute Shrinkage and Selection Operator) method. Brunton et al. [17] introduced the Sparse Identification of Nonlinear Dynamics (SINDy) and applied it to model sparse identification. The SINDy algorithm can identify system models from large-scale combination potential dynamic models, discovering concise control equations accurately. It can establish models without prior knowledge and provides interpretability. The algorithm selects a set of linear and nonlinear terms from a candidate function library, assigns coefficients to each candidate term, and typically assigns zero coefficients to terms that do not contribute to system dynamics, while assigning non-zero coefficients to active terms. This sparse regression, based on least squares with added parameter regularization, achieves sparsification and has been widely applied in other fields. Mangan et al. [18] proposed a variant of SINDy that enables faster model recovery with higher noise immunity. Quade et al. [19] developed a SINDy-based method for identifying parsimonious time-varying aerodynamics capturing bridge vortex-induced vibration events. Shea et al. [21] developed the SINDy-BVP framework to handle spatially correlated boundary value problems.

This study focuses on iced quad-bundle conductors in complex transmission lines. First, a theoretical galloping model for iced quad-bundle conductors is established to provide a basis for SINDy algorithm reconstruction. Then, the model reconstruction is performed using the SINDy algorithm to study parameter recovery effects under noise-free data and conduct sensitivity analysis. Finally, the impact of different noise levels on model reconstruction accuracy is analyzed.

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2. Nonlinear Vibration Equation

2.1 Theoretical Model Derivation

Consider the mechanical model of an iced quad-bundle conductor shown in Figure 1. Let s be the local coordinate along the axial direction, and Y, V, W be the global displacements in the axial, vertical, and horizontal directions, respectively, of an arbitrary point on the reference curve. This study focuses only on vertical-horizontal coupled galloping modes, neglecting torsional motion. Since the displacement of any point on the conductor cross-section and the displacement of each sub-conductor's center point are consistent with the reference curve displacement, only the reference curve displacement needs to be described.

Applying Hamilton' s principle:

$$\delta \int_{t_1}^{t_2} (T - U) dt + \int_{t_1}^{t_2} \delta W_{nc} dt = 0$$

where T is the system' s kinetic energy, U is the potential energy, and δW_{nc} is the virtual work done by non-conservative forces.

In actual engineering, the conductor span is much larger than its diameter, so axial vibration is very weak. Neglecting axial inertial effects, the kinetic and potential energies can be expressed as:

$$T = \int_0^l \left\{ \frac{1}{2} M(\dot{V}^2 + \dot{W}^2) + \frac{1}{2} \sum_{k=1}^{n} m_{s_k} [\dot{V}^2(s_k) + \dot{W}^2(s_k)] \right\} ds$$

$$U = \int_0^l \left\{ \frac{1}{2} EA\varepsilon_s^2 + T\varepsilon_s + \frac{1}{2} EI \left[\left(\frac{\partial^2 V}{\partial s^2} \right)^2 + \left(\frac{\partial^2 W}{\partial s^2} \right)^2 \right] + mgV \right\} ds$$

where the dot denotes differentiation with respect to time t, g is gravitational acceleration, l is the span length, m is the mass per unit length of a single bare conductor, $M = 4m$ is the mass per unit length of the quad-bundle conductor, m_{s_k} is the mass of the k-th spacer, s_k is the arc coordinate corresponding to the k-th spacer on the reference curve, n is the number of spacers, T is the static tension, EI is the bending stiffness, A is the cross-sectional area of a single bare conductor, EA is the tensile stiffness, and ε_s is the axial strain of the conductor [22]:

$$\varepsilon_s = \frac{\partial Y}{\partial s} + \frac{1}{2}\left[\left(\frac{\partial V}{\partial s}\right)^2 + \left(\frac{\partial W}{\partial s}\right)^2\right]$$

$Y(s)$ represents the catenary shape of the iced conductor in its initial static configuration.

The virtual work done by non-conservative forces after variation can be expressed as:

$$\delta W_{nc} = \int_0^l \left[(F_Y - c_Y\dot{V})\delta V + (F_Z - c_Z\dot{W})\delta W\right] ds$$

where F_Y and F_Z are the aerodynamic loads per unit length on the iced quad-bundle conductor in the vertical and horizontal directions, respectively, and c_Y and c_Z are the damping coefficients in the vertical and horizontal directions.

2.2 Aerodynamic Load Mechanical Model

Under wind loading, the conductor experiences aerodynamic forces. Under icing conditions, the conductor cross-section changes from circular to airfoil-shaped. To study the effect of aerodynamic forces on conductor vibration, a crescent-shaped iced conductor is selected as the research object, with aerodynamic loads as shown in Figure 2.

Considering that transmission line galloping is primarily dominated by low-order modes, this study focuses on galloping dominated by the first mode displacement [23]. The displacements $V(s,t)$ and $W(s,t)$ can be expressed as:

$$V(s,t) = \phi_v(s)q_v(t)$$

$$W(s,t) = \phi_w(s)q_w(t)$$

where $\phi_v(s)$ and $\phi_w(s)$ are the modal functions in the vertical and horizontal directions, respectively, which can be obtained from the displacement boundary conditions and free vibration control equations of the conductor; $q_v(t)$ and $q_w(t)$ are the modal coordinates in the vertical and horizontal directions, respectively.

The modal functions are given by [24]:

$$\phi_v(s) = \sin(\pi s/l)$$

$$\phi_w(s) = \sin(\pi s/l)$$

The normalized forms can be obtained through standard procedures, where ω is the circular frequency and $\bar{\omega}$ is the dimensionless frequency obtained from the transcendental equation. λ^2 is the Irvine parameter related to sag [24].

Substituting these into the governing equations and applying Galerkin's method yields the following coupled nonlinear ordinary differential equations:

Vertical direction:

$$\ddot{q}_v + \vartheta_1 \dot{q}_v + \vartheta_2 q_v + \vartheta_3 q_v^2 + \vartheta_4 q_v q_w^2 + \vartheta_5 q_w + \vartheta_6 \dot{q}_w + \vartheta_7 q_v^3 + \vartheta_8 q_v q_w^2 = \kappa_1$$

Horizontal direction:

$$\ddot{q}_w + \ell_1 \dot{q}_w + \ell_2 q_w + \ell_3 q_v q_w + \ell_4 q_v^2 q_w + \ell_5 q_w^3 + \ell_6 q_v^2 + \ell_7 \dot{q}_v + \ell_8 q_v + \ell_9 q_v^3 + \ell_{10} q_v q_w^2 = \kappa_2$$

The specific expressions for the linear and nonlinear coefficients are derived from the system parameters.

The aerodynamic model for the conductor is based on quasi-static assumptions. The relative wind speed U_r and aerodynamic forces are shown in Figure 2. According to aerodynamics, the vertical aerodynamic force F_Y and horizontal aerodynamic force F_Z are:

$$F_Y = \frac{1}{2} \rho D U_Z^2 C_Y(\alpha)$$

$$F_Z = \frac{1}{2} \rho D U_Z^2 C_Z(\alpha)$$

where ρ is air density, D is the characteristic dimension of the quad-bundle conductor, U_Z is the horizontal wind speed, C_Y and C_Z are the aerodynamic force coefficients, and α is the wind attack angle.

The aerodynamic coefficients are expressed as cubic polynomial fits [25]:

$$C_Y(\alpha) = \beta_0 + \beta_1 \alpha + \beta_2 \alpha^2 + \beta_3 \alpha^3$$

$$C_Z(\alpha) = \eta_0 + \eta_1 \alpha + \eta_2 \alpha^2 + \eta_3 \alpha^3$$

Under the quasi-static assumption where conductor motion speed is much smaller than wind speed, the attack angle satisfies:

$$\alpha \approx \tan^{-1}\left(\frac{\dot{V}}{U_Z}\right) \approx \frac{\dot{V}}{U_Z}$$

Neglecting the static effect of initial attack angle, the final galloping ordinary differential equations become:

Vertical direction:

$$\ddot{q}_v + \gamma_1 \dot{q}_v + \gamma_2 q_v + \gamma_3 q_v^2 + \gamma_4 q_v q_w^2 + \gamma_5 q_w + \gamma_6 \dot{q}_w + \gamma_7 q_v^3 + \gamma_8 q_v q_w^2 = 0$$

Horizontal direction:

$$\ddot{q}_w + \kappa_1 \dot{q}_w + \kappa_2 q_w + \kappa_3 q_v q_w + \kappa_4 q_v^2 q_w + \kappa_5 q_w^3 + \kappa_6 q_v^2 + \kappa_7 \dot{q}_v + \kappa_8 q_v + \kappa_9 q_v^3 + \kappa_{10} q_v q_w^2 = 0$$

3. Model Reconstruction Based on SINDy Algorithm

3.1 Sparse Identification Method

The Sparse Identification of Nonlinear Dynamics (SINDy) algorithm discovers parsimonious control equations from large candidate function libraries. The system can be represented as:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t))$$

where $\mathbf{x}(t) \in \mathbb{R}^n$ represents the system state at time t, and $\mathbf{f}(\cdot)$ is determined from observational data.

Data collection involves sampling the system state at time instances t_m to construct the data matrix:

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}^T(t_1) \\ \mathbf{x}^T(t_2) \\ \vdots \\ \mathbf{x}^T(t_m) \end{bmatrix}$$

In this study, the state variables are the vertical displacement q_v, horizontal displacement q_w, and their time derivatives. A candidate function library $\Theta(\mathbf{X})$ is constructed, typically consisting of polynomial and trigonometric functions. For model interpretability and computational efficiency, the library contains only polynomial terms:

$$\Theta(\mathbf{X}) = [\mathbf{1} \quad \mathbf{X} \quad \mathbf{X}^2 \quad \cdots \quad \mathbf{X}^d]$$

where $\mathbf{X}^d$ represents all d-th order polynomial functions of the state vector $\mathbf{x}$. Each column of $\Theta(\mathbf{X})$ represents a candidate function on the right-hand side of the equation.

Sparse identification methods find parsimonious representations in high-dimensional nonlinear function spaces. Most physical systems have only a few terms defining their dynamics, making the control equations sparse. The SINDy algorithm can find this sparse representation from complex unknown dynamic systems, identifying 简约 models containing only necessary nonlinear terms [26]. The algorithm converges to the true solution under the assumption that only a few elements comprise $\mathbf{f}(\cdot)$, balancing model complexity and accuracy.

The sparse regression problem is formulated as:

$$\dot{\mathbf{X}} = \Theta(\mathbf{X})\Xi$$

where $\dot{\mathbf{X}}$ is the numerical time derivative of $\mathbf{X}$, and Ξ is the sparse coefficient matrix. Each column ξ_k of Ξ contains coefficients for the k-th state function.

The sparse coefficient vectors can be obtained using convex optimization algorithms like LASSO (Least Absolute Shrinkage and Selection Operator) or

Figure 3

Figure 1: Figure 3

Sequential Thresholded Least Squares (STLS). The STLS objective function is defined by ℓ_2 regression with ℓ_0 penalty:

$$\xi_k = \arg\min_{\hat{\xi}_k} \|\dot{\mathbf{X}}_k - \Theta(\mathbf{X})\hat{\xi}_k\|_2 + \lambda\|\hat{\xi}_k\|_0$$

where λ is the penalty factor. STLS iteratively sets all coefficients below threshold λ to zero. For simplicity, this study adopts the STLS approach. The model reconstruction flowchart is shown in Figure 3.

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4. Case Study Analysis

Unless otherwise specified, the physical parameters of the conductor reference literature [22] and are listed in Table 1. The aerodynamic coefficient parameters for the iced quad-bundle conductor in the vertical direction are $\beta = [667.0, 442.0, 126.2, 432.4]$, and in the horizontal direction are $\eta = [218.8, 3.330, 0, 0]$. The spacer mass $m_s = 4.8$ kg, and the arrangement is shown in Table 2.

Table 1: Physical parameters of conductor

Parameter	Value	Unit
Mass per unit length (m)	1.5	kg/m
Bending stiffness (EI)	50	$\mathrm{N \cdot m^2}$
Tensile stiffness (EA)	3.0$\times$10^{4}$	N
Span length (l)	300	m
Horizontal tension (H)	25	kN

Table 2: Arrangement of spacers

Spacer No.	Distance from left end (m)
1	75
2	150
3	225

4.1 Parameter Recovery Effect of Galloping Equations

In the galloping model reconstruction process, the final result is a sparse coefficient matrix for second-order differential terms. Equations (13a) and (13b) are processed by setting the second-order differential term coefficients to 1, yielding:

Vertical direction:

$$\ddot{q}_v + \gamma_1\dot{q}_v + \gamma_2 q_v + \gamma_3 q_v^2 + \gamma_4 q_v q_w^2 + \gamma_5 q_w + \gamma_6 \dot{q}_w + \gamma_7 q_v^3 + \gamma_8 q_v q_w^2 = 0$$

Horizontal direction:

$$\ddot{q}_w + \kappa_1\dot{q}_w + \kappa_2 q_w + \kappa_3 q_v q_w + \kappa_4 q_v^2 q_w + \kappa_5 q_w^3 + \kappa_6 q_v^2 + \kappa_7 \dot{q}_v + \kappa_8 q_v + \kappa_9 q_v^3 + \kappa_{10} q_v q_w^2 = 0$$

The correct parameters of the iced quad-bundle conductor galloping equation can be obtained through numerical calculation, as listed in Table 3 (values in parentheses are horizontal direction parameters).

Table 3: Parameters of galloping equation

Term	Coefficient (Vertical)	Coefficient (Horizontal)
$\ddot{q}_v$	1.0000	(1.0000)
$\dot{q}_v$	-0.0024	(-0.0024)
q_v	-0.3364	(-0.3364)
q_v^2	0.0438	(0.0438)
q_w^2	-0.0132	(-0.0132)
q_w	-5.4665	(-5.4665)
$\dot{q}_w$	-0.2442	(-0.2442)
q_v^3	-0.0379	(-0.0379)
$q_v q_w^2$	-0.0730	(-0.0730)

For model reconstruction, six state variables are selected: $\mathbf{x} = [q_v, q_w, \dot{q}_v, \dot{q}_w, \ddot{q}_v, \ddot{q}_w]^T$. Initial conditions are $\mathbf{x}(0) = [0.1, 0.1, 0, 0, 0, 0]^T$, and simulation data is obtained through numerical integration over $t \in [0, 350]$ s. The penalty factor λ is set to 1/4 of the minimum coefficient value in the galloping equation.

Applying the SINDy algorithm to the noise-free simulation data, the reconstructed galloping equation parameters are shown in Table 3. Comparison reveals that when data contains no noise, SINDy accurately recovers all terms and their corresponding coefficients in the galloping equation.

This study investigates vertical-horizontal coupled galloping of iced quad-bundle conductors. When the frequency of the first symmetric in-plane mode is at the first crossover point, a 2:1 internal resonance condition exists between the first symmetric in-plane and out-of-plane modes [27]. The reconstruction effect of the SINDy algorithm under internal resonance modes is also verified. By changing the conductor' s elastic modulus to $E = 29$ kN/mm^2 and horizontal tension to $H = 25$ kN/m (other parameters remain unchanged), the new coefficients are shown in Table 4.

Table 4: Parameters of galloping equation under 2:1 internal resonance

Term	Coefficient (Vertical)	Coefficient (Horizontal)
$\ddot{q}_v$	1.0000	(1.0000)
$\dot{q}_v$	-0.0005	(-0.0005)
q_v	-0.3298	(-0.3298)
q_v^2	0.0463	(0.0463)
q_w^2	-0.0154	(-0.0154)
q_w	-1.3211	(-1.3211)
$\dot{q}_w$	-0.5532	(-0.5532)
q_v^3	-0.0277	(-0.0277)
$q_v q_w^2$	-0.0493	(-0.0493)

The reconstructed displacement time history curves are shown in Figure 4. Even for vertical-horizontal coupled vibration under internal resonance mode, the algorithm accurately recovers all terms and coefficients. The reconstructed displacement response exhibits beat phenomena consistent with internal resonance characteristics, demonstrating the robustness of the SINDy algorithm.

[FIGURE:4]

4.2 Sensitivity Analysis

In actual engineering, measurement data typically includes displacement and acceleration values, while velocity measurements are difficult to obtain directly and require numerical differentiation of displacement data or other approximation methods. Since velocity measurements are approximate values, sensitivity analysis is necessary to examine parameter recovery accuracy under noise influence.

Figure 5

Figure 2: Figure 5

Gaussian white noise with amplitudes of 0.01, 0.03, and 0.05 is added to the accurate velocity measurements. The SINDy algorithm successfully recovers all terms of the galloping equation. As noise amplitude increases, the mean coefficient error of the galloping equation also increases, with cubic term errors significantly larger than linear term errors. At a noise amplitude of 0.05, the mean coefficient errors for linear and cubic terms are 9.56% and 21.05%, respectively. This occurs because as noise increases, the algorithm gradually recovers non-existent terms, and the cubic nonlinear terms are more active than linear terms, leading to significantly reduced recovery accuracy for cubic terms.

4.3 Impact of Different Noise Amplitudes on Model Reconstruction Accuracy

As mentioned, increasing noise amplitude significantly increases the mean coefficient error of recovered galloping equations. To quantitatively measure the similarity between reconstructed and true models, the coefficient of determination (R^2) is adopted as the evaluation metric. R^2 assesses model goodness-of-fit from a statistical perspective and eliminates dimensional effects.

The R^2 metric is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - f_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

where y_i are measured values, f_i are regression values, $\bar{y}$ is the mean value, and N is the number of data points. Higher R^2 values indicate better model reconstruction accuracy.

Numerical simulation results for R^2 across the entire time domain are shown in Figure 7. At noise amplitude 0.05, the R^2 values for both vertical (q_v) and horizontal (q_w) displacement time histories exceed 0.99, indicating high reconstruction accuracy. When noise amplitude is within 0.1, R^2 values remain above 0.95, demonstrating that the SINDy algorithm can accurately reconstruct the true galloping model even under measurement noise. The horizontal direction reconstruction accuracy is generally higher than the vertical direction.

[FIGURE:7]

To more clearly compare differences between reconstructed and true models, data from the steady-state response period (200-300 s) is analyzed. Figure 8 shows local displacement time histories at noise amplitudes of 0.05, 0.1, and 0.15. Even when parameter recovery introduces non-existent terms, the reconstructed model maintains high accuracy under moderate noise.

Figure 9

Figure 3: Figure 9

[FIGURE:8]

4.4 Impact of Data Amount on Model Reconstruction Accuracy

Previous analyses used complete numerical simulation data. However, actual engineering data is limited. To better reflect practical conditions, reconstruction accuracy is studied using different data amounts. Randomly and non-repeatedly extracting 30,000, 10,000, 5,000, and 1,000 data points from the complete dataset (with noise amplitude 0.05) as algorithm inputs, the relative errors in vertical galloping amplitude for reconstructed models are 0.83%, 5.25%, 9.45%, and 13.21%, respectively. Horizontal galloping amplitude relative errors are 1.03%, 5.12%, 10.91%, and 15.97%, respectively.

Figure 9 shows local displacement time histories for different data amounts. The SINDy algorithm achieves high reconstruction accuracy with only 10,000 data points ($R^2 > 0.95$). Figure 10 shows R^2 curves for different data amounts, confirming that minimal data quantities are sufficient for high reconstruction accuracy.

[FIGURE:10]

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5. Conclusions

This study establishes a theoretical model for vertical-horizontal coupled galloping of iced quad-bundle conductors in complex transmission lines and performs model reconstruction using the SINDy algorithm with specific case analyses. The main conclusions are:

1. With noise-free data, the SINDy algorithm accurately recovers the structure and parameters of both non-resonant and internal resonance galloping models, demonstrating the algorithm' s robustness.

2. Sensitivity analysis shows that as noise amplitude increases, the mean coefficient error of galloping equations increases, with cubic term errors significantly larger than linear term errors. At noise amplitude 0.05, linear and cubic term mean coefficient errors are 9.56% and 21.05%, respectively. This occurs because the algorithm gradually recovers non-existent terms as noise increases, and cubic nonlinear terms are more sensitive than linear terms.

3. When noise amplitude is within 0.1, the R^2 values for reconstructed displacement time histories exceed 0.95. At noise amplitude 0.05, R^2 reaches

0.99. Even when parameter recovery introduces non-existent terms, the reconstructed model maintains high accuracy under moderate noise.

4. The SINDy algorithm achieves high reconstruction accuracy with minimal data. At noise amplitude 0.05, only 10,000 data points are needed to achieve $R^2 > 0.95$, demonstrating the algorithm' s data efficiency.

These research findings provide important theoretical foundations for verifying anti-galloping designs and formulating anti-galloping strategies for transmission lines.

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Figure 1

Figure 4: Figure 1

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Figures

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