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Integrated Framework for Feature Selection and Dynamic Performance Prediction of Overhead Conductor Rail

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Abstract

Overhead conductor rail (OCR) is essential for traction power supply. However, as operating speeds increase, the dynamic performance of the pantograph-overhead conductor rail system (POCR) deteriorates significantly. To achieve low-cost and efficient monitoring, a sparse autoencoder (SAE) is introduced to evaluate node importance based on the encoding weight matrix. By incorporating a minimum spacing constraint, the master nodes contributing most significantly to the dynamic performance of the POCR are identified and found to be predominantly distributed at the supports. Subsequently, a bidirectional long short-term memory (BiLSTM) model is developed to predict the contact force and contact point movement using the vertical displacements of these master nodes as inputs. Results indicate that the root mean square error for contact force and contact point movement are 0.096 and 0.087, respectively, demonstrating the accuracy of the proposed method in capturing non-linear dynamic responses of the POCR.

Keywords: electrified railway, overhead conductor rail, dynamic performance, feature selection, contact force, deep learning.

1 Introduction

In electrified railways, the catenary system is a vital component for power delivery to trains. Overhead conductor rail (OCR) is primarily utilised in urban rail transit and mountainous tunnel railways, offering several advantages [1], unnecessary wire tension, large current-carrying capacity, and a minimal number of components, as illustrated in Figure 1. As operating speeds continue to rise, the dynamic interaction of the pantograph-overhead conductor rail system (POCR) gradually deteriorates due to the non-uniform distribution of local stiffness, as coupled vibrations and high contact force peaks [1, 2]. This not only induces electrical arcing but also potentially leads to the fatigue failure of OCR's components. Consequently, precise monitoring of the vibrational state of the OCR is significant for preventing the degradation of current collection quality and mitigating the fatigue failure of components.

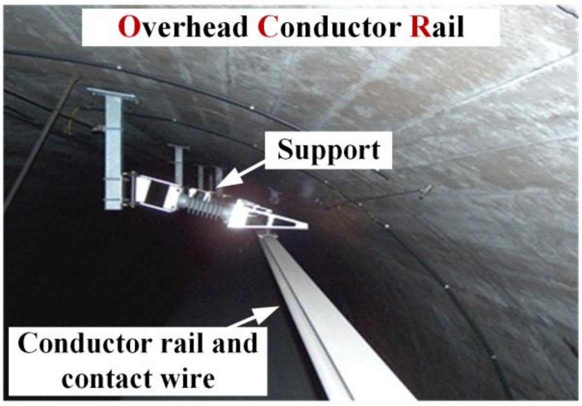


Figure 1 OCR system.

When monitoring the OCR, achieving an accurate characterisation of the conductor rail's vibration state requires the deployment of a dense array of measuring points. Due to the extensive length of the OCR, combined with the constraints such as the complex electromagnetic environment within railway tunnels, restricted installation space, and prohibitive sensor costs, it is unfeasible to achieve full sensor coverage across the entire line [3]. Therefore, determining how to deploy a limited number of sensors at key locations is a key technical challenge for achieving low-cost and high-efficiency monitoring [4].

Among various data-driven algorithms, autoencoders have demonstrated outstanding performance in non-linear feature extraction and dimensionality reduction [5]. However, traditional deep learning methods are frequently regarded as black boxes, lacking explicit physical significance. In this study, a sparse autoencoder (SAE) is utilised to extract key features from the dynamic responses of the POCR. It was observed that the encoder weight matrix of the SAE shows sensitivity information regarding the contribution of finite nodes to the full-field dynamic characteristics. Utilising the weight matrix, the master nodes are identified from the set of finite element nodes. A deep learning model based on the bidirectional long short-term memory (BiLSTM) is established, utilising the vibration displacement of the master nodes as inputs, which accurately captures the contact force and the contact point movement of the POCR.

2 Methods

2.1. Model of POCR

In this study, a finite element model (FE model) of the OCR is developed using absolute nodal coordinate formulation (ANCF) [1, 2]. ANCF elements have been proven effective in representing the nonlinearities of the railway catenary system. The model parameters are shown in Table 1. Linear three-dimensional spring elements are employed to model supports of the OCR. To simulate the dynamic behaviour of the pantograph, a lumped mass model, commonly used in pantograph-catenary dynamics, is adopted. The POCR FE model consisting of 30 spans is developed for numerical simulation. Finally, to ensure the accuracy of the numerical simulation and eliminate the influence of boundary effects on the contact force, only the results from the middle spans are selected for analysis.

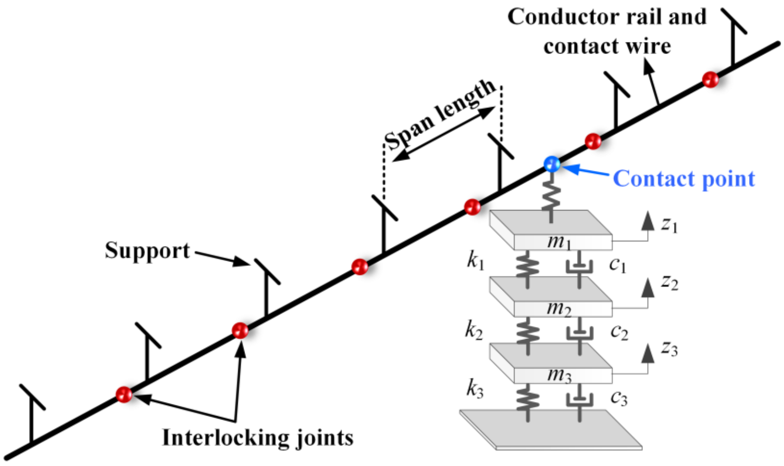


Figure 2 Scheme of the OCR FE model.

Span number	Span length	Linear Density	Equivalent section area	Support stiffness
30	8 m	8.1 kg/m	2322×10^{-6} m^2	50000 N/m

Table 1: OCR parameters.

2.2. Dimensionality Reduction and Feature Selection

The OCR FE model selected for analysis comprises 353 spatial finite element nodes, from which the vertical displacements are initially extracted. Then, the SAE is introduced to perform dimensionality reduction on the multi-node data. Within this framework, the encoder maps the high-dimensional vibration responses into a low-dimensional feature space, while the decoder is employed to reconstruct the original signals. The effectiveness of the developed sparse autoencoder for displacement dimensionality reduction is validated by assessing the reconstruction error [5].

A node importance evaluation index is proposed based on the encoding weights of the trained autoencoder. By calculating the norms of the weights corresponding to each input dimension within the encoder, the contribution of different spatial nodes to the low-dimensional features is quantitatively determined. Subsequently, a stepwise screening strategy, incorporating a minimum spatial spacing constraint, is employed to select master nodes from the entire node set, thereby preventing excessive spatial concentration of the selected nodes. By mapping the identified master nodes back to the original node set, their precise positions along the entire OCR model could be determined.

2.3. Deep learning framework

Long short-term memory (LSTM) networks effectively mitigate the gradient vanishing problem encountered by traditional recurrent neural networks when processing long-duration sequences by incorporating gating mechanisms, including input, forget, and output gates. To address the significant forward and backward temporal correlations characteristic of POCR dynamic responses, a BiLSTM network is adopted. The BiLSTM is composed of a pair of LSTM sub-networks with identical structures but opposing directions of temporal propagation [6]. Specifically, the forward LSTM layer processes the sequence chronologically to characterise the influence of historical information on the current state. Conversely, the backward LSTM layer processes the sequence in reverse order to incorporate supplementary constraints from future time steps. In this study, a two-layer BiLSTM network is constructed, with dropout layers introduced after each BiLSTM layer to enhance the generalisation capability of the model under limited sample conditions.

3 Results

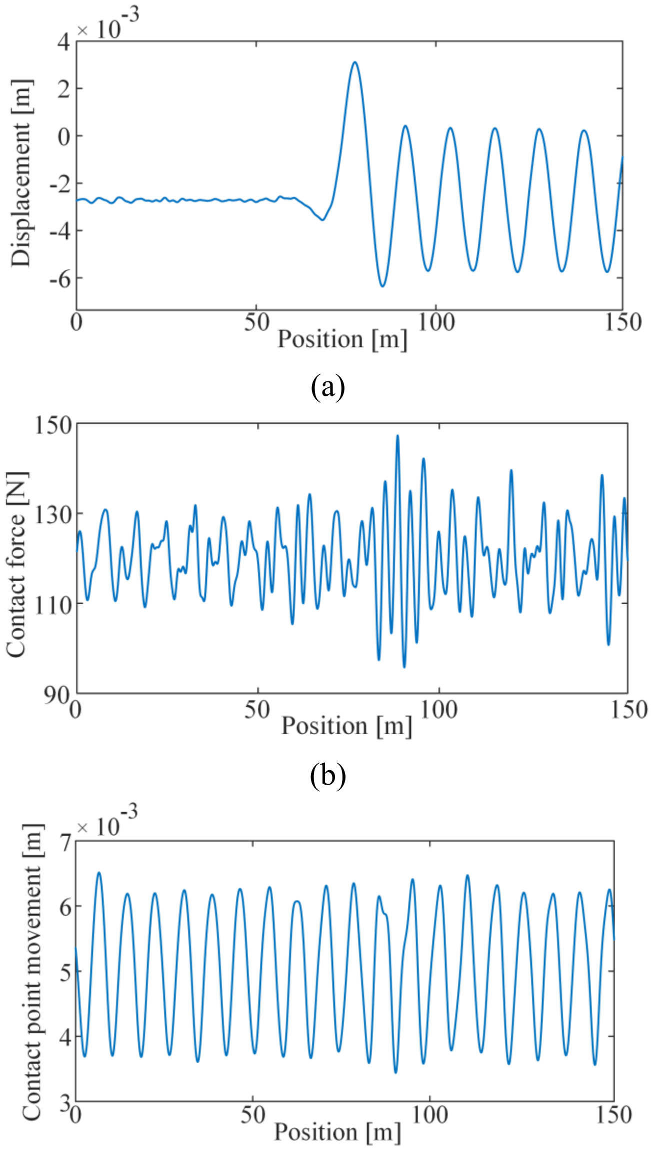
3.1 Model validation and data acquisition

In this paper, the developed POCR model is validated based on previous work [2]. Table 2 presents the comparison of the statistical data of the contact force obtained from measurement and simulation. These indicators are crucial for describing the dynamic interaction of the POCR[1]. It is observed that the standard deviation exhibits the highest absolute relative error among the four indicators, at 7.52 %, which is significantly smaller than the 20 % threshold specified in EN 50318 [7]. The analysis indicates that the validation results are well within the acceptable range.

Parameter	Simulation (N)	Measurement (N)	Error (N)
Standard deviation	4.72	4.39	7.52
Maximum	131.22	131.52	0.23
Minimum	112.94	112.09	0.76
Average	120.60	122.37	0.19

Table 2: Statistical comparison between measurement and simulation contact force.

Subsequently, the vertical displacements of the selected 353 nodes within the middle span, alongside the contact force and the contact point movement, are extracted as shown in Figure 3.



(a)

(b)

(c)

Figure 3 Dynamic responses of POCR: (a) vertical displacement of mid-span node; (b) contact force; (c) contact point movement.

3.2 Selection of master nodes

Dimensionality reduction is performed on the multi-node signals using the developed SAE, with the latent dimension set to 64. Relative errors for all nodes are calculated, resulting in an average relative error of 1.25% and a maximum relative error of 3.91%. Figure 4 presents the time-domain curves of both the reconstructed and original displacement of the mid-span node, indicating that the two are in good agreement. Weight coefficients for each node are calculated using the method described previously. To prevent excessive spatial concentration of the selected master nodes, a minimum spacing constraint of 12 nodes is applied. Figure 5 illustrates the node weight, with the identified master nodes highlighted in red.

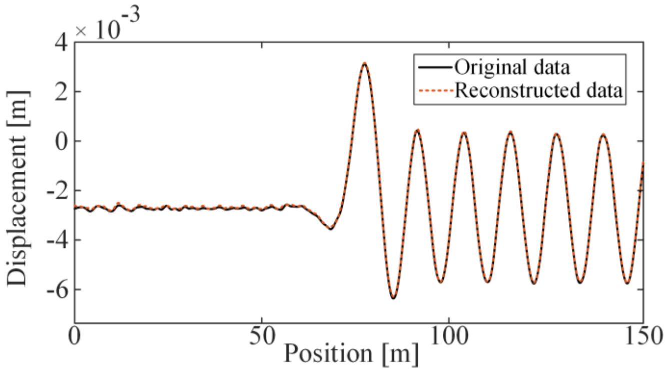


Figure 4 Comparison between original data and reconstructed data of mid-span node.

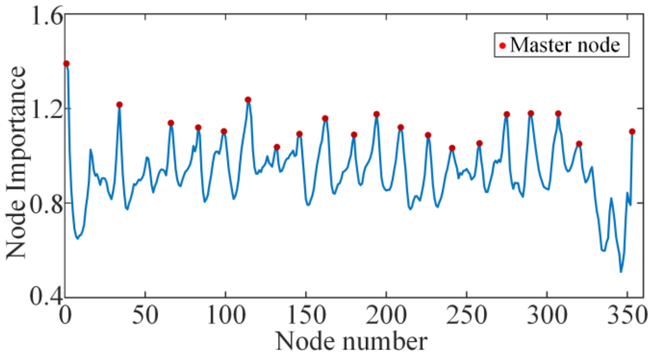


Figure 5 Node importance of selected master nodes.

By mapping the identified master nodes back to the global nodes of the OCR, their spatial positions along the entire system are obtained, as shown in Figure 6. It is observed that the majority of the master nodes coincide with the OCR supports.

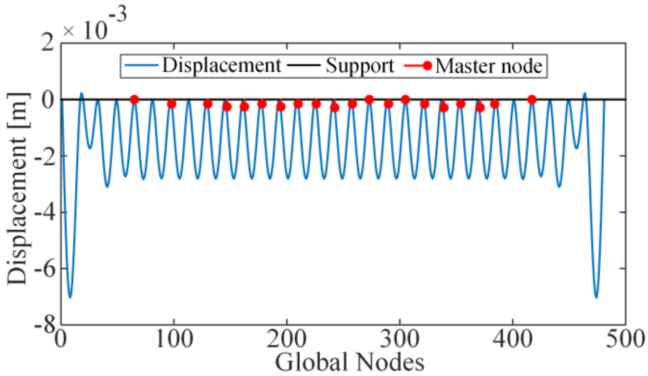
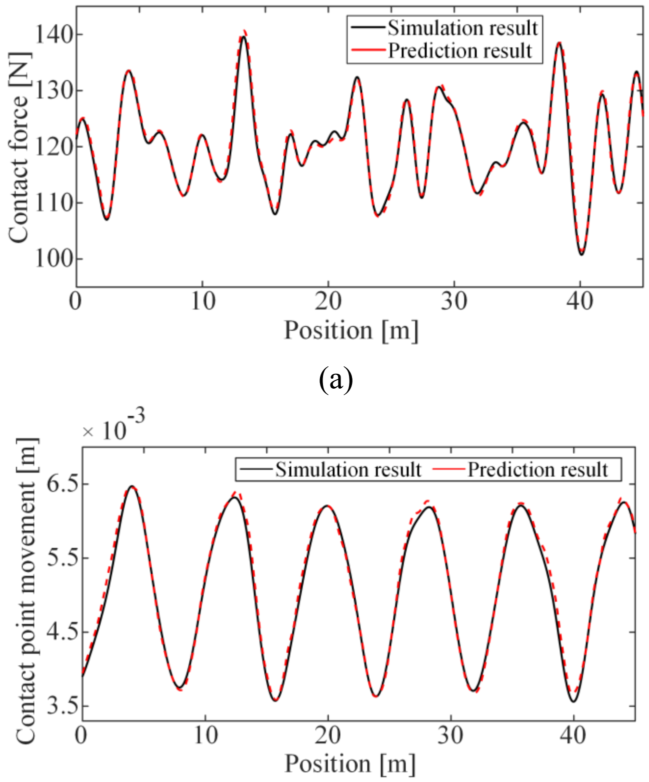


Figure 6 The locations of the master nodes along the OCR line.

3.3 Performance evaluation

The vertical displacements of the master nodes are utilised as inputs for the prediction model, while the contact force and the contact point movement are considered as the outputs. Prior to training, all the data are normalised to ensure numerical stability. The first 70% of the dataset is utilised for training, while the remaining 20% reserved for testing. In this study, the root mean square error (RMSE) and the R-Square (R^2) are employed as evaluation metrics. Figure 7 illustrates the time-domain comparisons between numerical results and prediction results for the contact force and contact point movement, respectively. Additionally, the RMSE for the contact force and contact point movement are 0.096 and 0.087, while the corresponding R^2 are 0.988 and 0.991. These metrics indicate that the prediction model exhibits high predictive accuracy.



(b)

Figure 7 Comparison of time-domain dynamic responses of prediction model and numerical model: (a) contact force; (b) contact point movement.

4 Conclusions and Contributions

A POCR finite element model using ANCF is developed and subsequently validated against experimental data, confirming its accuracy. A node importance evaluation index is proposed utilising the encoding weight matrix of the SAE, enabling the effective identification of master nodes that contribute most significantly to the full-field dynamic characteristics of the POCR. The results show that the master nodes are predominantly distributed at supports of the OCR. Furthermore, a prediction model is established, utilising the vertical displacements of the master nodes as inputs, while the contact force and contact point movement are designated as outputs. The corresponding RMSE are 0.096 and 0.087, respectively, demonstrating that the prediction model accurately captures the complex non-linear dynamic responses of the POCR.

Acknowledgements

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