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The Digitalisation of Railway Pantograph-Catenary System for Predicting Dynamic Performance Based on Recurrent Neural Network

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Abstract

In high-speed rail operations, the interaction performance of the pantograph-catenary system is of great importance as it directly determines the current collection quality and operational safety of the high-speed train. In this work, addressing the tremendous computational cost of the finite element method (FEM), a digital tool for fast simulations of pantograph-catenary interaction, is proposed using the deep learning technique. A dataset containing 30000 cases of pantograph-catenary interaction is generated by a mature FE model. An LSTM-based neural network is proposed to handle the inherent nonlinearity between the input model parameters and the output contact force. The analysis of the prediction performance indicates that the contact forces predicted by the digital model and FEM have high similarity, but the computational efforts of the proposed digital model can be neglected. The statistical analysis points out that almost all the prediction results have an error of less than 5.75% in terms of the contact force standard deviation.

Keywords: High-Speed Railway; Pantograph-Catenary Interaction; Deep Learning; LSTM; Contact Force; Digital Model

1 Introduction

The numerical simulation of pantograph-catenary interaction, as shown in Figure 1, has been a widely adopted approach to investigate its dynamic performance and evaluate the current collection quality. Nowadays, various types of numerical models have been developed world while [1]. In 2016, Bruni et al. [2] compared the results of some mainstream ones to set up a benchmark for the validation of numerical accuracy. But the huge computational cost of the numerical simulation is always a big concern for researchers in this field. That is why different scholars propose some efficient simulation approaches [3–5] instead of using a full FEM (finite element model) of the catenary. The rapid development of artificial intelligence techniques provides a new opportunity for developing a data-driven model of pantograph-catenary interaction. In this paper, a Recurrent Neural Network (RNN) is proposed to learn the FEM model of pantograph-catenary interaction based on a number of simulation results. By training the deep neural network based on long short-term memory (LSTM) networks [6], the proposed network is able to simulate the pantograph-catenary interaction for a real-time application. The numerical accuracy of the proposed data-driven model is demonstrated based on the simulation result of the FEM model.

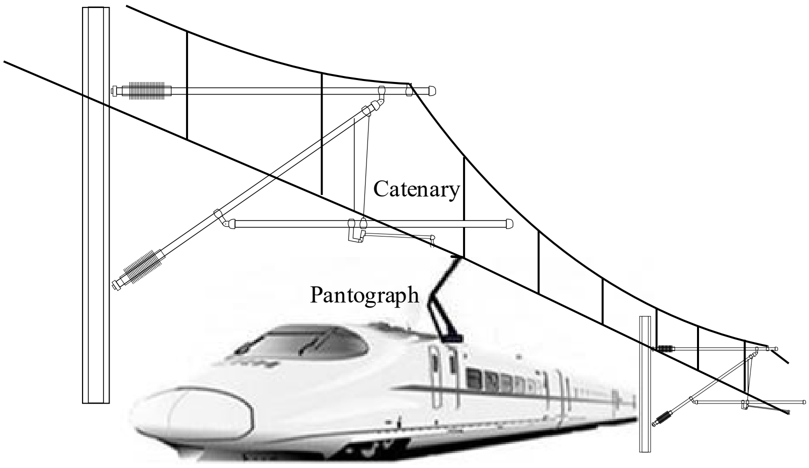

Figure 1**.** Schematic of a pantograph-catenary system

2 Methods

The proposed deep learning approach to digitalising the pantograph-catenary model is illustrated in Figure 2. Generally, this approach takes the model parameters of pantograph-catenary interaction as the input for the FE model and a deep neural network based on LSTM. Through a number of numerical simulations, the FE model provides a tremendous amount of simulation data with different model parameters. These data are divided into training data and testing data. The training data are used to train the neural network to learn the inherent data dependencies between the input model parameters and the output contact force. The testing data are used to validate if the digital model can output the results with acceptable accuracy. In this section, the details of the neural network adopted to digitalise the pantograph-catenary model are described.

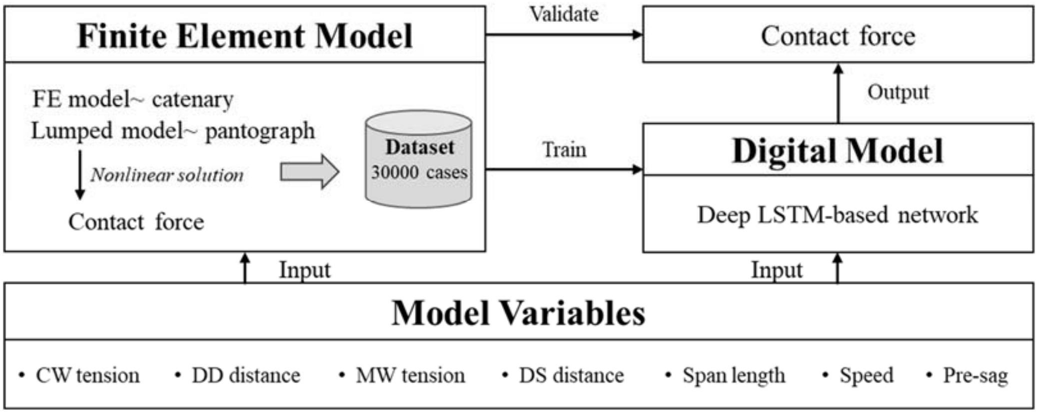

Figure 2. Framework of the digital model

The proposed network architecture is presented in Figure 3. The network contains one input layer, one output layer, several LSTM layers and one fully connected layer, as shown in Figure 3. A 0.3 'dropout ratio' dropout layer is added after the LSTM layers to avoid overfitting. This network's deep structure aims to capture the strong nonlinearity of the pantograph-catenary dynamics. After an LSTM layer, a fully connected (FC) layer is typically added to map the predicted sequence to the desired output size.

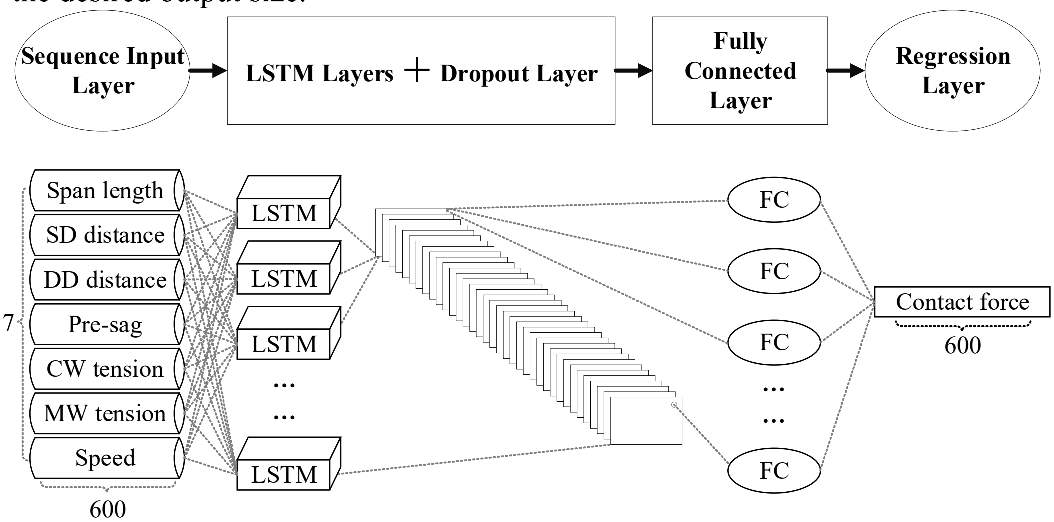

Figure 3. Network architecture for simulating pantograph-catenary interaction

The main purpose of the digital model is to establish the complex nonlinear relationship between the main model parameters and the dynamic performance. According to En 50367, the main indicator to represent the current collection quality is the contact force filtered within 0-20 Hz, which is taken as the output in the neural network. The catenary with 15 spans is built in the FE model, and the contact forces in the central four spans are adopted to generate the dataset for training the neural network. The contact force is decritised into 600 points, which is sufficient to describe the dynamic characteristic within 20 Hz. Therefore, a fully connected layer with 600 neurons is added before the output layer. The main six structural parameters of the catenary and the train speed are taken as the input model parameters as follows. Each of them is extended to the same dimension as the output contact force.

- ***Geometry parameters:*** span length (L_s), steady arm-dropper distance (D_{sd}), dropper-dropper distance (D_{dd}), pre-sag (P_{sag})
- ***Tension parameters:*** contact wire tension (T_{cw}), messenger wire tension (T_{mw})
- ***Operation parameters:*** speed (v)

The potential of the digital model does not attempt to cover all the cases of pantograph-catenary systems in the world. Normally the optimisation of structural parameters is performed at a given speed. Thus, a limited speed range is reasonable for generating the dataset. In this work, a high-speed range is considered, and the ranges of all the parameters are defined as follows according to the design specification.

Span length: 50 – 60 m; ***Steady arm-dropper distance:*** 4 – 6 m;
Dropper-dropper distance: 6 – 12 m; ***Pre-sag:*** 0 - 1.5‰;
Contact wire tension: 22000 – 28500 N;
Messenger wire tension: 17000 – 23000 N; ***Speed:*** 250 – 350 km/h;

3 Results

A neural network with hidden layers of two LSTM layers, '600 LSTMs + 400 LSTMs', is trained by the first 24000 cases obtained by FE simulations. The last 6000 cases are used to check the accuracy of the prediction. The errors of the predicted contact forces' standard deviation, maximum value, and mean value against the FEM results are presented in Figure 4. Note that the digital model only takes no more than 0.4 s to compute the contact forces in each case which costs more than 1200 s in traditional FEM simulation. According to En 50367, the contact force standard deviation is the most important indicator to represent the current collection quality. It is seen from Figure 4 (a) that 99.70% of the predicted results have an error of less than 5%. The maximum error of the standard deviation reaches 9.393%. According to the benchmark results [2], the contact force standard deviations evaluated by ten mainstream software have a deviation of up to 15.4%. Thus, it can be inferred that the results predicted by the digital model have acceptable accuracy. Speaking of the maximum contact force shown in Figure 4 (b), 99.48% of the predicted results have an error of less than 5%. As shown in Figure 4 (c), the mean contact forces evaluated by the digital model do not have significant errors against the FEM results.

It is also seen from Figure 4 (a) that the maximum error of contact force standard deviation occurs in case 3346. The contact force evaluated by both the digital model and FE model in this 'worst case' is presented in Figure 5. It is seen that even in the 'worst case', a good agreement can still be observed from the contact forces, which further demonstrates the acceptance of the proposed digital model.

To statistically analyse the prediction error, the histograms of the prediction error of contact force standard deviation, maximum contact force, and mean contact force are presented in Figure 6. It is seen that the prediction errors generally follow the normal distribution. In most engineering applications, three-sigma limits are used to set the upper and lower control limits in a statistical quality control, which means that 99.73% of data observed following a normal distribution lies within three standard deviations of the mean. In physics, a stricter criterion of 5 standard deviations is more likely to be used, which ensures an almost 100 % (99.99994%) confidence. In this analysis, both confidence levels are plotted. As for the contact force standard deviation in Figure 6 (a), 99.73% of prediction errors are no more than 3.67%, while almost 100% of cases have an error lower than 5.75%. For the maximum contact force in Figure 6 (b), it is seen that 99.73% of prediction errors are no more than 4.56%, while almost 100% of cases have an error lower than 7.53%. For the mean contact force in Figure 6 (c), almost 100% of cases have an error lower than 1%.

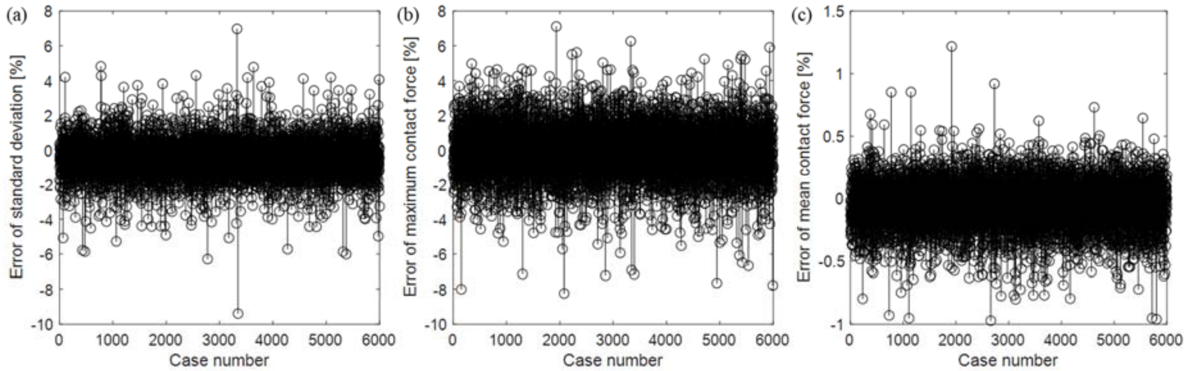

Figure 4. Errors of the predicted contact force standard deviation (a), maximum contact force (b) and mean contact force (c) against the FEM results

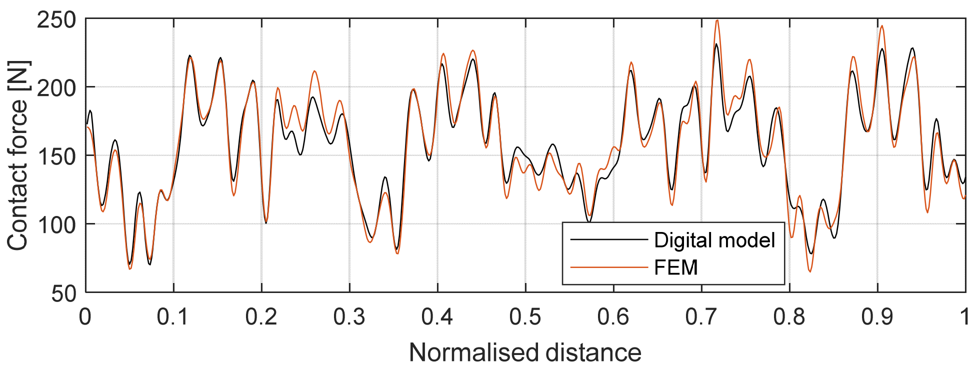

Figure 5. The comparison of contact force evaluated by digital model and FEM. This is the worse case that has the biggest prediction error in the contact force standard deviation

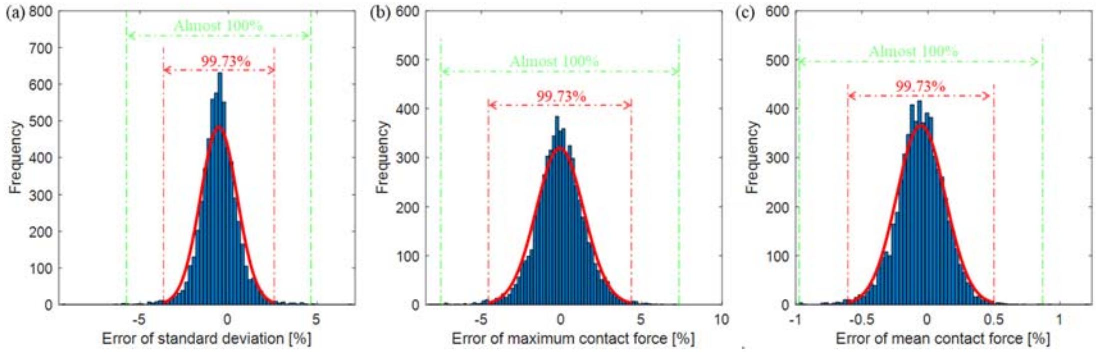

Figure 6. Histograms of the prediction error of contact force standard deviation (a), maximum contact force (b) and mean contact force (c) against the FEM results

4 Conclusions and Contributions

In this study, an LSTM-based neural network is proposed to learn a FE model of a railway pantograph-catenary system. The analysis results indicate that the contact forces evaluated by the digital model and FEM have high similarity, and the computational efforts of the digital model can be neglected. The statistical analysis points out that almost all the prediction results have an error of less than 5.75% in terms of the contact force standard deviation.

Acknowledgements

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