Inversion prediction of back propagation neural network in collision analysis of anti-climbing device

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Abstract
Targeting to improve the calculation efficiency of the finite element simulation, we introduce the back propagation neural network–based machine learning method to carry out the inversion prediction framework. The inversion collision model is established based on the inversion prediction framework. Then, the prediction results are compared with the finite element simulation results of the anti-climbing device to verify the feasibility of the inversion collision model. The average prediction errors of velocity, displacement, interface force, and internal energy of the anti-climbing device are 3.7%, 4.31%, 3.4%, and 1%, respectively, and the cost time of the inversion collision model is less than 5 min. The results show that the inversion collision model constructed by back propagation neural network can significantly improve the calculation efficiency and greatly reduce the calculation time under the condition of ensuring accuracy. It will provide a new evaluation method and possibility for partially replacing the required experimental and simulation results for the crashworthiness and the safety of the anti-climbing device.

Keywords
Machine learning, back propagation neural network, anti-climbing device, inversion prediction framework, inversion collision model

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Introduction
The crashworthiness of the structure plays a vital role in the passive safety performance of the rail vehicles, which determines the safety of the lives and property of the passengers.¹,² The performance of vehicle structure energy absorbers is affected by the following main factors: material,³ geometry,⁴ and loading mode.⁵ It is generally analyzed using experimental tests and numerical simulations based on finite element analyses.⁶,⁷ The experiment test is the most reliable and effective method to study the passive safety of rail vehicles, and second, through simulation. Especially, in the past 10 years, simulation analysis software has been widely used in the rail vehicle industry as a design and analysis tool.⁸ To study the structural crashworthiness of the car body, the European Commission conducted dynamic and static tests on its supported vehicle safety program to improve the passive safety of the rail vehicle.⁹ The British Bombardier Company and the US Federal Railway Administration conducted a series of

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comparative tests from 1999 to 2006, including a single-vehicle crashing into a rigid wall, two vehicles hitting a rigid wall, two trains colliding, and so on, and the detailed test data were used for crashworthiness analysis.\textsuperscript{10–14} Due to the high cost of full-scale impact tests, a scale model is usually used to test. Considering the enormous economic cost, workforce cost, and time cost of train crashworthiness tests, many train crashworthiness are simulated and analyzed based on nonlinear finite element method (FEM) and multi-body dynamics (MBD) software.\textsuperscript{15} In a computer simulation, parameter changes and evaluation of various designs and configurations can be realized quickly and cheaply. Computer-aided engineering technology, such as FEM and MBD method, can significantly help to reduce the cost of vehicle development. In the study of occupant safety and protection, the FEM is usually used to evaluate the crashworthiness of passenger cars.\textsuperscript{16,17} It also plays a vital role in the study of a rail vehicle collision and post-derailment behavior, especially in the study of derailment guided by collision.\textsuperscript{18,19} Besides, in the study of wheel–rail contact, the FEM is generally chosen to analyze the nonlinearity of the contact surface.\textsuperscript{20,21} Considering the complexity of the whole train structure, although the FEM can be used to build a detailed model with high accuracy, there is also an unavoidable drawback, that is, the time requirement, according to the complexity of the system studied and the accuracy of the calculation results required, the simulation running time may vary from seconds to hours or even days.\textsuperscript{22–24} An alternative to the FEM is the MBD method. As a simplified simulation tool, the MBD method is very popular in solving dynamic problems involving vehicles. Because of the simplified method, MBD method runs fast, but when it comes to highly non-linear modes, it is still time-consuming and can only provide limited calculation accuracy.\textsuperscript{25} Based on this, this article explores a framework of inversion collision simulation analysis using the back propagation (BP) neural network based on machine learning (ML).

ML\textsuperscript{26} is the study of computer algorithms, which can improve the performance of a task based on their own previous experience. In the past 30 years, the application of ML in engineering has achieved more and more success. Learning methods such as random forests and neural networks have been used in engineering, business, and scientific practice in an astonishing range of applications.\textsuperscript{27} In recent years, ML has become more and more popular in the railway industry and has been applied in various fields, such as monitoring the performance of railway car bogies,\textsuperscript{28} intelligent rail breakage detection,\textsuperscript{29} and vehicle condition monitoring.\textsuperscript{30} M Taheri and M Ahmadian\textsuperscript{31} introduced ML technology into vehicle dynamics research, used MB simulation data to train the Kriging model, and established an alternative element to replace all force elements in the secondary suspension system of MBD model. Tang et al.\textsuperscript{32} and Nie et al.\textsuperscript{33} improved computational efficiency by training parallel random forest algorithm (PRBF) model and Legendre polynomial regression model to construct alternative elements.

Although these modeling methods can extract model parameters from experimental or simulation data to construct a qualified collision simulation system, most of them only consider the small deformation or elastic deformation stage involved in a certain collision velocity and do not study the large deformation in the vehicle system. This limitation makes it difficult to extend the research results from elastic deformation to large plastic deformation prediction. Because the collision system involves more contact nonlinearity, material nonlinearity, and geometric nonlinearity,\textsuperscript{34} it is difficult to predict the collision of rail vehicles and components in different initial velocities under the same model parameters. So, the inversion collision model based on BP neural network is proposed to improve the computational efficiency of the traditional FEM on the premise of satisfying certain accuracy. It was used to predict the calculation results under other unknown conditions based on the given simulation data.

In this article, the collision response data (speed, displacement, impact force, and internal energy) of the anti-climbing device at the front end of the car body structure are mainly studied. The first case is to consider the comparison of simulation and test data to correct the finite element model; the second case is to obtain the training data needed for inversion prediction through the adjusted finite element model and divide the training data into training input data and training output data, in which we obtain the inversion collision model by iterative optimization of the mathematical inversion model. In the third case, the inverse collision model derived from the second case is used to predict the collision response data under unknown conditions.

\textbf{Inversion theory based on ML}

\textit{Introduction}

The purpose of this section is to build a mathematical inversion model that estimates $y = f(x)$ where $f$ is a black box function or computational codes that convert the input $x$ to the output $y$, as well as built mathematical mapping expressions from the input and output of training data set. The training data set $\{x_i, y_i\}$ is obtained from simulation or experiment test data, where $i = 1, 2, ..., N; j = 1, 2, ..., M$. $N$ is the total number of time history corresponding to each initial velocity, and $M$ is the total number of working conditions corresponding to different initial velocities. $x_i^{[j]}$ denotes the input characteristic data at the $i$th moment under the initial velocity $v_j$ condition. $y_i^{[j]}$ denotes the output...
characteristic data at the $i$ moment under the initial velocity $v_i$ condition. The optimal function $f(x)$ of $f(x)$ is found by the training data set. In this study, $x$ is the input under different conditions, $y$ is the velocity, displacement, impact force, and internal energy corresponding to different collision times under input $x$. The mathematical inversion model based on ML is mainly used to replace the force element relationship of large deformation and to reduce the time cost and workforce and money cost of simulation calculation and experiment test while ensuring certain accuracy. The inverse collision model was divided into two stages: the model training stage and model prediction stage. In the training stage of the process, a neural network model is built for training samples. It can learn a black box model from input to output without too much artificial feature design.

**Constructing inversion collision model**

The basis of predictive research using a BP neural network is that it can fit any non-linear function and has a certain generalization ability. Lapedes and Farber first applied a neural network to prediction and used neural network to study and predict the time series simulation data generated by a computer. In this article, the BP neural network in ML is used to construct the inversion collision model. The training sample set is given as follows: $\{(x^{[1]}, y^{[1]}), (x^{[2]}, y^{[2]}), \ldots, (x^{[m]}, y^{[m]})\}$. The multilayer feedforward neural network is constructed as shown in Figure 1. In this study, we used an eight-layer network (including an input layer of two units, seven hidden layers, and output layer of one unit).

The neural network learning process consists of two parts: signal forward propagation and error backward return. The training sample set is transmitted from the input layer to the output layer through the hidden layer in turn. If the output layer does not match the expectation, the error is sent back as an adjustment signal layer by layer, and the connection weight between neurons is adjusted to reduce the error. After repeated learning, the error is reduced to an acceptable level: $x = a^0 = [x_1, x_2]; a^{[1]} = [a_1^{[1]}, a_2^{[1]}, \ldots, a_i^{[1]}]; a^{[2]} = [a_1^{[2]}, a_2^{[2]}, a_3^{[2]}, \ldots, a_i^{[2]}], \ldots, a^{[m]} = [a_1^{[m]}, a_2^{[m]}, a_3^{[m]}, \ldots, a_i^{[m]}]; a^{[m+1]} = \hat{y}$. From the forward propagation we can see that

$$
\begin{align*}
\hat{y} &= w^{[1]}a^0 + b^{[1]} \\
a^{[1]} &= \sigma(z^{[1]}) \\
z^{[1]} &= w^{[1]}a^0 + b^{[1]} \\
a^{[2]} &= w^{[2]}a^{[1]} + b^{[2]} \\
&\vdots \\
z^{[m]} &= w^{[m]}a^{[m-1]} + b^{[m]} \\
a^{[m]} &= \sigma(z^{[m]})
\end{align*}
$$

where $\sigma$ is the sigmoid function, and it is the commonly used non-linear function in BP neural works as an activation function. The sigmoid function is defined by equation (2) and the output range is $[0, 1]$. The partial derivative can be calculated everywhere in the sigmoid

$$\sigma(z) = \frac{1}{1 + \exp^{-z}} \quad (2)$$

The loss function of the $i$th sample is defined as

$$L(y^{(i)}, y^{(i)}) = \frac{1}{2}(y^{(i)} - y^{(i)})^2 \quad (3)$$

The cost function of the whole training set is defined as

$$J(w, b) = \frac{1}{m} \sum_{i=1}^{m} L(y^{(i)}, y^{(i)}) \quad (4)$$

The ultimate goal is to minimize $J(w, b)$. The gradient descent method is often used to solve the problem and adjust the parameters in the direction of negative gradient of the target. Formula (5) can be obtained by introducing learning rate $\eta$ into Formula (3)

$$w := w - \eta \frac{\partial J(w, b)}{\partial w}$$

$$b := b - \eta \frac{\partial J(w, b)}{\partial b} \quad (5)$$

Through reasonable training data input and output characteristic selection, the training data are brought into the mathematical inversion model, and the iterative optimization is repeated. By continuously updating $w, b$, we find the $w$ and $b$ of parameters that minimize

![Figure 1. The multilayer feedforward neural network structure. Ebp: error back propagation.](image)
Finally, the inversion collision model training is completed.

**Evaluating model performance**

Model training accuracy evaluation: In the case of sufficient training data, the training data set \( \{x, y\} \) can be divided into the training sample set and the validation sample set. Using the validated sample set to judge and compare each mathematical inversion model, the mathematical inversion model with the least error was selected. In order to obtain acceptable inversion prediction accuracy with limited training data, we used S-fold cross-validation method. The mathematical inversion model with the minimum average error of validation is selected during model training.

Accuracy evaluation of inversion prediction: In order to quantitatively characterize the prediction accuracy of the inversion collision model, goodness of fit is introduced in the article. The coefficient of determination is given by

\[
R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}
\]

where \( y_i \) is the true value, \( \hat{y}_i \) is the predicted value, and \( \bar{y} \) is the mean value of the true value. \( SS_{res} \) is the means the residual sum squares, \( SS_{tot} \) is the means the total sum of squares. \( R^2 \) is between 0 and 1, and the larger the numerical value, the higher the fitting accuracy is. The goodness of fit introduced above can reflect the fitting situation of prediction results in most cases. But for the time series data with a small fluctuation \((y_i - \bar{y})\), when its denominator is close to 0, it will lead to the occurrence of \( \frac{\sum (y_i - \bar{y})}{\sum (y_i - \bar{y})^2}\), which will lead to the occurrence of \( R^2 < 0 \). In this case, the fitting accuracy of the inversion prediction model cannot be truly reflected. Therefore, we propose an improved goodness-of-fit \( \hat{R}^2 \) to measure the inversion prediction results in this case

\[
\hat{R}^2 = \min(1, \max(0, R^2, R^2_{pos} + \frac{MRE}{MRE_{pos}}))
\]

where \( R^2 \) is the general goodness of fit, \( R^2_{pos} \) is a positive goodness of fit reference value, \( MRE \) is the average relative error of the current calculated data, and \( MRE_{pos} \) is the average relative error of the corresponding goodness-of-fit reference value data.

**The construction of inversion prediction framework**

Figure 2 shows the basic framework of the inverse prediction process based on ML, which is used to study complex non-linear relationships, especially the large deformation of the anti-climbing device to improve
computational efficiency. The equations listed in this article are considered in the program codes of the inversion collision model. The inversion steps are as follows:

1. Building the finite element model verified through experiment test.
2. According to the established finite element model, the training data are obtained, which are divided into training input data and training output data, and the inverse collision model is obtained through training optimization. Equations (1)–(5) were used in the process of obtaining the inversion collision model.
3. The initial velocity is used as the input of the inversion collision model, and the collision response data are used as the output of the inversion collision model. Based on the obtained inversion collision model, the collision response data of velocity, displacement, impact force, and internal energy under different initial velocities (unknown condition) are predicted. Equations (6) and (7) were used for accuracy evaluation of inversion prediction.

This article creatively combines the BP neural network with the practical application of rail vehicle collision analysis to improve the efficiency of traditional finite element simulation. Taking the anti-climbing energy absorption device collision analysis as the research object, the collision response data obtained through finite element simulation are used as the input of inversion collision model, and the theoretical formulas mentioned in sections “Introduction,” “Constructing inversion collision model,” and “Evaluating model performance” are applied to the optimization of the inversion collision mathematical model and the evaluation of the performance of the inversion collision model. Finally, the framework of inversion prediction is obtained, which can be used to support engineering design.

**Finite element model simulation and verification**

**Finite element modeling of anti-climbing device**

The anti-climbing device is composed of an anti-climbing tooth, guide beam, energy absorption beam, aluminum honeycomb, reinforcing plate, mounting plate, and mounting base. A partial cross-sectional view of the anti-climbing device is shown in Figure 3.

The material parameters of the anti-climbing device are shown in Table 1.

On purpose to simulate the energy absorption characteristics of plastic deformation of the anti-climbing device more realistically, the components such as energy absorption beam, guide beam, anti-climbing tooth, mounting plate, mounting base, and reinforcing plate were modeling using the material model *MAT_24: PICEWISE_LINEAR_PLASTICITY, from the LS-DYNA 3D and 2D material library. The aluminum honeycomb was modeled using the material model *MAT_3: PLASTIC_KINEMATIC from the LS-DYNA 2D material library for shell Belytschko-Tsai shell element. There are 10,856 solid elements, 583,314 shell elements, and 516,480 nodes of the finite element model with the average mesh size 6 mm, as
shown in Figure 4. The anti-climbing device is installed integrally on the front end of the experiment test trolley. The major contact algorithms were *CONTACT_AUTOMATIC_SINGLE_SURFACE and *CONTACT_AUTOMATIC_SURFACE_TO_SURFACE in the article. The coefficient of friction between the components was 0.2. We used the sliding instead of rolling to simulate the motion of the experiment test trolley.

**Experimental test scheme**

In the experiment test, the anti-climbing device is installed at the front end of the test trolley. The traction motor drives the experiment test trolley to impact the rigid wall along the track. The collision scene and local enlargement view are shown in Figure 4. The experiment test equipment consists of an experiment test trolley, an anti-climbing device, a force-measuring rigid wall, and a trolley track. The speed sensor is used to monitor the velocity and displacement changes of the anti-climbing device, and the force sensor on the rigid wall is used to measure the impact force between the anti-climbing device and the rigid wall.

The basic test method for the collision test of the vehicle body energy-absorbing device is as follows: the impact test piece is fixed at the front of the moving trolley, the motor is used to accelerate the trolley to a predetermined speed, and a speed measurement system is installed at a distance of 2 m from the front of the rigid wall. When the front end of the rigid wall is 2 m, the trigger sends a command, and the speed test system tests the instantaneous speed of the trolley. The two high-speed camera systems installed at the same time on the side and the upper side record the energy-absorbing components during the impact at the rate of 4000 frames per second. The deformation and transient impact force acquisition system collects the force of each force sensor in real time.

**Verification of finite element model**

In case 1, the experiment test trolley impacted the rigid wall at an initial velocity of 16.21 m/s, and no braking measures are taken during the collision. The experiment test and simulation deformations of the anti-climbing device in the process of collision are shown in Figure 5.

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**Table 1.** The material parameters of anti-climbing device.

| Component               | Material | Element | Thickness (mm) | Mass (kg) |
|-------------------------|----------|---------|----------------|-----------|
| Energy absorption beam  | Q310     | Shell   | 2.50           | 14.75     |
| Guide beam              | Q235A    | Solid   |                | 11.90     |
| Reinforcing plate       | SUS304   | Shell   | 3.00           | 12.41     |
| Anti-climbing tooth     | Q345     | Solid   |                | 14.86     |
| Mounting base           | Q355     | Solid   | 16.00          | 12.35     |
| Aluminum honeycomb      | A5052    | Shell   | 0.19           | 3.67      |
| Mounting plate          | Q355     | Solid   | 4.00           | 2.00      |

Q310, Q235A, Q345, Q355, and SUS304 are different steels, and the A5052 is magnesium–aluminum alloy. The standard of metal material used in the article is GB. They have different mechanical properties.
Since the material stiffness of the anti-climbing tooth and mounting base is much larger than the stiffness of the material in the deformation zone, the slight deformation of the anti-climbing tooth and mounting base caused by collision is negligible.

Figure 5 shows that progressive collapse and eight folds occurred in the whole anti-climbing device during the experiment test and simulation. The entire impact process of simulation and experiment lasted 64 and 60 ms, respectively. The errors of measurement may cause a difference of 4 ms. The horizontal compression displacement of the anti-climbing device during impact is shown in Figure 6. The horizontal compression displacement of the anti-climbing device was measured by the displacement’s variation of the nodes in the mounting base relative to the anti-climbing tooth.

As shown in Figure 6, as the collision time increases, both the simulation and the experiment test results show a tendency that the horizontal compression displacement first increases and then decreases. The recovery of deformation of some components results in compression displacement decreased after the collision. The simulation result of the final anti-climbing device shows that the maximum compression displacement is 464 mm, which is a 6-mm difference from the 458 mm, which was maximum compression displacement of the experiment test, and the deviation between the data is 1.31%. Generally speaking, the finite element model

**Figure 5.** The deformations of the anti-climbing device from experiment and simulation: side view at (a) 10 ms (experiment test–simulation comparison), (b) 30 ms (experiment test–simulation comparison), (c) 50 ms (experiment test–simulation comparison), and (d) 64 and 60 ms (experiment test–simulation comparison).
The proposed model can accurately reproduce the full deformation mode and displacement change process of the anti-climbing device.

The horizontal velocity of the anti-climbing device is obtained by measuring the horizontal velocity of the node in the mounting base. From Figure 7, it can be seen that the horizontal velocity of the anti-climbing device decreases rapidly in the initial stage of the collision until it drops to zero. Then, with the end of the collision process, the anti-climbing device rebounds at a low velocity. The final rebound velocity of simulation and experiment is the same. The difference is that the change of horizontal velocity in simulation decreases faster than that in test.

The horizontal acceleration of the anti-climbing device is obtained by measuring the horizontal acceleration of the node in the mounting base. As shown in Figure 8, the simulation results of the horizontal acceleration of the anti-climbing device are consistent with the experiment test results, and they all change in the same range of amplitude. The average acceleration of the simulation and experiment test is close to each other, but there are some errors in the peak and valley corresponding to the specific time point.

The impact force of the anti-climbing device varies with the compression displacement as shown in Figure 9. The horizontal impact force of the anti-climbing device was obtained by measuring the interface force between the rigid wall and anti-climbing tooth.

Figure 6. The horizontal compression displacement with time.

Figure 7. The variation of horizontal velocity with time.

Figure 8. The variation of horizontal acceleration with time.

Figure 9. The variation of impact force with compression displacement.
test are 1598 and 1631 kN, respectively. The relative error is very tiny. The average impact force from the simulation is 477.4 kN and that from the experiment test is 447 kN. In general, the finite element simulation calculation value of the impact force is larger than the experiment test value. The maximum relative error between the simulation value and the experimental value is 6.8%, which meets the requirement of EN15227 standard that the maximum relative error between simulation and experimental is less than 10%.

The variation of the internal energy of the anti-climbing device with displacement is shown in Figure 10.

It can be seen from Figure 10 that the internal energy obtained by simulation and experiment test of the anti-climbing device is 199 and 188 kJ, respectively. The difference is 11 kJ, and the relative error is 5.85%, which also meets the requirements of EN15227 standard.

By establishing the finite element model of crash simulation for the anti-climbing device, the simulation results of the finite element model are in good agreement with the experimental test results, and the comparison result with the test data verifies the correctness of the finite element model of crash simulation. In this article, the displacement, velocity, impact force, and internal energy of the anti-climbing device corresponding to different initial velocities are calculated by the established finite element model, which provides necessary training data for the following inversion collision model.

**Training of inverse collision model**

The finite element model validated is simulated and the training data of displacement, velocity, impact force, and internal energy varying with time at different initial velocities (18, 14, 12, and 10 m/s) are obtained. In order to train the model, the displacement variable was introduced to enhance the generalization ability of other inversion variables. The mathematical inversion model is as follows

\[
(v_0, t) \rightarrow d \\
(v_0, d, t) \rightarrow y
\]

(8)

where \(v_0\) is the initial velocity under different working conditions, \(v_0 = \{18\text{ m/s}, 14\text{ m/s}, 12\text{ m/s}, \text{ and } 10\text{ m/s}\}\). The \(d\) is the estimation value of displacement, \(t\) is the time series, and \(y\) is the predicted value of the inversion collision model (it can be output parameters such as velocity, displacement, impact force, and internal energy).

The fitting training results of the mathematical inversion model are shown in Figures 11–14. The
average goodness of fit for velocity, displacement, interface force, and internal energy training is shown in Figure 15.

From the training results of the mathematical inversion model and the average goodness of fit of the training, it can be seen that both the overall goodness of fit and the inversion prediction result of local fluctuations have achieved satisfactory results. Especially, for the training of velocity, displacement, and internal energy, the goodness of fit is above 0.99. Even for the training of strong non-linear impact force, the goodness of fit is 0.898. Thus, the inversion collision model corresponding to each physical quantity is well trained.

**Prediction and error analysis of inverse collision model**

In this section, the optimized inversion collision model is used to predict the simulation results of velocity, displacement, interface force, and internal energy varying under 16 m/s operating conditions. In addition, we verify the prediction accuracy of the inversion collision model by the finite element simulation data under the same condition. Figures 16–19 depict the inversion prediction results and prediction error of velocity, displacement, interface force, and internal energy, respectively.

From Figure 16, it is clear that the inversion collision model can accurately predict the velocity change of the anti-climbing device. The coincidence degree of simulation and inversion results is high, with an average prediction error of 3.78% and a maximum prediction error of 39.1%. In the short time (5 ms) when the rebound occurs after the velocity drops to zero, the larger prediction error occurs. The higher prediction accuracy at other times can completely meet the requirements of calculation accuracy.

From Figure 17, it can be seen that the prediction accuracy of the inversion collision model for
displacement variation with time is higher, the maximum prediction error is 6.98%, and the average prediction error is only 4.31%. The inversion collision model proposed in this article can well learn the variation law and can accurately predict the deformation trend and maximum value of the displacement.

Figure 18 shows that the inversion collision model can predict the trend of interface force on the whole, and it is consistent with the simulation results. It also can reflect some peaks and valleys of impact force very well. However, the prediction of local details still needs further improvement. For the initial peak value, the prediction accuracy of the trough is higher than that of the peak. The maximum prediction error of the prediction accuracy is 13.8% from the initial peak to the interface force before it drops to zero. For the scenario that simulated mean value of interface force is 410 kN, the predicted mean value of interface force is 396 kN, and the average relative error of interface force is 3.4%. The inversion collision model proposed in this article can accurately predict the mean value of the interface forces, but the prediction error of the initial peak value is large, and the parameters of the inversion collision model need to be further revised.

From Figure 19, the inversion collision model can predict the changing trend of internal energy with displacement better. The maximum prediction error at the beginning of the crash is 25.9%. With the collision proceeding, the prediction error decreases rapidly, the average prediction error is 1%, and the prediction accuracy is higher.

As shown in Table 2, the computational efficiency and accuracy of the above methods are compared. The

| Method        | VAvRE (%) | DAveRE (%) | FAveRE (%) | EAveRE (%) | Training time (min) | Prediction time (min) | Simulation time (min) | T raining | Prediction | Simulation |
|---------------|-----------|------------|------------|------------|---------------------|-----------------------|------------------------|-----------|------------|------------|
| Simulation    | –         | –          | –          | –          | –                   | –                     | 600                    |           |            |            |
| Inversion     | 3.78      | 4.31       | 3.4        | 1          | 4.33                | 0.003                  | 4.333                  |           |            |            |

VAvRE is the average relative error of the predicted velocity, DAveRE is the average relative error of the predicted displacement, FAveRE is the average relative error of the predicted impact force, and EAveRE is the average relative error of the predicted internal energy.
accuracy and computational efficiency of the ML inversion algorithm are measured based on the simulation calculation.

By comparing the simulation and inversion data of velocity, displacement, interface force, and internal energy, it can be concluded that the inversion collision model proposed in this article can accurately predict the variation law of velocity, displacement, interface force, and internal energy while satisfying the calculation accuracy. The mean value of the interface force can be predicted well through the inversion collision model, but the initial peak value of interface force cannot predict well.

**Conclusion**

We proposed a framework of the inverse collision prediction to reduce the simulation time without a sacrifice of accuracy. The approach used in the study can be summarized as follows. The first step, the finite element model of the anti-climbing device, was developed based on the experimental test method. The next step was to create a mathematical inversion model that can learn the relationship between input and output data. In the third step, we developed the inversion collision model to predict the collision simulation results under unknown conditions. The main conclusions from the study are summarized as follows:

1. The inversion collision model can provide high prediction accuracy with a small set of training samples. The average prediction errors of velocity, displacement, interface force, and internal energy of the anti-climbing device are 3.7%, 4.31%, 3.4%, and 1%, respectively.
2. The time cost of the proposed inversion collision model in training is only 4.333 min, which is much lower than that of finite element simulation calculation. The inversion collision model can significantly improve the calculation efficiency of inversion prediction, and they are not sensitive to the size of training samples.
3. The inversion collision model shows a satisfying result in the collision analysis of structure with strong nonlinearity and large deformation.

The inversion collision model proposed in this article can be used to guide the crashworthiness design of the anti-climbing devices, and it can be used to optimize existing structures such as anti-climbing device by the predicted collision response data. In the next work, we will study the application of the inversion collision model in a rail vehicle collision to support the engineering design.

**Author contributions**

The authors’ contributions are as follows: T.Z. was in charge of the whole trial; Y-R.L. wrote the manuscript; S-N.X. and Z.T. were assisted with simulation analyses; J-K.X. and Z-B.L. were assisted with laboratory analyses; S-D.X. was assisted with data analyses.

**Availability of data and materials**

The data sets supporting the conclusions of this article are included within the article.

**Declaration of conflicting interests**

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