Structural Monitoring and Maintenance, *Vol. 8, No. 2 (2021) 151-166*
DOI: https://doi.org/10.12989/smm.2021.8.2.151

Machine learning aided rail corrugation monitoring for railway track maintenance

Sakdirat Kaewunruen*, Jessada Sresakoolchai [a] and Gaoman Zhu [b]

School of Engineering, University of Birmingham, Birmingham B15 2TT, UK

(*Received September 11, 2020, Revised January 12, 2021, Accepted January 21, 2021*)

Abstract. Urban rail transit is a critical infrastructure system that supports urban economic and social development. It has a significant mass transportation capacity while enables environmental benefits. Public transport is a way to resolve large-scale urban road traffic problems and contributes towards sustainable development. However, with the operations of railway vehicles on curves, unbalanced and undulated wears often appear on rails, especially on the low rail. This rail surface defect, so-called 'rail corrugation', directly affects the service life of rolling stocks and track components. The high-frequency vibrations caused by train-track interaction over rail corrugations also impair passenger ride comfort and generate excessive noises. In severe cases, the defects may even endanger the safe passage of a railway vehicle. In practice, rail corrugation has brought huge challenges to the reliable operations and maintenance of railway networks. With the continuous expansion of railway lines and the increasing traffic demands, any existing rail corrugation test method is not enough to meet the actual needs of track maintainers to promptly identify and mitigate rail surface defects. Therefore, this investigation aims to establish a new technique to prognose and classify rail corrugations efficiently and effectively. This study adopts D-track dynamic simulation package to obtain over thousands of vibration data in the form of axle box accelerations from train-track interactions under different conditions. Neural network models have been developed to recognize the rail corrugations and then classify their severity to aid the planning and prioritization of rail track maintenance activities. The models have been trained and tested using the vibration data, achieving the accuracy of over 90%. The optimal model has then been highlighted. The investigation has demonstrated the potential of the neural network to detect and classify rail corrugations, which can be used practically for curved track condition monitoring and maintenance planning.

Keywords: rail corrugation; dynamic analysis; artificial neural network; machine learning; monitoring; maintenance

1. Introduction

In the process of urban development, cities at different scales and stages of development have different requirements for urban transportation. This means there is an urgent need for transportation technology and transportation tools that can meet development needs. Urban rail transit has the distinctive characteristics of large passenger flow, high speed, high efficiency, high safety, punctuality, and environmental friendliness. This series of advantages have attracted the

*Corresponding author, Ph.D., E-mail: s.kaewunruen@bham.ac.uk
[a] Ph.D., E-mail: jss814@student.bham.ac.uk
[b] Student, E-mail: gxz893@student.bham.ac.uk

http://www.techno-press.org/?journal=smm&subpage=7 ISSN: 2288-6605 (Print), 2288-6613 (Online)

attention of government agencies in various countries. Urban rail transit plays a vital role in solving the problems of sustainable development of cities, such as traffic congestion, energy consumption, and environmental pollution. At the same time, it also plays an important role in people's daily travel life (Li 2014).

During the development of urban rail transit (Cao *et al*. 2016), it is extremely important to ensure continuous operation and maintenance of the railway infrastructure system such as embankment (Zhang *et al*. 2018), ballast (Ngamkhanong *et al*. 2017), sleeper (Kaewunruen 2014), or railway bridge (Xia *et al*. 2014, Ajmal and Mohammed 2018). The monitoring of the structural health of railway infrastructure systems is one of the main challenges in railway maintenance and operation, especially in underground trains or subway systems. As the public has a huge demand for faster and more frequent train services, the time for railway personnel and track maintainers to inspect and maintain railway infrastructure is extremely limited. The time without trains, in the middle of the night, in various countries is not sufficient for railway personnel to fully inspect and maintain the railway. For example, the track access availability is around 3 hours in Tokyo, 1-2 hours in Hong Kong, and perhaps 5 minutes in London (Kaewunruen and Mohammed 2018). In some places, railway operations may be suspended for large-scale maintenance work. The continuous operation and maintenance of railways is a huge challenge in their development.

Rail corrugation is a major type of rail surface damages often found on curved tracks. It is a periodic wave-like irregularity that appears along the longitudinal surface of the rail (i.e., low rail). The rail corrugation needs to be managed by rail grinding and polishing activities, in order to enable smooth ride comfort and lower noise radiation. The severity of rail corrugations is the key parameter for track maintenance planning and prioritization. If the size of rail surface defect is relatively small in depth, the maintenance regime such as grinding can be performed quickly without too much effort (e.g., within 3 hours of trackwork or track possession). On this ground, the early classification of rail corrugations can dramatically improve the track maintenance program. With the continuous expansion of railway lines and the continuous increase in labour costs, existing track corrugation testing equipment in the field is not sufficient to meet the actual needs of railway maintenance personnel to carry out necessary track inspections for rail defect classifications (Kaewunruen *et al*. 2019). Therefore, it is very important to develop a more feasible and effective monitoring method that can guide track maintenance engineers to plan and prioritise track maintenance work. This study will evaluate the use of artificial neural network to aid rail corrugation monitoring and classification. The use of dynamic vehicle-track interactions in the form of axle box acceleration (generally obtained from train ride measurements) has been used to explore the new alternative method for prognosing rail corrugations. This study uses the D-track dynamic simulation package to obtain the vibration data of the vehicle-track systems under different conditions. Classifications of the rail corrugation through neural network training are demonstrated to achieve the goal for rail corrugation monitoring and classification.

2. Rail corrugation

2.1 Corrugation background

Rail corrugation refers to a type of rail head defect that appears on the surface of the rail after it has been used in the railway system, which has periodic characteristics and resembles a wave shape. It is commonly observed in curved tracks that cater all kinds of train services, ranging from

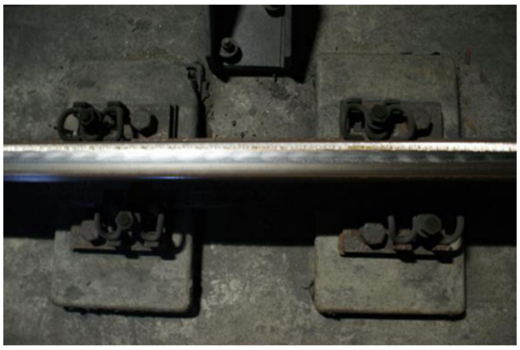


Fig. 1 Rail corrugation (Liu 2018)

light rail, metro, suburban, freight and highspeed rail systems. The rail is initially non-corrugated but has a certain degree of roughness. This initial roughness combined with other factors (such as traction, creep and friction characteristics at the wheel-rail contact) will stimulate dynamic loads and cause certain damage to the rail, thereby changing the initial profile (Grassie and Kalousek 1993). The wavelength and degree of severity depend on the rail structure, rail geometry, traction system, rail vehicle performance, and wheel-rail interaction.

2.2 Rail corrugation formation theory

The self-excited vibration theory was proposed by Suda (1991). Matsumoto *et al*. (2002) argued that the generation of rail corrugation is related to the natural frequency of the vertical vibration of the wheelset. Clark *et al*. (1988) presented that wheelset lateral stick-slip vibration theory. On a small radius curve, when the frequency of the sleeper is close to the lateral natural frequency of the wheelset, the wheelset will vibrate laterally, resulting in periodic relative sliding. This will cause corrugations. At the same time, the wavelength is equal to an integer multiple or fraction of the sleeper pitch (Vadillo *et al*. 1998). Chen *et al*. (2010) proposed that friction-coupled self-excited vibration causes rail corrugation. This theory states that when the slip force between the wheel and rail reaches a saturated state, friction coupling self-excited vibration between the wheel and rail will occur, resulting in rail corrugation. The rail corrugation wavelength obtained from this viewpoint is basically the same as the actual line rail corrugation wavelength.

2.3 The hazards of rail corrugation

When a train passes through a corrugation part of curved track section, such defect will cause severe vibrations of the wheelset, bogie and body. Reciprocally, track components are excited excessively, radiating noises and impairing ride comfort. This kind of vibrations not only seriously affects the comfort of subway vehicles, but also aggravates the damage of vehicles and track components, shortens the service life of railways, wheels and related equipment, and increases maintenance costs. In a study by Remennikov and Kaewunruen (2008), the secondary vibration of the ground was regenerated in the surrounding environment (such as nearby buildings and structures). Rail corrugations can also produce unpleasant noise. If the railway corrugation is severe, it will also cause the rails and axles to break, which will affect driving safety. On this ground, early warning of rail corrugation can help track maintainers to develop suitable preventative maintenance programs, which are very timely and cost effective. If the defect is severe, major corrective maintenance can be time consuming and very costly.

2.4 Current status of corrugation detection technology

At present, the methods for detecting rail irregularities are mainly divided into two categories, which are divided into the string measurement method and the inertial reference method (Zhang 2007). The string measurement method has some flaws. The “baseline” used as a reference for measurement is in a state of change along with the level of rail irregularities. For sinusoidal irregularities, the transfer function ratio (the ratio between the measured value and the actual value) is not equal to 1 but is between 0 and 2. When measuring non-sine waves, the orbital irregularities may have a transfer function ratio greater than 2 (Xu and Dai 2007, de Melo *et al*. 2020, Kaewunruen *et al*. 2021). Therefore, the string measurement method cannot truly and reliably reflect the irregularities of the rail. Many countries have also gradually transitioned from the original string test method to the inertial reference method (Luo *et al*. 2006).

According to the above two methods, the actual detection methods in different countries are not the same (Zhang 2007). Japan measures the original basic data through the three-point chord measurement method and obtains railway irregularities after compensation and correction of the data (Yzawa and Takeshita 2002). Russia divides the vehicle speed into three different grades and uses the axle box acceleration integration method to carry out the quadratic integration, and then filters the low-frequency signal components that affect the detection results through a filter. Australia directly integrates the collected axle box acceleration signal twice to obtain the amplitude of the railway irregularity displacement. In the United States, both the string measurement method and the inertial reference method are used. In order to obtain data on the uneven surface of the railway, Germany directly uses photoelectric scanning technology. This is of great significance for improving the efficiency of rail corrugation testing and saving costs.

However, before conducting a more detailed study of rail corrugation in the field, the first thing that needs to be tackled is how to detect rail corrugation quickly and effectively in order to reduce the railway sector’s capital investment in human and material resources.

Rail corrugation is a common defect found in the rail. It can be detected by visual inspection, image processing, or dynamic responses. However, using machine learning techniques to detect and classify corrugation is new. This study aims to apply machine learning to detect corrugation because it is fast and cost-efficient. In addition, this study uses accelerations as features to do predictions which easy to collect using axle box acceleration sensors so there is no or little additional cost for equipment installation.

3. Train vibration data using multibody simulations

The main function of the railway track dynamics analysis model is to couple the various components of the vehicle and the track structure to determine the influence of the load on the stress, strain and deformation of each component, and to correctly express their complex interactions. Such a model provides a basis for predicting orbital performance and serves as a technical means for orbital design and maintenance (Oscarsson and Dahlberg 1998).

Cai (1994) studied a detailed model of track dynamics and wheel-rail interaction by initially creating the D-track for dynamic simulation. Iwnick (1998) set the benchmark (Manchester benchmark) in 1998. Steffens (2005) used the Manchester benchmark parameters to compare the

Table 1 The input and the output of the D-track software

Input				Output
Track	Vehicle	Irregularity	Variety	
• Rail type • Axial force • Sleeper type • Spacing • Track bed stiffness • Track bed • Damping • Pad damping • Pad stiffness	• Speed • Tare mass • Carry mass • Primary suspension stiffness • Primary suspension damping • Wheel dimension • Hertzian contact coefficient	• Corrugation • Dipped joint • Dipped weld • Peaked weld • Arbitrary profile • Wheel flat	• Speed • Irregularity length • Irregularity depth • Center of irregularity • Rail analysis position • Sleeper analysis position	• Acceleration • Force and pressure • Moment and shear • Bending moment • Displacement

performance of various dynamic simulation programs and developed a user interface for D-track. However, the original D-track still had problems, because its numerical results are often lower. Leong (2007) revised the procedure on the basis of Steffens' Manchester benchmark and obtained the new Benchmark. Leong verified the revised results, and the difference between the numerical results is less than 15% (Kaewunruen and Chiengson 2018).

In the D-track software, through adjusting the parameters, different railway models are designed, and through operation, the DARTS (Dynamic Analysis of Track Structure) model automatically calculates a variety of output parameters during the simulation process. In this study, the package has been used to obtain over a thousand of train vibration data (i.e., axle box acceleration). The aim is to reuse the axle box accelerations that are commonly measured onboard a train to aid the monitoring and classification of rail corrugations on curved tracks.

In order to design a suitable railway model, each component needs to be designed safely and meet the requirements. The choice of all track components is important. D-track has parameter libraries for various components of vehicles and tracks. A parameter library has been established for various components in the system, including vehicles, bogies, wheels, tracks, rail pads, sleepers and track bed materials. By selecting parameters and inputting data in the "Track", "Vehicle", "Irregularity", "Analysis" and "Comments" windows of D-track, different railway models can be designed. In this study, AS50, AS53, AS60 type track and 106t Coal Wagon, Manchester, RQTY Container Wagon type vehicles are used. Meanwhile the vehicle speeds are set at 60, 70, 80, 90, 100, 110, and 120 km/h.

Kaewunruen (2018) shown different intervals often experience "unbalanced" velocities, which usually lead to "short-distance" low-orbit corrugations. At an unbalanced speed, the train travels at a speed that causes a centripetal force. The wheels acting on the lower rail will bear more weight or load than the wheels on the outer rail. Because the wheel-rail interaction produces additional dynamics and bending effects, the rail will be subjected to excessive wheel load and wear. Track ripple defects on steep curves are often related to the 30 mm to 100 mm wavelength band. In this study, the wavelengths of rail corrugation are set at 30, 40, 50, 60, 70, 80, 90, and 100mm. At the same time, in order to compare with the rail without corrugation, a model without corrugation will be established.

As shown in Table 2, the general parameters of each part of the railway track structure are combined to build 567 different models.

Table 2 Selection and input of different parameters of D-track railway model

Parameters	Input
Track type	AS50, AS53, AS60
Vehicle type	106t Coal Wagon, Manchester, RQTY Container Wagon
Vehicle speed (km/h)	60, 70, 80, 90, 100, 110, 120
Wavelength (mm)	0, 30, 40, 50, 60, 70, 80, 90, 100

Liu (2018) found the relationship between track irregularity in irregularity amplitude, wavelength and vehicle speed. The detail can be shown as follows:

(1) On the premise that the vehicle speed and the wavelength of the irregularity are kept constant, increasing the amplitude of the irregularity will result in greater dynamic response such as the force between the wheel and the rail and the vehicle vibration.

(2) Under the premise that the amplitude of the irregularity and the speed of the vehicle are kept constant, the wavelength of the irregularity becomes shorter, and the impact will be larger and non-linear. At the same time, the influence of the periodic resonance wavelength and the sensitive wavelength will be more obvious.

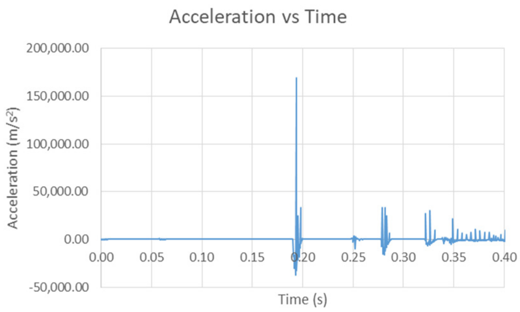
(3) Under the premise that the irregularity amplitude and the irregularity wavelength are kept constant, as the vehicle speed increases, its nonlinearity increases and its influence increases.

TIME(s)	X-RAIL(m)	ACON1	ACON2	A-RAIL	A-R.S.	A-TY
0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
5.00E-04	6.67E-03	3.91E-02	0.00E+00	-1.54E-02	-1.04E-02	-8.94E-03
1.00E-03	1.50E-02	-3.32E-02	0.00E+00	2.56E-02	4.12E-03	4.99E-03
1.50E-03	2.33E-02	1.15E-03	0.00E+00	-2.10E-02	-4.62E-03	-3.65E-03
2.00E-03	3.17E-02	7.54E-02	0.00E+00	-6.64E-03	-1.49E-02	-1.29E-02
2.50E-03	4.00E-02	2.02E-02	0.00E+00	1.98E-02	6.30E-03	7.73E-03
3.00E-03	4.83E-02	1.08E-01	0.00E+00	-3.48E-02	-1.32E-02	-1.07E-02
3.50E-03	5.67E-02	1.34E-01	0.00E+00	1.88E-02	-1.22E-02	-9.85E-03
4.00E-03	6.50E-02	4.87E-02	0.00E+00	1.62E-02	1.17E-02	1.30E-02
4.50E-03	7.34E-02	3.58E-02	0.00E+00	-5.90E-02	-2.58E-02	-2.27E-02
5.00E-03	8.17E-02	-8.44E-02	0.00E+00	3.25E-02	-1.05E-02	-8.92E-03
5.50E-03	9.00E-02	-2.02E-01	0.00E+00	3.54E-02	2.49E-02	2.42E-02
6.00E-03	9.84E-02	-2.25E-01	0.00E+00	-5.46E-02	-1.42E-02	-1.30E-02
6.50E-03	1.07E-01	-2.50E-01	0.00E+00	2.06E-02	-3.24E-03	-3.40E-03
7.00E-03	1.15E-01	-1.88E-01	0.00E+00	2.97E-02	2.17E-02	1.93E-02

Fig. 2 The acceleration output of D-track software

TIME(s)	X-RAIL(m)	ACON1	ACON2	A-RAIL	A-R.S.	A-TY
0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
5.00E-04	6.67E-03	3.91E-02	0.00E+00	-1.54E-02	-1.04E-02	-8.94E-03
1.00E-03	1.50E-02	-3.32E-02	0.00E+00	2.56E-02	4.12E-03	4.99E-03
1.50E-03	2.33E-02	1.15E-03	0.00E+00	-2.10E-02	-4.62E-03	-3.65E-03
2.00E-03	3.17E-02	7.54E-02	0.00E+00	-6.64E-03	-1.49E-02	-1.29E-02
2.50E-03	4.00E-02	2.02E-02	0.00E+00	1.98E-02	6.30E-03	7.73E-03
3.00E-03	4.83E-02	1.08E-01	0.00E+00	-3.48E-02	-1.32E-02	-1.07E-02
3.50E-03	5.67E-02	1.34E-01	0.00E+00	1.88E-02	-1.22E-02	-9.85E-03
4.00E-03	6.50E-02	4.87E-02	0.00E+00	1.62E-02	1.17E-02	1.30E-02
4.50E-03	7.34E-02	3.58E-02	0.00E+00	-5.90E-02	-2.58E-02	-2.27E-02
5.00E-03	8.17E-02	-8.44E-02	0.00E+00	3.25E-02	-1.05E-02	-8.92E-03
5.50E-03	9.00E-02	-2.02E-01	0.00E+00	3.54E-02	2.49E-02	2.42E-02
6.00E-03	9.84E-02	-2.25E-01	0.00E+00	-5.46E-02	-1.42E-02	-1.30E-02
6.50E-03	1.07E-01	-2.50E-01	0.00E+00	2.06E-02	-3.24E-03	-3.40E-03
7.00E-03	1.15E-01	-1.88E-01	0.00E+00	2.97E-02	2.17E-02	1.93E-02

(a)



(b)

Fig. 3 The chosen acceleration output of D-track software (a) Examples of measurement point; (b) Measurement points in a sample

Liu (2018) established a dynamic model for the relationship between the frequency of rail corrugation irregularities and the frequency of vibration acceleration and concluded that the frequencies of the two are equal. Based on this principle, the rail corrugation characteristics can be studied by studying vibration acceleration. Through D-track, accelerations of wheel/rail contact, rail and sleeper can be obtained, as shown in Figs. 2 and 3.

In this study, the acceleration of wheel-rail contact1 will be used for research and neural network training.

4. Artificial neural network

4.1 Development of artificial neural network

Since the vibration acceleration data can be obtained, an artificial neural network can be established for training and testing. Artificial neural networks have been widely used in the fields of pattern recognition, signal processing, intelligent control, and system modelling due to their advantages of distributed storage of information, parallel processing, and self-learning capabilities. This is good for processing problems which need to consider many factors and inaccurate information (Tiğdemir 2014). For these reasons, this study adopts the artificial neural network method for predictive model development.

Artificial Neural Network (ANN) is based on the basic principles of neural networks in biology (CSDN 2019). It simulates the processing mechanism of the human brain's nervous system to complex information. A neural network is a computational model consisting of a large number of nodes (or neurons) connected to each other. These neurons are distributed in a series of units. There are three main types of processing units in the network: input units, output units and hidden units. The input unit receives various forms of information from the outside. This is the data that the neural network is designed to process or learn. Data from the input unit passes through one or more hidden units. The job of the hidden unit is to convert the input into content that the output unit can use. Most neural networks are fully connected from one layer to another. These connections are called 'weighted'. The larger the number, the greater the influence of one unit on another, similar to the human brain. The other end of the network is the output unit, which is where the network responds to the given and processed data. Parallel and distributed information processing functions are obtained through network conversion and dynamic behavior (Jain *et al.* 1996).

4.2 Neural network training

Any artificial neural network (ANN) model can be established using a designed computation architecture with various number of layers and hidden nodes. Generally, a specific architecture of ANN can yield certain level of accuracy and computation performance. In this study, a number of ANN architectures (forming various ANN models) are assessed to identify the optimal ANN model that can yield the best outcome.

4.2.1 Training of the first neural network model

The purpose of this study is to monitor rail corrugation, so this study first uses a single output layer corresponding to the corrugation value of the model. The input layer contains 1,117 nodes which are accelerations from D-track simulation as shown in Figs. 2 and 3. 567 D-track model

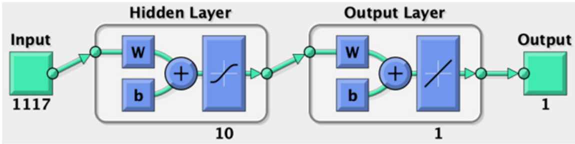
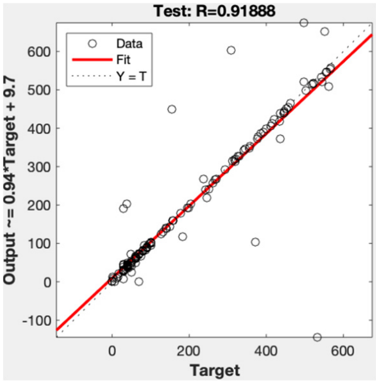
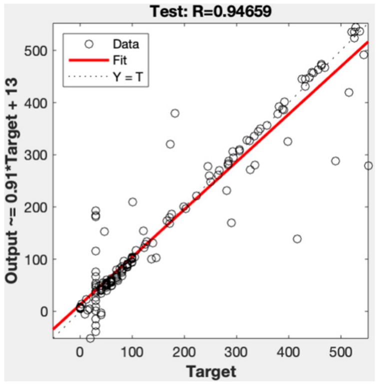


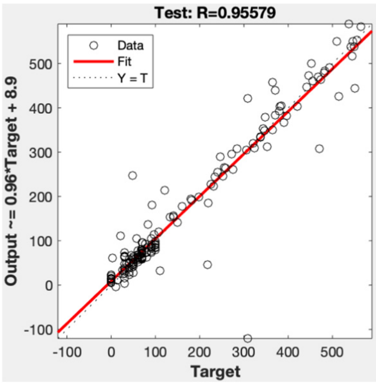
Fig. 4 Neural network of the first NN model (The number of hidden layers = 10)



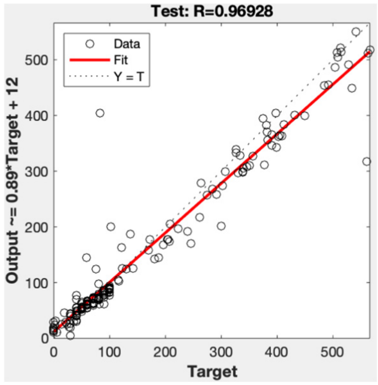
(a) The number of hidden nodes = 10



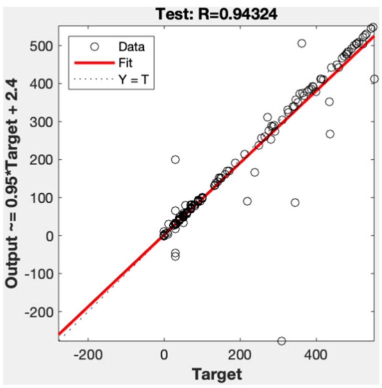
(b) The number of hidden nodes = 11



(c) The number of hidden nodes = 12



(d) The number of hidden nodes = 13



(e) The number of hidden nodes = 14

Fig. 5 The degree of fit of the first NN model (the number of hidden nodes = 10, 11, 12, 13, 14) samples are analyzed through railway track dynamics, and 1,117 wheel-rail contact accelerations were obtained at 1,117 different time nodes. The output of the first model is the size of corrugation.

When designing neural networks, the main emphasis is on experimentation and discussion of multiple model schemes. In the process of selecting the hidden layer, if the number of hidden nodes is too few, the network cannot have the necessary learning ability and information processing ability. On the contrary, if it is too much, it will not only greatly increase the complexity of the network structure, but the network is more likely to be overfitting, and the learning speed of the network will become very slow. In the process of neural training, only a small number of hidden nodes are selected first, and then the number of hidden nodes is continuously increased until satisfactory performance is obtained. The training process is performed to repeatedly adjust the weight and threshold according to the error between the target value and the network output value, until the error reaches a predetermined value (Karsoliya 2012).

Initially, the training data set containing 397 random parts (70%) among the 567 available parts is selected as the learning stage. In the remaining 30% of the data set, 15% is used to verify the model, and the other 15% is used to test the model.

In this study, the different numbers of hidden nodes are tired. It is found that R is 0.57 when the number of hidden nodes is 1 and the accuracies increase when the number of hidden nodes increases up to 15 which R is 0.94. After that, the accuracies decrease significantly when the number of hidden nodes is more than 20 which might be resulted from the overfitting. Therefore, to demonstrate the results of the models in this study, the number of hidden nodes is set up from 10 nodes and increased continuously, and the correlation coefficients of the test are compared to select the optimal number of hidden nodes.

When the number of hidden nodes = 10, the neural network in Fig. 4 can be obtained.

Through neural network training, the test correlation coefficient results are as Fig. 5.

Through continuous experimentation, it can be found that when the number of hidden nodes is 13, the correlation coefficient of the test is the highest.

4.2.2 Training of the second neural network model

In this study, when analyzing the dynamics of the railway track through D-track, not only the rail corrugation of the track surface is defined, but also parameters such as speed, track type, and vehicle type are selected. Based on the previous NN model, a new combined model containing two outputs is proposed. The input is the same as the first model. The first output is still the rail corrugation value of the corresponding model. The second output is the rolling stock’s speed of the corresponding model.

As in the first model, the numbers of hidden nodes are tired. To demonstrate the performance of the model, the number of hidden nodes is set to start from 10, the following neural network can be shown in Fig. 6.

Through neural network training, the test correlation coefficient results are shown in Fig. 7.

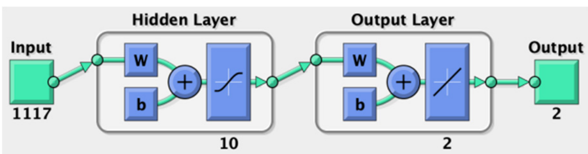
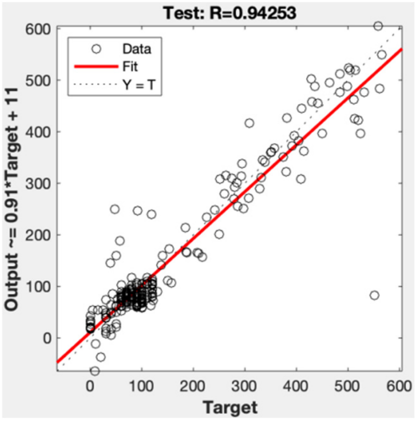
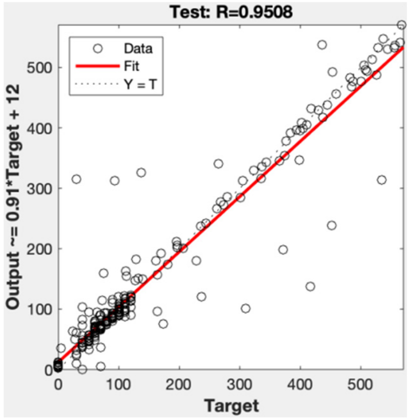


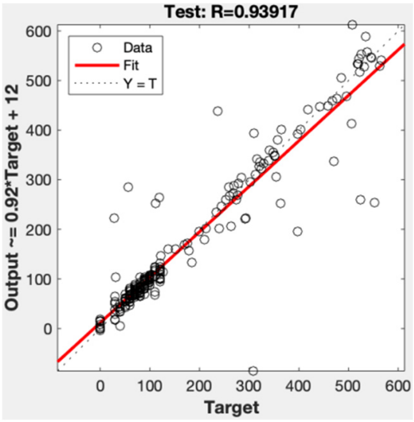
Fig. 6 Neural network of the second NN model (the number of hidden nodes = 10)



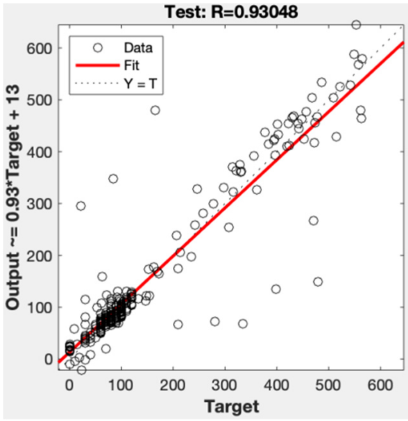
(a) The number of hidden nodes = 9



(b) The number of hidden nodes = 10



(c) The number of hidden nodes = 11



(d) The number of hidden nodes = 12

Fig. 7 The degree of fit of the second NN model. (the number of hidden nodes = 9, 10, 11, 12)

Because when the number of hidden nodes is 11, 12, the test correlation coefficient is lower than the result of the number of hidden nodes of 10. Therefore, this study considers reducing the number of hidden nodes, and compares the correlation coefficients of the test.

Through neural network training, it can be found that when the number of hidden nodes is 10, the correlation coefficient of the test is the highest.

4.2.3 Training of the third neural network model

The comparison of the two models is not sufficient to explain the influence of the output node on the correlation coefficient. In order to make the research more rigorous, it will compare the third new combination model with three outputs - adding orbital types as the third output. The output layer consists of three data nerves, as follows:

Output 1: Rail corrugation value (0, 30, 40, 50, 60, 70, 80, 90, 100)
Output 2: Vehicle speed (60, 70, 80, 90, 100, 110, 120)
Output 3: Track type (AS50, AS53, AS60)

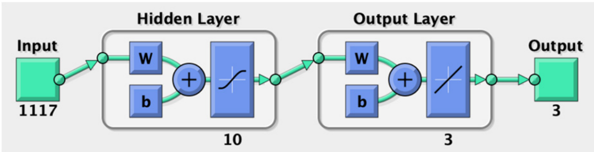
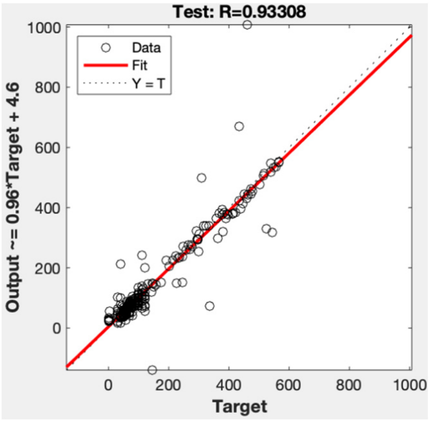
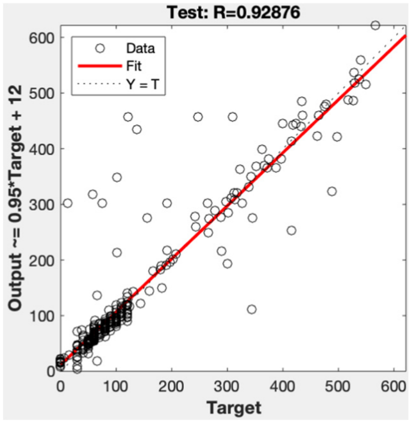


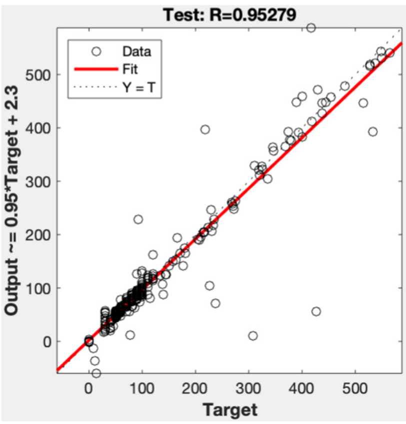
Fig. 8 Neural network of the third NN model (the number of hidden nodes = 10)



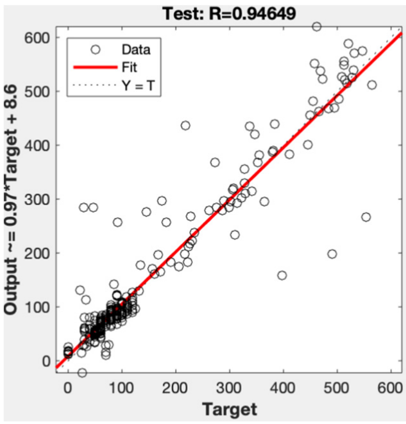
(a) The number of hidden nodes = 10



(b) The number of hidden nodes = 11



(c) The number of hidden nodes = 12



(d) The number of hidden nodes = 13

Fig. 9 The degree of fit of the third NN model (the number of hidden nodes = 10, 11, 12, 13)

The input layer is the same as the previous two models. When the number of hidden layers = 10, the following neural network can be shown in Fig. 8.

Through neural network training, the test correlation coefficient results are shown in Fig. 9.

Through continuous experimentation, it can be found that when the number of hidden nodes is 12, the correlation coefficient of the test is the highest.

Table 3 Output layers of these three NN models

Classification of NN models	Output layer
The first NN model	Rail corrugation
The second NN model	Rail corrugation and vehicle speed
The third NN model	Rail corrugation value, vehicle speed and track type

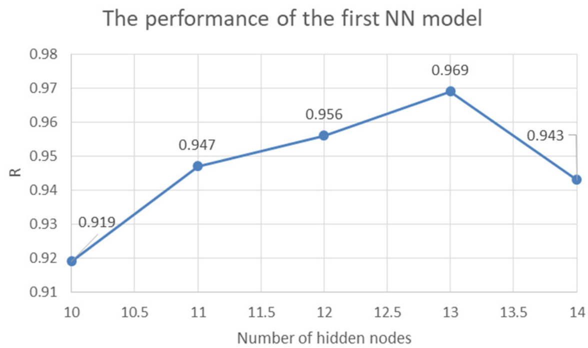


Fig. 10 The tests correlation coefficients of the different hidden nodes of the first NN model

5. Results and discussion

In the artificial neural network training process, the three possible neural network models have achieved excellent results, and the correlation coefficients of the tests are all very high. The first NN model has only one output layer of rail corrugation values. This is because, for train vibration quantifications, not only the rail corrugation of the track surface is defined, but there are also several variables such as speed, track type, and vehicle type. Therefore, parameter variables are added to the model to explore the most suitable NN model. The second NN model has two output layers, rail corrugation value and vehicle speed. The comparison of the two models is not enough to explain the influence of the output layer on the correlation coefficient. Therefore, a third neural network model is established, which includes three output nodes of rail corrugation value, vehicle speed and track type. For other variables, the three NN models remain consistent.

The first NN model has only one output layer of rail corrugation values. Through continuous experiments, when the hidden layer is 13, the tested correlation coefficient is the highest where $R = 0.969$.

The second NN model has two output layers, rail corrugation value and vehicle speed. When the number of hidden layers is 9, the best result will be displayed, and the tested correlation coefficient is the highest where $R = 0.951$.

The third NN model includes three output layers of rail corrugation value, vehicle speed and track type. Experiments show that when the number of hidden nodes is 12, the tested correlation coefficient is the highest where $R = 0.953$.

Comparing the results of the hidden nodes of the three NN models, the results show that the NN model with one output layer has the best test correlation coefficient.

On the other hand, the fewer the output layers, the shorter the training time of the artificial neural network. The experiment shows that the NN model with only one output layer has the

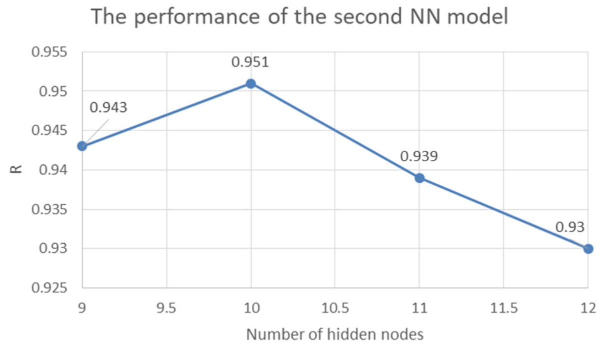


Fig. 11 The tests correlation coefficients of the different hidden nodes of the second NN model

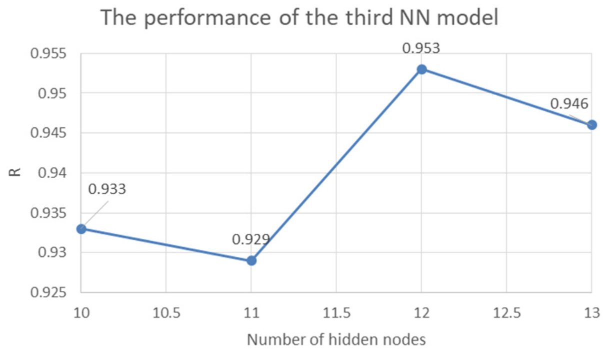


Fig. 12 The tests correlation coefficients of the different hidden layers of the third NN model

shortest training time. By comparison, it can be found that the first NN model with only one output layer of rail corrugation value has the best results, and it is the most suitable NN model for monitoring rail corrugation based on this study.

Moreover, this study also shows that it is not that the more hidden nodes, the greater the correlation coefficient R obtained. It is not that the more layers and the more nodes, the better the results obtained. However, as the number of hidden layers increases, the model will appear to be overfitting and resulting in lower predicted accuracy. While training the neural network, it is necessary to consider the number of effective hidden nodes for training to avoid overfitting affecting the training results.

6. Conclusions

In this study, the D-track software is first used to simulate the railway track dynamics providing over a thousand of train vibration data. Through the selection and input of parameters and data such as vehicle type, track type, and track surface roughness, 567 railway simulations under different conditions are designed. Then through the simulation of D-track software, the acceleration of wheel-rail contact is obtained. After obtaining the acceleration of wheel-rail contact, Matlab's artificial neural network is used for training, and three neural network (NN) models with different output layers are established. The input layers of the three NN models are all acceleration of wheel-rail contact obtained by D-track software. The output layer of the first NN model only has the rail corrugation value. The output layer of the second NN model contains two layers which are rail corrugation value and vehicle speed. The third NN model contains three output layers including rail corrugation value, vehicle speed and track type. Each NN model obtains the optimal test correlation coefficient R of the model by adjusting the number of hidden nodes. Comparing the best results of the three models, it is found that the NN model with only one output layer containing rail corrugation values is the best. On the other hand, when there are fewer output layers, neural network training is faster. In this regard, the NN model with only one output layer is also the best. All in all, the most suitable model is the NN model containing only one output node, which is the rail corrugation value.

Most of the rail corrugation detection methods require railway personnel to conduct on-site surveys of their tracks within a specific time, and then perform on-site maintenance. These methods have great restrictions on the time and location of maintenance. In this study, D-track is used to obtain the dynamic simulation of the railway track, and then the artificial neural network is used to achieve the purpose of monitoring the rail corrugation status. Such a novel method reduces the harsh conditions for monitoring the rail condition. This is a feasible and more effective detection method. Practically, the results from this study can be applied by collecting acceleration data from axle boxes then applying the developed model to detect corrugation. The novel ANN established in this study is not only a very effective diagnostic method for rail corrugation, but also can be applied to other railway loss monitoring. Future work will include the commercial translation of the neural networks to various field studies.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, S.K., J.S., G.Z.; methodology, J.S., G.Z.; software, S.K.; validation, J.S., G.Z.; formal analysis, J.S., G.Z.; investigation, S.K., J.S., G.Z.; resources, S.K.; data curation, J.S., G.Z.; writing—original draft preparation, J.S., G.Z.; writing—review and editing, S.K.; visualization, J.S., G.Z.; supervision, S.K.; project administration, S.K.

Acknowledgments

Financial support from European Commission is gratefully acknowledged for H2020-MSCA-RISE Project No. 691135 "RISEN: Rail Infrastructure Systems Engineering Network," which enables a global research network that tackles the grand challenge in railway infrastructure resilience and advanced sensing under extreme events (www.risen2rail.eu).

References

Ajmal, P.C. and Mohammed, A. (2018), "Finite element analysis based fatigue life evaluation approach for railway bridges: a study in Indian scenario", *Struct. Monitor. Maint., Int. J.*, **5**(4), 429-443.

https://doi.org/10.12989/smm.2018.5.4.429
Cai, Z. (1994), "Modelling of rail track dynamics and wheel/rail interaction."
Cao, B.Y., Ding, Y.L., Zhao, H.W. and Song, Y.S. (2016), "Damage identification for high-speed railway truss arch bridge using fuzzy clustering analysis", *Struct. Monitor. Maint., Int. J.*, **3**(4), 315-333. https://doi.org/10.12989/smm.2016.3.4.315
Chen, G.X., Zhou, Z.R., Ouyang, H.J., Jin, X.S., Zhu, M.H. and Liu, Q.Y. (2010), "A finite element study on rail corrugation based on saturated creep force-induced self-excited vibration of a wheelset–track system", *J. Sound Vib.*, **329**(22), 4643-4655. https://doi.org/10.1016/j.jsv.2010.05.011
Clark, R.A., Scott, G.A. and Poole, W. (1988), "Short wave corrugations-an explanation based on stick-slip vibrations", *Applied Mechanics Rail Transportation Symposium*, Vol. 96, pp. 141-148.
CSDN (2019), "Introduction to Artificial Neural Networks", Retrieved 1 July, 2020, from https://blog.csdn.net/htrdchh/article/details/87903720.
Grassie, S.L. and Kalousek, J. (1993), "Rail corrugation: characteristics, causes and treatments", *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, **207**(1), 57-68. https://doi.org/10.1243/PIME_PROC_1993_207_227_02
Iwnick, S. (1998), "Manchester benchmarks for rail vehicle simulation", *Vehicle Syst. Dyn.*, **30**(3-4), 295-313.
Jain, A.K., Mao, J. and Mohiuddin, K.M. (1996), "Artificial neural networks: A tutorial", *Computer*, **29**(3), 31-44. https://doi.org/10.1109/2.485891
Kaewunruen, S. (2014), "Monitoring in-service performance of fibre-reinforced foamed urethane material as sleepers/bearers in railway urban turnout systems", *Struct. Monitor. Maint., Int. J.*, **1**(1), 131-157. https://doi.org/10.12989/smm.2014.1.1.131
Kaewunruen, S. (2018), "Monitoring of rail corrugation growth on sharp curves for track maintenance prioritisation", *Int. J. Acoust. Vib.*, **23**, 35-43.
Kaewunruen, S. and Chiengson, C. (2018), "Railway track inspection and maintenance priorities due to dynamic coupling effects of dipped rails and differential track settlements", *Eng. Fail. Anal.*, **93**, 157-171. https://doi.org/10.1016/j.engfailanal.2018.07.009
Kaewunruen, S., Osman, M.H.B. and Rungskunroch, P. (2019), "The total track inspection", *Front. Built Environ.*, **4**, 84. doi: 10.3389/fbuil.2018.00084
Kaewunruen, S., Sresakoolchai, J. and Thamba, A. (2021), "Machine learning-aided identification of train weights from railway sleeper vibration", *Insight-Non-Destructive Test. Condition Monitor.*, **63**(3), 151-159. https://doi.org/10.1784/insi.2021.63.3.151
Karsoliya, S. (2012), "Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture", *Int. J. Eng. Trends Technol.*, **3**(6), 714-717.
Leong, J. (2007), "Development of a limit state design methodology for railway track", Queensland University of Technology.
Li, H.F. (2014), "Research on the Wave Wear Detection System of Metro Track", Master; Southwest Jiaotong University.
Liu, L. (2018), "Research on rail corrugation detection method based on vehicle axle box vibration acceleration", Master; Southwest Jiaotong University.
Luo, L.Z., Wu, W.G. and Chai, X. (2006), *Control of Track Smoothness of Wheel-Rail System*, Beijing: China Railway Press.
Matsumoto, A., Sato, Y., Ono, H., Tanimoto, M., Oka, Y. and Miyauchi, E. (2002), "Formation mechanism and countermeasures of rail corrugation on curved track", *Wear*, **253**(1-2), 178-184. https://doi.org/10.1016/S0043-1648(02)00097-2
de Melo, A.L.O., Kaewunruen, S., Papaelias, M., Bernucci, L.L.B. and Motta, R. (2020), "Methods to Monitor and Evaluate the Deterioration of Track and Its Components in a Railway In-Service: A Systemic Review", *Front. Built Environ.*, **6**, 118. https://doi.org/10.3389/fbuil.2020.00118
Ngamkhanong, C., Kaewunruen, S. and Baniotopoulos, C. (2017), "A review on modelling and monitoring of railway ballast", *Struct. Monitor. Maint., Int. J.*, **4**(3), 195-220. https://doi.org/10.12989/smm.2017.4.3.195
Oscarsson, J. and Dahlberg, T. (1998), "Dynamic train/track/ballast interaction-computer models and full-

scale experiments", *Vehicle Syst. Dyn.*, **29**(S1), 73-84. https://doi.org/10.1080/00423119808969553

Remennikov, A.M. and Kaewunruen, S. (2008), "A review of loading conditions for railway track structures due to train and track vertical interaction", *Structural Control and Health Monitoring: The Official Journal of the International Association for Structural Control and Monitoring and of the European Association for the Control of Structures*, **15**(2), 207-234. https://doi.org/10.1002/stc.227

Steffens, D.M. (2005), "Identification and development of a model of railway track dynamic behaviour", Queensland University of Technology.

Suda, Y. (1991), "Effects of vibration system and rolling conditions on the development of corrugations", *Wear*, **144**(1-2), 227-242. https://doi.org/10.1016/0043-1648(91)90017-O

Tiğdemir, M. (2014), "Re-evaluation of the AASHTO-flexible pavement design equation with neural network modeling", *PloS one*, **9**(11), e113226. https://doi.org/10.1371/journal.pone.0113226

Vadillo, E.G., Tárrago, J., Zubiaurre, G.G. and Duque, C.A. (1998), "Effect of sleeper distance on rail corrugation", *Wear*, **217**(1), 140-145. https://doi.org/10.1016/S0043-1648(97)00239-1

Xia, Y.X., Ni, Y.Q. and Zhang, C. (2014), "Evaluation of torsional response of a long-span suspension bridge under railway traffic and typhoons based on SHM data", *Struct. Monitor. Maint., Int. J.*, **1**(4), 371-392. https://doi.org/10.12989/sss.2014.14.5.785

Xu, Y.L. and Dai, Y.H. (2007), *Rail Transit Public Affairs Management*, Shanghai: Tongji University Press, pp. 25-27.

Yzawa, E. and Takeshita, K. (2002), "Development of measurement device of track irregularity using inertial mid-chord offset method", Quarterly Report of RTRI, **43**(3), 125-130.

Zhang, W. (2007), "Research on short-wave track irregularity recognition method based on axle box spectrum", Master; Beijing Jiaotong University.

Zhang, Q., Gao, Y., Zhang, H.X., Xu, F. and Li, F. (2018), "Risk identification, assessment and monitoring design of high cutting loess slope in heavy haul railway", *Struct. Monitor. Maint., Int. J.*, **5**(1), 67-78. https://doi.org/10.12989/smm.2018.5.1.067

HL