Prediction of Wheel and Rail Roughness Parameters Using Artificial Neural Network

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Abstract

Wheel and rail reprofiling costs millions of dollars around the world. The wheel/rail roughness is one of the important parameter which be able to effect on wheel/rail wear. The use of an artificial neural network to predict the wheel/rail roughness parameters can help to improve the design of the wheel/rail profiles. Wheel/rail roughness can define as the shorter frequency of real wheel/rail surfaces relative to the troughs. There are several roughness parameters, but the arithmetical mean roughness (Ra) is the common parameter, it is indicating the average of the absolute value along the sampling length. In this paper, both rail and wheel roughness were measured experimentally using Alicona profilometer and replica material, then, the arithmetical mean height of the wheel and rail was predicted using artificial neural networks. The results showed that the neural network predicted the wheel and rail roughness parameter efficiently.

Keywords: Wheel/rail roughness, artificial neural network, Matlab, roughness parameters, Alicona profilometer, and replica material.

1. Introduction to Railway System

1.1 Railway System

The railway train running along a track is one of the most complicated dynamical systems in engineering. Bogie is one of the most important part on the railway system. It consists of the following parts: wheelset, axle box, wheels, suspension, elastic elements, and damping. The wheelset comprises two wheels rigidly connected by a common axle. The wheelset is supported on bearings mounted on the axle journals. The wheelset provides the necessary distance between the vehicle and the track, the guidance that determines the motion within the rail gauge, and the means of transmitting traction and braking forces to the rails to accelerate and decelerate the vehicle. The design of the wheelset depends on the type of the vehicle, the type of braking system used, and the construction of the wheel centre and the position of bearings on the axle. The axle box is the device that allows the wheelset to rotate by providing the bearing housing and also the mountings for the primary suspension to attach the wheelset to the bogie or vehicle frame. The axle box transmits longitudinal, lateral, and vertical forces from the wheelset on to the other bogie element. The wheels and axles are the most critical parts of the railway rolling stock. Mechanical failure or exceedance of design dimensions can cause derailment. Solid wheels have three major elements: the tyre, the disc, and the hub, and mainly differ in the shape of the disc. The suspension is the set of elastic elements, dampers and associated components which connect wheelsets to the car body. If the bogie has a rigid frame, the suspension usually consists of two stages: primary suspension connecting the wheelsets to the bogie frame and secondary suspension between the bogie frame and the bolster or car body [1]. The elastic elements (springs) are components which return to their original dimensions when forces causing them to deflect are removed. The Damping is usually provided in railway vehicle suspension by the use of viscous or friction damping devices [1].

1.2 Railway Track

The typical shape and construction profiles of a ballasted track are illustrated in Figure (1). The rail track sleeper is used to transmit the wheel load to the ballast medium. In addition, it has functions such as maintaining track alignment and gauge, restraining longitudinal and lateral rail movements, and providing strength and stability to track structure. The rail joints are used to join rails depending on the required position of the rails [2].

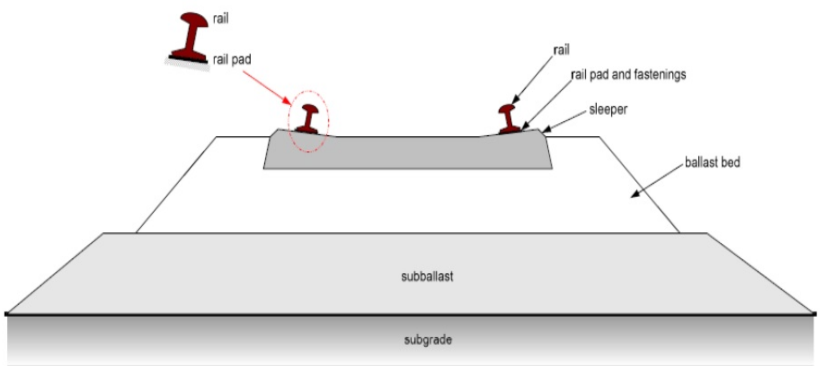

Figure 1: Rail track components and their arrangements [2]

1.3 Wheel Set

The wheel set is placed attached to the railway bogie. Bogie is a structure underneath a train to which axles and hence wheels are attached through bearings. Bogies are classified according to their configurations in terms of the numbers of axles, the design and structure of the suspension systems [2]. Generally, the railway wheel set has 6 degrees of freedom broadly classified as translational and rotational degrees of freedom parts such as in Figure (2). The translational degrees of freedom comprise three components that is translation along: X-axis, Y-axis, and Z-axis.

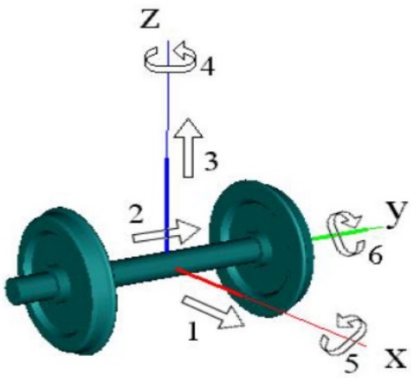

Figure 2: Wheel set degrees of freedom [2]

1.4 Rail

Railway lines are made of straight sections and curves. Train driving on the curves essentially differs from that one on straight sections. On the curves railway gauge is widened (when curve radius is less than 350 m). Rails are longitudinal steel members that are placed on spaced sleepers to guide the rolling stock. Support of traffic load and guidance of vehicles are the two main tasks of the rails. For both tasks the correct contact geometry between wheel and rail is essential. In addition to that rails are used to accommodate and transfer the wheel/axle loads into the supporting sleepers. The most commonly used profile is flat-bottom rail and is divided into three parts such as in Figure (3) [2]:

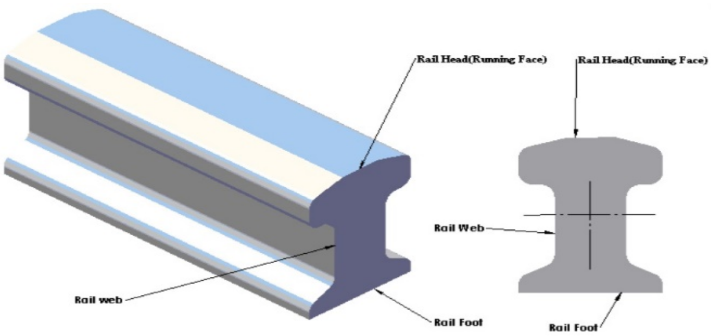

Figure 3: Flat bottom rail parts [2]

1.5 Rail-Wheel Interaction

The dynamic behavior of railway vehicle is greatly affected by the rail-wheel dynamic interactions. This interaction (wheel/rail) mainly depends on wheel/rail contact geometry. The changes in contacting geometry of rail/wheel depends on different parameters like the variation of wheel and rail profile, track gauge, rail inclinations, railhead surface irregularities, and flexibility of rail support. The main parameters influencing the wheel rail contact geometry are the profiles of wheels and rails, rail inclination and track gauge [2]. Figure (4) shows the general wheel rail interactions from the front and side view respectively.

A) B)

Figure 4: Front views (A), and side view (B) of wheel/rail contact interface [2]

1.6 Wheel/Rail Wear

The profile change of rails on curves makes a large contribution to track maintenance cost. The profile change on wheels can also be significant, especially on a curved track. Damage mechanisms such as wear and plastic deformation are the main contributors to profile change. Another growing problem for many railways is rolling contact fatigue. Wear is the loss or displacement of material from a contacting surface. Material loss may be in the form of debris. Material displacement may occur by transfer of material from one surface to another by adhesion or by local plastic deformation. There are many different wear mechanisms that can occur between contacting bodies, each of them producing different wear rates. Wheel/rail wear is shown in Figure (5).

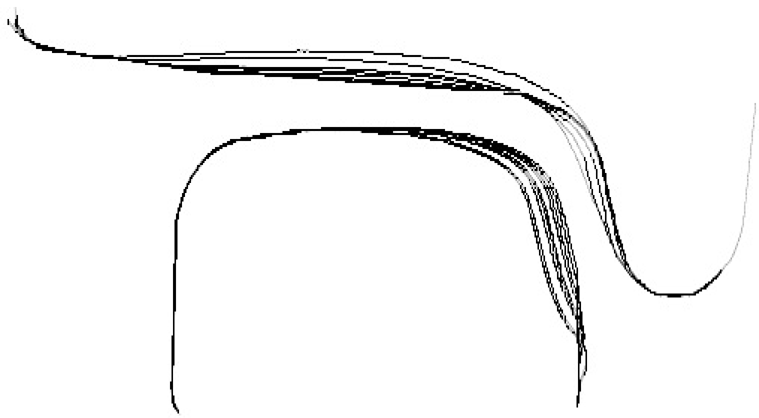

Figure 5 Form change of wheel and rail from the Stockholm test case [1]**.**

1.7 Roughness Parameters:

Roughness average (R_a), it called centre line average value or arithmetic average. Among Height Parameters, the roughness average (Ra) is the most widely used because it is a simple parameter to obtain when compared to others. The roughness average is described as follows [3]:

$$R_a = \frac{1}{L} \int_0^L |Z(x)| \quad (1)$$

Where $Z(x)$ is the function that describes the surface profile analyzed in terms of height (Z) and position (x) of the sample over the evaluation length "L" , such as in Figure (6).

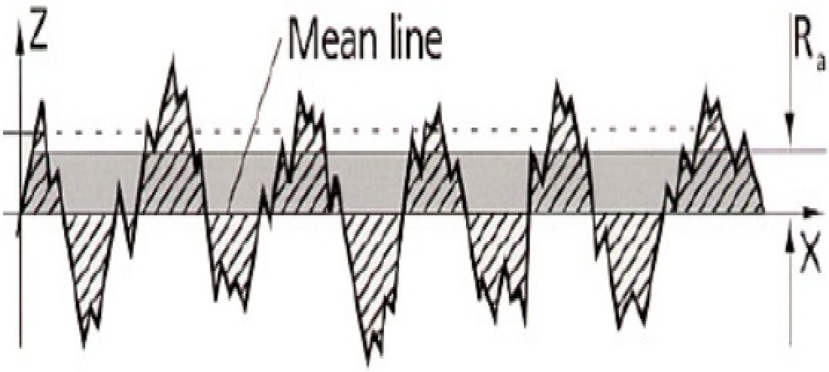

Figure 6: Profile of a surface (Z). It represents the average roughness Ra [3]

2. Artificial Neural Networks (ANN)

2.1 Introduction to Neural Networks

Artificial neural networks (ANN) are, as their name indicates, computational networks which attempt to simulate, in a gross manner, the networks of nerve cell (neurons) of biological (human or animal) central nervous system [4]. An ANN consists of interconnected processing units. The general model of a processing unit consists of a summing part receives N input values, weights each value, and computes a weights sum. The weighted sum is called the activation value. The output part produces a signal from activation value [5]. The use of neural networks offers the following useful properties and capabilities Nonlinearity, input-output mapping, adaptively, evidential response, contextual information, fault tolerance, uniformity of analysis and design, very large scale integrated implement ability, and neurobiological analogy [6].

The activation function is illustrated in Figure (7).

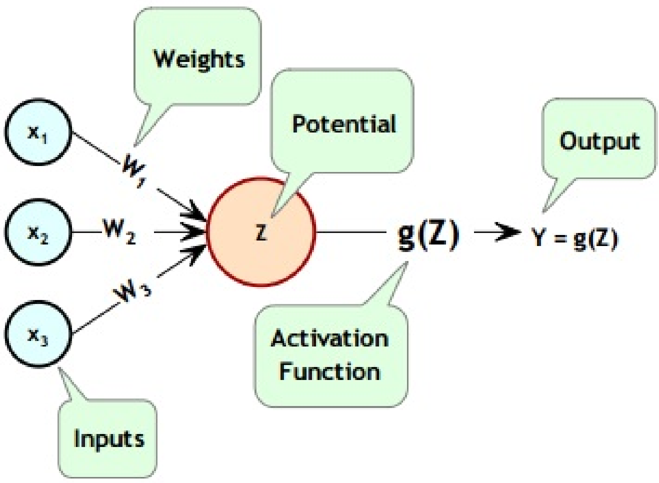

Figure 7: A Neural Net Perceptron [7]

As shown in Figure 7, perceptron consists of the following five components [7]:
Inputs: X1, X2, and X3; weights: W1, W2, and W3; potential: $Y(n) = \sum_{i=1}^{3} W_i W_i$; activation function: g(Z); and the output:

Y = g(Z).

Although theoretically any differential function can be used as an activation function, the sigmoid function is the most commonly used. Figure (8) shows the sigmoid activation function.

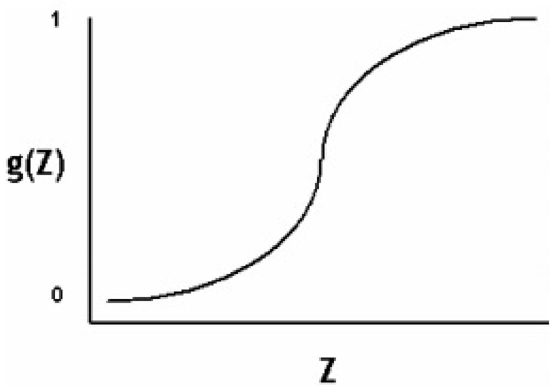

Figure 8: A Sigmoid Activation Function [7]

In practice, the most common sigmoid activation function is the logistic function that maps the potential into the range 0 to 1. The sigmoid function (also known the logistic function) is defined in the general form [7]:

$$f(x) = \frac{1}{1+e^{-Z}} \tag{2}$$

Since 0 < g(Z) < 1, the logistic function is very popular for use in networks that output probabilities.

2.2 The Multilayer Perceptron Neural Network

Multilayer perceptron network is an important class of neural networks. The network consists of a set of sensory units that constitute the input layer and one or more hidden layer of computation modes. The input signal passes through the network in the forward direction. The network of this type is called multilayer perceptron (MLP). The Multilayer perceptron are used with supervised learning and have led to the successful backpropagation algorithm. The disadvantage of the single layer perceptron is that it cannot be extended to multilayered version. In multilayer networks there exists a nonlinear activation function. The widely used non-linear activation function is logistic sigmoid function. The MLP network also has various layers of hidden neurons [8]. Figure (9) illustrates the architecture of the multilayer perceptron [9].

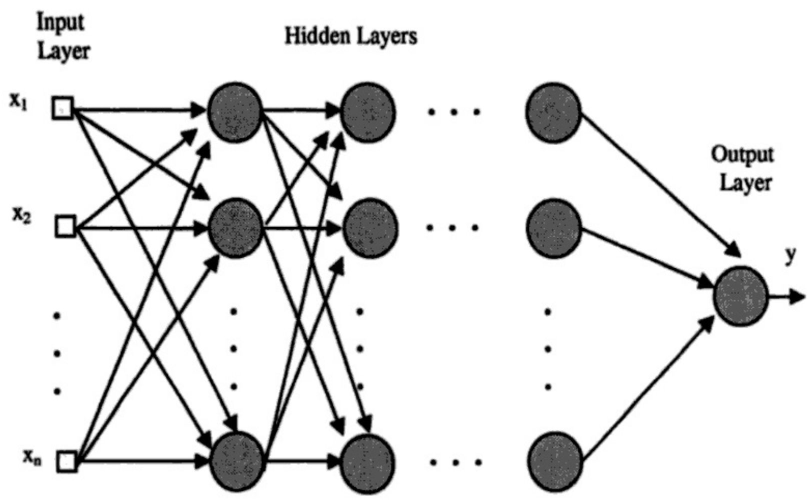

Figure 9: Organization in layers of the multilayer perceptron [9]

1.3 Feedforward neural network

Feedforward neural network is consists of a layered structure with information following from the inputs, at the bottom of the diagram, to the outputs at the top such as in Figure (10) [10].

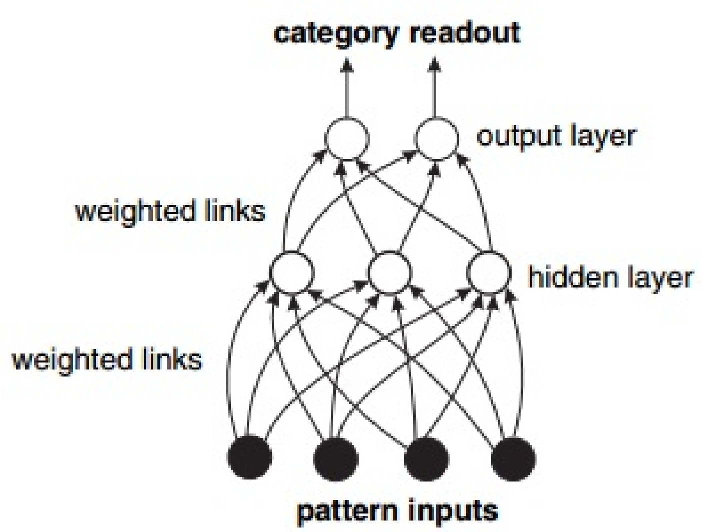

Figure 10: Simple feedforward neural network [10]

3. Prediction of the of wheel/rail roughness parameters using artificial neural network

The twin disc rig, replica material, and Alicona profilometer shown in Figure (11) were used for wheel and rail arithmetic average roughness (R_a) measurement such as shown in Table (1), and then, the neural network was used for wheel/rail arithmetic average roughness prediction.

Twin disc rig test   Replica material   Alicona profilometer

Figure 11: The twin disc rig, replica material and Alicona profilometer

Matlab toolbox used to design and training the neural network, and then, it was used to predict the arithmetic average roughness (R_a). The inputs of the neural network were load, speed, yaw angle, test time, and wheel/rail profile; while the output of the neural network is the arithmetic average roughness (R_a). The load was changed from 1000N to 4000N in steps of 100N, the speed was 660rpm, the yaw angle was 0.4degree, and the test time was 10min. The wheel/rail profiles were measured using Alicona profilometer.

Figure (12) shows the neural network toolbox used to predict the arithmetic average roughness.

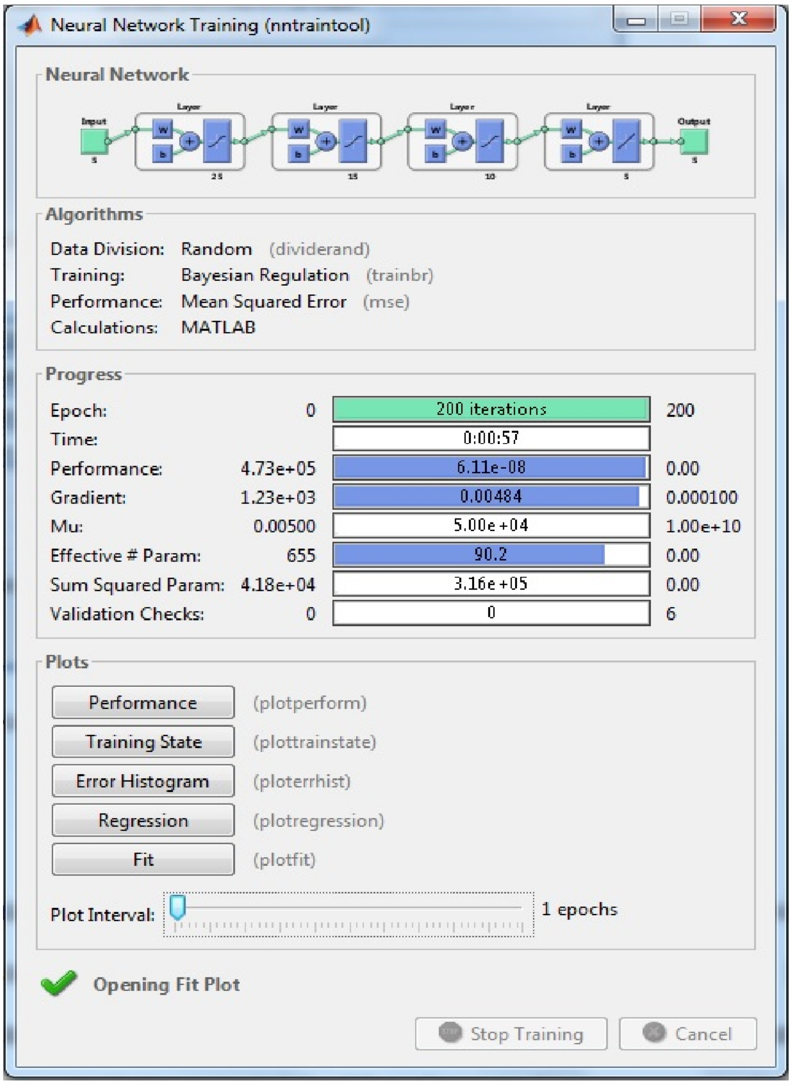

Figure 12: MATLAB training window

Table 1 shows the wheel/rail arithmetic average roughness measured using Alicona profilometer, and predicted using neural network.

Table 1 Arithmetic average roughness (wheel/rail) measured using Alicona profilometer, and predicted using neural network

Sample	R_a meaused for wheel (µm)	R_a predicted using NN for wheel (µm)	Error %	R_a meausred for rail (µm)	R_a predicted using NN for rail (µm)	Error %
1	1.49	1.46	2.05	1.37	1.36	0.72
2	1.69	1.67	1.19	1.59	1.56	1.88
3	1.88	1.87	0.53	1.76	1.74	1.13
4	1.94	1.91	1.57	1.87	1.88	0.53
5	1.98	1.96	1.02	1.93	1.96	1.55
6	2.03	2.02	0.49	1.96	1.95	0.51
7	2.11	2.12	0.47	1.98	1.97	0.50
8	2.12	2.10	0.95	2.11	2.13	0.94
9	2.13	2.15	0.93	2.13	2.10	1.40
10	2.18	2.17	0.46	2.17	2.15	0.92
11	2.22	2.21	0.45	2.20	2.23	1.36
12	2.23	2.24	0.44	2.22	2.21	0.45
13	2.25	2.27	0.88	2.24	2.22	0.89
14	2.36	2.38	0.84	2.32	2.30	0.86
15	2.41	2.40	0.41	2.38	2.39	0.42

The MAPE for wheel roughness was equal to 0.84%; therefore, the accuracy of NN model was 99.16%.

The MAPE for rail roughness was equal to 0.94%; therefore, the accuracy of NN model was 99.06%.

Figure (13) shows the arithmetic average roughness actual, and predicted using neural network (for wheel surface).

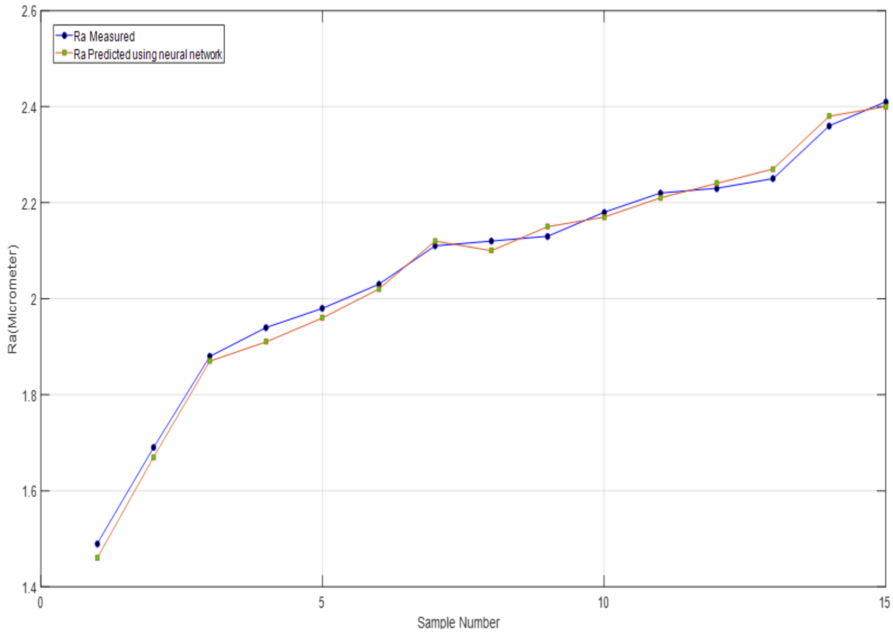

Figure 13: Arithmetic average roughness measured, and predicted using neural network (for wheel surface)

Figure (14) shows the arithmetic average roughness measured, and predicted using neural network (for rail surface).

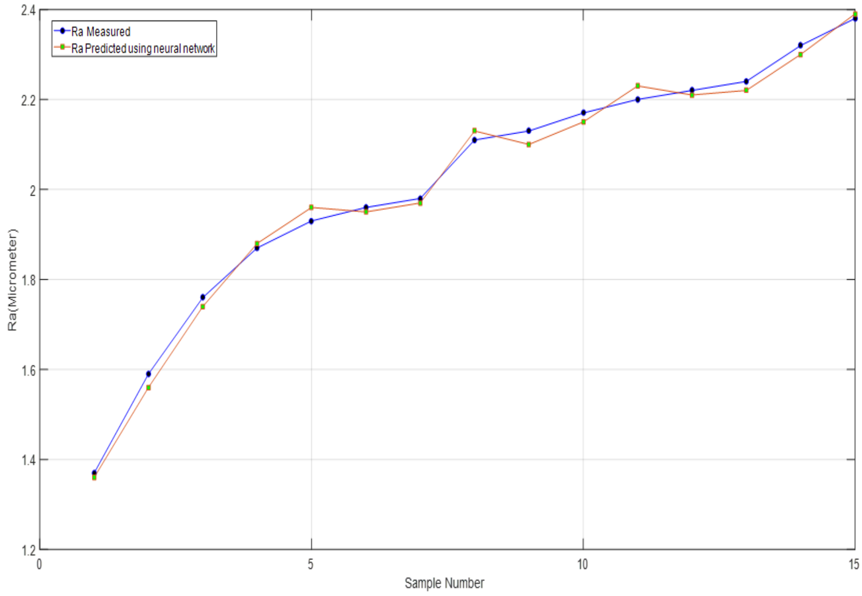

Figure 14: Arithmetic average roughness measured, and predicted using neural network (for rail surface)

As an example, Figure (15) shows the MATLAB performance plot, it shows a good performance for the neural network during roughness parameter prediction.

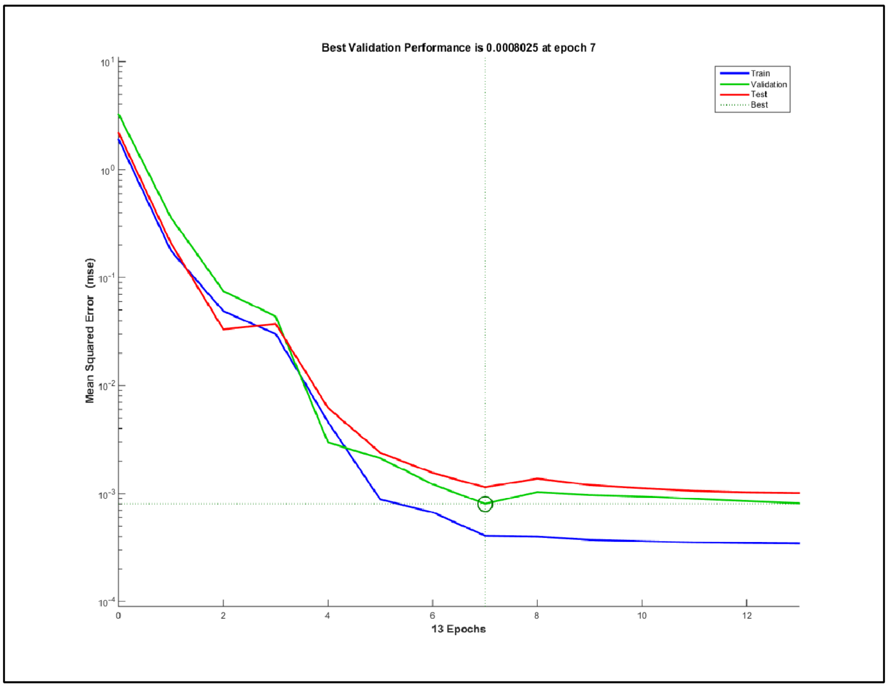

Figure 15: MATLAB performance plot for wheel roughness

4. Discussion and Conclusion

The percentage error for wheel and rail roughness parameter prediction was calculated, and the results show good prediction of wheel and rail roughness parameter in term of percentage of error, where the wheel and rail roughness parameter predicted using the NN was close to wheel and rail roughness parameter measured.

The MAPE for wheel roughness was equal to 0.84%, then, the accuracy of NN model was 99.16%; while the MAPE for rail roughness was equal to 0.94%, then, the accuracy of NN model was 99.06%. Therefore, the accuracy of the artificial neural network model was between 99.06% and 99.16%; (for unseen data).

The wheel and rail roughness can have established using the replica material and profilometer methods presented in this paper and compared with the results from the neural network techniques. The major finding in this work is that the Alicona profilometer can be used for wheel and rail roughness measurements. The replica material and Alicona profilometer are effective tools for the wheel and rail roughness measurements. An advantage of using the replica method is that it is a permanent record of wheel and rail roughness.

The neural network is an effective tool for the wheel and rail roughness prediction. This work can be used to promote the use of predictive maintenance strategies by railway operators. It can for example help in understanding remaining life of wheels or rails and in planning of maintenance interventions.

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