# Investigating the Effects of Neural Network Parameters on Railway Wheel Wear Prediction

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## Abstract

The prediction of wheel wear is still a great challenge for railway systems. This work examines the effect of radial basis function neural network (RBFNN) parameters such as spread, goal, maximum number of neurons, and number of neurons to add between displays on wheel wear prediction. VAMPIRE vehicle dynamic software was used to produce the vehicle performance data to train, validate, and test the neural network. The wheel wear was calculated using an energy dissipation approach and contact position on straight track. The neural network simulation results were implemented using the Matlab program. The percentage error for wheel wear prediction was calculated. Also, the accuracy of wheel wear prediction using the neural network was investigated and assessed in terms of mean absolute percentage error (MAPE). The results reveal that the railway wheel wear prediction using neural network is dependent on the correct selection of the neural network parameters.

**Keywords** wheel wear, wear prediction, railway systems, radial basis function neural network, Matlab, Vampire.

## 1. Introduction

Artificial neural network is currently used to solve a wide range of complex engineering problems. It has the ability to learn by example, consequently, it is a very useful for simulation of any correlation that is difficult to describe with physical models or other mathematical approaches [1]. Though perfect prediction is seldom possible, neural networks can be used to make reasonably good predictions in a number of cases. In particular, feedforward neural networks have been used frequently in this respect [2].

The prediction of wheel wear is a significant issue in railway vehicles. The aim of this work is to investigate the effect of RBFNN parameters on wheel wear prediction.

## 2. Radial Basis Function Neural Network

Radial basis function neural network (RBFNN) has an input, hidden, and output layer such as in Figure 1.

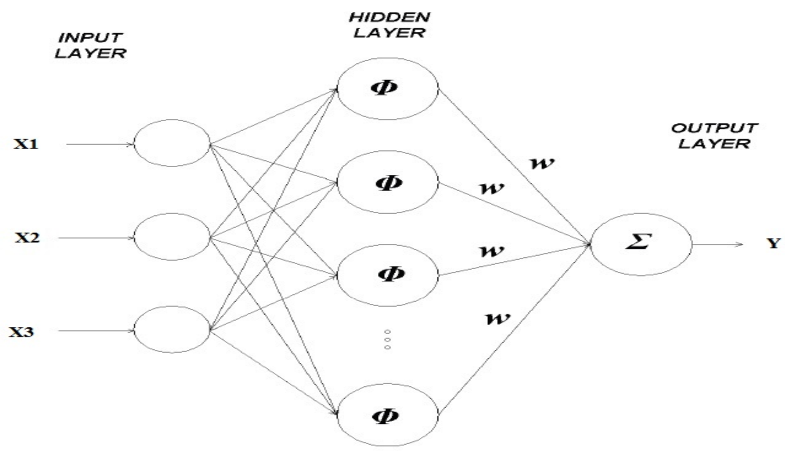


**Figure 1: Radial Basis Function Network Architecture [3]-[5]**

Where $X_1, X_{2,} X_3 \ldots, X_m$ are the inputs, $\emptyset$ is the activation function, and W is the weights [4], [5].

The output of RBFNN can represented such as shown in the following equation [6], [3], [4]:

$$y = \sum_{j=1}^{m} W_j \emptyset_j \tag{1}$$

The common activation function of RBFNN is the Gaussian function ($\emptyset$) [3]-[7]:

$$\emptyset(x) = \exp\left(\frac{-r^2}{2\sigma^2}\right) \tag{2}$$

$$r = || x - c || \tag{3}$$

Where C are the centres, x are the inputs, and $\sigma$ is the width of activation function.

Euclidean distance method is the most common method which can used to calculate the width of activation function for RBFNN such as shown in the following equation [8], [7], [9]:

$$E_{dist} = \sqrt{\sum_{i=1}^{n} (X_i - c_i)^2}\ , i = 1,2,3,\ldots, n \tag{4}$$

Where: $X_i$ are the inputs, $c_i$ are the centres, and n is the vector dimension.

The least mean square algorithm (LMS) is the most common algorithm which can used for adapting the weights of the output layer for the RBFNN such as shown in the following equation [8], [7]-[10]:

$$W(t+1) = W(t) + \mu\,(y(t) - y_m(t))\Phi^T(t) \tag{5}$$

Where $W(t+1)$ is the updated weights, $W(t)$ is the previous weights originally set to zero, $y(t)$ is the desired output, $y_m(t)$ is the output of the network, $\Phi^{T}(t)$ is the hidden layer output (Gaussian output), and μ is the learning factor of the RBFNN. The learning factor is a positive gain factor term that controls the adaptation rate of the algorithm ($0 < \mu \leq 1$).

The mean square error (MSE) is used for measuring the performance of the RBFNN such as shown in the following equation [11], [12], [13]:

$$\mathrm{MSE} = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (t_i - y_i)^2 \qquad (6)$$

Where $t_i$ is the target output and $y_i$ is the estimated output.

In this paper, the "newrb" Matlab command is used to create and train the RBFNN, the design of RBFNN takes six arguments: input vector, target vector, mean square error goal, spread, maximum number of neurons, and the number of neurons to add between displays. These parameters are explicitly set by the user using trial and error.

In this work, the inputs of the neural network are the stiffness parameter, running distance, wheel profile, first derivative of wheel profile, second derivative of wheel profile; while the output of the neural network is the wheel wear.

Radial basis function neural network (RBFNN) is designed in this work using Matlab program using newrb command [14], [15], [16]:

$$\mathrm{Net} = \mathrm{newrb}\ (\mathrm{P}, \mathrm{T}, \mathrm{goal}, \mathrm{spread}, \mathrm{MN}, \mathrm{DF}) \qquad (7)$$

Where:
P: is the input vectors
T: is the target vectors
Goal: is the mean squared error goal (MSE)
Spread: is the spread of radial basis functions

MN: is the maximum number of neurons
DF: is the number of neurons to add between displays

The function newrb iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons have been reached. The radial basis function neural network architecture is shown in Figure 2.

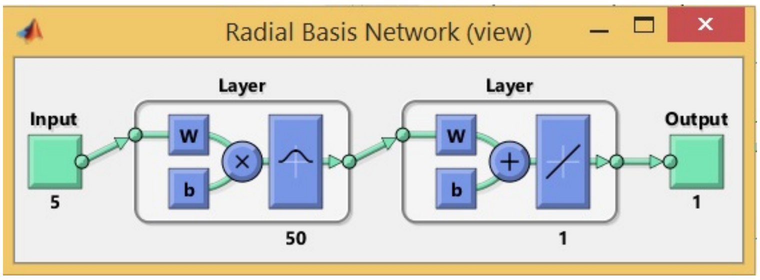


**Figure 2: Radial basis function neural network architecture**

## 3. VAMPIRE Vehicle Dynamics Software

VAMPIRE uses a multi-body modelling method that enables the user to assemble a mathematical model of almost any rail vehicle configuration. The VAMPIRE pro. 6.30 was used in this work to perform the simulations. The VAMPIRE GUI is shown in Figure 3. For wheel wear prediction, the transient analysis programme is run and the energy expended per unit distance travelled calculated for each wheel/rail contact. This is the product of creep force and creepage (Tγ), is one of the output types available in the transient programme. Experimental work has demonstrated that the amount of metal removed through wheel is proportional to the energy dissipated in the wheel–rail contact. Therefore, the expected wear of wheel can be studied and predicted by calculating the energy dissipated between wheel and rail (Tγ) [17], [18].

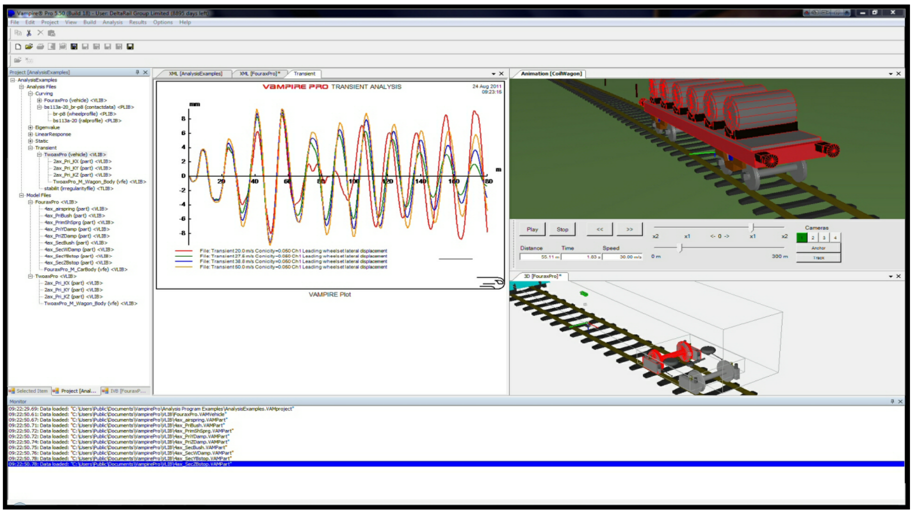

**Figure 3: VAMPIRE vehicle dynamics software platform [17], [18]**

## 4. Effects of RBFNN Parameters on Wheel Wear Prediction

In this section, the effect of the RBFNN parameters on wheel wear prediction was investigated. VAMPIRE vehicle dynamics software was used to collect data to train, validate, and test the neural network model.

In this work, an artificial neural network was developed to predict railway wheel wear in case of changing parameters such as vertical bush stiffness, lateral bush stiffness, lateral bush stiffness, and vertical shear stiffness. All results shown in this work are for unseen data.

### A. Effect of Spread Parameter on Wheel Wear Prediciton

The vertical bush stiffness simulation was used to investigate the effects of the spread parameter of RBFNN on wheel wear prediction. Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN with different values of spread are shown in Figure 4.

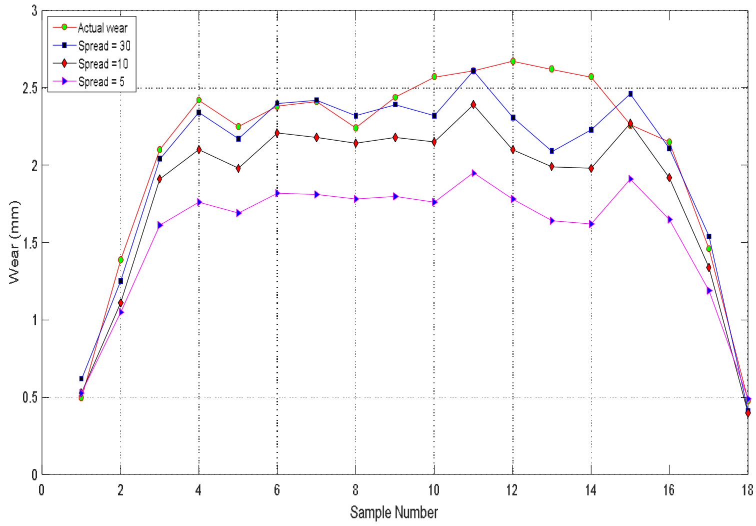


**Figure 4: Actual wheel wear and predicted using RBFNN; with different values of spread**

Wheel wear predicted using VAMPIRE, wheel wear predicted using RBFNN, and the percentage error are shown in Table 1. The mean absolute percentage error (MAPE) was 10.98% at spread of 30, was 14.70% at spread of 10, and was 32.36% at spread of 5.

**Table 1: Actual wheel wear and predicted using RBFNN, and error; with different values of spread**

| Sample Number | Actual wheel wear (mm) | Wear predicted using RBFNN (mm) spread = 30 | Error% | Wear predicted using RBFNN (mm) spread = 10 | Error% | Wear predicted using RBFNN (mm) spread = 5 | Error% |
|---|---|---|---|---|---|---|---|
| 1 | 0.50 | 0.62 | 19.02 | 0.53 | 5.13 | 0.53 | 5.45 |
| 2 | 1.39 | 1.25 | 11.47 | 1.11 | 25.23 | 1.05 | 31.72 |
| 3 | 2.10 | 2.04 | 3.05 | 1.91 | 9.96 | 1.61 | 30.56 |
| 4 | 2.42 | 2.34 | 3.72 | 2.10 | 15.54 | 1.76 | 37.50 |
| 5 | 2.25 | 2.17 | 3.89 | 1.98 | 13.80 | 1.69 | 33.27 |
| 6 | 2.38 | 2.40 | 0.83 | 2.21 | 7.79 | 1.82 | 31.07 |
| 7 | 2.41 | 2.42 | 0.07 | 2.18 | 10.78 | 1.81 | 33.27 |
| 8 | 2.24 | 2.32 | 3.49 | 2.14 | 4.63 | 1.78 | 26.03 |
| 9 | 2.44 | 2.39 | 2.13 | 2.18 | 11.54 | 1.80 | 35.09 |
| 10 | 2.57 | 2.32 | 10.56 | 2.15 | 19.19 | 1.76 | 45.74 |
| 11 | 2.61 | 2.61 | 0.10 | 2.39 | 9.32 | 1.95 | 33.65 |
| 12 | 2.67 | 2.31 | 15.49 | 2.10 | 27.40 | 1.78 | 49.74 |
| 13 | 2.62 | 2.09 | 25.03 | 1.99 | 31.51 | 1.64 | 59.86 |
| 14 | 2.57 | 2.23 | 15.43 | 1.98 | 29.88 | 1.62 | 58.24 |
| 15 | 2.26 | 2.46 | 8.30 | 2.27 | 0.52 | 1.91 | 17.99 |
| 16 | 2.15 | 2.11 | 2.09 | 1.92 | 11.85 | 1.65 | 30.79 |
| 17 | 1.46 | 1.54 | 5.49 | 1.34 | 8.84 | 1.19 | 21.96 |
| 18 | 0.48 | 0.41 | 18.14 | 0.40 | 21.71 | 0.49 | 0.63 |

## B. Effect of mn Parameter of RBFNN on Wheel Wear Prediction

The lateral bush stiffness simulation was used to investigate the effects of the mn parameter of RBFNN on wheel wear prediction. Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN with different values of mn are shown in Figure 5. Where the mn is the maximum number of neurons of RBFNN.

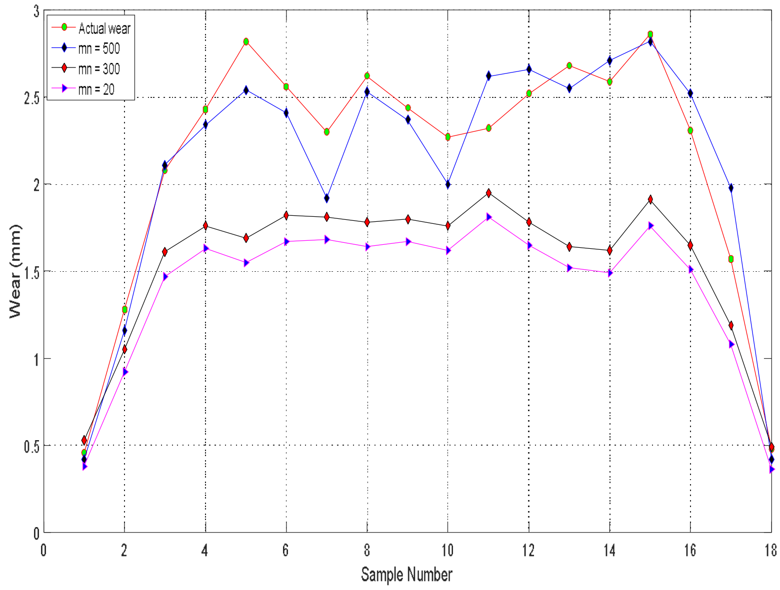


**Figure 5: Actual wheel wear and predicted using RBFNN; with different values of mn**

Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN, and the percentage error are shown in Table 2. The mean absolute percentage error was 9.11% when mn was 500, was 36.39 % when mn was 300, and was 49.31% when mn was 20.

**Table 2: Actual wheel wear and predicted using RBFNN, and error; with different values of mn**

| Sample Number | Actual wheel wear (mm) | Wear predicted using RBFNN (mm) mn =500 | Error% | Wear predicted using RBFNN (mm) mn =300 | Error% | Wear predicted using RBFNN (mm) mn =20 | Error% |
|---|---|---|---|---|---|---|---|
| 1 | 0.456 | 0.42 | 7.51 | 0.53 | 14.39 | 0.38 | 17.87 |
| 2 | 1.28 | 1.16 | 10.40 | 1.05 | 21.46 | 0.92 | 38.48 |
| 3 | 2.08 | 2.11 | 1.60 | 1.61 | 29.21 | 1.47 | 40.78 |
| 4 | 2.43 | 2.34 | 3.75 | 1.76 | 37.96 | 1.63 | 49.26 |
| 5 | 2.82 | 2.54 | 10.86 | 1.69 | 66.94 | 1.55 | 81.24 |
| 6 | 2.56 | 2.41 | 6.45 | 1.82 | 40.98 | 1.67 | 52.93 |
| 7 | 2.30 | 1.92 | 19.75 | 1.81 | 26.92 | 1.68 | 37.08 |
| 8 | 2.62 | 2.53 | 3.24 | 1.78 | 46.89 | 1.64 | 59.41 |
| 9 | 2.44 | 2.37 | 3.08 | 1.80 | 35.17 | 1.67 | 45.48 |
| 10 | 2.27 | 2.00 | 13.46 | 1.76 | 29.11 | 1.62 | 40.23 |
| 11 | 2.32 | 2.62 | 11.29 | 1.95 | 18.97 | 1.81 | 28.17 |
| 12 | 2.52 | 2.66 | 5.15 | 1.78 | 41.32 | 1.65 | 52.79 |
| 13 | 2.68 | 2.55 | 5.21 | 1.64 | 63.68 | 1.52 | 76.35 |
| 14 | 2.59 | 2.71 | 4.17 | 1.62 | 59.69 | 1.49 | 73.33 |
| 15 | 2.86 | 2.82 | 1.14 | 1.91 | 49.31 | 1.76 | 61.89 |
| 16 | 2.31 | 2.52 | 8.04 | 1.65 | 40.43 | 1.51 | 52.74 |
| 17 | 1.57 | 1.98 | 20.45 | 1.19 | 31.60 | 1.08 | 45.94 |
| 18 | 0.48 | 0.42 | 14.02 | 0.49 | 0.95 | 0.36 | 33.63 |

### C. Effect of Goal Parameter of RBFNN on Wheel Wear Prediction

The lateral shear stiffness simulation was used to investigate the effects of the goal parameter of RBFNN on wheel wear prediction. Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN with different values of goal are shown in Figure 6. Where the goal is denotes the mean squared error goal.

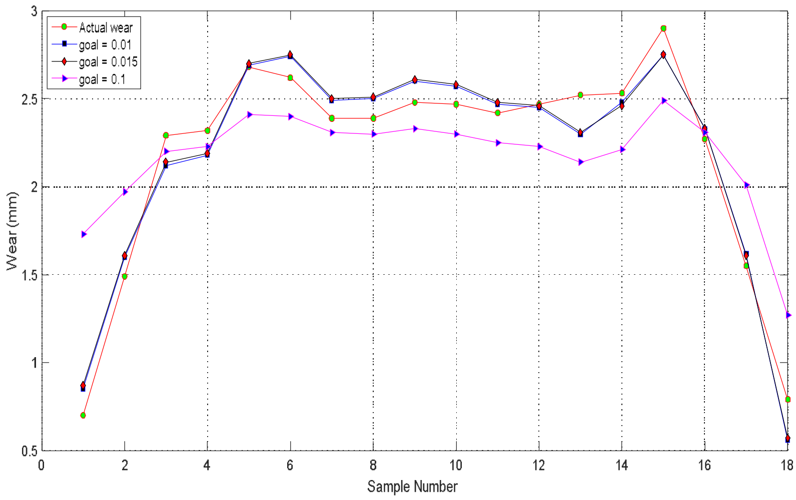


**Figure 6: Actual wheel wear and predicted using RBFNN with different values of goal**

Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN, and the percentage error are shown in Table 3. The mean absolute percentage error was 9.01% when goal was 0.01, was 9.45% when goal was 0.015, and was 14.55% when goal 0.1.

**Table 3: Actual wheel wear and predicted using RBFNN, and error; with different values of goal**

| Sample Number | Actual wheel wear (mm) | Wear predicted using RBFNN (mm) Goal = 0.01 | Error% | Wear predicted using RBFNN (mm) Goal = 0.015 | Error% | Wear predicted using RBFNN (mm) Goal = 0.1 | Error% |
|---|---|---|---|---|---|---|---|
| 1 | 0.70 | 0.85 | 16.84 | 0.87 | 19.31 | 1.73 | 59.26 |
| 2 | 1.49 | 1.60 | 6.94 | 1.61 | 7.40 | 1.97 | 24.46 |
| 3 | 2.29 | 2.12 | 8.06 | 2.14 | 7.09 | 2.20 | 4.01 |
| 4 | 2.32 | 2.18 | 6.66 | 2.19 | 6.22 | 2.23 | 4.33 |
| 5 | 2.68 | 2.69 | 0.20 | 2.70 | 0.57 | 2.41 | 11.30 |
| 6 | 2.62 | 2.74 | 4.28 | 2.75 | 4.79 | 2.40 | 9.09 |
| 7 | 2.39 | 2.49 | 4.10 | 2.50 | 4.61 | 2.31 | 3.55 |
| 8 | 2.39 | 2.50 | 4.18 | 2.51 | 4.57 | 2.30 | 3.90 |
| 9 | 2.48 | 2.60 | 4.65 | 2.61 | 5.03 | 2.33 | 6.52 |
| 10 | 2.47 | 2.57 | 3.96 | 2.58 | 4.38 | 2.30 | 7.22 |
| 11 | 2.42 | 2.47 | 1.88 | 2.48 | 2.25 | 2.25 | 7.76 |
| 12 | 2.47 | 2.45 | 0.75 | 2.46 | 0.43 | 2.23 | 10.69 |
| 13 | 2.52 | 2.30 | 9.47 | 2.31 | 8.79 | 2.14 | 17.43 |
| 14 | 2.53 | 2.48 | 1.93 | 2.46 | 2.56 | 2.21 | 13.99 |
| 15 | 2.90 | 2.75 | 5.32 | 2.75 | 5.35 | 2.49 | 16.45 |
| 16 | 2.27 | 2.33 | 2.49 | 2.33 | 2.64 | 2.31 | 1.44 |
| 17 | 1.55 | 1.62 | 4.25 | 1.61 | 3.91 | 2.01 | 23.02 |
| 18 | 0.79 | 0.56 | 41.98 | 0.57 | 39.58 | 1.27 | 37.45 |

### D. Effect of df Parameter of RBFNN on Wheel Wear Prediction

The vertical shear stiffness simulation was used to investigate the effects of the df parameter of RBFNN on wheel wear prediction. Wheel wear predicted using VAMPIRE, and wheel wear predicted using RBFNN with different values of df are shown in Figure 7. Where df represents the number of neurons to add between displays.

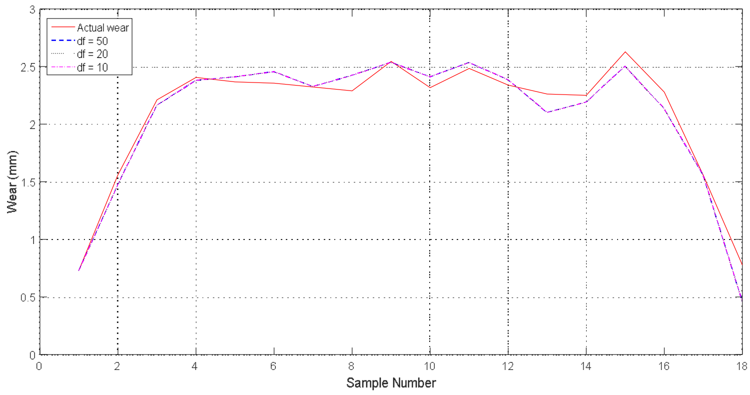


**Figure 7: Actual wheel wear and predicted using RBFNN with different values of df**

Wheel wear predicted using VAMPIRE, wheel wear predicted using RBFNN, and the percentage error are shown in Table 4. The mean absolute percentage error was 6.65% when df was 50, was 6.65% when df was 20, and was 6.65% when df was 10. The simulation results show that the changing of df parameter had no effect on the accuracy of wheel wear prediciton.

**Table 4: Actual wheel wear and predicted using RBFNN, and error; with different values of df**

| Sample Number | Actual wheel wear (mm) | Wear predicted using RBFNN (mm) df = 50 | Error% | | Wear predicted using RBFNN (mm) df = 20 | Error% | Wear predicted using RBFNN (mm) df = 10 | Error% |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.73 | 0.72 | 1.07 | | 0.72 | 1.07 | 0.72 | 1.07 |
| 2 | 1.56 | 1.47 | 5.88 | | 1.47 | 5.88 | 1.47 | 5.88 |
| 3 | 2.21 | 2.16 | 2.14 | | 2.16 | 2.14 | 2.16 | 2.14 |
| 4 | 2.40 | 2.38 | 1.15 | | 2.38 | 1.15 | 2.38 | 1.15 |
| 5 | 2.36 | 2.41 | 1.93 | | 2.41 | 1.93 | 2.41 | 1.93 |
| 6 | 2.35 | 2.45 | 4.05 | | 2.45 | 4.05 | 2.45 | 4.05 |
| 7 | 2.32 | 2.32 | 0.29 | | 2.32 | 0.29 | 2.32 | 0.29 |
| 8 | 2.29 | 2.42 | 5.49 | | 2.42 | 5.49 | 2.42 | 5.49 |
| 9 | 2.54 | 2.53 | 0.24 | | 2.53 | 0.24 | 2.53 | 0.24 |
| 10 | 2.31 | 2.41 | 3.87 | | 2.41 | 3.87 | 2.41 | 3.87 |
| 11 | 2.48 | 2.53 | 2.07 | | 2.53 | 2.07 | 2.53 | 2.07 |
| 12 | 2.34 | 2.38 | 1.85 | | 2.38 | 1.85 | 2.38 | 1.85 |
| 13 | 2.26 | 2.10 | 7.65 | | 2.10 | 7.65 | 2.10 | 7.65 |
| 14 | 2.25 | 2.19 | 2.80 | | 2.19 | 2.80 | 2.19 | 2.80 |
| 15 | 2.63 | 2.50 | 5.05 | | 2.50 | 5.05 | 2.50 | 5.05 |
| 16 | 2.28 | 2.136 | 6.76 | | 2.13 | 6.76 | 2.13 | 6.76 |
| 17 | 1.55 | 1.55 | 0.01 | | 1.55 | 0.01 | 1.55 | 0.01 |
| 18 | 0.77 | 0.46 | 67.40 | | 0.46 | 67.40 | 0.46 | 67.40 |

## 5. Conclusion

This work investigated the effect of RBFNN parameters on wheel wear. The effect of spread, mn, goal, and df parameters on wheel wear prediction were examined. The mean absolute percentage error (MAPE) was calculated as:

- The MAPE was 10.98% when spread was 30, it was 14.70% when spread was 10, and it was 32.36% when spread was 5 during the change of spread parameter test.
- The MAPE was 9.11% when mn was 500, it was 36.39 % when mn was 300, and it was 49.31% when mn was 20 during the change of mn parameter test.
- The MAPE was 9.01% when goal was 0.01, it was 9.45% when goal was 0.015, and it was 14.55% when goal was 0.1 during the change of goal parameter test.
- The MAPE was 6.65% when df was 50, it was 6.65% when df was 20, and it was 6.65% when df was 10 during the change of df parameter test.

The effects of the RBFNN parameters such as spread, goal, maximum number of neurons, and number of neurons to add between displays on wheel wear prediction was investigated. The simulation results show that the accuracy of wheel wear prediction was influenced by change of spread, mn, and goal; while the change of df parameter has no effect on the wheel wear prediction using RBFNN. Therfore, it can be concluded that the railway wheel wear prediction using neural network is dependent on the correct selection of the neural network parameters.

Finally, the VAMPIRE vehicle dynamic software can assist in using the neural network in railway wheel wear prediction; where several simulations were carried out in this work using VAMPIRE software to produce the data to train, validate, and test the neural network model.

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