# Prediction of thermal-induced buckling failures of ballasted railway tracks using Artificial Neural Network (ANN)

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# Prediction of thermal-induced buckling failures of ballasted railway tracks using Artificial Neural Network (ANN)

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## Abstract

The present study investigates the potential of the implementation of machine learning techniques in analysing the buckling phenomena of ballasted railway tracks induced by extreme temperature. In this study, Artificial Neural Networks (ANNs) have been established to determine the design relationship between various ballasted track conditions and outputs namely safe temperature and buckling temperature. The variables that are taken into account in the objective function of the optimisation problem are the lateral resistance of ballasted track provided by ballast-sleeper, torsional resistance provided by fastening systems, and dimensioning of the cross sections. Due to its complexity in parameter combinations, the objective of the study is to create predictive models with the aim of minimising the usage of scarce resources. Comprehensively, all three hundred and fifty-three datasets of the safe and buckling temperatures derived from previous FE results have been collected and trained. The optimal ANN architecture with a very high rate of accuracy has been determined. Note that the performance of the optimal ANN architecture has been assessed by employing the mean squared error (MSE) and the coefficient of determination ($R^2$). Thus, the neural network model can be applied to help estimate buckling temperature for the complex track models in order to detect track buckling in summer.

**Keywords:** ballasted railway track, track buckling, extreme temperature, structural stability, artificial neural network, machine learning.

## 1 Introduction

At present, railway track buckling is one of the serious issues in the railway system [1-3]. Hence, railway infrastructure developments related to adaptation to future heatwave are expected. This is because the summer heat can significantly increase the rail temperature and cause the rail to expand, leading to a build-up of axial compression force in continuous welded rail (CWR). Although CWR provides a smooth ride and has a lower maintenance cost in comparison to a jointed rail, it still suffers from the drawbacks as the track can lose its lateral alignment and get buckled when the rail temperature reaches a certain limit [4-7]. Based on the evidence [8-10], track buckling can cause derailment and cause a huge loss of assets and can also result in the loss of passenger lives. It is important to note that track buckling around the world usually occurs in conventional railway ballasted tracks due to the poor track conditions and track lateral misalignment. Buckling analysis has been widely performed to obtain the significant parameters and track conditions influencing track buckling and corresponding safe and buckling temperatures [11-14].

Previous studies showed that lateral resistance provided by ballast and sleeper is the major factor influencing the buckling strength and buckling phenomena [15]. The lateral resistance can be evaluated by performing a Single Sleeper (Tie) Push Test (STPT) [16-19]. This method provides the ballast-sleeper contact force encountering sleeper movement which can be represented as a track lateral resistance. While the minor factors include torsional resistance between sleepers and rails provided by fasteners. It is important to note that different factors can significantly create different phenomena of railway tracks exposed to extreme temperature. It is noted that the traditional beam theory is very limited in proposing a number of parameters into the calculation of the buckling temperature [20, 21]. Hence, FE model can help achieve more complex structures with more parameters. However, FE analysis uses high computational time and needs a large memory consumption. As a result, to further expand the previous results from FE model, machine learning can be used to save time and increase efficiency in predicting buckling phenomena of railway tracks. It is important to note that these parameters are compounded and create realistic results from the complicated valuables that cannot be predicted analytically.

An artificial neural network (ANN), a type of machine learning, is a simplified mathematical model that can simulate the function of natural biological neural networks to learn from the experience for solving new problems. Unlike traditional model-driven methods, machine learning is a novel data-driven method to explore and build algorithms that learn from known data and predict unknown data. Most traditional statistical models have certain requirements or assumptions for the specific distribution of data. However, in reality, data may not meet those assumptions or requirements. In this case, the machine learning method is more reasonable. The machine learning method does not need to make any assumptions about the data distribution, and the results produced can also be evaluated by a cross-validation method [22]. Machine learning technique has been widely used in civil and railway applications especially for predicting the properties of materials of track components based on the proportion of the ingredients e.g. recycled concrete [23], rubberised concrete [24] etc. More examples on railway track applications includes track response quantification [25], train weight prediction [26], fault detection [27-30], railway safety and accident identification [31, 32]. Hence, this paper is the first to use machine learning in predicting buckling phenomena of ballasted railway tracks.

The aim of this paper is to establish a machine learning approach capable of predicting the safe and buckling temperatures considering various compositions of parameters. This paper presents the optimal architecture for estimating the safe and buckling temperatures of ballasted railway tracks. The datasets have been collected from the previous numerical studies based and are input into different ANN models to quantify the performances and obtain the best model [33, 34]. The optimal ANN models are found to be capable of managing the complicated relationships between the inputs and outputs and of designing track components to encounter the extreme temperature. The ANN models are then compared with the traditional multiple linear regression models and show a higher accuracy in comparison to the multiple linear regression models. The suggested ANN architecture can be used further in order to accurately predict the buckling phenomena and help improve track conditions to encounter extreme heat in summer.

## 2 Railway Track Buckling

According to previous studies, the major parameters affecting buckling strength of ballasted railway tracks is the lateral resistance provided by ballast and sleeper components. The torsional resistance by fastening systems is also considered. In general, track lateral misalignment can be a significant factor that undermines the buckling strength. This study also includes the effect of unconstrained length that can help increase the lateral restraint. This method can be either a spot replacement method or improving ballast-sleeper constrain at particular spans. Note that only a few studies have considered an unconstrained length in buckling analysis. Figure 1 shows the arrangement of typical ballasted track with the idealised tensionless spring representing the lateral stiffness of ballasted track. It also presents the lateral resistance curve that can be represented by the tensionless lateral spring connected to the sleeper ends. Note that the lateral resistance curve is usually derived by the sleeper push test. The elastoplastic curve generally presents the resistance curve considering the lateral resistance force ($F_p$) and the sleeper displacement. Note that the lateral stiffness is the lateral resistance force over the displacement limit of sleeper ($F_p/W_p$).

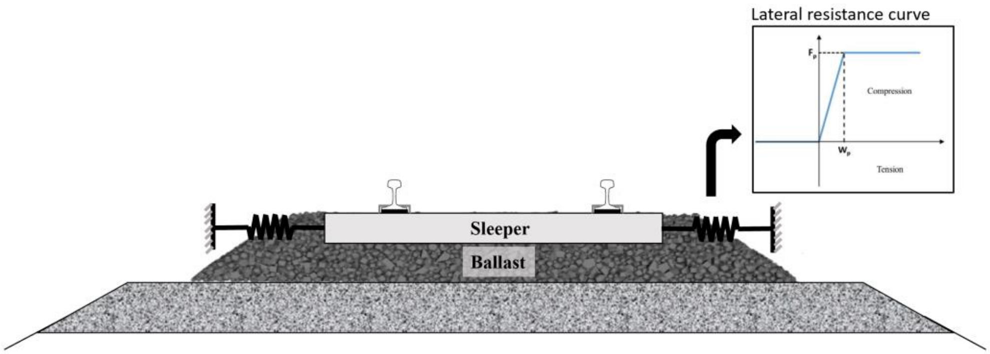


**Figure 1 Ballasted railway track.**

In buckling mechanism, if the rail temperature is over the neutral temperature or stress-free temperature, the compression axial force in the rails builds up. The rail can be buckled when the compression force reaches its limit or buckling resistance. It should be noted that buckling resistance is affected by track and element types and track conditions. The relationship between rail temperature and lateral displacement is typically plotted as seen in Figure 2. It can be seen that there are two types of buckling depending on the post-buckling path: sudden buckling and progressive buckling. In the pre-buckling stage, the rails are exposed to the temperature over neutral temperature and the axial force is linearly increased. As for the sudden buckling (also called "Snap-through"), the track buckles explosively with no external energy after reaching its maximum temperature (upper critical temperature, $T_{Bmax}$) and becomes unstable in its post-buckling stages. This temperature can be defined as a "buckling temperature". Besides, $T_{Bmin}$ represents the lower bound which can buckle the track if sufficient energy is supplied. It can also be defined as a "safe temperature" since the track cannot buckle if it experiences a temperature below this temperature. Moreover, progressive buckling can occur when the $T_{Bmin}$ cannot be differentiated from $T_{Bmax}$. In this case, track lateral displacement is gradually increased after buckling and the critical temperature is defined as $T_P$. In this study, both minimum and maximum temperatures will be predicted using ANN. Note that the snap-through buckling mode can be obtained when the minimum and maximum temperatures are obtained while the progressive buckling failure modes can be obtained when temperatures are crossed over meaning that the only one output is predicted.

**Figure 2 Buckling path.**

## 3 Methodology

An artificial neural network (ANN) is a data prediction framework based on existing features created from the human mind structure. 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. This network is made of some functional blocks, which are named neurons. Neurons are connected by weights, which are usually randomly selected at first. Weights in a learning process are increased or decreased by some epochs to eventually achieve the desired network which can predict it by reasonable accuracy [22].

Therefore, in a trained neural network, the desired output can be achieved by receiving the inputs considering the updated weights as shown in Figure 3. The network improves over time by comparing the desired input and output calculating the error. The improvement of the machine learning model from time to time indicates the accuracy if the prediction model can be improved and the predicted results are reliable. Usually, nonlinear activation functions like sigmoid (tansig and logsig) are used because of its better response than others.

**Figure 3 Artificial neural model.**

The general ANN architecture includes three main layers: input layer, hidden layer and output layer, as shown in Figure 4. This figure shows the multilayer feed forward network that is considered in this study. The input layer receives various forms of information from the outside. This is the information that the neural network is designed to process or learn. Data from the input layer passes through the hidden layers that consist of the number of hidden neurons. Role of the hidden layers is to convert the input information into content that the output layer can use.

**Figure 4 ANN architecture.**

### 3.1 Data collection

The datasets have been collected from the previous numerical studies [33, 34]. Table 1 presents the input parameters considered in this study. The input includes major parameters affecting track buckling strength: lateral stiffness, displacement limit of sleeper, fastening torsional system, track lateral misalignment. Track unconstrained length is also considered to help strengthen the buckling strength by restraining the track laterally to encounter the lateral movement of sleeper that can be achieved by spot replacement method [14, 34, 35]. Due to the limited studies on the influences of track unconstrained length, 350 datasets are introduced to the ANN models for predicting the output parameters. Note that the output variables are the safe and buckling temperatures. These two values can also help predict the buckling failure modes. Snap-through buckling mode occurs If the buckling temperature is higher than safe temperature. However, when the two parameters are crossed over (safe temperature > buckling temperature) meaning that only one output is presented while another is a trivial solution. This represents the progressive buckling mode since only one temperature is obtained.

**Table 1 Input parameters.**

| Input parameters | Range | Unit |
|---|---|---|
| Lateral stiffness, $F_p/W_p$ ($x_1$) | 200-2600 | N/mm |
| Displacement limit of sleeper, $W_p$ ($x_2$) | 0.5-2 | mm |
| Fastening torsional resistance ($x_3$) | 75-225 | kNm/rad |
| Track lateral misalignment ($x_4$) | 8-32 | mm |
| Track unconstrained length ($x_5$) | 6-30 | m |

### 3.2 ANN architecture

All imported datasets are randomly divided into three parts for training, validation and testing, respectively. The fixed allocation ratios of datasets between training, validation and testing aspects are 70%, 15% and

15%, respectively. The datasets for training are utilised for training models by modifying weights. The validation sets are used to adapt the model selection, that is, to do the final optimisation and determination of models, such as choosing the number of hidden neurons and hidden layers, while the testing set is purely to prove the generalisation of the trained models. In this study, the number of neurons is varied from 1 to 15. The model description is written in the form of "input parameters – hidden layer – output parameters". Table 2 presents ANN models with different architectures (hidden neurons).

**Table 2 ANN architecture models used in this study.**

| Model | ANN Architecture |
|---|---|
| 1 | 5 1 2 |
| 2 | 5 5 2 |
| 3 | 5 10 2 |
| 4 | 5 15 2 |

This paper uses Levenberg–Marquardt (LM) as an algorithm to predict the output parameters. LM is an algorithm that provides a solution of the numerical nonlinear minimisation. The significance of LM algorithm is that it can simultaneously achieve the advantages of the Gauss–Newton method and the gradient descent algorithm by changing parameters. Furthermore, LM algorithm can improve the shortcomings of other algorithms. The LM algorithm is a type of upgraded Newton method shown in Eq. (1)

$$x_{k+1} = x_k - [J^T J + uI]^{-1} J^T e \tag{1}$$

where, I indicates the identity matrix, e represents a vector, J is a Jacobian matrix, $x_k$ denotes the weight at epoch K, and u is a damping factor. In order to improve the accuracy, u can be increased or dropped according to the success or failure of steps, and then the performance function can be enhanced.

### 3.3 Performance Evaluation of ANN Architecture

In order to investigate the performance of the trained models in this study, two statistical analyses named Mean Squared Error (MSE) and the coefficient of determination ($R^2$ value) are employed. MSE is the average value of the cost function for minimising the sum of squared errors (SSE) during the linear regression model fitting process. This represents the mean square error between the predicted and the actual value. MSE value is calculated according to Eq. (2) [36]. The lower MSE value indicates a model with higher accuracy.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y'_i - y_i)^2 \tag{2}$$

where n is the number of samples, and $(y'_i - y_i)$ is the result of the input value minus the predicted value on the testing sets being processed. Moreover, $R^2$ value is employed as an assistance method to determine the performance of trained models defined in Eq. (3). $R^2$ value exhibits the percentage of real value changes, which can be influenced by the variation of the predicted value. The range of $R^2$ value is from zero to one. Considering Eq. (3), the numerator part represents the sum of the squared difference between the real value and the predicted value, similar to MSE. The denominator part represents the sum of the squared difference between the real value and the mean [37]. If the result is close to 0, it means that the model fits poorly. If the result is close to 1, it means that the model is error-free. Generally, the larger the $R^2$ value is, the better the model fitting effect is.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y'_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

# 4 Results and Discussions

## 4.1 Optimal ANN architecture

In this study, four models of ANN architecture are firstly considered and compared to potentially create the best ANN model for predicting the safe and buckling temperatures of ballasted railway tracks. It is found that only one hidden layer can appropriately provide high accuracy of the prediction values compared to the target values. The number of neurons is varied from 1 to 15. The model description is written in the form of "input parameters – hidden layer – output parameters". Figure 5 presents the predicted values employed by the first ANN architecture 5-1-2 against the actual or target values. The $R^2$ values for safe and buckling temperatures are presented separately. It is shown that this architecture should not be used to as a predictive model since it cannot not perform well as shown by the low $R^2$ value especially for the safe temperature. Furthermore, the number of neurons must be increased to improve the performance of ANN model.

(a) (b)

(c)

**Figure 5 Predicted value vs actual value analysed by model 1 (5-1-2): a) safe temperature b) buckling temperature and c) Both safe and buckling temperatures.**

After increasing the number of neurons until the performance is accepted, Figure 6 presents the predicted temperatures based on Model 4 against the actual temperatures of buckling phenomena of ballasted railway tracks. This model includes 15 neurons in the hidden layer. It is clear that the $R^2$ values are significantly higher than those obtain in Model 1 with lesser neurons. The $R^2$ value of safe temperature prediction model is much higher than that in Model 1 and the curve shows a significant better trend in comparison to Model 1. Table 3 compares the performance of each model for both output predictions. The prediction performances of both outputs show the similar trends. It is clear that increasing a number of neurons can significantly reduce MSE and increase $R^2$. It should be noted that Model 4 has $R^2$ value of 0.9921 which is fairly high leading to the fact that increasing a number of neurons to over 15 will not improve the performance of the model. On this ground, it can be concluded that, based on the provided datasets, 1 hidden layer with 15 neurons can give a high accuracy for predicting safe and buckling temperatures of ballasted railway tracks considering different track conditions.

(a) (b)

(c)

**Figure 6 Predicted value vs actual value analysed by model 1 (5-15-2): a) safe temperature b) buckling temperature and c) Both safe and buckling temperatures.**

**Table 3 Mean square error and R-square values of each model architecture.**

| Model | Architecture | MSE | | | $R^2$ | | |
|---|---|---|---|---|---|---|---|
| | | $T_{min}$ | $T_{max}$ | Total | $T_{min}$ | $T_{max}$ | Total |
| 1 | 5-1-2 | 185.46 | 134.46 | 159.96 | 0.4091 | 0.8797 | 0.8111 |
| 2 | 5-5-2 | 26.63 | 53.29 | 39.96 | 0.9139 | 0.9501 | 0.9517 |
| 3 | 5-10-2 | 12.96 | 62.30 | 37.63 | 0.9584 | 0.9432 | 0.9554 |
| 4 | 5-15-2 | 7.75 | 5.40 | 6.57 | 0.9753 | 0.9949 | 0.9921 |

## 4.2 Comparative analysis

As shown previously, Model 4 represents the best ANN architecture for predicting the safe and buckling temperatures of railway tracks. This model is chosen to be used from now on to compare with another prediction method and perform parametric study. It is noted that linear regression is commonly used to obtain the relationship between the dependent and independent variables. In this section, linear regression with multiple variables (also called Multi Linear Regression (MLR)) is used to compare the results with the ANN model. Note that MLR is a simple and well-known technique that can help to establish a relationship between the factors and predicted output values. The general equation of MLR is presented in Eq. 4.

$$y = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_m x_m \tag{4}$$

where, y is the predicted value, $x_m$ is the independent variables, $a_0$ is the y-intercept, and $a_m$ indicates the regression coefficients. It is noted that MLR is conducted using data analysis tools in Microsoft Excel. The regression coefficients are obtained while $x_1$, $x_2$, $x_3$, $x_4$, and $x_5$ represent the lateral resistance, lateral displacement limit, torsional resistance, unconstrained length, and lateral misalignment, respectively. After obtaining the coefficients, the equations for predicting safe and buckling temperatures can be drawn separately as shown in Eqs. 5-6.

$$y_1 = 50.731 + 0.00878x_1 + 7.265x_2 + 0.080x_3 - 1.624x_4 - 0.032x_5 \tag{5}$$

$$y_2 = 77.458 + 0.0294x_1 + 15.609x_2 + 0.034x_3 - 1.335x_4 - 2.096x_5 \tag{6}$$

Where $y_1$ and $y_2$ represent the safe temperature and buckling temperature, respectively.

The prediction accuracy of both models can be defined by the MSE and $R^2$ as presented in Table 4. It is evident that the $R^2$ values of MLR are relatively low while the MSE values are significantly high compared to those obtained by the optimal ANN model. These phenomena are observed when predicting both output values. On this ground, it can be concluded that ANN model gives a higher accuracy for predicting buckling phenomena than the traditional MLR method. This is because of the ability of MLR that can only describe the linear relationship between input and output parameters only while, in fact, the relationship between track conditions and buckling phenomena is more complex than linear relationship.

**Table 4 Comparison between MLR and ANN (5-15-2).**

| Predicted values | MSE | | $R^2$ | |
|---|---|---|---|---|
| | MLR | ANN (5-15-2) | MLR | ANN (5-15-2) |
| $T_{min}$ | 56.57 | 7.75 | 0.8182 | 0.9753 |
| $T_{max}$ | 191.03 | 5.40 | 0.8204 | 0.9949 |

### 4.3 Parametric study

After obtaining the optimal ANN architecture, the approximate general functions can be employed considering the weighted inputs and the transfer function to create the outputs. For multiple-layer networks, the layer number determines the superscript on the weight matrix, as shown in Figure 7. In the two-layer tansig/purelin network, the appropriate notation is used. This network can be used as to approximate general functions. It can approximate any function with a finite number of discontinuities arbitrarily well, given sufficient neurons in the hidden layer.

**Figure 7 Multilayer networks with weight matrix.**

In this section, the final weights of each parameter have been calculated in order to study the effects of each parameter on both safe and buckling temperatures. Note that the results can be calculated directly from MATLAB without knowing weight matrix. However, it can be calculated only one by one. A weight matrix can be obtained and used to create the function to help calculate the results automatically for parametric studies. Figure 8 shows the contour of safe and buckling temperatures considering the lateral stiffness from ballast and sleeper and torsional resistance provided by fastening system. It is found that increasing torsional resistance provided by the fastening system can help increase the safe temperature but there is no influence on the buckling temperature. As for the lateral stiffness, increasing the displacement limit from 1mm to 2mm can significantly increase the buckling temperature since the lateral resistance with higher displacement limit yields at higher lateral resistance force.

(a) (b)

(c) (d)

**Figure 8 Safe ($T_{min}$) and buckling ($T_{max}$) temperatures.**

Figure 9 presents the effects of track lateral misalignment on the safe and buckling temperatures. It is notable that, overall, buckling temperatures decrease as the misalignment amplitude increases. On the other hand, the lateral misalignment has a very slight effect on safe temperature in comparison to buckling temperature. Considering the unconstrained length and initial misalignment, the safe and buckling temperatures are compared in Figure 10. The overall results show that railway tracks are generally buckled within the same ranges when the unconstrained length is larger than 18 m whereas railway tracks with 6 m and 12 m buckled with much higher temperature. It is clear from this figure that increasing misalignment tends to shift the buckling mode from snap-through buckling to progressive buckling for all cases of unconstrained length since the buckling temperatures are quite close to the safe temperatures. These results agree well with the previous FE results [33, 34].

**Figure 9 Effects of track lateral misalignment on the safe and buckling temperatures.**

**Figure 10 Effects of track unconstrained length on the safe and buckling temperatures.**

# 5 Conclusions

This paper is the first to establish a machine learning aided design for predicting buckling phenomena of ballasted railway tracks. It is well known that the buckling strength of ballasted track is affected by many factors that are not combined linearly. This shows that track buckling capacity calculation is complex and it may take large memory storage and time consumption to evaluate the buckling strength via the computer simulation. This paper considers four different ANN architectures with five input parameters and two output values while the number of hidden layers is set as 1. It is found that the accuracy of the model increases significantly when the number of hidden neurons is increased from 1 to 15. It is notably that only one hidden layer is sufficient to create a proper neural network as the $R^2$ values are already high. The best ANN model consists of a hidden layer with 15 hidden neurons and is used to compare with the multilinear regression. The optimal ANN presents the $R^2$ values of about 0.975 and 0.995 for safe temperature and buckling temperature, respectively, which are much higher than those obtained by the traditional regression method. The predicted outputs can be used to estimate the buckling failure modes by calculating the difference between the buckling and safe temperatures. This paper will provide a pathway for improving the predictive model of buckling phenomena of ballasted railway tracks. Therefore, the neural network model can be applied to help predict buckling failure mode for the complex track models in order to detect track buckling in summer.

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