Towards autonomous health monitoring of rails using a FEA-ANN based approach

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Abstract. The current UK rail network is managed by Network Rail, which requires an investment of £5.2bn per year to cover operational costs [1]. These expenses include the maintenance and repairs of the railway rails. This paper aims to create a proof of concept for an autonomous health monitoring system of the rails using an integrated finite element analysis (FEA) and artificial neural network (ANN) approach. The FEA is used to model worn profiles of a standard rail and predict the stress field considering the material of the rail and the loading condition representing a train travelling on a straight line. The generated FEA data is used to train an ANN model which is utilised to predict the stress field of a worn rail using optically scanned data. The results showed that the stress levels in a rail predicted with the ANN model are in an agreement with the FEA predictions for a worn rail profile. These initial results indicate that the ANN can be used for the rapid prediction of stresses in worn rails and the FEA-ANN based approach has the potential to be applied to autonomous health monitoring of rails using fast scanners and validated ANN models. However, further development of this technology would be required before it could be used in the railway industry, including: real time data processing of scanned rails; improved scanning rates to enhance the inspection efficiency; development of fast computational methods for the ANN model; and training the ANN model with a large set of representative data representing application specific scenarios.

Keywords: Rail Monitoring, Finite Element Analysis, Artificial Neural Network, Optical Scanning.

1 Introduction

In the UK, Network Rail is accountable for "20,000 miles" of track around Great Britain which leads to massive expense in time and cost in track maintenance. Network Rail must undergo projects such as the £8.6m track renewal in Newcastle in 2018 due to worn rail profiles, all summing up to an operating cost of £5.2bn in 2019 [1].

Worn rails are caused by the repeated use of the wheels over the rail. Various studies have shown the different types of wear that the railhead profile undergoes. The wear is categorised into four areas: gauge corner creaking, corrugation, side wear, and rolling contact fatigue [2]. Gauge corner cracking is caused by a speed-induced shear force acting laterally across the railhead, which leads to micro-cracking through the railhead [3]. It often happens when a train travelling at low speed around curves produces a wheel squeal, causing a lateral micro-slip across the railhead [4]. Corrugation wears cause a hardening of the railhead due to vibrations of the train, which causes hardened strips familiar with the motion direction [5]. This type of wear causes an uncomfortable riding experience for the passengers and it eventually leads to track renewal [2]. Side wear is caused when trains are crabbing due to the wheels not being parallel with the track, causing railhead wear [2]. The two significant factors that increase this type of wear are decrease of curve's radius and axial load [6], which can increase the intensity of rail wear on the curves by 2.25 times when the axle load increases from 12 tonne per axis to 18 tonne per axis [7]. The final type of wear is rolling contact produced by the pressure generated due the rolling of the wheels over the railhead, which could lead to cracks in the rail over long period of time [2].

Welding is the current method of joining two rails together. The rail welds are more susceptible to damage formation than a standard rail due to three reasons. First, a geometrical irregularity is created along the wheel-rail interface, leading to dynamic axle load variations and dynamic contact stress amplification. The second reason is the presence of material inhomogeneities at the rail surface. The third reason is internal material inhomogeneities or defects in the weld [8].

Machine learning is a part of the artificial intelligence branch. This technology is used to learn from data with minimal human intervention. One of the machine learning technologies is the artificial neural networks (ANNs), which have been extensively used in a wide range of applications in the last few decades. ANNs are typically created from three main types of architecture: feed-forward, competitive, and recurrent networks, with each having their own strengths and weaknesses [9]. In the feed-forward neural networks approach information is only processed in one direction. The ANN works by series of inputs linked to hidden layers defended by neurons where mathematical functions are applied to describe the relationships between inputs and outputs. For example, ANN models have been used in railway applications for the identification of defects in wheels using data generated from sensors [10]. Other machine learning techniques (e.g. polynomial, radial basis function, and Kriging) have been also used in engineering applications. It was reported that Kriging could have greater performance than ANNs for small data sets. Also, for applications where the nonlinearity of the problem is reasonably small, polynomials might also be a preferable option [11].

The use of ANN models to monitor the health of the rail is found to be limited. Despite the generated knowledge in rail wear and tracks, there is a limited study showing how ANNs can enable the prediction of stresses using optically scanned data. This paper aims to establish a new concept for autonomous health monitoring of rails using a FEA-ANN based approach for the prediction of stress levels in worn rails that are optically scanned. ANNs are used due to its ability to capture non-linearities.

2 Methodology

Fig. 1 shows an overview of the methodology and the key steps. This methodology aims to enable the prediction of stresses using scanned data only by utilising an ANN predictive model trained with FEA data. The first step of the methodology is to model worn profiles of the rail and use them as an input into a FEA model to predict the stresses in the rail. The predicted stresses from the FEA model are then used to train an ANN model. A rail geometry representing a worn profile is then optically scanned. The scanned data is used as an input into the ANN model to calculate the stresses based on nodal coordinates from the scanned rail.

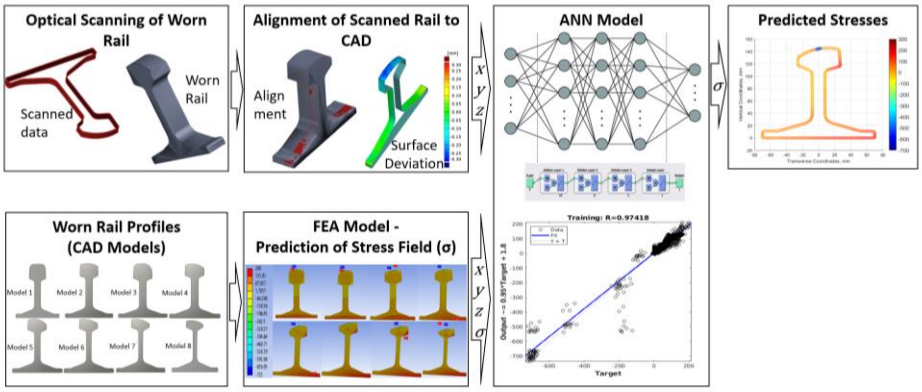

Fig. 1. Overview of the methodology.

2.1 FEA Model

Eight CAD models representing eight different worn rail profiles were created based on the BS113A flat headrail with no wear. The worn profiles of the were modelled by gradual removal of material from the railhead and the web. The material removal of the web is aimed to represent loss of material due to corrosion. The eight worn rail profiles (see Fig.1) were imported into ANSYS Mechanical.

The interaction between the rail and the wheel generates a contact area. The contact varies depending on the rail-wheel contact interaction as well as the applied load. In this study, it is assumed that the train is travelling on a straight line, and only vertical forces are induced on the track and the rail. For a vertical load, Vo et al. [12] determined that the contact patch has an ellipsoidal shape with an area of 164.15 mm^2. The dimensions of the ellipse determined by Vo et al. [12] were projected into the railhead to represent the contact area in the FEA model. The maximum weight for a 4-axle train is 101.6 tonne [13]. The load per wheel was calculated to be 12.7 tonne (124.5 kN). The applied pressure in the FEA model is 758.5 MPa based on the contact area of 164.15 mm^2 and the maximum wheel load of 124.5 kN.

The rails are manufactured with hot-rolled and hardened steel. The steel used in railroad track is typically 1084 or equivalent. This is a medium carbon steel with 0.7% to 0.8% carbon and 0.7% to 1% manganese. The mechanical properties are an ultimate tensile strength of 780 MPa, a yield stress of 510 MPa, a shear stress of 468 MPa, a Youngs' modulus of 207 GPa, and a Poisson's ratio of 0.3.

The rails are clamped to sleepers with the use of fasteners. It is assumed that the sleepers are spaced at 650 mm. The fasteners are modelled using ground linear springs in the vertical, lateral, and longitudinal directions at intervals of 650mm to represent the spacing of the sleepers. Fig. 2 shows the FEA model with the applied springs and the mesh which is more refined in the location where the pressure load is applied. The model is meshed with quadratic elements. A spring stiffness of 26,000 N/mm is assumed in the vertical direction and 90,000 N/mm in the lateral and longitudinal directions. Due to symmetry in the longitudinal direction, a half rail model is used with an applied zero displacement in the longitudinal direction to the face of symmetry. The use of ground spring elements enabled the numerical conversion of the model without the need to apply additional boundary conditions. Static elastic analyses were performed.

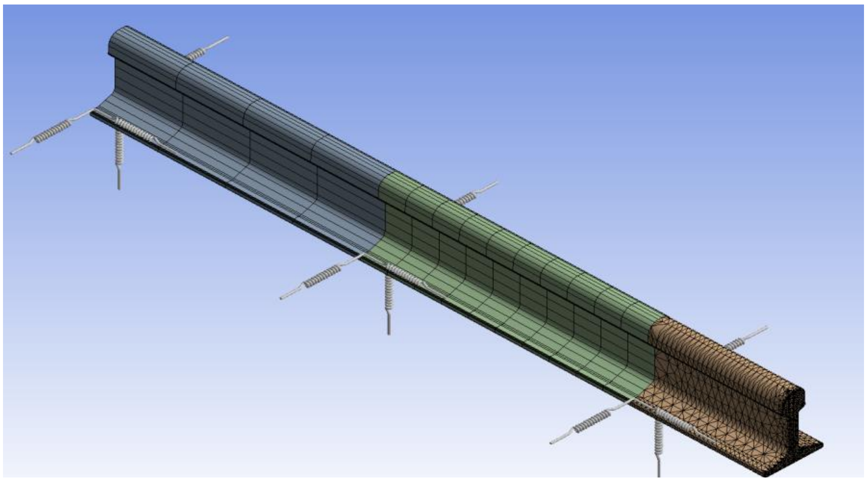

Fig. 2. FEA model.

2.2 ANN Model

An ANN model is created in MATLAB using the back-propagation network. The training algorithm of the back-propagation network consist of multilayer feed-forward neural network, where: first, inputs are presented to the network and errors are calculated; second, sensitivities are propagated from the output layer to the first layer; then, weights and biases are updated [14]. In this study, the Levenberg–Marquardt method is used together with Bayesian regularization in training the neural networks [15]. The performance of the neural networks is calculated using the mean square error method. The ANN model was constructed with three hidden layers, since this is the minimum required to delivery good accuracy [16]. The three hidden layers are constructed with 10, 6 and 2 neurons, respectively. Tan-sigmoid transfer function (tansig in the MATLAB library) is used for each of the hidden layers. The ANN model was trained with FEA data. The FEA data was stored in a database representing the nodal coordinates in the lateral and vertical directions and the associated nodal stresses extracted at the outer edge of the rail. This data allows the ANN to approximate the relationship between nodal coordinates and nodal stress value. The coordinates of the scanned and aligned nodes are then used as an input in the ANN model to predict the stress values.

3 Results and Discussion

3.1 Analyses of FEA predicted stresses

The contour plot of the predicted maximum principal stress can be seen in Fig. 1 for the 8 worn rail profiles. It was found that the maximum principal stresses increase by increasing the rail wear. The areas where the stresses are most affected are Nodes A, B and C (see Fig. 3). An increase in the stress to 196 MPa can be seen at node C. The maximum principal stresses were analysed to find out whether they would exceed the fatigue strength of the material, which can lead to a fatigue crack initiation in the rail. The fatigue strength of the rail material is approximated using the endurance limit approach, where the fatigue strength is approximately 50% of the ultimate strength. Using this approach, the fatigue strength is estimated to be 340 MPa. Comparing the predicted peak maximum principal stress of 196 MPa with the approximated fatigue strength of 340 MPa, it can be concluded that the worn rail profile is safe from any crack initiation for the applied load in the FEA model. It needs to be mention than in curves, the centrifugal forces will induce forced in the lateral direction, leading to more significant stress and potential fatigue crack initiation.

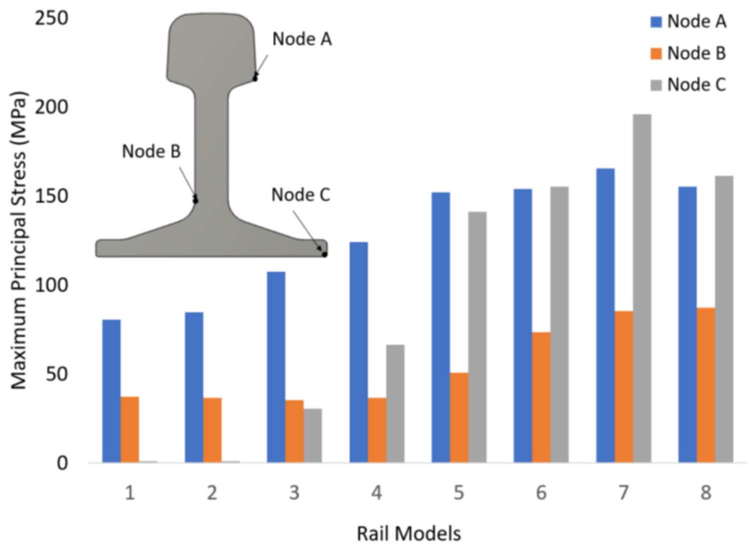

Fig. 3. Predicted maximum principal stresses in three key locations of the rail for eight profiles.

3.2 Preliminary verification of the ANN model

A worn rail geometry was created in ANSYS SpaceClaim which was different from the eight geometries from Fig.1. The geometry was built layer by layer on the Ultimaker 2+ 3D printer using a polymer material in order to represent a physical shape of a worn rail. The 3D printed rail was optically scanned using the Creo 3D optical scanner, followed by alignment to the original CAD geometry using the GOM Inspect software.

The alignment was conducted using the best-fit algorithm which is based on the minimum error calculations after all nodes were selected. The alignment step transfers the scanned coordinates into the same position as the FEA using translations and rotations. The alignment is needed because the ANN model uses the coordinates of the FEA as an input in the ANN model. After the alignment step, the surface deviations were calculated (see Fig. 1). The results showed that the maximum surface deviation is 0.30 mm, which is small compared to the overall detentions of the rails. The CAD geometry of the worn rail was imported into the FEA model in ANSYS Mechanical, while the optically scanned and aligned data points from the 3D printed rail were used as an input in the ANN model to predict the stresses. The ANN model was trained with the FEA data from the eight profiles using the nodal coordinates of the mesh and the predicted stress field of the outer edge of the rail. Best training performance was achieved at route mean square error of 530.7 at 454 epochs (see Fig. 4). Fig. 5a shows the predicted maximum principal stresses from the ANN model, while Fig. 5b displays the predicted maximum principal stresses from the FEA model in ANSYS. It can be seen that a very similar distribution of the maximum principal stress is predicted with the ANN model using only the coordinates of the worn rail profile. This suggests that, in the proposed methodology, the ANN model is capable of predicting the stresses in the rail. However, a validation is required to increase the the confidence of the predicted stresses.

The utilisation of the proposed methodology could enable the monitoring of rails and predicting their conduction and associated structural integrity risks. However, achieving this goal would require to overcome many challenges, including: (i) the ability to scan the entire rail quickly and process the data in real time; (ii) the utilisation of scanners with high scanning rates to increase inspection efficiency; (iii) the provision of fast computational methods to process the scanned data and conduct fast calculations within the ANN model; (iv) training the ANN model with a large set of representative data considering more realistic industrial scenarios and more loading conditions.

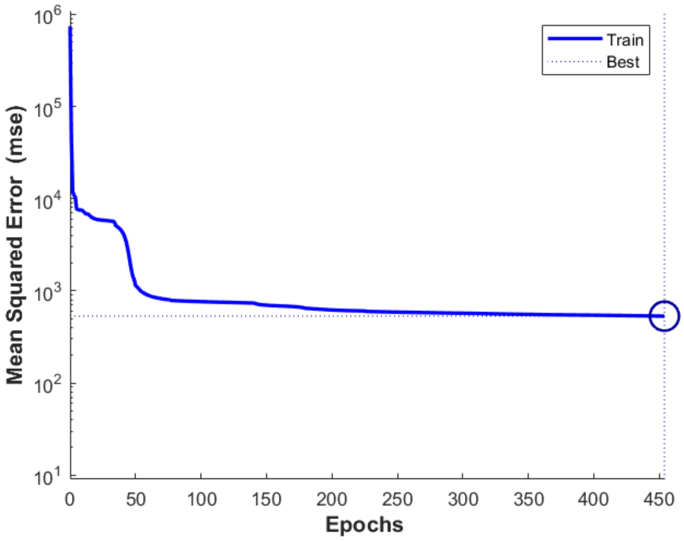

Fig. 4. Training Performance of the ANN Model

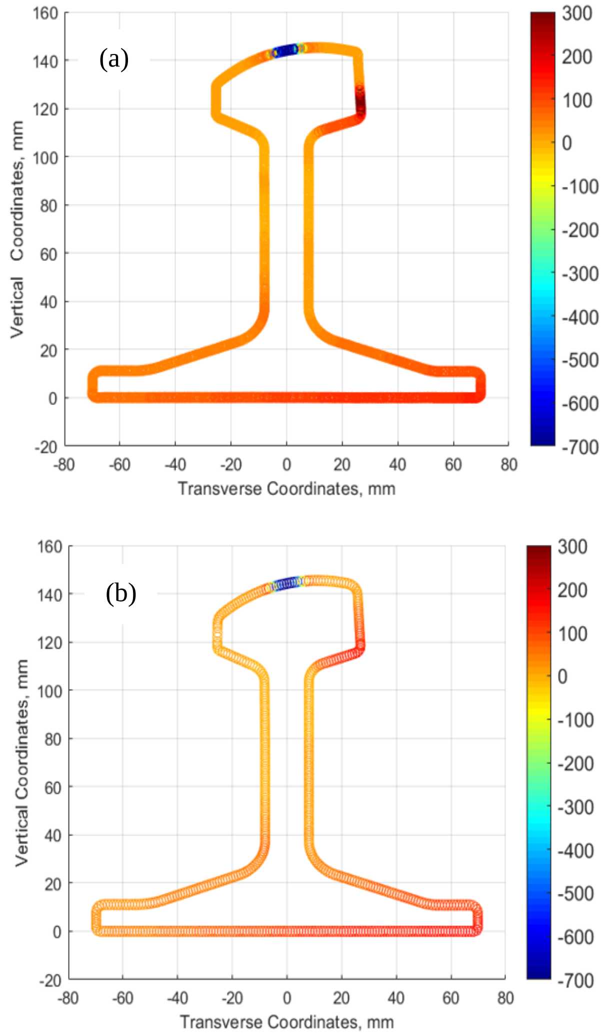

Fig. 5. Maximum principle stresses in MPa: (a) ANN model (scanned data); (b) FEA model .

4 Conclusions

The following conclusions were derived from this research work:

- A FEA model was developed to predict the stresses in a rail subject to vertical loads induced in the rail-wheel contact. The results showed that by increasing the loss of material due to wear and corrosion, the stress levels in the rail increase.
- A methodology for using FEA data into an ANN model to enable the prediction of stresses using optically scanned data of worn rails was developed. This was verified

using a 3D printed worn rail by comparing the predicted stresses by a FEA model and an ANN model, which were in good agreement.

- The work presented a proof of concept which showed the potential of integrating FEA and ANN models to deliver fast prediction of stresses, which can be incorporated in technologies for real-time health monitoring of rails.
- Further investigation and extensive validation of the proposed models on industrial scenarios from the railway sector is needed, including traveling in curvatures and junctions. This will be the focus of the future research.

References

1. Westlake, J.: Network Rail Limited Annual report and accounts (2009), https://cdn.networkrail.co.uk/wp-content/uploads/2019/07/Annual-report-and-accounts-2019-Chief-financial-officers-review.pdf, last accessed 2021/06/16.
2. Robinson, M.: Fatigue in railway infrastructure. 1st edn. Elsevier (2009).
3. Frost, M.: Railway Management and Engineering. Proceedings of the Institution of Civil Engineers – Transport 169(2), 121–121 (2016).
4. Chen, G.: Friction-Induced Vibration of a Railway Wheelset-Track System and Its Effect on Rail Corrugation. Lubricants 8(2), 18 (2020).
5. Al Nageim, H., Mohammed, F.,Lesley, L: Numerical results of the LR55 track system modelled as multilayer beams on elastic foundation. Journal of Constructional Steel Research 46(1–3), 347(1998).
6. Povilaitienė, I., Podagėlis, I.: Research into rail side wearing on curves. Transport 18(3), 124–129 (2003).
7. Peran, Z.: Dynamic Forces between the Rails and the Wheels of Railway Vehicle. PROMET - Traffic Transportation 28(1), 63-69 (2016).
8. Lewis, R., Olofsson, U.: Wheel-rail interface handbook. Woodhead Publishing Limited (2009).
9. Sariev, E., Germano, G.: Bayesian regularised artificial neural networks for the estimation of the probability of default. Quantitative Finance 20(2), 311–328 (2019).
10. Krummenacher, G., Ong, C.S., Koller, S., Kobayashi, S., Buhmann, J.M.: Wheel Defect Detection with Machine Learning. IEEE Transactions on Intelligent Transportation Systems 19(4), 1176–1187 (2018).
11. Kianifarm M.R., Campean, F.: Performance evaluation of metamodelling methods for engineering problems: towards a practitioner guide. Structural and Multidisciplinary Optimization 61, 159–186 (2020).
12. Vo, K.D., Tieu, A.K., Zhu, H.T., Kosasih, P.B.: A 3D dynamic model to investigate wheel-rail contact under high and low adhesion. International Journal of Mechanical Sciences 85, 63–75 (2014).
13. Network Rail, Network Statement 2019, https://www.networkrail.co.uk/wp-content/uploads/2019/03/Network-Statement-2019.pdf, accessed 2021/06/16
14. Burden, F., Winkler, D.: Bayesian Regularization of Neural Networks. In: Livingstone D.J. (eds) Artificial Neural Networks. Methods in Molecular Biology™, Vol458. Humana Press (2008).
15. Reed, R.D.: Neural Smithing, MIT Press, Cambridge, MA (1999)
16. Uzair, M., Jamil, N.: Effects of Hidden Layers on the Efficiency of Neural networks. IEEE 23rd International Multitopic Conference (2020).