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Development of Random forests regression model to predict track degradation index: Melbourne case study

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Abstract

In rail infrastructure maintenance management systems, Track Degradation Index (TDI) is considered as a representative of quality of rail tracks. This index is usually developed based on the deviation rate or standard deviation of track geometry parameters. In this regard, prediction of future TDI is an important task as it can be employed to determine when and where maintenance and renewal activities must be deployed. In this study, a track geometry data set from Melbourne tram network has been used as the case study and gauge deviation parameter is selected as the main parameter to develop TDI. For prediction of the future TDI, Random Forests (RF) model as a Machine Learning (ML) model is used to predict the future TDI of the data set. Since TDI is a continuous variable, Random Forests Regression (RFR) model is applied. In this study, RF model has added two algorithms to the basic Decision Trees (DT) model including bagging and random subspace method. These algorithms can reduce the overfitting problem and over-focus on special features. Based on the results of this study, adjusted R^2 value of the proposed prediction model is 0.93, which demonstrates that the model has the satisfying performance in predicting the TDI.

Keywords: *Melbourne tram, track degradation index, gauge deviation, random forests*

1. Introduction

In recent years, due to problems related to excessive use of private transportation such as road congestion, increase in road accidents and negative environmental impacts, the role of public transportation has been highlighted by urban decision makers. In this regard, rail systems as an efficient mode of public transport, which are safer, cheaper, and have less conflict with traffic flow, are more attractive (Knowles & Ferbrache, 2016). On the other hand, in parallel with the increase in using rail transport, their infrastructure is subjected to more pressure and dynamic stresses. In other words, more demand of public transport services can accelerate the degradation rate of rail infrastructure components. Rate of degradation in rail systems is not high but if the gradual degradation of rail systems is not treated properly, they can lead to rail failure. Since railway transport systems carry a large number of passengers compared to other modes of transport, any rail failure can lead to significant human casualties and huge financial loss (Ahac & Lakusic, 2017).

One of the important rail track failures is due to track geometry defects. Deviation of track geometry parameters from the predefined thresholds can potentially contribute to serious problems such as rail derailment and drop in passenger ride comfort. Track geometry parameters can be divided into five main classifications including gauge, alignment, profile, cross-level and twist (Zarembski et al. 2017). In order to maintain rail transport services reliable, safe and completive, monitoring the quality and health of rail track geometry is one of the important tasks of rail organisers. To regularly monitor the quality of rail tracks, rail organisations employ track degradation indices. These indices are used to quantify the condition of rail tracks numerically. In addition, by defining thresholds for these indices, they can be used by rail infrastructure maintenance management systems to determine the appropriate times of maintenance and renewal operations of rail components (Andrade and Teixeira 2015).

This study aims to develop a model to predict the future value of TDI based on the current state over the data of Melbourne tram network. Most studies carried out for predicting TDI have focused on the heavy rail track degradation while light rail track degradation has not received proper attention and this paper aims to fill this gap. Furthermore, predicting the TDI of tram systems can assist tram rail operators in establishing maintenance strategies. In the following sections, we first summarise the existing literature on rail track degradation indices and prediction models. Section 3 presents the case study of this research, which includes the Melbourne tram data. Section 4 explains the development of TDI based on gauge deviation variable. Section 5 presents the development of the models to predict track gauge deviation index. Section 6 presents the results and discussion of the study. Finally, Section 7 provides the conclusions of this study along with directions for future research.

2. Literature review

The literature review of this study is divided into two sections. In the first section, several TDIs developed and used by different rail operators are discussed. In the second section, a review of studies associated with rail track degradation modelling is provided.

2.1. Existing TDI

In this section, examples of TDI are represented. Different statistical formulas and mathematical equations have been used to construct the track degradation index.

In Poland, a synthetic track quality coefficient is applied to assess the track geometry condition based on the Standard Deviation (SD) of different track geometry parameters. The proposed index is represented by (Chudzikiewicz et al. 2017):

$$J = \frac{S_z + S_y + S_w + 0.5.S_e}{3.5} \tag{1}$$

where, J is the proposed track degradation index, S_z denotes the SD of vertical deflections, S_y denotes the SD of horizontal deflections, S_e represents the SD of track gauge and S_w is the SD of track twist. The chord length of 10 m (determines the length of measure for track geometry data collection) is used in this study.

In the USA, a track roughness index was created by Amtrak for determining the rail track condition. This index can be computed by means of taking the average of squared deviation over a 20 m chord length as follows (Liu et al. 2015):

$$r^2 = \frac{1}{n}\sum_{i=1}^{n}(d_i)^2 \tag{2}$$

where, r^2 denotes track roughness index value, n is the number of measurements and d_i denotes the value of gauge deviation throughout the studied year. The proposed index can be applied to gauge, alignment, cross-level and profile.

In China, the national railroads use the total of SD of track geometry parameters for determining overall track quality index as follows (Li et al. 2016).

$$TQI = \sum_{i=1}^{n} \sigma_i \tag{3}$$

where, TQI denotes the track quality index and σ_i represents the SD of track geometry parameters. In this study, two different lengths for evaluating the overall track quality are recommended. In this context, for high speed rail networks, a length of 500 m is proposed and for conventional rail networks, a length of 200 m is proposed.

In Iran, a Track Geometry Index (TGI) for individual parameters and an Overall Track Geometry Index (OTGI) based on combination of SD values and the mean values of the track geometry parameters have been developed. A chord length of 19 m is applied for collecting track geometry parameters. These parameters are track gauge, profile, alignment and twist. For instance, the following equation is used for calculating the TGI of alignment parameter (Sadeghi, 2010):

$$AI = \frac{\left|\bar{x}_{AllignLeft}\right| + 3 \times SD_{AllignLeft} + \left|\bar{x}_{AllignRigh}\ \right| + 3 \times SD_{AllignRight}}{2} \tag{4}$$

For calculating the OTGI, the following formulate has been proposed:

$$OTGI = \frac{\frac{a}{2} \times GI^{+} + \frac{\acute{a}}{2} \times GI^{-} + b \times AI + c \times PI + d \times TI}{\frac{a + \acute{a}}{2} + b + c + d} \tag{5}$$

where $OTGI$ represents the overall track geometry index, GI^{-} denotes the negative gauge index, GI^{+} denotes the positive gauge index, PI, AI and TI represent, respectively, the profile, alignment and twist indices, a, $\acute{a}$, b, c, and d are constant parameters which range between 0.08 and 1.00, depending on track class and density of defects.

Swedish National Rail Network uses a new track quality index to evaluate the track geometry condition. This index is constructed based on SD of track geometry parameters. The chord length of 12 m has been used to measure the deviations. This index is formulated by the following equation (Odolinski & Smith 2016):

$$Q = 150 - \frac{100\left[\frac{\sigma_H}{\sigma_{H_{lim}}} + \frac{\sigma_S}{\sigma_{S_{lim}}}\right]}{3} \tag{6}$$

where Q represents the index for evaluating track geometry condition, σ_H is the average of SDs of left and right profile, σ_s is the SD of other track geometry parameters including horizontal deviation, gauge and cross-level, $\sigma_{H_{lim}}$is the allowable limit of σ_H, and $\sigma_{S_{lim}}$ is the allowable limit of σ_S.

Most of the indices disused in this section have simplicity in their development but their correlation with last gauge deviation which represent the current condition of rail track is not satisfying.

2.2. Existing rail track prediction models

In this section, a number of studies based on statistical and ML models applied to predict track degradation rates and gauge deviation have been provided.

Exponential regression as a type of non-linear regression technique can produce the best fit for a set of data. Sadeghi and Askarinejad (2010) elaborated an exponential regression model to estimate the rate of rail track degradation. In their study, changes in the Track Geometry Index (TGI) and the Track Structure Index (TSI) were targeted and regarded as dependent parameters. The TSI is mainly based on the condition of rails, ballast and sleepers, whereas the TGI is mainly based on the condition of gauge, twist, cross-levels and alignment. They used time period, passing tonnage in MGT, initial TSI, initial TGI and the average train running speed as the predictor variables in their degradation model. Based on analyses of a test zone, two equations for predicting future TSI and TGI were utilised. The comparison of the research outcomes represented that the sensitivity of TGI to the independent predictor is greater than that of TSI.

Shang & Bérenguer (2014) elaborated a maintenance management framework based on hierarchical Petri Nets (PN) to model rail track degradation and develop maintenance strategies. PNs are useful graphical-mathematical models consisting of different elements including nodes, transitions and places. In this study, the number of identified defects related to track gauge deviation was used to predict the track degradation over rail service life. The proposed model has the ability and flexibility to work with different inspection methods to predict the risk of track failure. Based on the results, the performance and effectiveness of the model in both preventive maintenance and reactive maintenance operations was acceptable.

Multi-stage regression is a class of linear regression models which has the capability to predict different stages of degradation process. Ahac and Lakušić (2015) elaborated a tram maintenance management framework by applying a multi-stage regression prediction model. In this study, data collected from Zagreb tram network were used. The track gauge deviation was regarded as the dependent variable and the passing tonnage in MGT, track-fastening system and the sum of operating days were considered as the predictor variables. Based on the results of the study, for a certain value of passing tonnage, the model calculated accurate predictions of gauge deviation. For values above that, the models did not produce reasonable predictions.

Karimpour et al (2018) elaborated an Adaptive Network-based Fuzzy Inference System (ANFIS) model to predict rail track degradation based on the gauge parameter. ANFIS is an Artificial Intelligence (AI) model developed based on Artificial Neural Networks (ANN) and fuzzy logic principles. The inference engine of the model is based on IF-THEN rules and ANN method is utilised to optimise the membership function of the model. In this study, data set of Melbourne tram network has been used. This study suggested that an accurate model is able to play a significant role in predicting the long-term performance of rail tracks. Gauge deviation parameters associated with the previous year and two years ago were among the main parameters in the model development. The results show that the model can predict the gauge deviation for coming year with acceptable accuracy.

Moridpour et al. (2017) elaborated an ANN model for predicting the tram track degradation using track maintenance data and addressing the curved sections only. In this research, Melbourne tram network was used as the case study. A multilayer feed-forward ANN model with three layers was applied in the research to predict the target variable. Different variables such as rail type, rail profile, passing tonnage in MGT and the instalment year have been included to predict the deviation of track gauge parameter. Based on the results of this study, the type of tracks and last gauge measurement, have a significant impact on the track geometry devotion. The developed model presented a reasonably good prediction accuracy.

Current indices developed in rail infrastructure are related to heavy rail and the behaviour of rail track degradation in last several years is not well addressed, which is important for developing a rail infrastructure maintenance management system.

3. Case study

In this study Melbourne tram network, as the longest tram network in the world, which includes 25 routes, over 1700 stops and 250 km of double tracks, is represented as the case study. In

2017, by organising more than 450 tram cars, almost 204 million passengers have been carried by the services provided by Melbourne tram system. The statistics demonstrates more than four hundred thousand increase in passenger growth compared to 2016 (PTV, 2017). Data set of this study is collected by Yarra Trams, which is the main operator of Melbourne tram network. The data set investigated in this research is composed of different track types including straights, curves, crossovers and H-crossings. This data set covers different track geometry parameters along with total traffic volumes and other rail structural parameters such as rail profile, track surface, rail support and rail type. The current data set comprises six consecutive years (from 2010 to 2015) and a chord length (the measuring distance for collecting track geometry parameters) of 10 m is used. In this study, a large number of track records (each track record consists of various information including track code, the place of gauge measurement, gauge deviation value, track structural properties) needed to be analysed in order to derive the gauge deviation of rail track sections. Data set preparation is done in two stages including data filtering and data segmentation.

In data filtering process, noisy and out of range data are removed in order to increase the accuracy and reliability of the index development. Determining distribution patterns of the current data is among common data filtration approaches. If the distribution of the data set follows the normal distribution, the value of $\bar{x} \pm 3\times$SD cover 99.7% of the data set. $\bar{x}$ represents the mean value of data and SD is the standard deviation of data (DeGroot & Schervish, 2012). In this research, Shapiro-Wilk tests have been conducted to check the normal distribution possibility of the data set. By analysing different track sections, it has been revealed that the changes in gauge deviation mainly follow normal distribution (Shapiro-Wilk test: *p-value*=0.819). Therefore, records deviating from the $\bar{x} \pm 3\times$SD are recognised and removed from the data set. In the next step data segmentation is applied.

Data segmentation is the process of converting track sections, consisting of track records, into different track segments which improve the process of data matching and data analysis. Based on the place of gauge measurement related to each track record and the chord length, track records are sorted out and track segments have been created. Each track segment contains an identification code (combination of the location details and track code). This unique code is then utilised to connect same track segments of six consecutive years with each other. Ultimately, by applying this code, gauge deviation values of each track segment for six consecutive years are determined and the multi-year data set is prepared.

4. Development of degradation index for Melbourne tram network

In this study, the conditions of rail track have been analysed with regard to gauge deviation for both positive gauge (rail heads divergence from the track centreline) and negative gauge (rail heads convergence toward the track centreline). TDI values can assist rail infrastructure decision makers in addressing efficient maintenance strategies. For this purpose, calculating TDI over the case study has been targeted.

In this study, the following formulate for determining track gauge degradation index has been used (Falamarzi et al. 2018).

$$TDI_i = \mu_i + \lambda_i \tag{7}$$

where, TDI_i represents the track deterioration index based on the gauge deviation value for segment *i*, μ_i is the mean value of gauge deviation values for the i^{th} track segment and λ_i represent the differential gauge deviation in the i^{th} segment.

The proposed index contains two terms. Mean value of gauge parameter (μ_i) is an essential factor for constructing the deterioration index as larger values represent more deviation from the primary gauge value and eventually more risk of degradation to the rail tracks. μ_i is calculated as follows:

$$\mu_i = \frac{1}{m}\sum_{t=1}^{m} G_{dev_t} \tag{8}$$

where, G_{dev_t} represents the gauge deviation in year t, and m denotes the number of years that data has been collected.

In addition, the differential gauge deviation (λ_i) is introduced into the index formulation. It should be noted that different track segments can have an incidentally identical mean value of gauge deviation but the ones with greater differential gauge deviation may reflect the quicker rate of deterioration in track gauge than the other segments with minor gauge deviation rate. Differential gauge deviation can be derived by dividing the sum of absolute value of differences between two consecutive gauge deviations by the total number of data collection years minus one for the i^{th} segment as follows:

$$\lambda_i = \frac{1}{m-1}\sum_{t=1}^{m-1} \left| G_{dev_{t+1}} - G_{dev_t} \right| \tag{9}$$

To numerically present how the proposed index performs on real data, a specimen track section (1000 m in length), which includes 10 track segments, is selected and TDI of the track segments are calculated in Table 1. In this table, μ_i and λ_i are calculated using Equation 8 and Equation 9, respectively. Then, TDIs have been computed using Equation 7.

Table 1: *TDI* values associated with the track segments of the specimen

Segment No.	Gauge deviations measured within 6 years						μ_i	λ_i	*TDI*
	2010	2011	2012	2013	2014	2015			
1	4.93	4.86	3.58	4.82	5.06	7.43	5.11	1.04	6.15
2	6.43	6.20	5.06	6.41	6.50	9.56	6.69	1.17	7.86
3	6.57	6.44	5.47	7.06	7.09	9.43	7.01	1.01	8.02
4	5.98	5.74	4.96	6.81	6.48	8.29	6.38	1.00	7.37
5	3.00	2.65	1.62	2.41	2.84	4.70	2.87	0.89	3.76
6	3.19	2.63	1.80	2.72	2.96	4.46	2.96	0.81	3.77
7	2.54	2.44	1.11	1.98	2.27	4.47	2.47	0.96	3.43
8	3.14	2.54	1.85	2.84	3.05	4.51	2.99	0.79	3.78
9	2.36	2.18	0.91	1.76	2.07	4.22	2.25	0.95	3.20
10	7.42	4.93	5.92	4.08	4.07	5.44	5.31	1.34	6.65

5. Development of (Random Forests Regression) RFR model

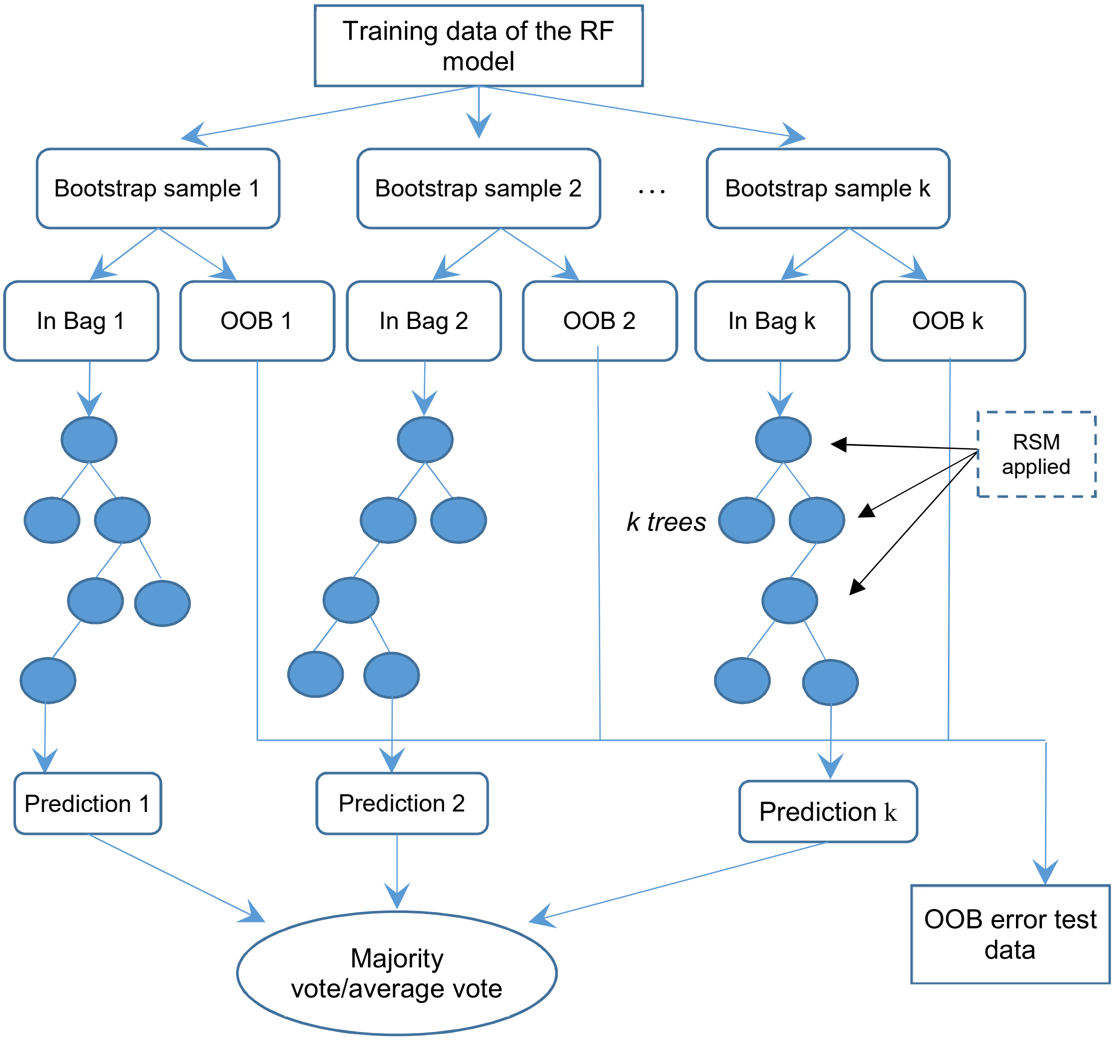
In this research, future TDI value (TDI_n), is considered as the target variable. In order to improve the accuracy of the proposed model, variables, which are effective and important in the prediction of the target variable, are analysed. For this purpose, one-way ANOVA analysis has been applied to categorical variables and Pearson Correlation test has been applied to continuous variables (Guler et al., 2011). Based on the results, the previous TDI (TDI_p), track surface (T_S) and rail type (R_T) are statistically significant to predict the target variable (*p-value* is less than 0.05). Afterward, the other parameters that are less significant are removed from the model development.

Recently, there has been a lot of interest in ensemble learning methods that generate many bootstrap samples and aggregate their results. Random Forest (RF) model is an ensemble-learning algorithm for classification and regression problems. RF models are developed based on the DT structure but with adding two additional features including bagging and Random Subspace Method (RSM). Bagging is a machine learning optimising algorithm designed to improve the accuracy and stability of machine learning models by creating several bootstrap samples. It also reduces variance during the problem solving and helps the model to avoid overfitting. RSM tries to reduce not over-focus on features that seems to be highly predictive or descriptive in the training data set. Ultimately, this method decreases the correlation between estimators in each bootstrap by training them randomly on a sample of features rather than the whole feature set (Hua et al. 2017; Toran Pour et al. 2017).

The development of RF model can be summarised in three main steps. In the first step, based on bagging method, a number of bootstrap samples (or trees) derived from the training data set are independently created. Each bootstrap randomly contains sample records of training data set with replacement. On average, each bootstrap sample approximately consists 63% of the training data set. In the second step, RSM method is applied. In basic DT, in each tree, each node is split by using the best split among all predictors. While in the RF model, each node is split using the best feature among a subset of randomly selected predictors at that node. Similar to the first step, replacement is also applied in this step. In the last step, the majority vote mechanism (alternatives or predictions that have more than half the votes are the major or final results) is considered for prediction in classification problems. In regression problems, the average vote mechanism (the average value of predictions is the major or final result) is considered for prediction (Santur et al. 2016; Sharma et al. 2018).

Calculating the prediction error during the model development is important in ensemble learning method. For this purpose, at each bootstrap sample, the data not included in the bootstrap or Out of Bags (OOB) are predicted by using the tree developed with the bootstrap data. Then OOB predictions are aggregated and the error rate (by comparing the real data and the ones predicted by the RF model) is calculated. In this context, the number of variables (*mtry*) which are randomly selected at each node (to be split) and the number of bootstrap samples have important roles. In our case as three independent variable are inserted, hence the value of *mtry* can be varied between one and three. By changing the value of *mtry* as well as the number of bootstrap samples (or consequently the number of grown trees), the error related to OOB predictions can be adjusted. By modifying the values of *mtry* and checking OBB error, the acceptable number of trees can be determined. In general, by increasing the number of trees, the rate of error will decrease (Genuer et al. 2010; Rodriguez-Galiano et al. 2012). The flowchart in Figure 1 illustrates the process of predicting the data in the RF model based on combination of bagging and RSM methods.

Figure 1: The process of predicting the data in the RF model

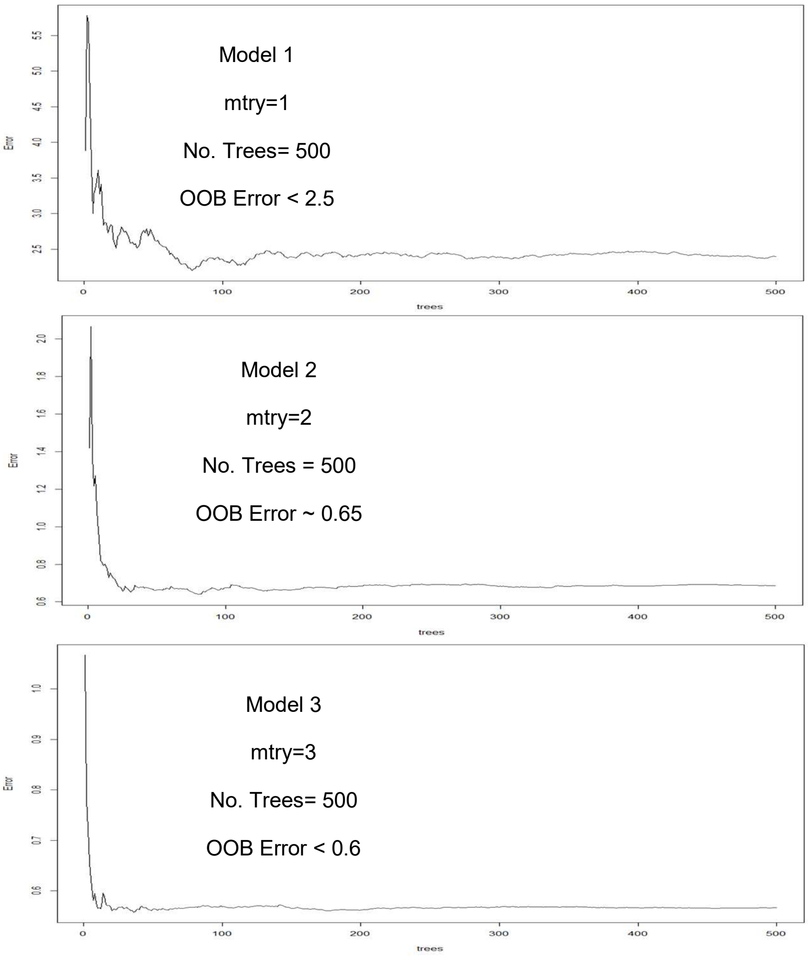


In the following section the result of developing the RFR model over the case study data set are presented and discussed.

6. Results and discussion

In this section, the results of the RF model are presented and the evaluation of the model is provided. For conducting evaluation analysis after the model development, total data set should be divided into training and testing data sets. In this context, 75% of the data were assigned to training, whereas the rest were assigned to testing and validating of the outcomes. In the development of the RF model, different values of *mtry* and different number of trees were used to examine the error rate derived from OOB predictions. Figure 2 shows the amount of error rate as a function of the number of trees for *mtry* values of one, two and three.

Figure 2: Changes in RF error rate as a function of trees



As shown in Figure 2, error rates for different *mtries* are decreased dramatically as the number of trees approaches ~30. Afterward, as the number of trees increases to 300, the error rate becomes stable. Hence this graph shows that the number of 300 trees is acceptable for decreasing the OOB error rate and, consequently, optimising the models.

Different approaches exist to numerically evaluate the model performance of the model. As in this study, the dependent variable is a continuous parameter, R^2, which determines the goodness of fit between the predicted values and observed values (Equation 10) and the Root Mean-Squared Error (RMSE) calculated by Equation 11, has been applied to assess the performance of the proposed model as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - f_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (10)$$

where, R^2 is the coefficient of determination, *N* represents the number of samples, f_i is the value predicted by the model, y_i denotes the observed data and $\bar{y}$ is mean value of y_i.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f_i)^2} \qquad (11)$$

In the following table, the values of R^2 and RMSE of the RFR models derived from the analysis of 300 trees are calculated and provided.

Table 2: The results of the model evaluation

Model No.	Predictor variable	Target variable	Adjusted R^2	RMSE
1	TGI_p, TS, RT	TGI_n	0.90	1.35
2	TGI_p, TS, RT	TGI_n	0.93	0.72
3	TGI_p, TS, RT	TGI_n	0.91	0.75

To graphically evaluate the model performance, the correlation between RFR predicted data versus observed data for Model 2 has been illustrated in Figure 3. As shown in this figure, real data and the data predicted by the model are close to each other and have a high correlation, which demonstrates that the model satisfactorily estimates the new data.

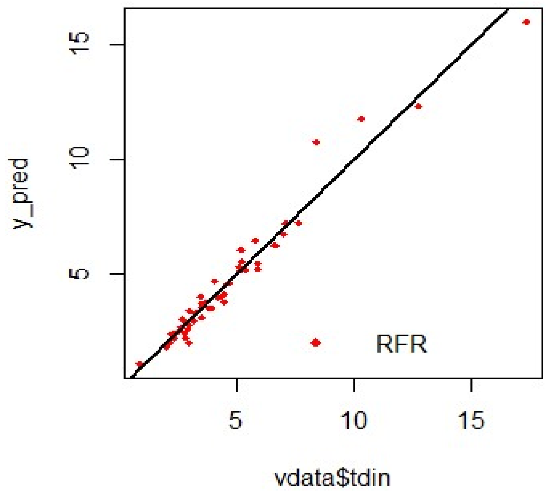


Figure 3: Real $\mathbf{TDI}_n$ versus RFR predicted $\mathbf{TDI}_n$

According to the results of Table 1, for Model 1, Adjusted R^2 is 0.90 and RMSE value is 1.35. For model 2, the values of Adjusted R^2 and RMSE are 0.93 and 0.72. For the last model, these values are 0.91 and 0.75 respectively. These results demonstrate the good performance of the proposed models in predicting the target variable without considerable error. By considering the combination of both RMSE and goodness of fit Adjusted R^2, Model 2 produces better results compared to the other models.

The results obtained in this analysis are consistent and in line with the previous findings on rail degradation models (Kawaguchi et al. 2005; Sadeghi & Askarinejad 2010; Falamarzi et al. 2018). Based on the previous findings and the current results, it can be expressed that the TDI as a representative of track geometry quality and a function of track gauge deviation is strongly dependent on the initial condition of track segments during its service life.

7. Conclusions and future research directions

In this study, we developed a machine learning method to forecast the future TDI based on the previous data. TDI is a useful measure for rail infrastructure maintenance management systems as well as prioritising and ranking rail track segments with maintenance need. The TDI formulated in this study is based on the mean value of gauge deviation of i^{th} track segment and the differential gauge deviation for the same segment over the past years. As a case study, data set from the Melbourne tram network rail was used. In this study, RFR model which is an extension of DT was used to predict the future TDI of the case study based on the previous TDI, track surface and rail type parameters. For the model development, 75% of the data was assigned to training data set and the rest for validating the results. It has been revealed that by increasing the number of trees during the model development, the OOB error rate was reduced. Evaluation of the proposed model showed that the RFR model is able to predict the future TDI and the predicted values approximated the real data very well with an acceptable error, RMSE value of 0.72. This is justified by the fact that the gauge deviation as the constituent element of TDI greatly depends on the previous states of the track condition throughout its service life. For future research directions, in order to compare the performance of the proposed model with the existing models, application of other ML methods such as SVM and ANN to predict TDI can be useful. Moreover, using different data sets for the model validation is suggested.

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