Hindawi
Journal of Advanced Transportation
Volume 2018, Article ID 6340504, 8 pages
https://doi.org/10.1155/2018/6340504

Research Article

Rail Degradation Prediction Models for Tram System: Melbourne Case Study

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Received 20 October 2017; Accepted 28 March 2018; Published 6 May 2018

Academic Editor: Paola Pellegrini

Tram is classified as a light rail mode of transportation. Tram tracks experience high acceleration and deceleration forces of locomotives and wagons within their service life and also share their route with other vehicles. This results in higher rates of degradation in tram tracks compared to the degradation rate in heavy rail tracks. In this research, gauge deviation is employed as a representative of track geometry irregularities for the predication of the tram track degradation. Data sets used in this research were sourced from Melbourne's tram system. For model development, the data of approximately 250 km of tram tracks are used. Two different models including a regression model and an Artificial Neural Networks (ANN) model have been applied for predicting tram track gauge deviation. According to the results, the performances of the regression models are similar to the ANN models. The determination coefficients of the developed models are above 0.7.

1. Introduction

Nowadays, tram system as an energy-efficient mode of public transit is developed and used in different places to facilitate the movement of people within suburbs, cities, and even countries [1, 2]. Based on examining successful implementations of trams systems and comparing them to other modes of public transport, it is evident that this mode has some practical advantages. As trams share the road with other vehicles, they are more accessible for commuters and passengers compared to underground metros [3, 4]. Tram stops are mostly not grade-separated and most of modern vehicles are low-floor. Consequently, boarding and alighting is easier and faster for passenger with disabilities and older people [5, 6].

Alongside the increase in tram demand and patronage, tram infrastructure should bear more loads and stresses. In other words, more frequencies of tram services or having larger weights on the rail tracks can lead to higher rates of degradation. It is notable that, in railway infrastructure, the rate of degradation is not quick. However, this process can lead to system failure with great human casualties and significant financial loss if necessary maintenance actions are not considered [6, 7]. To keep the tram services reliable and comfortable, implementing efficient maintenance strategies is necessary [8]. In this context, in Australia, Public Transport Victoria (PTV) spent more than 63 million AUD between 2014 and 2015 for the maintenance and renewal activities of tram networks [9].

In this regard, infrastructure maintenance management systems are designed for optimisation and implementation of maintenance and renewal activities. The main goal of such systems is to determine when and how to carry out maintenance activities [10]. Practices related to railway infrastructure maintenance management systems can be classified into different categories including monitoring and inspection of railway components, prediction modelling of railway track degradation, and creation of short/long term maintenance and renewal strategies [11]. It should be mentioned that prediction modelling of track degradation is the fundamental prerequisite for developing efficient and cost-effective maintenance strategies of a tram system. It is evident that, without accurately predicting the future condition of rail tracks, designing and providing preventive maintenance strategies are not conceivable [12].

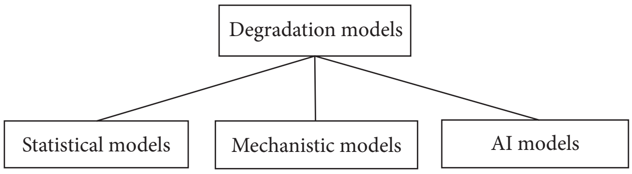

Figure 1: Main categories of degradation models.

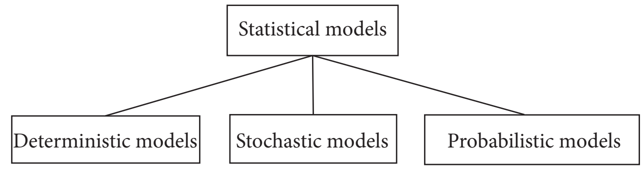

Figure 2: Main categories of statistical models.

Several studies have been conducted in the field of heavy rail degradation analysis and modelling. However limited studies have attempted to carry out the tram track degradation modelling. This research aims to develop models to predict the tram track degradation based on the condition of rail tracks in the past years. For this purpose, predicting deviation of track gauge as an indicator of degradation of whole tram track infrastructure has been targeted. Gauge deviations predicted by the models can be used by tram track maintenance management systems to address appropriate maintenance/renewal decisions.

This paper is organised as follows. The relevant previous studies on rail track degradation prediction modelling will be explained in the second section. The data sets which have been used in this research will be described in the third section, followed by the model development afterwards. Then, the results will be presented and discussed in the fourth section. The final section concludes with the summary of the findings of this research and suggests future research directions.

2. Literature Review

Track degradation models combine different methods and engineering techniques to bring equations which can be used to predict the future condition of rail tracks by considering the influencing parameters on degradation of rail tracks. By examining the railway literature, the degradation models can be categorised into three main categories including mechanistic models, statistical models, and Artificial Intelligence (AI) models (Figure 1).

2.1. Mechanistic Models. Mechanistic models are considered as the primary and traditional models which are employed to forecast the level of degradation of railway tracks. This model type is based on mechanical characteristics of track components which result in rail degradation. Japanese experience has resulted in a model to assess the track deterioration due to the ballast settlement under train repeated loading passage [13]. In this study, ballast settlement as an indicator of track degradation was considered as the dependent variable and number of loading, vertical acceleration to initiate slip, and vertical acceleration in ballast layers (ballast acceleration) were considered as the independent variables. The following equation is provided to predict the settlement of a tamped track under repeated loading by train passage:

$$y = \gamma \left(1 - e^{-\alpha x}\right) + \beta x, \qquad (1)$$

where y represents the ballast settlement, x represents the repeated number of loading carried by the track, α represents the vertical acceleration required to initiate slip, β is proportional to ballast acceleration and to sleeper pressure, and γ is a constant coefficient correspondent to the initial compacting of the ballast material.

A research team at the technical university of Munich calculated the rate of ballast settlement as the dependent variable. Ballast pressure, preloading period, and the total number of passing axles were used as independent variables [14]. In this research the rate of settlement was calculated by the equation shown as follows:

$$s = a \times p \times \ln \Delta N + b \times p^{1.21} \times \ln N, \qquad (2)$$

where s represents the settlement rate, p represents the ballast pressure and could be calculated through the Zimmermann method, ΔN denotes a preloading period in addition to the first passing axles, N in the second term is the total number of passing axles and the parameters a and b are constant coefficients.

2.2. Statistical Models. A statistical degradation model as a type of mathematical model is based on input and output variables. In statistical models, having sufficient historical data records about rail tracks is essential. Statistical models can be divided into deterministic models, stochastic models, and probabilistic models (Figure 2). Different practices have been done in track degradation modelling by employing statistical models.

Westgeest et al. [15] conducted a linear regression model to predict the effective contributors to the track deterioration progress and the volume of maintenance required over a long period of time. In this research, Key Performance Indicator (KPI) which is a combination of track geometry parameters including longitudinal levelling, horizontal alignment, cross-level, twist, and gauge was considered as the dependent variable. Tamping history (the process of packing track ballast in order to increase the durability of tracks), passing tonnage, soil type, sleeper type, and closeness to switches were considered as the independent variables. According to the result of the analysis, segments with switches have higher degradation rates than others. Segments containing concrete sleepers degrade slower than segments with hardwood sleepers. Subsoil clay has a little negative influence on degradation and on the contrary passing tonnage has a positive influence on the degradation value.

Andrade and Teixeira [16] developed a Bayesian model in Lisbon-Oporto line to assess rail track degradation through its life cycle. The purpose of this study was to investigate the evolution of uncertainty associated with track degradation parameters over the rail track life cycle. In this study standard deviation of longitudinal levelling defects was considered as the main dependent parameter and primary standard deviation measured after tamping operations or renewal, the rate of deterioration, and the accumulated tonnage since tamping operations or renewal were considered as independent variables. The results of the study showed that, at the design stage, the uncertainty associated with degradation rates is relatively large, but it dramatically reduces as more track inspection data is gathered.

Ahac and Lakušić [8] applied multistage regression models on different Zagreb tram track segments to develop a maintenance-planning framework. Multistage regression model is a type of linear regression model which has the capability to cope with different stages of degradation phases or to cope with the degradation process between two restorations or consecutive maintenances. For developing the model, gauge deviation difference value was considered as the dependent variable and cumulative exploitation intensity, which is the result of multiplication of daily gross mass of trams with passengers in Million Gross Tonnes (MGT), and the total number of exploitation days were considered as the independent variables. Based on the findings of this research, gauge degradation can be split into three main phases including moderate increase in tram track gauge taken place in the first phase which is followed by faster growth in gauge degradation in the second phase. In the third phase and for values above 45 MGT the model does not provide the gauge degradation accurately.

2.3. Artificial Intelligence (AI) Models. AI techniques reproduce the cognitive skills of human experts to assist users facing intricate decision-making processes [17, 18]. Various AI models such as Artificial Neural Networks (ANN) and decision support systems (DSS) have been used in track degradation modelling.

Sadeghi and Askarinejad [19] developed an ANN model to evaluate railway track quality condition. They examined the possibility of having correlation between track geometrical defects and track structural problems. In their study, the network input was standard deviations of track geometry data (gauge, profile, alignment, and twist) and the output variable is the prediction of defect density (defect density is defined as the ratio of the amount of defected length of a railway segment to the total length of the segment) of track structural components. The best performance of the model was achieved when the ANN model with 25 neurons in the hidden layer was developed and standard deviations of profile, alignment, and twist were considered as the input variables.

Guler [20] elaborated a DSS to perform railway track maintenance and renewal management in Turkish State Railway. The proposed decision support system was designed by conducting comprehensive literature reviews and interviewing with domain experts. The parameters used in their model include ballast, tamping history, type of sleeper, gauge value, track class, number of trains, age of rails, speeds, and cost analysis. Different M&R (maintenance and renewal) operations were addressed in this study such as ballast renewal, sleeper renewal, rail grinding, rail renewal, and rail lubrication. Four different levels of M&R actions were introduced including doing nothing, regular maintenance actions (preventive maintenance), corrective maintenance, and renewal. The proposed DSS has a capability to renew itself by changing or including new rules.

3. Case Study and Data Preparation

Melbourne tram network consists of 250 km of double tracks (including 25 routes and more than 1700 stops) considered as one of the largest tram networks in the world. By employing 450 in-service tram cars, more than 203 million journeys have been provided in 2016 which demonstrates the 12 percent patronage growth compared to 2015. Along with the increase in Melbourne tram patronage, it has been understood that the expenses related to rail infrastructure such as tracks, switches, and crossings have grown gradually and constantly.

It is clear that there is a direct relationship between the number of passengers travelling by trams and the infrastructure expenses as the increase in trips and tram frequencies can result in more pressure and stress on the infrastructure components. In this study, the data set is provided by Yarra Trams which is the operator of Melbourne tram network. The current data set is composed of different section types including curves, straight sections, H-crossing, and crossovers. There is a wide range of parameters covered in the data set but the major parameters are deviation of track geometry parameters (e.g., gauge, twist, and longitudinal levelling) at different years, curve radii, annual tonnage in MGT, track surface (asphalt and concrete surfaces), rail profile (the cross-sectional shape of a rail which is represented by kilogram per metre), rail type (Grooved and T-shapes), rail support (or rail ties categorised into concrete and steel sleepers), location of routes, and track installation date. The data was collected from 2009 to 2015. It is noted that in this study curve and straight sections as the two major groups of the track sections have been studied. Tracks are divided into 20 m length segments which have homogeneous characteristics.

As a large number of records related to tram track should be analysed in this research, data preparation steps must be applied before developing models as follows:

(i) Data segmentation

(ii) Segment analysis

(iii) Data matching and aggregation

(iv) Elimination of outliers.

At the first step, data collected from Yarra Trams have been examined and by defining the track segment, the characteristics of rail tracks included in the data set are structured. In this step, a unique identification has been assigned to each segment. At the second step, by means of segment identification, the condition of track segments with regard to the mentioned parameters is reanalysed and determined. At the third steps, data sets related to each year are prepared and by applying data matching techniques, the

Table 1: List of dummy variables.

Variables	Converted dummy variable
Rail support	Concrete = 1 and steel sleepers = 0
Rail type	Grooved = 1 and T-shapes = 0
Track surface	Asphalt = 1 and concrete = 0
Rail profile	42 kg = 1 and others = 0
	57 kg = 1 and others = 0
	60 kg = 1 and others = 0
	96 lb = 1 and others = 0

condition of track segments in consecutive years is extracted and then the data sets are aggregated. In the last steps, track segments which lack the information for different years or outlier segments with invalid parameters are identified and eliminated from the data set.

4. Model Building

Tram track gauge value is considered as one of the most important track geometry parameters. Rail track degradation, which appears as gradual increase in gauge deviation from prescribed values during track exploitation, can lead to poor passenger ride quality, safety issues, and higher maintenance costs.

In this research in order to have a broader picture of track degradation modelling, two different techniques including linear regression and ANN techniques have been applied. Regression models are useful and easy to understand statistical processes for both researches and industry applications. ANN models are also applied successfully in heavy rail maintenance systems and demonstrate significant relationship between effective variables. Based on the applied techniques (regression or ANN), the condition of track segments (repaired or unrepaired), and the type of tracks (curve or straight), totally eight different models have been developed and analysed as follows.

4.1. Development of Regression Model. For developing regression models (including models for repaired segments and unrepaired segments), SPSS statistics software is used. Based on reviewing the relevant research, input variables including track gauge deviation in previous year (G_{t-1}), curve radii, MGT, rail support (R_S), track surface (T_S), rail profile (R_P), and rail type (R_T) are selected. The output variable is track gauge in current year (G_t). MGT, curve radii, and G_{t-1} parameters are continuous parameters but the other parameters including rail support, rail profile, track surface, and rail type are categorical variables. For developing a regression model involving categorical variables, dummy variables which take 0 and 1 must be defined to represent categorical variables. The list of dummy variables which have been used to develop a primary regression model is represented in Table 1.

Before developing the models, determining which variables are significant in prediction of the output variable is important. For this purpose, Pearson Correlation analysis has been done for continuous parameters and one-way ANOVA analysis has been applied for categorical variables. According to the result of these analyses, G_{t-1}, T_S, and R_T are significant (p value is less than 0.05) in prediction of the output variable and the other variables are removed from the computations. It must be noted that although the effect of MGT in prediction of the gauge deviation parameter is negligible, its effect lies in G_{t-1} which has great impact on the output variable.

According to the literature, different methods exist to evaluate the performance of the developed models. To obtain an indication of goodness of fit between the observed and predicted values, the coefficient of determination (R^2) has been used. Beside R^2 which provides useful information on the goodness of fit of a model, the mean-squared error (MSE) has been used to evaluate the performance of the models in this research (see (3)). This error is a suitable indicator for the quality of the adjustment of the model and is defined by

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y^{i}_{\mathrm{actual}} - y^{i}_{\mathrm{predicted}}\right)^2, \quad (3)$$

where MSE is the mean-squared error, N represents the number of samples, $y_{\mathrm{predicted}}$ is the value predicted by the model, and y_{actual} is the actual value. The results of the proposed regression models are discussed in Section 5.

4.2. Development of ANN Model. ANN as an AI technique consists of a number of independent interconnected neurons which can communicate with each other via weighted connections. In ANN models, a neuron can produce an outcome using values directly derived from other neurons. In this study, MATLAB as a numerical analysis software was used. Similar to the literatures [19, 21–24], the widely used multilayer feed-forward network is applied. In this model type, the neurons are arranged in a layered architecture and the signals are conveyed layer by layer in a forward direction style through the network. The mathematical mechanism of a neuron in ANN model can be formulated as follows:

$$O_i = A \cdot \left(\sum_{j=1}^{n}\omega_j \cdot I_j + B_i\right), \quad (4)$$

where A is the transfer (activation) function, ω_j is the synaptic weight of the jth in-edge, I_j is the in-edge, I_j is the input labelled with the jth in-edge, and B_i is the bias associated with the ith neuron. The error back propagation algorithm as supervised learning is used for the purpose of training data set. This type of algorithm is common procedure of training. In this algorithm the error signals deriving from the difference between the actual and expected outputs are back-propagated from the output layer to the previous layers to update the weights of connections and biases were adjusted repeatedly based on the computed errors of the network [22]. In this study, the 70 percent of data set was assigned for training the networks and the remaining data was dedicated to test the performance of the networks. The testing data were independent of training data. A four-layered network (Figure 3) has been considered in this study which contains an input layer, two hidden layers, and an output layer. A tan-sigmoid function (TANSIG) was used for the hidden layers

Table 2: Results of regression models for repaired segments.

Segments type	Variables	Coefficients	Standard error	t-statistics	Significance	Adjusted R^2	MSE
Straight segments	Constant	1.72	0.09	18.43	0.00	0.72	1.72
	G_{t-1}	1.06	0.02	42.43	0.00		
	T_S	−0.38	0.15	−2.55	0.01		
Curve segments	Constant	1.22	0.31	3.87	0.00	0.76	1.60
	G_{t-1}	0.99	0.08	12.39	0.00		
	T_S	1.38	0.45	3.04	0.00		

Table 3: Results of regression models for unrepaired segments.

Segments type	Variables	Coefficients	Standard error	t-statistics	Significance	Adjusted R^2	MSE
Straight	Constant	0.64	0.01	84.68	0.00	0.91	0.70
	G_{t-1}	1.06	0.00	467.71	0.00		
	T_S	0.04	0.01	2.80	0.00		
Curve	Constant	1.74	0.36	4.86	0.00	0.86	0.94
	G_{t-1}	1.06	0.02	62.96	0.00		
	R_T	−1.02	0.36	−2.83	0.00		

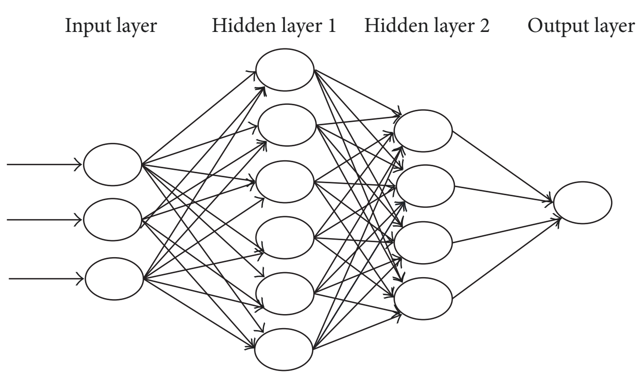

Figure 3: A typical architecture of a four-layered ANN model.

and a linear transfer function (PURELIN) was used for the output layer.

Based on the findings from the regression model, four different ANN models (with the combination of explanatory variables mentioned before) have been developed for repaired segments and unrepaired segments. For each model different numbers of neurons in hidden layers were considered (7, 10, 15, 20, and 25). The results of the proposed ANN models are discussed in the following section.

5. Results and Discussions

In this section, results and analyses of the model development with respect to the model type, track condition, and track type are provided and discussed. Also the comparison of the models is summarised at the end of the section as follows.

5.1. Regression Analyses. In this section, four linear multiple regression models which have provided acceptable results in terms of R^2 and MSE in prediction of track gauge (G_t) for repaired segments and unrepaired segments are selected and the results of the regression analysis are represented in Tables 2 and 3. According to the results of the degradation model for the repaired straight segments (Table 2), G_{t-1} and T_S are significant at a 95 percent confidence level (p value is less than 0.05) to estimate the current gauge. But the impact of G_{t-1} on gauge deviation is higher than T_S. Previous gauge deviation with positive coefficient has a clear correlation with current gauge deviation. The coefficient of track surface is negative and with regard to its definition (track surface: asphalt = 1 and concrete = 0), it can be expressed that the rate of degradation in the repaired straight segments surfaced with asphalt will be lower compared to those surfaced with concrete. Adjusted R^2 is larger than 0.72 and the value of MSE is 1.72 which means that results of the model are in an acceptable range.

According to the results of the model for the repaired curve segments (Table 2), like the previous regression model, G_{t-1} and T_S are significant at a 95 percent confidence level (p value is less than 0.05) to estimate the current gauge. Previous gauge deviation with positive coefficient has a clear correlation with current gauge deviation. Contrary to the previous model but with higher coefficient, track segments surfaced with asphalt have higher degradation rate than those covered by concrete. Adjusted R^2 is 0.76 and the value of MSE is 1.60 which means that results of the model are satisfying.

According to the results of the model for the unrepaired straight segments (Table 3), similar to the previous regression model, G_{t-1} and T_S are significant at a 95 percent confidence level (p value is less than 0.05) to estimate the current gauge. Previous gauge deviation with positive coefficient is an effective contributor to the degradation rate. Also, track segments surfaced with asphalt have higher degradation rate to those covered by concrete. Adjusted R^2 is 0.91 and the value of MSE is 0.70 which means that results of the model are satisfactory.

Based on the results of the model for the unrepaired curve segments (Table 3), G_{t-1} and R_T are significant at a 95 percent confidence level (p value is less than 0.05) to estimate

Table 4: Results of ANN models for repaired segments.

Segments type	Number of neurons in the first hidden layer	Neurons in the second hidden layer	Adjusted R^2	MSE
Straight	10	7	0.77	3.09
	15	10	0.71	3.62
	20	15	0.36	5.50
	25	*20*	*0.77*	*2.37*
Curve	10	7	0.43	10.14
	15	10	0.42	7.45
	20	*15*	*0.78*	*2.20*
	25	20	0.40	7.81

Table 5: Results of ANN models for unrepaired segments.

Segments type	Number of neurons in the first hidden layer	Neurons in the second hidden layer	Adjusted R^2	MSE
Straight	10	7	0.91	0.50
	15	10	0.90	0.60
	20	15	0.91	0.48
	25	*20*	*0.91*	*0.48*
Curve	10	7	0.81	1.64
	15	10	0.77	1.32
	20	15	0.44	3.84
	25	*20*	*0.87*	*0.86*

the current gauge. Previous gauge deviation with positive coefficient is again determined as an effective contributor to the degradation rate. Also, R_T is identified to have impact on track degradation in which Grooved rails have greater resistance to degradation than T-shapes rails. Adjusted R^2 is 0.86 and the value of MSE is 0.94 which means the results of the model are satisfactory.

These results are consistent with previous findings on rail track degradation models [25, 26] which demonstrate that geometry condition of a track within its life time is strongly dependent on its initial level. Also these studies [2, 27] support the results of this research about the influence of rail type and track surface on rail track degradation.

5.2. ANN Analyses. In Tables 4 and 5, the results of ANN models for both repaired and unrepaired segments are shown. These models are based on the explanatory variables mentioned in previous regression models. In this concept, the values of performance indicators of the models, R^2 and MSE, have been changed based on the number of neurons in the proposed models. According to the results, for the repaired straight segments (Table 4) the best results are achieved when the number of neurons in the first hidden layer is 25 and the number of neurons in the second hidden layer is 20 as adjusted R^2 equals 0.77 and MSE value is 2.37.

For repaired curve segments, this condition is true when the number of neurons in the first hidden layer is 20 and the number of neurons in the second hidden layer is 15 as adjusted R^2 equals 0.78 and MSE value is 2.20.

Furthermore, for the unrepaired straight segments (Table 5) if the number of neurons in the first hidden layer is 25 and the number of neurons in the second hidden layer is 20 the result of the model is preferable to the other networks as adjusted R^2 equals 0.91 and MSE value is 0.48.

For unrepaired curve segments, this condition is true when the number of neurons in the first hidden layer is 25 and the number of neurons in the second hidden layer is 20 as adjusted R^2 equals 0.87 and MSE value is 0.86.

5.3. Comparison of the Models. Table 6 shows the comparison of the results using the regression and ANN methods. According to the results of this table, the performance of regression models in prediction of gauge deviation in repaired segments compared to the ANN model is somewhat better in terms of validation errors, while the coefficient of determinations of the ANN model is slightly higher. On the other hand, in unrepaired segments the condition of the proposed ANN model compared to the regression models is more desirable in terms of both validation errors and coefficient of determinations.

6. Conclusion and Future Studies

The gauge value is one of the important geometric parameters which can be used as an indicator of rail degradation and ride comfort in tram system. Prediction of the future condition of gauge can assist tram operators in establishing tram maintenance management systems to reduce maintenance cost and improve service quality. Rail track degradation prediction

Table 6: Comparison of results.

Model	Type	Adjusted R^2	MSE
Repaired straight segments	Regression	0.72	1.72
	ANN	0.77	2.37
Repaired curve segments	Regression	0.76	1.60
	ANN	0.78	2.20
Unrepaired straight segments	Regression	0.91	0.70
	ANN	0.91	0.48
Unrepaired curve segments	Regression	0.86	0.94
	ANN	0.87	0.86

models will assist rail infrastructure organisations in applying appropriate maintenance strategies. In this research, the data sets of Melbourne tram have been examined. To predict the tram track degradation, four regression models in terms of being repaired or unrepaired and straight or curved have been developed. Then four ANN models were created. According to the results of this research, the performances of both regression and ANN models in predication of rail degradation are approximately similar and acceptable. The determination coefficients of the models are above 0.7.

For future research directions alongside the ANN techniques and regression models, using other statistical methods such as stochastic models and machine learning models for predicting tram track degradation and comparing them with the current models can improve the overall judgment on the deterioration of rail track segments. It must be noted that, for increasing the accuracy and efficiency of predication models, more effective cooperation between tram network operators, maintenance divisions, and research institutions is needed.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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