Nonlinear Estimation Model for Rail Track Deterioration

M. Karimpour, L. Hitihamillage, N. Elkhoury, S. Moridpour, R. Hesami

Abstract—Rail transport authorities around the world have been facing a significant challenge when predicting rail infrastructure maintenance work for a long period of time. Generally, maintenance monitoring and prediction is conducted manually. With the restrictions in economy, the rail transport authorities are in pursuit of improved modern methods, which can provide precise prediction of rail maintenance time and location. The expectation from such a method is to develop models to minimize the human error that is strongly related to manual prediction. Such models will help them in understanding how the track degradation occurs overtime under the change in different conditions (e.g. rail load, rail type, rail profile). They need a well-structured technique to identify the precise time that rail tracks fail in order to minimize the maintenance cost/time and secure the vehicles. The rail track characteristics that have been collected over the years will be used in developing rail track degradation prediction models. Since these data have been collected in large volumes and the data collection is done both electronically and manually, it is possible to have some errors. Sometimes these errors make it impossible to use them in prediction model development. This is one of the major drawbacks in rail track degradation prediction. An accurate model can play a key role in the estimation of the long-term behavior of rail tracks. Accurate models increase the track safety and decrease the cost of maintenance in long term. In this research, a short review of rail track degradation prediction models has been discussed before estimating rail track degradation for the curve sections of Melbourne tram track system using Adaptive Network-based Fuzzy Inference System (ANFIS) model.

Keywords—ANFIS, MGT, Prediction modeling, rail track degradation.

I. INTRODUCTION

MODERN transport organizations have shifted their focus from construction and expansion of the transport infrastructure and moved towards how to intelligently maintaining them. This was taken place due to many reasons such as budget restrictions and running out of land space. Transport organizations currently focus on exploring the solutions for developing a maintenance management system that will help them to accurately predict the time and location that maintenance should be carried out. This will help the authorities to optimize cost management and maintenance.

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Many researches around the globe have presented a number of different types of degradation prediction models, and most of these models are developed for heavy rail. Since there are differences in the structure and performance of heavy and light rail systems, it is not possible to use such degradation prediction models to predict the degradation of light rail tracks. Consequently, it is needed to develop a model which is capable of predicting the degradation of light rail tracks. Therefore, this particular research study will focus on developing a degradation prediction model for light rail network with the focus on tram network of Melbourne, Australia. The map of the current Melbourne tram network is shown in Fig. 1. Melbourne tram network [1] is the largest metropolitan tram network in the world and it covers 250 km of rail tracks that runs 31,500 scheduled tram services per week .

The data for the Melbourne tram network have been collected through inspection on-sight and stocked in a non-digitized way for a long time. The rail maintenance used to be planned traditionally and according to the collected data accumulated over many years and based on the experience of experts in the field. This procedure has changed since the introduction of new rail track inspection vehicles. These vehicles run through rail tracks and detect a large amount of data from infrastructure condition. Based on this data, degradation model of rail tracks will be developed in order to predict the degradation of rail tracks and estimate the maintenance procedures needed in the future. In this paper, the models that were proposed in the literature to predict rail track degradation are presented, and then, an Adaptive Network-based Fuzzy Inference System (ANFIS) model is proposed to predict the tram track degradation.

II. LITERATURE REVIEW

Previous studies on rail track degradation have represented number of models that are capable of predicting degradation. Almost all these models used a common set of parameters such as age of the rail, axle load in Million Gross Tone (MGT), speed and track curvature when developing and predicting rail track degradation. One of the popular models that have been used to predict rail track degradation is the statistical models. A statistical model uses large sets of data, and the aim of these sorts of models is to identify a general trend or a pattern in rail track degradation. One of the early studies on these types of models was utilized in the 1980s [2]. The expectation behind the experiment was to acquire an understanding of the basics of degradation mechanisms of railroad tracks. The Model that they proposed was capable of describing the rail track degradation immediately after

tamping. The degradation is estimated according to the factors such as the traffic volume, dynamic axel loading and the speed. Hierarchical Bayesian Models (HBMs) are flexible statistical models that provide a prediction of the railway degradation. Their study considered longitudinal level defects and horizontal alignment defects as the two main quality parameters in relation to the degradation of rail track geometry [3]. The structure of this model adopts the quality parameters as random variables that can be uncertainly calculated by a prior distribution [4]-[6]. However, these models rely on other statistical models such as Markov models, especially in the case of high numerical data [7], [8].
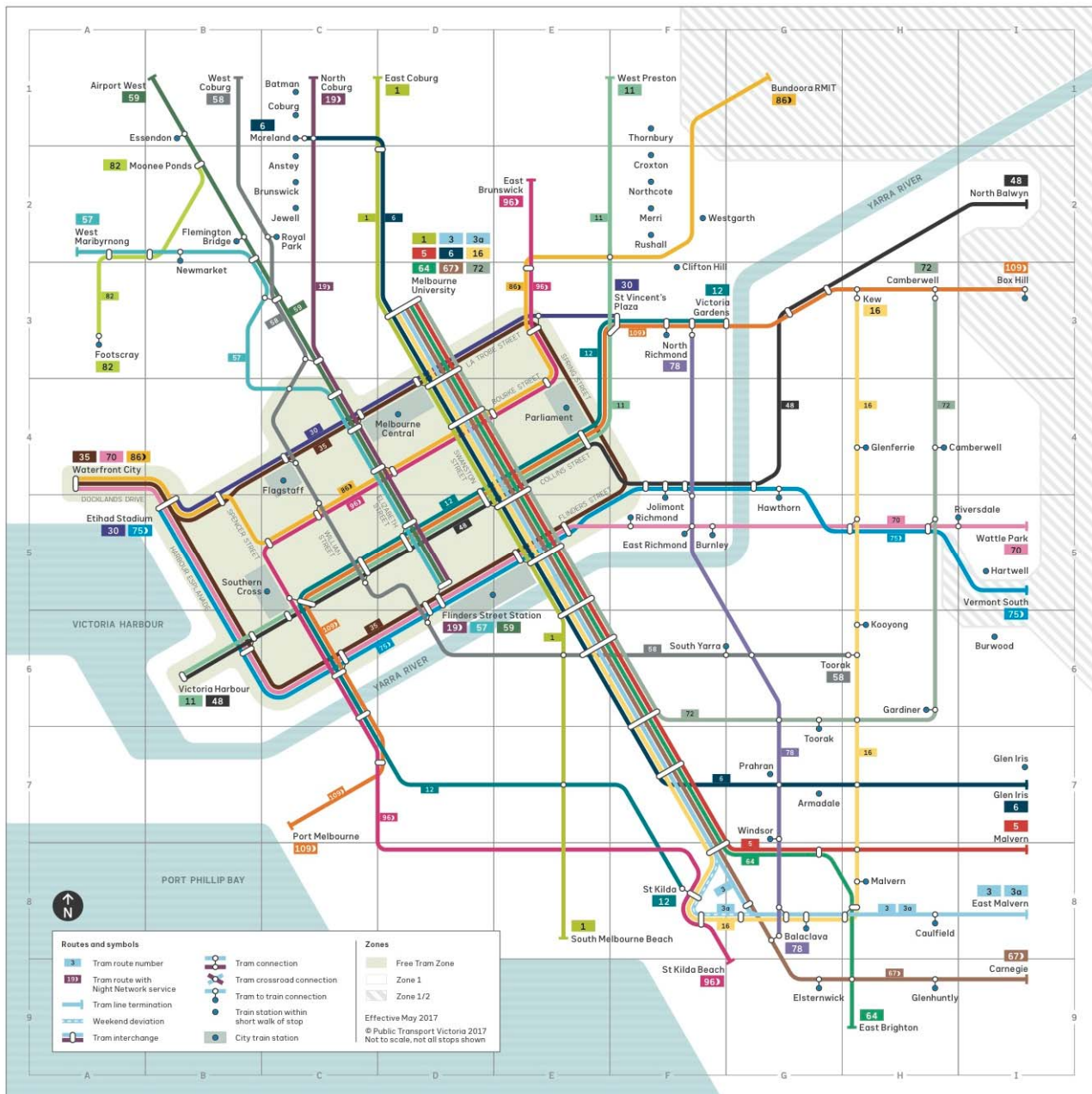

Fig. 1 Melbourne tram network

Stochastic models are also a part of statistical models that aim to understand the influence of time on degradation events and predict their performance. A stochastic model was developed in order to predict the degradation of the Portuguese railway Northern Line [9].

Artificial neural networks have been used to predict the degradation of railways [10], [11]. The artificial intelligence models used for track degradation prediction in Iran and used parameters such as degradation including the combined track record index (CTR), traffic volume (i.e. light, heavy), speed,

geographic location (i.e. plain, hilly, and mountainous), curves radius and gradient to predict the rail degradation [12]. The study compared the model predictions to the observed data of one of the sets. Consequently, this comparison showed that the following year CTR indices were at the same level as the CTR indices of the previous year or slightly lower than that. Furthermore, another study presented an artificial neural network model to predict the degradation of tram tracks using maintenance data in Melbourne. The data were categorized into three categories such as inspection data, load data, and repair data. Inspection data were collected for Melbourne tram network from 2009 to 2013, covering different types of segments of four routes such as straights, curves, H-crossings and crossovers [13]. Out of these segments, curves were the focus since they have a higher failure rate than the other segments [14], [15]. Load data consisted of the MGT without passengers and the frequency which was represented by the number of trips per day.

In this paper, ANFIS model is used to predict the tram track degradation by considering a dataset of 3,860 rail track points which is divided into 70% as the training data and 30% as the testing data.

III. Methodology

In this paper, ANFIS is used to estimate the gauge value for $t+1$ if the data for $t-n$ are available. The dataset consists of 3,860 different samples of gauge values between 2010 and 2015. Many parts of the railway had minor or major maintenance through these years. Thus, linear models are not able to have an accepted rate of error in these years; though, in this paper a fuzzy model is proposed and the results show the superiority of nonlinear models in the maintenance modeling. In this paper, an ANFIS model is proposed with three most important inputs consisting of two previous values for gauge and the MGT value. The dataset is divided into two sections including the training and the test set. 70% of the data are used for training the system and 30% for testing.

An adaptive network can be considered as Fig. 2 and is a feed-forward multilayer network in which, each node plays a particular action on the input with a set of parameters relating to the node [16]. Circle nodes have no parameter, while the square nodes, which are adaptive, have different parameters that need to be estimated. If the network has L layers and the jth layer has $\#(j)$ nodes, the node in the ith position of jth layer can be written as (1).
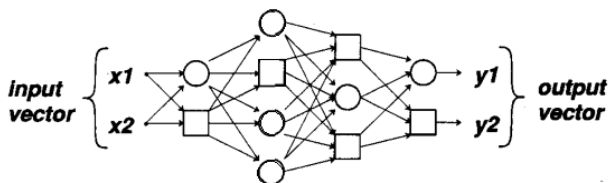

Fig. 2 Simple adaptive network

$$O_i^j = O_i^j(O_1^{j-1}, \dots, O_{\#(j-1)}^{j-1}, m, n, \dots) \tag{1}$$

where m, n, etc. are the parameters related to this node. The O_i^j represents the node output and the function. Considering that a set of training data has q entries, the sum squared error could be measured as (2).

$$E_q = \sum_{m=1}^{\#L} (T_{m,q} - O_{m,q}^L)^2 \tag{2}$$

where $T_{m,q}$ is the mth component of qth target. The rate of error from the output node at L, i can be derived from (3).

$$\frac{\partial E_q}{\partial O_{i,q}^j} = \sum_{m=1}^{\#(j+1)} \frac{\partial E_q}{\partial O_{m,q}^{j+1}} \frac{\partial O_{m,q}^{j+1}}{\partial O_{i,q}^j} \tag{3}$$

If θ is a parameter of the network, $\frac{\partial E_q}{\partial \theta}$ can be written as (4).

$$\frac{\partial E_q}{\partial \theta} = \sum_{O^* \in S} \frac{\partial E_q}{\partial O^*} \frac{\partial O^*}{\partial \theta} \tag{4}$$

S is the nodes that their output depends on θ. $\frac{\partial E}{\partial \theta}$ can be written as (5).

$$\frac{\partial E}{\partial \theta} = \sum_{q=1}^{q} \frac{\partial E_q}{\partial \theta} \tag{5}$$

The update formula for θ can be written as (6).

$$\Delta\theta = -\gamma \frac{\partial E}{\partial \theta} \tag{6}$$

in which γ is the learning rate which can be defined as:

$$\gamma = \frac{j}{\sqrt{\sum_\theta (\frac{\partial E}{\partial \theta})^2}} \tag{7}$$

in which j is the step size. The change in j results in the convergence speed.

As mentioned, 2,700 samples of the gauge data were used to train the system. The input data are gauge values for $year_{t-2}$, $year_{t-1}$ and MGT, and the output of the system is the gauge values for $year_t$ The trained system antecedent membership functions are presented in Fig. 3.

The trained system is then tested on the test data and the observed values and the estimated values are compared which are plotted in Fig. 4.

To show the accuracy of the model, the observed values versus the estimated values are plotted in Fig. 5.

The r-square value for the model is 0.60. By considering both the above figures and the value of r-square, it is clear that the system is able to predict the values with a good accuracy respect to the messy nature of the data.
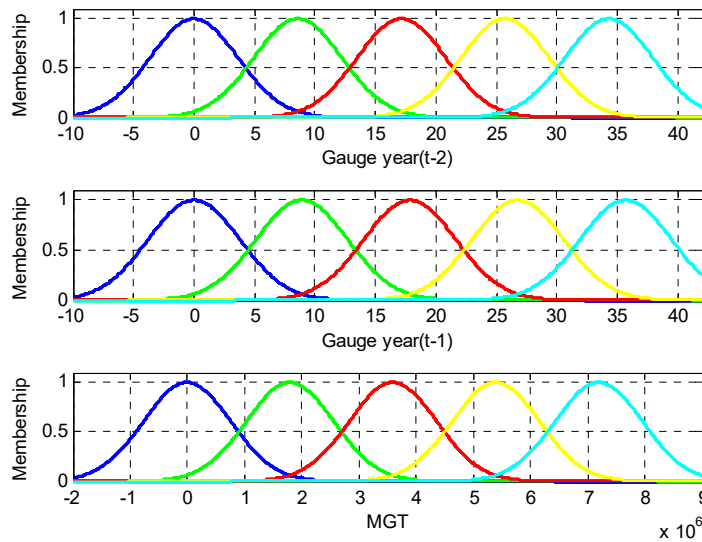
Fig. 3 Membership function of the antecedents, i.e. the gauge values for $year_{t-2}$, $year_{t-1}$ and MGT
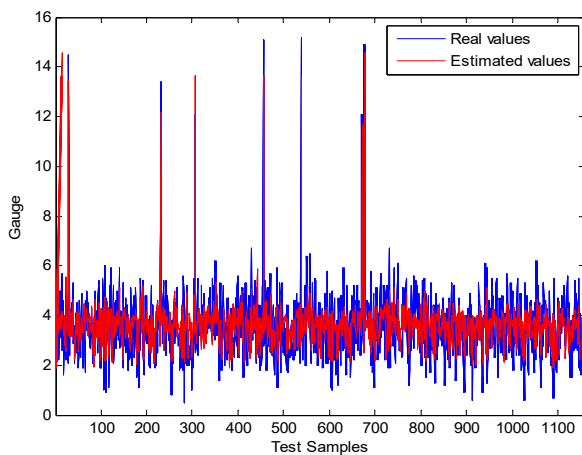

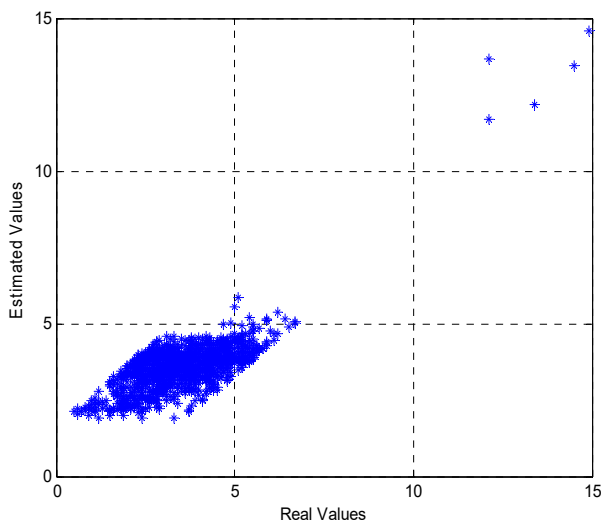Fig. 4 The observed and estimated values on 30% of the data

TABLE I
STATISTICAL PARAMETERS OF MODEL

Criteria	Model
R square	0.6001
MSE	0.7350
Total Samples	3860
Training Samples	2700
Testing Samples	1160
Number of inputs	3

As Table I indicates, when in developing the model 3,860 samples have been used to train and test this particular ANFIS model. Nearly about 70% of the samples have been randomly selected to train the model, while 30% of the data have been used to test the model.

IV. CONCLUSION

It is very important for maintenance authorities to have superior knowledge on how the light rail tracks degrade overtime according to different influencing factors to decrease the amount of money that needs to be invested in maintenance. The most important indicator of the rail degradation is the gauge value. To model the gauge values, two most important factors are the gauge values for previous years and the MGT. In this paper, an ANFIS model is put forward to model rail track degrading using the data between 2010 and 2015. The model is trained by 70% of the data and tested on the rest. The results show that the model is able to predict the gauge values for the next coming year by the r-square value of 0.60 and the MSE of 0.73 which seems to be accurate enough due to the noisy nature of the data.

Fig. 5 The real values versus the estimated values

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