Tram Track Degradation Prediction

A thesis submitted in fulfilment of the requirements for the degree of Master of Engineering

Lalith Hitihamillage

Bachelor of Engineering (Civil Engineering) RMIT University

School of Engineering
College of Science, Engineering and Health
RMIT University

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Declaration

I certify that, except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; and any editorial work, paid or unpaid, carried out by a third party is acknowledged.

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June 2018
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Abstract

Transport organisations have historically focused on major construction and expansion of infrastructure. After completing the expansion of transport networks, the emphasis has increasingly shifted from developing new infrastructure to intelligently maintaining the existing ones. In recent years, economic constraints have influenced budget allocation to transport sectors. This has resulted in emphasizing the development of maintenance management systems in transport sectors, particularly in transport infrastructure. Maintenance management systems assist organisations in deciding when and how to maintain transport infrastructure facilities to enhance cost efficiency.

The Melbourne tram network is the largest urban tram network in the world, consisting of around 250 kilometres of double track and running 31,400 scheduled tram services every week (Yarra Trams 2018). Yarra Trams operates and maintains Melbourne's iconic tram network on behalf of Public Transport Victoria. Yarra Trams organises the timetables, service deliveries and changes, tram arrival information via tram TRACKER, tram maintenance, as well as the construction and maintenance of the tram infrastructure. Many parameters are involved in ensuring that the Melbourne tram system operates to its safe and best practice standards. Track infrastructure is one of the fundamental elements of the tram system. The condition of the tram infrastructure can influence the system’s operation, either directly or indirectly. To keep the track infrastructure in a reasonable condition over years and to obtain the most benefit out of its life cycle, a maintenance and renewal regime is required. The provision of a maintenance plan to recover the serviceability of tram tracks from defects and damages and preventing further wear is essential for such a large network. Currently, tram track maintenance activities are achieved by manual inspections across the network. Yarra Trams usually has a fixed number of maintenance teams who are responsible for visual inspection of the status of the tram tracks and identification
of whether tracks need maintenance. Furthermore, they estimate an approximate
time period during which maintenance should be carried out. Since the inspections
are done visually, human error is inevitable. Mistakes in the inspection and
detection of track faults and inaccurate prediction of maintenance time frames are
challenges of the current maintenance system. In addition, prioritising
maintenance projects is often a significant challenge. Poorly planned maintenance
schedules may result in high maintenance and operational costs due to very early
or late maintenance of tram tracks. Occasional unnecessary maintenance and
replacement of tram tracks or maintenance at very late stages of damage is very
costly.

The case study for this research is the Melbourne tram network and the necessary
data for the research were collected from the entire network. The aim of this
research is to develop an artificial intelligence model (Adaptive Network-based
Inference System (ANFIS)) to predict conditions of track in the future years based
on the most influential parameters identified via statistical analysis and a literature
review. According to the literature and the statistical analysis, gauge and total
annual loading have been utilized as the two key parameters in the model
development. The total data set was randomly divided into two separate sets
which were used as the training and testing sets. Two ANFIS models are
developed for straight and curve sections. The model developed through this
research is capable of predicting the future gauge values with an r-square value for
the curve model of 0.60 while that of the straight model is around 0.78. A simple
Artificial Neural Network (ANN) model is then proposed which managed to
produce an r-square value of 0.4587 for curves and 0.5813 straight sections.
List of Publications

Journal papers


Conference papers


# Terms and Definitions

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
</tr>
<tr>
<td>ANFIS</td>
<td>Adaptive Network-based Fuzzy Inference System</td>
</tr>
<tr>
<td>AS</td>
<td>Analytical Segment</td>
</tr>
<tr>
<td>CTR</td>
<td>Combined Track Record Index</td>
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<tr>
<td>CWR</td>
<td>Continuously Welded Rail</td>
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<tr>
<td>CEN</td>
<td>European Committee for Standardization</td>
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<tr>
<td>DC</td>
<td>Degradation Coefficient</td>
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<tr>
<td>FIS</td>
<td>Fuzzy Inference System</td>
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<tr>
<td>ITDM</td>
<td>Integrated Track Degradation Model</td>
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<tr>
<td>HS</td>
<td>High Leg Side wear</td>
</tr>
<tr>
<td>HLT</td>
<td>High Leg Total wear</td>
</tr>
<tr>
<td>HBM</td>
<td>Hierarchical Bayesian Model</td>
</tr>
<tr>
<td>LT</td>
<td>Lower Leg Top wear</td>
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<tr>
<td>LLT</td>
<td>Lower Leg Top wear</td>
</tr>
<tr>
<td>MGT</td>
<td>Million Gross Tons</td>
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<tr>
<td>MSE</td>
<td>Mean Square Error</td>
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<tr>
<td>NN</td>
<td>Neural Network</td>
</tr>
<tr>
<td>ORE</td>
<td>Office for Research and Experiments</td>
</tr>
<tr>
<td>RAMS</td>
<td>Reliability, Availability, Maintainability and Safety</td>
</tr>
<tr>
<td>SD_{LL}</td>
<td>Standard Deviation of Longitudinal Level defects</td>
</tr>
<tr>
<td>SD_{HA}</td>
<td>Standard Deviation of Horizontal Alignment defects</td>
</tr>
<tr>
<td>TQI</td>
<td>Track Quality Indices</td>
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<tr>
<td>TGI</td>
<td>Track Geometry Index</td>
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<tr>
<td>TSI</td>
<td>Track Structure Index</td>
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<tr>
<td>T</td>
<td>Time</td>
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<tr>
<td>UIC</td>
<td>International Union of Railways</td>
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Chapter 1 Introduction

1.1 Introduction

New and major construction work and infrastructure expansion have historically been the main focus of major transportation organizations. Recently however, for many reasons, including economic constraints as well as restrictions on land acquisition, most of these organizations have been forced to change their emphasis from constructing new infrastructure to intelligently maintaining their existing systems. This has led to increased dependency on maintenance management systems. These systems aim to assist organizations in deciding when and how to maintain transport infrastructure facilities to enhance cost-effectiveness and eliminate safety issues.

Maintenance management systems are utilized in most of the largest organizations in the transport industry in Australia, such as Yarra Trams. Yarra Trams is the governing body which operates Melbourne's iconic tram network. The Melbourne tram network is the largest urban tram network in the world, consisting of 250 kilometres of double track covering 24 tram routes and it runs 31,400 scheduled tram services every week (Victoria, 2017, Yarra Trams, 2018). Yarra Trams organizes the news, maps, timetables, service changes, and real-time tram arrival information for the tram system as well as the construction and maintenance of the tram infrastructure (Yarra Trams, 2018, Victoria).

Many parameters are involved in ensuring that the Melbourne tram system operates to safe and best practice standards. The track infrastructure is one of the fundamental elements of the tram system. The condition of the tram infrastructure influences the system’s operation, either directly or indirectly. To keep the track infrastructure in a reasonable condition over years and to obtain the most benefit from its life cycle, a maintenance and renewal regime is required. The provision of a maintenance plan to maintain the serviceability of tram tracks despite defects and damage and prevent further wear is essential for such a large network. Currently, a limited number of maintenance teams from Yarra Trams conduct
visual inspections across the network in order to identify track performance and defects. Furthermore, they estimate an approximate time period during which maintenance should be carried out. Since the inspections are done visually, human error is inevitable. These errors can lead to inaccurate prediction of maintenance time frames. In addition, prioritizing maintenance projects is often a significant challenge. Poorly planned maintenance schedules may result in high maintenance and operational costs for reasons including very early or late maintenance of tram tracks, occasional unnecessary maintenance and replacement of tram tracks, or maintenance at very late stages of damage.

In an effort to counter this problem, a model is required to predict the degradation of tram tracks which can be used to optimize the time and cost of maintenance and replacement activities. This will be done by analyzing and trending the tram track geometry measurements over a period of time to find the correlation between these variables and track degradation, allocate a reasonable weight to each variable and develop a model to predict track deterioration/degradation based on tram track variables. By preventing unnecessary maintenance actions, disturbance/interruption of traffic will be reduced and delays experienced by private car drivers and tram passengers will be reduced.

1.2 Background

In general, track maintenance planning concerns the type of maintenance and the time when it should be done. Current practice in the Australian urban rail industry mostly relies on the experience and knowledge of experts to solve the track maintenance planning problem. Although the manual planning process usually takes a group of experts more than 7 days, many constraints may not be satisfied or overlooked. It is also difficult to document the experts’ experience and knowledge and pass them onto the next generation of experts. A systematic modelling approach that is general, efficient, and practically implementable will assist the urban rail industry in gaining significant cost savings and operational benefits in the long run. Since track maintenance costs represent a large
proportion of the total operating costs, there is a need to develop models which can predict the future rail degradation.

Many researchers have studied road infrastructure maintenance planning (Golabi and Pereira, 2003, Ng et al., 2009, Li et al., 2010). Studies have also been conducted on rail track maintenance planning of train systems for a single train route (Higgins et al., 1999) and for large-scale railroad networks (Ouyang et al., 2009, Sadeghi, 2010, Sadeghi and Askarinejad, 2010, Peng and Ouyang, 2012). Maintenance planning for tram tracks (light rails) differs from that for roads and even train tracks due to the different nature of degradation, maintenance activities and traffic operation. Trams are mainly mixed with normal traffic and tram wagons have considerably different weights and sizes compared to train wagons.

A review of the literature has revealed that very limited research has been conducted on the maintenance of tram tracks. This reinforces the need to develop a degradation prediction model for tram tracks.

1.3 Research Questions

The following questions are studied in the research:

- What are the factors influencing the tram track degradation process?
- How can track degradation be modelled and future tram track conditions predicted?

1.4 Research Objectives

The broad aim of this research project is to optimize planned and emergency maintenance tasks and timings for tram tracks. Consistent with that broad aim, the following specific objectives are identified:

- Understand the factors affecting the degradation of tram tracks,
- Develop a degradation prediction model for tracks as a function of the influencing factors.
- Evaluate the time and type of maintenance required for deteriorated rail
tracks.

1.5 Thesis structure

The thesis is structured to follow each stage of the research in the order in which it was undertaken. The thesis includes six chapters and the summary of what is included in each chapter is provided in Figure 1.1.

Figure 1.1: Thesis Structure
Chapter 2 discusses current and past knowledge about heavy rail and light rail (tram) track degradation. The chapter includes a review of past studies carried out around the globe on the identification of models for the prediction of track degradation and their effectiveness. It presents the positive and the negative outcomes of the selected models.

Chapter 3 introduces the framework and the methodology followed in conducting the research. It explains what model type is used with the chosen data for the rest of the research work and the procedure followed in creating the model of track degradation identification for trams.

Chapter 4 contains the steps followed in analysing the data. It provides an understanding of how the data were obtained and the resources from which the data were obtained.

Chapter 5 provides a comprehensive discussion of the development of track degradation prediction model. This chapter contains details about the modelling process and analysis of the test data. It also provides the model validation results.

Chapter 6 is the final chapter of the thesis and provides the main outcomes and discoveries of the research. It includes suggestions for future work to develop this research in a way that should benefit tram maintenance. This chapter is followed by the references used during the research.
Chapter 2 Review of Rail Track Degradation Models

2.1 Introduction

Until very recently, most transportation companies mainly directed their focus to building and expanding tram and train networks. They heavily depended on the knowledge and the experience of experts. They prioritised the short-term safety of the infrastructure without being too concerned about future needs. However, these transportation companies shifted their interest from expanding and adding new tracks to the networks to maintaining the current ones and maximising the usage of the current assets. This was due to the completion of major parts of the networks and limitations of land and capital. In order to conduct maintenance effectively, it is necessary to have a unified framework for maintenance decision-making to help to reduce operating and maintenance costs, while at the same time helping to maintain high safety standards.

This chapter includes a literature review of current and past studies of different types of modelling, such as mechanistic, statistical, stochastic and mechanical-empirical models. It also discusses how accurate these models are and the advantages and disadvantages of these models. Next, it discusses the gap in knowledge and the necessity of finding a suitable model for the prediction of tram-track maintenance planning.

2.2 Properties of rail road tracks

A number of common types of rail tracks are used around the world. Of these, the most common type is the traditional ballasted track, also known as ‘classical tracks’ or ‘conventional tracks’. This particular type is the oldest and it has been used since the beginning of the railways. The other type is the concrete slab track, which is the modern alternative to the ballast track (Esveld, 2001). On a classic ballasted rail track, the rail is mounted onto a wooden or concrete sleeper. The sleeper sits on top of a bed of ballast, which again lies above the sub-ballast layer.
This acts as a transition layer to the formation. Top ballast is placed between the sleepers and on the shoulders to provide longitudinal and lateral stability, as shown in Figures 2.1 and 2.2 (Veit, 2007, Sadeghi, 2010, Yousefikia et al., 2014a). These figures show a cross-section of the two types of classic track which depicts the difference between train track and tram track. The nature of ballasted track necessitates that the track can and will move under load; routine maintenance (especially tamping) is always required to restore line and level, and clean or replace ballast regularly. In addition, ballasted track is a massive structure that makes it impossible to be used in tunnels or subways and especially on urban roads as tram track.

Figure 2.1: Typical ballasted train track (Esveld, 2001)
The difference between a ballast track and an embedded track is that instead of ballast a rigid concrete slab is used to transfer the load and provide track stability. The major advantages of this type of track over ballast track are that they are low maintenance, have high availability, and have low structure height and low weight. Resilience is introduced into the track system with the aid of elastomeric components. Different types of slab track systems have been used and they are commonly used in building embedded rail slab tracks for trams.

Slab track with grooved rails such as that shown in Figure 2.2 is used due to the surface being shared with road vehicles or pedestrian zones and sidewalks. The track often should be synchronized with the road surface or pavement. Figure 2.3 shows a typical wheel - rail interfaces in tram track with embedded grooved rail compared to ballasted track with T-Rail used in heavy rail.
Figure 2.3: Difference between heavy rail (shown in blue) and light rail wheel (shown in green)

Figure 2.3 shows how a typical heavy rail and a light rail wheel sits on top of the track. It clearly indicates the difference when a tram wheel sits on the groove rail. This helps trams to make tighter corners than heavy rail trains. In light rail they use much smaller radiuses mainly because they have to build in brown-fill areas such as city centers.

2.3 Railroad track degradation

The degradation of rail track geometry is usually quantified in terms of track geometry defects and rail surface faults. Track geometry defects include longitudinal level defects, horizontal alignment defects, cant defects, gauge deviations, gauge wear and track twist as a function of distance along the track, whereas surface faults include corrugation and long and short waves (Quiroga and Schnieder, 2013).

In recent years, these defects have been generally measured using automated measuring systems and saved as digitized data. Many infrastructure decision-makers tend to combine all these defects into a track quality index, which is typically a function of the standard deviations of each defect and/or a vehicle’s permissible speed (El-Sibaie and Zhang, 2004, Li et al., 2010, Sadeghi and Askarinejad, 2010).
In horizontal curves when a vehicle turns, the outer wheels have to travel further than the inner wheels, but rail vehicle wheels are usually mounted on a solid axle so they turn at the same speed. On a road vehicle, this is usually achieved by allowing the wheels to move independently, and fixing the front wheels in an arrangement known as Ackermann steering geometry. Trains and trams can turn corners without wheels slipping because the outer horizontal part of the wheels has a slightly tapered rim. The guide flange (ridge) is on the inside to prevent the vehicle from slipping sideways off the rails. The horizontal (cone-shaped) rim makes contact with the slightly convex top of a steel rail in different horizontal places so that the outer wheel has a larger effective diameter than the inner wheel (Heckl and Abrahams, 2000). With both tram and train wheels, this happens naturally, because the wheels are cone-shaped sloping surfaces and the inside diameter is a few millimetres larger than the outside. As the track starts to curve, the train tries to run straight. The wheel flange presses against the side of the curved rail so that the "contact point" between rail and wheel moves a few millimetres outwards, making the effective diameter of the outer wheel temporarily larger, and the effective diameter of the inner wheel effectively becomes temporarily smaller. This technique works well on large-radius curves that are canted, but not as well on tight curves. (Larsson, 2004) studied the wear mechanism of rails as a function of curve radius and showed that rail degradation in tight curves due to rail wear is an important issue in railway infrastructure. Figure 2.4 it shows a worn curve section due to periodic loading.

Figure 2.4: Rail gauge wear on curve due to periodic loading
Urban trams often use very tight curves, sometimes with a radius of much less than 50 metres, so that canting may be impossible, because the track surface must be flush with the road surface. Therefore, investigating track degradation in tram curves due to rail wear is a major concern for transport agencies.

2.4 Track degradation models

At this point we have a brief understanding of the formation and the differences between train and tram track structures and their degradation. In this section we shift our focus to observe and understand the different types of degradation prediction models that are available from past and present studies. This will help to gain knowledge about how these models work and the accuracies of these particular models.

2.5 Classification of track degradation prediction models

A number of models for predicting track degradation are used around the world and they can be categorized into four major groups: statistical (empirical) models, mechanistic models, mechanical-empirical models and artificial intelligence models.

Mechanistic degradation models are based on the mathematical description of the mechanical degradation phenomena of track components. This particular model type covers the calculation of strain and settlement of track layers in order to reduce track defects and maintenance needs.

Statistical models are based on data collected by monitoring track performance and the variables affecting it, including traffic, track geometry and maintenance. The data are used as inputs to develop a model which predicts track degradation. In this literature review statistical models are further classified into three categories: deterministic, probabilistic and stochastic models, while the
A probabilistic model is further categorized into two sub-categories, namely continuous probability distribution and Markov models.

Mechanical-empirical models are types of hybrid models which use mechanistic and statistical models in order to assess the track conditions of rail and tram tracks.

The fourth model type is artificial intelligence models, and these are a special type of models since they use human-like thinking when in use. They can be categorized into another two types: artificial neural networks (ANNs) and neuro-fuzzy models. Figure 2.5 presents the division of these degradation prediction models based on the literature used in this research.

![Figure 2.5: Degradation Model Categories](image-url)
### 2.5.1 Mechanistic models

Mechanistic models are based on knowledge and understanding of the behaviour of a system’s components. Railway track mechanistic modelling involves establishing the mechanical properties of the track components, either by theory or by testing. Mechanistic models can be developed based on laboratory data collected during experiments. Such models are then utilized to calculate the forces and magnitudes of stress to which particular sections of the track or the full track are subject, along with progressive track settlement and total track settlement. It is also possible to utilize these mechanical models to identify defects in the components of individual elements of the track.

The existing literature includes some studies which have attempted to create mechanistic models based on data obtained from laboratory studies to interpret the railway track degradation process. This section of the thesis discusses some of these models, which are considered as pioneering models in mechanistic degradation prediction modelling and have been used all around the world to develop similar types of models under different conditions.

Sato (1995) used an empirical track settlement model based on studies from the 1950s on track degradation due to ballast settlement when it undergoes repeated loading by trains passing (Satoh, 1959, Satoh et al., 1961, Sato et al., 1995). Equation 2.1 shows the settlement equation (Sato, 1995).

\[ y = \gamma(1 - e^{-\alpha x}) + \beta x \]  

\[ \text{Equation 2.1} \]

where, \( y = \) settlement

\( \gamma = \) constant dependent on the initial packing of ballast material.
α = vertical acceleration required to initiate to slip and this is measured for stone plates under a spring on a vibrating plate.

β = a coefficient proportional to sleeper pressure and ballast acceleration. This is also affected by the type and condition of the ballast and the presence of water.

x = repeated number of loadings or tonnage carried by track

The key variables considered for this particular equation are traffic (or passed tonnage for which the units are million tons/year), time (age), track conditions, and presence of water. The choice of the variables used in Sato’s 1995 study was corroborated by another model produced by Demharter at The Technical University of Munich (Demharter, 1982). Demharter’s research also presented a series of equations that allow the prediction of settlement rate from ballast pressure based on laboratory experiments carried out in very controlled conditions. The difference is that the German model does not consider humidity as a factor. Instead, vehicle characteristics are considered as a critical variable. Experiments representative of vehicles passing a dipped joint were used in this particular case to establish a set of equations to calculate the rate of settlement. The log of axle passes multiplies the ballast pressure as follows in Equation 2.2:

\[ S = a \times p \times \ln \Delta N + b \times p^{1.21} \times \ln N \]  

Equation 2.2

where,

the first part of the equation represents fast settlement immediately after a maintenance action

\( \Delta N = \) pre-loading period comprising the first passing axles and \( \Delta \) should be \(<10000\)

\( N = \) represents the total number of passing axles.
p=Ballast pressure can be calculated by the Zimmermann method (Demharter, 1982).

a= constant between 1.57-2.23

b=constant between 3.04-15.2

A quality index has been used to examine the settlement development in research carried out by Hummitszch at the Technical University of Graz in Austria (Hummitszch, 2005). The quality index represents the accelerations in vehicles caused by track irregularities (Veit, 2006). This index includes horizontal and vertical deviations in the tracks combined with the shortage of super-elevation, elevation and speed. Equation 2.3 provides an exponential development of the track quality index over time, according to which the track becomes rougher, it creates more dynamic forces with trains passing and hence increases the settlement.

\[ Q = Q_0 \times e^{-b \times t} \]  
Equation 2.3

where,

\[ Q = \text{Track quality index} \]

\[ Q_0 = \text{Initial track quality} \]

Shafahi and his research team used a mechanistic model to predict track quality. The study was carried out at the Sharif University of Technology, Teheran in Iran and used data from Iranian railways. The researchers used a reconstructed version of a model proposed by the Office for Research and Experiments (ORE) of the International Union of Railways in 1988. The researchers then proposed a model which was a simple model of track degradation in a more general form of a product of the power function as shown in Equation 2.4 (Shafahi et al.2009)

\[ E = 36.57 \times T^{-0.0418} \times P^{0.2955} \]
where,

\[ E = \text{a track degradation index (in this paper (Shafahi et al., 2008) the Combined Track Record (CTR) index was categorised into five categories (0-50=failed), (50-60=medium),(60-70=good),(70-80=very good and (80-100=excellent).} \]

\[ T = \text{total accumulated tonnage since the track was new (in million tonnes)} \]

\[ P = \text{design axle load (in tonnes)} \]

A total of 523 observations were carried out and all estimated parameters were within the 95% confidence interval. However, the model produced an \( R^2 \) value of 0.1190, indicating that the model is not very accurate. In the study the researchers used this model to make a comparison between three model types and determine which model type produced more accurate predictions. When their \( R^2 \) values were considered the Office for Research and Experiments (ORE) model predictions were very poor.

Zhang, Murray and Ferreira (2000) presented an Integrated Track Degradation Model (ITDM) to predict track behaviour. The research conducted at the Queensland University of Technology proposed a track degradation model capable of considering the degradation effects due to the interactions between track components. It used mechanistic relationships and covered all the major factors which may influence the service life of track components (Zhang et al., 2000). The ITDM version used in the study carried out only an analysis of rail wear since the interactive relationship between grind and rail fatigue was yet to be established. In order to develop the equation for wear, it was assumed that the wear at the rail and wheel contact area is of the deformation wear type. This was based on the methodology of Clayton and Steel (1987). According to the study by Ghonem and Kalousek (1984), the sliding between the rail and wheel is considered proportional to the angle of attack of the wheel-set to the track.
The equations used in ITDM for calculating rail top and gauge face wear are provided below in Equations 2.5, 2.6 and 2.7.

ITDM model equation for the high rail:

$$W_{hr\_top} = 7.61 \times 10^{-6} k_h k_{l\_hr\_top} W_t \sin \Psi$$  \hspace{1cm} \text{Equation 2.5}

ITDM model equation for the top of the low rail:

$$W_{lr\_top} = 9.5 \times 10^{-6} k_h k_{l\_lr\_top} W_t \sin \Psi$$  \hspace{1cm} \text{Equation 2.6}

ITDM model equation for the rail gauge face:

$$W_{hr\_gauge} = 12.1 \times 10^{-6} k_h k_{h\_gauge} C_1 P l \sin \Psi \quad R \leq 500$$  \hspace{1cm} \text{Equation 2.7}

$$W_{hr\_gauge} = 12.1 \times 10^{-6} k_h k_{h\_gauge} C_1 P l \sin \Psi (1.7 - 0.0014R) \quad 500 < R < 1200$$

where,

$C_1$ = constant accounting for the wheel profile and flange angle (3.5- 4.4)

$H$ = hardness of rail material (BH)

$k_h$ = rail material hardness correction factor

$k_{l\_hr\_top}$ = lubrication correction factor for high rail top
kl_hrgauge = lubrication correctness factor for high rail gauge

kl_lrtop = lubrication correction factor for the lower rail top

P_l = lateral wheel load on high rail (kN)

Ψ = Angle of attack in radian

R = curve radius in m

Whr_top = high rail gauge wear in mm² per wheel pass

Wlr_top = low rail gauge wear in mm² per wheel pass

Whr_gauge = high rail gauge wear in mm² per wheel pass

The effect of material hardness on wear is non-linear (Mutton et al., 1982), and this effect was taken into account by extrapolating data from facilities for accelerated service track (FAST) (Clayton and Steel, 1987). Equation 2.8 produces the correction factor for rail material hardness.

\[ K_h = 51.05e^{-0.0512H} \]  

Equation 2.8

where,

\( K_h \) = rail material hardness correction factor

\( H \) = hardness of rail material (BH)

Lubrication reduces the wear rate of the rails by reducing the coefficient of friction. Laboratory studies by Tyfour et al. (1996) indicated that the coefficient of friction ranges from 0.115 for well-lubricated conditions, to 0.497 for dry friction. These results are consistent with the simulation results of 0.1-0.56 (Mutton et al., 1982). However, in practice Australian heavy haul lines consider the friction...
coefficient to vary from 0.15 to 0.335, representing a variation in wear performance of 1.6:1. To quantify this effect on high and low rails, and on rail top gauge faces, different relationships for lubrication correction factors have been developed (Zhang et al., 2000).

As the literature points out, the mechanistic approach to rail track degradation prediction provides thorough knowledge and understanding of the behaviour of railway track when it experiences vehicle loading. However, in order to do so, it relies heavily on the data collected on the mechanical properties of the track parameters, such as track gauge wear, which are difficult to quantify. In addition, these factors differ from one part of the track to another. As a result, it is hard to use the knowledge gained from a mechanistic model and generalize that to apply the findings or use them to solve a similar problem elsewhere in the same track or the same network. This means that in an effort to build a universal degradation prediction model, mechanistic models are not the best approach. This explains the lack of studies which utilize this type of model for track degradation prediction.

2.5.2 Statistical models

Statistical models are another type of degradation prediction model which have been used in degradation prediction studies mainly due to their transparency. For researchers their transparency provides a better understanding of how the models operate compared to some other models, such as artificial intelligence models. To simplify and present an explanation of what statistical models are, it is possible to describe them as a group of mathematical models that incorporate a set of assumptions concerning the triggering sample data and similar data from a larger population. A statistical model represents, often in considerably idealized form, the data generation process.

The assumptions embodied by statistical models describe a set of probability distributions, some of which are assumed to adequately approximate the distribution from which a particular data set is sampled. The probability
distributions inherent in statistical models are what distinguish statistical models from non-statistical, mathematical models.

A statistical model is based on mathematical equations that make a relationship between one dependent variable and a number of random and non-random variables. These statistical models can be classified into three categories: deterministic, probabilistic and stochastic (Figure 2.6).

Figure 2.6 Classification of statistical degradation models

The objective of statistical degradation models is to find a general pattern for the statistical distribution of the track geometry using collected data on rail track conditions. The initial studies conducted in the 1980s by the Office for Research and Experiments (ORE) of the International Union of Railways (UIC) helped to gain knowledge about the fundamentals of the degradation mechanism of railroad tracks.
The proposed model, which was designed based on data examined by ORE, contains two parts. The first part of the model explains the degradation immediately after tamping, which is expressed as \( e_0 \) in the equation mentioned in the latter part. The second part of the equation explains the degradation according to the traffic volume, which is represented in the equation by the letter \( T \). The dynamic axle loading and speed are represented in the equation as \( 2Q \) and \( v \) respectively. The ORE model discussed in Equation 2.9 has been analysed based on data acquired from American and Indian railways.

\[
e = e_0 + hT^\alpha(2Q)^\beta v^\gamma
\]

Equation 2.9

where,

- \( h \) is a constant
- \( \alpha, \beta \) and \( \gamma \) are to be obtained from the experimental data.

A statistical analysis was conducted on the federal railway network in Switzerland by Zwanenburg (2009) in order to improve the life expectancy of the complete railway switch and crossing system, including their components. In this study, single and multiple parameter analysis were performed on switch and crossing life expectancy (Zwanenburg, 2009). Through single parameter analysis it was concluded that four parameters: soil quality, switch angle, percentage of freight trains and speed, have an effect on the life-time distribution of standard turnouts. From the multi-parameter analysis it was identified that the percentages of freight trains and the frog angle have a significant effect (Yousefikia et al., 2014a). The modelled equation is presented in Equation 2.10 below:

\[
y = s + ax_1 + bx_2 + cx_3 + dx_4
\]

Equation 2.10

where,

- \( Y \) = life-time expectancy of the switch and crossing
\( x_1 = \) percentage of freight trains.

\( x_2 = \) frog angle

\( x_3 = \) variable related to soil quality of subgrade

\( x_4 = \) speed

In recent times a number of approaches have been proposed to identify the non-linear characteristics of track quality degradation (Sadeghi and Askarinejad, 2010).

### 2.5.2.1 Deterministic track degradation models

Deterministic models are a type of statistical model in which the outcomes are precisely determined through known relationships among states without any room for random variation. In other words, in deterministic models the output of the model is fully governed by the parameters and the initial conditions that are used. In this type of model, a given input will always produce the same output.

The deterministic models that have been used in track degradation prediction models do not differ much from the general description provided above. When developing such models in degradation prediction, a large set of parameters is required related to trains or trams and the design and the operation of the track, for example axle load, line speed and traffic.

Most of the research studies have confirmed a linear relationship with track defects and accumulated tonnage. Accumulated tonnage is measured in million gross tons (MGTs) and this is calculated based on the operational data and then by summing all the axle loads of the train passages for a given section. Equation 2.11 presents the linear relationship which is used to estimate the standard deviation of longitudinal levelling defects for each section.
\[
\sigma = c_1 + c_0 T
\]  

Equation 2.11

where,

\(\sigma\) = standard deviation of longitudinal-levelling defects (mm)

\(C_1\) = initial standard deviation measured after renewal or tamping operations (mm)

\(C_0\) = degradation rate (mm/MGT)

\(T\) = accumulated tonnage between maintenance operations (MGT)

In spite of the fact that a number of research papers have established non-linear characteristics of track quality degradation, such as the polynomial (Jovanovic, 2004), exponential (Veit, 2007) multi-stage linear (Chang et al., 2010) models, the linear relationship is still frequently used in other research studies (Liu et al., 2010, Andrade and Teixeira, 2012).

Prematilaka et al. (2010) presented a deterministic rail degradation prediction model which was developed at the University of Auckland which uses similar types of parameters to those mentioned earlier. The paper provides a detailed account of the development of two prediction models for 50kg/m and 91 & 90lb/yd rails using statistical software which was originally developed at the University of Auckland known as “R”. The rail degradation data used in the study were collected from the New Zealand rail-wear gauge (Livneh, 1996, Premathilaka, 2007, Premathilaka et al., 2010).

The independent variables used in this study are as follows:

- Age of rail at time of inspection (t) in years,
- Radius of the curve (r) in meters,
• Cant on curve (C) in mm,

• Posted speed on the curve (s) in km/h,

• Annual tonnage in million gross tonnes (MGTs)

As mentioned earlier, this particular study developed two model forms for 50kg/m rails and for 91 & 90lb/yd rails. For the 50kg/m rails, different types of models were investigated, including linear and non-linear, to determine the most appropriate form of equations and the final model was formed as a product of step-wise regression. The developed model for 50kg/m produced a R² value of 0.62 for the high leg side wear (HS) and 0.61 for lower leg top wear (LT). For the 91 &90lb/yd rail model, the researchers adopted the same form of equations as those used for the 50kg/m rails with the minor change of the addition of 6 points at the end of both equations in order to adjust the calculations so that the field measurements were comparable. The equations were used to determine both high leg total wear (HLT) and lower leg total wear (LLT). The model produced a R² value of 0.71 for the HLT and 0.61 for the LLT.

Considering the R² value obtained lies within the range of low to high 0.60. while theoretically this may not seems to be a good indication to suggest that model provides highly accurate predictions on rail track degradation practically this model can be quite useful providing that same type of mathematical models with R² value of 0.5 have proven to be very useful in decision making involved with infrastructure asset management (Livneh, 1996, Premathilaka et al., 2010).

2.5.2.2 Probabilistic track degradation models

The basic idea of a probabilistic model, as the name suggests, is that it provides a distribution of possible outcomes and the probability of them occurring according to the input data. The analysis of the probability of track degradation becomes a difficult task to achieve, since various dependent variables are involved. They can be categorized into many categories, including environmental factors (humidity,
temperature etc.), the type and quality of the materials used for the structure, and the construction standards of the structure.

Andrade and Teixeira (2015) presented a hierarchical Bayesian model (HBM), which is a statistical model developed in order to predict the degradation of train tracks in Portugal by using one of the main train lines which runs from Lisbon to Oporto. It evaluates two major quality indicators related to rail track geometry degradation:

- The Standard Deviation of Longitudinal Level defects (SD\_LL),
- The Standard Deviation of Horizontal Alignment defects (SD\_HA).

Bayesian models differ from classical statistical models due to the fact that they assume parameters as random variables, the uncertainty of which can be quantified by prior distribution. This prior distribution p(θ) is then combined with the traditional likelihood p(y|θ) to obtain the posterior distribution of the parameters of interest (Andrade and Teixeira, 2015). The posterior distribution p(y|θ) of the parameters θ given the observed data y can be computed according to Bayes’ rule as presented in Equation:

\[
p(\theta|y) = \frac{p(y|\theta)p(\theta)}{\int p(y|\theta)p(\theta)\,d\theta} \propto p(y|\theta)p(\theta)
\]

Equation 2.12

It has been identified that the calculation of the prior distribution is a very important step in all Bayesian model applications. Nevertheless, in almost all cases in practical applications, it is notable that the joint posterior distribution p(y|θ) has a reasonably high dimension, and integration through numerical methods must rely on Markov Chain Monte Carlo (MCMC) methods. These particular methods are built such that their stationary distribution is the desired posterior distribution (Bernardo, 2003, Ntzoufras, 2009, Andrade and Teixeira, 2015). Finally, when the HBM model was applied to a sample of operational and maintenance data, it was found that HBM is a poor indicator of SD\_HA when compared to the quality indicated for SD\_LL, indicating that horizontal alignment
defects seem to be less predictable (López-Pita et al., 2007, Andrade and Teixeira, 2015, Vale and M. Lurdes, 2013).

Markov models are generally used to model randomly alternating systems where it is assumed that the future states depend entirely on the present conditions and not on incidents which happened in the past. In this literature review, Markov models which are based on time analyse the infrastructural elements of rail or tram tracks at different condition levels over a considerable period of time. Markov models can be used as a substitute for some of the stochastic models where a wide range of dependencies can be taken into consideration. An application of a maintenance management model designed for Iranian railways by Shafahi et al. (2009) used a track quality index calculated between the ranges of 0 to 100. It was decided based on factors such as track unevenness, twist, alignment and gauge measurements (Zimmermann, 1996, Simson et al., 2000, Shafahi and Hakhamaneshi, 2009). The 100-unit range was then projected onto 5 states in the Markov model. Transition probabilities for the transition matrix were then established from changes in the track quality index over time. Lyngby et al. (2008) presented a model which could be used as an alternative to the previously mentioned model (N. Lyngby et al., 2008). The proposed model was a 50-state Markov model and it was used to represent the variation in twist over time. In this treatment each of the states represents the twist on a track section up to 50mm. Alternative degradation rates were given for the model, depending on whether the track section was straight, curved or a transition section (N. Lyngby et al., 2008). This particular model was used to optimize the frequency of track geometry inspections.

Data on the degradation, inspection and maintenance of a single 1/8 of a mile section of the United Kingdom railways were used to produce a Markov model by Prescott and Andrews (2013) in order to produce degradation distributions which were used to define transition rates within the Markov model (Prescott and Andrews, 2013). The model considers the changing degradation rate of the track section following maintenance. The model was used to analyse the effects of changing the level of track geometry degradation at which maintenance is
required for the section. Podofillini et al. (2006) used a reliability, availability, maintainability and safety (RAMS) approach to rail failure modelling (Podofillini et al., 2006).

2.5.2.1 Stochastic models

Stochastic modelling is another possible method of approaching the track degradation problem. A rail track is reliable when it performs its predetermined tasks under operating conditions for a specific period of time. When this stops, the track is considered to have failed and the likelihood of this occurrence within a short period is known as the hazard rate. This notion is involved in many methods and approaches to maintenance analysis (Mishalani and Madanat, 2002, Zakeri and Shahriari, 2012). One of the hazard rate’s behaviours is known as the bathtub curve, shown in Figure 2.7.

![Hazard Rate Behaviour](image)

Figure 2.7: Hazard Rate Behaviour (Haibel, 2012)

The full lifecycle of a rail track can be divided into three stages and the occurrence of the hazard rate can be described according to the three stages. A graph such as the above with a local time-dependent hazard rate can be used to demonstrate the relationship between the life-time of the track and the track failures that occur during its existence.
Phase one (a) - phase one is the section known as early-life failures in the graph and as the name suggests that particular section shows the early failures of the track that become visible at the beginning of the life of the track. These are characterised by a high failure rate and this is indicated in the graph with a steeper downward curve. This keeps decreasing as time passes. This is a result of many possible factors, such as initial weaknesses or defects in the material, poor quality control, inadequate manufacturing methods, human errors and initial settlement.

Phase two (b) – during phase two, the hazard rate remains almost constant. Only random failures occur during this period of the track and they may be due to various reasons such as drastic changes in the environment. This particular phase is shown in blue and is known as useful life failures.

Phase three (c) - this phase of the track is known as the wear out period and during this period, the failure rate spikes up. This increase may be due to several factors, such as track wear due to ageing, fatigue cracking, corrosion and creep, poor maintenance, wear due to friction, and incorrect overhaul practices.

Critical failure progression is a defined limit in degradation models where it is assumed that any degradation beyond this point is at a critical stage. However, in reality it is quite possible and exists in more than one particular level. Failure progression can be specified in various ways, but the gamma process is the most common model of failure progression (Meier-Hirmer et al., 2009). This process is a continuous time stochastic process. In this process the degradation is assumed to be linear with time.

Guler et al (2011) introduced a geometry degradation model capable of analysing the effects various track properties, environmental conditions, and maintenance renewal policies have on the degradation of each of the track parameters measured by recording vehicles (Guler et al., 2011). The study found that the increase in rate of geometry degradation is due to natural disasters such as flood and rockfalls alone and is not influenced by snow or landslides. The study also indicated that an increase in factors such as curvature, gradient and line speed also results in
increased rate of geometry degradation, which means that the sleeper type and rail type (continuously welded rail (CWR) or jointed rail) has an effect on geometry degradation, with CWRs degrading at a slower rate. Nevertheless, the results of the study show that an increase in the annual passing tonnage decreases the degradation rates. This leads to the invalidation of the model, as it is broadly known that increasing annual tonnage increases degradation rates.

Quiroga and Schneider (2012) developed a model which was a heuristic-based method for tamping intervention scheduling. The model was then further developed into a Monte Carlo simulation to model track ageing and restoration by making use of 20 years’ worth of track measurement train data obtained from the French railway operator SNCF (Quiroga and Schnieder, 2012). However, this model ignores the first 3 months’ measurement data after the intervention, on the assumption that all train tracks experience bedding in. Therefore, it includes only datasets where the time period between tamps is at least one full year to increase the accuracy of the model. This adds to the decrease of the applicability of this model in the UK, along with the assumption that the track undergoes exponential degradation, as there is no evidence to substantiate the claim that the track undergoes an exponential degradation pattern (Quiroga and Schnieder, 2012).

Vale (2013) proposed a stochastic model for geometric track degradation over time. The study was carried out in Portugal using one of their busy Northern railways lines as a case study. The study performed a statistical and probabilistic analysis for different vehicle speed groups in accordance with the European Committee for Standardization (CEN). The model used for analysis of the three parameters of the Dagum distribution in the study was defined by \( f(x) \), which was the distribution function mentioned in Equation 2.13 (Vale and M. Lurdes, 2013):

\[
f(x) = \left[ 1 + \left( \frac{x}{\beta} \right)^{-\alpha} \right]^{-k}, \quad x > 0
\]

Equation 2.13

The analytical Dagum density function is expressed by Equation 2.14:
\[
f(x) = \frac{\alpha \times k \times x^{\alpha k - 1}}{\beta \times \left(1 + \frac{x}{\beta}\right)^{\alpha k + 1}}, \quad x > 0
\]

Equation 2.14

where in both equations,

\(\alpha, \beta\), and \(\kappa\) are positive parameters,

Parameter \(\beta\) is a scale parameter,

\(\alpha\) and \(\kappa\) are shape parameters

In this case study 52 probabilistic distributions were tested with EasyFit software, including the exponential, the Gamma, the logistics and the Dagum. This fourth mentioned model incorporates 21-time intervals, with each time interval containing three speed groups. Since the degradation on the left and the right rail was similar, the analysis comprises the degradation rate of both rails in a total of 63 cases, which were all performed together.

Finally, the research work indicated that:

- The degradation rate of the standard deviation of the longitudinal level was similar for both rails.

- The Dagum distribution allowed a good fitting of all the real data of the 63 cases

- The scale parameter \(\beta\) depends linearly on the mean degradation rate of the standard deviation of longitudinal level, being lower for higher maximum permissible vehicle speeds (\(R^2\) value of 0.7987).

The literature on all the statistical models indicates that there are both advantages and disadvantages to this type of approach as with any other approaches. Among the advantages of this approach is that models with a transparent structure and based on a considerable amount of research stand out. However, statistical models
also have some disadvantages. Statistical track models rely heavily on historical degradation data, which are generally not available for many railway and tram track systems. In addition, statistical models lack the flexibility to incorporate future changes in traffic patterns or maintenance practices.

2.5.3 Combined mechanistic and empirical models

Combined mechanistic and empirical models are a collaboration of mechanical and statistical models. These models are formed based on an understanding of the behaviour of a system’s mechanical components, coupled with direct observations, measurements and extensive data records. Sadeghi and Askarinejad (2010) conducted in-depth research to improve the current track degradation modelling techniques using a thorough field investigation. The research followed a combined method of mechanical and empirical approaches. Comprehensive track field data were collected and analysed over a period of two years on approximately 100km of railway line in central Iran (Sadeghi and Askarinejad, 2010). The main parameters affecting the rate of track degradation were categorised into three groups as follows:

- Track quality indices (TQIs),
- Traffic parameters,
- Maintenance parameters.

Furthermore, in this particular research the total equivalent million gross tons (EMGTs) passing the track in a time period (T) and the average running speed (V) were taken into consideration under traffic and maintenance parameters. Especially during major maintenance operations, the time (T) becomes the key maintenance parameter.

The Track Geometry Index (TGI) and Track Structure Index (TSI) are the most common TQIs used around the world and hence are used in Sadeghi and
Askarinejad study. These two indices are not independent variables. The TGI index presents only the geometric conditions of the track, such as profile, twist, gauge and alignment, which directly influence the riding comfort of the track. TSI represents the mechanistic conditions of the track, such as the condition of the rails, sleepers, fastening systems, sub-grades and even the drainage systems. TSI is relevant to the actual condition of the tracks and can indicate the probable degradation of the track.

During the research, in the modelling some mathematical expressions were developed for the correlation between the main effective parameters and the track degradation coefficient (DC). Data gained from observing the track over a period of one year were used to develop an equation which represents the change in DC over time. This equation was further developed into a track degradation model by combining the constructed correlations between the track degradation coefficient and track quality, loading and maintenance conditions (Sadeghi & Askarinejad 2010).

This degradation model was presented in two forms. One form is based on the data from the observation of track geometry decay over time, which is represented in Equation 2.15, and the other form is based on visual inspections of the mechanistic conditions of the elements of the track which are represented in Equation 2.16.

\[
\frac{TGI_2}{TGI_1} = \alpha_4 \exp(\beta_1 V + \beta_2 EMGT + \beta_3 TGI_1) \times [\lambda_1 T^4 + \lambda_2 T^3 + \lambda_3 T^2 + \lambda_4 T + 1]
\]

Equation 2.15

\[
\frac{TSI_2}{TSI_1} = \alpha'_4 \exp(\beta'_1 V + \beta'_2 EMGT + \beta'_3 TGI_1) \times [\lambda'_1 T^4 + \lambda'_2 T^3 + \lambda'_3 T^2 + \lambda'_4 T + 1]
\]

Equation 2.16
where,

\( TGI_1 = \) Present Track Geometry Index

\( TGI_2 = \) Future Track Geometry Index

\( TSI_1 = \) Present Track Structure Index

\( TSI_2 = \) Future Track Structure Index

\( T = \) time

In addition, the researchers developed a formula presented in Equation 2.17 for the correlation between the \( TGI_2 \) and \( TSI_2 \) since there were limitations in carrying out both inspections.

\[
TSI_2 = \eta_1 \times \eta_2 \times \eta_3 \times \eta_4 \times TGI_2
\]

Equation 2.17

where,

\( \eta_1 \) to \( \eta_4 \) = factors representing the influences of the train speed (\( v \)), Equivalent Million Gross Tons (EMGT) and Time (\( T \))

Obtaining linear correlations between the ratios of \( TGI_2/TGI_2 \) and influencing parameters, the following expressions are obtained for \( \eta_1 \) to \( \eta_4 \)

\[
\eta_1 = \kappa_3 V + \kappa_3
\]

\[
\eta_2 = \kappa_3 EMGT + \kappa_4
\]
\[ \eta_3 = \kappa_2 T G I_1 + \kappa_6 \]

\[ \eta_4 = \kappa_7 T + \kappa_8 \]

\( \kappa_1 \) to \( \kappa_8 \) are constant coefficients.

The degradation models are separately developed for curves, turn-outs, straight line sections, tunnel lines and bridge lines because the behaviour of tracks is different in different track sections.

Ahac and Lakusic (2015) proposed tram track maintenance planning by gauge degradation modelling. This study, which was carried out in Croatia at the University of Zagreb, used a mechanical-empirical model which determines the rate of degradation by statistical regression analysis. Regression defines the degradation speed of the dependent variable, which is the observed parameter of the track quality as a function of the independent variable, which is the period of track exploitation. Two types of tram tracks (an indirect elastic rail fastening system and a stiffer direct elastic rail fastening system) were observed during the study. The model used in the research was based on the results of track gauge monitoring performed on different Zagreb tram track segments, which were also categorized according to homogeneous characteristics of track degradation factors and maintenance history, and constructed with the use of the above-mentioned rail fastening systems (Ferreira and Murray, 1997, Jovanovic, 2004, Ahac and Lakušić, 2015).

The results produced by the proposed model show that the correlation between the rate of tram track gauge degradation during exploitation and the stiffness of its fastening system can be described by dividing the results into three groups:

- Values of tram track exploitation intensity to approximately 35 MGTs,
- After increase in exploitation intensity above 35 MGTs and
• For values of tram track exploitation intensity above 45 MGTs.

The mechanical empirical model estimates equal regression coefficients with very high determination coefficients (0.95≤R²≤0.98) for values of approximately 35 MGT, which suggests that in the early stage of tram track exploitation the effect of fastening system stiffness on gauge degradation is negligible. However, for increases in exploitation intensity above 35 MGTs, the gauge degradation speed significantly decreases on tracks with indirect elastic fastening systems and for tram track exploitation intensities above 45 MGT, the proposed model does not provide an accurate prediction of gauge degradation behaviour. In order to increase the accuracy of models, more tram track gauge monitoring is required.

In conclusion, modelling results have shown that the period of notable gauge degradation during tram track exploitation is shorter in the case of the indirect elastic fastening system with lower stiffness. In this respect, to optimize track maintenance procedures and extend the life cycle of the tracks, it would be desirable to adjust the track geometry quality control and maintenance cycles according to track stiffness. In addition, when selecting structural elements for new tramway tracks, preference should be given to indirect elastic rail fastenings.

According to the researchers, the research was limited by the availability and form of the input data on tram tracks which were needed for the creation of the database on which the modelling was carried out. This may have caused the lack of accuracy of this particular prediction model which is presented in this research. In order to increase the accuracy of the model, further monitoring of tram tracks is required.

Based on the knowledge derived from the literature, mechanical empirical models are a combination of the features of mechanical and statistical models. Since they contain features of both types, they provide greater accuracy and are applicable throughout a network, unlike mechanical models alone which provide a thorough understanding of a particular section or sections subjected to study. However, these types of models are covered in only a limited number of studies.
2.5.4 Artificial Intelligence models

Artificial intelligence (AI) models are machine learning models that are currently used in predicting degradation in infrastructures such as bridges and railway tracks around the world. This is a relatively new area of research and AI is on the verge of becoming one of the most popular model types for predicting degradation. In this particular research, AI models are divided into two main sub-categories: Artificial Neural Networks (ANNs) and Neuro-fuzzy models, which shown in Figure 2.8.

![Figure 2.8: Classification of Artificial Intelligence Models](image)

Machine learning ANNs are a group of models developed based on the idea of biological neural networks. These are used to estimate functions that may be dependent on large numbers of inputs and unknowns. ANNs are commonly presented as a system of interconnected ‘neurons’ which exchange messages between each other. The connections have numeric weights that can be tuned based on experience, making neural nets adaptive to inputs and capable of learning.
Neuro-fuzzy models are a combination of ANNs and fuzzy logic. Hybrid intelligent systems use a combination of these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structures of neural networks. This section provides a review of studies which have used these new models in order to calculate train track degradation.

Shafahi et al. (2009) presented a comparison of four models including an established model in order to predict track degradation. The four models were a mechanistic model suggested by the ORE of the IUR and three new models, the Markov chain model, ANNs and Neuro–fuzzy models. The study, which was carried out at Sharif University of Technology in Teheran, used an established model suggested by ORE with some adaptations in order to compare the results obtained from the other three models. In the study the track’s state was defined in terms of the combined track record index (CTR) rating out of 100, where the best possible track condition is 100 and the statistics were defined as five intervals of CTR. They were 0-50= failed, 50-60= medium, 60-70= good, 70-80= very good and 80-100= excellent, which is similar to those used in Iranian railways. The data used in the study were also obtained from the Iranian railway network (Davidian and Giltinan, 1995, Shafahi and Hakhamaneshi, 2009)

2.5.4.1 Artificial neural networks model (ANNs)

For this study the track condition data were available in the form of surveys conducted on multiple tracks of identical types inspected at a single point in time. In Shafahi et al’s work, it was considered that the track started its life at some point in the past in near-perfect condition and was then subjected to a sequence of duty cycles that caused its condition to deteriorate. It was assumed that the duty cycle was for one year for the track, which means it had undergone one years’ worth of weather and traffic loading. CTR was used to describe the track condition. The factors used as effective items of track degradation in the study were as follows (Nauck et al., 1997, Shafahi and Rasooli, 2001, Shafahi and Hakhamaneshi, 2009):
• CTR index of a year, the previous year, and two and three years before, classified from 1 to 5.

• Traffic volume or traffic load, which was divided into two groups, light and heavy traffic.

• Maximum allowable speed, which was classified into 5 classes: maximum speed less than 60 km/h in speed class 1, (60-80km/h) in speed class 2, (80-100km/h) in speed class 3, (100-120km/h) in speed class 4 and more than 120km/h in speed class 5.

• Geographical location, which was classified into three classes: plain, hilly, and mountainous areas

• The maximum gradient of the block, which was classified into five classes: maximum gradient of the block from 0% - 0.5%: gradient class 1; 0.5% - 1% gradient class 2; 1% - 1.5% gradient class 3; 1.5% - 2% gradient class 4; and 2% -3% gradient class 5

• Minimum radius of curves in the block which was classified into 7 classes: maximum radius of curves less than 250 m radius class 1; 250 - 400m radius class 2; 400 – 750m class 3; 750-1000m class 4; 1000 – 2000m class 5; 2000 – 4000m class 6; and radiuses larger than 4000m class 7.

In building the neural network model the following steps were followed:

First step – the topology of the network was created with the inclusion of parameters such as number of layers and nodes of the network, type of network, initial and activation functions.

Second step - on the basis of the training process in a network the weighted parameters were corrected and the data of every situation as training data for many times were shown to the network.
Third step- the neural network was examined using some known data to enable probable errors to be corrected

A network with 3 layers and 5 neurons in the internal layer was selected as the optimal network. The data were then randomly directed into two sets: a training set which included 82% of the data and a test set with 18% of the data. In their paper, the authors included the ANN model’s comparison of the model predictions and observed data for one of the sample data sets used. It had 33% within one level wrong and 67% correct. The predictions by the neural network showed that the following year’s CTR indexes were at the level of the CTR of the previous year or one level lower.

Guler (2013) proposed an ANN model capable of predicting rail track degradation using data collected from a 180-km long track section between Arifiye and Eskisehir in Turkey over a period of two years. The track was divided into analytical segments (ASs) of uniform characteristics utilizing a special segmentation algorithm to build an ANN model which can predict track degradation. In the study for the ANN model ten input and one output parameters were considered. The parameters used in the study were, Traffic load, Speed, Curvature, Gradient, Cross level sleeper type, Rail type, Rail length, Falling rock land slide, Snow and Flood. The model output variable was selected as the track degradation rate. Through a segmentation process 820 samples were obtained for utilization in the ANN model and these samples were randomly split into two groups of subsets, a training set and a testing set. For this research 70% of the data were used as the training set and 30% of the total data set were used as the testing set. The developed model was able to produce results for twist, gauge, alignment, cross level and levelling and the R2 values produced were 0.727, 0.795, 0.765, 0.831 and 0.742 respectively. This indicates that the developed ANN model was successful in its predictions on degradation (Brion and Lingireddy, 1999, Berggren et al., 2008, Guler, 2014).

Moridpour et al (2015) presented an ANN model to predict the degradation of tram tracks using maintenance data in Melbourne. The data were categorised into
three categories: inspection data, load data and repair data. Inspection data were collected from the Melbourne tram network from 2009 to 2013, covering different types of segments of four routes: straights, curves, H-crossings and crossovers. These segments were the focal point since they have a higher failure rate than the other segments (Yousefikia et al., 2014b, Moridpour et al., 2016). Load data consisted of million gross tonnes (MGTs) without passengers and the frequency, which was represented by the number of trips per day.

2.5.4.2 Neuro-fuzzy models

A fuzzy set is defined by its membership function which usually ranges on the interval (0, 1). A proposition (p) which restricts the possible values of variable (x) is represented by means of a membership function (\(\mu_p(x)\))(Zimmermann, 1996). Hybrid neuro-fuzzy models are one of the modern neuro-fuzzy approaches used in track degradation modelling and other infrastructure degradation modelling around the world. They are popular due to the large variety of interesting applications they provide for the user. A neural network and a fuzzy system are combined in a homogeneous architecture. The system may be interpreted as a special neural network with fuzzy parameters or as a fuzzy system implemented in parallel distributed form.

With the above-mentioned conditions, a neuro-fuzzy network model was developed by Shafahi et al.(2008) and as mentioned in the previous section, the authors presented a table which interprets the results of comparison of the model predictions and observed data for a sample data set. According to the table, 27% of results had one level wrong and 73% correct (Shafahi et al., 2008).

When comparing the outputs of these two artificial intelligence models, it is clear that the Neuro-fuzzy model improved its results by 6% over the neural network model. At the end of Shafahi et al’s (2008) study all the results obtained from all four models were listed in a table, according to which the ORE model produced an \(R^2\) value of 0.1190, the Markov chain model had an \(R^2\) value of 0.8317, the ANN model had an \(R^2\) value of 0.7243 and finally the Neuro-Fuzzy network
model produced and R² value of 0.8096 (Shafahi et al., 2008). The table also gives the “a” and “b” values for the observation estimation relation form (Observation – Estimation relation Form: \( y=ax+b\) (x=observation, y=estimation)).

When the coefficient “a” is close to 1 and “b” is close to 0 the model is considered to be a good model predictor of the actual observations. The R² values produced through the ANN (with a=1.0352 and b=0.0171) and the Neuro-Fuzzy network (a=0.8749 and b=0.6443), which were 0.7243 and 0.8096 respectively, showing that they predict track degradation better than the established ORE model with an R² value of 0.1190.

ANNs are becoming much more popular among researchers and look very promising for degradation modelling in the future for a number of reasons. The main reason is that they have higher accuracy rates compared to other approaches. The major drawbacks of these models are the lack of literature, since they are relatively new for degradation prediction and it is hard to understand the structure of the models and how they work. ANNs lack transparency, which discourages researchers from using them in their studies.

All the models considered in the literature review are summarised in Table 2.1 for easy comparison of their qualities.
Table 2.1: Summary of rail track degradation approaches and model types

<table>
<thead>
<tr>
<th>Approach</th>
<th>Model type</th>
<th>Model variables</th>
<th>Strengths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanistic models</td>
<td>Mechanical model</td>
<td>Traffic (Passed tonnage)</td>
<td>Oldest type of models in degradation prediction. Provide a thorough knowledge about the behavior of railway tracks. Large amount of research has been carried out using this type of model.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time (Age)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Traffic conditions (gauge, twist etc.)</td>
<td></td>
</tr>
<tr>
<td>Statistical models</td>
<td>Probabilistic</td>
<td>Speed, Axle load, Mechanistic data such as gauge and twist, Soil quality, Gradient, Rail type, Curve radius</td>
<td>A basic methodology in degradation analysis. Considerable amount of literature available. The model structure is transparent.</td>
</tr>
<tr>
<td>Deterministic</td>
<td>models</td>
<td>Age of the rail (t), Annual tonnage (T), Angle of attack, Curvature, Speed</td>
<td>The model structure is transparent. Modelling process is straightforward.</td>
</tr>
<tr>
<td>Stochastic models</td>
<td></td>
<td>Operating time, Line speed, Curvature, Gradient</td>
<td>Considerable amount of literature available.</td>
</tr>
<tr>
<td>Artificial intelligence</td>
<td>Artificial Neural Networks</td>
<td>Traffic volume, Speed, Maximum gradient of the block, Curve radius</td>
<td>Provide predictions with greater accuracy than other models. Modern type of</td>
</tr>
</tbody>
</table>
### 2.5.5 Limitations of existing studies

The major issue to date is that limited research has been carried out on how to predict tram track maintenance, possibly because it is a relatively new area compared to train track maintenance. Almost all the papers discussed in the literature review are based on heavy rail tracks. Therefore, there is a need to find or develop a model suitable for tram tracks.

All the models that have been discussed have advantages and disadvantages. Mechanistic models are some of the oldest methods that have been used over time all around the globe to predict track maintenance. Mechanistic wear and tear on a section of a track is taken into consideration in this type of modelling. However, it is hard to find recent research carried out using this type of model, most probably due to the poor effectiveness and inconvenience of such models. Mechanistic models are quite good when a particular part of the section needs to be repaired. In that case, thorough data observation could be carried out on the mechanical degradation of that particular section, and it would be possible to develop a highly accurate model to predict the maintenance requirements for that section. However, it would be hard to use it on another part of the track since degradation varies...
from place to place along the track and throughout the network, making this approach less effective and inconvenient.

In contrast, statistical models provide better prediction of maintenance needs for the entire network since they use larger data sets of mechanistic and other data for analysis and generalisation. Therefore, they give a better understanding of the track behaviour of the full track or the network and are more attractive for modelling track degradation.

Stochastic modelling is a very good approach when dealing with large data sets, since it allows the use of large numbers of variables. It uses large sets of observation data in order to produce good models with better accuracy and it will not work with few observations. However, in general, the accuracy of these types of models is not the same as other models due to errors in variables at various stages of the modelling. This is also applicable to gamma process and Markov models.

Mechanical and empirical combined models are another good option for predicting tram track degradation models since they also use large data sets and allow the development of separate models for different track sections, for example curves, turnouts and straight lines. These models can easily be used to project future maintenance more accurately, which helps to reduce costs.

AI models are new types of models which provide higher accuracy levels but they lack transparency in their structure and operation, making them difficult to understand and model. The lack of literature is a major issue for this type of model.

2.6 Summary

This chapter has provided a review of the current literature on existing methods of degradation prediction for train and tram tracks around the globe. There is lack of literature available around light rail and hence the majority of the literature reviewed in this chapter is related to heavy rail. Based on the literature reviewed we have identified four main approaches and categorised the models used in these studies. The literature review also includes their variables, the accuracy of the
models, and their strengths and weaknesses, and provides a foundation for the understanding of which type of model is suitable for application to the rest of this research.
Chapter 3 Research Framework

3.1 Introduction

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 economic restrictions, the rail transport authorities are in pursuit of improved, modern methods which can provide precise prediction of rail maintenance time and location. The expectation of such a method is to develop models to minimize the human error that is strongly related to manual prediction. Such models will help transport authorities to understand how track degradation occurs over time with changes in 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 minimise the maintenance cost/time and secure their vehicles. The rail track characteristics which 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 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 behaviour of rail tracks. Accurate models increase track safety and decrease the cost of maintenance in the 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 the Melbourne tram track system using the Adaptive Network-based Fuzzy Inference System (ANFIS) model.

The goal of this research is to develop a light rail track degradation prediction model which will help to identify the different sections of the light rail with a onestep-ahead prediction ANFIS model. Million gross tonnes (MGTs) and Gauge have been used as
the key parameters in developing the model along with rail type, rail profile and track surface.

This chapter discusses the past and the present of Melbourne tram network. It then discusses the obtained data set which will be used in the model developing stage and its nature by analysing them. At the end of the chapter it provides the statistical information such as means and standard deviation for straight and curve sections.

3.1.1 Melbourne tram network

Trams in Melbourne are an iconic transportation mode which has a deep connection with the city and its people. It has a long proud history back to the late 1800s when the trams were pulled by horses. Since that era trams have become a distinctive part of Melbourne’s character.

Melbourne’s cable tram system was initially started in 1885 and it evolved into one of the world’s largest with 75 km of double track. After opening and closing the first electrical tramline in the late 1800, in 1906 electric tram systems were opened in St Kilda and Essendon. This kick-started the continuous operation of Melbourne’s electric tram system.

Currently Melbourne has the largest operating tram network in the world with 250 km of double track. It had a fleet of 501 trams as at November 2014 to cover the network. These trams are divided into nine classes:

- A-Class
- B-Class
- C-Class (Citadis)
- C2-Class (Bumblebee)
- D-Class Combino (3-Car)
- D2-Class Combino (5-Car)
- E-Class
- W-Class
• Z- Class

Figure 3.1: Iconic W-Class tram (Yarra Trams, 2016)

Of these classes the W-Class shown in Figure 3.1 has been used as the iconic representative of the Melbourne tram system. W-Class trams were introduced to Melbourne in 1923 as a new standard design. The W-Class was the mainstay of Melbourne’s tramway system for 60 years. A total of 752 trams of 12 variants were built, the last of which was in 1956.

There are more than 1700 tram stops spread across the network with more than 400 having level access. The stops are roughly 400-500m apart for easy accessibility of the passengers. Seventy-five per cent of Melbourne’s tram network operates on shared roads with other vehicles. The tram system is currently operated by Keolis Downer, trading as Yarra Trams. Although it is a mammoth task to deliver a punctual service, Yarra Trams have set their target in the high 70s every month.

A high volume of passengers uses the Melbourne tram network daily and the figure for annual usage is a staggering 203 million boarding according to the statistics collected for the years 2015-2016.
3.1.2 Area of study

![Melbourne’s tram network](image)

Figure 3.2: Melbourne’s tram network

Yarra Trams operate 24 tram routes and the free city circle tourist tram. The network map is depicted in Figure 3.2. The longest tram route in the network is route 75 which has a full length of 22.8 km.

3.2 Data Set

The data set used in this research was collected and provided by Yarra Trams. The data set received included data from 2010 to 2015. The data were combined using the ArcGIS software. They included straight sections, curve sections, h-crossings and cross overs.

Then MATLAB software was utilized to match the data and extract them to a separate file. MATLAB includes a multi-paradigm numerical computing platform and a fourth-generation programming language. A proprietary programming language developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and
interfacing with programs written in other languages, including C, C++, C#, Java, Fortran and Python. This software has been widely used across all engineering disciplines for data mining and model development.

3.2.1 Data matching and Extracting

Data matching in MATLAB was carried out in the manner shown in the following figure.

![Figure 3.3: Data selection algorithm](image)

Figure 3.3: Data selection algorithm
The matching process was done by starting with the ID. If the ID matches from one year to the other the program moves on to matching other categories such as Km and m. If all of them match, those data are separated into a master file. This master file is used in the modelling to train and predict the future values.

### 3.2.2 Straight Sections

Since the straight dataset was much greater than that of the curve section data, the extraction of the data was carried out with the help of different software such as R. The algorithm of the data extraction is as follows:

1. Connect the R to the dataset
2. Obtain the data related to straight sections.
3. Transfer the data to text file format
4. Read the file with MATLAB
5. Follow the exact data matching procedure stated in Data Set section in 3.2.1.

### 3.2.3 Curve sections

The data received for curve sections were comparatively small and hence did not utilized the R software in the process prior to match and extract the Data related to Curve sections.

### 3.2.4 Nature of the data

The data provided for the Melbourne tram network by Yarra Trams were very messy, meaning that it was not possible to obtain clearly interpretable information from them. The reason for that is because the data included many noisy values and different maintenance data between 2010 and 2015. Sample raw data for curves and straight sections are presented in Figure 3.4 and Figure 3.5.
Figure 3.4: 50 Sample data on straights

The graphical output provided in Figure 3.4 and Figure 3.5 shows the behaviour of the gauge value degradation for straight sections, and make it clear that gauge degradation does not follow a regular pattern. The messy nature of the data emphasizes the necessity of an advanced model to predict future values of degradation.

Figure 3.5: 50 sample data on curves
Figure 3.5 presents the behaviour of the raw data for curve sections. From the graphical output it is possible to conclude that the curve data are even more irregular when compared to the straight sections. This may be due to reasons such as experiencing different MGTs combined with different rail types, and there may also have been errors in data collection.

The outlook of the data sets could change when they contain noisy data or maintenance data in them. It is not possible to accurately point out what the actual reason is but it is certainly possible to make a guess on the probable cause by observing their trend lines. Change in magnitude of the data due to noisiness or maintenance could be depicted by the graphs in Figure 3.6 and Figure 3.7. In these two graphs two different types of data behaviour shown and they are labelled as Type 1 and Type 2. In Figure 3.6 it depicts the Type 1 which simulates the behaviour of a data set which contains noisy data and Figure 3.7 which shows the behaviour of a data set which contains either maintenance or noisy data.

![Figure 3.6: Data with noise](image)

However, the detection of Type 1 noise in the data as depicted in Figure 3.6 is much easier than the detection of Type 2 which is denoted in Figure 3.7. The reason is that when maintenance occurs the gauge value improves. It will deviate its path of following the usual trend line of decay values and change its cause to follow new
trend line. In such a situation, something similar to Type 2 will occur. Figure 3.7 presents a scenario for year x where noisy data have been combined with maintenance data.

![Graph](image)

Figure 3.7: Data with noise or maintenance data which cannot be clearly defined

Figure 3.6 indicates some sort of maintenance occurred at year x which caused grade degradation to improve while Figure 3.7 indicates the noisy nature of the data or perhaps some maintenance occurs. Due to maintenance in some parts of the track it starts to deteriorate at a greater rate after year x. This scenario is depicted in Figure 3.8. Different models and different systems could be utilized to model this system. If the data do not include too much noise and maintenance like that seen in Figure 3.9 they could be easily modelled by linear models such as regression models or other linear models such as those used to model dynamic systems like time series or other methods. However, based on the data in hand this is not a viable option.
As a result of not being able to use linear models such as time series, non-linear models such as ANFIS models or ANN models should be used to predict the future degradation of rail tracks.
Data without maintenance for straight sections and curve sections obtained from the Yarra Trams network are shown in Figure 3.10 and Figure 3.11.

Figure 3.10: Data without maintenance for straight sections

Figure 3.11: Data without maintenance for curve sections
As Figure 3.4 and Figure 3.5 show, the data include substantial noise and maintenance between 2010 and 2015. Therefore, in the present research two different methods, ANN and ANFIS, were utilized to model the system.

The data show that there is a major difference between different sections such as curves and straights. The data for gauge values in the straight sections are much higher than they are for curve sections, which means that these sections need many more periodic inspections than curves. This finding is based on the results produced through the developed model in this study. Table 3.1 presents the means and the standard deviations for the straight and curves sections of the rail tracks.

Table 3.1: Means and standard deviations for straights and curves.

<table>
<thead>
<tr>
<th>Section of track</th>
<th>Mean $\sigma$</th>
<th>Standard deviation $\mu$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Straights</td>
<td>2.8207</td>
<td>3.9185</td>
</tr>
<tr>
<td>Curves</td>
<td>1.3579</td>
<td>3.5320</td>
</tr>
</tbody>
</table>

As shown in Table 3.1 from both mean and standard deviation, it could be understood that higher gauge values are more common in straight sections which need to have more common inspections.

3.3 Summary

This chapter has presented the research framework of the thesis, and it also discussed the research methodology of this study. It presented the details regarding the location of the study took place and the datasets collected for model development. MATLAB software was utilised in matching, extracting and conducting statistical analysis during this stage of the research. After the statistical analysis, it was identified that the variables such as MGT and history of gauge values to be the most common variable which impacts gauge degradation. Therefore, this research will focus on the MGT in the model development stage as the variable which most affects tram track degradation which will be discussed in the next chapter.
Chapter 4 Model Development

4.1 Introduction

After carrying out a statistical analysis on the obtained data, the outcome provided a better understanding of its behavioral nature. After the data analysis stage which discussed in the previous chapter, as the next step it was required to develop a model which could predict the future rail track degradation by utilizing the information acquired during the data analysis stage. Due to the noisy behavior of the data it was decided to develop an ANFIS as the primary degradation prediction model and another ANN model as the secondary model to compare the results.

This chapter discusses the history and the origin of both Artificial Neural Networks (ANNs) and Adaptive Network based Fuzzy Inference System (ANFIS) models. It describes the basic method of operations of these models and why we utilized these models in the present research. Finally, it presents the outputs and results of these models.

4.2 Artificial Neural Networks (ANNs)

During a simple task that we carry out every day, such as reading a book or writing a letter, we utilize a complex biological neural network. As humans we possess a highly interconnected set of nearly $10^{11}$ neurons to assist reading, motion, breathing and thinking. Some parts of the neural structure have been established by experience while others we possess from birth.

Scientists have only started to understand how biological neural networks operate. Their complexity and advanced nature make it difficult to study them. However, the neural networks we are discussing in this research are actually a type of artificially produced neural networks. They are extremely simple compared to their biological counterparts. Although networks of these artificial neurons do not have a fraction of the power of the human brain, they can be trained to perform useful functions.
The history of neural networks goes back as far as the late 19th and early 20th centuries, based on interdisciplinary work in physics, psychology and neurophysiology by such scientists as Hermann von Helmholtz, Ernst Mach and Ivan Pavlov (Hagan et al., 1996). Early studies emphasized general theories of learning, vision, conditioning etc. but did not involve any specific mathematical models of neuron operation.

The beginning of the modern neural networks started in the 1940s with the work of Warren McCullah and Walter Pitts (in 1943). These two scientists demonstrated that in theory networks of artificial neurons possess the ability to compute an arithmetic or logical function. Their work is widely regarded as the origin of the neural network field (Hagan et al., 1996).

The very first practical application of the ANN came in the late 1950s, when Frank Rosenblatt invented perceptron networks and associated learning rules (Hagan et al., 1996). Rosenblatt and his colleagues built a perceptron network and demonstrated its ability to perform pattern recognition. However, it was later shown that the basic perceptron network could only solve a limited class of problems (Hagan et al., 1996).

Around the same period Bernard Wilrow and Ted Hoff proposed a new learning algorithm and used it to train adaptive linear neural networks. They were quite similar in capabilities and structure to Rosenblatt’s perceptron. This rule is known as the Windrow-Hoff learning rule and it is still utilized today (Hagan et al., 1996).

For about 10 years research on neural networks was largely suspended due to some limitations of the above-mentioned networks, and progress of neural network studies was hindered due to the unavailability of powerful digital computers to carry out experiments. This caused many active researchers in the field at that time to leave the field.

A few glimpses of the rise in neural network studies seemed to surface during the 1970s and during the 1980s research on neural networks grew exponentially. This was due to the availability of new personal computers and workstations, which rapidly
grew in capability. Furthermore, there were new concepts introduced to the field at that time.

Two new concepts, the use of statistical mechanics to explain the operation of a certain class of recurrent network, and back-propagation algorithms for training multilayer perceptron networks, were key developments in the 1980s.

These new developments reignited work in the field of neural networks and provided the opportunity to many researchers spread across the planet to write and publish a large number of papers on this subject and many more applications of the neural networks have been found across many fields ever since. This opened the doors for much new theoretical and practical work which is carried out at present.

At present neural networks have inexorably taken a front seat as key mathematical/engineering tools across many fields

Examples of fields that have utilized neural network applications during the last few years are shown in Table 4.1.

Table 4.1 Applications of Neural Networks in different fields of study (Hagan et al., 1996).

<table>
<thead>
<tr>
<th>Field</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aerospace</td>
<td>High performance aircraft autopilots, flight path simulations,</td>
</tr>
<tr>
<td></td>
<td>aircraft control systems, auto-pilot enhancement</td>
</tr>
<tr>
<td>Automotive</td>
<td>Automobile autonomous driving</td>
</tr>
<tr>
<td>Banking</td>
<td>Credit application evaluation, exchange rate forecasting</td>
</tr>
<tr>
<td>Medical</td>
<td>Electroencephalogram (EEG) and electrocardiogram (ECG)</td>
</tr>
</tbody>
</table>
As indicated by the applications in different fields, neural networks can be used for various things to different extents. The potentials that these ANN models provide is much more than that one expects.

4.2.1 Biological inspiration for ANNs

Artificial neural networks (ANNs) are remotely related to their equivalents in biology. Although the construction of ANNs was inspired by their biological counterparts, they possess a fraction of the power that neurons in the human brain possess.

The human brain has a large number of highly connected elements known as neurons. These neurons consist of three principal components: dendrites, cell bodies and axons. The point of contact between an axon of one cell and a dendrite of another cell is called a synapse. The function of the neural network inside the brain is determined by a chemical process which includes the arrangements of neurones and the strength of individual synapses. For a human being, some of these neural structures are defined at birth and the rest develop as the person ages. Figure 4.1 shows a diagram of a biological neuron.

![Figure 4.1 Drawing of biological Neurons](image)
As mentioned earlier, artificial networks do not approach the same level of complexity as the biological neural networks in the human brain. The two main similarities between the biological and artificial neural networks are that the building blocks of both networks are simple computational devices that are highly connected and the connections between neurons determine the function of the network.

4.2.2 NEURON MODEL

4.2.2.1 Single Input Neuron

![Figure 4.2: Single input neuron](image)

Figure 4.2 presents a simple example of a single input neuron. In the diagram $p$ and 1 are inputs, $w$ represents a weight and $b$ represents a bias. The scalar input $p$ is multiplied by the scalar weight $w$ to form $wp$, which is one of the terms sends to the summer. The input 1 is multiplied by the bias $b$ and then it is passed on to the summer. The summer output, which is known as the net input, is passed in to the transfer function which is indicated by $f$. This transfer function then produces the scalar neuron output $a$. *(Hagan et al., 1996)*

The neuron output is calculated as Equation 4.1:

$$a = f(wp + b)$$

Equation 4.1
4.2.2.2 Multiple-input Neurons

In these sorts of models, a neuron typically has more than one input. A neuron with R inputs is depicted in Figure 4.3.

![Multiple-Input Neuron](image)

Figure 4.3: Multiple-Input Neuron

4.2.3 Transfer functions

Transfer functions are mathematical representations which are used to describe the inputs and outputs of the black box of an ANN model. A particular transfer function is chosen to satisfy some specification of the problem that the neuron is attempting to solve. A number of transfer functions have been utilized according to different models for different purposes depending on the results required. Of those, hard limit transfer functions, linear transfer functions and log sigmoid transfer functions are commonly utilized by researchers (Hagan et al., 1996).
4.2.3.1 Hard limit transfer function

In a hard limit transfer function such as that shown in Figure 4.4, if the input is less than zero then the output generated by that output will be zero. When the input is more than or equal to zero the output will be equal to one (Hagan et al., 1996).

\[ a = \text{hardlim}(n) \]

Figure 4.4: Hard Limit Transfer Function

4.2.3.2 Linear Transfer function

The output of a linear transfer function is equal to its input:

\[ a = n \]

This can be presented in a figure, an example of which is shown below in Figure 4.5.

\[ a = \text{purelin}(n) \]

Figure 4.5: Linear Transfer Function
4.2.3.3 Log-sigmoid transfer function

A log-sigmoid transfer function takes the input which has any value between negative infinity to positive infinity and compresses the output into the range 0 to 1. This can be expressed as shown in the Equation 4.2:

\[ a = \frac{1}{1 + e^{-n}} \]  

Equation 4.2

This is more commonly utilized in multilayer networks rather than single layer networks which are trained using the back-propagation algorithm (Hagan et al., 1996).

4.3 ANN Models

Two separate ANN models were developed for curve sections and straight sections in this research and in these two models two separate training methods were utilized. For the curve sections, the Levenberg-Marquadt training method was used while the Gradient Decent method was used for the straight sections. The main reason to utilise these two training methods is because they provided lower error figures on our curve and straight validation data sets respectively. Although the training methods are different in these two models all the other parameters, such as the training samples, testing samples and the number of inputs are identical in both models. In order to create these two models, the NN toolbox in MATLAB was utilized.

In order to improve the results of these two models, back propagation was utilized. Back propagation is a method used in ANNs to calculate the error contribution of each neuron after a set of data is processed. In the context of learning, back propagation is commonly used by the gradient descent optimization algorithm to adjust the weight of neurons by calculating the gradient of the loss function. This
technique is also sometimes called backward propagation of errors, because the error is calculated at the output and distributed back through the network layers.

Using these two separate models for the curve sections and the straight sections, the following outputs were created.

Figure 4.6: Observed and estimated values on 30% of the data for curve sections.
According to Figure 4.6 and Figure 4.7 it is clear that there is a major difference between the real and estimated gauge values for the curve sections and straight sections. Having a larger amount of data available for straight sections than curve sections with noisy data might have affected this fluctuation in range.

To demonstrate the accuracy of the ANN models, the observed values versus the estimated values for curve sections and straight sections are plotted in Figure 4.8 and Figure 4.9.
Figure 4.8: Real values versus estimated values for curve sections

Figure 4.9: Real values versus estimated values straight sections

Results of the ANN models for the curve sections and the straight sections are provided in Table 4.2.
As the results suggest, the ANN model produces better R square values for the straight sections than the curve sections.

### 4.4 Adaptive Network-based Fuzzy Inference System (ANFIS)

The ANFIS technique was originally presented by Jang in the early 1990s (Jang, 1993). ANFIS is a simple data learning technique that uses fuzzy logic to transform given inputs into a desired output through highly interconnected neural network processing elements and information connections, which are weighted to map the numerical inputs into an output. ANFIS combines the benefits of the two machine learning techniques (fuzzy logic and neural networks) into a single technique (Jang, 1993). An ANFIS works by applying neural network learning methods to tune the parameters of a fuzzy inference system (FIS). There are several features that enable ANFIS to achieve great success and some of these are mentioned below.

- It refines fuzzy IF-THEN rules to describe the behaviour of a complex system;
- It does not require prior human expertise;
- It is easy to implement;
- It enables fast and accurate learning;
- It offers desired data sets; greater choice of membership functions to use; strong generalization abilities; excellent explanation facilities through fuzzy rules; and

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Curves</th>
<th>Straights</th>
</tr>
</thead>
<tbody>
<tr>
<td>R square (R^2)</td>
<td>0.4587</td>
<td>0.5813</td>
</tr>
<tr>
<td>MSE</td>
<td>1.0054</td>
<td>2.9155</td>
</tr>
<tr>
<td>Total samples</td>
<td>3860</td>
<td>3860</td>
</tr>
<tr>
<td>Training samples</td>
<td>2700</td>
<td>2700</td>
</tr>
<tr>
<td>Testing samples</td>
<td>1160</td>
<td>1160</td>
</tr>
<tr>
<td>Number of inputs</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 4.2 Statistical parameters of ANN models.
• It is easy to incorporate both linguistic and numeric knowledge for problem solving.

4.4.1 Fuzzy Inference System

Fuzzy inference (reasoning) is the actual process of mapping from a given input to an output using fuzzy logic. This process involves membership functions, fuzzy logic operators and if-then rules. Fuzzy inference systems have been successfully applied in fields such as data classification and decision analysis.

4.4.2 Steps of Fuzzy Reasoning

The steps of fuzzy reasoning can be simply presented in three steps as shown in Figure 4.10 and they are:

• Comparing the input variables with the membership functions on the antecedent part to obtain the membership values of each linguistic label (fuzzification).
• Combining the membership values on the premise part to obtain the firing strength of each rule.
• Aggregating the qualified consequences to produce a crisp output. (defuzzyfication).

Figure 4.10  Steps of Fuzzy Reasoning
4.4.3 Fuzzy reasoning approaches

Two fuzzy reasoning approaches are widely used around the world and they are the Mamdani method and the Sugeno method.

4.4.3.1 Mamdani Method

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory. It was proposed in 1975 by Ebrahim Mamdani (Mamdani and Assilian, 1975) as an attempt to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. Mamdani's effort was based on Zadeh's paper on fuzzy algorithms for complex systems and decision processes (Zadeh, 1973). Although the inference process described in the next few sections differs somewhat from the methods described in the original paper, the basic idea is much the same.

4.4.3.2 Sugeno Method

This section discusses the Sugeno, or Takagi-Sugeno-Kang, method of fuzzy inference. Introduced in 1985 (Sugeno, 1985), this method is similar to the Mamdani method in many respects. The first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are the same. The main difference between the Mamdani and Sugeno methods is that the Sugeno output (Figure 4.11) membership functions are either linear or constant. The advantages in both methods are listed below (MathWorks, 1994-2018):

4.4.3.3 Advantages of the Sugeno Method

- It is computationally efficient.
- It works well with linear techniques (e.g., PID control).
- It works well with optimization and adaptive techniques.
- It has guaranteed continuity of the output surface.
- It is well suited to mathematical analysis.
4.4.3.4 Advantages of the Mamdani Method

- It is intuitive.
- It has widespread acceptance.
- It is well suited to human input.

Figure 4.11: Differences in outputs between Mamdani and Sugeno methods

In the present research, the Sugeno method was utilized and the membership functions used for curves and straight sections are shown in Figure 4.12 and Figure 4.13, respectively.
Figure 4.12: Membership function of antecedents for Gauge values and MGT for curves

Figure 4.13: Membership function of antecedents for Gauge values and MGT for Straight sections
The number of membership functions and their shape are selected to have the least mean squared error (MSE) on the training data. The trained system is then tested on the test data and the observed values and the predicted values are compared, as shown in Figure 4.14 and Figure 4.15.

Figure 4.14: Observed and predicted values on 30% of data for curve sections.

Figure 4.15: Observed and predicted values on 30% of data for straight sections.
As Figure 4.15 shows, straight sections are responsible for more frequent and violent fluctuations in comparison to curves. To unveil the key reason, it should be considered that switches and bridges which are more in danger of degradation are mostly quantified as straight sections. The spikes in both graphs reach a height of 14 mm in some samples. This occurrence of less frequent spikes could be explained as possibly the result of noisy data in the curve sections, but this would not be a valid argument to explain the straight sections data since the spikes in that graph are more frequent. This high decay in gauge of the straight sections could be due to several reasons. It could be due to sub-classes of the straight sections that are eventually categorized as straight sections. These sections tend to suffer greater degradation in gauge than the other sections of the track. As a result, this increase the overall gauge degradation in the straight sections. For the maintenance purposes it will be helpful to separate the different straight sections which does not require regular inspections from the ones that require regular inspections. This separation will help to prioritise the maintenance work and allocate the resources for those which need the most attention. By staying ahead of maintenance planning and execution it will cut down extra costs and interruptions to the services. Table 4.3 shows the means and standard deviations of the two different sections.

Table 4.3: Mean and Standard deviation for curves and straights section.

<table>
<thead>
<tr>
<th></th>
<th>Curves</th>
<th>Straights</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma_{rd})</td>
<td>1.3579</td>
<td>2.8207</td>
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<tr>
<td>(\sigma_{ed})</td>
<td>0.9766</td>
<td>2.4594</td>
</tr>
<tr>
<td>(\mu_{rd})</td>
<td>3.5320</td>
<td>3.9185</td>
</tr>
<tr>
<td>(\mu_{ed})</td>
<td>3.6160</td>
<td>4.0932</td>
</tr>
</tbody>
</table>

(*Real data is abbreviated as \(rd\) and estimated data is \(ed\))

The above table indicates the means and standard deviations for the real and predicted gauge values for curves and straights and it clearly shows massive differences in standard deviations between curve data and straight data in both real and predicted values. The numbers clearly demonstrate the nature of both different sections in tram
tracks. For instance, the values for the standard deviation in curves and straights, which are 1.36 and 2.82 respectively, indicate that the deviation in the gauge values is greater in straight sections. In addition, their mean values of 3.53 and 3.92 for curves and straights indicate that the straight sections face higher gauge values. Based on both means and standard deviations it appears that higher gauge values are more common in straight sections which therefore need to have more frequent inspections.

To show the accuracy of the model, observed values versus the estimated values are plotted in Figure 4.16 and Figure 4.17. As this figure shows, the curve data may contain a few outliers which can be seen on the top right corner of the curve graph. In the graphical presentations provided in Figure 4.16 and Figure 4.17, it is visible that the model has predicted these outliers accurately, given that they appear quite close to the regression line.

Figure 4.16: Real values versus estimated values for curve sections
Moreover, Figure 4.16 and Figure 4.17 depict that the concentration of the gauge values lies within 0 to 5 in both graphs, while for the straight sections there is a considerable spread in gauge values from 5 to 10. This indicates a higher probability of degradation on straight sections than on curves.

The R² value for the curve model is 0.60 while that of the straight model is around 0.78. Considering both the above figures and the values of R², it is clear that the system is able to predict the values with a high accuracy.
Table 4.4  Statistical parameters of ANFIS model

<table>
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<th>Criteria</th>
<th>Curves</th>
<th>Straights</th>
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<tr>
<td>R squared ($R^2$)</td>
<td>0.6001</td>
<td>0.7808</td>
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<tr>
<td>MSE</td>
<td>0.7350</td>
<td>1.7335</td>
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<tr>
<td>Total Samples</td>
<td>3860</td>
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<tr>
<td>Training Samples</td>
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</tr>
<tr>
<td>Number of inputs</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

As the above table indicates, 3,860 observations were used to train and test ANFIS models for predicting the gauge values for curves and straight sections. Despite the fact that the model for straight sections shows a better $R^2$ value, the MSE has increased form curve sections to straight sections. This is possibly due to the fact that the straight section data are spread more than the curve data, as shown in Figure 4.16 and Figure 4.17.

4.5 Summary

This chapter provided an introduction to the ANFIS and ANN. It discussed the history and the origin of both ANFIS and ANN. It described the basic method of operations of these models and why we utilised these models in the present research. Finally, it presents the outputs and results of these models. Based on the results presented it was convinced that for this type of prediction models, ANFIS provides a better result than ANN under the given circumstances but how ever there is still more room to explore and some of these avenues which could be conducted as the future research will be discussed in the next chapter.
Chapter 5 Conclusion and Future Research

5.1 Conclusion

In recent decades, transport organizations have shifted their focus from construction and expansion of the transport infrastructure to how to intelligently maintain it. In order to do so, it requires a thorough understanding of the behaviour of the system. That is the reason why organizations responsible for maintaining and running tram networks such as Yarra Trams have directed their focus to understanding the processes of rail track degradation. This has taken place due to many reasons such as budget restrictions and the lack of land space. Predicting the maintenance work accurately by identifying the defects of the track due to degradation as early as possible and carrying out maintenance work on time could help to cut unnecessary costs related to track failure, damage to the rolling assets and labour.

Many researchers around the globe have presented a number of different types of degradation prediction models and most of these models have been 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 necessary to develop a model which is capable of predicting the degradation of light rail tracks. That is the main reason and the key foundation of the present research.

5.2 Research contribution

It is crucial for maintenance authorities to have extensive knowledge of how light rail tracks degrade over time according to different influencing factors, in order to decrease the amount of money that needs to be expended on maintenance. The present study helps by focusing on the development of an artificial intelligence model in order to predict degradation of tram tracks. These model predictions possess the ability to use the data collected for MGT and gauge values in previous years and predict the degradation value for future years. The research presents two different types of models: ANFIS and ANN. ANFIS model is the primary model and ANN models were used to compare the strengths of the predictions. The contributions of the present
research can be summarised as follows:

- The literature has identified the current models which exist in rail track degradation and the parameters which are related to track degradation. The thorough literature review also identified that there is a lack of models for light rail track degradation prediction compared to heavy rail track degradation prediction.

- In the model development stage relevant data was gathered on the Melbourne tram network data between 2010 to 2015 via Yarra Trams. Then software such as ArcGIS was used to extract the necessary data for analysis. During this stage SPSS and MATLAB software were used to analyse and identify the trends of degradation related to gauge values (measured in mm) and total annual loadings measured by MGTs. Then the data were used to develop an Adoptive Network-based Fuzzy Inference System to predict one step-ahead predictions of the future gauge values. In simpler terms, this model was then capable of predicting the future degradation values one year at a time. The ANFIS model developed in this research was 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 coming year by the R-squared value of 0.60 and 0.78 for the curves and straight sections. This model could be utilized to predict the degradation for 2016 onwards and the maintenance work could be scheduled according to the predictions. Another ANN model was then developed as a secondary model, which was utilised to compare the accuracy of the main ANFIS model.

5.3 Future research

- In future research it would be possible to include different types of parameters and adopt a different type of model approach. The present research utilized only two parameters: MGTs and gauge values. This was due to the noisy nature of the data and missing data. However, with the appropriate data set it would be possible to use other parameters, including independent variables such as speed and curve radii and dependent variables such as twist to improve the accuracy of this type of model.
• In future research, it would be possible to consider incorporating other functors to build a model for rail track degradation prediction. In this research for the ANFIS and ANN models MGT and gauge values have been used but, in the future, it is possible to use more factors such as twist to measure rail degradation.

• It is possible to explore the relationship between human factors and rail degradation. We can incorporate the correlation between human behaviour in this case particularly driver behaviour and how it affects rail degradation. For example, when drivers drive their trams in an on and off manner just like car drivers where they use rapid acceleration and heavy braking instead of gradual acceleration and gradual braking, this causes the wheels and the rails to wear out more quickly. This also has serious effects on other mechanical components such as the brakes of the tram. In future research it is possible to consider these factors as external factors that affect rail degradation and incorporate them in future models. It is possible to develop a non-linear constant to use in the models as a correction factor and thereby improve the model prediction.

• Research could be conducted on how rail degradation affects the safety of the carriages and the passengers, since rail failure due to degradation and safety issues which could arise for carriages and passengers are inter-connected. Safety of the assets and the commuters are a priority in any form of transportation services. In the rail industry this is the most important priority and managers are always looking to improve it. Therefore, it will be a great contribution to the future if it is possible to explore the effect of rail track degradation related to the safety of the carriages and commuters.

• Further research could be conducted on other important sections of the rail track such as H crossings and cross overs. These different sections have different wear patterns and identifying them and modelling their degradation will help to broaden knowledge of how maintenance should be performed and what sections should become the priorities of the track. Covering all the sections will help to develop a model or multiple model which can be applied universally to optimise maintenance work.
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Rail ware cross section


