An empirical rail track degradation model based on predictive analysis of rail profile and track geometry

AN EMPIRICAL RAIL TRACK DEGRADATION MODEL BASED ON PREDICTIVE ANALYSIS OF RAIL PROFILE AND TRACK GEOMETRY

by

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Abstract

It is generally observed that the condition of rail tracks degrades rapidly over time until and unless effective maintenance is carried out. In the rail industry, rail maintenance actions are usually reactive, which means that maintenance is carried out after a defect has been identified. Unfortunately, this approach can lead to general safety concerns and may result in costly maintenance. Predictive maintenance, which aims to predict the future behaviour of track degradation based on the analysis of already recorded data, can be used to identify defects in advance, thus providing a solution for the above safety and cost concerns.

Two important questions for which answers are sought in predictive maintenance of rail track are: where does the fault occur and when. The aim of the research presented in this thesis is to develop a novel predictive rail track degradation model that answers the above questions. The proposed model consists of an alignment component for effective alignment of data and a degradation component for understanding rail track degradation based on rail profile and track geometry parametric analysis.

The thesis takes an incremental approach to data alignment proposing three different algorithms namely, distance alignment, fixed window based alignment and parameter based alignment. It is proven that the latter approach provides the most accurate data alignment algorithm.

The degradation component of the proposed model is based on a comprehensive multivariate and univariate analysis. In multivariate analysis, parameters of a base file i.e. a file consisting of parameters belonging to the same segment of the rail track at a given time of measurement are predicted using all other parameters of the same file. In univariate analysis, every parameter of a given base file is predicted, temporally, from the corresponding parameters in the previous base files. Such contribution analysis manifests the level to which each parameter contributes in predicting other parameters and over time. Subsequent to univariate and

multivariate analysis the predictive errors are thresholded into either exceedences i.e. they exceed the threshold line, needing immediate maintenance, or normal i.e. they are below the threshold line, needing no immediate maintenance.

The research presented in this thesis shows that in multivariate analysis, rail profile parameters were predicted with 97% prediction accuracy below threshold, whereas track geometry parameters were predicted with 99% prediction accuracy below threshold. Both univariate and multivariate analysis will serve as the basis in monitoring track conditions and thus finding track degradation problems. This will greatly aid in planning predictive track degradation by providing an objective means of evaluating track conditions and hence the over all life of the rail track will increase.

Dedicated to,
My Father Faiz Muhammad and
My mother Naseem Akhtar,
For their,
Inspiration,
Scarifies,
Love

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Research Publications

Journal Papers

1. Faiz, R., Edirisinghe, E., "Decision Making for Predictive Maintenance in Asset Information Management", Interdisciplinary Journal of Information, Knowledge and Management, Volume 4, pages 23-36, ISSN 1555-1237, 2009.
2. Faiz, R., Singh, S., "Information Analysis of Rail Track for Predictive Maintenance", WSEAS Transactions on Computers Volume 8, Issue 7, Pages: 1123-1133, ISSN: 1109-2750, 2009.

Conference Papers

1. Faiz, R., Singh, S., "Time Based Information Analysis of UK Rail Track", IEEE International Conference of Computing in Engineering, Science and Information, pp 200-209, ICC 2009.
2. Faiz, R., Singh, S., "Condition Monitoring of Track Geometry in UK Rail", IEEE International Conference of Computing in Engineering, Science and Information, pp 182-190, ICC 2009.
3. Faiz, R., Singh, S., "Time Based Predictive Maintenance Management of UK Rail Track", IEEE International Conference of Computing in Engineering, Science and Information, pp 376-383, ICC 2009.
4. Faiz, R., Singh, S., "Predictive Maintenance Management of Rail Profile in UK Rail", IEEE International Conference of Computing in Engineering, Science and Information, pp 370-375, ICC 2009.
5. Faiz, R., Singh, S., "Rail Profile Condition Monitoring Information Analysis of UK Rail Track", IEEE International Conference of Computing in Engineering, Science and Information, pp 191-199, ICC 2009.
6. Faiz, R., Singh, S., "Predictive Maintenance Management of Rail Track", Proceedings of the 3rd International Conference on European Computing Conference**,** Tbilisi, Georgia, ISSN: 1790-5117, ISBN: 978-960-474-088-8, Pages: 35-40, 2009.

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List of Acronyms

TG..Track Geometry

ALIGMS..Mean of Alignment using Short chord

ALIGML..Mean of Alignment using Long chord

TOPML...Mean of Top using Long chord

TOPRS..Top Right with Small chord

TOPLS..Top Left with Small chord

CURV...Curvature

CANTDEF...Cant Deficiency

RP..Rail Profile

GSW..GAUGE Side Wear

FSW...Field Side Wear

HW...Head Width

HWR..Head Width Remaining

VW...Vertical Wear

ERD..Estimated Rail Depth

FP..Fish Plate Clearance

ID...Inclination Deviation

Chapter 1

Introduction

This chapter introduces the key problem addressed by the research presented in this thesis and provides an overview of the proposed solution. It also further highlights the novel contributions made by the thesis.

1.1. Research Problem

When a train runs on a track, the train, which is a dynamic structure, interacts with the track, which is yet another dynamic structure. Specifically, dynamic effects in the compound structures, i.e. train and track, become more evident when the train speed increases and loads get heavier. Oscillations and vibrations of the train/track system then induce increased track degradation thus resulting in decreased passenger comfort and increased rail safety concerns. When a rail track is loaded by the weight of the train superimposed by high frequency load variations, it undergoes small non-elastic deformations. Thus when unloaded, the track will not return to its original shape/orientation but to a position very close to the original. After many passages of trains on a rail-track, all small non-elastic deformations will add up, differently in different parts of the track to give a new track position. This will result in degradation of various track geometry related features such as track alignment and track level, over time. Depending on the sub ground (the part of the track which lies beneath the ground) the wavelength of these track irregularities will be of the order of hundreds of metres. The uneven track will induce low frequency wavering of the train. Thus, the track load variations will increase which will adversely affect rail profile and track geometry.

Generally, rail track maintenance is a difficult task, which is highly dependent on the knowledge of rail track condition. Rail tracks degrade over time and faults are developed due to rail traffic carrying heavy loads, aging, external forces and being subject to adverse weather changes. After being used for some time, rail tracks will not be straight and level as they were when new, thus resulting in track degradation [1]. The degradation of track is further explained through the rail profile i.e. the shape of the rail and track geometry, looking at the track in three dimensions (3D). The changes in rail profile and track geometry parameters caused by the repeated traffic loading and the severity of the damage depends on the quality and the behaviour of the ballast (crushed stones over the ground), the sub-ballast (crushed stones underground), and the sub grade. There is a more or less linear relationship between track degradation and frequency of loaded trains, in which case change in track parameters will be slower.

1.2. Research Motivation

A rail track exposed to train traffic will degrade which will change track alignment and track level. The loss of track level and alignment can be restored by appropriate maintenance. Reasons for loss of track level and alignment are difficult to ascertain and are often a result of experience judgements and analogy [1]. Often, some parts of a track are more prone to degradation than other parts of the same track. One of the most important railway engineering tasks is effective and robust condition monitoring, as track degradation problems can have a serious effect on the safety of train operations. In order to determine an effective condition monitoring strategy it is necessary to analyse the rail profile and track geometry.

In the rail industry, rail companies spend substantial amount of money for rail track maintenance. For example Network Rail is planning to reduce rail track maintenance cost from 705 in 2009/10 to 640 in 2013/14 million pounds [2]. The rail company who was the client for this project had similar objectives and thus was interested in investigating possibilities of cost saving. One way is to have effective and pragmatic rail track degradation models through which the track degradation process can be predicted. Such predictive track degradation models will result in key benefits like:

1. An increase in track quality will result in increased reliability.
2. Longer track life would result in better punctuality of trains and, therefore, less emergency interventions.
3. Better planning for rail track possessions will reduce the cost of rail track maintenance.

1.3. Aims and Objectives

Mentioned below are the aims and objectives of the research presented in this thesis:

1.3.1. Aim

Develop a novel rail track degradation model based on predictive analysis of rail track parameters. Such a pragmatic model is essential for effective and efficient rail track maintenance.

1.3.2. Hypothesis

Comprehensive predictive analysis of the rail track can lead to better maintenance and thus reducing effort and time consumed in overall rail track maintenance.

1.3.3. Objectives

1. To conduct a thorough literature review in order to determine what has been published on predictive maintenance of rail tracks and what models have been proposed for rail track degradation. This will lead to the understanding of research gaps that can be investigated within the scope of the research presented in this thesis. The scope of the literature review is extended to

explore rail profile and track geometry parameters in order to develop their comprehensive understanding to facilitate predictive analysis in rail track degradation.

2. To develop a data alignment method for both modalities i.e. rail profile and track geometry as data alignment is a pre processing step for all further predictive analysis, which will assist in track maintenance.

3. To conduct predictive analysis of rail profile and track geometry parameters which will serve as basis for a degradation model.

4. To develop a novel rail track degradation model based on the comprehensive predictive analysis for effective and efficient condition monitoring of rail tracks.

1.4. Methodology

The proposed model combines a data alignment component as a pre processing stage and a subsequent degradation component for analysing the rail track degradation process based on the detailed analysis of rail profile and track geometry parameters.

Due to time constraints, data analysis was restricted to univariate and multivariate analysis. As all parameter data were statistical in nature the univariate and multivariate analysis tools within the popular statistical data analysis tool, SPSS was used in the experimentation.

Data alignment i.e. the requirement that all parameter data should belong exactly to the same location of the track over time is essential for any further analysis. Thus the most apparent way of aligning, all four base files i.e. an excel file having parameter data of both modalities is to align as per Mile and Yard information i.e.

distance alignment. However a univariate correlation analysis performed subsequently revealed negative correlation of some parameters in both modalities, proving this alignment approach to be ineffective. Further analysis revealed that this was due to inaccuracy of the Global Positioning System (GPS) information recorded. As an alternative solution, a fixed window approach to data alignment was proposed. The subsequent predictive analysis revealed better prediction results as compared to the previous approach but its inability to pinpoint the exact location on the track where maintenance is required, made it practically ineffective. Appreciating the inaccuracies of the recorded track locations and excessive data processing required in both distance and fixed window based alignment approaches, a parameter based data alignment method is finally proposed, which addresses all limitations of the previously proposed alignment methods.

The rail track degradation analysis component is responsible for both predictive maintenance of rail tracks through univariate analysis and detecting signs of track degradation through multivariate analysis. It is based on comprehensive multivariate and univariate data analysis. Multivariate predictive analysis investigates the signs of degradation before critical rail track failures can occur. The predictive error calculated in both univariate and multivariate analysis is subsequently threshold for either being excessive or normal in terms of the track component life degradation process. The degradation component will help the model to raise a timely alarm in the rail track maintenance process by monitoring the exceedence values of track modalities, through multivariate predictive analysis, as a possible sign of track degradation.

The univariate predictive error analysis serves as a basis for predictive maintenance via the use of both rail track modalities. The predictive error in both univariate and multivariate predictive analysis is ultimately thresholded according to rail industry standards and exceedences in all parameters of both modalities are calculated. The proposed model explores track degradation by looking at the exceedences of parameter values. It manifests the level to which each parameter contributes in predicting other parameters through predictive multivariate analysis and proves that the latest parameter values, in base files, are most appropriate for predictive analysis through univariate analysis.

1.5. Thesis Contributions

Following are the significant research contributions made by the research presented in this thesis [Note - the references quoted are the conference and journal papers that resulted from the work presented in this thesis.]:

1. A comprehensive time and parameter based correlation analysis that will help in the behavioural understanding of rail profile and track geometry parameters [3].

2. Proposal of a data alignment approach based on distance alignment, which works as a pre-processing stage to the track degradation model [4], [5], [6], [7]. The negative correlation figures obtained for parameters lead to making an informed judgement that the original GPS data recordings have not been precise and hence this approach will not result in a pragmatic solution for track maintenance [8], [9].

3. Proposal of a fixed window based data alignment method to overcome the inaccurate recording of GPS information and the reduction of excessive information loss in distance alignment. This approach increased the accuracy of subsequent prediction as compared to the use of the distance based approach by pointing to 10 yard segments of the track. However more precise predictions were not possible and thus one tenth of the information was lost in the process of alignment.

4. Proposal of a parameter based alignment method as a pre processing component of the track degradation model to overcome the short comings of the distance and window based alignment approaches. Through such alignment,

the exact location on the track is not highlighted but it did not lose any parameter information in the process of alignment, and thus made it possible to have further predictive analysis.

5. Proposal of a univariate data analysis approach that leads to predictive maintenance of rail tracks and a multivariate data analysis approach which highlights signs of degradation in rail tracks. The multivariate analysis manifests the level to which each parameter contributes in predicting other parameters. The predictive error in both univariate and multivariate predictive analysis is then thresholded according to rail industry standards, and exceedences in all parameters of both modalities are calculated, providing valuable input for predictive maintenance.

6. Proposal of a novel rail track degradation model by combining pre processing component analysis, which is responsible for effective data alignment, and degradation component analysis, which is based on a comprehensive multivariate and univariate predictive data analysis of rail profile and track geometry parameters.

1.6. Thesis Organization

For clarity of presentation the thesis is organized into several chapters as follows:

Chapter 1 presents an overview of the thesis by defining the key problems addressed in the thesis and motivation behind the solutions proposed. In particular, it explains the aims and objectives of the research and the methodology followed in reaching a solution to the research questions/problems. Finally, it provides a summary of the main research contributions of the thesis.

Chapter 2 presents the definitions of track modalities, namely, rail profile and track geometry. This chapter further explains each modality through illustrative explanation of parameters that are used in the rail industry to define them. It further provides information on the general practical approaches currently used by the rail industry in maintaining rail profile and track geometry.

Chapter 3 presents a literature review of track maintenance via the use of condition monitoring. It presents and reviews various track degradation models proposed in the literature.

Chapter 4 presents a distance based, alignment method which is essential for any further analysis of data for predictive maintenance. After alignment, the parameters of each modality are explored through correlation analysis.

Chapter 5 presents an attempt to solve the constraints of the distance alignment based approach by the use of a fixed window based data alignment method, based on which univariate and multivariate predictive analysis is explained.

Chapter 6 provides a parameter based data alignment method addressing the shortcomings of the distance and fixed window based data alignment approaches. After setting the foundations, through the use of this parameter based alignment method, an effective univariate and multivariate predictive analysis is presented in detail.

Chapter 7 after effective univariate and multivariate predictive analysis of rail profile and track geometry parameters, a novel degradation model is proposed which looks at signs of degradation through multivariate predictive analysis and contributes to predictive maintenance through univariate analysis of rail track parameters.

Chapter 8 concludes the research, emphasising the novelty of the work presented in the thesis. It further highlights the scope for future research.

Chapter 2

Rail Profile and Track Geometry

The novel degradation model is based on the predictive analysis of both rail profile and track geometry. Therefore, this chapter thoroughly investigates both modalities by exploring their parameters (set of features) so as to provide the basis for an upcoming predictive analysis.

2.1. Introduction

As railroad productivity increases at a faster rate than most other industries, there is a greater emphasis on modelling several operations of quality and service [20]. With safety as a dominant factor, various degradation models are employed to ensure optimum track conditions at all times. There are always irregularities and the amplitude of the irregularities varies strongly. It is highly unlikely to have a perfectly smooth rail track as rail roughness with a broad spectrum of wavelengths is always present on the running surfaces of the rails [10].

In order to cope with track degradation problems, as they can have serious impact on the safety of train operations, track needs to be maintained. Maintenance of accurate rail profile and track geometry is vital for reducing rail track degradation and failures. Track geometry is fundamental for the safe passage of vehicles as any failure may result in disastrous consequences, so both track modalities need to be thoroughly investigated. This chapter explores the literature on the parameters i.e. set of features for both modalities in detail.

2.2. Rail Profile

A rail is a rolled shaped longitudinal steel bar laid from one end to other in two parallel lines on sleepers to form a track which directly guides the train wheels evenly and continuously. They can be viewed as the vital part of the rail track, as it absorbs all vertical and lateral forces. Rail profile has been the object of continuous improvement since the emergence of railways. Over centuries rail profiles have undergone many changes in their shape and structure, finally resulting into today's standard shape of flat bottom or vignoles type.

The subject of determining the proper profile of the rail has long been a controversy [10]. Due to this reason rail has been the subject of discussion and improvement since the appearance of railways. The choice of rail profile is dependent on traffic load and expected life time. The current rail profile consists of the head, the web and the base or foot as shown in figure 2.1. This shape in the context of stability is not only advantageous but also favourable. The top flange is ideal for vehicles to run on, while the bottom flange enables the rail to be installed and secured very well.

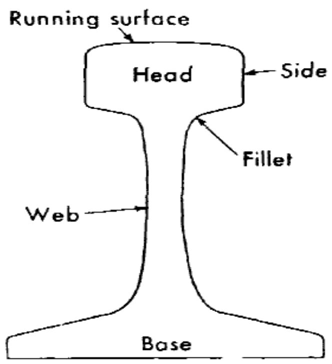

Figure 2.1 Profile of Rail [32]

The rail profile is usually recorded manually using a steel GAUGE. In order to best monitor the condition of rail profile, it is viewed by cameras and a laser, on both sides and web of rail profile separately, which ultimately helps to obtain an in-depth rail profile analysis. During this exercise, as cameras take the view of only the top head and web, the fillet portion is always shadowed (out of view).

The profile or vertical surface profile is defined in figure 2.2 as the average height of the two rails. The left and right profiles are the vertical height of the left and right rails. The profile is defined as the vertical deviation of the midpoint of the two rails from the track's nominal elevation. Using the correct sign conventions, a positive deviation in a profile refers to an upward vertical deviation of the track, and a negative deviation in profile represents a downward vertical deviation of the track.

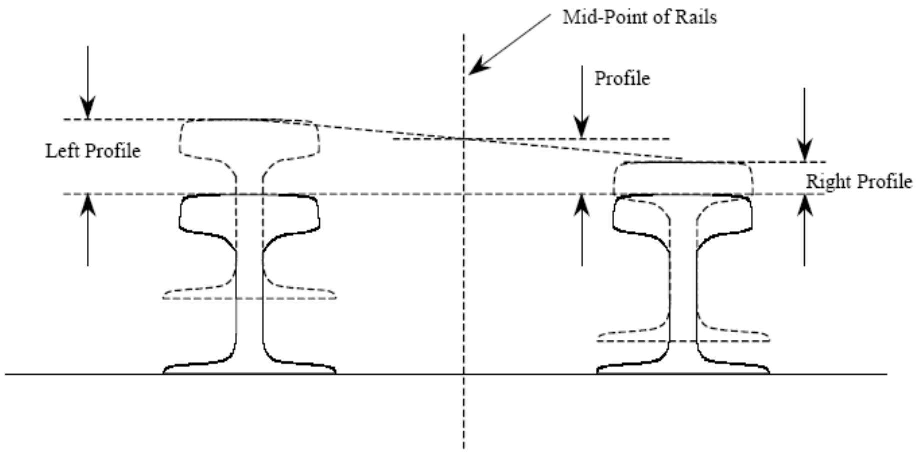

Figure 2.2 Vertical Surface of Rail Profile [31]

Parameters to be taken into account are [11]:

1. Speed
2. Axle load
3. Traffic on the track
4. Sleepers spacing
5. Life time and eventual reuse

Rail defects and joints can cause large impact loads to be transmitted to components below the substructure. Fasteners hold the rails firmly on the sleepers and resist forces in all directions.

2.2.1. Types of Rail Profile Maintenance

Track degradation is primarily dependent on two track modalities i.e. rail profile and track geometry. The rail profile makes a large contribution to the process of track degradation. The subject of determining the proper profile to use with either the wheel or rail has long been a matter of controversy [20]. Rail wear and plastic degradation are the main contributors to the changing rail profile. This has a dramatic impact on other track parameters and their maintenance. Some common ways of maintaining rail profile are:

2.2.1.1. Rail Grinding

Abnormalities in rail track geometry can give rise to very high dynamic loads. These abnormalities can either be a result of manufacture imperfections, generally known as rolling defects, or occur during operation in which case they are classified as corrugations.

Rail corrugation is plastic deformation which adversely affects passenger comfort and results in noise and fatigue. Corrugation is developed as a result of rail/wheel interaction which affects the linkage conditions across the contact area under heavy traffic conditions and it varies in wavelength. One answer to the corrugation problem is surface defect maintenance or rail grinding. Rail grinding is the process to maintain a predetermined rail profile to maximise rail life and minimise rolling resistance. This will reduce wear and corrugation in the rails. Through rail grinding the rail profile is restored thus maintaining a suitable rail profile over a long period of time, as a result of which the vehicles stability is increased and corrugation and wheel rail noise is reduced [12].

2.2.1.2. Lubrication of Rails

Wear being a consequence of friction between wheel and rail, makes lubrication a crucial requirement for the cost efficient operation of rail track. Wear in the rail reduces rail life in most cases as a dry rail wears at a significantly higher rate than a lubricated rail therefore lubrication is used to reduce the friction and wear. Experiments have shown that proper lubrication can reduce both rail and wheel wear 10 to 15 times in a 400 meters curve radius and 2 to 5 times in a 600 meter curve radius [13]. This will lead to significant cost savings for rail infrastructure over time.

2.2.1.3. Rail Transposition

As most trains cannot lean (or tilt) into curves to counteract the centrifugal (G) force, the track is canted (one rail raised above the other) into the curve so that the forces are at equilibrium at the maximum line speed. The difference between heights of two rails on a curve is called the track cant.

Transposition is generally carried on tight curves where rail profile wear on the higher rail is the main cause of rail replacement. During this process the higher rail is changed to the low rail of the curve. Rail transposition requires rail grinding as the rail profile of transposed curves gives tight contacts, high contact stresses and less lubrication. Transposed curves that are not profiled would wear at higher rates over time.

2.2.1.4. Rail Straightening

Even if the rail ends of mechanical joints are cropped before rail welding, a certain amount of rail is not aligned properly. This non alignment can also be consequence of surface welding to restore the rail profile. Rail fatigue cracking or corner GAUGE cracking is chiefly caused by variety of stress concentration due to corrosion and mechanical damage, because of rail defects. This will ultimately result in rail cracking [14]. In order to answer such problems the rail needs to be corrected. Rail straightening is the process of removing kinks by stretching the joint of the track. It is commonly performed on previously mechanically jointed track that were upgraded by rail welding.

2.2.2. Rail Profile Parameters

In order to achieve part of the first objective of this research, all rail profile parameters need to be explored in detail to facilitate any further analysis. Rails guide trains and distribute wheel loads, minimizing the phenomena of deflection. Practices have evolved and become common in monitoring the rail profile and keeping it in conformance with researched profiles that offer maximum rail life. However, preventative measures to maintain the accepted profile have not been widely adopted [15]. Rail defects are the most critical defects that affect the safety of train operations. Such critical rail defects can affect the structural integrity of the rail or the safety of the train operations. All parameters explained below are as described in the interviews conducted with rail engineers [17]:

2.2.2.1. GAUGE Side Wear

GAUGE Side Wear is the amount to which rail has worn from standard GAUGE Sides as explained in Figure 2.3. It is the lateral wear on GAUGE face from original template measured 14mm below the crown of the rail.

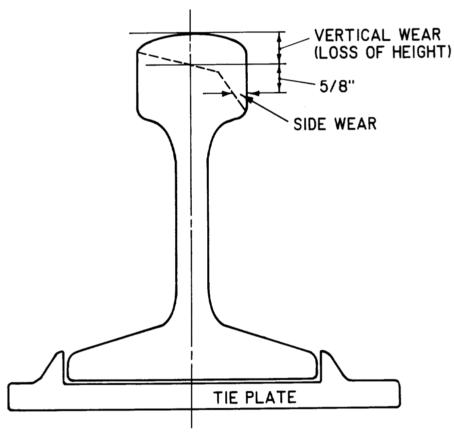

Figure 2.3 Rail Profile Cross Sectional View [32]

2.2.2.2. Field Side Wear

Rail wear can be on either the inner or the outer side of the rail. Rail wear measurements on the inner sides i.e. GAUGE sides of the rail is GAUGE Side Wear. Field Side Wear is the wear measurements on outer side of rail, measured 14mm below the crown of rail as shown in figure 2.4.

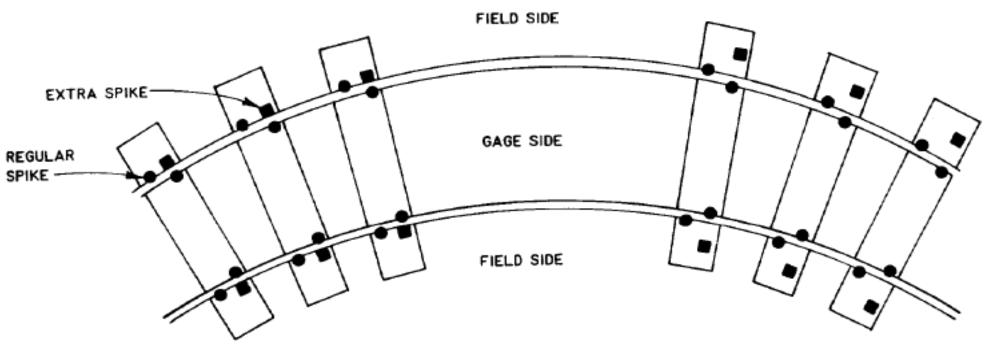

Figure 2.4 GAUGE and Field Side Wear [32]

2.2.2.3. Vertical Wear

Rail wear measurements also consist of a vertical head wear measurement. Vertical head wear is the amount to which rail has worn vertically from the standard as shown in figure 2.3.

2.2.2.4. Head Width

Head Width is the total width of the head which is the running surface, as shown in figure 2.1.

2.2.2.5. Head Width Remaining

The life of a rail is determined by the head loss limit, which is a relative measure of the ratio of a worn rail head to that of a new rail head. So Head Width Remaining is the limit to which the head of the rail can wear.

2.2.2.6. Estimated Rail Depth

Estimated Rail Depth is the amount to which the rail has worn vertically (from base till head) from standard. It is the original, as new, rail height at the centreline minus the existing Vertical Wear.

2.2.2.7. Fish Plate Clearance

The frequent running of trains on a rail track may result in head and side wear of the rail from standard, as a result of which the rail wheel gets closer to the Fish Plate. To avoid the rail wheel coming close to the Fish Plate, this rail wheel has to be kept at a minimum distance from the Fish Plate known as the Fish Plate Clearance. The Fish Plate Clearance is the minimum rail depth allowable accounting for GAUGE Side Wear to prevent wheel strikes on the Fish Plates. Its calculation is specific to different rail weights.

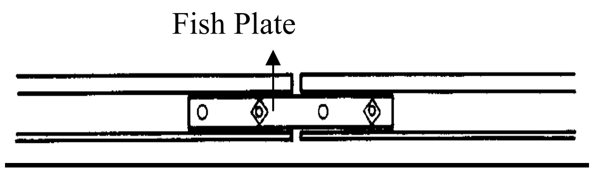

Figure 2.5 Fish Plate [32]

2.2.2.8. Inclination Deviation

Inclination Deviation is the angle between absolute vertical positions of rail and the inclined position to which both rail are inclined towards each other.

2.2.2.9. Lip width

Traction and braking forces in the longitudinal movement of rail will result in plastic deformation (accumulation of metal) of the rail head which is the running surface [18]. Such rail wear is one of the most important factors causing re-profiling and replacement reduction of the rail track component life cycle. This worn rail results in substantial part of railway systems operating costs [19].

2.2.3. Rail Profile Literature

After exploring rail profile parameters it important to explore how are they analysed in literature. A number of methods have been proposed which monitor the rail profile and compare it with theoretical profiles that offer maximum rail life. One among them is an automatic wheel inspection system which was proposed by Brekke [20] which can operate in a dynamic environment for monitoring freight car wheels flange height, flange thickness, rim thickness, diameter, and angle of attack. Such a comprehensive wheel examination system does more than simply increase efficiency. It contributes to an improved wheel maintenance program through increased accuracy and enhanced information assessment as extended wheel life and reduced track maintenance generate substantial business benefits.

The geometry of the interface between steel wheels and steel rails can create conditions which affect the dynamics of a vehicle, and lead to rail and wheel corrugation and noise. It is usually expected that the worn profile of the wheel is uncontrollable and must be regularly corrected. Due to the unique dynamics that exist between the rail and wheel, rail vehicle dynamics are often difficult to model accurately. There has been number of models describing wheel/rail relationship in different contexts. One among such was proposed by Smith and Kalousek [21] which was a design technique for a wheel-rail system to be created to suit steered axle vehicles. Such a system will reduce maintenance costs by being almost self-perpetuating and will reduce the incidence of certain kinds of wheel and rail corrugation. It enables wheel and rail profiles when used on steered axle vehicles to generate little noise and greatly reduce corrugation.

The interaction between wheel and rail remains a systemic problem that cannot be disassociated with the behaviour of the vehicle on the track. Therefore it is suggested that, as a consequence rail contact stress there is decrease in service life of the wheel resulting and in the vehicle stability which results in wheel and rail fatigue problems [22]. Consequently, the prediction of wear on wheel and rail becomes increasingly important in determining system performance as a function of system design parameters such as the track GAUGE, wheel set tolerances, and profile shapes for a given track topology. Among different contact systems, much work has been done in wear regime. The wear regime is primarily associated with tight curvature and not necessarily associated with extremes of axle load as it is present under light axle load conditions in, for example, trams and commuter operations. It however seems that the stress regime is less understood. The stress regime is primarily associated with straight track and results in greater changes in contact shape and contact stress than those associated with the wear regime [22].

Numerical procedures for reliable wheel and rail wear prediction are infrequent having no universal rail profile wear mechanism nor is there any simple correlation between rail profile and friction coefficient [23]. Such a tool would be useful in maintenance management and optimisation of the transport system and its components. The simulation techniques and computer power together with tribological knowledge developed by Roger [24] do, however, suggest computer aided rail profile wear prediction. The author explains a numerical procedure to simulate profile evolution due to uniform wear to a degree of accuracy sufficient for application to vehicle dynamics simulation.

While many railway engineers are exploring the benefits of the latest lubrication technologies, bogie types and metallurgies, the wheel and rail contact mechanics are often overlooked or poorly controlled. The geometry of the wheel and rail contact relate to the surface of the wheel and rail interaction, having profound effects on wear, fatigue, corrugation, stability and derailment. Magel and Kalousek [25] developed a model to quantify the performance of rail profiles when loaded by a large number of measured new and worn wheels. The contact mechanics principles were further applied in a discussion of several aspects of rail grinding, including surface roughness, surface width and rail grinding interval. Even though the details of a given railway operation can vary tremendously, the fundamental laws of physics are universal. This model also reviews the relationship of contact mechanics to wheel and rail performance by considering factors such as contact stress, conformity and curving. In addition, the consequences of applying a one point conformal contact were also explored. It was suggested that wheel and rail interaction can be improved by spreading wear across the wheel tread to help it maintain its favourable shape, delaying the onset of wheel hollowing and the formation of a false flange on the wheel. Maintaining the compatible wheel profile is critical for minimal contact stress, favourable steering and good wheel set stability all of which prolong rail life.

Track inspection ensures high operating safety, appropriate maintenance schedule and ultimately results in low maintenance costs. An embedded system methodology for real time analysis of rail profile was proposed by Alippi et al [26]. The methodology allows the designer to effectively balance the computational complexity versus accuracy trade off.

In order to analyse the shape of rail head Jin et al [27] proposed a method for detection of rail wear. This method was based on near infrared, non contact measurement and image processing technology which worked in specific contexts only. The correct corners on the curve were detected successfully and than compared with relevant points on a standard rail curve. This assists in calculating rail wear values accurately. These improvements on non-contact techniques were applied to inspecting vehicles and provide the primary data more accurately and scientifically than previous types of mechanical devices. Application of infrared scanning and Charged Couple Device improve condition monitoring of non-contact measurement.

An approach for contact mechanics analysis of the rail profile was proposed by Telliskivi and Olofsson [28]. It was based on the half-space assumption as well as on a linear elastic material model. The half-space assumption puts geometrical limitations on the contact of the rail with the wheel. This means that significant dimensions of the contact area must be small compared with the relative radii of the curvature of each rail and wheel profile.

The alteration in wheel and rail profiles due to wear involves considerable vehicle and track maintenance costs and effects the operation safety and riding comfort of the vehicles. The extended sphere of problems of wheel and rail wear prediction can be answered by predicting the combined wear process, of the rail and wheel system under specified operation conditions. A simulation procedure was proposed by Zobory [29] which determines both the magnitude of the rail profile wear for the track sections of different curvature i.e. right rail and left rail distinctly and the wheel wear i.e. right wheels and left wheels distinctly.

2.3. Track Geometry

Track geometry is the study and analysis of rail track in three dimensions (3D). As explained in figure 2.6, the X-axis defines the distance along the track towards the direction of the travel, Y defines the axis parallel to the running surface and Z defines the axis perpendicular to the running track. Track geometry has ballasts, sleepers, rail, and clips etc.

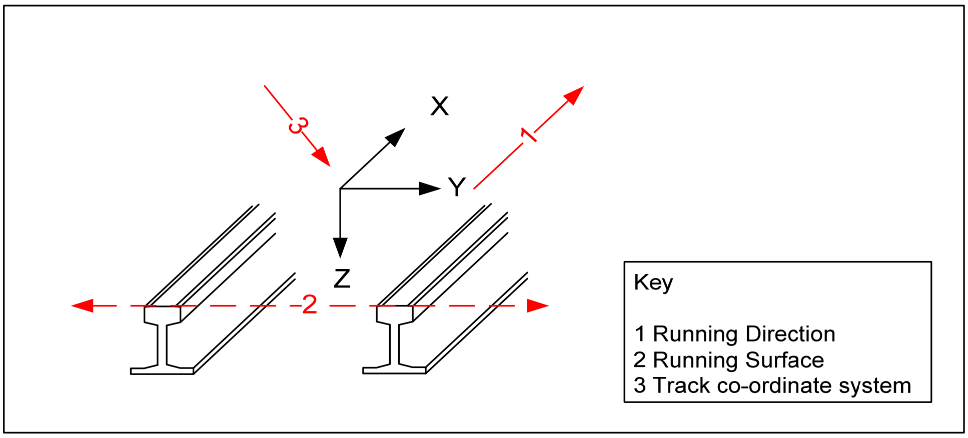

Figure 2.6 Track Geometry in 3D

The interaction between track superstructure components under a moving wheel load causes a large impact load, which increases with increasing track irregularity and train speed. This is because impact load increases with an increase in the size of the gap underneath the sleepers. The impact load increases the stresses on the ballast which, as a result, increases ballast settlement and ultimately results in a larger gap underneath the sleepers. Thus, degradation of track geometry tends to get faster.

Track geometry can deteriorate because of frequent passage of heavy traffic, climate changes (weather), variations in soil conditions and geotechnical movements. Common effects of trains on rail track which result in more frequent rail track deterioration thus resulting in maintenance of track follow:

1. The number of trains passing through the track is directly proportional to the rate of rail deterioration of track i.e. higher number will result in fast track deterioration.
2. A track may be subjected to heavy trains instead of light ones.
3. Speed has an important influence on track deterioration as high speed tilt trains are worse than average speed trains.
4. Better rail profile (stronger steels) gives less deterioration than rail profiles (weaker steels).
5. Track laid on blast deteriorates faster than slab track.
6. The stability of the track is dependent on type of soil it is laid on.
7. A thicker and cleaner ballast layer is better than a thinner or dirtier blast layer.
8. The rate of deterioration of curved track is faster than tangent track.
9. Track deterioration can also be prevented by better drainage.

Each rail track is essentially composed of two structures:

2.3.1. Superstructure

This is the part of the track which is above the ground. The superstructure, consisting of the rails, fasteners and sleepers, has received the most attention in past. Rails guide trains and distribute wheel loads without deflection, with the fasteners hold rails firmly against the sleepers and resisting forces in all directions. Sleepers distribute wheel loads from the rails and fasteners to the ballast.

2.3.2. Substructure

The substructure is mainly ballast which is the main source of deterioration of track geometry. The ballast is crushed, sieved and angular hard rocks that are impact as well as crush resistant. Primarily it is meant to maintain track geometry and resist forces by increasing the load area which reduces pressure on the sub grade. It also acts as a good energy absorber from passing trains. It is electrical resistant and a vegetation growth inhibitor. One of the main important functions of ballasts is to facilitate maintenance of track geometry by rearranging particles.

2.3.3. Types of Track Geometry Maintenance

The other track modality which directly contributes in the process of rail track degradation is track geometry. The vertical downwards force at the point where the rail comes in contact with the wheel of the moving train tends to lift up the rail and sleepers some distance away from the contact point. Such vertical movement causes a pumping action in the ballast which increases the ballast degradation by exerting a higher force on the ballast and causing pumping up of underlying materials. Thus track geometry tends to degrade at an accelerating rate. Track that has lost its geometry needs to be maintained. Some common ways of track geometry maintenance are:

2.3.3.1. Rail replacement

Condition analysis of track data helps to predict the rail life and to plan the replacement actions. One of the fundamental reasons for rail replacement is the occurrence of rail failures. Rails may need to be replaced because of excessive rail wear, fatigue defects or derailment damage. Rail replacement is often done in combination with other major maintenance activities such as sleeper replacement.

2.3.3.2. Sleeper replacement

Sleeper replacement is done either mechanically or manually. Sleeper replacement productivity is greatly dependent on the compactness of defective sleepers to be replaced. If the distance between the sleepers to be replaced is high then the sleepers replacement productivity will be low and vice versa.

2.3.3.3. Ballast maintenance

Ballast provides large voids for drainage and storage of fouling materials. Fouling is the term used for the dirt build up in clean ballast. Ballast settlement increases with an increase in fouling. As the degree of fouling increases large voids will be filled by fouling materials and the permeability of the ballast will slowly decrease. The cause of fouling material is critical because the effect of fouling material on ballast is highly dependent on the type of fouling material and also how the voids in the ballast were filled up.

2.3.3.4. Tamping or resurfacing

One of the most effective ways of restoring the geometry of the track is by maintenance tamping, especially when high lifts are required. Tamping is the process by which ballasts are packed around the sleepers to ensure the correct position for the location, speed and curvature. This process of maintenance tamping involves lifting sleepers to a desired level and inserting tamping tines into the ballasts with the lifted sleeper between each pair of tines. Effective maintenance tamping at the same time is found to be main source of ballast breakdown.

2.3.4. Track Geometry Parameters

In order to achieve other part of first objective of this research, all track geometry parameters needs to be explored in detail to facilitate any further analysis [17]. Degradation in track geometry will cause the track to move away from the design geometry in both the vertical and horizontal planes and this deterioration away from the design can cause discomfort for passengers and eventually become unsafe for the passage of trains. To ensure the track can be repaired in good time, the deterioration must be detected and the worst areas should be prioritised so that engineers can maintain the track based on an urgency basis.

The requirement for track maintenance all around the world is determined by track geometry measurement vehicles to determine the track condition [30]. One of the basic methods for recording track geometry is using string of either 35m or 70m length. However, for accurate and high speed data collection, network rail uses a fleet of dedicated Track Recording Vehicles equipped with lasers, cameras and gyroscopes. These vehicles record the 3 dimensional position of the track.

2.3.4.1. GAUGE

GAUGE is the distance between the two rails, measured at right angles to the rails in a plane below the top surface of the rail head. Therefore, the term GAUGE, when discussing track geometry, is the lateral deviation of the width or distance between the rails. It is the lateral deviation of the track from its nominal GAUGE measured at 14mm below the rail crowns standard (1435mm). A widening of the GAUGE corresponds to a positive deviation, while a negative deviation corresponds to a narrowing of the GAUGE. Figure 2.7 explains how the deviation of the track from its nominal GAUGE can be computed, subtracting nominal deviation from actual deviation.

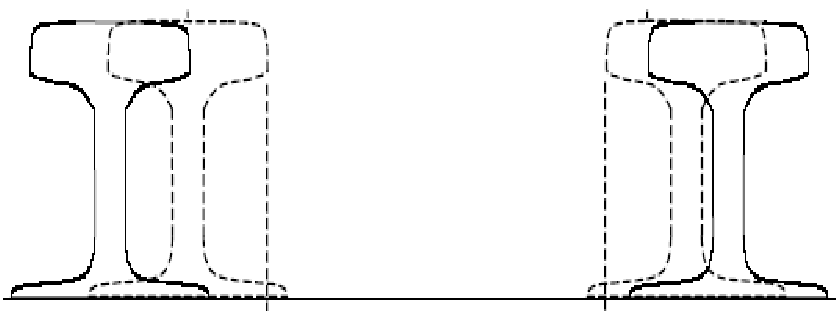

Figure 2.7 GAUGE [31]

2.3.4.2. Alignment

Alignment is the lateral deviation of the midpoint of the two rails from the nominal centre line of each rail of the track. It is the average of the lateral position of each rail to the track centre line and it is measured separately for the left and right rails in a manner similar to the GAUGE. A positive deviation in the alignment as explained in figure 2.8 denotes a lateral deviation of the track to the left, while a negative deviation in the alignment represents a lateral deviation of the track to the right [31]. Alignment can be further analysed by calculating means of different lengths. For instance if we want to measure mean of horizontal alignment of left and right rails it can either be measured using a short string of 35m or using a long string of 70m.

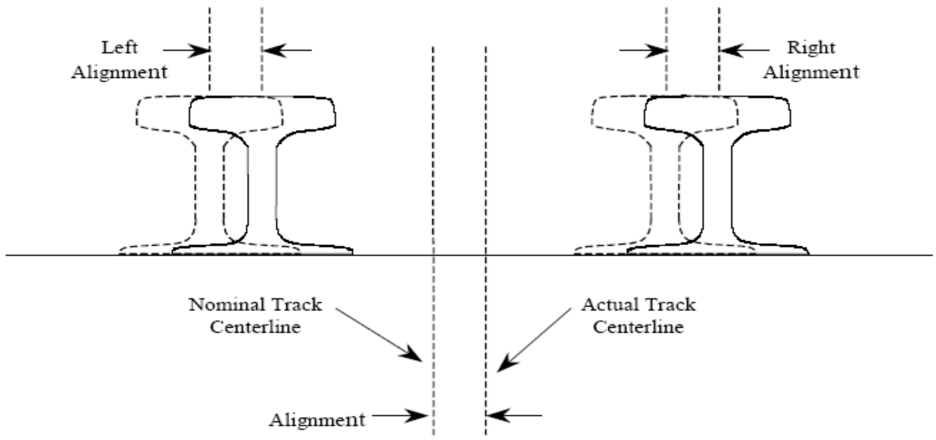

Figure 2.8 Alignment [31]

2.3.4.3. ALIGMS

ALIGMS is the variation in lateral rail centre line derived by combining the lateral profiles of each rail over a 35m. It is the mean of horizontal alignment of left and right rails measured using a short string of 35m length.

2.3.4.4. ALIGML

ALIGML is the variation in lateral rail centre line derived by combining the lateral profiles of each rail over 70m. It is the mean of horizontal alignment of left and right rails measured using a long string of 70m length.

2.3.4.5. TOPML

TOPML is the variation in the vertical profile on the right and left rail in direction of travel measured of a 70m. It is the mean of vertical alignment of top head of left and right rail measured using a long string of 70m length.

2.3.4.6. TOPRS

TOPRS is the vertical alignment of top right head of rail. It is the variations in the vertical profile on the right rail in the direction of travel measured with a long string of 35m length.

2.3.4.7. TOPLS

TOPLS is the vertical alignment of top left head of rail. It is the variations in the vertical profile on the left rail in direction of travel measured with a long string over 70m length.

2.3.4.8. CURV

CURV is an abbreviation of curvature, is the spatial rate of turn in the horizontal plane of the track as explained in figure 2.9. It can be measured by measuring the distance between centres of string to the centre of rail in a curve.

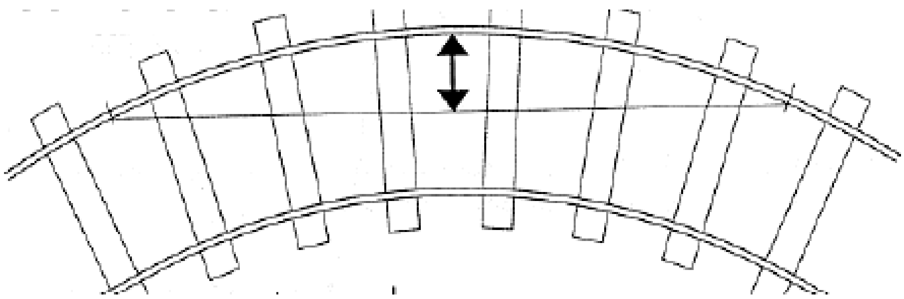

Figure 2.9 CURV [32]

A track can be either of three types: tangents, curves, and spirals. A tangent track refers to straight track and a curve track refers to a track with measurable curvature. The term spiral track refers to the section of the track that acts as a smooth transition between tangents and curves as shown in figure 2.10.

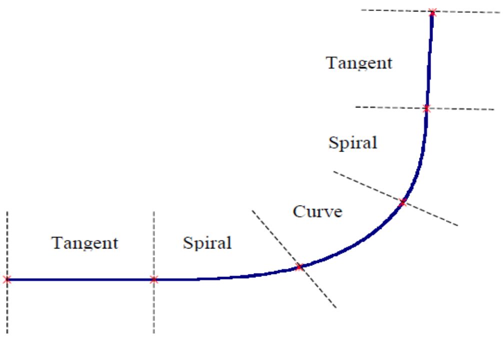

Figure 2.10 Spiral Track [31]

Track curves are typically identified by degrees. As explained in Figure 2.11 a one-degree curve is defined as a curved section of the track with a radius such that a 100-ft cord corresponds to a one-degree arc.

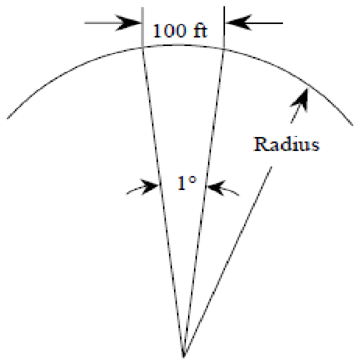

Figure 2.11 Track Curves [31]

2.3.4.9. CANTDEF

As most trains cannot lean or tilt into curves to counteract the centrifugal (G) force, the track is canted (one rail raised above the other) into the curve so that the forces are at equilibrium at the maximum line speed as explained in figure 2.12. It is then desirable to have cant deficiency as some amount of uncompensated lateral acceleration remains in the track plane [33]. The difference between heights of two rails in a curve is called as track cant. This parameter calculates whether the cant is sufficient to ensure the comfort of passengers and safety of trains. So it is the difference in actual cant from the ideal design.

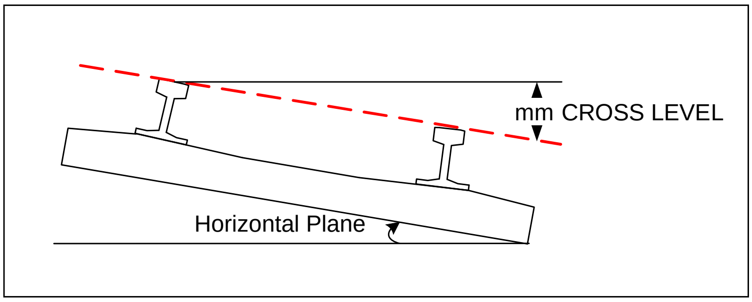

Figure 2.12 CANT DEF

2.3.4.10. CROSS LEVEL

CROSS LEVEL is the difference in elevation between the top surfaces of the two rails measured at right angles to the track as explained in figure 2.13. On curves, CROSS LEVEL is often referred to as cant or super elevation. On curves, the track will have a designed CROSS LEVEL to counteract the G forces involved in a train changing direction at speed. CROSS LEVEL is the height difference between the left and right rail at the point of measurement. So the CROSS LEVEL, not to be confused with the super elevation, is the amount of vertical deviation between the left and right rail from their intended distance. In other words, it is the intended increase in elevation of the outer rail above the inner rail in curve. The intended distance refers to the amount of super elevation. For instance, if the super elevation is zero, then any difference between the elevation of the left and right rail is the CROSS LEVEL.

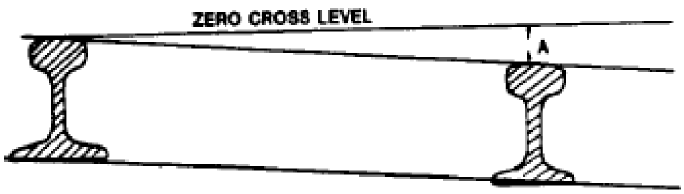

Figure 2.13 CROSS LEVEL [32]

If the super elevation, however, is positive, for example, then the CROSS LEVEL is the deviation from this super elevation. A positive CROSS LEVEL refers to the case when the left rail is above the right rail, and a negative CROSS LEVEL refers to an instance when the left rail is below the right rail [31].

Super elevation is the amount of elevation that the outer rail in a curve is raised above in comparison to the inner rail as explained in figure 2.14. This is done to compensate centrifugal forces that the vehicle will experience when travelling through a curve. For that reason the outer rail may be raised, or super elevated so as to tip the train inward. Super elevation can either be positive i.e. when the left rail is raised above the right rail or a negative i.e. when the right rail is raised above the left rail.

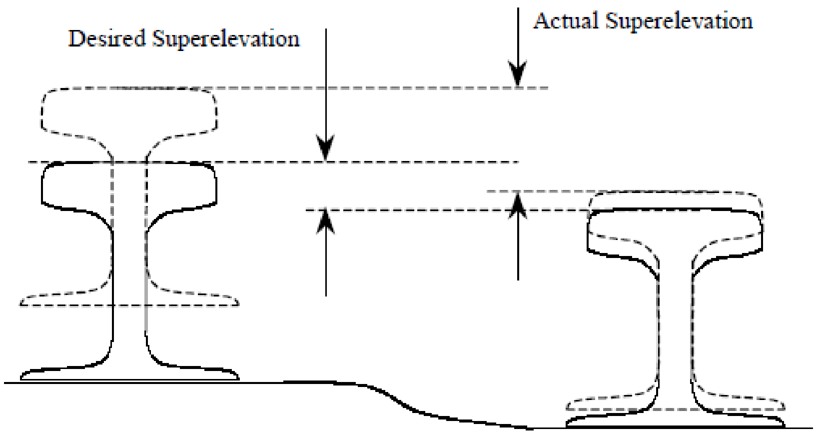

Figure 2.14 Super Elevation [31]

2.3.4.11. DIPPED LEFT OR DIPPED RIGHT

A Fish Plate is a joint that is used to join two rails together longitudinally. When the joint wears out it dips on inner sides of either rail left or right rail as shown in the diagram 2.15. Series of dips at regular intervals in one or both rails of track can also cause derailment [34].

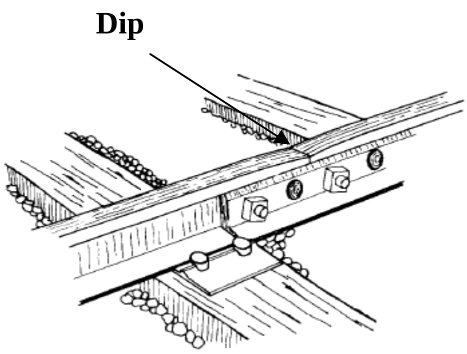

Figure 2.15 DIPPED Joint [32]

2.3.4.12. TWIST

TWIST is the changing height difference in CROSS LEVEL over a predetermined distance as explained in figure 2.16. In the UK train bogies or wagons generally have a wheelbase of 3 or 5 metres, so this is used in the TWIST calculation. It is the measure of large change in CROSS LEVEL over a fixed distance. The distance can be either 3m (TWIST1) or it can be 5m (TWIST2). Severe TWIST faults in the track can cause derailments at even low speeds by wheel unloading. An example of a serious TWIST is where at point ‘a’ the rails are level to each other, but 3 metres away there is a difference of 15mm. This gives a ratio of (3000mm / 15mm) 1:200 the ratio of 1:90 the line will be closed to traffic.

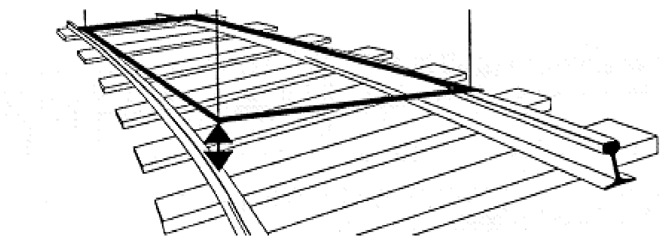

Figure 2.16 TWIST [35]

2.3.5. Track Geometry Literature

After exploring track geometry parameters it important to explore how are they analysed in literature. Track maintenance policies have traditionally been viewed as engineering led decisions [36]. So there is a need to focus effort into the development of degradation models to assist track maintenance so as to maximise overall financial benefit to rail users [36]. The results of such research has the potential to bring benefits in terms of lower operating costs for rail infrastructure users, as well as improved transit times and reliability of train arrivals. In order to run a safe railway, it is fundamental to know the condition of track components. Track condition monitoring is based on understanding the surface quality (e.g. surface defects on rail, cracks, ties, corrugation, grind marks, etc.), internal rail defects, movements of components from their actual position (sinking or moving track), any change in the amount present (e.g. under or over ballasts), rail wear, etc.

Track response, which is assumed to be stationary, when fixed rail track is subjected to moving trains with varying load, can be determined in a coordinate system following the load. Fryba [37] proposed a method to treat a discretely supported rail by developing the support reactions into Fourier series (making the support continuous but non-uniform) and then the moving load problem was solved with respect to a coordinate system following the load. He also reviewed the train track interaction problem. He investigated vibrations of solids and structures under moving loads (the train or wheel). Knothe and Grassie [38] and Popp et al [39] have presented state-of-the-art reviews in the field of train-track interaction. A survey of railway track dynamics and modelling of the train-track interaction was given by Dahlberg [40].

Ford [41] investigated load cycles when they are not equal i.e. if they do not have the same amplitude. He describes the curve of permanent strain for the first cycle, against the ratio of applied stress and failure stress. He also explained the situations of varying the load in the ballast which are useful in understanding variations in track geometry.

Shenton [42] proposed a model which simulates track deterioration based on several factors (e.g. dynamic forces, rail profile and sleeper spacing) influencing the track deterioration. A logarithmic settlement law was presented which may be considered reasonable over a short period of time, but it might significantly underestimate the settlement in the case of large numbers of loading cycles.

Frohling [43] investigated relationships between train and track parameters. He also explored the dynamic response of the vehicle and measured differential track settlements. Based on his measured results, differential settlement of the track was dominated by the variation of the track stiffness.

Peplow et al [44] presented a method which inter relates the components of the track parameter to represent its complex interactions in determining the net effect of traffic loads on the stresses, strains and deformations. Several comprehensive models have been developed.

In many track models the track stiffness and damping and the track mass are discretized. Then the mass of the track sleepers, ballast etc. is modelled by use of rigid masses and the track stiffness and damping are modelled by springs and dampers. In a model proposed by Dahlberg [45] the maintenance of the track is collected in a maintenance element in the track model.

In the numerical simulations presented by Augustin et al [46] the vehicle, the rail, rail pads and sleepers are a discrete system. The ballast was modelled as a hypo elastic material with inter granular strain. The initial state of the track was defined by the state of the ballast and the initial ballast height or the initial ballast densities were diverse.

The track can be modelled by track parameters and can be explained through its modal parameters [47]. The physical deflections of the track are determined by modal superposition and often the vehicle is modelled by use of rigid masses, springs and viscous dampers. If a more detailed response of the vehicle is of interest, then it could be convenient to use modal analysis also for the vehicle deformations. Modal analysis of a wheel set makes it possible to include elastic deformations of the wheel set without a large increase of the number of degrees of freedom of the compound train track system.

The modal analysis technique requires linear models [48]. Every so often track models comprise non linear track elements. Nonlinearities can be found in studded rubber rail pads and in the ballast-sub grade material. In such track models the material properties may be selected to display the physical behaviour of the non-linear track elements. Nonlinearities in the track have been treated as extra loads on a linear track model. The extra loads give a force displacement relationship for the track comparable with the nonlinear characteristics of the real track.

Dahlberg [49] investigated linear and non-linear track models and compared it with the track measurements of the Swedish National Rail Administration. Experimental results revealed that linear track models can be used for one single axle load only and that the wheel load distributes differently into the two track models. Problems with using viscous damping models in the track were also highlighted.

Though various rail profile and track geometry parameters have been explored in literature, the scope of parameters has been limited in number and extent to which they are analysed. Current literature does not thoroughly explore comprehensive set of parameters in rail profile and track geometry to benefit predictive analysis in understanding the over all degradation process of rail track.

2.4. Conclusion

The railway track system is an important part of the transportation infrastructure of a country, and plays a significant role in sustaining a healthy economy. Irrespective of rail asset type, whether it is overhead line equipment or rail track, their users need to handle an essential issue: how to keep them operational for as long as possible, and as economically as possible, without sacrificing reliability or safety.

The answer, of course, is appropriate maintenance [16]. These problems can be mitigated by conducting an effective and efficient rail track maintenance based on detailed predictive analysis of rail track modalities, i.e. rail profile and track geometry. This chapter besides explaining rail profile and track geometry parameters in detail explored their use in literature. Comprehensive literature review of rail profile and track geometry parameters in this chapter highlighted a gap in present literature i.e. the lack of their in-depth analysis.

Chapter 3

Rail Track Maintenance Management

This chapter gives an overview of rail track maintenance management regime described in the literature. As the objective of the thesis is to propose a track degradation model, the last section of this chapter explores rail track degradation models in the literature.

3.1. Introduction

Railroads are actively trying to increase throughput with a new age of faster, heavier, and longer trains. Unfortunately the pressure on rail road to reduce operating costs usually result in cutting or eliminating investment in research because it often does not generate a short term return on investment. There is a need to replace the manual rail track inspecting methods by a quicker, more consistent and cost effective means of rail track monitoring [85]. With safety as a dominant factor, railroad owners and managers employ various techniques to ensure optimum rail track conditions at all times.

Track irregularities can appear in either the rail profile or in the form of geometrical variations. Track maintenance is essential to enhance the safety and reliability of high speed and high density rail vehicles transportation [50]. At the present day is impossible to talk about high speed railway without taking rail track defects into account [51].

3.2. Rail Track Maintenance

The nature of rail transportation is such that it is very expensive, to construct but has a long life and low maintenance costs [53]. Track maintenance can range from isolated spot defects to complete relaying and replacement of the track bed [52]. One of the most challenging tasks, in recording track design, is to measure how much a track has moved from its original design. One major consequence of not maintaining a track is large sudden movements of track makes it unsafe and may also cause stress on surrounding components which may result in passenger discomfort. In a business context these defects can cause:

1. Restriction in the speed of the train
2. Delays in timetables
3. Potential sudden failures
4. Further damage to infrastructure
5. Potential derailment

All of above will ultimately result in the dissatisfaction of passengers. To ensure safe passage of trains, the UK railway has imposed minimum requirements for the quality and maintenance of rail infrastructure. Also when the track condition is close to its minimum quality standard set by Network Rail, it gets closer to derailment which may result in higher repairing and maintenance costs.

Maintenance can be either corrective/reactive i.e. fixing on failure or it can be preventive i.e. failure prediction before they can happen [54], [55]. As it is often very difficult to predict all maintenance, and thus in reactive/corrective maintenance, expert judgments are made on the basis of imperfect information and previous experiences with a relatively short-term view of the future impacts on maintenance. In contrast to reactive/corrective maintenance, predictive maintenance avoids excessive cost normally incurred by corrective maintenance [56]. It helps in preventing components or systems from malfunctioning and ensures that they carry out their intended functions throughout their service life [57], [58].

One of the major criticisms of maintenance systems employed for rail transportation is that they model the data rather than modelling the problem [59]. The overall aim should be to develop a model which can be used to evaluate alternative maintenance strategies and to prioritise maintenance effort across a railway network. Such a model can also be used to investigate the benefits of changes in track design standards, changes in track components (e.g. rail, sleeper types), and simulate the likely effect on business activity of changes in track maintenance policies and design standards. This is particularly so in cases where current practices rely on traditional conservative engineering judgment.

Track maintenance is one of the most crucial elements in the rail industry today, and track condition monitoring is one of the standard measures of maintenance used to identify and assess track wear.

3.2.1. Rail Track Condition Monitoring

An asset centric approach is essential for the success of an asset intensive organisation. In rail industry effective rail track condition monitoring is a major determinant of track degradation process [60]. Rail track condition monitoring is becoming increasingly important in effective understanding of predictive rail track maintenance. [61]. It is fundamental to boost the safety and reliability of trains. Reactive repairing, which is essentially, repairing track only when some of its parameters exceed their allowed deviations, is a costly way of track maintenance. Therefore predictive track deterioration is a powerful way in improving track planning [77]. Timely and accurate diagnosis in finding all vulnerable areas in the track i.e. part of the track which deteriorates faster than rest of the track, helps to focus on those track parts which really require attention, and prevents any vulnerable areas being overlooked [77].

Rail is the essential component of track system that is chiefly affected by surface defects. The wheel/rail interaction leads to an inevitable rail surface wear that causes, if not maintained, track components to degrade. Recently, interest has grown for the development of a system for assessing track condition based on track geometry. Therefore, there is a need for a real time predictive system to measure track geometry. Bonaventura et al [94] developed a system which was tested using seven different track profiles. This system can provide in real time how a railroad is likely to be able to prevent numerous costly derailments from ever taking place.

Track defects, not to be confused with rail defects, are deviation of actual from theoretical values of the tracks geometrical characteristics. Tracks defects are macroscopic and geometric in nature and are exclusively the consequence of train traffic. Usually they are rectified during track maintenance. In contrast to track defects, rail defects may occur due to initial manufacturing imperfections of the rail or by a wheel burn caused by the train wheels. They are mechanical and microscopic in nature and in most cases, are irreversible [62]. The total stresses developed in the rail are the sum of:

1. Wheel rail contact
2. Rail bending on ballast
3. Bending of the rail head on the web
4. Thermal effects
5. Plastic stresses, remaining in the rail after the removal of the external loads.

Because of these stresses and other factors rails may become defective in the track in any one of the following ways [11]:

1. Broken rail

Any rail which is separated into two or more pieces or a rail from which a piece of metal becomes detached, causing a gap in the running surface is a broken rail.

2. Cracked rail

Anywhere along stretch of the rail, irrespective of the profile section involve one or more gaps of no set patterns, apparent or not, the progression of which could lead to breakage of the rail fairly rapidly.

3. Damaged rail

Any rail which is neither cracked nor broken, but shows other defects on the rail surface is damaged rail.

The quality of track geometry can be evaluated by various models. One such model, based on practical approach was introduced by Berggren et al [63] for the evaluation of vertical track geometry quality and rail roughness with the goal to introducing better guidance for maintaining tracks and rails. The model calculates vertical wheel rail interaction forces from measured track or rail irregularities by using a wavelength weighting of measured rail roughness. This helps in assessment of the track condition which results in a substantial improvement in track monitoring.

Real time simulation models are one of the ways for evaluation of track geometry [45]. Recent developments and testing of this real time simulation model has increased substantially. Such a system is intended to demonstrate the ability of accurately finding and locating segments in a track that have a high risk of a geometry-related derailment. It is only through greater awareness and growing trust that the railroad industry will begin to evaluate and one day rely on these new powerful methods for assessing and maintaining track safety. Armed with such a system it can provide information in real time, about a railroad, and is more likely to be able to prevent numerous costly derailments from ever taking place.

It is reasoned that fractal analysis has the potential to evaluate track substructure condition. Based on this hypothesis, an empirical study was undertaken by Hyslip et al [64] to correlate the fractal indices to areas of track with known substructure conditions. There are indications that fractal analysis can provide information on the cause of geometry roughness and thereby aid in identifying useful remedial actions. Fractal analysis is an analytical technique that can be applied to characterize and to quantify irregular patterns that are chaotic and random; as track geometry data are classified. Application of Fractal analysis to railway track geometry data and to develop numerical indices based on this analysis for use in track condition assessment, improved safety and efficiency of operations and diagnosis of the cause of poor track condition [64].

The term “track class” refers to the Federal Railroad Administration (FRA) track class designations [31]. The classes range from 1 to 6, with track class 1 designating the worst track and class 6 identifying the best track. Track classes are determined by the deviations from the ideal track i.e. a track with nominal parameters. Although the standard deviations of the profile data for the class 4 tracks vary, they are closer to each other when compared to the values for the class 5 and 6 tracks. This is also true for the alignment data. This difference across the track classes yields a distinctive value, or range of values, for the standard deviations of each class of track.

One crucial railway engineering tasks is effective and robust condition monitoring, as track degradation problems can have a serious affect on the safety of train operations [65]. In order to comprehend the track degradation process it is essential to understand ways of track condition monitoring. In the UK rail industry, companies like Network Rail monitor track condition by either standard deviation or discrete exceedence.

3.2.1.1. Standard Deviation (SD)

(SD) is the square root of the average squared deviation of values around the mean, so, it can be thought as an average amount by which all values deviate from mean. Standard deviation (SD) gives the roughness of track. The lower the value of SD the better the track (at 0 it would be ideal) and the higher the value of SD the more rough the track. SD is not only easy to calculate, interpret and use but it gives an overview of the whole track quality for which it is calculated [66]. It is therefore, one of the measures of track maintenance as it tells maintenance engineers how to prioritise maintenance.

3.2.1.2. Discrete Exceedence

Situations where there are large track movements over small distances can jeopardise the safety of the track. To monitor these situations track engineers have two levels of exceedence. Level 1 includes TWIST, Tops, Alignment and GAUGE. When exceedence in any one of these is observed unambiguous actions are taken, for instance “Close the line” or if the exceedence is serious than Repair it within 36 hours. Whereas at level 2 the position of the exceedence is marked by paint [66].

Certain discrete track parameter exceedences require an emergency speed restriction to be imposed to reduce the risk of derailment and ensure passenger comfort. One of the side effects of this is the delay caused to trains traversing the area. In the UK the cost of a speed restriction ranges from around £40 to over £200 per minute per train depending upon the type of route and is paid to affected parties by the organisation causing the delay [66]. The knock on effect to other trains is also taken into account. By far the biggest cause of train delays is infrastructure problems, so Network Rail pays a great deal of money to train operators each year. Most of the very large costs are related to speed restrictions imposed to ensure the safe passage of trains over poor quality track or damaged rails.

Poor quality track related speed restrictions cannot be removed until the defect is repaired and the site has been reassessed as safe by Track Recording Vehicles or the local track engineer is sure the fault has been rectified and has adequate proof. This means that a simple track fault can cause weeks of delays even if it was repaired within hours of detection. The same is true of all major tracks engineering work such as track renewals.

3.3. Track Degradation Model

Track component life models can be classified based on track component and its maintenance activity under consideration, into either failure models or degradation models. Component failure in track component failure models is when a component has to be replaced. A component failure can either be physical component failure i.e. rail, sleeper etc failure or an economic failure where it is not cost effective to repair the component so it is replaced rather than repaired. Most components of the physical systems either degrade or fail to perform their desired functionality over time [67]. This results in degradation in performance of system and, in some situations, leads to failures. The degradation process and its effects on the system failure are often uncertain. The answer is lies in predictive maintenance, which is the combination of technical and administrative actions to retain a component in or restore it to a state in which it can perform its desired function [68], [69].

Effective predictive track maintenance is periodically performed to rectify track irregularities. In order to determine an effective maintenance strategy it is necessary to use an appropriate degradation model for track irregularities in accordance with the purpose of the analysis. In the case of component degradation, a component does not necessarily malfunctions, but rather there is degradation in performance of a component, hence it is required to be maintained.

In general there are two main types of track component degradation models: mechanistic or empirical [78]. Mechanistic models attempt to simulate failure mechanism by mathematical computations. These models are also classified as engineering models because they attempt to define physical properties of components and its complete loading environment. Mechanistic i.e. engineering models are relatively more sophisticated as they tend to have complex algorithms which involve significant processing time. These models require comprehensive understanding of track components in order to improve the performance under various conditions.

Empirical models are relatively simple and are primarily based on experimental or observational data. They involve statistical modelling in which large volumes of experimental data are explored using correlation analysis for parameter behaviour understanding and regression analysis for predictive maintenance management. In contrast to mechanistic models, empirical models are highly dependent on experimental data in their development. Therefore their scope is limited to experimental data and hence can not be extended beyond the range of experimental data. Still, because empirical models are relatively simple as they involve simpler algorithmic computation or data analysis methods they require less computational time.

Mechanistic relationships have been employed in an Integrated Track Degradation Model (ITDM) for track degradation analysis by Zhang et al [78]. ITDM deals with the whole track system or with individual components and serves as a tool for analysis of track degradation. It facilitates comprehensive and reliable prediction of track degradation through a wide range of parameters including measurement of each track component behaviour, estimation of errors in the modelling process and input parameters and integration of the inter relationships between various degradation types. Unlike existing approaches, ITDM framework is primarily based on mechanistic relationships for the prediction of track behaviour and takes into account degradation effects due to the interaction between track components, enabling prediction of either overall track condition or the condition of individual track components, starting from any initial track status.

Most of the existing track component life degradation models have been designed by and for a specific railway system. An empirical approach is regarded as the best method to develop an accurate track component life degradation model, especially with regard to rail profile and track geometry degradation and maintenance [71]. Since such empirical models were based on specific track data so the results were specific to the planning of that track only. They have resulted in cost savings of 5 to 10 percent [70].

White [4] proposed an empirical model by which he explored the implications of track parameters with respect to various degrees of curvature. The track parameters (left rail alignment, right rail alignment, GAUGE, CROSS LEVEL, left rail vertical profile, and right rail vertical profile) analysis revealed a significant amount of useful information and various parameters behaved significantly differently at different sections of the track, which were strongly dependent on the track curvature. The alignment and profile parameters did not seem to be significantly affected by track curvature. The GAUGE standard deviation decreased with a softer curvature, whereas the CROSS LEVEL standard deviation increased. Standard deviation of the CROSS LEVEL was also observed to increase with the degree of curvature. In the left hand curves the CROSS LEVEL is significantly greater than zero, whereas in the right hand curve the CROSS LEVEL is significantly below zero. A similar situation was observed for the alignment as well.

Degradation of rail track parameters has long been determined by fatigue defects and wear. However, rail grinding removes many defects before they become visibly large. Simson [72] presented a model which deals with the track maintenance planning. His model simulates the impacts of degrading railway track conditions and related maintenance work, in contrast to conventional models that mainly use expert systems. The model yields the benefits of undertaking a given maintenance strategy, when compared with a base case scenario. The model investigates "what if" scenarios, in which case, the track engineer can weigh up the possible benefits in reduced operating costs from upgrading track infrastructure or from the use of improved maintenance equipment.

Kawaguchi et al [73] presented two degradation models to estimate alignment irregularity growth on ballasted track. One was a model to evaluate plans, such as track structure improvements or changes to transportation conditions, and the other was to decide on a daily or monthly track schedule. To evaluate the efficiency of both models, actual and estimated irregularity growth data was compared with a statistical modelling approach. Analytical modelling programs have become less complicated and far more practical. Computer modelling with "what if" analysis allows the user to test various situations without spending the time, money, and equipment to test them on a track.

Kramp [31] research project characterizes and model railroad track irregularities, as well as user-defined track irregularities, with varying parameters. The fundamental purpose of this study was to analytically create tracks with the irregularities necessary to reproduce the input provided by actual track. The characteristics of the irregularities associated with the alignment and profile data, were determined by performing statistical analysis. In statistical analysis, since the calculated means of the alignment and profile data were all zero, then the irregularities that exist in the alignment and profile of the tracks were all equally distributed about zero. This signifies that the important value obtained from the statistical analysis will be the standard deviation. Therefore, a small standard deviation means that the irregularities are smaller, where a larger standard deviation means that the irregularities are larger and more dispersed about the mean.

There is a need for more reliable Switches and Crossings (S&C) which require less costly maintenance and renewal. Trains running over S&C causes degradation of tracks components. The rate of this degradation depends primarily on the track geometry and the condition of the track material. In addition to the relation of rail track degradation with track geometry and the state of the track material there is also a relation between track geometry and the state of the material, i.e. bad material causes more track geometry degradation. This relation also exists the other way round, i.e. bad track geometry will result in bad state of the track material. To correct the geometry of the track, maintenance and renewal actions like tamping and grinding are carried out. To repair worn track materials, they can be replaced or repaired at the site. Zwanenburg [35] proposed a degradation model of Switches and Crossings (S&C) which combine several databases of the Swiss Federal Railways. Statistical analysis was performed to retrieve the life time expectancy of complete railway switches (points) & crossings and their respective components, e.g. point rails, stock rails etc.

The expected life time were attributed to different parameters which influenced the speed of geometrical degradation or wear of the material, e.g. total train loads, axle loads, the main direction of the trains, the speed and the quality of the foundation. In recent years there has been a growing use of rail track maintenance models, as track component life models can have serious affect on the safety of train operations by exploring various track parameters. In order to determine an effective condition monitoring strategy it is necessary to analyse track geometry [74].

In order to ensure the effectiveness of track maintenance, it is necessary to investigate track parameters and their effects on the wear. Sadeghi and Akbari [74] explored the effects of geometrical track parameters on the vertical and lateral wear by conducting a field investigation. The research explains that the amount of rail wear in switch differs from point to point. It also concludes that the most influential geometric parameter in the switch wear is GAUGE deficiency particularly for lateral wear where as CROSS LEVEL is not a significant factor in switches wear. On the other hand, in straight railway lines, the GAUGE deficiency is the most significant geometric factor influencing the rail wear and CROSS LEVEL influences only the Vertical Wear. So as the CROSS LEVEL increases, Vertical Wear decreases. In contrast to inner rail of the curves, narrow GAUGE, high super elevation, and widened GAUGE were influential in the lateral wear. Where as Vertical Wear is highly influenced by high super elevation and narrow GAUGE. Additionally, on the outer rail of the curves, narrow GAUGE, broad GAUGE and high super elevation are prominent in the case of lateral wear and broad GAUGE, narrow GAUGE, and high super elevation are significant factors in the case of Vertical Wear.

An empirical track degradation model with enhanced decision support system especially for track was developed by the European Rail Research Institute (ERRI). Its objective was to support the decision making process with respect to the maintenance and renewal work plan. The system was based on decision rules and degradation models based on condition of track components and track geometry. These rules form the basis of possible maintenance and renewal activities. The Eco track database consist of network information, design and operating, superstructure and infrastructure, geometry measurements, other inspections and measurements, work history and finally map data of a railway network. The system does not require all mentioned data and is able to produce decisions with limited data. However, availability of more and better information will improve the reliability and quality decisions made [75].

Dan [53] proposed a predictive track degradation model, DeCoTrack (Degradation Cost of Track) for railroad by combining empirical data in a mechanical engineering model. The model simulates changes in degradation rate of the track due to changes in traffic type. The current model is also designed to simulate degradation of the super structure sleeper and ballast. According to this model, rail degradation is generated by wear and fatigue. Both rail wear and fatigue vary in strength depending on the part of the track i.e. straight or curved, as a narrow curve implies greater wear than tangent track. It explains how wear and fatigue are influenced by curvature and that a narrow curve track will make wear the major factor to limited rail life. Its output includes both track component life time and the estimated degradation cost over time.

Track deterioration through deviation from its original geometrical position has the most adverse effects on track maintenance. Hawari [76] investigated track degradation by looking into relationship between rail/wheel and track degradation on one hand. The objective of the research was to assist in managing train/track interaction in order to minimize track degradation. The focus of the research was on wheel/rail vertical forces, vertical track alignment and rail profile defects to help in understanding the desired relationship between track degradation and train characteristics.

Selection of suitable genetic algorithms for a given problem is mainly dependent on the concept of a fitness landscape. Effectiveness of such a solution is dependent on the definition of a fitness function and a set of search operators which are entirely dependent on the problem definition. In such a scenario the search operators characterize a regional composition, as a multi-dimensional landscape, upon which evolving individuals shift. Bowers [82] investigated that embryogeny mapping can only be successful if the modularity formed during the process of mapping is convenient to establish a relationship between useful structures in the phenotype and elements of the genotype. Besides consequences of such a mapping process are investigated and in particular how useful traits in phenotypes can influence the behaviour of genotypes during the process of evolution. The research concludes a representation which enables such a relationship between genotype and phenotype in the form of a computational model of embryogeny.

Although there are many degradation models proposed in literature, the scope of the models have been limited by the number track parameters utilised. In other wards the degradation models proposed in literature are not based on a comprehensive set of rail profile and track geometry parameters and are therefore more likely to suffer from inaccuracies.

3.4. Conclusion

The degradation process of a rail track is principally dependent on accurate maintenance of both track modalities i.e. rail profile and track geometry. Rail profile wear and plastic degradation are the main contributors of changing rail profile. Rail profile and track geometry standards are fundamental for the safe passage of vehicles, failing to be so may result in disastrous consequences. Hence both rail profile and track geometry parameters have significant impact on track maintenance. Therefore degradation models that utilise more comprehensively defined, larger sets of parameters will work more effectively. In chapters 4-6 we propose data alignment methods that are used to align, data captured in rail track parameter measurements and finally in chapter 7 a novel degradation model is proposed.

The answer to track degradation problem, as it can have serious consequences on the safety of train operations, is appropriate maintenance through regular condition monitoring. Rail track can be kept operational for a longer period of time by monitoring the condition of the track on regular basis it. This chapter besides explaining condition monitoring and degradation models explored condition monitoring in relation to track degradation process in literature.

Chapter 4

Data Analysis

This chapter makes two contributions. One contribution is that this chapter sets up foundations for understanding parameters by analysing correlations in both modalities i.e. track geometry and rail profile. During the course of analysis all significant correlations in both modalities are identified and analysed. The second contribution is linear regression analysis of track geometry parameters.

4.1. Introduction

Parameters values, in both modalities, are the variables which further explain each modality in great detail. During the course of analysis all significant correlations of both modalities are identified and analysed. One type of such analysis is univariate correlation analysis which is basically correlating the same parameter over time. The other type of analysis is multivariate correlation analysis in which each parameter is correlated with the rest of the parameters in both modalities. Both type correlation analyses will help in parameter behaviour understanding in both, over time and with rest of the parameters.

The second contribution of this chapter is univariate and multivariate analysis linear regression of track geometry parameters. The objective of this regression analysis is to see how well we can predict one parameter from other. Such analysis will be useful in predicting parameters among themselves and over time.

4.2. Experimental Design

Both Rail Profile (RP) and Track Geometry (TG) had number of statistical values of parameters which in itself explaining in great detail of what they are. Altogether we had four base files, of different dates as represented by (1) which means the oldest and (4) means the latest, for same patch, of both modalities that were analysed. All parameter data given for analysis was recorded for LTN1 i.e. Liverpool Street to Norwich rail track. Due to the large size of the LTN line it was split into two parts i.e. LTN1 and LTN2. The data files, which in this thesis are referred to as base files, have Mile and Yard information for each parameter value recorded as shown in Table 4.1.

Table 4.1 Base Files of Rail Profile and Track Geometry

ELR	Track ID	Mile	Yards	Rail Section	Measurement Data	P1	P2	..Pn
LTN1	2100	4	376	Bs113afb	09/10/2007	1.38	78	……
LTN1	2100	4	379	Bs113afb	09/10/2007	0.79	83	……
LTN1	2100	4	388	Bs113afb	09/10/2007	2.19	54	……
LTN1	2100	4	393	Bs113afb	09/10/2007	0.87	79	……

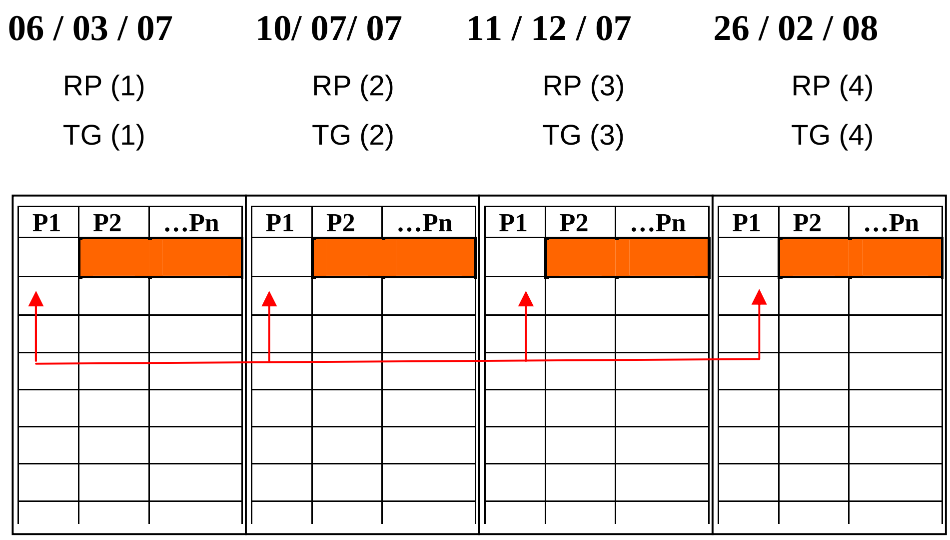

Figure 4.1 Univariate (Time Based) Analysis in Rail Profile and Track Geometry Base Files

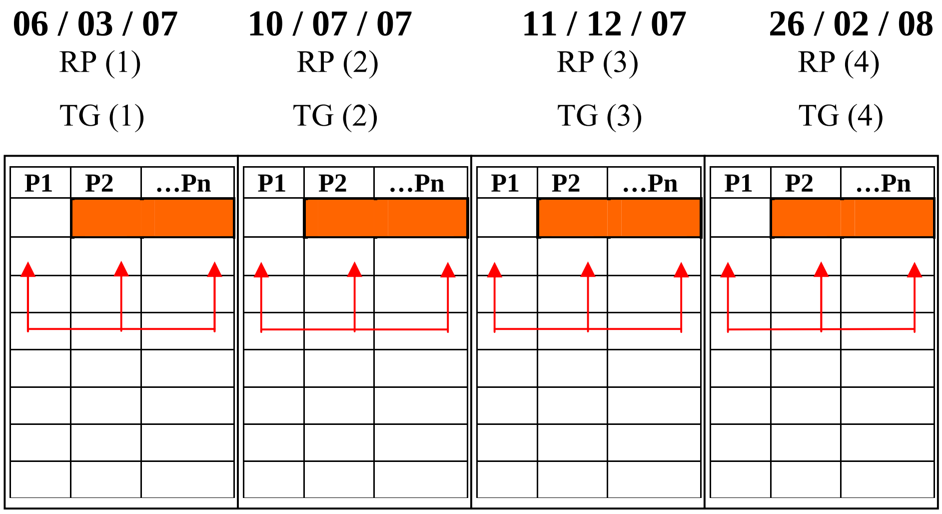

Figure 4.2 Multivariate (Parameter Based) Analysis in Rail Profile and Track Geometry Base Files

4.3. A Distance Alignment Method

As all base files were recorded at different dates of the year, they were not perfectly aligned with each other. So until all base files are aligned appropriately with each other any analysis will be meaning less and hence aligning all base files is essential for any further analysis. Because each base file in both modalities had distance information, in Mile and Yard column, so all base files can be aligned with each other based on exact Mile and Yard information. Mile and Yard information in all base files was converted into yards as shown in the Table 4.2, 4.3, and 4.4 to make it more comparable in the process of alignment. In such a process of alignment parameters, of both modalities, in all base files are aligned based on exact Miles and Yards (M&Y) information in each base file. This alignment is essentially based on finding the nearest in each base file. This process of alignment involves finding the nearest distance (Mile and Yard information) match, for all parameters, in all four base files, in each modality.

The process of alignment starts with the first Mile and Yard value of any base file and finding its nearest value in other base files. This process of searching involves an exhaustive search of finding the nearest match of Mile and Yard values in all other base files. All the Mile and Yard information whose nearest matches are not found are discarded. This will result in discarding complete rows from the final base file. Hence in each modality, the final base file, which is output at the end of the alignment process, will have parameter values aligned based on nearest matching of Mile and Yard value in all base files.

Table 4.2 Distance Mile and Yard based Alignment

Row No	M&Y 1	M&Y 2	M&Y 3	M&Y 4
1	375	375	376	363
2	375	375	376	366
3	378	378	379	366
4	378	378	379	369
5	381	381	382	372

In Mile and Yard Table 4.2, the four base files are represented as separate M&Y columns, each row representing a different measurement of the parameter at a M&Y value. In the distance alignment method, the maximum M&Y value per row is obtained and is compared with the M&Y values of adjoining rows of other columns (i.e. in the rest of the base files) for determining its nearest. For example in the first row of Table 4.2, 376 of M&Y3 is the maximum amongst 375 in M&Y1, 375 in M&Y2 and 363 in M&Y4. As the values represented in the other base files are not exactly same as 376, we search for the closest match for it in each of the other base files (i.e., M&Y1, M&Y2 and M&Y4), first comparing with the values in row 2 and then moving to adjoining rows, until the nearest match is found in each base files. In current illustrated in Table 4.3, first row entry in the final alignment file would be 375 for M&Y1, 375 for M&Y 2, 376 for M&Y3 (i.e. the max) and 375 in M&Y4 (not illustrated). All previous rows in M&Y4 from 363 till 375 are discarded as their nearest match could not be found in the rest of the base files. Thus ultimately each row of the final aligned base file will have the nearest M&Y matches found from the different base files.

Table 4.3 Distance Mile and Yard based Alignment

Row No	M&Y 1	M&Y 2	M&Y 3	M&Y 4
1	375	375	376	375
2	375	375	376	375
3	378	378	379	378
4	378	378	379	381
5	381	381	382	384

As shown from Table 4.3 Mile and Yard information is in ascending order. Thus all row entries of M&Y4 which are discarded could not have found nearest match from any other base file, M&Y1, M&Y2 or M&Y3. By aligning row 1, row 2 gets aligned automatically. Thus in this scenario, row 3 of M&Y 3 having 379, is the maximum among 378 in M&Y1, 378 in M&Y 2 and 378 in M&Y4 but as they are not exactly the same as 379 so we compare this maximum value with second row value of M&Y1, M&Y2 and M&Y4, for its nearest match, and continue until we find a value which is equal to or less than 379. But all values of the subsequent rows of M&Y1, M&Y2 and M&Y4 exceed 379. Thus row 3 is aligned as illustrated. .

Investigating Mile and Yard Table 4.3 further, row 4 of M&Y1 has 378, M&Y2 has 378 and M&Y3 has 379 and M&Y 4 has 381. In row 5 of M&Y1 has 381, M&Y2 has 381, M&Y3 has 382 which are closer in magnitude to row 4 value of M&Y4, i.e. 381. Therefore M&Y1, M&Y 2 and M&Y3 values of row 4 are discarded. In the final table, Table 4.4, the updated row 4 M&Y1 has 381, M&Y2 has 381 and M&Y3 382 which are now aligned with M&Y4 381.

Table 4.4 Distance Mile and Yard based Alignment

Row No	M&Y 1	M&Y 2	M&Y 3	M&Y 4
1	375	375	376	375
2	375	375	376	375
3	378	378	379	378
4	381	381	382	381
5	384	381	382	384

The Pseudo code for the distance based alignment approach described above can be written as follows.

Pseudo code:

```
Convert all Mile and Yard distance measurements into Yards
Initialize
*Ctr1 = First row of Base File_1
*Ctr2 = First row of Base File_2
*Ctr3 = First row of Base File_3
*Ctr4 = First row of Base File_4
[note: the '*' refers to the 'address of']

DistAlign  (Ctr1, Ctr2, Ctr3, Ctr4)
{
   For each row i (where i = 1…n)
   {
  Ctr_max= MaxYards (Ctr1,Ctr2,Ctr3,Ctr4 )
       If  (Ctr1 ==Ctr2 == Ctr3 ==Ctr4)
        {
         Make it as a row in a new aligned base file & then
        increment *Ctr1 & *Ctr2 & *Ctr3 & *Ctr4 by 1
        }/*end if*/

            Else
            {
            Increment *Ctr1 till *Ctr4 by +1 , +2, ...+N  and decrement *Ctr1
            till *Ctr4 by +1 , +2, ...+N   until  same OR closest value to Ctr_maxs
            is found
            Make it as a row in a new aligned base file
            } /* end else*/
      }/*end for*/
```

} / end DistAlign */*

Output:(All rows with nearest Mile and Yard information are aligned in a new excel file and all remaining mile and Yard values are discarded along with their parameter values as their nearest match can not be found)

However, one potential problem of this approach is the likelihood of losing information during the process of alignment, as a lot of rows whose nearest Mile and Yard information was not found were discarded. This also resulted in loss of parameter data in both modalities. As a result of which few parameter correlation over time resulted in negative. However there can never be a negative correlation when the same parameter is correlated with itself over time. This was because of the fact that that during the process of alignment many parameter data are lost, some of the parameters had negative correlation over time i.e. univariate correlation.

Hypothetically, this distance (Mile and Yard) alignment is an ideal way of alignment as one knows the start and end of the rail track in each base file for both modalities. However this hypothesis does not reconcile with the experimental results as there were many negative correlations when a parameter was correlated with itself over time. This is because the parameter data is misaligned in all base files. One main reason that distance alignment is not effective excessive parameter data is lost during the process of alignment. Due to which some parameter univariate correlation resulted in negative values.

4.3.1. Correlation Analysis

As misuse, misunderstanding, and inaccuracy of predictions are often the result of not appreciating the nature of the data in hand, so data understanding is essential before any further analysis is carried out [79], [80]. In scientific research it is often necessary to analyse the correlations between more than two parameters, in order to understand parameter data influences [81].

One aim of this research is to investigate the correlations between different track parameters with an aim of understanding them individually and their relationship to other parameters. This was done by exploring correlations among all the parameters in both modalities. Such correlation analysis leads to in depth parameter behaviour understanding in both ways, i.e. over time and with rest of the parameters in each modality.

In order to understand the state of the art in track maintenance i.e. the way the rail engineers conduct track maintenance along with how track engineer's maintenance documents are used, all track parameters are analysed through correlation analysis. Correlations are divided into multivariate and univariate correlations. In multivariate correlations each parameter is correlated with the rest of the parameters, in each base files [9], so as to develop an understanding of parameter behaviour with rest of the parameters and along the time [8]. To do so each parameter of both modalities is correlated with itself in all base files. Such correlation analysis will help in understanding individual parameters behaviour over time [3]. Significant univariate and multivariate correlations analysis are those whose theoretical hypothesis does not reconcile experimental results.

All the hypotheses drawn in correlation analysis are based on the parameter explanation of both modalities in chapter-2. After calculating univariate and multivariate correlations in both modalities significant correlations are divided into high, medium, low and very low categories.

- All correlations are computed at 0.01 level of significance or 99% level of confidence.
- High Correlation is < 1 & > 0.75
- Medium Correlation is < 0.75 & > 0.50
- Low Correlation is < 0.50 & > 0.25
- Very Low Correlation is < 0.25 & > 0.00
- * means that either one or both parameter values are missing so correlation can not be computed.

Table 4.5 Rail Profile Multivariate Significant Correlation

Parameters	Hypo thesis	Experimental Results			
		Rail Profile 1	Rail Profile 2	Rail Profile 3	Rail Profile 4
Left Estimated Rail Depth Left Head Width	- High	+ Medium	+Medium	+Medium	+Medium
Left Vertical Wear Left Estimated Rail Depth	+ High	- High	- Medium	- Medium	- Medium
Left GAUGE Side Wear Left Head Width	- High	- Low	- Low	- Low	- Low
Left Field Side Wear Left GAUGE Side Wear	+ OR – Low to High	- Low	- Low	- Low	- Low
Left Head Width Left Head Width Remaining	- High	+ Very Low	+ Low	+ Low	+ Low
Left Head Width Left Inclination Deviation	+Low to High	+ Very Low	- Very Low	- Very Low	+ Very Low
Right GAUGE Side Wear Right Vertical Wear	+ High	+ Very Low	+ Very Low	+ Very Low	+ Very Low
Right Field Side Wear Right Head Width	+ High	-Low	- Low	- Low	- Very Low
Right Lip width Right Field Side Wear	+ High	*	- Low	- Very Low	- Very Low
Right Lip width Right Vertical Wear	+ High	*	- Very Low	- Very Low	- Very Low

4.3.1.1. Rail Profile Multivariate Significant Correlation

In multivariate correlation analysis of rail profile parameters as explained in Table 4.4 following significant correlations are reconciled with hypothesis developed based on parameter understanding.

1. There is strong negative relationship that exists between Head Width and Estimated Rail Depth in hypothesis. This means that Head Width is inversely proportional to Estimated Rail Depth, so if Head Width decreases than Estimated Rail Depth will increase. But unlike in experimental results where there is a positive, medium, correlation in all four base files between Head Width and Estimated Rail Depth. So the experimental results do not reconcile with theoretical hypothesis. If the correlation between them can only be high negative, so why is there a medium positive correlation in above base files?

2. There is strong positive relationship that exists between Vertical Wear and Estimated Rail Depth in hypothesis. This means that Vertical Wear is directly proportional to Estimated Rail Depth, i.e. when Vertical Wear increases Estimated Rail Depth will increase as well. But unlike in experimental results where there is a negative high correlation in first base file and negative, medium, in second, third and fourth. If the correlation between them can only be high positive, so why is there high a negative correlation in above base files?

3. There is strong negative relationship that exists between Head Width and GAUGE Side Wear in hypothesis. This means that GAUGE Side Wear is inversely proportional to Head Width i.e. when GAUGE Side Wear will increase Head Width decreases. But unlike in experimental results where there is a negative, low, negative correlation in all four base files. If the correlation between them can only be high negative, so why is there a low negative correlation in above base files?

4. There exists no direct relationship between GAUGE Side Wear and Field Side Wear in hypothesis i.e. when GAUGE Side Wear increase Field Side Wear may decrease or increase But unlike in experimental results where there is a consistent negative, low, correlation in all four base files. If their can be any correlation positive or negative and it can even vary from high to very low, so why is there a negative correlation in above base files?

5. There is a strong negative relationship that exists between Head Width and Head Width Remaining in hypothesis. This means that Head Width Remaining is inversely proportional to Head Width i.e. when Head Width decrease Head Width Remaining, will increase. But unlike in experimental results, there is a consistent positive, low, correlation in all four base files. If the correlation between them can only be high negative, so why is there a positive correlation in second and third base files?

6. There positive correlation between Head Width and Inclination Deviation in hypothesis. This means that Inclination Deviation is directly proportional to Head Width i.e. when Inclination Deviation increase Head Width will increase as well. But unlike in experimental results where there is a mix of relationship between Head Width and Inclination Deviation as in first base file it is low positive and then in second and third it is low negative at the end it is again changes back to low positive. If the correlation between them can only be positive, so why is there a negative correlation in second and third base file?

7. There is strong positive relationship that exists between Vertical Wear and GAUGE Side Wear in hypothesis. This means that Vertical Wear is directly proportional to GAUGE Side Wear i.e. when Vertical Wear increase GAUGE Side Wear will increase as well. But unlike in experimental results where there is a positive, low, correlation in all four base files between Vertical Wear and GAUGE Side Wear. If the correlation between them can only be high positive, so why is there a consistent low positive in above base files?

8. There is strong positive relationship that exists between Head Width and Field Side Wear in hypothesis. This means that Field Side Wear is directly proportional to Head Width i.e. when Field Side Wear increases Head Width will increase. But unlike in experimental results where there is a negative, low relationship between Head Width and Field Side Wear. If the correlation

between them can only be high positive, so why is there a consistent low negative in above base files?

9. There can only be a strong positive relationship between lip width and Field Side Wear in hypothesis. This means that lip width is directly proportional to Field Side Wear i.e. when lip width will increase Field Side Wear will increase. But unlike in experimental results where there is a very positive, low, correlation in all four base files between lip width and Field Side Wear. If the correlation between them can only be high positive, so why is there a low positive correlation in above base files?

10. There is strong positive relationship that exists between Vertical Wear and lip width in hypothesis. This means that lip width is directly proportional to Vertical Wear i.e. when lip width increase Vertical Wear will increase as well. But unlike in experimental results where there is a very negative, low, correlation in all four base files between Vertical Wear and lip width. If the correlation between them can only be high positive, so why is there a very low negative correlation in above base files?

Table 4.6 Track Geometry Multivariate Significant Correlation

Parameters	Hypo thesis	Experimental Results			
		Track Geometry 1	Track Geometry 2	Track Geometry 3	Track Geometry 4
ALIGMS TWIST1	+ High	- Low	- Low	*	+ Low
ALIGMS TWIST2	+ High	- Low	- Low	*	+ Low
TOPRS TWIST2	+ High	- Very Low	- Very Low	- Very Low	- Very Low
TOPRS TWIST1	+ High	- Very Low	- Very Low	- Very Low	- Very Low
TWIST2 CROSS LEVEL	+ High	- Very Low	- Very Low	- Very Low	- Very Low
TWIST1 CROSS LEVEL	+ High	- Very Low	- Very Low	- Very Low	- Very Low
TOPLS ALIGMS	+ High	- Very Low	- Very Low	*	+ Very Low
TOPRS ALIGMS	+ High	+ Very Low	+ Very Low	*	- Very Low
TOPRS ALIGML	+ High	- Very Low	+ Very Low	*	- Very Low
TOPLS ALIGML	+ High	- Very Low	- Very Low	*	+ Very Low
GAUGE ALIGML	+ High	+ Very Low	+ Very Low	*	- Very Low
ALIGMS CANT DEF	+ High	+ Very Low	+ Very Low	*	- Very Low
GAUGE CANT DEF	+ High	- Very Low	+ Very Low	*	+ Very Low
TWIST2 DIPPED RIGHT	+ Low to High	*	- Very Low	- Very Low	- Very Low
TWIST1 DIPPED RIGHT	+ Low to High	*	- Very Low	- Very Low	- Very Low

4.3.1.2. Track Geometry Multivariate Significant Correlation

In multivariate correlation analysis of track geometry parameters as explained in Table 4.5 following significant correlations are reconciled with hypothesis developed based on parameter understanding.

1. There is a high positive correlation between ALIGMS and TWIST1 in hypothesis. This means that ALIGMS is directly influenced by TWIST1 i.e. when ALIGMS will increase TWIST1 will increase as well. But unlike in experimental results where in first and base file there is a low negative correlation and in last file there is a low, positive, correlation between ALIGMS and TWIST1. If the correlation between them can only be high positive, so why is there a low positive correlation in first and second base file?

2. There is a high positive correlation between ALIGMS and TWIST2 in hypothesis. This means that ALIGMS is directly influenced by TWIST2 i.e. when ALIGMS will increase TWIST2 will increase as well. But unlike in experimental results where in first and base file there is a low negative correlation and in last file there is a low, positive, correlation between ALIGMS and TWIST2. If the correlation between them can only be high positive, so why there is a low positive in first and second base files? Also ALIGMS correlation with TWIST1 is exactly the same as ALIGMS correlation with TWIST2.

3. There is a high positive correlation between TOPRS and TWIST2 in hypothesis. This means that TOPRS is directly influenced by TWIST2 i.e. when TOPRS will increase TWIST2 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between TOPRS and TWIST2. If the correlation should be high positive, so why is there a consistent very low negative correlation in all four base files?

4. There is a high positive correlation between TOPRS and TWIST1 in hypothesis. This means that TOPRS is directly influenced by TWIST1 i.e. when TOPRS will increase TWIST1 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between TOPRS and TWIST1. If the correlation should be high positive, so why is there a consistent very low negative correlation in all four base files?

5. There is a high, positive, correlation between CROSS LEVEL and TWIST2 in hypothesis. This means that CROSS LEVEL is directly influenced by TWIST2 i.e. when CROSS LEVEL will increase TWIST2 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between CROSS LEVEL and TWIST2. If the correlation should be high positive, so why is there a consistent very low negative correlation in all four base files?

6. There is a high positive correlation between CROSS LEVEL and TWIST1 in hypothesis. This means that CROSS LEVEL is directly influenced by TWIST1 i.e. when CROSS LEVEL will increase TWIST1 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between CROSS LEVEL and TWIST1. If the correlation should be high positive, so why is there a consistent very low negative correlation in all four base files?

7. There is a high, positive, correlation between TOPLS and ALIGMS in hypothesis. This means that ALIGMS is directly influenced by TOPLS i.e. when ALIGMS will increase TOPLS will increase as well. But unlike in experimental results in first and second base files there is a very low negative correlation and in last base file a very low positive between ALIGMS and TOPLS. If the correlation should be high positive, so why is there a very low negative correlation in first and second base files?

8. There is a high positive correlation between TOPRS and ALIGMS in hypothesis. This means that ALIGMS is directly influenced by TOPRS i.e. when ALIGMS will increase TOPRS will increase as well. But unlike in experimental results in last base file where there is a very low negative correlation and in first and second base files a very low positive correlation between ALIGMS and TOPRS. If the correlation should be high positive, so why is there a very low negative correlation in all base files? Also ALIGMS

correlation with TOPRS is exactly the opposite of ALIGMS correlation with TOPLS?

9. There is a high positive correlation between TOPRS and ALIGML in hypothesis. This means that ALIGML is directly influenced by TOPRS i.e. when ALIGML will increase TOPRS will increase as well. But unlike in experimental results in first and last base files where there is a very low negative correlation and in second base file a very low positive correlation between ALIGML and TOPRS. If the correlation should be high positive, so why is there a very low negative correlation in first and last base file?

10. There is a high positive correlation between ALIGML and TOPLS in hypothesis. This means that ALIGML is directly influenced by TOPLS i.e. when ALIGML will increase TOPLS will increase as well. But unlike in experimental results in first and second base files where there is a very low negative correlation and in last base file a very low positive correlation between ALIGML and TOPLS. If the correlation should be high positive, so why is there a very low negative correlation in first and second base file?

11. There is a high positive correlation between ALIGML and GAUGE in hypothesis. This means that ALIGML is directly influenced by GAUGE i.e. when ALIGML will increase GAUGE will increase as well. But unlike in experimental results in last base file where there is a very low negative correlation and in first and second base files a very low positive correlation between ALIGML and GAUGE. If the correlation should be high positive, so why is there a very low negative correlation in last base file?

12. There is a high positive correlation between ALIGMS and CANT DEF in hypothesis. This means that CANT DEF is directly influenced by ALIGMS i.e. when CANT DEF will increase ALIGMS will increase as well. But unlike in experimental results in last base file where there is a very low negative

correlation and in first and second base files a very low positive correlation between ALIGMS and CANT DEF. If the correlation should be high positive, so why is there a very low negative correlation in last base file?

13. There is a positive correlation between CANT DEF and GAUGE in hypothesis which can vary from low to high. This means that if CANT DEF will change GAUGE will change as well. But unlike in experimental results in first base file where there is a very low negative correlation and in second and last base files a very low positive correlation between CANT DEF and GAUGE. If the correlation should be positive and can vary from low to high, so why is there a very low negative correlation in first base file?

14. There is a positive correlation between TWIST2 and DIPPED RIGHT in hypothesis which can vary from low to high. This means that DIPPED RIGHT is directly influenced by TWIST2 i.e. when DIPPED RIGHT will increase TWIST2 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between TOPRS and DIPPED RIGHT. If the correlation should be positive and can vary from low to high, so why is there a consistent very low negative correlation in all base files?

15. There is a positive correlation between TWIST1 and DIPPED RIGHT in hypothesis which can vary from low to high. This means that DIPPED RIGHT is directly influenced by TWIST2 i.e. when DIPPED RIGHT will increase TWIST2 will increase as well. But unlike in experimental results where there is a consistent very low negative correlation between DIPPED RIGHT and TWIST2. If the correlation should be positive and can vary from low to high, so why is there a consistent very low negative correlation in all base files?

Table 4.7 Rail Profile Univariate Significant Correlation

Hypo thesis	**R_P File 1<->File 4**		**R_P File 2<->File 3**		**R_P File 3<->File 4**	
	Parameter	**Correlation**	**Parameter**	**Correlation**	**Parameter**	**Correlation**
+ High	E R Dep_1 E R Dep_4	-Very Low	E R Dep_2 E R Dep_3	+ High	E R Dep_3 E R Dep_4	+ High
+ High	F P Clear_1 F P Clear_4	+ Very Low	F P Clear_2 F P Clear_3	+ High	F P Clear_3 F P Clear_4	+ Medium
+ High	H Width_1 H Width_4	-Very Low	H Width_2 H Width_3	+ High	H Width_3 H Width_4	+ Medium
+ High	Incl Dev_1 Incl Dev_4	+ Very Low	Incl Dev_2 Incl Dev_3	+ Very Low	Incl Dev_3 Incl Dev_4	+ Low
Hypo thesis	**R_P File 1<->File 2**		**R_P File 2<->File 4**		**R_P File 1<->File 3**	
	Parameter	**Correlation**	**Parameter**	**Correlation**	**Parameter**	**Correlation**
+ High	E R Dep_1 E R Dep_2	- Very Low	E R Dep_2 E R Dep_4	+ High	E R Dep_1 E R Dep_3	- Very Low
+ High	F P Clear_1 F P Clear_2	+ Very Low	F P Clear_2 F P Clear_4	+ Medium	F P Clear_1 F P Clear_3	- Very Low
+ High	H Width_1 H Width_2	+ Very Low	H Width_2 H Width_4	+ Medium	H Width_1 H Width_3	+ Very Low
+ High	Incl Dev_1 Incl Dev_3	+ Very Low	Incl Dev_2 Incl Dev_4	+ Very Low	Incl Dev_1 Incl Dev_3	- Very Low

4.3.1.3. Rail Profile Univariate Significant Correlation

In univariate correlation analysis of rail profile parameters as explained in Table 4.6 following significant correlations are reconciled with hypothesis developed based on parameter understanding as well as explored each parameter over time. Now theoretically when a parameter is correlated with itself it is highly positively correlated so:

1. Estimated Rail Depth is highly, positively, correlated in 2-4, 2-3, and 3-4 base files. But there is a negative, very low, correlation in base files 1-4, 1-3 and 1-2. In these files not only its value has changed from high to low but also the sign is changed from positive to negative. If the correlation can only positive, so why is there a negative correlation in 1-4, 1-3 and 1-2 base files?

2. Fish Plate Clearance is, positively, highly correlated in 2-3 and positive medium in 3-4 and 2-4 base files. It has a low positive correlation in 1-2 and in 1-4. But there is a negative, very low, correlation in base files 1-3. If the correlation between them can only positive, so why is there a negative correlation in 1-3?

3. Head width is highly positively correlated in 2-3 and medium positive in 3-4 and 2-4 base files. It has a low positive correlation in 1-2 and in 1-3. But there is a very low negative correlation in base files 1-4. If the correlation between them can only high positive, so why is there a negative correlation in 1-4?

4. Inclination Deviation has low positive correlation in 1-4, 1-2, 2-3, 2-4 and 3-4 base files. But there is a very low negative correlation in 1-3 base files. If the correlation between them can only positive, so why is there a negative correlation in 1-3?

One answer to the question as why there are negative correlations is offset. Offset is change in distance from where the value of the parameter was recorded in different times like in case of all base files.

Table 4.8 Track Geometry Univariate Significant Correlation

Hypo thesis	**T_G File 2<->File 3**		**T_G File 3<->File 4**		**T_G File 1<->File 2**	
	Parameter	**Correlation**	**Parameter**	**Correlation**	**Parameter**	**Correlation**
+ High	*	*	*	*	ALIGMS_1 ALIGMS_2	- Low
+ High	*	*	*	*	ALIGML_1 ALIGML_2	+ Low
+ High	TOPRS_2 TOPRS_3	+ Very Low	TOPRS_3 TOPRS_4	+ Low	TOPRS_1 TOPRS_2	-Very Low
+ High	TOPLS_2 TOPLS_3	+ Very Low	TOPLS_3 TOPLS_4	+ Low	TOPLS_1 TOPLS_2	- Very Low
Hypo thesis	**T_G File 1<->File 4**		**T_G File 1<->File 3**		**T_G File 2<->File 4**	
	Parameter	**Correlation**	**Parameter**	**Correlation**	**Parameter**	**Correlation**
+ High	ALIGMS_1 ALIGMS_4	- Very Low	*		ALIGMS_2 ALIGMS_4	- Very Low
+ High	ALIGML_1 ALIGML_4	+ Very Low	*		ALIGML_2 ALIGML_4	- Very Low
+ High	TOPLS_1 TOPLS_4	+ Very Low	TOPLS_1 TOPLS_3	+ Very Low	TOPRS_2 TOPRS_4	- Very Low
+ High	TOPRS_1 TOPRS_4	-Very Low	TOPRS_1 TOPRS_3	-Very Low	TOPLS_3 TOPLS_4	- Very Low

4.3.1.4. Track Geometry Univariate Significant Correlation

In univariate correlation analysis of track geometry parameters as explained in Table 4.7 following significant correlations are reconciled with hypothesis developed based on parameter understanding as well as explored each parameter over time. Now theoretically when a parameter is correlated with itself it is highly positively correlated:

1. But unlike in experiments where ALIGMS has a consistent negatively correlation in base files 1-2, 2-4 and 1-4. If the correlation should be positive one, so why is consistent negative correlation in all base files?

2. But unlike in experiments where ALIGML has a positive correlation in base files 1-2 and 1-4 and a negative, very low, correlation in 2-4. If the correlation should be positive one, so why is there a negative correlation in 2-4 base file?

3. But unlike in experiments where there is a negative, very low, correlation in base files 1-2, 1-3, 1-4 and 2-4 and a low positive correlation in 2-3 and 2-4 base files. If the correlation should be positive one, so why is there a negative correlation in 1-2, 1-3, 1-4 and 2-4base files?

4. But unlike in experiments where there is a negative, very low, correlation in base files 1-2, 1-2 and 2-4 and has a low, positive, correlation in 2-3, 1-3, 1-4 and 3-4 base files. If the correlation should be positive one, so why is there a negative correlation in 1-4 and 2-4 base files?

According to theoretical hypothesis, ideally, a parameter is highly positively correlated with itself. But in some cases the theoretical hypothesis does not reconcile with the univariate correlation analysis of both modalities. One answer for this mismatch of experimental results with theoretical hypothesis is parameter data offset. Offset is the number of yards displaced from original location of data recording in different base files. The only way to over come this problem is to align start of each base file i.e. all base files have exactly same starting point according to Mile and Yard information.

4.3.2. Linear Regression Analysis

Linear regression estimates the coefficients of the linear equation, involving one or more independent parameters that best predict the value of the dependent parameter. In linear regression the objective is to know how well linear parameters can be predicted from rest of parameters.

The less the prediction error the better the dependent parameter can be predicted from rest of the set of independent parameters. To make prediction error comparable it is standardized. In Tables 4.8 * means that parameter data was not recorded and in Tables 4.9 * show that as dependent parameter can not be predicted by itself so there is no value.

Table 4.9 Track Geometry Univariate Linear Regression

Dependent Parameters	Contribution of Independent Parameters			Prediction Error
	1	2	3	
CROSS LEVEL	0.03	0.34	0.70	0.12
GAUGE	0.11	0.41	3.71	0.09
CURV	0.28	1.24	*	0.05
CANTDEF	0.12	0.82	*	0.02

4.3.2.1. Track Geometry Univariate Linear Regression

Below is univariate track geometry linear regression analysis of significant parameters. Such parameter interpretation is based on rail track parameter understanding of each parameter over time [4].

1. **CROSS LEVEL**

   The highest mean value of coefficient amongst three independent parameters is 0.70 in third base file. This means that if CROSS LEVEL of third base file goes up by one mm then the dependent CROSS LEVEL will go up (because of positive relationship between them) by 0.70 mm. Where as, the lowest values is 0.03 in first base file.

2. **GAUGE**

   The highest coefficient mean value amongst three independent parameters is 3.71 in third base file. This means that if GAUGE of third base file goes up by one mm then the dependent GAUGE will go up (because of positive relationship between them) by 3.71 mm. Where as, the lowest values is 0.11 in first base file.

3. **CURV**

   The highest mean value of coefficient amongst three independent parameters is 1.24 in third base file. This means that if CURV of third base file goes up by one mm then the dependent CURV will go up (because of positive relationship between them) by 1.24 mm. Where as, the lowest values is 0.28 in first base file.

4. **CANT DEF**

   The highest mean value of coefficient amongst three independent parameters is 0.82 in third base file. This means that if CANT DEF of third base file goes up by one mm then the dependent CANT DEF will go up (because of positive relationship between them) by 0.82 mm. Where as, the lowest values is 0.12 in first base file.

Table 4.10 Track Geometry Multivariate Linear Regression

Independent Parameters	Contribution of Dependent Parameters			
	DIPPED LEFT	**CANT DEF**	**CROSS LEVEL**	**CURV**
DIPPED LEFT	*	0.00	0.21	0.01
DIPPED RIGHT	0.28	0.01	0.02	0.06
CANT DEF	0.00	*	0.45	3.3
GAUGE	0.00	0.09	0.07	0.38
CROSS LEVEL	0.00	0.52	*	3.05
CURV	0.00	0.20	0.28	*
TOPLS	0.01	0.00	0.07	0.00
TOPRS	0.00	0.00	0.05	0.00
TOPML	0.00	0.00	0.00	0.00
ALIGML	0.00	0.00	0.02	0.02
ALIGMS	0.00	0.00	0.12	0.08
TWIST2	0.00	0.00	0.10	0.01
TWIST1	0.00	0.00	0.18	0.00
Prediction Error	0.16	0.60	0.61	0.42

4.3.2.2. Track Geometry Multivariate Linear Regression

Below is multivariate neural network predictive analysis of significant track geometry parameters. The analysis investigates how much a parameter contributes in predicting other parameters and also the predictive error of each parameter while being predicted by rest of the parameters [5], [6].

1. **DIPPED LEFT**

   The highest coefficient mean value amongst all independent parameter is DIPPED RIGHT 0.28 which means that if DIPPED RIGHT goes up by one mm then DIPPED LEFT will go up (because of positive relationship between them) by 0.28 mm, whereas rest of all the parameters except TOPLS have the lowest value of 0.00.

2. **CANT DEF**

   The highest mean value of coefficient amongst all independent parameter is DIPPED RIGHT 0.52 which means that if CROSS LEVEL goes up by one mm then CANT DEF will go down (because of negative relationship between them) by 0.28 mm, whereas the lowest mean is 0.52 of CROSS LEVEL.

3. **CROSS LEVEL**

   The highest mean value of coefficient amongst all independent parameter is CURV 0.28 which means that if CURV goes up by one mm then CROSS LEVEL will go up (because of positive relationship between them) by 0.28 mm, whereas rest of the parameters, CANT DEF has the lowest mean value of 0.45.

4. **CURV**

   The highest mean value of coefficient amongst all independent parameter is CANT DEF 3.3 which means that if CANT DEF goes up by one mm then CURV will go up (because of positive relationship between them) by 3.3 mm, whereas rest of the parameters, ALIGMS has the lowest mean value of 0.08.

4.4. Conclusion

The distance alignment method should offer an ideal way of alignment hypothetically. However, our experiments revealed that some of the parameters in both rail profile and track geometry resulted in negative correlations over time. This univariate negative correlation is a consequence of excessive parameter data loss during the process of data alignment. Such excessive parameter data loss adds to ineffectiveness of alignment and therefore emphasises the need for a better and effective data alignment method. . This leads to the conclusion that better and more effective ways of alignment. Therefore chapter 5 and 6 proposes two further, improved approaches to data alignment.

Chapter 5

Fixed Window Alignment Based Predictive Analysis

This chapter focuses on neural network based univariate and multivariate predictive analysis of both rail profile and track geometry parameters. The analysis is based on fixed window alignment and will be utilised in predicting rail track degradation.

5.1. Introduction

In chapter-4 it was concluded that the linear regression analysis based on the distance alignment of data is not effective due to excessive parameter loss. Thus in order to have an effective predictive analysis, limitations that result from using the distance alignment based approach have to be removed. Another problem with using such a point based predictive analysis is that it does not necessarily match with the general trends of the actual track data taken over different test dates. In order to solve the above mentioned problems, it is necessary to evolve an approach that is relatively unaffected by the minor variations in rail profile and track geometry parameter data across different test dates of the year. In current experiments average value of each section of 10 yards for each type of parameter is calculated. Hence each 10 yard section of the track represents average of parameter values in both modalities.

5.2. A Fixed Window Alignment

Each base file in both modalities has distance information which explains Mile and Yard information in two different columns. In fix section window approach of alignment, data is segmented into sections which represent the areas/segments of rail track rather than the exact locations. This method can lead to faster processing and subsequent analysis due to the use of segments as the analysis unit, instead of the exact points at which measurements have been taken. Such improvement of the processing speed is valuable for large volumes of data. Experiment shows that there are an average of three rows of records for rail profile datasets and an average of forty rows of records for track geometry datasets in one segmented area. Each base file in both modalities is individually aligned. For each segmented area of 10 yards we calculate the average modulus value of each type of parameter and represent these parameters with the calculation results for this 10 yards section area.

In current experiments a fixed window size approach is used in which the whole track is divided into sections of 10 yards each. The window size is restricted to 10 as the maximum variation, in all four base files, is within 10 yards. One major limitation of such alignment is its potential to lose information. This is because the parameter values of each 10 yard section of the track are averaged out as one Mile and Yard value. The second major constraint is locating exact Mile and Yard information on a track. Predicting the error is one aim of our analysis and locating it on the track is the next. Neural network predictive analysis leads segment of 10 yards. Therefore a 10 yards section of the track has to be visited by maintenance people as the exact location within that segment will not be known.

The pseudo code for the fixed window based alignment approach presented above can be written as follows:

Pseudo code

```
Convert all Mile and Yard information into Yards [Note: * refers to 'address of']
Ctr =1st value of Base File_N (N=1,2,3,4)
FixwindowAlign  (*Ctr)
        {
                While (*Ctr != EOF)
                {
```

*for (*Ctr<10 ; *Ctr++)*

{

Calculate AverageValue of Row_1 till Row_10

}

Each AverageValue calculated is stored as one row in a new aligned base file

} / end While*/*

} / end FixwindowAlign */*

(All parameters values along with corresponding Yard information are averaged and stored in a new file)

5.3. Neural Network Analysis

Neural networks (NN) are trainable systems that can learn to solve complex problems from a set of examples and generalize the acquired knowledge to solve future problems as in case of predictive maintenance [99]. As the basis of the research is to conduct regression analysis to support predictive analysis, so most commonly used tool i.e. NN was selected for the job [95]. NN is mainly used for regression analysis unlike genetic algorithms which are mainly used for optimization purposes [96].

NN is an interconnected group of artificial neurons that use a mathematical or computational model for information processing [83]. A computational NN is a set of non linear information modelling tools consisting of input and output layers plus one hidden layer [84]. The connections between neurons in each layer have associated weights, which are iteratively adjusted by the training algorithm to minimize prediction error so as to give accurate predictions. The type of NN used in current predictive analysis is Multi Layer Perceptron (MLP) which uses supervised learning algorithm [86]. The ability of MLP to be used as an arbitrary function approximation mechanism has made MLP to be utilized for supervised learning [68]. The architecture involves two hidden layers and activation function for the hidden layer and output layer. The activation function associates the weighted sums of units in a layer to the values of units in the next layer.

Current neural network analysis is based on univariate and multivariate analysis of both track geometry parameters and rail profile significant parameters. The objective of multivariate NN analysis is to see how well we can predict one significant parameter from other. In which case, each parameter is predicted by rest of the parameters, in all base files, in each modality. During the process of prediction 70% data in each base of both modalities is used for training and 30% for testing purposes in order to calculate two important aspects. One is the contribution of all independent parameters is calculated while predicting significant dependent parameter. And the second aspect is prediction error which is calculated for all significant dependent parameters predicted by rest of the independent parameters in each base file. Prediction error is the difference between the predicted and actual value of the dependent parameter in each base of both modalities. This process is repeated in each base file for both modalities and mean of contribution and predictive error are represented in Tables from 5.1 till Table 5.4.

Univariate analysis involves predicting each parameter of both modalities over time. During the process of prediction data of first three base files in both modalities is used for training to predict latest base file for testing purposes. Two main aspects are recorded during univariate predictive analysis. One is the contribution of all independent parameters which is calculated while predicting dependent parameter. The second aspect is the prediction error which is calculated for all dependent parameters predicted by independent parameters over time. The process involves predicting all significant parameters of both modalities from latest base files. The NN was trained until there was no further decrease in prediction error and afterwards prediction error was calculated. Thus showing that NN was not over trained and hence prediction can not further be minimized. Such predictive error analysis will be useful in analysing predictive rail track degradation.

Table 5.1 Rail Profile Multivariate Predictive Analysis

Independent parameter	Contribution of Dependent Parameters					
	Left Head Width Remaining	Left Fish Plate Clearance	Left Inclination Deviation	Right Head Width Remaining	Right Fish Plate clearance	Right Inclination Deviation
Left Head Width Remaining	*	0.04	0.03	0.39	0.05	0.01
Left Fish Plate Clearance	0.03	*	0.04	0.03	0.06	0.02
Left Inclination Deviation	0.00	0.00	*	0.00	0.00	0.52
Left GAUGE Side Wear	0.01	0.05	0.01	0.00	0.00	0.01
Left Field Side Wear	0.00	0.01	0.01	0.00	0.00	0.00
Left Head Width	0.13	0.07	0.03	0.09	0.03	0.02
Left Estimated Rail Depth	0.03	0.07	0.02	0.04	0.02	0.02
Left Vertical Wear	0.03	0.33	0.03	0.04	0.04	0.04
Right Head Width Remaining	0.03	0.05	0.02	*	0.05	0.01
Right Fish Plate Clearance	0.03	0.01	0.02	0.01	*	0.02
Right Inclination Deviation	0.00	0.00	0.38	0.00	0.00	*
Right GAUGE Side Wear	0.00	0.01	0.01	0.01	0.03	0.02
Right Field Side Wear	0.01	0.00	0.02	0.01	0.01	0.02
Right Head Width	0.02	0.01	0.03	0.10	0.06	0.02
Right Estimated Rail Depth	0.01	0.02	0.02	0.04	0.06	0.03
Right Vertical Wear	0.02	0.02	0.03	0.01	0.32	0.01
Prediction Error	0.00	0.00	0.18	0.00	0.00	0.15

5.3.1. Rail Profile Multivariate Predictive Analysis

Described below is the multivariate NN predictive analysis of left and right rail profile parameters which were summarised in Table 5.1. The analysis investigates the contribution of significant parameters in predicting other parameters. It further calculates the predictive error of each parameter when being predicted by rest of the parameters. * indicates as dependent parameter can not be predicted by itself and hence there is no value.

1. Left Head Width Remaining

a. Left Head Width is the highest contributor (0.13) and left Inclination Deviation, right Inclination Deviation, left Field Side Wear and right GAUGE Side Wear are the lowest contributors (0.00) in predicting left Head Width Remaining.

b. No prediction error (0.00) shows that left Head Width Remaining can be predicted with very high confidence by these independent parameters.

2. Right Head Width Remaining

a. Left Head Width Remaining is the highest contributor (0.39) and left Inclination Deviation, right Inclination Deviation and left Field Side Wear are the lowest contributors (0.00) in predicting right Head Width Remaining.

b. No prediction error (0.00) shows that left Head Width Remaining can be predicted with very high confidence by these independent parameters.

3. Left Fish Plate Clearance

a. Left Vertical Wear is the highest contributor (0.33) and left Inclination Deviation, right Inclination Deviation and right Field Side Wear are the lowest contributors (0.00) in predicting left Fish Plate Clearance.

b. No prediction error (0.00) shows that left Fish Plate Clearance can be predicted with very high confidence by these independent parameters.

4. Right Fish Plate Clearance

a. Right Vertical Wear is the highest contributor (0.32) and left Inclination Deviation, right Inclination Deviation, left GAUGE Side Wear and left Field Side Wear are the lowest contributors (0.00) in predicting right Fish Plate Clearance.

b. No prediction error shows that left Fish Plate Clearance can be predicted with very high confidence by these independent parameters.

5. Left Inclination Deviation

a. Right Inclination Deviation is the highest contributor (0.38) and right GAUGE Side Wear, left GAUGE Side Wear and left Field Side Wear are the lowest contributors (0.01) in predicting left Inclination Deviation.

b. Very low prediction error (0.18) shows that left Inclination Deviation can be predicted with very high confidence by these independent parameters.

6. Right Inclination Deviation

a. Left Inclination Deviation is the highest contributor (0.52) and left Field Side Wear is the lowest contributor (0.00) in predicting right Inclination Deviation.

b. Very low prediction error (0.15) shows that left Inclination Deviation can be predicted with very high confidence by these independent parameters.

Table 5.2 Rail Profile Univariate Predictive Analysis

Dependent Parameter	Contribution of Independent Parameters			Prediction Error
	1	2	3	
Left GAUGE Side Wear	0.09	0.41	0.49	0.67
Right GAUGE Side Wear	0.13	0.52	0.34	0.78
Left Field Side Wear	0.09	0.22	0.68	0.88
Right Field Side Wear	0.32	0.36	0.31	0.97
Left Head Width	0.36	0.27	0.36	0.22
Right Head Width	0.50	0.29	0.19	0.31
Left Head Width Remaining	0.49	0.19	0.30	0.02
Right Head Width Remaining	0.46	0.19	0.34	0.01
Left Vertical Wear	0.56	0.40	0.02	0.20
Right Vertical Wear	0.46	0.39	0.13	0.35
Left Estimated Rail Depth	0.53	0.31	0.15	0.12
Right Estimated Rail Depth	0.44	0.37	0.18	0.10
Left Fish Plate Clearance	0.57	0.40	0.01	0.22
Right Fish Plate Clearance	0.53	0.40	0.05	0.46
Left Inclination Deviation	0.20	0.33	0.45	0.26
Right Inclination Deviation	0.27	0.47	0.24	0.24

5.3.2. Rail Profile Univariate Predictive Analysis

Described below is the univariate NN predictive analysis of left and right rail profile parameters which were summarised in Table 5.2. The analysis investigates the contribution of significant parameters in predicting other parameters. It further calculates the predictive error of each parameter when being predicted by rest of the parameters over time.

1. Left Head Width Remaining

a. Highest value of left Head Width Remaining is in first base file (0.49) and in second base file it is the lowest contributor (0.19).

b. Very low prediction error (0.02) shows that left Head Width Remaining can be predicted with very high confidence over time.

2. Right Head Width Remaining

a. Highest value of right Head Width Remaining is in first base file (0.46) and in second base file it is the lowest contributor (0.03).
b. Very low prediction error (0.01) shows that right Head Width Remaining can be predicted with very high confidence over time.

3. Left GAUGE Side Wear

a. Highest value of left GAUGE Side Wear is in third base file (0.49) and in first base file it is the lowest contributor (0.09).
b. High prediction error (0.67) shows that left GAUGE Side Wear can be predicted with low confidence over time.

4. Right GAUGE Side Wear

a. Highest value of right GAUGE Side Wear is in second base files (0.52) and in first base file it is the lowest contributors (0.13).
b. High prediction error (0.78) shows that right GAUGE Side Wear can be predicted with low confidence over time.

5. Left Field Side Wear

a. Highest value of left Field Side Wear is in third base file (0.68) and in first base file it is the lowest contributor (0.09).
b. Very high prediction error (0.88) shows that left Field Side Wear can be predicted with low confidence over time.

6. Right Field Side Wear

a. Highest value of right Field Side Wear is in second base file (0.36) and in third base file it is the lowest contributor (0.31).

b. Very high prediction error (0.97) shows that right Field Side Wear can be predicted with very low confidence over time.

7. Left Head Width

a. Highest value of left Head Width is in first and third base file (0.36) and in second base file it is the lowest contributor (0.27).
b. Low prediction error (0.22) shows that left Head Width can be predicted with very high confidence over time.

8. Right Head Width

a. Highest value of right Head Width is in first base files (0.50) and in third base file it is the lowest contributors (0.19).
b. Low prediction error (0.31) shows that right Head Width can be predicted with very high confidence over time.

9. Left Vertical Wear

a. Highest value of left Vertical Wear is in first base file (0.56) and in third base file it is the lowest contributor (0.02).
b. Low prediction error (0.20) shows that left Vertical Wear can be predicted with very high confidence over time.

10. Right Vertical Wear

a. Highest value of right Vertical Wear is in first base file (0.46) and in third base file it is the lowest contributor (0.13).
b. Low prediction error (0.35) shows that right Vertical Wear can not very well be predicted with very high confidence over time.

11. Left Estimated Rail Depth

a. Highest value of left Estimated Rail Depth is in first base file (0.53) and in third base file it is the lowest contributor (0.15).
b. Very low prediction error (0.12) shows that left Estimated Rail Depth can be predicted with very high confidence over time.

12. Right Estimated Rail Depth

a. Highest value of right Estimated Rail Depth is in first base file (0.44) and in third base file it is the lowest contributor (0.18).
b. Low prediction error (0.10) shows that right Estimated Rail Depth can be predicted with very high confidence over time.

13. Left Fish Plate Clearance

a. Highest value of left Fish Plate Clearance is in first base file (0.57) and in third base file it is the lowest contributor (0.01).
b. Low prediction error (0.22) shows that left Fish Plate Clearance can be predicted with very high confidence over time.

14. Right Fish Plate Clearance

a. Highest value of right Fish Plate Clearance is in first base file (0.53) and in third base file it is the lowest contributor (0.05).
b. Medium prediction error (0.46) shows that right Fish Plate Clearance can be predicted with average confidence over time.

15. Left Inclination Deviation

a. Highest value of left Inclination Deviation is in third base file (0.45) and in first base file it is the lowest contributor (0.20).
b. Low prediction error (0.26) shows that left Inclination Deviation can be predicted with very high confidence over time.

16. Right Inclination Deviation

a. Highest value of right Inclination Deviation is in second base file (0.47) and in third base file it is the lowest contributor (0.24).
b. Low prediction error (0.24) shows that right Inclination Deviation can be predicted with very high confidence over time.

Table 5.3 Track Geometry Multivariate Predictive Analysis

Independent Parameters	Contribution of Dependent Parameters								
	TWIST1	TWIST2	ALIGMS	ALIGML	TOPLS	TOPRS	TOPML	GAUGE	DIPPED RIGHT
TWIST1	*	0.66	0.03	0.03	0.02	0.06	0.03	0.11	0.09
TWIST2	0.59	*	0.05	0.05	0.05	0.03	0.03	0.05	0.00
ALIGMS	0.04	0.02	*	0.29	0.06	0.04	0.13	0.36	0.02
ALIGML	0.04	0.07	0.14	*	0.03	0.03	0.10	0.05	0.02
TOPLS	0.02	0.02	0.03	0.03	*	0.50	0.26	0.05	0.06
TOPRS	0.03	0.02	0.08	0.02	0.51	*	0.21	0.06	0.25
TOPML	0.01	0.01	0.06	0.06	0.09	0.08	*	0.03	0.04
GAUGE	0.04	0.02	0.33	0.02	0.03	0.02	0.05	*	0.03
DIPPED RIGHT	0.01	0.07	0.02	0.02	0.03	0.18	0.05	0.11	*
CURV	0.04	0.03	0.03	0.03	0.02	0.02	0.05	0.13	0.09
CROSS LEVEL	0.02	0.02	0.03	0.31	0.01	0.01	0.06	0.06	0.01
CANT DEF	0.02	0.03	0.05	0.01	0.01	0.01	0.02	0.02	0.02
DIPPED LEFT	0.03	0.03	0.06	0.03	0.16	0.05	0.02	0.04	0.37
Prediction Error	0.09	0.08	0.50	0.62	0.25	0.24	0.50	0.71	0.43

5.3.3. Track Geometry Multivariate Predictive Analysis

Described below is the multivariate NN predictive analysis of track geometry parameters which were summarised in Table 5.3. The analysis investigates the contribution of significant parameters in predicting other parameters. It further calculates the predictive error of each parameter when being predicted by rest of the parameters. * indicates that as dependent parameter can not be predicted by itself and hence there is no value.

1. TWIST1

a. TWIST2 is the highest contributor 0.59 and DIPPED RIGHT and TOPML are the lowest contributor (0.01) in predicting TWIST1.

b. Very low prediction error 0.09 shows that TWIST1 can predicted with very high confidence by these independent parameters.

2. TWIST2

a. TWIST1 is the highest contributor (0.66) and TOPML is the lowest contributor (0.01) in predicting TWIST2.

b. Very low prediction error 0.08 shows that TWIST2 can predicted with very high confidence by these independent parameters.

3. ALIGMS

a. GAUGE is the highest contributor (0.33) and DIPPED RIGHT is the lowest contributor (0.02) in predicting ALIGMS.

b. Medium prediction error 0.50 shows that ALIGMS can be predicted with average confidence by these independent parameters.

4. ALIGML

a. ALIGMS is the highest contributor (0.29) and CANT DEF is the lowest contributor (0.01) in predicting GAUGE.

b. Medium prediction error 0.62 shows that GAUGE can be predicted with average confidence by these independent parameters.

5. TOPLS

a. TOPRS is the highest contributor (0.51) and CROSS LEVEL and CANT DEF are the lowest contributors (0.01) in predicting TOPLS.

b. Low prediction error 0.25 shows that TOPLS can be predicted with high confidence by these independent parameters.

6. TOPRS

a. TOPLS is the highest contributor (0.50) and CROSS LEVEL and CANT DEF are the lowest contributors (0.01) in predicting TOPRS.

b. Low prediction error 0.24 shows that TOPRS can well be predicted with high confidence by these independent parameters.

7. TOPML

a. TOPLS is the highest contributor (0.26) (TOPRS with second highest value of 0.21) and CROSS LEVEL and CANT DEF are the lowest contributor (0.02) in predicting TOPML.

b. Medium prediction error 0.50 shows that TOPML can be predicted with less confidence by these independent parameters.

8. GAUGE

a. ALIGMS is the highest contributor (0.36) and CANT DEF is the lowest contributor (0.02) in predicting GAUGE.

b. Medium prediction error 0.71 shows that GAUGE can be predicted with average confidence by these independent parameters.

9. DIPPED RIGHT

a. DIPPED LEFT is the highest contributor (0.37) and TWIST2 is the lowest contributor (0.00) in predicting DIPPED RIGHT.

b. Medium prediction error 0.43 shows that DIPPED RIGHT can be predicted with average confidence by these independent parameters. .

Table 5.4 Track Geometry Univariate Predictive Analysis

Dependent Parameters	Contribution of Independent Parameters			
	1	2	3	Prediction Error
TWIST1	0.11	0.30	0.57	0.40
TWIST2	0.17	0.29	0.52	0.38
ALIGMS	0.19	0.80	*	0.72
ALIGML	0.74	0.25	*	0.67
TOPML	0.32	0.62	0.61	0.60
TOPRS	0.01	0.27	0.70	0.49
TOPLS	0.04	0.19	0.75	0.43
CROSS LEVEL	0.04	0.35	0.60	0.02
GAUGE	0.00	0.60	0.38	0.49
CURV	0.20	0.79	*	0.09
CANT DEF	0.06	0.93	*	0.20

5.3.4. Track Geometry Univariate Predictive Analysis

Described below is the univariate NN predictive analysis of track geometry parameters which were summarised in Table 5.4. The analysis investigates the contribution of significant parameters in predicting other parameters. It further calculates the predictive error of each parameter when being predicted by rest of the parameters over time. * indicates as dependent parameter can not be predicted by itself and hence there is no value.

1. TWIST1

a. TWIST1 of third base file is the highest contributor (0.57) and TWIST1 of first base file is the lowest contributor (0.11) in predicting TWIST1 over time.

b. Medium prediction error of 0.40 shows that TWIST1 can be predicted with average confidence over time.

2. TWIST2

a. TWIST2 of third base file is the highest contributor (0.52) and TWIST2 of first base file is the lowest contributor (0.17) in predicting TWIST2 over time.
b. Medium prediction error (0.38) shows that TWIST2 can be with average confidence predicted over time.

3. ALIGMS

a. ALIGMS of second base file is the highest contributor (0.80) and ALIGMS of first base file is the lowest contributor (0.19) in predicting ALIGMS over time.
b. High prediction error (0.72) shows that ALIGMS can be predicted with less confidence over time.

4. ALIGML

a. ALIGML of first base file is the highest contributor (0.74) and ALIGML of second base file is the lowest contributor (0.25) in predicting ALIGML over time.
b. High prediction error (0.67) shows that ALIGML can be predicted less confidence over time.

5. TOPML

a. TOPML of second base file is the highest contributor (0.62) and TOPML of first base file is the lowest contributor (0.32) in predicting TOPML over time.
b. Medium prediction error (0.60) shows that TOPML can be predicted with average confidence over time.

6. TOPRS

a. TOPRS of third base file is the highest contributor (0.70) and TOPRS of first base file is the lowest contributor (0.01) in predicting TOPRS over time.
b. Medium prediction error (0.49) shows that TOPRS can be predicted with average confidence over time.

7. TOPLS

a. TOPLS of third base file is the highest contributor (0.75) and TOPLS of first base file is the lowest contributor (0.04) in predicting TOPLS over time.
b. Medium prediction error (0.43) shows that TOPLS can be predicted with average confidence over time.

8. CROSS LEVEL

a. CROSS LEVEL of third base file is the highest contributor (0.60) and CROSS LEVEL of first base file is the lowest contributor (0.04) in predicting CROSS LEVEL over time.
b. Very low prediction error (0.02) shows that CROSS LEVEL can be predicted with very high confidence over time.

9. GAUGE

a. GAUGE of second base file is the highest contributor (0.60) and GAUGE of first base file is the lowest contributor (0.00) in predicting GAUGE over time.
b. Medium prediction error (0.49) shows that GAUGE can be predicted with average confidence over time.

10. CURV

a. CURV of second base file is the highest contributor (0.79) and CURV of first base file is the lowest contributor (0.20) in predicting CURV over time.
b. Very low prediction error (0.09) shows that CURV can be predicted with very high confidence over time.

11. CANT DEF

a. CANT DEF of second base file is the highest contributor (0.93) and CANT DEF of first base file is the lowest contributor (0.06) in predicting CANT DEF over time.
b. Low prediction error (0.20) shows that CANT DEF can be predicted with very high confidence over time.

5.3.5. Summary of Predictive Analysis

Current predictive analysis of both track geometry and rail profile parameters is divided into univariate and multivariate analysis. The objective of multivariate NN analysis is to see how well we can predict one parameter from other. Where as, univariate analysis involves predicting each parameter of both modalities over time. Such predictive error analysis will be useful in analysing predictive rail track degradation.
In comparison to distance alignment, fixed window alignment:

1. Computational complexity is reduced.
2. Prediction accuracy of most of the parameters is improved as Mile and Yard information along with parameter data is averaged instead of being discarded.

Besides excessive data loss in fixed window alignment, its inability to pin point exact location on the track, as it merely highlights a 10 yard section on the track, limits it to be a pragmatic solution.

5.4. Conclusion

In fixed size window method, data is segmented into 10 yard sections representing areas of track rather than exact location. However, there are two main constraints of this approach. One major limitation is its information loss during the process of alignment. This is because each 10 yard section of the track is average out as one mile yard value. The second major constraint is locating exact mile yard information on a track. Therefore NN predictive analysis can not find exact location of the track rather it highlights track segment of 10 yard (averaged as one mile yard value).

So for any mile yard value in predictive analysis a 10 yard section of the track has to be visited by rail maintenance people. This inability of the fixed alignment method to locate exact location on the track and losing one tenth of parameter data makes it inefficient and therefore less attractive before rail maintenance people. Hence such rail track predictive analysis is not applicable in real life and in analysing rail track degradation process because of the fact that its losses information during the process of alignment and its inability to locate exact position on the track.

Chapter 6

Parameter Alignment Based Predictive Analysis

This chapter explores predictive analysis based on a parameter based alignment method that addresses limitations of previous alignment methods. It then thresholds each parameter of both rail profile and track geometry to determine possible exceedences. Such threshold analysis is extremely helpful in modelling the rail track degradation process.

6.1. Introduction

Effectiveness of predictive error analysis is dependent on the effectiveness of data alignment in both modalities [87]. Without data being properly aligned any analysis across multiple data streams of both rail profile and track geometry would be ineffective. This was shown to be the case in distance alignment and fix window alignment approach because of excessive parameter data loss and failure to find exact location on the track. Therefore in this chapter a parameter based alignment method is proposed which sets up the foundations for future univariate and multivariate predictive analysis of all parameters in both modalities.

As in rail industries multiple thresholds can be used to categorise the experimental data into various categories such as good, satisfactory and poor. Thus all parameter values in the predictive analysis which increases over the threshold line are exceedences, i.e. they exceed threshold line and hence needs immediate maintenance or normal i.e. they are below threshold line and hence needs no immediate maintenance. Such categorisation of data would be more meaningful and therefore help engineers in predictive maintenance.

6.2. A Parameter Based Alignment

Despite some promising work automated data alignment methods are still in their infancy, since equivalences and differences manifest themselves at all levels [88]. A general purpose solution to data alignment problem is automatic identification of equivalence classes or aliases, and then aligning data across each modality by shifting accordingly [89]. This work has the potential to significantly reduce the amount of human work involved in matching entities and creating correct alignment to multiple heterogeneous rail track data of both rail profile and track geometry.

The key to our underlying algorithm is aligning each parameter data over time based on best column correspondence, which should improve parameter correlation, significantly, over time. Aligning any one parameter will result in alignment of all parameters as all parameter recording starts at the same time.

Parameter based alignment is based on finding the closest match for each parameter value over time. This is being done by shifting each parameter one row up in the first step and calculating minimum absolute error over time in all base files. In second step same parameter is moved one row down and again minimum absolute error is calculated. The process of moving rows up and down is continued until parameter rows in all four base files are synchronized at such a position that there is minimum absolute error between columns of the same parameter.

Hypothetically in all four base files of each modality if any one parameter (e.g. TWIST1) of any modality is aligned accurately i.e. finding the best column correspondence such that there is minimum absolute error between all four base files over time should result in automatic alignment of rest of the parameters.

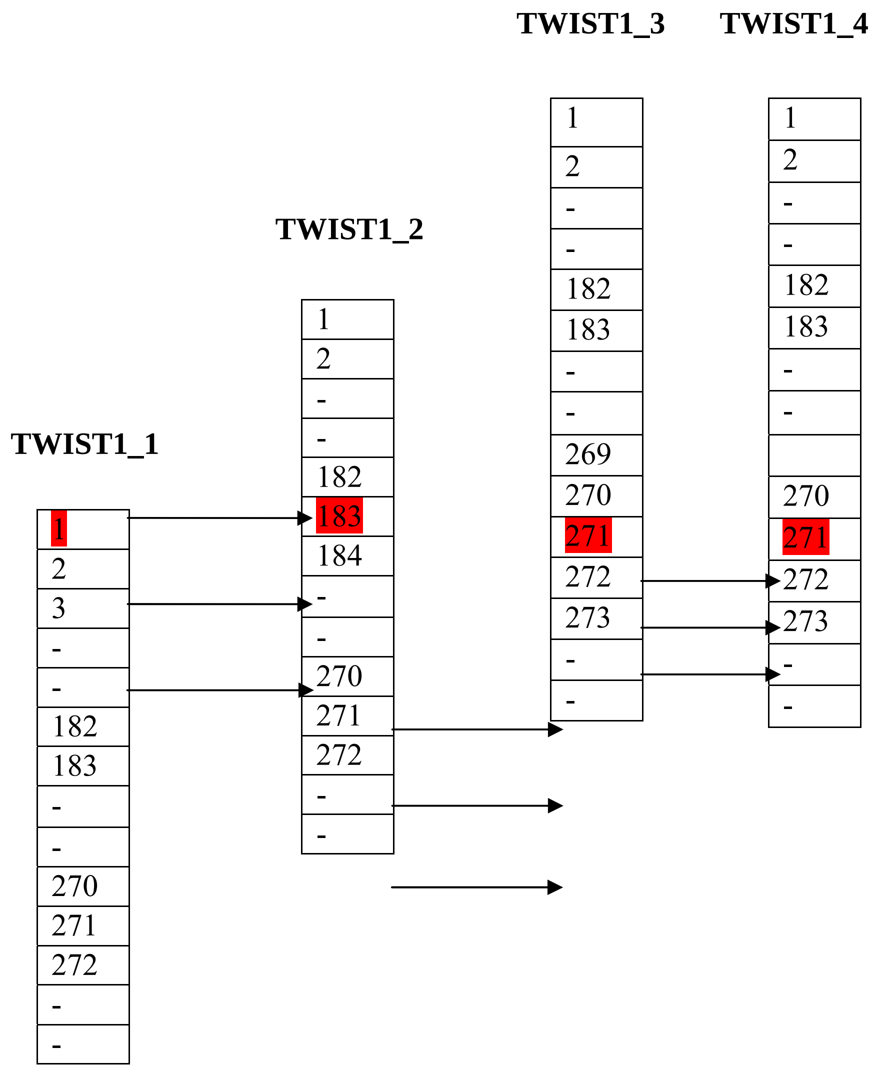

Figure 6.1 Parameter Based Alignment

In the process of aligning TWIST1 each of the other base file is paired with the TWIST1, and the difference is calculated i.e. TWIST1- TWIST2, TWIST1- TWIST3, and TWIST1- TWIST4. As the first step, TWIST2, TWIST3, and TWIST4 are moved one row up in relation to TWIST1 and in second step TWIST2, TWIST3, and TWIST4 are moved one row down. Minimum absolute error is calculated when both steps above are used.

This process of shifting rows up and down and calculation of minimum absolute error is continued until the minimum absolute error between all pairs is found.

Figure 6.1 illustrates the stage where TWIST2 was 183 rows above TWIST1, TWIST3 was 271 rows above TWIST1 and TWIST4 was 271 rows above TWIST1.

At that stage of alignment TWIST2, TWIST3, and TWIST4 needs to align in such a way that there is minimum absolute error among themselves. The fact that only at this level of row shifting there is a minimum absolute error is reconciled through the fact that at this level of shifting not only there was minimum absolute error in (TWIST1- TWIST2, TWIST1- TWIST3, and TWIST1- TWIST4) but also there was minimum absolute error between (TWIST1- TWIST2, TWIST2- TWIST3, and TWIST3- TWIST4). Thus there was minimum absolute error in all above base file combinations. This re-assurance guarantee that only at this stage of shifting TWIST in all base files (over time) is the ideal scenario of alignment that can possibly exist. After finding the minimum absolute error in all base file combinations as above the data columns of all parameters are aligned accordingly. This will result in a new parameter based aligned file.

As all parameter values are recorded at the same time, aligning one will ultimately result in automatic alignment of rest of the parameters. The pseudo code for the parameter based data alignment approach presented above can be given as follows:

Pseudo code

Inputs: TWIST from Base File_1 is TWIST1. Similarly we obtain TWIST2, TWIST3 and TWIST4 in addition to TWIST1, which become the inputs.

ParamAlign (TWIST1, TWIST2, TWIST3, TWIST4)

{

STEP 1

for i =2 to 4

{

While (($TWIST_1$ – $TWIST_i$) != Min_Diff)

{

increment *$TWIST_i$ relative to *$TWIST_1$ by 1 && decrement *$TWIST_i$ relative to *$TWIST_1$ by 1

Min_Diff = ($TWIST_1$ – $TWIST_i$)

Align start of base file 1 with start of base file i

}/* while*/

}/* end for*/

STEP 2

```
While ((TWIST1 - TWIST2)! = Min_Diff)
{
increment TWIST2 relative to TWIST1 by 1 && decrement TWIST2 relative to TWIST1 by 1
Min_Diff = (TWIST 1 – TWIST 2)
Align start of base file 1 with start of base file 2
}
    While ((TWIST2 – TWIST3)! = Min_Diff)
    {
    Increment TWIST3 relative to TWIST2 by 1 && decrement TWIST3 relative to TWIST2 by 1
    Min_Diff = (TWIST 2 – TWIST 3)
    Align start of base file 2 with start of base file 3
    }
        While ((TWIST_3 - TWIST_4)! = Min_Diff )
        {
        increment TWIST4 relative to TWIST3 by 1 && decrement TWIST4 relative to TWIST3 by 1
        Min_Diff = (TWIST 3 – TWIST 4)
        Align start of base file 3 with start of base file 4
        }
}/* end ParamAlign*/
```

Output: All rows of TWIST1 are aligned with the nearest values of TWIST2, TWIST3 and TWIST4 in an excel file as shown in Figure 6.1.

6.3.1. Effectiveness of Parameter based Alignment

The improvement introduced by the parameter based alignment can be evaluated by inspecting the line graphs of any parameter over time. Ideally all parameter behaviours should be similar to its behaviour in next base file over time. Therefore an ideal case of alignment will result in similar behaviour of each parameter over time and thus resulting in minimum absolute error between same parameter over time. The effectiveness of parameter based alignment was re-assured when all the significant correlation in rail profile and track geometry, which were showing negative correlation of different parameters over time, based on distance (Mile and Yard) alignment were changed into positive correlations. This evidence of changing all negative correlations into positive was reconfirmation that this parameter based alignment is the best that alignment can get.

6.3. Threshold Exceedences of Track Geometry and Rail Profile Parameters

In railway industries, exceedences are used to emulate the amount of defects. According to most rail industry standards all parameter values are filtered by a 10% threshold line which separates the data into two sections [17]. All parameter values over the threshold line are called as exceedences (as they exceed threshold line). Therefore those parameter value needs to be maintained as highlighted in figure 6.1. Parameter values below threshold are considered to be normal and therefore need not to be maintained.

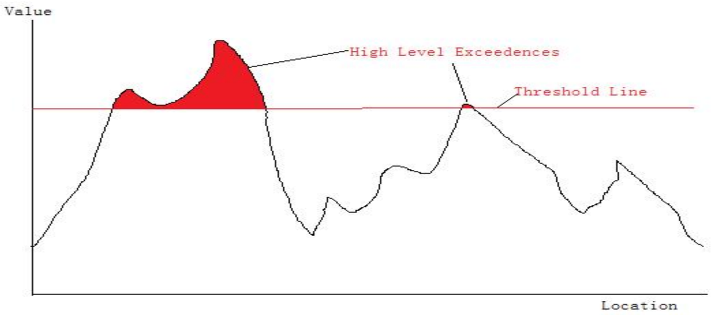

Figure 6.2 Exceedence and Normal Values along the Track

Table 6.1 tabulates the exact threshold values of all parameters of both modalities. The exceedence line was drawn at 90% which is according to rail industry conventions. Hence all parameter values of both modalities over threshold are classified as exceedences. In table 6.1 * indicates that against DIPPED LEFT and RIGHT no values were recorded. Therefore their threshold can not be calculated.

Table 6.1 Threshold Values of Track Geometry and Rail Profile

Track Geometry		Rail Profile	
Parameters	**Threshold Exceedence 10%**	**Parameters**	**Threshold Exceedence 10%**
TWIST1	2.75	Left GAUGE Side Wear	0.25
TWIST2	3.95	Right GAUGE Side Wear	0.25
ALIGMS	1.5	Left Field Side Wear	0.45
ALIGML	2.55	Right Field Side Wear	0.25
TOPML	4.25	Left Head Width	70.75
GAUGE	3.55	Right Head Width	70.85
CROSS LEVEL	41.25	Left Head Width Remaining	9.9
TOPRS	3.05	Right Head Width Remaining	10
TOPLS	2.95	Left Vertical Wear	5.95
CURV	16.1	Right Vertical Wear	5.95
CANTDEF	26.8	Left Estimated Rail Depth	157.6
DIPPED LEFT	*	Right Estimated Rail Depth	157.4
DIPPED RIGHT	*	Left Fish Plate Clearance	13.05
		Right Fish Plate Clearance	12.55
		Left Inclination Deviation	6.05
		Right Inclination Deviation	0.45

As common in the rail industry [17], one practice is to see whether the data values exceed the particular warning levels or not. That is, comparing prediction accuracy for all parameters in both track modalities, companies prefer to see whether such accuracy can lead to the ability of early warning of future faults. This emulation is illustrated in figure 6.2 where upper black line represents the actual value and lower blue line represents the prediction value. In general by comparing the two lines, the prediction performance is proven to be good.

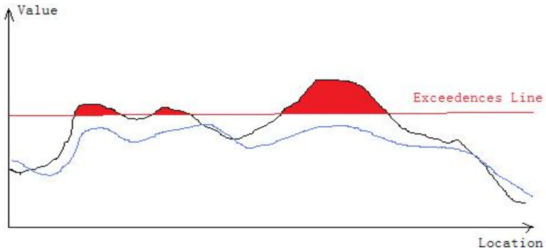

Figure 6.3 Emulation of the Gap between Prediction Value and Actual Value

Univariate and multivariate NN predictive analysis of both rail profile and track geometry parameters is divided into the following four categories:

1. **00**: Actual predicted values are both under the threshold line. It represents the correct prediction for exceedence.

2. **01**: Actual value is under the threshold line but the predicted value is above the threshold line. It represents the wrong prediction for exceedence.

3. **10**: Actual value is above the threshold line but the predicted value is under the threshold line. It represents the wrong prediction for exceedence.

4. **11**: Actual predicted values are both above the threshold line. It represents the correct prediction for exceedence.

The objective and pattern of univariate and multivariate predictive analysis is the same as explained in section 5.3. After calculating the threshold for all parameters in both modalities, both univariate and multivariate predictive errors are thresholded into either exceedence or normal categories. This helps in visualising prediction accuracy.

The pseudo code for the error threshold calculation approach presented above can be listed as follows:

Pseudo code

```
  ExceedenceError ( RPi and TGi)
  /*Where (i = 1..n and j = 1..m)*/
  {
          for i =1 to n and j= 1 to n
          {
                  If  (Actual data > Threshold)
                  Actual datai = 1
                          Else
                          Actual datai = 0
  /* Actual data is categorised into either over or under threshold*/

  If (Predicted data > Threshold)
  Assign 1 to all such values
          Else
          Assign 0
  /* Predicted data is categorised in either over or under threshold*/
          }/* end for*/
  % Prediction over threshold = No. of correct predictions over threshold /
                                   Total number of predictions
  % Prediction under threshold = No. of correct predictions under threshold /
                                   Total number of predictions
  /* Prediction Accuracy calculated as, % of Correct Predictions over threshold &
  % of Correct Predictions under threshold*/
}/*End ExceedenceError */
```

Output: All Parameters in both Rail Profile and Track Geometry are categorised into either exceedence or normal.

Table 6.2 Rail Profile Univariate Threshold Predictive Analysis

Dependent Parameter	Contribution of Independent Parameter			% of Correct Predictions		% of Incorrect Predictions	
	1	2	3	Below Threshold 00	Above Threshold 11	Below Threshold 01	Above Threshold 10
Right GAUGE Side Wear	0.16	0.44	0.39	90	0	9	0
Right Field Side Wear	0.13	0.28	0.58	85	0	14	0
Right Head Width	0.28	0.30	0.40	90	0	9	0
Right Head Width Remain	0.00	0.26	0.73	86	5	8	0
Right Vertical Wear	0.30	0.24	0.45	92	0	7	0
Right Est Rail Depth	0.27	0.64	0.07	71	5	9	14
Right Fish Plate Clearance	0.25	0.31	0.43	91	0	8	0
Right Inclined Deviation	0.09	0.24	0.66	82	0	17	0
Left GAUGE Side Wear	0.28	0.29	0.42	88	1	11	1
Left Field Side Wear	0.13	0.60	0.26	95	0	0	4
Left Head Width	0.20	0.31	0.48	82	2	12	3
Left Head Width Remain	0.04	0.13	0.81	85	4	10	0
Left Vertical Wear	0.06	0.41	0.52	88	0	11	0
Left Estimated Rail Depth	0.29	0.56	0.14	80	4	9	5
Left Fish Plate Clearance	0.09	0.22	0.68	91	0	8	0
Left Inclined Deviation	0.27	0.38	0.34	97	0	2	0

6.3.1. Rail Profile Univariate Threshold Predictive Analysis

This section provides the details of univariate NN predictive analysis of left and right rail profile parameters which were summarised in Table 6.2. It investigates how much a parameter contributes in predicting itself over time and indicates its predictive error, as a percentage, when being predicted by rest of the parameters over time. The prediction error is then threshold into either exceedence or normal.

1. Right GAUGE Side Wear

a. Right GAUGE Side Wear of the second base file is the highest contributor (0.44) and right GAUGE Side Wear of first base files is the lowest contributor (0.16) in predicting right GAUGE Side Wear over time.

b. 90% of correct predictions made under the threshold shows that the right GAUGE Side Wear can be predicted with very high confidence, under the threshold, over time.

2. Right Field Side Wear

a. Right Field Side Wear of the third base file is the highest contributor (0.58) and right Field Side Wear of first base file is the lowest contributor (0.13) in predicting right Field Side Wear over time.

b. 85% of correct predictions made under the threshold shows that the right Field Side Wear can be predicted with very high confidence, under the threshold, over time.

3. Right Head Width

a. Right Head Width of the third base file is the highest contributor (0.40) and right Head Width of first base file is the lowest contributor (0.28) in predicting right Head Width over time.

b. 90% of correct predictions made under the threshold shows that the right Head Width can be predicted with very high confidence, under the threshold, over time.

4. Right Head Width Remaining

a. Right Head Width Remaining of the third base file is the highest contributor (0.73) and right Head Width Remaining of first base file is the lowest contributor (0.00) in predicting right Head Width Remaining over time.

b. 86% of correct predictions made under the threshold shows that the right Head Width Remaining can be predicted with very high confidence, under the threshold, over time.

5. Right Vertical Wear

a. Right Vertical Wear of the third base file is the highest contributor (0.45) and right Vertical Wear of second base file is the lowest contributor (0.20) in predicting right Vertical Wear over time.

b. 92% of correct predictions made under the threshold shows that the right Vertical Wear can be predicted with very high confidence, under the threshold, over time.

6. Right Estimated Rail Depth

a. Right Estimated Rail Depth of the second base file is the highest contributor (0.64) and right Estimated Rail Depth of third base file is the lowest contributors (0.07) in predicting right Estimated rail Depth over time.

b. 71% of correct predictions made under the threshold shows that the right Estimated Rail Depth can be predicted with high confidence, under the threshold, over time.

7. Right Fish Plate Clearance

a. Right Fish Plate Clearance of the third base file is the highest contributor 0.43) and right Fish Plate Clearance of first base file is the lowest contributor (0.25) in predicting right Fish Plate Clearance over time.

b. 91% of correct predictions made under the threshold shows that the right Fish Plate Clearance can be predicted with very high confidence, under the threshold, over time.

8. Right Inclination Deviation

a. Right Inclination Deviation of the third base file is the highest contributor (0.66) and right Inclination Deviation of first base file is the lowest contributor (0.09) in predicting right Inclination Deviation over time.

b. 82% of correct predictions made under the threshold shows that the right Inclination Deviation can be predicted with high confidence, under the threshold, over time.

9. Left GAUGE Side Wear

a. Left GAUGE Side Wear of the third base file is the highest contributor (0.42) and left GAUGE Side Wear of first base file is the lowest contributors (0.28) in predicting left GAUGE Side Wear over time.

b. 88% of correct predictions made under the threshold shows that the left GAUGE Side Wear can be predicted with very high confidence, under the threshold, over time.

10. Left Field Side Wear

a. Left Field Side Wear of the second base file is the highest contributor (0.60) and left Field Side Wear of first base file is the lowest contributor (0.18) in predicting left Field Side Wear over time.

b. 95% of correct predictions made under the threshold shows that the left Field Side Wear can be predicted with very high confidence, under the threshold, over time.

11. Left Head Width

a. Left Head Width of the third base file is the highest contributor (0.48) and left Head Width of first base file is the lowest contributor (0.20) in predicting left Head Width over time.
b. 82% of correct predictions made under the threshold shows that the left Head Width can be predicted with high confidence, under the threshold, over time.

12. Left Head Width Remaining

a. Left Head Width Remaining of the third base file is the highest contributor (0.81) and left Head Width Remaining of first base file is the lowest contributor (0.04) in predicting left Head Width Remaining over time.
b. 85% of correct predictions made under the threshold shows that the left Head Width Remaining can be predicted with very high confidence, under the threshold, over time.

13. Left Vertical Wear

a. Left Vertical Wear of the third base file is the highest contributor (0.52) and left Vertical Wear of first base file is the lowest contributors (0.06) in predicting left Vertical Wear over time.
b. 88% of correct predictions made under the threshold shows that the left Vertical Wear width can be predicted with very high confidence, under the threshold, over time.

14. Left Estimated Rail Depth

a. Left Estimated Rail Depth of the second base file is the highest contributor (0.56) and left Estimated Rail Depth of third base file is the lowest contributor (0.14) in predicting left Estimated Rail Depth over time.
b. 80% of correct predictions made under the threshold shows that the left Estimated Rail Depth can be predicted with high confidence, under the threshold, over time.

15. Left Fish Plate Clearance

a. Left Fish Plate Clearance of the second base file is the highest contributor (0.68) and left Fish Plate Clearance of third base file is the lowest contributor (0.09) in predicting left Fish Plate Clearance over time.
b. 91% of correct predictions made under the threshold shows that the left Fish Plate Clearance can very well be predicted with very high confidence, under the threshold, over time.

16. Left Inclination Deviation

a. Left Inclination Deviation of the second base file is the highest contributor (0.38) and left Inclination Deviation of first base file is the lowest contributor (0.27) in predicting left Inclination Deviation over time.
b. 97% of correct predictions made under the threshold shows that the left Inclination Deviation can be predicted with very high confidence, under the threshold, over time.

Table 6.3 Track Geometry Threshold Univariate Predictive Analysis

Dependent Parameters	Contribution of Independent Parameters			% of Correct Predictions		% of Incorrect Predictions	
	1	2	3	Below Threshold 00	Above Threshold 11	Below Threshold 01	Above Threshold 10
TWIST1	0.18	0.25	0.56	89	0	10	0
TWIST2	0.16	0.11	0.72	90	0	8	0
ALIGMS	0.73	0.26	*	87	0	12	0
ALIGML	0.84	0.15	*	86	0	12	0
TOPML	0.02	0.33	0.64	90	0	9	0
CROSS LEVEL	0.03	0.22	0.74	89	9	1	0
GAUGE	0.04	0.16	0.79	95	1	3	0
TOPRS	0.22	0.11	0.66	91	0	9	0
TOPLS	0.11	0.24	0.64	90	0	9	0
CURV	0.25	0.74	*	87	6	3	2
CANT DEF	0.13	0.86	*	88	2	7	1
DIPPED LEFT	*	0.00	0.99	*	*	*	*
DIPPED RIGHT	*	0.95	0.04	*	*	*	*

6.3.2. Track Geometry Threshold Univariate Predictive Analysis

Detailed is the univariate NN predictive analysis of track geometry parameters which were summarised in Table 6.3. It investigates how much a parameter contributes in predicting itself over time and indicates its predictive error, as a percentage, when being predicted by rest of the parameters over time. The prediction error is then thresholded into either exceedence or normal. * mean that no values were recorded.

1. TWIST1

a. TWIST1 of the third base file is the highest contributor (0.56) and TWIST1 of first base file is the lowest contributor (0.18) in predicting TWIST1 over time.

b. 89% of correct predictions made under the threshold shows that the TWIST1 can be predicted with very high confidence, under the threshold, over time.

2. TWIST2

a. TWIST2 of the third base file is the highest contributor (0.72) and TWIST2 of second base file is the lowest contributor (0.11) in predicting TWIST2 over time.

b. 90% of correct predictions made under the threshold shows that the TWIST2 can be predicted with very high confidence, under the threshold, over time.

3. ALIGMS

a. ALIGMS of the first base file is the highest contributor (0.73) and ALIGMS of second base file is the lowest contributor (0.23) in predicting ALIGMS over time.

b. 87% of correct predictions made under the threshold shows that the ALIGMS can be predicted with very high confidence, under the threshold, over time.

4. ALIGML

a. ALIGML of the first base file is the highest contributor (0.84) and ALIGML of second base file is the lowest contributors (0.15) in predicting ALIGML over time.
b. 86% of correct predictions made under the threshold shows that the ALIGML can be predicted with very high confidence, under the threshold, over time.

5. TOPML

a. TOPML of the third base file is the highest contributor of (0.64) and TOPML of first base file is the lowest contributor of (0.02) in predicting TOPML over time.
b. 90% of correct predictions made under the threshold shows that the TOPML can be predicted with very high confidence, under the threshold, over time.

6. CROSS LEVEL

a. CROSS LEVEL of the third base file is the highest contributor (0.74) and CROSS LEVEL of first base file is the lowest contributor (0.03) in predicting CROSS LEVEL over time.
b. 89% of correct predictions made under the threshold shows that the CROSS LEVEL be predicted with very high confidence, under the threshold, over time.

7. GAUGE

a. GAUGE of third base file is the highest contributor (0.79) and GAUGE of first base file is the lowest contributor (0.04) in predicting GAUGE over time.

b. 95% of correct predictions made were under threshold shows that GAUGE can be predicted with very high confidence under threshold over time.

8. TOPRS

a. TOPRS of the third base files is the highest contributor (0.66) and TOPRS of first base files is the lowest contributor (0.22) in predicting TOPRS over time.
b. 91% of correct predictions made under the threshold shows that the TOPRS can be predicted with very high confidence, under the threshold, over time.

9. TOPLS

a. TOPLS of the third base file is the highest contributor (0.64) and TOPLS of first base file is the lowest contributor (0.11) in predicting TOPLS over time.
b. 90% of correct predictions made under the threshold shows that the TOPLS can be predicted with very high confidence, under the threshold, over time.

10. CURV

a. CURV of the second base file is the highest contributor (0.74) and CURV of first base file is the lowest contributor (0.25) in predicting CURV over time.
b. 87% of correct predictions made under the threshold shows that the CURV can be predicted with very high confidence, under the threshold, over time.

11. CANT DEF

a. CANT DEF of the second base file is the highest contributor (0.86) and CANT DEF of first base file is the lowest contributor (0.13) in predicting CANT DEF over time.
b. 88% of correct predictions made under the threshold shows that CURV can be predicted with very high confidence, under the threshold, over time.

12. DIPPED LEFT

a. DIPPED LEFT of the second base file is the highest contributor (0.00) and DIPPED LEFT of third base file is the lowest contributor (0.98) in predicting DIPPED LEFT over time.
b. As DIPPED LEFT had not enough data the error calculation was not possible.

13. DIPPED RIGHT

a. DIPPED RIGHT of second base file is the highest contributor (0.95) and DIPPED RIGHT of third base file is the lowest contributor (0.04) in predicting DIPPED RIGHT over time.
b. As DIPPED RIGHT had not enough data the error calculation was not possible.

Table 6.4 Left Rail Profile Multivariate Contribution Analysis

Independent Parameters	Contribution of Dependent Parameters							
	GAUGE Side Wear	Field Side Wear	Head Width	Head Width Remaining	Vertical Wear	Estimated Rail Depth	Fish Plate Clearance	Inclination Deviation
GAUGE Side Wear	*	0.22	0.22	0.13	0.14	0.24	0.26	0.10
Field Side Wear	0.20	*	0.25	0.12	0.06	0.26	0.06	0.17
Head Width	0.24	0.25	*	0.20	0.12	0.27	0.08	0.18
Head Width Remaining	0.04	0.00	0.15	*	0.01	0.05	0.04	0.13
Vertical Wear	0.15	0.16	0.14	0.15	*	0.11	0.41	0.12
Estimated Rail Depth	0.14	0.18	0.17	0.19	0.17	*	0.10	0.17
Fish Plate Clearance	0.22	0.11	0.08	0.11	0.45	0.08	*	0.12
Inclination Deviation	0.00	0.00	0.00	0.08	0.02	0.00	0.01	*

6.3.3. Left Rail Profile Multivariate Contribution Analysis

Presented is the multivariate NN predictive contribution analysis of left rail profile parameters which were summarised in Table 6.4. The analysis investigates how much a parameter contributes in predicting other parameters thus showing the level to which it is correlated with rest of the parameters. * indicates that as the dependent parameter can not be predicted by itself and hence there is no value.

1. **Left GAUGE Side Wear**

   Head Width is the highest contributor (0.24) and Inclination Deviation is the lowest contributor (0.00) in predicting left GAUGE Side Wear from rest of the parameters.

2. **Left Field Side Wear**

   Head Width is the highest contributor (0.25) and Inclination Deviation is the lowest contributor (0.00) in predicting left Field Side Wear from rest of the parameters.

3. **Left Head Width**

   Field Side Wear is the highest contributor (0.25) and Inclination Deviation is the lowest contributor (0.00) in predicting left Head Width from rest of the parameters.

4. **Left Head Width Remaining**

   Left Head Width is the highest contributor (0.20) and Inclination Deviation is the lowest contributor (0.08) in predicting left Head Width Remaining from rest of the parameters.

5. **Left Vertical Wear**

   Fish Plate Clearance is the highest contributor (0.45) and Head Width Remaining is the lowest contributor (0.01) in predicting left Vertical Wear from rest of the parameters.

6. **Left Estimated Rail Depth**

   Left Head Width is the highest contributor (0.27) and Inclination Deviation is the lowest contributor (0.00) in predicting left Estimated Rail Depth from rest of the parameters.

7. **Left Fish Plate Clearance**

   Left Vertical Wear is the highest contributor (0.41) and Inclination Deviation is the lowest contributor (0.01) in predicting left Fish Plate Clearance from rest of the parameters.

Table 6.5 Right Rail Profile Multivariate Contribution Analysis

Independent Parameters	Contribution of Dependent Parameters							
	GAUGE Side Wear	Field Side Wear	Head Width	Head Width Remaining	Vertical Wear	Estimated Rail Depth	Fish Plate Clearance	Inclination Deviation
GAUGE Side Wear	*	0.26	0.21	0.12	0.14	0.26	0.25	0.18
Field Side Wear	0.21	*	0.23	0.25	0.07	0.22	0.04	0.18
Head Width	0.22	0.28	*	0.44	0.11	0.32	0.06	0.12
Head Width Remaining	0.03	0.00	0.11	*	0.01	0.01	0.03	0.12
Vertical Wear	0.16	0.14	0.15	0.03	*	0.10	0.50	0.15
Estimated Rail Depth	0.16	0.20	0.21	0.08	0.09	*	0.25	0.10
Fish Plate Clearance	0.22	0.05	0.10	0.06	0.53	0.09	*	0.15
Inclination Deviation	0.00	0.00	0.00	0.04	0.01	0.00	0.02	*

6.3.4. Right Rail Profile Multivariate Contribution Analysis

Below is multivariate NN predictive contribution analysis of right rail profile parameters which were summarised in Table 6.5. The analysis investigates how much a parameter contributes in predicting other parameters thus showing the level to which it is correlated with rest of the parameters. * indicates that as dependent parameter can not be predicted by itself and thus there is no value.

1. **Right GAUGE Side Wear**

   Right Head Width is the highest contributor (0.22) and Inclination Deviation is the lowest contributor (0.00) in predicting right GAUGE Side Wear from rest of the parameters.

2. **Right Field Side Wear**

   Right Head Width is the highest contributor (0.28) and Inclination Deviation is the lowest contributor (0.00) in predicting right Field Side Wear from rest of the parameters.

3. **Right Head Width**

   Right Field Side Wear is the highest contributor (0.23) and Inclination Deviation is the lowest contributor (0.00) in predicting right Head Width from rest of the parameters.

4. **Right Head Width Remaining**

   Right Head Width is the highest contributor (0.44) and Inclination Deviation is the lowest contributors (0.04) in predicting right Head Width Remaining from rest of the parameters.

5. **Right Vertical Wear**

   Right Fish Plate Clearance is the highest contributor (0.53) and Head Width Remaining and Inclination Deviation are the lowest contributors (0.01) in predicting right Vertical Wear from rest of the parameters.

6. **Right Estimated Rail Depth**

   Right Head Width is the highest contributor (0.32) and Inclination Deviation is the lowest contributor (0.00) in predicting right Estimated Rail Depth from rest of the parameters.

7. **Right Fish Plate Clearance**

   Right Vertical Wear is the highest contributor (0.50) and Inclination Deviation is the lowest contributor (0.02) in predicting right Fish Plate Clearance from rest of the parameters.

8. **Right Inclination Deviation**

   Right GAUGE Side Wear and Field Side Wear are the highest contributor (0.18) and Estimated Rail Depth is the lowest contributors of (0.10) in predicting right Inclination Deviation from rest of the parameters.

9. **Left Inclination Deviation**

   Left Head Width is the highest contributor (0.18) and left GAUGE Side Wear is the lowest contributor (0.10) in predicting left Inclination Deviation from rest of the parameters.

Table 6.6 Rail Profile Multivariate Predictive Error Analysis

Dependent Parameters	% of Correct Predictions		% of Incorrect Predictions	
	Below Threshold 00	Above Threshold 11	Below Threshold 01	Above Threshold 10
Left GAUGE Side Wear	96	48	4	52
Right GAUGE Side Wear	96	57	4	43
Left Field Side Wear	97	69	3	31
Right Field Side Wear	99	44	1	56
Left Head Width	97	56	3	44
Right Head Width	97	56	3	44
Left Head Width Remaining	76	44	24	56
Right Head Width Remaining	51	57	24	43
Left Vertical Wear	91	66	9	34
Right Vertical Wear	95	59	5	41
Left Estimated Rail Depth	95	58	5	42
Right Estimated Rail Depth	93	57	7	43
Left Fish Plate Clearance	99	19	1	81
Right Fish Plate Clearance	97	52	3	48
Left Inclination Deviation	99	1	1	99
Right Inclination Deviation	100	1	0	99

6.3.5. Rail Profile Multivariate Predictive Error Analysis

Below is the multivariate NN predictive analysis of left and right rail profile parameters which were summarised in Table 6.6. The analysis investigates predictive error of all parameters, as a percentage, when being predicted by the rest of the parameters. The prediction error is then thresholded into either exceedence or normal.

1. Left GAUGE Side Wear

a. 96% of correct predictions made under the threshold shows that the left GAUGE Side Wear can very well be predicted under threshold from the rest of the parameters.

b. 48% of correct predictions made over the threshold shows that the left GAUGE Side Wear can be predicted over the threshold from the rest of the parameters.

2. Right GAUGE Side Wear

a. 96% of correct predictions made under the threshold shows that right the GAUGE Side Wear can very well be predicted under the threshold from the rest of the parameters.

b. 57% of correct predictions over threshold shows that the right GAUGE Side Wear can be predicted over the threshold from the rest of the parameters.

3. Left Field Side Wear

a. 97% of correct predictions made under the threshold shows that the left Field Side Wear can be predicted with very high confidence, under the threshold from rest of the parameters.

b. 69% of correct predictions made were over threshold which shows that left Field Side Wear can well be predicted over the threshold from the rest of the parameters.

4. **Right Field Side Wear**

a. 99% of correct predictions made under the threshold shows that the right Field Side Wear can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 44% of correct predictions made over the threshold shows that the right Field Side Wear can be predicted over the threshold from the rest of the parameters.

5. **Left Head Width**

a. 97% of correct predictions made under the threshold which shows that left Head Width can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 56% of correct predictions made over the threshold shows that the left Head Width can be predicted over the threshold from the rest of the parameters.

6. **Right Head Width**

a. 97% of correct predictions made under threshold shows that the right Head Width can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 56% of correct predictions made were over threshold which shows that right Head Width can be predicted over threshold from the rest of the parameters.

7. **Left Head Width Remaining**

a. 76% of correct predictions made under threshold shows that the left Head width Remaining width can be predicted with high confidence under the threshold from the rest of the parameters.

b. 44% of correct predictions made over the threshold shows that the left Head Width Remaining can be predicted over the threshold from the rest of the parameters.

8. Right Head Width Remaining

a. 51% of correct predictions made under the threshold shows that the right Head Width Remaining width can be predicted under the threshold from the rest of the parameters.

b. 57% of correct predictions made over the threshold shows that the right Head Width Remaining can be predicted over the threshold from the rest of the parameters.

9. Left Vertical Wear

a. 91% of correct predictions made under the threshold shows that the left Vertical Wear width can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 66% of correct predictions made over the threshold shows that the left Vertical Wear width can well be predicted over the threshold from the rest of the parameters.

10. Right Vertical Wear

a. 95% of correct predictions made under the threshold shows that the right Vertical Wear width can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 59% of correct predictions made over the threshold shows that the right Vertical Wear width can well be predicted over the threshold from the rest of the parameters.

11. Left Estimated Rail Depth

a. 95% of correct predictions made under the threshold shows that the left Estimated Rail Depth can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 58% of correct predictions made over the threshold shows that the left Estimated Rail Depth can be predicted over the threshold from the rest of the parameters.

12. Right Estimated Rail Depth

a. 93% of correct predictions made under the threshold shows that the right Estimated Rail Depth can be predicted with very high confidence under the threshold from the rest of the parameters.
b. 57% of correct predictions made over the threshold shows that the right Estimated Rail Depth can be predicted over the threshold from the rest of the parameters.

13. Left Fish Plate Clearance .

a. 99% of correct predictions made under the threshold shows that the left Fish Plate Clearance can be predicted with very high confidence under the threshold from the rest of the parameters.
b. Only 19% of correct predictions made over the threshold shows that the left Fish Plate Clearance can not very well be predicted over the threshold from the rest of the parameters.

14. Right Fish Plate Clearance .

a. 97% of correct predictions made under the threshold shows that the right Fish Plate Clearance can be predicted with very high confidence under the threshold from the rest of the parameters.
b. 52% of correct predictions made over the threshold shows that the right Fish Plate Clearance can be predicted over the threshold from the rest of the parameters.

15. Left Inclination Deviation

a. 99% of correct predictions made under the threshold shows that the left Inclination Deviation can be predicted with very high confidence under the threshold from the rest of the parameters.
b. Only 1% of correct predictions made over the threshold shows that the left Inclination Deviation can not be predicted over the threshold from the rest of the parameters.

16. Right Inclination Deviation

a. 100% of correct predictions made under the threshold shows that the right Inclination Deviation can be predicted with very high confidence under the threshold from the rest of the parameters.
b. Only 1% of correct predictions made over the threshold shows that the right Inclination Deviation can not be predicted over the threshold from the rest of the parameters.

Table 6.7 Track Geometry Multivariate Contribution Analysis

Independent Parameters	Contribution of Dependent Parameters										
	TWIST1	TWIST2	ALIGMS	ALIGML	TOPML	CROSS LEVEL	GAUGE	TOPRS	TOPLS	CURV	CANT DEF
TWIST1	*	0.48	0.10	0.04	0.08	0.03	0.07	0.10	0.07	0.01	0.01
TWIST2	0.54	*	0.07	0.04	0.10	0.03	0.05	0.07	0.07	0.01	0.01
ALIGMS	0.09	0.07	*	0.23	0.03	0.00	0.07	0.26	0.26	0.01	0.01
ALIGML	0.01	0.06	0.13	*	0.04	0.01	0.06	0.06	0.06	0.03	0.03
TOPML	0.01	0.01	0.00	0.03	*	0.03	0.03	0.03	0.02	0.01	0.00
CROSS LEVEL	0.03	0.06	0.04	0.11	0.04	*	0.11	0.00	0.04	0.43	0.35
GAUGE	0.01	0.02	0.02	0.11	0.06	0.08	*	0.01	0.01	0.07	0.02
TOPRS	0.11	0.08	0.21	0.08	0.23	0.01	0.10	*	0.45	0.01	0.00
TOPLS	0.10	0.09	0.19	0.09	0.26	0.05	0.09	0.46	*	0.01	0.01
CURV	0.02	0.09	0.07	0.07	0.04	0.55	0.16	0.01	0.02	*	0.44
CANT DEF	0.04	0.02	0.04	0.06	0.03	0.30	0.09	0.00	0.00	0.28	*
DIPPED LEFT	0.02	0.01	0.02	0.08	0.03	0.02	0.12	0.00	0.02	0.02	0.01
DIPPED RIGHT	0.02	0.00	0.02	0.04	0.03	0.00	0.10	0.02	0.01	0.04	0.02

6.3.6. Track Geometry Multivariate Contribution Analysis

Described below is the multivariate contribution analysis of track geometry parameters which were summarised in Table 6.7. The results show how much a parameter contributes in predicting other parameters thus indicating the level to which it is correlated with rest of the parameters. * indicates that as the dependent parameter can not be predicted by itself hence there is no value.

1. **TWIST1**

   TWIST2 is the highest contributor (0.54) and ALIGML, TOPML and GAUGE are the lowest contributors (0.01) in predicting TWIST1 from the rest of the parameters.

2. **TWIST2**

   TWIST1 is the highest contributor (0.48) and TOPML and DIPPED LEFT are the lowest contributors (0.01) in predicting TWIST2 from the rest of the parameters.

3. **ALIGMS**

   TWIST1 is the highest contributor (0.10) and TOPML and GAUGE is the lowest contributors (0.00) in predicting ALIGMS from the rest of the parameters.

4. **ALIGML**

   ALIGMS is the highest contributor (0.23) and TOPML is the lowest contributors (0.03) in predicting ALIGML from the rest of the parameters.

5. **TOPML**

   TOPLS is the highest contributor (0.26) and ALIGMS, CANT DEF, DIPPED LEFT and DIPPED RIGHT are the lowest contributors (0.03) in predicting ALIGML from the rest of the parameters.

6. CROSS LEVEL

CURV is the highest contributor (0.55) and DIPPED LEFT and DIPPED RIGHT are the lowest contributors (0.00) in predicting CROSS LEVEL from the rest of the parameters.

7. GAUGE

CROSS LEVEL is the highest contributor (0.11) and TOPML is the lowest contributors (0.03) in predicting GAUGE from the rest of the parameters.

8. TOPRS

TOPLS is the highest contributor (0.46) and CROSS LEVEL, CANT DEF and DIPPED LEFT are the lowest contributors (0.00) in predicting TOPRS from the rest of the parameters.

9. TOPLS

TOPRS of third base files is the highest contributor (0.45) and CANT DEF is the lowest contributors (0.00) in predicting TOPLS from the rest of the parameters.

10. CURV

CROSS LEVEL is the highest contributor (0.43) and TWIST1, TWIST2, ALIGMS, TOPML, TOPRS, TOPLS are the lowest contributors (0.01) in predicting CURV from the rest of the parameters.

11. CANT DEF

CURV is the highest contributor (0.44) and TOPML TOPRS are the lowest contributors (0.00) in predicting CANT DEF from the rest of the parameters.

Table 6.8 Track Geometry Multivariate Predictive Error Analysis

Dependent Parameters	% of Correct Predictions		% of Incorrect Predictions	
	Below Threshold 00	Above Threshold 11	Below Threshold 01	Above Threshold 10
TWIST1	98	76	2	24
TWIST2	99	72	1	28
ALIGMS	99	37	1	63
ALIGML	100	5	0	95
TOPML	100	5	0	95
CROSS LEVEL	100	67	0	33
GAUGE	99	35	1	65
TOPRS	98	71	2	29
TOPLS	98	72	2	28
CURV	99	85	1	15
CANT DEF	99	72	1	28
DIPPED LEFT	*	*	*	*
DIPPED RIGHT	*	*	*	*

6.3.7. Track Geometry Multivariate Predictive Error Analysis

Described below is the multivariate NN predictive analysis of track geometry parameters which were summarised in Table 6.8. The analysis investigates predictive error of each parameter, in percentage, when being predicted by rest of the parameters over time. The prediction error is then threshold into either exceedence or normal. * indicates that the corresponding parameter values were not recorded.

1. TWIST1

a. 98% of correct predictions made under the threshold shows that the right TWIST1 can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 76% of correct predictions made over the threshold shows that the TWIST1 can be predicted with high confidence, over the threshold, from the rest of the parameters.

2. TWIST2

a. 99% of correct predictions made under the threshold shows that the right TWIST2 can be predicted with very high confidence under the threshold from the rest of the parameters.

b. 72% of correct predictions made over the threshold shows that the TWIST2 can be predicted with high confidence, over the threshold, from the rest of the parameters.

3. ALIGMS

a. 99% of correct predictions made under the threshold shows that the right ALIGMS can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 37% of correct predictions made over the threshold shows that the ALIGMS can be predicted over the threshold from the rest of the parameters.

4. ALIGML

a. 100% of correct predictions made under the threshold shows that the right ALIGML can be predicted with very high confidence, under the threshold, under the threshold from the rest of the parameters.

b. 5% of correct predictions made over the threshold shows that the ALIGML can not be predicted over the threshold from the rest of the parameters.

5. TOPML

a. 100% of correct predictions made under the threshold shows that the right TOPML can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 5% of correct predictions made were over threshold which shows that TOPML can not be predicted over threshold from rest of the parameters.

6. CROSS LEVEL

a. 100% of correct predictions made under the threshold shows that the right CROSS LEVEL can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 67 % of correct predictions made over the threshold shows that the CROSS LEVEL can be predicted over the threshold from the rest of the parameters.

7. GAUGE

a. 99% of correct predictions made under the threshold shows that the right GAUGE can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 35 % of correct predictions made over the threshold shows that the GAUGE can be predicted over the threshold from the rest of the parameters.

8. TOPRS

a. 98% of correct predictions made under the threshold shows that the right TOPRS can be predicted with very high confidence, under the threshold, from the rest of the parameters.

b. 71 % of correct predictions made over the threshold shows that the TOPRS can be predicted with high confidence, over the threshold, from the rest of the parameters.

9. TOPLS

a. 98% of correct predictions made under the threshold shows that the right TOPLS can be predicted with very high confidence, under the threshold, from the rest of the parameters.
b. 72 % of correct predictions made over the threshold shows that the TOPLS can be predicted with high confidence, over the threshold, from the rest of the parameters.

CURV

a. 99% of correct predictions made under the threshold shows that the right CURV can be predicted with very high confidence, under the threshold, from the rest of the parameters.
b. 85 % of correct predictions made over the threshold shows that the CURV can be predicted with very high confidence, over the threshold, from the rest of the parameters.

10. CANT DEF

a. 99% of correct predictions made under the threshold shows that the right CANT DEF can be predicted with very high confidence, under the threshold, from the rest of the parameters.
b. 72 % of correct predictions made over threshold shows that the CANT DEF can be predicted with very high confidence, over the threshold, from the rest of the parameters.

6.3.8. Summary of Predictive Analysis

Current NN analysis of both track geometry and rail profile parameters is divided into univariate and multivariate analysis. The objective of multivariate neural network analysis is to see how well we can predict one parameter from other. Where as, univariate analysis involves predicting each parameter of both modalities over time. Such predictive error analysis will be useful in analysing predictive rail track degradation. In comparison to both distance and fixed window alignment parameter based alignment:

1. Computational complexity is reduced.
2. Prediction accuracy of most of the parameters is improved.
3. Adds in effectiveness of predictive analysis by retaining exact Mile and Yard locations instead of being discarded (distance alignment) or averaged (fixed window alignment).

6.4. Conclusion

Effectiveness of predictive analysis is dependent on the effectiveness of data alignment, without data being properly aligned any analysis across multiple data streams of both rail profile and track geometry would be ineffective as it was the case in distance alignment and fix window alignment. Hence in this chapter a new effective parameter based alignment method is proposed. Unlike both previous data alignment approaches, no parameter data is lost in the process of parameter based alignment, hence it can pinpoint the exact location on the track which makes it a pragmatic solution for rail track maintenance. Such a level of alignment across multiple data streams of both rail profile and track geometry sets up the foundations for predictive analysis.

Chapter 7

Track Degradation Model Based on Predictive Analysis of Rail Profile and Track Geometry

This chapter is aimed at modelling the degradation process of a rail track based on univariate and multivariate predictive analysis of both rail modalities as presented in chapter 6. The novel model is composed of two fundamental components: an Alignment component (parameter based alignment) and Degradation component (based on predictive analysis of track parameters).

7.1. Introduction

Rail accidents are often blamed on track degradation, which emphasises the need for sophisticated maintenance planning and in depth data analysis techniques accompanied by effective and reliable track component degradation models [96]. This led to the introduction of a better and more robust rail degradation models. Rail track degradation modelling is complicated due to the large number of parameters in both rail profile and track geometry and their diversified interactions amongst themselves and over time [98].

The key motivation of this thesis is to analyse the degradation process of a rail track which can lead to behaviour understanding of significant parameter in both ways i.e. respective to other parameters and over time. Such a rail track degradation model will optimize train schedules and will improve the rail track life time. Besides it will reduce rail track defects, which may require time intensive repair.

7.2. Components of Degradation Model

This chapter proposes a proposed degradation model based on predictive analysis of rail track modalities. The novel model has a pre processing component, which sets the basis for any further analysis, an Alignment component based on parameter based alignment method and a track degradation component which is divided into univariate and multivariate predictive analysis in both modalities.

7.2.1. Alignment Component

This first component of novel track degradation model is an alignment component which is based on parameter based alignment. Such alignment offers a pragmatic solution to predictive rail maintenance as explained in chapter 6.

Data alignment, as a pre-processing step, is widely used in multiple areas including business and engineering. Effective alignment is vital for all predictive analysis [83]. Ineffective alignment may result in inaccurate track location or maintenance staff having to examine unnecessarily large sections of track instead of looking at the exact location of the track. Due to the above reason predictive analysis based on ineffective alignment will be less useful for rail maintenance [97].

Data alignment refers to the synchronization of multiple data streams around a fixed parameter, facilitating their NN analysis. It essentially involves aligning data streams of both rail profile and track geometry as measured on different dates. The situation arises because in many rail companies various Train Recording Vehicles are responsible for data collection at different times, so a substantial amount of data is created. This may result in massive data heterogeneity which leads to ineffective location, sharing or comparing recorded data. To date, most approaches to data alignment require manual effort [83].

Automated assistance in data alignment, which may involve matching or merging of data, is therefore urgently needed for effective predictive condition monitoring which can assist in track maintenance. The general class of problem exemplified above is of finding similarities between various modalities of rail track i.e. rail profile and track geometry.

7.2.1.1. Limitations of Distance Alignment

Below are few important constraints of distance alignment:

1. Too much data is being lost in the process of alignment. This is because the alignment is based on synchronizing each Mile and Yard information with it's nearest match in all four base files. Thus all rows who's nearest match for Mile and Yard information is not found are discarded from the final aligned base file.

2. The final aligned file revealed negative univariate correlations (correlating same parameter over time) of many parameters in both rail profile and track geometry. This was essentially as a consequence of misalignment in base files, as a result of which any predictive analysis based on such alignment is not effective. Hence there is a need for a better and effective alignment method for any further predictive analysis.

7.2.1.2. Limitations of Fix Window Alignment

Below are few limitations of fixed window alignment:

1. One tenth of total data is being lost in the process of alignment. This is because of the alignment based on averaging 10 rows of Mile and Yard information into one representing a 10 yard rail track section. Thus the size of the final aligned base file was reduced by 90% and hence significant amount of parameter data was lost.

2. Univariate and multivariate predictive analysis based on such alignment was unable to locate the exact location of the track. Instead a section of 10 yards on the track was highlighted. Predictive analysis based on such alignment is therefore not a pragmatic solution for rail track maintenance as large section of the track need to be inspected by rail maintenance staff instead of the exact locations.

7.2.1.3. Parameter Based Alignment

This alignment approach offers a pragmatic solution to predictive rail maintenance as it answers all limitations of previous alignment approaches.

1. Parameter based alignment is based on finding the closest match for each parameter value over time. This is done by shifting each parameter one row up in the first step and calculating the minimum absolute error over time in all base files. In the second step same parameter is moved one row down and once again the minimum absolute error is calculated. The process of moving rows up and down is continued until parameter rows in all four base files are synchronized at such a position that there is minimum absolute error between columns of same parameter.

2. Due to the fact that there is no loss of parameter data unlike in the fix window based alignment approach, predictive analysis based on parameter based alignment pin points the exact location on the track. Such predictive analysis presents a pragmatic solution in rail maintenance.

3. As a result of parameter based alignment all negative correlations in univariate correlation analysis that resulted from distance based alignment approach, are converted into positive correlations. This confirms the fact that parameter based alignment is comparatively better for further predictive analysis.

7.2.2. Degradation Component

One of the most popular approaches to track maintenance is considering predictive maintenance instead of reactive maintenance. In predictive rail track maintenance, detecting and solving a problem early e.g. track component breakage or degradation, results in a cheaper and more efficient solution than reactive maintenance, when a bigger problem occurs at a later date. The second component of rail track degradation model is based on univariate and multivariate predictive analysis of both rail profile and track geometry parameters.

7.2.2.1. Multivariate Rail Profile Predictive Analysis

One crucial aspect of the novel rail track degradation model is rail profile multivariate predictive analysis, which is carried out to determine how much each parameter contributes in predicting other parameters. Such an analysis would help in understanding inter-parameter relationships in the context of predictive analysis. As explained in Table 6.4 and Table 6.5 GAUGE Side Wear, Field Side Wear and Head Width of both left and right rail are the highest contributors in predicting rest of the parameters. In other words these parameters are more important as they contribute more in predicting the rest of the parameters.

As these parameters not only are highly correlated amongst themselves but are also more significant, their contribution, in predicting rest of the parameters will play a significant role in the effectiveness of degradation component. In such a case all such significant parameters should have high accuracy in predicting the rest of the parameters. Less prediction error over and under the threshold will lead to high prediction accuracy. Such hypothesis is observed in experimental results illustrated in Table 6.6 which shows 97% prediction accuracy below threshold. Below are various rail profile parameters and their behaviour amongst themselves in predictive analysis as explained in Tables 6.4, 6.5 and 6.6:

1. GAUGE Side Wear is the amount to which the rail has worn from the standard GAUGE Sides and Head Width is the total width of the head. In both left and right rails these parameters are inter dependent. Thus they are highly correlated in predicting GAUGE Side Wear, Head Width is the highest contributor and vice versa.

2. Field Side Wear is the measurement of side wear on the outer side of the rail and Head Width is the total width of the head. In both left and right rails both of these parameters are inter dependent. So they are highly correlated and so is the case in prediction that while predicting Field Side Wear, Head Width is the highest contributor and vice versa.

Those parameters which are less important should contribute less in predicting the rest of the parameters. An example is the case as Inclination Deviation which does not have any direct, positive or negative, correlation with any parameter of left or right rail. Further in predictive analysis Inclination Deviation is the least contributor in predicting other parameters in both the left and the right rail and has the lowest prediction accuracy both over and under threshold.

In summary all highly correlated significant parameters, i.e. GAUGE Side Wear, Field Side Wear and Head Width of both left and right rails, have high contribution to predicting rest of the parameters giving high prediction accuracy. On the other hand insignificant parameters, which are not highly correlated with other parameter, have not only less contribution but also lower prediction accuracy in predicting rest of the parameters. This reconciliation of significant and insignificant parameter behaviour in predictive analysis would enhance the effectiveness of rail track degradation model based on rail profile multivariate predictive analysis.

7.2.2.2. Multivariate Track Geometry Predictive Analysis

The aim of track geometry multivariate predictive analysis is to investigate how much each parameter contributes in predicting other given parameters in the context of track geometry. Such an analysis will help in understanding inter-parameter relationships in predictive analysis. As explained in Table 6.7 ALIGMS and ALIGML, TOPRS and TOPLS, CURV and CROSS LEVEL are the highest contributors in predicting rest of the parameters. In other words these parameters are more important as they contribute more in predicting the rest of the parameters. Thus ALIGMS and ALIGML, TOPRS and TOPLS, CURV and CROSS LEVEL are not only highly correlated amongst themselves but are also the highest contributors in predicting rest of the parameters. Further less prediction error over and under the threshold will lead to high prediction accuracy. Such hypothesis is reconciled with experimental results explained in Table 6.8 which shows 99% prediction accuracy below threshold. Below are various rail profile parameters and their behaviour in predictive analysis:

1. TWIST1 and TWIST2 are essentially the same except that TWIST1 is measured at 3m and TWIST2 at 5m. Thus they are highly correlated in predicting TWIST1, TWIST2 is the highest contributor and vice versa.

2. ALIGMS and ALIGML are essentially the same except that ALIGMS is mean of alignment measured with small chord and ALIGML is mean of alignment measured with long chord. Thus they are highly correlated in predicting ALIGMS, ALIGML is the highest contributor and vice versa.

3. TOPRS and TOPLS are essentially the same except that TOPRS is top alignment of right rail measured with small chord and TOPLS is top alignment of left rail measured with small chord. Thus they are highly correlated in predicting TOPRS, TOPLS is the highest contributor and vice versa.

4. GAUGE is the distance between the two rails, measured at right angles to the rails in a plane below the top surface of the rail head, where as CROSS LEVEL is the difference in elevation between the top surfaces of the two rails measured at right angles to the track. Thus they are interdependent and hence change in GAUGE will change CROSS LEVEL directly. As shown in the experiments, GAUGE is the maximum contributor in predicting CROSS LEVEL and CROSS LEVEL is the maximum contributor in predicting GAUGE.

5. CURV, CANT DEF and CROSS LEVEL, all three are interdependent on each other and hence change in curvature (CURV) will change CROSS LEVEL and CANT DEF directly. As shown in the experiments CURV, CANT DEF are the maximum contributors in predicting CROSS LEVEL and CANT DEF are the maximum contributors in predicting CURV and CROSS LEVEL, CURV are the maximum contributor in predicting CANT DEF.

All highly correlated significant parameters not only have high contribution but also high prediction accuracy in predicting rest of the parameters. This enhances the effectiveness of the proposed rail track degradation model based on track geometry multivariate predictive analysis.

7.2.2.3. Univariate Rail Profile and Track Geometry Predictive Analysis

Another aspect of novel rail track degradation model is univariate predictive analysis of rail profile and track geometry parameters as explained in Table 6.2 and Table 6.3. Such analysis not only explores contribution of all parameters in both modalities in predicting other parameters but also sets foundations in understanding parameter behaviour over time.

1. All parameters in both left and right rail profile and track geometry have lowest contribution in first base file and the highest contribution the last base file.

2. The percentage of correct and incorrect predictions over threshold is near to zero. Hence no parameter in both left and right rail profile and track geometry exceeded threshold.

7.3. Novel Rail Track Degradation Model

Excessive wear of rail track and fatigue induce cracks in the rails and can cause derailments [90]. To avoid such incidents, it is essential to monitor the condition of the track regularly. In order to conduct effective condition monitoring, it is essential to have comprehensive analysis of track geometry parameters (GAUGE, alignment, curvature, CROSS LEVEL, surface quality, etc) and rail profile (head wear, side wear etc) parameters. Such robust analysis of the track parameters will help in understanding the rail track degradation process and will streamline maintenance regime, thus enabling optimum use of time and resources so that the rail track is kept in better shape and there will be fewer incidents [3] related to safety compromises. Furthermore this will help in generating early warnings and safety critical problems, thus preventing fatal accidents.

The aim of current research is to develop a novel rail track degradation model by combining the alignment component for effective alignment and the degradation component, for analysing the rail track degradation based on rail profile and track geometry parameters. The degradation component is based on comprehensive multivariate and univariate analysis. Both multivariate and univariate analysis are further explained through the amount of contribution that each parameter makes while predicting rest of the parameters and the predictive error analysis. Such contribution analysis manifests the level to which each parameter contributes in predicting other parameters where as the threshold analysis serves as signs of track degradation and will cause an alarm indicating the need for rail track maintenance by looking at exceedence values of track modalities. On the other hand in univariate contribution analysis is the amount of contribution that each parameter makes while predicting rest of the parameters over time. Predictive error in both univariate and in multivariate analysis is thresholded into either exceedence or normal. The univariate predictive error analysis serves as basis in predictive maintenance through the analysis of both rail track modalities. Univariate prediction can be mathematically expressed as:

Let

$\omega = Ғ\,(p, x_j)$

Where

ω is the predictive contribution

Ғ is the univariate prediction function

p is parameter to be predicted

x_j is it's predictor which is the value of the same parameter at time j

Therefore,

If,

$\omega_1 = Ғ(p, p3)$

$\omega_2 = Ғ(p, p2)$

$\omega_3 = Ғ(p, p1)$

Where p1, p2, p3 are the parameters used for predicting p

Then

$$\omega_1 >> \omega_2$$

$$\omega_1 >> \omega_3$$

Note: higher the value of j, more recent is the parameter value and hence better the prediction.

Track geometry and rail profile multivariate analysis explain degradation of each parameter from its standard. This can be done by looking at threshold exceedence of the parameters. If any parameter value exceeds the threshold not only such parameter has to be maintained but all those parameters which have high correlation need immediate attention. This is because of high interdependence of these parameters which will have a direct influence on each other. The extent of correlation can be judged from the multivariate contribution analysis. Higher the contribution, higher will be the interdependence and hence there will be a high correlation. Such contribution analysis of each parameter in both modalities along with threshold exceedence will give a comprehensive degradation understanding of each parameter. Multivariate analysis can be mathematically expressed as:

Let

$$\omega = Ꞙ(p_i, p_j)$$

Where,

ω is the predictive contribution

Ꞙ is the multivariate prediction function

Parameter p_i is to be predicted by parameter p_j where $i \neq j$

Therefore,

If,

$$\omega = \text{₣}(p_i, p_j)$$

Then

$$\omega\ max_k = \text{₣}(p_i, p_j)$$

Where

ω max is the highest contributor from p_j among all set parameters k in both Rail Profile and Track Geometry and parameter k is the highest contributor of predicting ω max_i of parameter i.

Both types of analysis will collectively serve as a basis in monitoring track conditions and thus finding track degradation problems. This will greatly aid in planning predictive track degradation by providing an objective means of evaluating track conditions and hence overall life of rail track will increase.

In order to visualize early warnings against track defects one common practice in rail industry is predictive maintenance of rail profile and track geometry. Variations in track geometry parameters e.g. CROSS LEVEL, alignment etc or in rail profile parameters e.g. rail Head Width, vertical rail wear etc are examples of track degradation. The degradation component answers this problem by categorising parameter values of both modalities into either exceedence or normal. Such parameter based categorisation would be more meaningful and therefore will help understanding the degradation process of the rail track over time.

7.3.1. Advantages of Degradation Model

Mentioned below are important advantages of novel rail track degradation model:

1. Such a model will cause alarms before the rail track defects can actually happen and will therefore reduce time intensive level_1 and level_2 rail track maintenance.

2. It has the ability to minimize unforeseen disruptions to operations in track maintenance.

3. Longer track life will result in reduction in track maintenance cost and better planning for track possessions.

4. Hence track reliability will increase which will result in better train punctuality.

7.3.2. Limitation of Degradation Model

1. In threshold analysis of the proposed degradation model the prediction of rail profile and track geometry parameter values over threshold were predicted with less accuracy as compared under threshold. The percentage of correct exceedence predictions in both rail profile and track geometry parameters are less than the percentages of correct predictions under threshold. This leads to the conclusion that the model did not predict peaks very efficiently during the course of univariate and multivariate predictive analysis of both track modalities.

2. Further during the process of parameter based alignment some Mile and Yard information were being lost.

7.4. Conclusion

Track component life models serve as a basis for track maintenance. They can range from very simple to very complex models and the choice of right and effective track model is influenced by the specific application involved. In the degradation component not necessarily any track component will malfunction, rather there is degradation in performance of a track component which can be analysed through track parameter values, and hence they require maintenance.

The key motivation of this thesis is to analyse the degradation process of rail track which can lead to significant parameter behaviour understanding in both ways i.e. with other parameters and over time. The proposed novel degradation model has two components: a parameter based alignment component, which is a pre processing component for any further analysis in both modalities. Second component is a degradation component, which is parameter based on univariate and multivariate predictive analysis in both modalities. Such a rail track degradation model will optimize train schedules and will improve the rail track life time. Besides it will reduce rail track defects which may require time intensive repair.

Chapter 8

Conclusion

This chapter highlights the research contributions made, summarises the key results obtained and draws relevant conclusions. The chapter further presents directions for further research and investigation.

8.1. Key Conclusions of the Research

In rail industry, rail maintenance actions are usually reactive, which means that maintenance is carried out after a defect has been identified [7]. Unfortunately this approach can lead to general safety concerns and may result in costly maintenance. Predictive maintenance, which aims to predict the future behaviour of track degradation based on the analysis of already recorded data, can be used to identify defects in advance, thus providing a solution for the above safety and cost concerns [91]. The research presented in this thesis leads to following conclusions:

1. Until all base files in both rail profile and track geometry are aligned appropriately with each other, no predictive analysis can be meaningful. As each base file in both modalities had distance information, recorded in a Mile and Yard column, all base files can be aligned with each other based on exact Mile and Yard information. Based on such hypothesis, the distance alignment method as proposed in chapter 4, should offer an ideal way of alignment. However, our experiments revealed that some of the parameters in both rail profile and track geometry resulted in negative correlations over time. Such negative univariate correlations were as a consequence of excessive parameter data loss during the process of distance alignment.

The above data loss adds to ineffectiveness of distance alignment and therefore emphasises the need for a better and effective data alignment method. This leads to the conclusion that better ways of alignment are needed for effective predictive analysis. Therefore in order to achieve the second objective of this thesis chapter 5 and 6 proposed two further, improved approaches to data alignment.

2. In chapter 5 a fixed window based size approach is used in which the entire track is divided into sections of 10 yards. The window size is restricted to 10 as the maximum variation, in all four base files, is within 10 yards. For each 10 yard section an average value of each parameter is calculated. Unfortunately such alignment results in loss information of parameter data its inability to locate exact Mile and Yard information on a track. Therefore a 10 yards section of the track has to be visited by track maintenance staff as the exact location within that segment will not be known.

3. In chapter 6 a new alignment approach, parameter based alignment, was presented. In this approach parameters were aligned based on their nearest matching value over time. This was done by shifting each parameter one row up in the first step and calculating minimum absolute error over time in all base files. The process of moving rows up and down is continued until parameter rows in all four base files are synchronized at such a position that there is minimum error between columns of same parameter over time.

   The improvement in parameter based alignment can be experienced by looking at line graphs of any parameter over time. Ideally all parameter behaviour should be similar to its behaviour in the next base file in time. Therefore an ideal case of alignment will result in similar behaviour of a parameter over time and thus resulting in minimum absolute error between same parameter over time.

The effectiveness of parameter based alignment was re-assured when all the significant correlations in rail profile and track geometry, which were showing negative correlation when predicting different parameters over time, based on distance (Mile and Yard) alignment were changed into positive correlations. In comparison to both distance and fixed window alignment parameter based alignment is simpler to compute and prediction accuracy of most of the parameters was improved. Besides it also adds effectiveness in the predictive analysis by retaining exact Mile and Yard locations instead of being discarded (distance alignment) or averaged (fixed window alignment). Once the second objective of the thesis is satisfied only then predictive analysis can be applied. Minimizing the prediction error is one aim of our analysis and locating it on the track is another.

Due to the fact that no data of rail profile and track geometry was lost in the process of parameter based alignment rail track maintenance staff can pin point exact location on the track, which makes it a pragmatic solution in track maintenance.

5. The key motivation of this thesis was to propose a degradation model for rail track through univariate and multivariate correlation analysis for significant parameter behaviour understanding and predictive analysis for understanding the track degradation process. The proposed novel degradation model has two components: a parameter based alignment component, which is a pre processing component for any further analysis in both modalities. The second component is a degradation component, which is further explained by univariate and multivariate predictive analysis in both modalities.

   Both multivariate and univariate analysis were further explained through contribution and predictive error analysis. The contribution analysis manifests the level to which each parameter contributes in predicting other parameters where as the threshold analysis serves as signs of track degradation and will cause an alarm in rail track maintenance by checking at exceedence values of track modalities. Besides this contribution analysis of each parameter in both modalities and threshold exceedence will give a comprehensive degradation understanding of each parameter.

Predictive error in both univariate and in multivariate analysis is threshold into either exceedence or normal. The univariate predictive error analysis serves as the basis of predictive maintenance of both rail track modalities therefore satisfying the third objective of the thesis.

Both alignment and degradation components, together serve as basis for monitoring track conditions and thus helps in predicting track degradation problems. Such a degradation model will greatly aid in planning predictive track degradation by providing an objective means of evaluating track conditions and hence over all life of rail track will increase. Hence the proposed model satisfies the fourth objective of the thesis.

The aim of current research was to develop a novel rail track degradation model which can reduce rail track defects which may require time intensive repair. The work presented in this thesis proves that the proposed predictive degradation model is not only effective but also is an efficient solution for rail track maintenance and will save time and cost.

8.2. Future Scope

Regardless of the sophistication of various rail track degradation models proposed in literature they are simply another way of ongoing track maintenance and therefore can not comprehend the complexity of track component life degradation in their entirety. Below are some prominent areas in which current research can be extended as future research:

1. One such aspect is peak prediction or time series analysis. This is because rail profile and track geometry parameter values over threshold were predicted with less accuracy as compared to under threshold. This leads to the conclusion that the model does not predict peaks in track data very efficiently. However in threshold predictive analysis, percentages of correct predictions of exceedence are less than percentages of correct predictions under threshold in both rail profile and track geometry parameters. This can be answered by exploring the variance in the time series of both modalities. A time series is a set of experimental data, with consistent a measurement method, measuring some activity (variance) over time [92]. The essence of the time series forecasting model is a formula that will predict the experimental patterns in a time series. For effective peak prediction the variance of the errors must be invariant i.e. constant [93]. This means that the variance for each subgroup of data is the same and does not depend on the level or the point in time.

2. Due to the fact that both modalities are highly interdependent on each other, a cross modality, multivariate threshold predictive analysis among all parameters of both modalities is worth analysing. Before such analysis cross modality multivariate parameter correlation analysis may result in other significant correlations. This would also help in any further cross modality threshold predictive error analysis of both modalities.

3. Another prominent research area is to explore track degradation in switches and curves. This is because the degradation process for straight track would be different for switches and curves as both modality parameters will behave differently.

4. The alignment issue as highlighted in the research and the proposed methods of alignment along with the univariate and multivariate degradation analysis to propose a novel model can be used in areas for instance normal road maintenance or even runway maintenance.

The current reactive rail track maintenance approach as explained in figure 6.2 is not only expensive to adopt but also more time consuming. In order to visualize early warnings against track defects one common practice in rail industry is predictive maintenance of rail profile and track geometry. The proposed predictive analysis based on parameter based alignment involved categorization of prediction error for each parameter in to either exceedence or normal. All parameter values, in both rail profile and track geometry, which are over threshold line, are exceedences i.e. they exceed threshold line and hence needs immediate maintenance. In comparison to reactive maintenance, which is essentially fixing rail defects after they have been identified, the proposed novel degradation model offers a pragmatic solution in rail track maintenance as explained in figure 6.3.

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