Physical Model-Based Predictive Maintenance for Rail Infrastructure

Annemieke Meghoe

Physical Model-Based Predictive Maintenance for Rail Infrastructure

Annemieke Angelique Meghoe

This dissertation has been approved by:

supervisor

Prof. dr. ir. T. Tinga

co-supervisor

Dr. ir. R. Loendersloot

Cover design: Annemieke Meghoe & Viren Mangal

Printed by: Gildeprint, The Netherlands

Lay-out: Annemieke Meghoe

ISBN: 978-90-365-4878-6

DOI: 10.3990/1.9789036548786

© 2019 Annemieke Angelique Meghoe, The Netherlands. All rights reserved. No parts of this thesis may be reproduced, stored in a retrieval system or transmitted in any form or by any means without permission of the author. Alle rechten voorbehouden. Niets uit deze uitgave mag worden vermenigvuldigd, in enige vorm of op enige wijze, zonder voorafgaande schriftelijke toestemming van de auteur.

PHYSICAL MODEL-BASED PREDICTIVE MAINTENANCE FOR RAIL INFRASTRUCTURE

DISSERTATION

to obtain
the degree of doctor at the University of Twente,
on the authority of the rector magnificus,
prof.dr. T.T.M. Palstra,
on account of the decision of the graduation committee,
to be publicly defended
on Thursday 19 December 2019 at 10.45 uur

by

Annemieke Angelique Meghoe

born on the 15th of August 1991
in Paramaribo, Suriname

Graduation committee:

Chairman/secretary	Prof. dr. G.P.M.R. Dewulf
supervisor:	Prof. dr. ir. T. Tinga
co-supervisor:	Dr. ir. R. Loendersloot
Committee Members	Prof. dr. ir. A. de Boer
	Prof. dr. ir. L.A.M. van Dongen
	Prof. dr. M.I.A. Stoelinga
	Prof. dr. ir. R.P.B.J. Dollevoet
	Prof. M. Berg

*To my husband,
Viren
and to my parents,
Jozef and Hilda*

Summary

The very first rails in the Netherlands were introduced in around 1839 and the maintenance activities over the past decades have been based mainly on experience from the past and from periodic inspections. With increasing traffic load, introduction of new vehicles and changing environmental conditions the prediction of rail damage becomes inaccurate and railway maintenance planning needs to be optimized. This thesis describes the utilization of physics-based models for rail damage prediction and railway maintenance planning optimization. A physical model is able to calculate the yet unknown future degradation if the current state of the system is known. To achieve this, numerical or mathematical descriptions of dominant failure mechanisms are usually used. However, physical failure models directly coupled with monitoring techniques for varying operating conditions in the rail infrastructure field are not available. Most of the research in this field is conducted at material level and the application in maintenance modelling is limited. Hence, the main objective of this research is the further development and application of the physics-based models within the rail-infrastructure for varying conditions and to use the outcome (e.g. critical parameters and Remaining Useful Life) for monitoring and maintenance purposes.

From the rail failure and maintenance cost database of Strukton Rail and also verified by literature study, it became apparent that wear and Rolling Contact Fatigue (RCF) are the most dominant degradation mechanisms for rail damage. Wear and RCF are caused by high stresses within the wheel-rail contact resulting from heavy loads and vehicle dynamics. Therefore, multi-body dynamics simulations are used to predict the dynamic behaviour and contact forces. However, the prediction for varying operation conditions means performing multiple simulations and can be time-consuming. Therefore, this thesis proposes the use of meta-models for both wear and RCF in order to increase the computational efficiency.

First, a sensitivity analysis is performed to investigate the dominant influence parameters related to operational conditions. The results from the sensitivity analysis show that rail profile, vehicle speed, rail cant, axle load, curve radius, material hardness, friction coefficient and the primary longitudinal and lateral stiffness of the train bogie are relevant. After gaining insight into the most dominant parameters the meta-models are developed that establish the relation between rail wear and the

usage profile of railway tracks. The geometry of these tracks also serves as input parameters of the meta-models. The fit of these models is based on a large data set generated from various scenarios. The selection of these scenarios is carried out by means of a Design of Experiments (DOE) method, known as the Latin Hypercube Sampling (LHS). This method randomly generates scenarios with different parameter settings. The best fit of the meta-model is then found by using the Response Surface Methodology.

The output of the meta-models for both wear and RCF are then validated with field measurements. Eddy current measurements were used to validate the performance of the RCF meta-models. The validation results were positive, but the model's only shortcoming was that it was unable to predict the size of a crack. Therefore, in order to fill this gap, data-driven methods were introduced and a hybrid method was developed.

The validation of the wear meta-models was performed with measured rail profiles using portable measuring devices like Railmonitor and MiniProf. Furthermore, due to the large uncertainty in the input parameters a stochastic approach was adopted in order to provide infrastructure managers the predicted rail wear with certain confidence bounds. The predicted mean and variance of the meta-model response, in this case the rail wear area, corresponded with the results of the field measurements.

Samenvatting

De allereerste spoorwegen in Nederland werden rond 1839 geïntroduceerd en de onderhoudsactiviteiten in de afgelopen decennia waren voornamelijk gebaseerd op ervaringen uit het verleden en op basis van periodieke inspecties. Met toenemende verkeersbelasting, de introductie van nieuwe voertuigen en veranderende omgevingscondities wordt de voorspelling van spoorschade onnauwkeurig en moet de planning van het onderhoud van het spoor worden geoptimaliseerd. Dit proefschrift beschrijft het gebruik van fysische modellen voor de voorspelling van spoorschade en optimalisatie van de onderhoudsplanung van het spoor. Een fysisch model kan de nog onbekende toekomstige degradatie berekenen als de huidige status van het systeem bekend is. Om dit te bereiken, worden meestal numerieke of wiskundige beschrijvingen van dominante faalmechanismen gebruikt. Fysische modellen direct gekoppeld aan bewakingstechnieken voor variërende operationele condities op het gebied van spoorweginfrastructuur zijn niet beschikbaar. Het meeste onderzoek op dit gebied wordt op materiaalniveau uitgevoerd en de toepassing in onderhoudsmodellering is beperkt. Het hoofddoel van dit onderzoek is daarom de verdere ontwikkeling en toepassing van de fysische modellen binnen de spoorweginfrastructuur voor variërende condities en om de uitkomst (bijvoorbeeld kritische parameters en resterende levensduur) te gebruiken voor monitorings- en onderhoudsdoeleinden.

Uit de database van spoorwegenstoringen en onderhoudskosten van Strukton Rail, en ook geverifieerd door literatuuronderzoek, werd duidelijk dat slijtage en Rolling Contact Fatigue (RCF) de meest dominante degradatiemechanismen zijn voor spoor schade. Slijtage en RCF worden veroorzaakt door hoge spanningen in het wiel-spoor contact als gevolg van zware belastingen en voertuigdynamiek. Daarom worden multi-body dynamics simulaties gebruikt om het dynamisch gedrag en de contactkrachten te voorspellen. De voorspelling voor variërende condities betekent echter dat meerdere simulaties moeten worden uitgevoerd en dat kan tijdrovend zijn. Daarom stelt dit proefschrift het gebruik van metamodellen voor zowel slijtage als RCF voor om de rekenefficiëntie te verhogen.

Eerst wordt er een gevoeligheidsanalyse uitgevoerd om de dominante invloedparameters te onderzoeken die verband houden met operationele condities. De resultaten van de gevoeligheidsanalyse tonen aan dat spoorstaafprofiel, voertuigsnelheid,

verkanting, asbelasting, boog radius, materiaalhardheid, wrijvingscoëfficiënt en de primaire longitudinale en laterale stijfheid van het treinstel relevant zijn. Na het verkrijgen van inzicht in de meest dominante parameters worden de metamodellen ontwikkeld die de relatie tussen spoorstaafslijtage en het gebruiksprofiel van spoorwegen bepalen. De geometrie van deze spoorwegen dient ook als invoerparameter van de metamodellen. De fit van deze modellen is gebaseerd op een grote dataset gegenereerd uit verschillende scenario's. De selectie van deze scenario's wordt uitgevoerd door middel van een Design of Experiments (DOE) methode, bekend als de Latin Hypercube Sampling (LHS). Deze methode genereert willekeurig scenario's met verschillende parameterinstellingen. De beste fit van het metamodel wordt vervolgens gevonden met behulp van de Response Surface Methodology.

De output van de metamodellen voor zowel slijtage als RCF wordt vervolgens gevalideerd met veldmetingen. Wervelstroømmetingen werden gebruikt om de prestaties van de RCF-metamodellen te valideren. De validatieresultaten waren positief, maar de enige tekortkoming van het model was dat het de grootte van een scheur niet kon voorspellen. Om deze tekortkoming op te heffen, zijn daarom data-aangedreven methoden geïntroduceerd en een hybride methode ontwikkeld.

De validatie van de slijtage metamodellen werd uitgevoerd door middel van gemeenten spoorstaafprofielen met behulp van draagbare meetapparatuur zoals Railmonitor en MiniProf. Bovendien werd vanwege de grote onzekerheid in de invoerparameters een stochastische aanpak gekozen om infrastructuurbeheerders de voorspelde spoorlijtage met zekere vertrouwensgrenzen te bieden. Het voorspelde gemiddelde en de variatie op het metamodel resultaat, in dit geval het spoorstaafslijtage oppervlak, kwam overeen met de resultaten van de veldmetingen.

Contents

Summary	vii
Samenvatting	ix
Nomenclature	xv
1 Introduction	1
1.1 Background	1
1.2 Problem statement	3
1.3 Research objective and research questions	4
1.4 Research approach & thesis outline	5
References	9
2 Critical component selection and failure modelling state of the art	11
2.1 Critical component selection	11
2.2 Dominant failure mechanisms	15
2.2.1 Wear	15
2.2.2 Rolling Contact Fatigue	19
2.2.3 Wear and Rolling Contact Fatigue	23
2.3 Concluding remarks	25
References	27
3 Rail wear and remaining life prediction using meta-models	31
3.1 Introduction	31
3.2 Methodology	33
3.2.1 Rail wear calculation	33
3.2.2 Sensitivity analysis	34
3.2.3 Meta-model	39
3.3 Numerical experiment results and discussion	42
3.3.1 Parametrization of rail profile	42
3.3.2 Sensitivity study results	45

3.3.3	Meta-modeling results	49
3.4	Conclusion	55
	References	57
	Appendices	61
3.A	Wheel profiles	61
3.B	Prediction results	62
3.C	Regression coefficients	63
4	Generic rail damage function based on physical models	65
4.1	Introduction	65
4.2	Methodology	67
4.2.1	Whole Life Rail Model	67
4.2.2	Numerical experiments	69
4.2.3	Fatigue life estimation	70
4.2.4	Wear rate calculation	73
4.3	Results and discussion	77
4.3.1	RCF damage function	77
4.3.2	Wear rate function	82
4.3.3	WLRM reconstruction	85
4.4	Conclusion	86
	References	89
5	A hybrid predictive methodology for head checks in railway infras- tructure	93
5.1	Introduction	93
5.2	Physics-based head check initiation model	96
5.2.1	Whole Life Rail Model	97
5.2.2	Meta-model	97
5.2.3	Damage evaluation	99
5.3	Data-driven head check evolution model	99
5.4	Health assessment	101
5.4.1	KPIs for number of defects	102
5.4.2	KPIs for density of defects	103
5.4.3	Stochastic KPIs	103
5.5	Results and discussion	104
5.5.1	Hit rate and accuracy of meta-models for crack initiation	105
5.5.2	Evolution model	105
5.5.3	KPI results	110
5.6	Conclusion	111
	References	113

6 Evaluation of rail wear prediction uncertainty for maintenance decision support **117**

6.1 Introduction 118

6.2 Methodology 119

6.2.1 Sensitivity analysis 119

6.2.2 Numerical uncertainty propagation analysis 121

6.2.3 Analytical uncertainty propagation analysis 124

6.2.4 Field measurements 126

6.3 Results and discussion 127

6.4 Conclusion 131

References 133

7 Discussion **135**

7.1 Current status 135

7.1.1 Contributions 135

7.1.2 Limitations and application 136

7.2 Outlook to future development 137

7.2.1 Link between design and predictive maintenance 138

7.2.2 Railway switch 139

References 141

8 Conclusions & recommendations **143**

8.1 Conclusions 143

8.2 Recommendations 146

Research deliverables **149**

Acknowledgements **151**

Nomenclature

Abbreviations

ABA	Axle Box Acceleration
ANN	Artificial Neural Networks
DC-FFT	Discrete Convolution Fast Fourier Transformation
EC	Eddy Current
FEM	Finite Element Model
FMECA	Failure Modes Effects and Criticality Analysis
IM	Infrastructure Manager
KPI	Key Performance Indicator
LHS	Latin Hypercube Sampling
MC	Monte Carlo
MGT	Mega Gross Ton
OFAT	One Factor at a Time
pdf	probability distribution function
RBF	Radial Basis Function
RCF	Rolling Contact Fatigue
RSM	Response Surface Methodology
RUL	Remaining Useful Life
SVM	Support Vector Machine

US	Ultrasonic
VI	Video Images
WLRM	Whole Life Rail Model

Greek Symbols

$\Delta\sigma$	applied normal stress range
$\Delta\tau$	shear stress range
γ	slip
ν	poission ratio
ϕ	spin creepage
σ_u	tensile fracture stress
$\sigma_{h,res}$	hydrostatic part of the residual stress
τ_f	friction stress
$\tau_{FL,red}$	reduced fatigue limit in shear
τ_{max}	maximum shear stress

Roman Symbols

ΔK	stress intensity factor range
ΔK_{th}	stress intensity factor threshold
$\dot{E}_d$	energy flow density
$\dot{m}_d$	mass flow density
A	contact area
a	semi-axis of the contact ellipse in moving direction
b	semi-axis of the contact ellipse in lateral direction
c_{dv}	material parameter
cof	coefficient of friction
D	total damage index
d	crack depth

E	elastic modulus
Ee	Elementary effect
f	traction coefficient
F_N	normal force
FI_{sub}	subsurface fatigue index
FI_{surf}	surface fatigue index
G	bulk shear modulus
H	hardness of material
h	wear depth
K	wear coefficient
k_x	longitudinal stiffness
k_y	lateral stiffness
MSE	Mean Squared Error
N_f	total fatigue life
N_i	crack initiation life
N_p	crack propagation life
p_0	maximum contact pressure
R	curve radius
R^2	coefficient of determination
R_a	surface roughness
s	crack depth growth
SI	Sensitivity Index
SSE	Sum of Squares Error
SST	Sum of Squares Total
T	tangential force
V	wear volume loss

v_{slip}	slip velocity
$V_{vehicle}$	vehicle speed
W_s	fracture energy

Chapter 1

Introduction

This chapter describes the motivation to start this PhD project and gives an overview on how the research is conducted and documented. The explanations for the initiation of this study can be found in the background and problem statement section, whereas the remaining sections describe the research questions and the research approach.

1.1 Background

Maintenance actions are required in order to increase the reliability, safety and availability of technical systems and components along with cost and downtime reduction [1, 2]. Maintenance is thus defined as the work, including all technical and administrative activities, performed to maintain a physical system or restore it to a situation in which it can execute its intended function [2–4]. Various maintenance concepts or strategies have been developed over the past decades, e.g. reliability centred maintenance, risk based maintenance, effectiveness centred maintenance, etc., which are used to determine how the maintenance will be organized and to select the most suitable maintenance policy [2]. The only type of maintenance policy that was used in the past is reactive maintenance in the form of corrective maintenance, also described as run-to-failure management [1]. In that case, a component is replaced only when it is broken.

With increasing customer demands, the production increased and most of the equipment has been automated. Therefore, the need for efficient and smart maintenance policies became more urgent so as to keep the production running with minimum downtime. Another condition that the new maintenance policy also had to meet is low maintenance costs. Therefore, the proactive maintenance policy was introduced. This policy in turn consists of preventive and opportunistic maintenance, see Figure 1.1 . Opportunistic maintenance is maintenance performed by using the opportunity of planned or unplanned downtime of the physical system [2, 5]. The

disadvantage of this type of maintenance is the extra maintenance costs and use of resources for systems that do not require maintenance yet. In preventive maintenance the aim is to clean, replace or repair a component shortly before it fails to perform its intended function. This is achieved by the condition-based and predictive maintenance policies. Previously, maintenance programs that consisted of preventive maintenance policies were based on calendar time or running hours.

Figure 1.1: The predictive maintenance policies (dashed region) within the maintenance landscape [6].

In condition-based maintenance the system is under real time or periodic monitoring and a change in its performance or output leads to maintenance actions. In this predictive maintenance policy the maintenance interval is determined based on information from diagnostics and prognostics [2]. Diagnostics are used to detect the damage and identify the present state of the asset. This information serves as input for the prognostics that calculates the Remaining Useful Life (RUL), which is the time up to the moment that the component fails to fulfil its intended function.

Similarly to other fields, railway track maintenance activities over the past decades have been based mainly on experience from the past (calendar time based maintenance) and on reactive maintenance (run to failure). In the case of calendar time-based maintenance, predictive models are based on historical data and with increasing traffic load and variation in operational conditions these models fail to predict the

actual remaining useful life of railway track components [7]. The outcome is that the components are replaced either too early or too late. The consequence of performing maintenance too early is that the component's lifetime has not been used to its full potential and the unnecessary use of resources including financial resources. On the other hand, the consequence of conducting maintenance too late is the large number of unexpected failures, leading to higher maintenance costs as unplanned maintenance needs to be scheduled. These statements indicate that a shift from reactive and calendar time-based maintenance to condition-based maintenance is required if infrastructure managers want to optimize their maintenance planning.

Besides the downtime and maintenance costs, the highest priority of train operators, asset owners and infrastructure managers is the safety of passengers. An example of train derailment caused by lack of maintenance actions such as grinding is the accident at Hatfield, UK, in the year 2000 [8]. This accident was caused by Rolling Contact Fatigue, which eventually led to broken rails. In 2002 a passenger train derailed in Potters Bar, UK, near a railway switch. After investigation, it was found that the railway switch's maintenance scheme was far short of what was required to guarantee a safe operation [9]. In conclusion, in order to keep the trains running safely and without disruptions, an efficient maintenance plan and condition-based maintenance for the different components of the rail infrastructure are essential.

1.2 Problem statement

This research is conducted in collaboration with Strukton Rail which is one of the leading rail infrastructure maintenance companies of the Netherlands and has close to 100 years of rail experience. Besides operating in the Netherlands they are also active internationally. However, for this thesis, operational and maintenance data of the Netherlands were utilized.

The problem that Strukton Rail is facing is the increase in maintenance costs due to unexpected failures caused by increasing traffic loads. These loads will increase in the coming years. Therefore, intense maintenance is required, while the time window to perform maintenance becomes smaller and the maintenance costs increase. Therefore, Strukton Rail is in search of reliable damage prediction models which can be easily included in their maintenance planning to make maintenance more efficient, predictable and manageable.

The very first rails in the Netherlands were introduced in around 1839 [10] and, as mentioned before, the maintenance intervals over the past decades have been based mainly on historical data and periodic inspections, i.e. calendar time-based maintenance. The current operating or environmental conditions are different from those in the past. Thus the maintenance intervals based on historic data are no longer valid and need to be updated. Therefore, the shift to predictive maintenance using both diagnostics and prognostics should take place sooner rather than later.

Diagnostics are performed mainly by monitoring the system's health, whereas

prognostics subsequently use this information to calculate the system's RUL by means of one of the following approaches: data-driven, physics-based or hybrid (data-driven + physics-based). The accuracy of the data driven approach depends largely on the amount, quality and relevance of the obtained data. If the data set is limited or the usage profile of the system has largely changed, the predictive model based on this data is not representative and accurate. On the other hand, the physics-based models are known to be very accurate but they do require a lot of computation time and are applicable only to a small range of systems. The advantage over the data driven models is the limited amount of historical data required [2].

Three research projects were initiated by Strukton Rail and conducted in collaboration with the University of Twente, two of them covering the data driven and the physics-based approach. The first research project is about the prediction of failures using big data techniques, which is called a "black box model". This topic follows the data-driven prognostics approach. The second research project, which is the main focus of this thesis, is the use of physical models of railway systems to predict their failure behaviour, which adopts the physics-based prognostics approach and yields a "white box model". Finally, the last project is concerned with optimizing maintenance strategies by using the output of the black and white box models.

1.3 Research objective and research questions

The objective of this research is the optimization of railway maintenance with the focus on the application of physics-based models for the most critical rail infrastructure components. The research scope is limited to rail infrastructure elements of the vehicle's guidance system such as tracks, switches and level crossings, because approximately half of the maintenance budget in the Netherlands is allocated to these systems [11]. Other technical fields e.g. energy supply system and communication system (signals) will not be addressed in this research. Thus, the main research question is formulated as:

How to apply physics-based models for appropriate monitoring and optimized predictive maintenance of critical components within rail infrastructure?

In order to answer the main research question, the following sub-questions need to be answered:

1. What are the most critical components (cost drivers, performance killers) within rail infrastructure that are also suitable for predictive maintenance modelling?
2. What are the dominant degradation mechanisms that cause the critical components to fail?
3. What physics-based models should be selected for the most critical components with single or multiple degradation mechanisms?

4. How to implement physics-based models for the most critical components with single or multiple degradation mechanisms?
5. What sensing strategy, inspection and processing methods are available to capture the relevant monitoring parameters or do new ones need to be developed?
6. How to couple the physics-based models with appropriate monitoring techniques at component and system level?

1.4 Research approach & thesis outline

In order to achieve the aim of this research, a robust research approach is adopted, as was proposed by [Tinga \[2\]](#), and this can also be used in fields other than rail infrastructure. The research approach contains the following steps:

1. Select suitable component: define and explain the selection criteria
2. Identify main degradation mechanism and load: understand the underlying physical mechanism properly (governing loads and knowledge of the material)
3. Model development:
  - a. Set up model for failure mechanism, e.g. wear model, fatigue model, deformation (crack) model, or develop a hybrid model
  - b. Search for the appropriate tool (software package, numerical or analytic model)
4. Derive relevant monitoring parameters that are required as input for the developed model
5. Perform usage, load and condition monitoring
6. Evaluate the model(s) using the monitoring results

By following the above-mentioned research steps, the research was divided into several parts which will be discussed in the remaining chapters of this thesis. The resulting outline of this thesis is as follows:

Chapter 2 The first task is to identify the critical components of the rail infrastructure and their failure modes/mechanisms. Once the failure modes and mechanisms are understood the physics-based modelling can be initiated and the relevant parameters can be extracted from the developed model. Finally, the appropriate monitoring technique should be chosen and/or developed. Chapter 2 therefore describes the selection of the most critical system and component within the railway network followed by their dominant degradation mechanisms. Systems or components are considered to be critical if their failures and maintenance activities are related to high costs (cost

drivers) and to low or negative performance of the system (performance killers). Finally, the track is chosen as the most critical system along with the rail as the most critical component. In addition, the state of the art in modelling the most dominant failure mechanisms in rail components, i.e. wear and fatigue, is discussed.

Chapter 3 From the results obtained in Chapter 2 it can be concluded that wear and Rolling Contact Fatigue (RCF) are the most dominant degradation mechanisms for railway tracks. Therefore, Chapter 3 focuses on understanding the rail wear mechanism and identifying difficulties in calculating the rail wear by using physical failure models and already monitored parameters. Physical failure models in combination with varying operating conditions for rail infrastructure elements are not available in the scientific literature yet. Most of the research in the rail infrastructure field is done at material level and the application in maintenance modelling is limited. Therefore, meta-models are developed during this study in order to calculate rail wear from operational conditions with the desired computation efficiency and accuracy.

Chapter 4 The focus of this chapter is on the development of a physics-based model for the second dominant failure mechanisms, i.e. RCF. In the past a lot of research has been conducted on crack initiation and crack propagation within rails. These studies are again mainly at material level. The idea is to use this knowledge and shift to the component level for maintenance purposes. The analysis at the material level can be very time-consuming, thus the challenge is to use high-level results and assumptions from previously developed models and couple them with operating conditions to deliver time to failure predictions with a certain confidence interval.

The RCF model developed in this study is based on a semi-empirical model, also known as the Whole Life Rail Model (WLRM). The WLRM was derived from only a limited set of regions and in order to use the concept of this model in a more general way new WLRMs for different types of steel grade with varying friction coefficient were developed during this study. For this purpose, mainly analytical expressions and numerical experiments were used rather than field experiments. In addition to having a widely applicable model, this also provided a more fundamental background for the empirical WLRM.

Chapter 5 The output of the meta-models for RCF, developed in Chapter 4, was validated with Eddy current measurements. Eddy current testing enables the detection of seed defects on the rail surface. The general outcome of the validation was positive; the only shortcoming of the model was that it could not predict the size of the crack. Therefore, the developed model is able to calculate only the initiation of cracks. However, in order to monitor RCF on rails it is required that a model can also predict the size of the crack such that it can be coupled with maintenance decision

tools. Consequently, data-driven techniques were adopted to fill in this gap and a hybrid method has been developed.

Chapter 6 A method that does not provide any confidence interval on the prediction is not very helpful if one wants to use the results of the prediction for maintenance decision-making and there is variation in the input. Therefore, in this chapter the meta-model developed in Chapter 3 is used to predict the amount of rail wear with certain confidence bounds after a specific number of wheel passages. As the meta-model is obtained from a physics-based model the randomness in the operation profiles can be covered by stochastic models. The uncertainty can also be reduced by usage, load or condition monitoring. Thus, the general idea is to use environmental and operating conditions and even maintenance activities as input for the developed meta-models and to predict the probability of the time to failure and/or the RUL distribution based on the calculated rail wear.

The relation between the above described chapters and the previously defined Sub-Research Questions (SRQ) and Research Steps (RS) is shown in Table 1.1 and an overall discussion on the integration of the various chapters is presented in Chapter 7. Finally, the conclusions and recommendations are put forward in Chapter 8.

Table 1.1: Structure of the thesis depicting the relation between the core chapters, the defined Sub-Research Questions (SRS) and Research Steps (RS).

Chapter	Description		1	2	3	4	5	6
2	Most critical component and dominant mechanism	SRQ	✓	✓				
		RS	✓	✓				
3	Wear meta-model development	SRQ		✓	✓			
		RS		✓	✓	✓		
4	RCF model development	SRQ			✓			
		RS		✓	✓			
5	Hybrid method development for RCF monitoring	SRQ				✓	✓	✓
		RS				✓	✓	✓
6	Rail wear prediction with uncertainty bounds	SRQ				✓	✓	✓
		RS				✓	✓	✓

References

- [1] R. Keith Mobley. *1 - Impact of Maintenance*, pages 1–10. Butterworth-Heinemann, Burlington, 2004. ISBN 978-0-7506-7798-1. doi: 10.1016/B978-075067798-1/50022-4.
- [2] T. Tinga. *Principles of Loads and Failure Mechanisms*. Springer Series in Reliability Engineering. 2013. ISBN 978-1-4471-4916-3 978-1-4471-4917-0. doi: 10.1007/978-1-4471-4917-0.
- [3] Hackman Hon Yin Lee and David Scott. Overview of maintenance strategy, acceptable maintenance standard and resources from a building maintenance operation perspective. *Journal of Building Appraisal*, 4(4):269–278, 2009. ISSN 1744-9545. doi: 10.1057/jba.2008.46.
- [4] Adriaan Goossens. *Maintenance policy selection for ships; an investigation using the analytic hierarchy process*. Phd thesis, University of Twente, 2015.
- [5] Édouard Thomas, Éric Levrat, and Benoît Iung. Overview on opportunistic maintenance. *IFAC Proceedings Volumes*, 41(3):245–250, 2008. ISSN 1474-6670. doi: 10.3182/20081205-2-CL-4009.00044.
- [6] Wieger Tiddens. *Setting sail towards predictive maintenance*. Phd thesis, University of Twente, 2018.
- [7] Rosmaini Ahmad and Shahrul Kamaruddin. An overview of time-based and condition-based maintenance in industrial application. *Computers & Industrial Engineering*, 63(1):135–149, 2012. ISSN 0360-8352. doi: 10.1016/j.cie.2012.02.002.
- [8] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Phd thesis, University of Twente, 2010.
- [9] Ian Coleman. *The Development of Modelling Tools for Railway Switches and Crossings*. Phd thesis, Imperial College London, 2014.
- [10] Coenraad Esveld. *Modern Railway Track*. MRT-Productions, second edition, 2001. ISBN 90-800324-3-3.
- [11] Arjen Zoeteman, Rolf Dollevoet, and Zili Li. Dutch research results on wheel/rail interface management: 2001–2013 and beyond. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 228(6):642–651, 2014. ISSN 0954-4097. doi: 10.1177/0954409714524379.

Chapter 2

Critical component selection and failure modelling state of the art

This chapter first describes the selection of the most critical component within the railway infrastructure followed by the determination of the most dominant failure mechanisms. Thereafter, the state of the art in modelling these dominant failure mechanisms is discussed.

2.1 Critical component selection

The railway infrastructure network consists of a large number of components. In order to make the shift from reactive to proactive maintenance, it is important to know which component or set of components requires the most attention and which requires the least. The components that require the most attention are considered as the critical components.

The railway infrastructure network can be structurally or functionally decomposed into different levels. The most common levels that will also be adopted in this research are the system and component level [1]. Systems or components are considered to be critical if their failures and maintenance activities are related to high costs (cost drivers) and to low or negative performance of the system (performance killers).

The most critical system for the rail network has been selected by using the Pareto analysis of failure frequency and maintenance cost data provided by Strukton Rail for the years 2014 and 2015 [2]. The Pareto analysis applies a method with the 20 – 80% rule. This rule suggests that 20% of the failures are responsible for 80% of the maintenance costs or downtime. A Pareto chart (i.e. a bar diagram) is plotted with

the first bar representing the system or component with the highest number of failure following with the second highest etc. A cumulative line is added in the chart and the 20 – 80% rule is applied, see Figure 2.1. Due to confidentiality reasons the values on the y -axis are not presented. From Figure 2.1 it can be concluded that the left hand side of the chart are responsible for 80% of the failures. Due to confidentiality the results for the maintenance costs are not presented in the Pareto chart. Instead the results are presented in pie charts, see Figure 2.2.

Figure 2.1: Pareto analysis for the number of failures occurred during 2014 and 2015.

From Figure 2.2 it can be seen that the overlapping components resulting in highest number of failures and maintenance costs are switches and tracks. These systems are considered as the most important cost drivers and performance killers. Due to modelling complexities of the switch, such as the combination of electrical and mechanical systems, stationary and non-stationary components, multiple failure mechanisms and widely varying rail profiles [3, 4], the track is chosen as the most critical component to focus on during this study. However, a similar approach to that developed for the track in this work can be followed for the switch to choose the most critical component and model the coupling between operational conditions, degradation models and RUL.

Furthermore, the selection of the most critical component of the track construction is also based on the failure frequency and the maintenance costs. The results revealed that the majority of failures for the track are related to the rail, welds and sleepers,

whereas the highest maintenance costs are incurred to keeping the ballast within operating norms, see Figure 2.3. Based on both pie charts depicted in this figure, the rail is selected as the most critical component. The same analysis was also performed by Rambali [2] under supervision of the University of Twente using another method, namely the Failure Mode and Criticality Analysis (FMECA), and similar results were obtained.

Finally, the analysis of the registered failure mode/mechanisms identified incorrect geometry, RCF and wear as the modes/mechanisms with the highest number (see

Figure 2.2: Cost drivers and performance killers at system level.

(a) Number of failures.

(b) Maintenance costs

Figure 2.3: Cost drivers and performance killers at component level.

Figure 2.4). Thus, the focus of this research with regard to the failure mechanisms will be on rail RCF and wear, as the incorrect geometry is related to degradation of components like the ballast, sleepers and underground, and the rail is chosen as the most critical component.

Figure 2.4: Causes for rail malfunctions.

2.2 Dominant failure mechanisms

This section will describe the different models for the most dominant failure mechanisms as selected in the previous section (i.e. wear and RCF), see Table 2.1.

Table 2.1: Overview of different models for wear and RCF.

Model	Mechanism		Nature		
	Wear	RCF	Empirical	Numerical	Theoretical
Archard's wear model	✓		✓		✓
Energy based models	✓		✓		
Dang Van criterion		✓		✓	✓
Shakedown theory		✓		✓	✓
Ratchetting model	✓	✓		✓	✓
Whole Life Rail Model	✓	✓	✓	✓	

2.2.1 Wear

Rail wear prediction models are rarely seen in literature as they are considered to be developed in the same manner as wheel wear prediction models [5]. Rail and wheel wear prediction started four decades ago when the first models were based primarily on laboratory and field tests. With the increasing computation power of computers two decades ago, numerical wear prediction models became more interesting and feasible. Wear prediction tools can be divided into two categories based on their approaches

[6]. The first group of wear prediction tools uses Archard's wear law [7] to calculate the wear depth whereas the approach of the other group is based on dissipated energy [8]. This section gives an overview of commonly used wear models.

Archard's wear model

In 1953 Archard [7] developed a sliding wear model for metal to metal contact surfaces, based on theoretical and empirical studies. This model indicates that the amount of wear volume loss V given in $[\text{mm}^3]$ is related to sliding distance s in $[\text{mm}]$, normal force F_N in $[\text{N}]$, hardness of material H in $[\text{N}/\text{mm}^2]$ and a dimensionless wear coefficient K :

$$V = K \frac{s F_N}{H} \quad (2.1)$$

The wear coefficient K depends on the surface conditions and is usually determined empirically, e.g. with pin on disk configuration measurements [9]. For simple calculations the wear coefficient can be derived from the wear chart of Jendel [9], see Figure 2.5. This chart was formed from a series of laboratory experiments for various levels of contact pressure (P), sliding velocity (v_{slip}) and hardness (H) of the material during dry conditions. Hence the wear coefficient depends strongly on the previously mentioned parameters.

Figure 2.5: Jendel's wear map [9].

Jendel [9] discretized the contact patch into $N_x \times N_y$ elements and implemented Archard's wear law for each element. For the implementation of the wear law at each element, the slip velocity at each element was first determined by means of the

following equation:

$$\bar{v}_{slip} = V_{vehicle} \left(\left\{ \begin{array}{c} v_x - \phi y \\ v_y + \phi x \end{array} \right\} - \frac{\partial \bar{u}(x, y)}{\partial y} \right) \quad (2.2)$$

where $V_{vehicle}$ is the vehicle speed in [m/s], v_x [-], v_y [-] and ϕ [1/m] are the longitudinal, lateral and spin creepage respectively, u is the elastic displacement in [m] and x and y are the Cartesian coordinates of the contact patch [9]. It should be noted that the elastic part in Equation (2.2) is ignored in Jendel's model and only rigid slip is considered. Enblom and Berg [10] extended Jendel's model by taking into account this elastic part. They compared the wear depth values obtained with the rigid slip only model (Jendel's model) with Enblom's model for a contact patch in pure and partial slip. They concluded that the model with only rigid slip underestimates the wear depth at certain locations as the distribution along the lateral direction of the contact patch deviates from the distribution obtained by Enblom's model. However, the total wear volumes of both models are in good agreement. They suggested that the deviation is due to the contribution of the spin. The results were indeed similar when the spin was ignored [10].

Energy based models

In energy-based models the wear volume is assumed to be proportional to the dissipated energy in the contact area. Zobory [11] developed three such models that are applicable to wheel-rail contact problems, namely: Dissipated Energy Based Wear Hypothesis, Normal Traction Based Wear Hypothesis and Simplified-Combined Wear Hypothesis. In the first model the proportionality between the energy flow density $\dot{E}_d$ and mass flow density $\dot{m}_d$ at an arbitrary point r_p occurring at time t is achieved by calculating the energy dissipation for the adhesive and sliding part of the contact patch separately:

$$\dot{m}_d(r_p, t) = k \cdot \dot{E}_d(r_p, t) \quad (2.3)$$

where k is the wear coefficient determined by several experimental studies, see Figure 2.6.

Thereafter, the Normal Traction Based Wear Hypothesis was developed. This hypothesis neglected the separation of the contact area and was based on the correlation between mass flow density, normal traction and slip velocity [11].

Finally, the third model was developed for a smooth implementation in the vehicle dynamics model and is basically a combination of the previous two models. The simulated wheel and rail profiles using the third model were in good agreement with the measured ones. The small differences were discussed to be the results of neglecting the effect of the switches in the simulation [11].

Besides Zobory's model, Pearce and Sherratt's model [8] also uses the energy approach to calculate wear and expresses the wear volume in terms of the wear number $T\gamma$. T denotes the tractive force and γ the slip at the wheel-rail contact. Pearce

Figure 2.6: Domains of mild and severe wear [11].

and Sherratt [8] developed a wear prediction method focusing on the wheel profile evolution based on the energy approach [12]. They presented three wear functions for each wear regime from mild to severe wear, depending on the wear number, see Table 2.2. Similar functions were first derived experimentally by Bolton and Clayton in 1984 [13].

Table 2.2: Wear functions for each wear regime [14].

Wear regime	Criteria	Wear function [$\mu\text{g}/\text{m}/\text{mm}^2$]
Mild wear	$T\gamma/A < 10.4$	$5.3T\gamma/A$
Transition region	$10.4 < T\gamma/A < 77.2$	55
Severe wear	$T\gamma/A > 77.2$	$61.9T\gamma/A$

The wear rate in [$\mu\text{g}/\text{m}/\text{mm}^2$] as function of the wear number $T\gamma$ (i.e. the wear function) can be expressed as follows [14]:

$$\dot{h} = K \frac{T\gamma}{A} \quad (2.4)$$

where A refers to the contact area and K to the wear coefficient which is determined by multiple twin disc tests [14]. These tests were performed for various contact conditions, such as different contact stresses and slip. The results of the tests implied that three wear regimes can be distinguished with their own wear coefficient, see Figure 2.7.

From previous research about the comparison between the wear models described

Figure 2.7: Wear regimes and coefficients [14].

above, namely Archard's wear law and the energy approach, it cannot be concluded which wear model is better according to Dirks [15]. Archard's wear law is usually used in the tribology field, thus it has been decided to use Archard's wear law for this study.

2.2.2 Rolling Contact Fatigue

In addition to the rail wear phenomena, RCF is as severe or causing even more challenges for railway tracks [16–19]. Two types of RCF are encountered for wheel-rail contact, namely surface and subsurface initiated RCF [15, 20, 21]. The latter is more dangerous as it cannot be detected by visual inspection. In the past, subsurface RCF occurred more often, but due to improved steel production techniques defects within the material, which can lead to crack initiation, are rarely found [22]. First the model for subsurface RCF is discussed, also known as Dang Van criterion [23], followed by the RCF model based on the shakedown theory [24], which can only predict whether a specific condition can cause surface or subsurface RCF.

Dang Van criterion

A model that can predict the initiation of subsurface RCF is based on the Dang Van criterion [23]. The subsurface fatigue index FI_{sub} derived from this criterion has been approximated by Ekberg et al. [20, 24]:

$$FI_{sub} = \frac{F_z}{4\pi ab}(1 + f^2) + c_{dv}\sigma_{h,res} \quad (2.5)$$

where F_z is the normal contact force, a and b are the semi-axis of the contact ellipse, f is the traction coefficient, c_{dv} is a material parameter and $\sigma_{h,res}$ is the hydrostatic part of the residual stress. Assuming that the compressive residual stresses do not have major effects and using the following presumption:

$$FI_{sub} \geq \tau_{FL,red} \quad (2.6)$$

where $\tau_{FL,red}$ is the reduced fatigue limit in shear [21] and is approximated as:

$$\tau_{FL,red} \approx \tau_{FL} \left(\frac{d}{d_0} \right)^{-1/6} \approx \frac{\sigma_u}{3} \left(\frac{d}{d_0} \right)^{-1/6} \quad (2.7)$$

then the simplified fatigue criterion is given by:

$$\frac{F_z}{4\pi ab} \gtrsim \frac{\sigma_u}{3} \left(\frac{d}{d_0} \right)^{-1/6} \quad (2.8)$$

where d is the size of the material defect, d_0 is the defect size of the initial crack, σ_u equals the tensile fracture stress and τ_{FL} is the unreduced fatigue limit in shear. Failure, i.e. subsurface RCF initiation, occurs when the subsurface fatigue index exceeds the fatigue limit of the material in pure shear [25].

Shakedown theory

The Shakedown diagram approach was used by Ekberg et al. [24] to predict the probability of RCF on wheels. This diagram, see Figure 2.8, is based on the Hertzian theory, hence the contact pressure distribution $p(x, y)$ is elliptical:

$$p(x, y) = p_0 \sqrt{1 - \left(\frac{x}{a} \right)^2 - \left(\frac{y}{b} \right)^2} \quad (2.9)$$

where a and b are the semi-axes of the contact patch and p_0 the maximum contact pressure:

$$p_0 = \frac{3F_z}{2\pi ab} \quad (2.10)$$

with F_z being the contact force in z -direction, i.e. in the direction normal to the rail.

Because full slip conditions are assumed, the shear stress is proportional to the contact pressure by means of the traction coefficient f :

$$\tau(x, y) = f \cdot p(x, y) \quad (2.11)$$

The traction coefficient f is also known as the utilized friction coefficient, which is

Figure 2.8: Shake down diagram [21].

defined as the lateral forces divided by the vertical force [24]:

$$f = \frac{\sqrt{F_x^2 + F_y^2}}{F_z} \quad (2.12)$$

The maximum shear stress which is also denoted as the yield limit in cyclic shear τ_0 is given by [21] :

$$\tau_0 = f \cdot p_0 \quad (2.13)$$

The boundary condition line BC in the shakedown diagram is derived from Equation (2.10) and (2.13) and results in:

$$\frac{p_0}{\tau_0} = \frac{3F_z}{2\pi ab\tau_0} = \frac{1}{f} \quad (2.14)$$

Damage occurs if the working point WP is located outside the boundary line BC, hence the surface fatigue index FI_{surf} is given as the minimum distance between WP

and BC [21]:

$$FI_{surf} = f - \frac{2\pi ab\tau_0}{3F_z} \quad (2.15)$$

Failure, in this case referred as RCF initiation, therefore occurs when $FI_{surf} > 0$. This indicates surface plasticity which eventually leads to surface initiated RCF. The disadvantages of the shakedown approach are the undefined relation to crack propagation and the deficiency to analyse the interaction between wear and RCF.

However, the fatigue damage D of rails can be formulated in terms of the number of wheel passages N via a power law [21]:

$$D = \frac{1}{N} = \alpha \cdot \sigma_a^\beta \quad \forall \quad \sigma_a > \sigma_{fl} \quad (2.16)$$

where σ_a is the stress amplitude, σ_{fl} is the fatigue limit and α and β are material parameters. An estimation of the fatigue damage D_i for each wheel passage has been adopted based on previous experimental research:

$$D_i = \frac{(FI_{surf,i})^4}{10} \quad \forall \quad FI_{surf} > 0 \quad (2.17)$$

and then the total damage for N wheel passages is calculated using the Palmgren-Miner rule [26, 27]:

$$D = \sum_{i=1}^N D_i \quad (2.18)$$

Note that $D = 1$ corresponds to failure.

As mentioned before, the shakedown approach explained until now applies for full slip conditions. In practice wheel-rail contacts on the tread are in partial slip, hence a more general approach is achieved by taking into account the local shear stress. In this case the local fatigue damage index is equal to [21]:

$$FI_{surf}(x, y) = f(x, y) - \frac{\tau_0}{p(x, y)} \quad (2.19)$$

where

$$p(x, y) = -\sigma_z(x, y) \quad (2.20)$$

$$f(x, y) = \frac{\sqrt{\tau_{zx}(x, y)^2 + \tau_{zy}(x, y)^2}}{p(x, y)} \quad \forall \quad |x| < a, |y| < b, z = 0 \quad (2.21)$$

The local damage for each strip is defined as the maximum surface fatigue index in

the contact patch for each wheel passage:

$$D(y)_i = \max_x \frac{\left(f(x, y) - \frac{\tau_0}{p(x, y)}\right)^4}{10} \quad \forall \quad \max_x \left(f(x, y) - \frac{\tau_0}{p(x, y)}\right) > 0 \quad (2.22)$$

2.2.3 Wear and Rolling Contact Fatigue

This section presents two models that take into account both wear and RCF, namely the ratcheting model [28] and the Whole Life Rail Model (WLRM) [29].

Ratcheting model

This ratcheting model [28] was first developed to calculate the amount of wear for ductile materials and is based on plastic strain accumulation. The material is discretized in $N_x \times N_z$ rectangular elements, where x is the direction of applied traction and z is the direction of material depth, see Figure 2.9, and then for each element the plastic strain $\Delta\gamma_n^{ij}$ is accumulated depending on the number of cycles and reaches a certain accumulated plastic strain value (γ_n^{ij}). Ratcheting failure (or RCF initiation) occurs when the accumulated plastic strain (γ_n^{ij}) for one element exceeds a certain critical strain value (γ_c). The considered element is regarded as a weak element and is removed from the material as wear or stays there and is considered as a crack, depending on the location of the element in the material. Franklin et al. [30] explain in a scheme how to distinguish whether a certain weak element is caused by wear or crack initiation.

Figure 2.9: Shear strain accumulation [31].

The plastic strain for each element (in column i and row j) per cycle n is calculated

as follows [30]:

$$\Delta\gamma_n^{ij} = C \left(\frac{\tau_{zx(max)}^j}{k_{eff}^{ij}} - 1 \right) \quad (2.23)$$

And the accumulated plastic strain is as follows:

$$\gamma_n^{ij} = \gamma_{n-1}^{ij} + \Delta\gamma_n^{ij} \quad (2.24)$$

where $\tau_{zx(max)}^j$ is the maximum orthogonal shear stress at the depth of row j , C is a material constant and k_{eff}^{ij} is the effective shear yield stress that is calculated as:

$$k_{eff}^{ij} = \beta k_0 \max \left(1, \sqrt{1 - e^{-\alpha \gamma^{ij}}} \right) \quad (2.25)$$

and α and β are material constants and k_0 is the initial yield stress.

Whole Life Rail Model

The Whole Life Rail Model (WLRM), see Figure 2.10, is developed from field observations by Burstow [29] and based on the dissipated energy in the wheel-rail contact. The advantage of this model is that it includes wear implicitly in the damage evaluation.

Figure 2.10: RCF damage index as a function of the wear number [22].

The damage index depends on the wear number $T\gamma$ which can be calculated as:

$$T\gamma = T_x\gamma_x + T_y\gamma_y \quad (2.26)$$

where T_x and T_y represent the tangential or shear forces and γ_x , γ_y the longitudinal

and lateral creepages, respectively. It can be seen that the effect of spin is neglected in the model which can lead to inaccurate estimations as in practice the spin plays a very important role, especially in curved tracks. Dirks et al. [25] suggested calculating the wear number locally (for each cell element in the contact patch) in order to include the spin effect. Hence the wear number becomes:

$$T\gamma(x, y) = T_x(x, y) \cdot (\gamma_x - (\phi \cdot y)) + T_y(x, y) \cdot (\gamma_y + (\phi \cdot x)) \quad (2.27)$$

Furthermore, the RCF damage index is based on observational data for the R220Mn rail grade and determines which degradation mechanism (RCF or wear) is dominant on a specific piece of track by means of the wear number $T\gamma$. The loading conditions between line section A-B in Figure 2.10 represent the RCF dominant region, B-C represent a combination of RCF and wear, and C-D represent the wear dominant region. The total damage calculation is similar to the shakedown approach, namely by employing the Palmgren-Miner rule [26, 27]:

$$D = \sum_{i=1}^N D_i \quad (2.28)$$

The majority of the tracks installed in the Netherlands are made of R260Mn steel grade and recently Hiensch and Steenbergen [32] investigated the RCF damage function for this type of rail. They concluded that the damage function of R260Mn coincides with R220Mn.

The WLRM is chosen as the prediction model for RCF in the current study due to the following advantages of the WLRM:

1. The input parameter required for the damage evaluation for the WLRM is a single variable (e.g. wear number).
2. The interaction between wear and RCF is incorporated.

2.3 Concluding remarks

For the most critical component selection an analysis at system level was first performed, followed by an analysis at component level. At the system level the Pareto analysis was employed and the most critical systems resulting from this analysis were tracks and switches. The track system was further investigated and a Pareto analysis and FMECA were performed at component level. The rail component turned out to be the most critical one due to the greatest number of failures and the highest maintenance costs. Hence, the remainder of this study will be focused on rail degradation. The most dominant rail degradation mechanisms were therefore also

determined through a Pareto analysis, which yielded the wear and RCF mechanisms as the most critical ones.

Various models are available for both degradation mechanisms and have been summarized in this chapter. From the state of the art study of the available models for both degradation mechanisms, two models have been selected for the work presented in this thesis. For the wear mechanism the model based on Archard's wear law is selected due to its physics-based nature, as will be further discussed in Chapter 3. The models based on the energy approach have an empirical nature which can lead to inaccurate wear predictions for varying operational conditions and are therefore not selected.

For the RCF mechanism the WLRM is chosen as a predictive model due to the convenience of merging it with maintenance decision tools. The WLRM will be elaborated in Chapter 4 to understand the model from a theoretical background. A more general WLRM is aimed to be developed in Chapter 4 for different friction conditions and steel grades, and will be compared to the WLRMs as developed by [Burstow \[29\]](#) and [Hiensch and Steenbergen \[32\]](#).

References

- [1] J. Carretero, J. M. Perez, F. Garcia-Carballeira, A. Calderon, J. Fernandez, J. D. Garcia, A. Lozano, L. Cardona, N. Cotaina, and P. Prete. Applying RCM in large scale systems: a case study with railway networks. *Reliability Engineering & System Safety*, 82(3):257–273, 2003. ISSN 0951-8320. doi: 10.1016/S0951-8320(03)00167-4.
- [2] Ishan Rambali. *Critical Component Selection on a Railway Track through RCM and MDCM Methods*. Bsc thesis, Anton de Kom University of Suriname, 2017.
- [3] Coenraad Esveld. *Modern Railway Track*. MRT-Productions, second edition, 2001. ISBN 90-800324-3-3.
- [4] Björn A. Pålsson. *Optimisation of Railway Switches and Crossings*. Phd thesis, Chalmers University of Technology, 2014.
- [5] R. Enblom. Deterioration mechanisms in the wheel-rail interface with focus on wear prediction: a literature review. *Vehicle System Dynamics*, 47(6):661–700, 2009. ISSN 0042-3114. doi: Pii90742163610.1080/00423110802331559.
- [6] A. Bevan, P. Molyneux-Berry, B. Eickhoff, and M. Burstow. Development and validation of a wheel wear and rolling contact fatigue damage model. *Wear*, 307(1-2):100–111, 2013. ISSN 0043-1648. doi: 10.1016/j.wear.2013.08.004.
- [7] J. F. Archard. Contact and rubbing of flat surfaces. *Journal of Applied Physics*, 24(8):981–988, 1953. ISSN 0021-8979. doi: 10.1063/1.1721448.
- [8] T. G. Pearce and N. D. Sherratt. Prediction of wheel profile wear. *Wear*, 144(1-2):343–351, 1991. ISSN 0043-1648. doi: 10.1016/0043-1648(91)90025-P.
- [9] T. Jendel. Prediction of wheel profile wear-comparisons with field measurements. *Wear*, 253(1-2):89–99, 2002. ISSN 0043-1648. doi: 10.1016/S0043-1648(02)00087-X.
- [10] R. Enblom and M. Berg. Simulation of railway wheel profile development due to wear - influence of disc braking and contact environment. *Wear*, 258(7-8): 1055–1063, 2005. ISSN 0043-1648. doi: 10.1016/j.wear.2004.03.055.
- [11] I. Zobory. Prediction of wheel/rail profile wear. *Vehicle System Dynamics*, 28(2-3):221–259, 1997. ISSN 0042-3114. doi: 10.1080/00423119708969355.
- [12] I. J. McEwen and R. F. Harvey. Interpretation of wheel/rail wear numbers. Technical Report British Rail Research TM VDY, 1986.
- [13] P. J. Bolton and P. Clayton. Rolling—sliding wear damage in rail and tyre steels. *Wear*, 93(2):145–165, 1984. ISSN 0043-1648. doi: 10.1016/0043-1648(84)90066-8.

- [14] A. Ward, R. Lewis, and R. S. Dwyer-Joyce. *Incorporating a railway wheel wear model into multi-body simulations of wheelset dynamics*, volume Volume 41, pages 367–376. Elsevier, 2003. ISBN 0167-8922. doi: 10.1016/S0167-8922(03)80150-5.
- [15] Babette Dirks. *Simulation and measurement of wheel on rail fatigue and wear*. Phd thesis, KTH Royal Institute of Technology, 2015.
- [16] Hans-Dieter Grohmann and Wolfgang Schoech. Contact geometry and surface fatigue—minimizing the risk of headcheck formation. *Wear*, 253(1):54–59, 2002. ISSN 0043-1648. doi: 10.1016/S0043-1648(02)00082-0.
- [17] G. Donzella, M. Faccoli, A. Ghidini, A. Mazzu, and R. Roberti. The competitive role of wear and rcf in a rail steel. *Engineering Fracture Mechanics*, 72(2):287–308, 2005. ISSN 0013-7944. doi: 10.1016/j.engfracmech.2004.04.011.
- [18] B. Dirks and R. Enblom. Prediction model for wheel profile wear and rolling contact fatigue. *Wear*, 271(1-2):210–217, 2011. ISSN 0043-1648. doi: 10.1016/j.wear.2010.10.028.
- [19] J. Brouzoulis. Wear impact on rolling contact fatigue crack growth in rails. *Wear*, 314(1-2):13–19, 2014. ISSN 0043-1648. doi: 10.1016/j.wear.2013.12.009.
- [20] A. Ekberg and E. Kabo. Fatigue of railway wheels and rails under rolling contact and thermal loading - an overview. *Wear*, 258(7-8):1288–1300, 2005. ISSN 0043-1648. doi: 10.1016/j.wear.2004.03.039.
- [21] A. Ekberg, B. Akesson, and E. Kabo. Wheel/rail rolling contact fatigue - probe, predict, prevent. *Wear*, 314(1-2):2–12, 2014. ISSN 0043-1648. doi: 10.1016/j.wear.2013.12.004.
- [22] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Phd thesis, University of Twente, 2010.
- [23] K. Dang Van, G. Cailletaud, J.F. Flavenot, A. Le Douaron, and H.P. Lieurade. Criterion for high cycle fatigue failure under multiaxial loading. *Biaxial and Multiaxial Fatigue*, pages 459 – 478, 1989.
- [24] A. Ekberg, E. Kabo, and H. Andersson. An engineering model for prediction of rolling contact fatigue of railway wheels. *Fatigue & Fracture of Engineering Materials & Structures*, 25(10):899–909, 2002. ISSN 8756-758x. doi: 10.1046/j.1460-2695.2002.00535.x.
- [25] B. Dirks, R. Enblom, A. Ekberg, and M. Berg. The development of a crack propagation model for railway wheels and rails. *Fatigue & Fracture of Engineering Materials & Structures*, 38(12):1478–1491, 2015. ISSN 8756-758x. doi: 10.1111/ffe.12318.

-
- [26] A. Palmgren. Lifetime of ball bearing. pages 339–341, 1924.
- [27] M. A. Miner. Cumulative damage in fatigue. *J. Appl. Mech.*, 12(3):A159–A164, 1945.
- [28] A. Kapoor and F. J. Franklin. Tribological layers and the wear of ductile materials. *Wear*, 245:204–215, 2000.
- [29] M. C. Burstow. Whole life rail model application and development: Development of a rolling contact fatigue damage parameter. Report, RSSB, 2003.
- [30] F. J. Franklin, T. Chung, and A. Kapoor. Ratcheting and fatigue-led wear in rail-wheel contact. *Fatigue & Fracture of Engineering Materials & Structures*, 26(10):949–955, 2003. ISSN 8756-758x. doi: 10.1046/j.1460-2695.2003.00703.x.
- [31] F. J. Franklin, J. E. Garnham, D. I. Fletcher, C. L. Davis, and A. Kapoor. Modelling rail steel microstructure and its effect on crack initiation. *Wear*, 265(9-10):1332–1341, 2008. ISSN 0043-1648. doi: 10.1016/j.wear.2008.03.027.
- [32] M. Hiensch and M. Steenbergen. Rolling contact fatigue on premium rail grades: Damage function development from field data. *Wear*, 394:187–194, 2018. ISSN 0043-1648. doi: 10.1016/j.wear.2017.10.018.

Chapter 3

Rail wear and remaining life prediction using meta-models¹

Abstract

The study presented in this chapter proposes a method to estimate the Remaining Useful Life (RUL) of railway tracks determined by wear and taking into account various track geometry and usage profile parameters. The relation between these parameters and rail wear is established by means of meta-models derived from physical models. These meta-models are obtained with regression analysis where the best fit is found from a relatively large set of numerical experiments for various scenarios. The specific parameter settings for these scenarios are obtained by using the Latin Hypercube Sampling (LHS) method. Furthermore, for the rail profile, which is one of the input parameters for the meta-model, it is shown that the evolution due to wear in moderate curves can be characterized by only one parameter, i.e. the vertical wear depth at the rail head. The findings in this chapter including the resulting meta-models are valuable for Infrastructure Managers (IM's) and can easily be implemented in maintenance decision support tools. Furthermore, the parameters required for the proposed method are already monitored by IM's as a common practice.

3.1 Introduction

Properly addressing the degradation of railway elements is an important topic in rail infrastructure asset management. One of the dominant mechanisms is the wear of

---

¹This chapter is reproduced from: Meghoo, A., Loendersloot, R. and Tinga, T. (2019). Rail wear and remaining life prediction using meta-models. *International Journal of Rail Transportation*, 1-26, doi:10.1080/23248378.2019.1621780

railway tracks. Material loss in the rail head alters the shape of rail profiles which changes the location of the wheel contact points and leads to instability of vehicles, especially during curving behavior. This can eventually cause derailment of trains. Rail grinding is then performed to restore the shape of rail profiles and ensure dynamic stability. This maintenance activity is part of either scheduled or reactive maintenance. Predicting rail wear beforehand can assist in properly scheduling the maintenance intervals. Hence, Infrastructure Managers (IM's) are looking for rail wear prediction tools that can support the maintenance planning and optimization based on the usage profile of railway tracks.

In scientific literature, a relatively limited amount of attention has been paid to rail wear prediction as compared to wheel wear prediction. This is due to the fact that the wear rate of wheels is higher. Hence, extensive descriptions on the wheel wear prediction procedure can be found in literature [1–5]. [Enblom and Berg](#) [6] proposed a procedure to predict rail wear similar to that of wheel wear. The amount of rail wear was overestimated when compared to field measurements and the authors therefore suggested to proportionally scale down the wear coefficients. [Dirks](#) [7] also developed a model to predict wheel and rail wear, but this model was only verified for the wheels. It should be noted that all the methods developed so far propose a numerically expensive procedure for the wheel/rail wear prediction. This makes existing methods unsuitable for application as real-time prognostic tool by IM's.

Computational time can be reduced considerably when predefined relations between wear rate and operating parameters are established. This relation can be obtained by performing a large set of numerical experiments that covers various scenarios and by using regression analysis to find meta-models representing the relation between input and output. [Karttunen et al.](#) [8] used this procedure to investigate the risk on wear and Rolling Contact Fatigue (RCF) for worn wheels. Subsequently, they followed a similar approach for rails and obtained a correlation between damage indices and parameters used to describe wheel and rail profile geometry as well as curve radius, cant deficiency and gauge width [9]. However, with their approach they only captured the influence of wheel, rail and track geometry parameters. Variation in usage profile or operational conditions like vehicle speed, axle load and vehicle type were not considered. Another drawback of this approach is the number of parameters required to define a worn wheel or rail profile. The shape of a worn rail for example is approximated by a combination of a straight line and a parabolic expression. This results in a total of 5 parameters required to describe the geometry of a worn rail profile. In this case, each parameter appears as an independent variable in the regression analysis.

The present study incorporates the dominant parameters related to both geometry and operational conditions, which are selected through a One Factor at a Time (OFAT) sensitivity analysis. Furthermore, during the parametrization of worn rail profiles an unique relation is established between the rail profile geometry and the vertical wear depth. This leads to a reduction in the number of parameters required

to describe a worn rail to only one. An additional advantage is that this is rather convenient for IM's as the vertical wear depth is already monitored as a common practice. Moreover, in previous research [9] the risk of wear is assessed qualitatively, whereas in the current research the absolute amount of wear (area) is calculated which can be translated into a Remaining Useful Life (RUL) prediction. The outline of this chapter is as follows: section 3.2 describes the methodology of rail wear calculation, the sensitivity analysis and the concept of meta-models. Section 3.3 presents the results and discussion of the numerical investigations for the various scenarios. And, finally the conclusions and recommendations are forwarded in section 3.4.

3.2 Methodology

This section describes the models and concepts used to derive meta-models for rail wear calculation in order to estimate the RUL of railway tracks. Subsection 3.2.1 describes the rail wear calculation process, subsection 3.2.2 the decision process to obtain the most dominant parameters and subsection 3.2.3 the meta-modeling theory.

3.2.1 Rail wear calculation

Figure 3.1 schematically shows the process of rail wear calculation, where different combinations of input parameters are fed into a multi-body dynamics simulation. The resulting wheel-rail contact parameters of these simulations serve as input for the physical models implemented in Matlab that yield the amount of wear area loss calculated with Archard's wear law. The aim of this study is to replace the entire (computationally expensive) process between input and output with meta-models such that a large range of track geometry and operational conditions can be evaluated efficiently by IM's.

Figure 3.1: Rail wear estimation process by means of numerical experiments.

Several multi-body dynamics software packages are (commercially) available. In this study the multi-body simulations are performed in VI-Rail. This software contains built in vehicle templates that can be customized [10]. The vehicles then consist

of car bodies, bogies and wheel sets, which are considered as rigid bodies and are mutually connected by means of primary and secondary suspensions. The track model can easily be built up by choosing the track geometry parameters like length, rail inclination and rail cant. The contact parameters, i.e. the contact area, normal contact load and slip conditions are then computed for each time step. These parameters are extracted and exported to a Matlab script for the local contact and wear analyses.

Wear results in material volume loss and can be subdivided into several wear mechanisms such as abrasive, adhesive, corrosive and surface fatigue wear [11]. In the case of wheel-rail interaction, adhesive wear is the most commonly observed wear mechanism [12]. Therefore the local wear model used in this research is based on the Archard's law for adhesive wear [13]. Archard demonstrated that the amount of wear volume loss V in mm^3 is proportional to the sliding distance s [mm] and normal contact load F_N [N] through a dimensionless wear coefficient K and that it is inversely proportional to the hardness of the material H [N/mm^2]:

$$V = K \frac{sF_N}{H} \quad (3.1)$$

The wear coefficient K depends on the surface conditions and is usually determined empirically e.g. with pin-on-disk tests [2, 14]. For the wear calculations in the current study the wear coefficient is estimated from the wear map published by Jendel [2], see Figure 3.2, and scaled down by a factor of 5.5 as suggested by Enblom and Berg [6]. Jendel's wear map is constructed from a series of laboratory experiments for various contact pressures, sliding velocities and hardness of the material under dry conditions. Hence, the wear coefficient is a function of the contact pressure (P) and slip velocity (v_{slip}) which both can be extracted from the results of the local contact model [15, 16].

The local contact model is based on the Hertzian contact theory and the simplified rolling contact theory developed by Kalker [17]. The normal contact problem yields a parabolic distribution for the contact pressure. The contact area between wheel and rail is assumed to be elliptic and is discretized in a set of elements. Kalker's simplified theory [17] yields the tangential stresses and divides the elliptic contact area into a stick and a slip region. Sliding velocities are then calculated for each element in the slip region [16].

3.2.2 Sensitivity analysis

Previous studies have shown that wheel/rail wear depends on a lot of parameters like curve radius, cant deficiency, braking and traction, maintenance activities such as grinding, worn wheel and rail profiles, coefficient of friction, primary stiffness of the bogie, track irregularities and lubrication [3, 9, 18, 19]. These governing parameters are clustered into 6 categories in the fish bone diagram in Figure 3.3. The track structure is decomposed in track superstructure and substructure, where the track

Figure 3.2: Jendel's wear map [2].

superstructure consists of rails, fasteners, railpads and sleepers and the substructure consists of ballast and subgrade [20]. Track sup. stiffness and damping then represents the equivalent/total track superstructure stiffness and damping in Figure 3.3.

In order to study the influence of each of these parameters on rail wear, a sensitivity study is performed. First, the parameters are screened by means of the One factor at a Time (OFAT) method and parameters with low sensitivity indices are excluded from further analysis. The OFAT analysis reduces only the number of design variables and does not give information on the parameter significance ranking and interaction effects between parameters. Hence, the remaining parameters are subjected to the method proposed by Morris [21] to rank them in order of importance.

One Factor At a Time (OFAT) method

The most influential parameters are determined by a local sensitivity analysis method, also known as the One Factor at a Time (OFAT) method. This method evaluates the relative contribution of one parameter to the output while the other $k - 1$ parameters are kept at their reference or base-line value [22]. Each parameter's contribution is defined by a sensitivity index SI [22]:

$$SI_i = \frac{D_{max,i} - D_{min,i}}{D_{max,i}} \quad (i = 1, \dots, k) \quad (3.2)$$

Figure 3.3: Fish bone diagram of rail wear influencing parameters.

where $D_{min,i}$ and $D_{max,i}$ represent the response values for the parameters at its minimum and maximum setting, respectively. Parameters with low sensitivity index are discarded from further analysis. Figure 3.4 shows a flowchart of the sensitivity analysis strategy followed in this study.

Morris method

Unlike OFAT, the Morris method is a global sensitivity analysis method that does not only determine the effect of each separate parameter on the response variable, but also provides insight into the correlation between parameters [21].

If one wants to take into account the influence of parameter x_i (for $i = 1, \dots, k$) on the response value y , the derivative of y with respect to x_i needs to be calculated. The results of the derivative can be equal to a) zero, b) non-zero constants or c) non-linear function of one or more parameters. These results are representatives for when the influence of parameter x_i on response value y is respectively a) negligible, b) linear or c) non-linear or correlated with other parameters [21].

The standardized effect of a parameter on the response value can be calculated as the variable which is also known as the Elementary effect Ee_i [21, 23, 24]. Hence, the Elementary effect Ee_i of parameter x_i to response value y and given a parameter vector $\mathbf{x} = [x_1, \dots, x_k]$ is defined as follows:

$$Ee_i(\mathbf{x}) = \frac{y(x_1, x_2, \dots, x_{i-1}, x_i + \Delta, x_{i+1}, \dots, x_k) - y(\mathbf{x})}{\Delta} \quad (3.3)$$

Figure 3.4: Sensitivity analysis strategy.

Note that only one parameter (x_i) from the vector $\mathbf{x}$ is changed, and that the Ee of x_i can be different for another combination of values in $\mathbf{x}$. Further, it is assumed that each parameter is normalized to the range $[0,1]$, and can only attain p different equally spaced values:

$$x_i \in \left\{0, \frac{1}{p-1}, \frac{2}{p-1}, \dots, 1\right\} \quad (3.4)$$

The step increase for one of the parameters used to determine its sensitivity thus equals one such spacing:

$$\Delta = \frac{1}{p-1} \quad (3.5)$$

Figure 3.5 visualizes the design spaces for the OFAT and Morris method, i.e. the sets of all possible combinations of the parameters x_i . If the influence of one parameter on the response value is being evaluated with OFAT, then for one Elementary effect two simulations are required: one for the baseline or reference case and for the other one a single parameter is changed by a certain amount (Δ). Figure 3.5a shows three example pairs of simulations (1-2, 3-4 and 5-6, with 1, 3 and 5 the reference values of x_1 , x_2 and x_3 respectively) using OFAT for a 3-parameter problem with 4 different equally spaced values (hence sampling density $p = 4$). Here the influence of each

parameter is evaluated separately, which explains the 3 pairs of simulations for this 3-parameter problem.

The Morris method also evaluates the change of each parameter on the response value but then the simulations are arranged such that a trajectory (1-2-3-4) is constructed, see Figure 3.5b. Due to this trajectory also the correlation between the parameters can be studied. The baseline or reference case for the Morris method is always the previous simulation of the trajectory. Hence, another advantage of the use of trajectories is the efficiency as less scenarios need to be evaluated. As can be seen from Figure 3.5 the Morris method requires 4 simulations ($k + 1$), where OFAT requires 6 simulations ($2k$) to obtain 3 Elementary effects.

Figure 3.5: The design space D visualized for a three-parameter problem and sampling density $p = 4$ [23].

In order to derive a representative set of sensitivity indices with the Morris method, r different trajectories are constructed in the design space to obtain a finite distribution of Elementary effects for each parameter. Hence, each parameter has a distribution that consists of r Elementary effects. The total number of simulations required by the Morris method is thus equal to $r(k + 1)$. In the OFAT analysis the sensitivities are typically only calculated relative to the baseline values, so then only one Ee value (or SI) is obtained instead of a distribution of Ee 's. However, it is also possible to generate a distribution of Ee 's using OFAT. In that case r repetitions would require $2rk$ simulations, which is (much) less efficient than the Morris method. Morris [21] and Campolongo et al. [25] suggest that a value of r in the range 5-15 should be sufficient. Ruano et al. [26] showed that the optimal number of trajectories r can be found by performing a convergence test on the values of the sensitivity parameters (mean and standard deviation).

The Morris method then calculates the mean value and standard deviation of the distribution of the Elementary effects for each parameter. A large mean value

for the Elementary effects indicates a high level of influence on the response value. The Morris method can be considered as an indirect regression analysis where the relation between input parameters and response value is studied. Therefore, the standard deviation can be regarded as the standard error of the regression analysis that estimates how closely the fitted model represents the relation between input parameters and response value. A large standard deviation, or standard error, then suggests that either the obtained fit is insufficient to predict the correct response value, requiring a higher order or non-linear model [27], or a strong correlation exists between the parameter under consideration and one or more of the other parameters [28]. A clear distinction between these two options (non-linear model or correlation between parameters) is impossible without physical knowledge about the considered process [24].

Figure 3.6 shows an example of a screening plot where the mean and standard deviation of the Elementary effects of 3 parameters, namely parameter *A*, *B* and *C* is plotted. Parameter *A* and *B* have the same standard deviation and parameter *B* and *C* have the same mean. Hence, parameter *B* and *C* have the same and larger importance than parameter *A*. Furthermore, *C* has a larger standard deviation than *B* which suggests that the relation between *C* and the response value is either non-linear or *C* is correlated with one or more parameters.

Figure 3.6: Screening plot example.

3.2.3 Meta-model

Meta-modeling or surrogate modeling is commonly used to find mathematical expressions for (relatively complex) physical processes and systems. Such an expressions or

computational model can be regarded as a transfer function that produces an output for a given input [21]. These models are usually developed for computationally expensive simulations or experiments and are used for several purposes e.g. understanding of the problem, prediction and optimization. Different type of meta-models are available e.g. Response Surface Methodology (RSM), Kriging, Radial Basis Function (RBF), Support Vector Machine (SVM), Artificial Neural Networks (ANN) etc. This study applies the least complex method, namely RSM that fits the data to either a linear or quadratic function using simple regression techniques. Other methods can be applied if RSM does not work. The data points used for the linear or quadratic fitting process are selected by Latin Hypercube Sampling (LHS) which will be discussed in the next subsection.

Latin Hypercube Sampling (LHS)

In order to obtain a subset of data points that properly represents the full response of all data points, a n -by- k design matrix $\mathbf{X}$ needs to be constructed which contains the k parameter values at n different ‘points’ in the complete design space D . These points are called scenarios or observations. Ideally, the larger the number of scenarios the better the accuracy of the model that is fitted. However, this would ultimately require a full factorial analysis for a k -dimensional space resulting in $n = p^k$ scenarios, where p is the sampling density for each parameter [24] (i.e. the number of different values a parameter can attain).

For computationally expensive simulations and a large value of k , full factorial analysis is not feasible. Hence, instead of a full factorial analysis the LHS method is proposed. This method reduces the number of scenarios or observations to be evaluated, while retaining a certain level of model accuracy. The sample points should be distributed in the k -dimensional hypercube in such a way that the space is uniformly filled. However, not all generated design matrices guarantee space-filling. Therefore, a number of randomly generated design matrices with a fixed number of scenarios n are compared to find the best design matrix $\mathbf{X}$ that fulfills the space filling criterion.

The space-filling criterion is based on the *maximin* distance where the minimum distance d_p between each possible pair of points ($\mathbf{x}^{(i_1)}, \mathbf{x}^{(i_2)}$) in design matrix $\mathbf{X}$, is defined as follows [24]:

$$d_p(\mathbf{x}^{(i_1)}, \mathbf{x}^{(i_2)}) = \left(\sum_{j=1}^k |x_j^{(i_1)} - x_j^{(i_2)}|^p \right)^{\frac{1}{p}} \quad (3.6)$$

For $p = 1$ this distance equals the rectangular distance and for $p = 2$ the Euclidean distance is used. The *maximin* distance is then obtained as the maximum value of vector d_p found across all combinations of points. The design matrix with the highest *maximin* value is considered to have the most uniform space-filling, and is thus selected for the analysis.

Regression analysis

The n scenarios obtained with LHS are evaluated according to the process depicted in Figure 3.1 and the response values are subjected to a regression analysis to obtain meta-models.

As already mentioned in the introduction, the objective of this study is to calculate rail wear by means of meta-models, hence for the response value in this study the absolute value of rail wear area is chosen. This value is defined as the amount of material that is worn off (in a 2D cross sectional view of the rail profile) with regard to the nominal/reference rail profile. An advantage for choosing the wear area as response value is the convenience in comparing modelling results with field measurements for worn off area of rail profiles.

Furthermore, the meta-models obtained by using RSM have a polynomial form of a certain order. In this study the quadratic form turned out to be sufficient and is given by [29]:

$$y(\mathbf{x}) = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{k+i} x_i^2 + \sum_{i=1}^{k-1} \sum_{j>i}^k \beta_{i,j} x_i x_j \quad (3.7)$$

One has to make sure that the number of observations is substantially larger than the number of regression coefficients (β 's) in order to have sufficient degrees of freedom. For the quadratic model the number of observations should be $n \geq 2k + \binom{k}{2} + 1$ [29].

The quality of the meta-model is assessed by the coefficient of determination R^2 which is defined as follows [30]:

$$R^2 = 1 - \frac{SSE}{SST} \quad (3.8)$$

The total sum of squares (SST) and the error sum of squares (SSE) are defined as follows:

$$SST = \sum_{i=1}^n (y_i - \bar{y})^2 \quad (3.9)$$

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.10)$$

where $\hat{y}_i$ is the predicted value by means of the fitted meta-model, y_i is the observed value (thus the response value obtained from the simulation) and $\bar{y}$ is equal to the mean of the observed values.

After obtaining an acceptable fit of the meta-model (R^2 is close to 1), a cross validation is performed to verify that the model is able to accurately predict rail wear for other scenarios than those used to obtain the fit, with certain accuracy. For this a separate design matrix is constructed and the model is validated by means of the

Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.11)$$

3.3 Numerical experiment results and discussion

The first part of this section describes the process for rail profile parametrization and the obtained results. This is important before proceeding with numerical experiments as the rail profile geometry is a relevant input parameter for the meta-model and needs to be described accurately. Thereafter, the results for the sensitivity study and the meta-model are presented.

3.3.1 Parametrization of rail profile

One of the conditions for the parameters in the design matrix is that they should be continuous. However, this is not the case for the measured rail profile, which is now classified as either new or worn. Thus, the objective of rail profile parametrization is to develop a library consisting of rail profiles from their new to worn condition such that each profile geometry is characterized by a single value. The aim is to correlate the rail profile geometry to a monitoring parameter or a maintenance indicator, in this case the vertical wear depth (measured at the railhead). To achieve this, a large data set consisting of 1200 rail profiles measured with UFM120 (measuring car), at the route between the cities Weesp and Almere, is utilized. The radii for the right hand sided curves on this track varied between 1000 and 4000 meters. The robustness of this method is validated with another 900 measured rail profiles on this same route but for the left hand sided curves.

The measured rail profiles are discretized into coordinate points from r_1 to r_{12} , see Figure 3.7. These randomly selected coordinate points are positioned between the lateral coordinates of -5 and 35 mm, because it is assumed that for moderate curves wheel-rail contact at the outer rail only occurs in this region. The Euclidean or normal distance of these coordinates to the corresponding coordinates (along the line normal to the profile) on a new rail profile of UIC54E1 are calculated. A correlation between the Euclidean distance dr_i (between worn and new profile) of each coordinate point i and the associated vertical wear depth h at position (0,0) or coordinate point r_2 in Figure 3.7, is established by means of a rational expression of the following form (for $i = 1 : 12$):

$$dr_i = \frac{p_{1,i}h}{h^2 + q_{1,i}h + q_{2,i}} \quad (3.12)$$

$p_{1,i}$, $q_{1,i}$ and $q_{2,i}$ for each coordinate point r_i are derived by performing a regression analysis on the 1200 measured rail profiles and presented in Table 3.1. Figure 3.8 shows the obtained fit for coordinate point r_4 . Similar plots can be obtained for the

other coordinate points. The derived equations now enable to reconstruct a worn rail profile based on only the vertical wear depth.

Figure 3.7: Rail profile discretization.

Table 3.1: Coordinate point fit parameters.

Coordinate point	p_1	q_1	q_2
r_1	0.07192	0.01395	0.447
r_2	2450	2.162e4	1.895e4
r_3	4.343e4	7.058e4	1.94e4
r_4	2.764e5	2.134e5	3.598e4
r_5	2.062e5	1.323e5	1.904e4
r_6	5.026e4	3.508e4	4046
r_7	1.333e5	1.304e5	1.726e4
r_8	6343	7.568e4	4.455e4
r_9	4.891e4	3.685e4	4180
r_{10}	2.915e5	2.427e5	2.788e4
r_{11}	7.306e4	9.344e4	1.275e4
r_{12}	2.593e4	7.109e4	3.665e4

In order to proof the validity of the obtained relation for the reconstruction of the rail profiles, the relative error in percentages between the Cartesian coordinate points of a measured rail profile with $h = 3$ mm (not used for the fitting procedure) and the reconstructed profile using Equation (3.12) and interpolating between the coordinate

Figure 3.8: Euclidean (normal) distance vs vertical wear depth h for r_4 .

points from r_1 to r_{12} , are plotted in Figure 3.9a. The relative error is calculated as the difference between the Cartesian coordinate points of measured and fitted rail profile divided by the associated vertical wear depth. Furthermore, the distribution of the maximum relative error between the fitted and measured profile is provided in Figure 3.9b, for almost 900 rail profiles. From the results shown in these figures it can be concluded that the fitted profile is similar to the measured one as the difference between the Cartesian coordinate points is less than 10% of the associated vertical wear depth for most cases.

Furthermore, the error values obtained are only slightly higher than those presented by Karttunen et al. [9]. However, they parametrized rail profiles for curves with radii between 450 m and 1240 m based on a parabolic expression and a straight line yielding a total of 5 parameters required to describe the profile geometry. The method proposed in this chapter uses only one parameter, namely h , to characterize a rail profile geometry for moderate curves. The magnitude of the error can be considered to be acceptable, especially since its absolute value is mainly due to misalignment as can be concluded from the clear trend observed in Figure 3.9 (not a random error).

Finally, Figure 3.10a shows parametrized rail profiles obtained for a specific LHS design matrix and Figure 3.10b shows the number of occurrences for these profiles in terms of the corresponding vertical wear depth. From the latter figure it can be

(a) Error between measured and fitted coordinates of rail profile with $h=3\text{mm}$. **(b)** Probability distribution of the relative errors.

Figure 3.9: Example and probability distribution of the relative errors between measured and fitted rail profiles.

concluded that the generated rail profiles are uniformly distributed from their new to worn condition as expected from the space-filling property of the LHS method.

(a) Example of a specific set of rail profiles generated by LHS. **(b)** Histogram of the worn rail profiles generated by LHS.

Figure 3.10: Worn rail profiles generated by a LHS design matrix for $n = 200$.

3.3.2 Sensitivity study results

A sensitivity study as described in Section 3.2.2 is performed to understand the behavior of the response value under influence of various parameters. Due to specific modeling challenges not all parameters presented in the fish bone diagram depicted in Figure 3.3 will be explored during this study. The multi-body dynamics model

developed for this purpose consists of only rigid bodies, hence parameters related to subgrade, ballast and track superstructure stiffness cannot be evaluated. This would require the use of flexible bodies in the multi-body model. Also, the track irregularities are not considered because as investigated by Pombo et al. [31] the influence of the track irregularities on the track loads that govern wear is only a local effect. The average degradation is the same as when no irregularities are considered. As will be mentioned in Section 3.3.3 the median or average value for the wear area on a specific track is chosen as the response value. Hence, the local effects caused by track irregularities can be neglected in this study.

The parameters that will be further explored in the sensitivity study are presented in Table 3.2 along with their respective intervals. The selection of these intervals (parameters ranges) are based on literature data [32–36] and field experience. Furthermore, the parameters related to lubrication, pollution and weather conditions are all captured by the coefficient of friction.

Table 3.2: Range of Parameters.

Parameter	Symbol	Unit	Minimum value	Maximum value	Base-line value
Curve radius	R	m	1000	4000	2000
Vehicle speed	V	m/s	11.11	44.44	33.33
Axle load	m	MT	9.4	26.67	11.12
Rail cant	$cant$	mm	0	100	100
Rail hardness	H	GPa	2.0	3.4	2.7
Vertical wear depth	h	mm	0	12	0
Coefficient of friction	cof	—	0.02	0.6	0.4
Wheel diameter	—	m	0.85	0.95	0.92
Longitudinal stiffness (primary suspension)	k_x	N/m	2.56e5	4.00e7	6.17e5
Lateral stiffness (primary suspension)	k_y	N/m	2.56e5	4.00e7	6.17e5
Vertical stiffness (primary suspension)	—	N/m	3.00e5	1.15e6	7.32e5
Vertical damping (primary suspension)	—	Ns/m	4000	28000	27000
Longitudinal stiffness (secondary suspension)	—	N/m	7.5e4	1.33e5	1.6e5
Lateral stiffness (secondary suspension)	—	N/m	7.5e4	1.33e5	1.6e5
Vertical stiffness (secondary suspension)	—	N/m	1.00e5	1.77e6	4.3e5
Longitudinal damping (secondary suspension)	—	Ns/m	4000	26000	40000
Lateral damping (secondary suspension)	—	Ns/m	8500	26000	8500
Vertical damping (secondary suspension)	—	Ns/m	7100	90000	7100

Following the steps of the sensitivity analysis strategy, see Figure 3.4, a base-line case is defined where the track length is equal to 800 meters. The first 50 meters of the track represent a straight track section followed by a transition curve with a length of 100 meters leading to the actual curve. UIC54E1 is chosen as the rail profile, s1002 as the wheel profile and the rail inclination is set to 1:40 [radians] for the base-line case. Further details on the remaining parameters are provided in Table 3.2. Then the selected parameters are changed one at a time (OFAT analysis) from the base-line and the median rail wear area on the actual curve is considered as the response value. The responses for each parameter at its minimum and maximum value are compared

and the calculated sensitivity indices are presented in Table 3.3. Parameters with a sensitivity index lower than 0.05 are discarded from further analysis, which means that only the top 9 parameters in Table 3.3 will be considered in the next step of the sensitivity analysis.

As discussed in Section 3.2.2 the resulting parameters from the OFAT analysis are subjected to the Morris method to gain insight in the correlation between parameters and to rank the parameters in order of significance. According to Figure 3.1 the input parameters should pass two processes before obtaining a value for the wear area, namely the VI-Rail environment and the Matlab environment. In order to prevent large errors caused by these two sequential processes, the Morris method is only applied to the first process, namely the multi-body dynamic process in the VI-Rail environment, and the wear number, which is the product of tangential force and slip, is chosen as the response value. This is justified because the wear rate is considered by Pearce and Sherratt [37] to be proportional to the wear number.

Furthermore, it should be mentioned that for the calculation of the wear number the material hardness H , which is one of the 9 parameters, is not required. The material hardness is an important parameter in the second process which is the wear area calculation (Equation 2.1), not in the first process. Hence, for the Morris method with the wear number as response value, the material hardness will not be taken into account. This means that the Morris method, as introduced in section 2.2.2, is applied as follows. The elementary effects are calculated using Equation (3.3), where the response value y is the wear number. The model in this case contains 8 parameters ($k = 9$ minus the hardness parameter H), which each can attain 5 values ($p = 5$), and are normalized to the $[0,1]$ interval by using the minimum and maximum values of the selected parameter range given in Table 3.2. From the total design space D , 15 samples ($r = 15$) are taken, which are determined by the method proposed by Ruano et al. [26]. This means that $r((k-1)+1) = 135$ analyses (VI-Rail simulations) have been performed to obtain the Elementary effects. The resulting absolute mean and standard deviation for each of the 8 distributions of Elementary effects (Ee_i) are shown in Figure 3.11.

In this study the absolute mean value of the Elementary effects has been used, because as suggested by Campolongo et al. [25] this will ensure that there is no loss on important information. For example if the distribution contains positive and negative values they will cancel each other out and this will result in a low mean value even if the parameter has a high influence on the response value.

Figure 3.11 shows the means and standard deviations of the elementary effects of the selected parameters on the wear number for two different wheel profiles: wheel profile s1002 in new condition and wheel profile HIT in worn condition, respectively. The HIT profile is a widely used wheel profile on Dutch railways and is actually a modified s1002 profile with an enlarged running band [38]. This profile was designed such that a more conformal contact is realized, which avoids the extreme dynamic behavior (i.e. lateral movements) of the vehicles when running on the track. The

Table 3.3: Results of the OFAT analysis.

Index	Parameter	Symbol	Unit	SI
1	Vertical wear depth	h	mm	0.89
2	Curve radius	R	m	52.94
3	Rail cant	$cant$	mm	0.72
4	Coefficient of friction	cof	—	2.37
5	Vehicle speed	V	m/s	0.39
6	Longitudinal stiffness (primary suspension)	k_y	N/m	0.39
7	Lateral stiffness (primary suspension)	k_y	N/m	3.96
8	Axle load	m	MT	0.33
9	Rail hardness	H	GPa	0.70
10	Vertical stiffness (primary suspension)	—	N/m	0.03
11	Vertical stiffness (secondary suspension)	—	N/m	0.01
12	Lateral stiffness (secondary suspension)	—	N/m	0.01
13	Longitudinal stiffness (secondary suspension)	—	N/m	0.00
14	Longitudinal damping (secondary suspension)	—	Ns/m	0.00
15	Vertical damping (secondary suspension)	—	Ns/m	0.00
16	Lateral damping (secondary suspension)	—	Ns/m	0.00
17	Vertical damping (primary suspension)	—	Ns/m	0.00
18	Wheel diameter	—	m	0.00

shapes of new and worn wheel profiles for s1002 and HIT can be found in Appendix A. Figure 3.11 only shows the results for s1002 new and HIT worn. The reason is that wheel profile s1002 worn is similar to the new HIT profile (which was the motivation for designing the HIT profile), and also a worn HIT profile has a similar shape, which is only shifted downwards due to a relatively low and constant wear rate compared to the wear rate of new s1002 wheel profiles.

From Figure 3.11a it can be seen that the influence of the next cluster of parameters consisting of k_x , k_y , V , m and $cant$ has rather low mean value and standard deviation values compared to h , R and cof . The vertical wear depth (h) (i.e. the amount of degradation of the profile) has a similar mean value as the cluster of parameters but a higher value for the standard mean deviation. This means that the influence of h on the response value (in this case the wear number) is more or less similar to the influence that vehicle speed (V) and mass of the train (m) have on the wear number. Furthermore, it can also be concluded that the vertical wear depth (h) is either correlated with other parameters or is non-linearly related to the response value. It can be explained that h is non-linearly related to the response value (wear number or wear area) as the wear rate of rails is higher in the beginning of their life. Figure 3.11a also demonstrates that the curve radius R has a large mean value and a high standard deviation value, hence R has a large influence on the response value and is non-linearly related to the response value. The latter conclusion is as expected

because Meghoe et al. [39] showed that the wear area is non-linearly related to the curve radius. Finally, the coefficient of friction (cof) has a similar standard deviation value as the cluster of parameters, but a high mean value which indicates a large influence on the response value.

Similar conclusions can be drawn from Figure 3.11b regarding the track's curve radius (R) and the coefficient of friction (cof). However, the behavior of the vertical wear depth (h) for s1002 new and HIT worn are completely different. This is due to the design of the HIT profile. The enlarged running band of the HIT wheel profile ensures that less wear is generated due to the conformal contact between wheel and rail [38]. Thus the influence of the rail profile evolution characterized by the vertical wear depth h is negligible for the worn HIT wheel profiles.

In summary, the first part of the sensitivity analysis (OFAT) enabled to select the 9 most dominant parameters, whereas the second part (Morris) revealed in more detail how (strongly) these parameters affect the response value (wear number). After these two analyses, it is decided to use the 9 initially selected parameters in the meta-model derivation, as will be described in the next subsection.

Figure 3.11: Estimated means and standard deviations of the elementary effect distributions. Note that the unit of Ee_i is the unit of the response value, i.e. the wear number.

3.3.3 Meta-modeling results

This subsection presents the derivation of the meta-models, as well as the results obtained by applying the meta-models for prediction, classification and validation purposes.

Meta-model derivation and wear prediction

Previous research by the authors [39] showed that results obtained with a single wagon passage in combination with damage accumulation provide wear area values that are in accordance with field measurements. From that work, it could be concluded that especially the simulated results for worn wheels are in accordance with measured data. Furthermore, it was concluded that only the first wheel of the bogie running on the outer rail is dominant for rail wear. Hence, the response value for the LHS scenarios in this work is defined to be the rail wear area (i.e. the material loss due to wear in a rail cross section) generated by the first wheel of the bogie. This wear area is calculated for each computation step (i.e. position on track) and the median value on the track from the position $x = 300$ meters on the actual curve is considered as the response value. The latter restriction is to ensure that transient behavior of the vehicle entering the circular curve radius is neglected.

According to Jendel [2] three wear regimes are possible, namely mild, severe and catastrophic. If per wear regime a meta-model of quadratic form as given in Section 2.3.2 is fitted (Equation (3.7)), for each expression of the meta-model the number of observations should be larger than the number of regression coefficients ($n \geq 2k + \binom{k}{2} + 1$). Then for $k = 9$, the number of observations per meta-model should be substantially larger than 55 and for three wear regimes (hence three meta-models) larger than 165. By taking into account the influence of outliers a number of observations of 200 would be sufficient. But in order to clearly show the two clusters of data points in Figure 3.12, 512 observations (i.e. model simulations) were chosen.

Figure 3.12 shows the comparison between the response values obtained with a fitted quadratic function (i.e. the meta-model), derived for wheel profile s1002 in new condition, and the response values as obtained from the individual numerical experiments. This figure shows a very poor correlation between the fitted and observed wear for the meta-model, as the points are not uniformly distributed around the solid line ($y = x$). Furthermore, the fitted model (on the x-axis) yields negative values for the wear area which have no physical meaning. These conclusions are confirmed by the coefficient of determination R^2 which is equal to 0.63 for this case. It is argued that the poor correlation is a result of the large spread in the data. As can be seen from this figure, the data can be split into two groups where one group consists of the smaller values presented at the bottom of the figure. The large spread in the data was discovered to be caused by the discontinuity in the wear coefficient as multiple types of wear or wear regimes are possible. Due to the different type of the wear mechanisms, e.g. mild and severe wear, a large spread in the data set is encountered and it is not possible to capture the different behaviors with a single model. Hence separate models corresponding to each type of behavior are developed. Plotting the mean wear coefficient value for each simulation, see Figure 3.13, clearly shows two clusters of data, each corresponding to a specific wear regime.

As mentioned before the wear coefficients used in this study originate from Jendel's wear map (Figure 2.5) and are scaled down by a factor of 5.5 as suggested by Enblom

Figure 3.12: Comparison between wear area values obtained with meta-model fit and wear area values obtained from numerical simulations for $n=512$.

and Berg [6]. Thus the wear coefficients plotted in Figure 3.13 correspond to wear coefficients K_1 , K_3 and K_4 in Figure 2.5. K_1 and K_4 represent the mild wear regime hereafter regarded as wear regime 1 and K_3 represent severe wear hereafter regarded as wear regime 2. Figure 3.14 shows the plot for the contact pressure versus the sliding or slip velocity for the number of simulations performed, while the colors of the points indicate to which wear regime they belong: regime 1 when $k \leq 2e-4$ and wear regime 2 when $k \geq 2e-4$. The boundaries of the wear regime from this plot are quite similar to those in Jendel's wear map and a clear distinction between the wear regimes of K_1 , K_3 and K_4 can be seen.

As explained before, the challenge regarding the large spread in the data due to discontinuity in the wear coefficient is solved by deriving separate meta-models for each wear regime. Moreover, also the range of the friction coefficient has been rearranged due to the high influence on the response value as concluded from the results of the Morris method in Section 3.2 (see Figure 3.11). The range is now set to 0.3 - 0.6. Figure 3.15 shows the results for the two meta-models, one for each wear regime. The coefficient of determination R^2 for wear regime 1 and 2 is equal to 0.95 and 0.96, respectively, demonstrating a very good correlation. Similarly, separate meta-models for friction coefficient range 0.02 to 0.15 and 0.15 to 0.3 are also derived and visualized in Appendix B. The regression coefficients for the six derived meta-models (HIT worn / s1002 new and 3 ranges of cof) are given in Appendix C. These coefficients show that the selection of the parameters from the sensitivity analyses are correct. This is because the regression coefficients are such that none of the parameters can be discarded from the resulting equation for each meta-model. If a parameter does not have a linear or non-linear relation with the response value (low mean, see

Figure 3.13: Wear coefficient values for various simulations.

Figure 3.14: Distinction between wear regimes from numerical results.

Figure 3.6) it is correlated with other parameters (large standard deviation, Figure 3.6). See for example x_1 and x_4 : nonzero values are only found in the correlation x_1x_i and x_4x_i , while β_1 , β_4 , β_{10} and β_{13} are equal to zero.

Classification using the curve radius R can also be considered as this parameter also has high mean values for the elementary effects, but for the curve radii range of 1000 - 4000 meters (moderate curves) the influence of R appeared to be minimal.

Figure 3.15: Comparison of predicted and observed values from numerical simulation ($n = 200$) of s1002 new.

Classification

Normally the wear regime is determined from the local contact model, which suggests that numerical experiments are still required to determine the wear regime. In order to overcome this challenge, additional meta-models are fitted for slip velocity and contact pressure again using the same variables from Table 3.2 as input. The results of these meta-models are shown in Figure 3.16.

Finally, the process of rail wear evaluation by means of meta-models is depicted in Figure 3.17. The first step is the wear regime determination where the meta-models for slip velocity and contact pressure are evaluated for the given input parameters, which have been selected through the OFAT analysis and optionally the Morris method. The results for the slip velocity and contact pressure are then inserted in Jendel's wear map and the wear regime is determined. Thereafter the rail wear area is calculated by means of the meta-model for the selected wear regime followed by an accumulation of the amount of wear generated by all first wheels of all bogies that pass the track. This is done by multiplying the number of passing bogies at certain conditions with the associated wear area. By comparing Figure 3.17 with Figure 3.1, it can be seen how the proposed method eliminates the need of software tools (i.e. VI-Rail and Matlab), that IM's do not have at their disposal, once the meta-models have been derived.

Furthermore, the proposed approach using the meta-models as presented in Figure 3.17 is 500 times faster than the classical prediction model in Figure 3.1 and

Figure 3.16: Comparison of predicted and observed values for s1002 new and friction coefficient between 0.3 and 0.6.

Figure 3.17: Rail wear estimation process by means of meta-models.

also leads to a drastic reduction in memory consumption, which is about a factor of 10,000. Another advantage of this method is the reduction of input parameters (e.g. rail profile geometry parameters from the work of [Karttunen et al. \[9\]](#)) to only a set of common parameters already monitored in practice.

Validation

Finally, the validation of the proposed method is performed with 90 randomly determined scenarios based on LHS for s1002 new. On the one hand the response values are calculated only on the basis of the specified input parameters and meta-models according to Figure 3.17 while on the other hand individual numerical experiments are performed according to Figure 3.1.

The “fit data” in Figure 3.18 represents the data points of the 200 random simulations used to obtain the meta-model and the “validation data” in these figures corresponds to the 90 randomly determined simulations for validation purpose. If the validation data points overlap the fit data points of the meta-model, the obtained meta-models are acceptable. As can be seen from Figure 3.18, for wear regime 2 the validation data overlaps the fit data while for wear regime 1 there is a certain deviation. As the wear in regime 1 is only mild wear, having only a minor influence on the total amount of wear, overall the meta-models are considered to be reliable. Furthermore, the mean squared error (MSE) of the predicted points for wear regime 1 and 2 is equal to $2.9498\text{e-}10$ and $3.7865\text{e-}09$, respectively. From these values and the given plots it can be concluded that the proposed method provides results with acceptable accuracy with a considerably reduced computational effort. The validation case is based on the s1002 new wheel profile. However, the same procedure can be repeated for any type of wheel as meta-models can be constructed for each type of wheel.

Figure 3.18: Comparison of predicted values and observed values against the fitted model.

3.4 Conclusion

The method proposed in this chapter has been demonstrated to enable RUL predictions for various usage profiles of railway tracks. The proposed method takes into account a large range of track geometry parameters. Typical operating conditions like vehicle speed, axle load and vehicle type characterized by the primary suspension’s stiffness of the bogie are also taken into account. Then a simple relation between these input parameters and the amount of rail wear is established by means of meta-models, which are derived from a large set of numerical experiments. The coefficient

of determination found for the meta-models are higher than 0.95 which proves the high accuracy of the model. These type of models are beneficial for IM's as a decision making tool, as they can predict the RUL quantitatively with a very limited computational effort. Furthermore, the presented correlation between rail profile geometry and wear depth is beneficial for IM's as they do not need to perform extra measurements as the vertical wear depth is already monitored.

Furthermore, separate meta-models were constructed for each wheel profile type in both new and worn condition, as large data sets of measured wheels were unavailable. Hence, parametrization of worn wheel profiles is recommended if it is desired to reduce the number of required meta-models. Finally, besides numerical validation as is done in the present work, validation with field data is also required. Hence, the next step of this research is to validate the method with wear area results from field measurements and account for uncertainties in the input data.

References

- [1] I. Zobory. Prediction of wheel/rail profile wear. *Vehicle System Dynamics*, 28 (2-3):221–259, 1997. ISSN 0042-3114. doi: 10.1080/00423119708969355.
- [2] T. Jendel. Prediction of wheel profile wear-comparisons with field measurements. *Wear*, 253(1-2):89–99, 2002. ISSN 0043-1648. doi: PiiS0043-1648(02)00087-XDoi10.1016/S0043-1648(02)00087-X.
- [3] R. Enblom and M. Berg. Simulation of railway wheel profile development due to wear - influence of disc braking and contact environment. *Wear*, 258(7-8): 1055–1063, 2005. ISSN 0043-1648. doi: 10.1016/j.wear.2004.03.055.
- [4] M. Ignesti, A. Innocenti, L. Marini, E. Meli, and A. Rindi. A numerical procedure for the wheel profile optimisation on railway vehicles. *Journal of Engineering Tribology*, 2014.
- [5] A. Ramalho. Wear modelling in rail-wheel contact. *Wear*, 330:524–532. ISSN 0043-1648. doi: 10.1016/j.wear.2015.01.067.
- [6] R. Enblom and M. Berg. Proposed procedure and trial simulation of rail profile evolution due to uniform wear. *Proceedings of the Institution of Mechanical Engineers Part F-Journal of Rail and Rapid Transit*, 222(1):15–25, 2008. ISSN 0954-4097. doi: 10.1243/09544097jrrt173.
- [7] Babette Dirks. *Simulation and measurement of wheel on rail fatigue and wear*. Phd thesis, KTH Royal Institute of Technology, 2015.
- [8] K. Karttunen, E. Kabo, and A. Ekberg. Numerical assessment of the influence of worn wheel tread geometry on rail and wheel deterioration. *Wear*, 317(1):77–91, 2014. ISSN 0043-1648. doi: 10.1016/j.wear.2014.05.006.
- [9] K. Karttunen, E. Kabo, and A. Ekberg. Estimation of gauge corner and flange root degradation from rail, wheel and track geometries. *Wear*, 366-367:294–302, 2016. ISSN 0043-1648. doi: 10.1016/j.wear.2016.03.030.
- [10] Vi-rail 17.0 documentation. Report, 2016.
- [11] Z. Li and J. J. Kalker. Simulation of severe wheel-rail wear. *Computers in Railways Vi*, 2:393–402, 1998. ISSN 1462-608x.
- [12] J. De Arizon, O. Verlinden, and P. Dehombreux. Prediction of wheel wear in urban railway transport: comparison of existing models. *Vehicle System Dynamics*, 45(9):849–866, 2007. ISSN 0042-3114 1744-5159. doi: 10.1080/00423110601149335.

- [13] J. F. Archard. Contact and rubbing of flat surfaces. *Journal of Applied Physics*, 24(8):981–988, 1953. ISSN 0021-8979. doi: 10.1063/1.1721448.
- [14] R. Lewis and U. Olofsson. Mapping rail wear regimes and transitions. *Wear*, 257(7-8):721–729, 2004.
- [15] R. Enblom. *On Simulation of Uniform Wear and Profile Evolution in the Wheel - Rail Contact*. Phd thesis, Royal Institute of Technology (KTH), 2005.
- [16] Martin Shahzamanian Sichani. *On Efficient Modelling of Wheel-Rail Contact in Vehicle Dynamics Simulation*. Phd thesis, KTH Royal Institute of Technology, 2016.
- [17] J. J. Kalker. *Three-Dimensional Elastic Bodies in Rolling Contact*. Springer Netherlands, first edition, 1990. ISBN 978-0-7923-0712-9.
- [18] B. Dirks and R. Enblom. Prediction model for wheel profile wear and rolling contact fatigue. *Wear*, 271(1-2):210–217. ISSN 0043-1648. doi: 10.1016/j.wear.2010.10.028.
- [19] A. Bevan, P. Molyneux-Berry, B. Eickhoff, and M. Burstow. Development and validation of a wheel wear and rolling contact fatigue damage model. *Wear*, 307(1-2):100–111, 2013. ISSN 0043-1648. doi: 10.1016/j.wear.2013.08.004.
- [20] E. T. Selig and J.M. Watres. *Track geotechnology and substructure management*. Thomas Telford Publications, London, UK, 1994.
- [21] Max D. Morris. Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33(2):161–174, April 1991. ISSN 0040-1706.
- [22] D.J. Pannell. Sensitivity analysis of normative economic models: Theoretical framework and practical strategies. *Agricultural Economics*, 16:139–152, 1997.
- [23] D. M. King and B. J. C. Perera. Morris method of sensitivity analysis applied to assess the importance of input variables on urban water supply yield – a case study. *Journal of Hydrology*, 477:17–32, 2013. ISSN 0022-1694. doi: 10.1016/j.jhydrol.2012.10.017.
- [24] A. I. J. Forrester, A. Sobester, and A. J. Keane. *Engineering design via surrogate modelling*. John Wiley and Sons Ltd., West Sussex, United Kingdom, first edition, 2008. ISBN 978-0-470-06068.
- [25] Francesca Campolongo, Jessica Cariboni, and Andrea Saltelli. An effective screening design for sensitivity analysis of large models. *Environmental Modelling & Software*, 22(10):1509–1518, 2007. ISSN 1364-8152. doi: 10.1016/j.envsoft.2006.10.004.

-
- [26] M. V. Ruano, J. Ribes, J. Ferrer, and Gürkan Sin. Application of the morris method for screening the influential parameters of fuzzy controllers applied to wwtps. *Water Science and Technology*, 63(10):2199–2206, 2011. ISSN 0273-1223. doi: 10.2166/wst.2011.442.
- [27] D. N. Gujarati. *Basics econometrics*. McGraw-Hill/Irwin, New York, US, 4 edition, 2003. ISBN 0-07-112342-3.
- [28] John O. Rawlings, Sastry G. Pantula, and David A. Dickey. *Applied Regression Analysis*. Springer-Verlag New York, New York, US, 2 edition, 1998. ISBN 978-0-387-98454-4. doi: 10.1007/b98890.
- [29] T.M. Cioppa. Efficient nearly orthogonal and space-filling latin hypercubes. *Technometrics*, 49:45–55, 2007.
- [30] M. H. A. Bonte. *Optimisation Strategies for Metal Forming Processes*. Phd thesis, University of Twente, 2007.
- [31] J. C. Pombo, Pereira M. Ambrósio, J. A. C., Dwyer-Joyce R. Lewis R., Ariaudo C., and Kuka N. Development of a wear prediction tool for steel railway wheels using three alternative wear functions. *Wear*, 271(1-2):238–245, 2011. ISSN 0043-1648. doi: 10.1016/j.wear.2010.10.072.
- [32] S. Steišūnasa, J. Dižob, G. Bureikaa, and V. Žuraulisa. Examination of vertical dynamics of passenger car with wheel flat considering suspension parameters. In *10th International Scientific Conference Transbaltica 2017: Transportation Science and Technology*.
- [33] M. Hiensch and M. Steenbergen. Rolling contact fatigue on premium rail grades: Damage function development from field data. *Wear*, 394:187–194, 2018. ISSN 0043-1648. doi: 10.1016/j.wear.2017.10.018.
- [34] I. Sebesan, D. Baiasu, and G. Ghita. An investigation of the influence of the suspension construction parameters on the performances of the railway vehicles. *Proceedings of the Romanian Academy Series a-Mathematics Physics Technical Sciences Information Science*, 15(4):379–387, 2014. ISSN 1454-9069.
- [35] A.G. Zolotas and R.M. Goodall. Modelling and control of railway vehicle suspensions. Report, 2007.
- [36] Paraic Quirke. *Drive-by detection of railway track longitudinal profile, stiffness and bridge damage*. Phd thesis, University College Dublin, 2017.
- [37] T. G. Pearce and N. D. Sherratt. Prediction of wheel profile wear. *Wear*, 144(1-2):343–351, 1991. ISSN 0043-1648. doi: 10.1016/0043-1648(91)90025-P.

- [38] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Phd thesis, University of Twente, 2010.
- [39] A. Meghoe, R. Loendersloot, R. Bosman, and T. Tinga. Rail wear estimation for predictive maintenance: a strategic approach. In *European Conference of the Prognostics and Health Management Society 2018*.

Appendix

3.A Wheel profiles

Figure 3.A.1: Wheel profiles in new and worn condition.

3.B Prediction results

Figure 3.B.1: Comparison of predicted values and observed values from numerical simulation ($n = 200$) of s1002 new for $cof = 0.02 - 0.15$.

Figure 3.B.2: Comparison of predicted values and observed values from numerical simulation ($n = 200$) of s1002 new for $cof = 0.15 - 0.3$.

3.C Regression coefficients

Table 3.C.1: Regression coefficients.

Regr. coef.	s1002 new cof: 0.02-0.15	s1002 new cof: 0.15-0.30	s1002 new cof: 0.30-0.60	HIT worn cof: 0.02-0.15	HIT worn cof: 0.15-0.30	HIT worn cof: 0.30-0.60
β_0	0.00	0.00	0.00	0.00	0.00	0.00
β_1	0.00	0.00	0.00	0.00	0.00	0.00
β_2	-1.87e-6	-2.43e-7	-3.09e-7	0.00	-4.54e-7	-2.27e-7
β_3	0.00	0.00	0.00	0.00	0.00	0.00
β_4	0.00	0.00	0.00	0.00	0.00	0.00
β_5	0.00	0.00	0.00	0.00	0.00	0.00
β_6	-9.12e-8	6.17e-9	8.25e-9	0.00	4.49e-9	2.79e-9
β_7	7.84e-10	-8.43e-13	-4.07e-12	0.00	3.71e-12	-4.76e-12
β_8	9.05e-10	6.42e-13	-5.86e-13	8.40e-12	-8.20e-13	9.82e-12
β_9	-7.02e-6	3.36e-7	4.07e-7	0.00	1.49e-7	1.47e-7
β_{10}	0.00	0.00	0.00	0.00	0.00	0.00
β_{11}	-5.45e-10	1.07e-11	2.02e-11	0.00	3.05e-11	3.51e-11
β_{12}	4.62e-07	-7.65e-09	-1.26e-08	0.00	-6.30e-09	1.48e-09
β_{13}	0.00	0.00	0.00	0.00	0.00	0.00
β_{14}	2.71e-05	-1.37e-06	-1.41e-06	0.00	-1.93e-07	-2.04e-07
β_{15}	3.44e-13	1.15e-14	3.32e-14	-6.69e-15	1.49e-14	1.47e-14
β_{16}	-6.32e-18	-2.05e-20	-7.88e-20	-4.59e-20	-4.20e-20	-7.34e-21
β_{17}	2.47e-18	1.17e-20	2.52e-20	-4.54e-20	2.10e-20	-2.34e-20
β_{18}	4.30e-10	-9.71e-11	-9.55e-11	0.00	-2.31e-11	-4.71e-11
$\beta_{1,2}$	-9.55e-8	1.77e-9	-4.57e-8	0.00	-1.53e-8	1.90e-8
$\beta_{1,3}$	1.25e-7	-5.94e-8	-4.57e-8	0.00	-1.53e-8	1.90e-8
$\beta_{1,4}$	0.00	0.00	0.00	0.00	0.00	0.00
$\beta_{1,5}$	0.00	0.00	0.00	0.00	0.00	2.31e-7
$\beta_{1,6}$	7.41e-10	5.64e-11	3.58e-11	0.00	4.93e-11	-4.71e-11
$\beta_{1,7}$	3.12e-13	4.01e-14	1.28e-14	-1.91e-13	-1.74e-14	1.75e-14
$\beta_{1,8}$	-5.06e-12	-5.16e-14	2.14e-14	2.24e-13	2.05e-13	2.31e-13
$\beta_{1,9}$	8.02e-08	-9.30e-10	-3.86e-10	0.00	4.15e-10	-2.48e-09
$\beta_{2,3}$	3.42e-08	1.87e-10	2.57e-10	0.00	-1.61e-10	-8.35e-11
$\beta_{2,4}$	1.55e-06	-1.49e-07	-8.12e-09	0.00	0.00	1.56e-07
$\beta_{2,5}$	-2.58e-07	5.23e-09	5.88e-09	0.00	2.17e-09	2.71e-09
$\beta_{2,6}$	-2.12e-11	-3.71e-13	-5.14e-13	-3.14e-13	1.13e-12	-3.18e-13
$\beta_{2,7}$	-1.30e-13	8.84e-16	5.39e-16	3.59e-16	4.06e-16	-9.25e-16
$\beta_{2,8}$	3.08e-14	-7.69e-16	-8.86e-16	6.02e-16	5.99e-16	-6.94e-16
$\beta_{2,9}$	3.69e-09	2.32e-11	1.52e-11	0.00	4.87e-11	-2.29e-11
$\beta_{3,4}$	0.00	0.00	0.00	0.00	0.00	0.00
$\beta_{3,5}$	-7.88e-06	7.16e-08	3.27e-08	0.00	2.62e-09	-1.30e-08
$\beta_{3,6}$	4.08e-10	4.94e-12	1.81e-11	0.00	3.39e-11	1.40e-11
$\beta_{3,7}$	1.61e-12	-4.36e-15	1.28e-14	2.85e-14	3.83e-14	2.36e-14
$\beta_{3,8}$	3.67e-12	8.34e-15	8.28e-15	-1.29e-14	2.46e-16	1.63e-14
$\beta_{3,9}$	-2.86e-08	-5.11e-10	-3.84e-10	0.00	-4.94e-10	-3.63e-10
$\beta_{4,5}$	0.00	0.00	0.00	0.00	0.00	0.00
$\beta_{4,6}$	3.82e-07	8.32e-09	7.55e-10	0.00	4.63e-09	-5.18e-09
$\beta_{4,7}$	7.81e-10	2.28e-11	1.03e-11	0.00	1.70e-11	1.35e-12
$\beta_{4,8}$	-1.27e-09	-8.50e-12	-3.59e-12	0.00	-1.76e-11	1.17e-12
$\beta_{4,9}$	0.00	0.00	-7.10e-08	0.00	0.00	-1.04e-09
$\beta_{5,6}$	1.68e-09	-2.15e-10	-2.18e-10	0.00	-9.00e-11	-1.39e-10
$\beta_{5,7}$	8.27e-13	1.01e-14	-2.24e-14	-2.63e-14	-4.33e-14	-1.05e-13
$\beta_{5,8}$	-2.36e-11	1.40e-13	1.51e-13	1.85e-14	5.11e-14	-2.23e-14
$\beta_{5,9}$	5.76e-08	1.29e-08	1.30e-08	0.00	3.95e-09	5.02e-09
$\beta_{6,7}$	-3.29e-15	3.25e-17	3.99e-17	-1.96e-17	-4.56e-17	2.06e-17
$\beta_{6,8}$	1.01e-15	2.30e-18	-2.99e-18	1.69e-17	4.01e-18	-2.81e-17
$\beta_{6,9}$	3.22e-12	-9.78e-13	-1.86e-12	3.91e-13	-2.10e-12	8.77e-13
$\beta_{7,8}$	-5.74e-18	9.16e-20	8.03e-20	3.87e-20	6.06e-20	1.48e-20
$\beta_{7,9}$	-4.82e-14	-5.59e-16	-6.69e-16	5.26e-16	-1.99e-15	1.87e-15
$\beta_{8,9}$	-1.86e-13	-9.97e-16	-8.67e-16	-3.38e-15	-2.98e-16	-2.83e-15

Chapter 4

Generic rail damage function based on physical models¹

Abstract

Railway tracks are plagued by surface defects that are a result of either the wear or Rolling Contact Fatigue (RCF) mechanism. Several scientific and engineering models have been developed to predict the damage rate due to these mechanisms. One such semi-empirical model is called the Whole Life Rail Model (WLRM), which has been successfully implemented in the past and is also easy for infrastructure managers to use for the maintenance planning of railway tracks. However, this model is material-dependent and is developed from a limited number of regions that cannot be considered as a representation of all possible scenarios. Therefore, this chapter presents a more fundamental approach to develop such models for different steel grades and various friction coefficients such that most of the possible scenarios are covered by the model. These scenarios are obtained by using the Latin Hypercube Sampling (LHS) method and are then evaluated by using vehicle dynamic simulations. The fatigue life and the wear rate are derived from analytical expressions of several physics-based models and a good correlation is found between the obtained WLRMs and those that already exists.

4.1 Introduction

Both wear and Rolling Contact Fatigue (RCF) are severe damage mechanisms for railway tracks [1, 2]. Generally the high maintenance costs in railway infrastructure

---

¹This chapter is based on: Meghoo, A., Loendersloot, R. and Tinga, T. (2019). Generic rail damage function based on physical models. *Wear* (under review, revision submitted)

are due to either controlling wear or preventing RCF. RCF probably causes the most severe failures in railway infrastructure. The Hatfield derailment, for example, is one of the worst nightmares in rail history [3]. The derailment of this train was caused by RCF, which produced head-checks, eventually leading to broken rails. Hence, the detection of RCF damage (through inspections) is very important, but the ability to predict the occurrence of RCF offers even more benefits.

Various damage indices have been developed by several researchers to address the prediction of crack initiation in rails. Examples of such models are the shakedown map [4], the Dang Van criterion [5], the Whole Life Rail Model (WLRM) [6, 7] and the ratcheting model [8]. Zacher [9] applied three of these models, namely shakedown map, Dang Van criterion and WLRM, for RCF crack prediction on the high speed line Cologne - Frankfurt. He concluded that the shakedown map could not explain the RCF damage, whereas the Dang Van criterion and the WLRM yielded similar and accurate results when compared with field observation data. Therefore, the shakedown map approach will not be considered in this study. Furthermore, the ratcheting model and the WLRM are the only models that also include the influence of wear besides RCF. Due to the large computation time of the ratcheting model for one scenario and the use of different rail steel micro-structures [8], it is difficult to cover all possible scenarios and the WLRM approach is chosen to be studied further.

In 2003, Burstow [6, 7] developed an empirical model, also known as the WLRM, to predict what location on a the track is prone to crack initiation. The prediction model is based on dissipated energy in the wheel-rail contact and as mentioned before it can also predict whether a specific track is dominated by RCF or wear. The WLRM has been established by using field observations from a total of six different sites and a time period of approximately two years. These are combined with detailed vehicle-track interaction analyses using vehicle dynamic simulations. Furthermore, the rail material involved in the research of Burstow [6, 7] is steel grade R220. Recently, Hiensch and Steenbergen [10] repeated the WLRM development process for steel grade R260Mn and R370CrHT and concluded that the behaviour of the R260Mn is similar to that of R220. They also mentioned that the same WLRM is applicable for all pearlitic steel grades, including R260. The WLRM for R370CrHT showed that the crack initiation limit is higher than for the pearlitic steel grades and thus an increase in fatigue life is expected.

The disadvantages of the empirical model are the time required for the field observations to determine the total number of cycles to failure or to crack initiation and its dependency on the type of steel grade. Due to the different available steel grades for rails from conventional to premium steel grades [11] different WLRMs are required. Furthermore, so far the WLRMs for R220, R260Mn and R370CrHT have been developed only for vehicle dynamic simulations performed with fixed friction coefficient values of 0.3 [6, 7] and 0.32 [10]. However, from the work of Marte et al. [12] who performed a sensitivity analysis for RCF damage and wear on the contact level, it can be concluded that the friction coefficient has a large influence on fatigue life. The

variation in friction coefficient is also quite evident in practice due to environmental or weather conditions, contamination and use of lubrication [13]. To summarize, the WLRM is a suitable and practical approach for predicting RCF, but has two severe limitations that prohibit application in a generic sense: it is material specific and uses a fixed coefficient of friction. The current work will therefore focus on developing a more fundamental background for this method, which will enable generalization of the WLRM to virtually any operational context.

The objective of this study is to reconstruct the WLRM for different types of steel grades such as R260 and R370CrHT, by using only analytical formulas and numerical experiments instead of field observations. These analytical formulas are obtained from physics-based models including Archard's wear law, semi-analytical expressions for crack initiation life and crack growth rates based on the Paris-Erdogan law. Thereafter, a comparison will be made with the WLRMs already developed by Burstow [6, 7] and Hiensch and Steenbergen [10]. Furthermore, the behaviour of the generalized WLRMs for various friction coefficients, material crack growth properties and rail surface roughness is studied. The outline of this chapter is as follows: Section 4.2 describes the methodology for the WLRM reconstruction which consists of the analytical expressions and the vehicle dynamic simulations, Section 4.3 presents and discusses the results and finally the conclusions are put forward in Section 4.4.

4.2 Methodology

By following the methodology as described in this section a generic rail damage function (or WLRM) can be established for rail tracks with a specific type of steel grade including specific material properties, varying rail surface roughness and operating in different environmental conditions (represented by the friction coefficient). Thus, this section first gives a description of the WLRM (subsection 4.2.1) and then presents the structure of the numerical experiments (subsection 4.2.2) which are used to reconstruct the WLRM which consists of two parts, namely the RCF damage function and the wear rate function. The physics-based models that are used to estimate the fatigue life and calculate the wear rate for the reconstruction of these functions are described in subsections 4.2.3 and 4.2.3, respectively. Finally, the merging of both functions is presented in the last subsection of Results and Discussion (Section 4.3).

4.2.1 Whole Life Rail Model

The WLRM for a specific material and coefficient of friction is depicted in Figure 4.1. The damage index of the WLRM depends on the wear number ($T\gamma$), a load parameter, that is obtained from vehicle dynamics simulations and can be calculated for a specific wheel-rail contact as:

$$T\gamma = T_x\gamma_x + T_y\gamma_y \quad (4.1)$$

where T_x and T_y represent the tangential or shear forces and γ_x , γ_y represent the longitudinal and lateral creepages. The x -axis is aligned with the track and the y -axis is perpendicular to the track.

Figure 4.1: WLRM showing the RCF damage index as a function of the wear number [3]. This plot has been developed for steel grade R220 and a coefficient of friction of 0.3.

The basic principle underlying the WLRM is that RCF and wear are competing mechanisms on a rail track. Fatigue cracks initiate and propagate into the material, but at the same time a wear process might remove the top layer of the track. The rates of both processes determine whether cracks can grow or whether these are continuously removed by the wear process. The RCF and wear rates will be determined by the loading conditions, as quantified by $T\gamma$. The loading conditions associated with line section A-B in Figure 4.1 represent the RCF dominant region, C-D represents the wear dominant region and B-C corresponds with a combination of RCF and wear. The total damage is calculated by employing the Palmgren-Miner rule:

$$D = \sum_{i=1}^k D_i \quad (4.2)$$

with

$$D_i = \frac{n_i}{N_i} \quad (4.3)$$

These equations state that there are k different scenarios (or contact conditions) and the damage index value D_i for each scenario is the ratio between the number of cycles (in this case the number of wheels passed) n_i with contact condition k and the number of cycles to failure N_i for the same contact condition. The contact condition

is represented by the wear number $T\gamma$ which is plotted on the x -axis of the WLRM function. Hence for a specific wear number, the damage index value can be obtained from Figure 4.1. Finally, failure (here defined as crack initiation) occurs when the accumulated damage index D reaches the value of 1. In case of a single scenario (constant contact conditions), the total number of cycles to failure can be obtained by inverting the damage index ($\frac{1}{D_i}$) as obtained from Figure 4.1.

4.2.2 Numerical experiments

The results obtained as output from a total of 200 numerical experiments are utilized for the development of both the RCF damage and the wear rate function. These numerical experiments are basically vehicle dynamics simulations in the VI-Rail environment [14], which yield the wear number and other contact conditions that have an influence on the number of cycles until failure. The selection of 200 scenarios is made by using Latin Hypercube Sampling (LHS), which ensures that the relevant scenarios, i.e. various combinations of dominant parameters, are covered. Previously a sensitivity analysis on the wear number was performed which resulted in eight dominant parameters [15]. These parameters are presented in Table 4.1 along with their minimum and maximum values that define the range of the parameters.

Table 4.1: Overview of most dominant parameters and their adopted ranges.

Parameter	Symbol	Unit	Min	Max
Curve radius	R	m	1000	4000
Vehicle speed	V	m/s	11.11	44.44
Axle load	m	MT	9.4	26.67
Rail cant	$cant$	mm	0	100
Vertical wear depth	h	mm	0	12
Coefficient of friction	cof	—	0.02	0.6
Longitudinal stiffness (primary suspension)	k_x	N/m	2.56e5	4.00e7
Lateral stiffness (primary suspension)	k_y	N/m	2.56e5	4.00e7

The multi-body dynamic simulations are performed with vehicles that consist of car bodies, bogies and wheel sets, which are considered as rigid bodies and are mutually connected by means of primary and secondary suspensions. The underground, ballast and track are also considered to be rigid and the effects of track irregularities are not considered. The simulated track length is equal to 800 metres, where the first 50 metres of the track consist of a straight track followed by a transition curve with a length of 100 metres leading to the actual curve. For the rail profile UIC54E1 is selected and for the wheel profile s1002. The contact parameters, i.e. wear number, contact area and normal contact load, are then computed for each wheel and for each time step. However, only the median value for the first wheel of the bogie on the track on all positions starting from $x = 300$ metres on the outer rail, is considered

for further analysis. Previous research by the authors [16] showed that the first wheel of the bogie running on the outer rail is dominant for rail wear. [Burstow \[6\]](#) also mentioned that RCF occurs mainly on the outer rail. Furthermore, the restriction of using the median value from $x = 300$ metres is to ensure that transient behaviour of the vehicle entering the curved track is ignored.

4.2.3 Fatigue life estimation

The first part of the WLRM represents the fatigue life in number of cycles as a function of the wear number. The wear number is calculated from the VI-Rail simulations and this section will describe how to estimate the fatigue life using analytical formulas and results from the vehicle dynamics simulations. The total fatigue life (N_f) is equal to the sum of the crack initiation life (N_i) and the crack propagation life (N_p) [17–19]:

$$N_f = N_i + N_p \quad (4.4)$$

Although the WLRM claims to perform a crack initiation prediction, the model was developed using field observation data of cracks which were visible with the naked eye. These cracks had a minimum crack length of ≈ 2 mm [6], which is much larger than the typical crack length at initiation. This is the reason that both crack initiation and crack propagation life will be considered to reconstruct the WLRM.

Crack initiation model

The adopted analytical equation for the crack initiation model derived by [Tanaka and Mura \[20\]](#), is based on a dislocation model and is given as follows [18]:

$$N_i = \frac{AW_s}{(\Delta\tau - 2\tau_f)^2} \quad (4.5)$$

where N_i stands for the number of cycles to failure (in this case failure is defined as the initiation of a crack), $\Delta\tau$ is the shear stress range, τ_f is the friction stress (approximated as half the fatigue limit) and W_s is the fracture energy defined as follows:

$$W_s = \frac{\Delta K_{th}^2}{2E} \quad (4.6)$$

where ΔK_{th} is the stress intensity factor at the crack growth threshold and E is the elastic modulus. Furthermore, the constant A depends on material properties and the manner in which the crack initiates e.g. along slip bands, along grain boundary or along inclusion [18]. For crack propagation it is assumed that cracks in rails undergo fracture mode I and II [2] and for crack initiation when the wheel forces are high and crack sizes rather small, the cracks will be closed due to mode I [21]. Therefore, in this study it is assumed that failure (i.e. crack initiation) occurs due to shear

(fracture mode II) and cracks are initiated along the slip bands [18]:

$$A = \frac{4G}{\pi(1-\nu)a_0} \quad (4.7)$$

where G is the bulk shear modulus, ν is the Poisson ratio and a_0 is the surface defect size that can be estimated from the surface roughness R_a [17, 19, 22]:

$$a_0 = 2.97R_a \quad (4.8)$$

This relation between the surface defect size and the surface roughness that was found by Murakami [22] by performing several fatigue tests, is chosen here to estimate the fatigue life. The reason for this is that the WLRM is developed for a typical type of RCF defects, namely head-checks [6], which occur mainly on the railhead surface and are considered to originate from surface initiated cracks rather than subsurface initiated cracks [3]. The locations where these surface defects occur have low fatigue strength and experience high stress concentrations [19]. The higher the surface roughness, the larger the surface defect size and thus the earlier the fatigue limit of the material is exceeded and failure occurs. In conclusion, a higher surface roughness means a decrease in fatigue life.

Based on the physical interpretation of the Von Mises yield criterion, Wang et al. [18] defined the following relations between the shear stress range ($\Delta\tau$) and the applied normal stress range ($\Delta\sigma$):

$$\Delta\tau = \frac{\sqrt{2}}{3}\Delta\sigma \quad (4.9)$$

and

$$\tau_f = \frac{1}{2}\left(\frac{\sqrt{2}}{3}\sigma_{fl}\right) \quad (4.10)$$

where σ_{fl} is the fatigue limit in terms of normal stress. By substituting Equation (4.6) to (4.10) in Equation (4.5) the number of cycles to crack initiation (N_i) can be represented as:

$$N_i = \frac{9\Delta K_{th}^2 G}{E(\Delta\sigma - \sigma_{fl})^2 \pi(1-\nu)a_0} \quad (4.11)$$

N_i can now be calculated for any material when the applied normal stress range is known from simulations (see Section 4.2.3) and some material properties which are obtained from fatigue tests are available.

Note that in the initiation phase of the fatigue process, the crack size does not change yet (that only occurs in the crack propagation phase). After N_i cycles the crack size is thus still a_0 , and these cycles are only required to accumulate such an amount of damage that the crack can start propagating.

Crack propagation model

The expression for the number of cycles until (a certain amount of) crack propagation (N_p) is derived from the Paris's law:

$$\frac{da}{dN} = C(\Delta K)^n \quad (4.12)$$

where a is the crack size, N the number of cycles to failure, ΔK is the stress intensity factor range and C and n are material constants.

N_p is derived from the analytical solution for the integral of Paris's law and is expressed as follows [17, 18]:

$$N_p = \frac{a_0^{(1-\frac{n}{2})} - a_{sc}^{(1-\frac{n}{2})}}{C\Delta\sigma^n\beta_1^n\pi^{\frac{n}{2}}(\frac{n}{2}-1)} + \frac{a_{sc}^{(1-\frac{n}{2})} - a_f^{(1-\frac{n}{2})}}{C\Delta\sigma^n\beta_2^n\pi^{\frac{n}{2}}(\frac{n}{2}-1)} \quad (4.13)$$

where a_{sc} is the crack size when the crack is visible with the naked eye, a_f is the crack size at failure and the geometrical constants $\beta_1 = 0.5\sqrt{\pi}$ and $\beta_2 = 1$. The second term in Equation (4.13) can be ignored as generally the number of cycles from initial crack size to visible crack size is much larger than the number of cycles from visible crack size to failure (e.g. fracture) [18] and typical values of n are larger than 2. Hence, the expression for the total fatigue life becomes:

$$N_f = \frac{9\Delta K_{th}^2 G}{E(\Delta\sigma - \sigma_{fl})^2 \pi(1-\nu)a_0} + \frac{a_0^{(1-\frac{n}{2})}}{C\Delta\sigma^n\beta_1^n\pi^{\frac{n}{2}}(\frac{n}{2}-1)} \quad (4.14)$$

Applied normal stress range calculation

The applied normal stress range $\Delta\sigma$, which is required for the total fatigue life (N_f) estimation, is calculated from the contact parameters that are obtained from the numerical simulations carried out in VI-Rail [14]. The evaluation of subsurface stresses is performed by using the elastic half space model as explained by Santos et al. [23]. The entire process from the input of contact parameters to the final value of the applied normal stress range is depicted in Figure 4.2. The contact parameters are represented by the normal contact load F_N and the semi-axes a and b of the elliptic contact area between wheel and rail. As RCF crack initiation can occur either on the surface or subsurface, the stress distribution within the material needs to be studied. As given in Equation (4.9) the applied normal stress range can be calculated from the shear stress range in the material. Due to the discrete contact of the wheels on the rail, the stress ratio ($R = \frac{\sigma_{min}}{\sigma_{max}}$) is equal to zero, thus the shear stress range equals the maximum shear stress ($\Delta\tau = \tau_{max}$). τ_{max} can be calculated from the maximum and minimum principal stress, σ_1 and σ_3 respectively, and is known to cause metal fatigue.

$$\tau_{max} = \frac{1}{2}(\sigma_1 - \sigma_3) \quad (4.15)$$

The principal stresses are calculated as the eigenvalues of the Cauchy stress tensor. This tensor is calculated by using the Discrete Convolution Fast Fourier Transformation (DC-FFT) method for elastic contacts as first described by Liu et al. [24] and also implemented by Bosman [25], for every element within the elliptical contact area which is discretized in $N_x \times N_y \times N_z$ elements. Then the applied normal stress range for each VI-Rail simulation (or each scenario) is calculated by using the maximum value of the shear stress range within the $N_x \times N_y \times N_z$ grid. The subsurface stresses can also be calculated by means of a Finite Element Analysis (FEA), but FEA was not suitable for the evaluation of 200 scenarios because the computation time is greater than with the DC-FFT method.

Figure 4.2: Applied normal stress range calculation process.

4.2.4 Wear rate calculation

Now the fatigue part of the WLRM has been defined, this subsection will address the second part of the WLRM, i.e. the wear part. In this chapter the well-known Archard's wear law [26] has been used to calculate the wear rate for rails. For val-

validation purposes the results obtained with Archard's approach are then compared with the experimental results obtained by Bolton and Clayton [27] which were based on the energy approach. The comparison between Archard's approach and the energy approach requires a variable that expresses the wear rate obtained from both approaches in the same units. This section first describes the calculation procedure by using Archard's approach, then the procedure when using the energy approach and finally the comparison of the wear rate resulting from these two approaches.

Archard's wear function

In 1953 Archard developed a sliding wear model for metal to metal contact surfaces, based on theoretical and empirical studies [26]. This model indicates that the amount of wear volume loss V is related to sliding distance s , normal force F_N and material hardness H :

$$V = K \frac{s F_N}{H} \quad (4.16)$$

where the wear coefficient K depends on the surface conditions and is usually determined empirically e.g. with pin on disc configuration measurements. For simple calculations the wear coefficient can be derived from the wear chart of Jendel [28], see Figure 4.3. This chart was formed from a series of laboratory experiments for various contact pressures, sliding velocities and hardness of the material during dry conditions. Hence, the wear coefficient depends strongly on the previously mentioned parameters. In this study the wear coefficients that were obtained from Jendel's wear chart were scaled down by a factor of 5.5 as suggested by Enblom and Berg [29].

The output of each numerical simulation in VI-Rail yields the elliptic contact area between wheel and rail for a specific scenario. This elliptic contact area is then discretized into $N_x \times N_y$ elements and the Archard wear law is implemented for each element. The expression for the wear depth $h(x, y)$ of every discretized element in the elliptical contact (with cartesian coordinates (x, y)) is derived by dividing the wear volume by the contact area which is assumed to be constant [30]:

$$h(x, y) = K(x, y) \frac{s(x, y) p(x, y)}{H} \quad (4.17)$$

where $p(x, y)$ is the normal contact pressure distribution (i.e. the normal force divided by the contact area) calculated by using the Hertzian theory.

As mentioned before, the elliptic contact area is divided into a number of elements, and the wear depth is calculated at each element. If the specific element is in slip, i.e. the wheel is sliding relative to the rail, the following condition is true:

$$\tau(x, y) \geq \mu p(x, y) \quad (4.18)$$

where $\tau(x, y)$ is the tangential stress in an element with coordinates (x, y) and μ is the friction coefficient in the contact. Then, the sliding distance for an element in slip

Figure 4.3: Jendel's wear map providing values of the dimensionless wear coefficient for different wear regimes [28].

can be calculated as:

$$s = \frac{dx}{V_{vehicle}} |v| \quad (4.19)$$

where dx is the longitudinal element length, which is passed by the moving wheel in a time period $t = \frac{dx}{V_{vehicle}}$, $V_{vehicle}$ the vehicle speed and v the magnitude of the slip velocity defined as follows:

$$|v| = \sqrt{(v_x)^2 + (v_y)^2} \quad (4.20)$$

with,

$$v_x(x, y) = V_{vehicle}(\gamma_x - \phi y) \quad (4.21)$$

$$v_y(x, y) = V_{vehicle}(\gamma_y + \phi x) \quad (4.22)$$

where γ_x , γ_y and ϕ are the longitudinal, lateral and spin creepage respectively, which are obtained as the output of the vehicle dynamic simulations. Note that creepage is defined as the slip velocity divided by the vehicle speed and is dimensionless except for spin creepage, which has the unit of [1/m] [16].

Finally, the amount of worn-off area from the rail is calculated from the wear depth results. As mentioned before, the wear depth is calculated for each discretized element in the elliptic contact area. Then for the same contact area the values of the

wear depth are summed up along the longitudinal direction (direction in which the train moves). This yields the wear depth as a function of the lateral coordinates of the elliptic contact area. Then the worn-off area for that contact area is determined as the integral of the wear depth over the lateral direction [16].

Energy approach

The wear rate described by the energy approach assumes that the wear volume loss is proportional to the dissipated energy in the wheel-rail contact area and is expressed in terms of the wear number $T\gamma$. Bolton and Clayton [27] tested the wear behaviour of various rail steels during rolling-sliding contact and plotted the wear rate for the various types of steel. This wear rate $\dot{W}$ is expressed as the material's weight loss (μg) per rolled distance (m) per contact area (mm^2):

$$\dot{W} = K \frac{T\gamma}{A} \quad (4.23)$$

where K is the wear coefficient which is determined from Figure 4.4 [31]. Note that these wear regimes correspond to the wear regimes in Jendel's wear map, see Figure 2.5, e.g. K_1 stands for mild wear, K_2 for severe wear and K_3 for catastrophic wear. However, the values for the wear coefficients from Jendel's wear map and Figure 4.4 are not the same.

Figure 4.4: Wear regimes and coefficients [31].

In order to compare the wear rates obtained from Archard's approach and the energy approach, a similar variable should be compared. Hence, the wear rate from the energy approach is divided by the steel density value $\rho = 7850 \text{ kg/m}^3$, which then yields the wear rate in wear area per contact area (i.e. dimensionless). Furthermore, for Archard's approach the worn area for each elliptic contact area is calculated and then divided by the magnitude of the elliptic contact area. In this way, both ap-

proaches yield the same definition for the wear rate.

4.3 Results and discussion

This section presents the results obtained by using the proposed methodology. First the results for the RCF damage function are presented, followed by the wear rate function results and finally the obtained WLRMs are discussed.

4.3.1 RCF damage function

This subsection presents the RCF damage functions for two types of steel, namely the conventional steel grade R260 and the premium steel grade R370CrHT, that are constructed from the numerical simulation results and the fatigue life estimation formula as explained in Section 4.2.3. Furthermore, the resulting effects on the RCF damage functions for variations in stress ratio, the crack growth material constants C and n , rail surface roughness and the friction coefficient are studied and discussed.

Figure 4.5 depicts the RCF damage function obtained for steel grade R260 for different stress ratios R (defined as the ratio between minimum and maximum applied load during fatigue crack growth testing [32]) and different values for the material constants C and n . The roughness value $R_a=0.4\mu\text{m}$ is similar to the roughness value for the rail specimen measured by Bolton and Clayton [27] during the wear rate testing. Furthermore, the material constants ΔK_{th} , C and n are obtained from literature. Both Maya-Johnson et al. [32] and Christodoulou et al. [33] performed fatigue tests for R260. However, the chemical compositions of their specimens were not identical. Table 4.2 shows the chemical composition for standard steel grade R260 and the chemical composition of the specimens used by Maya-Johnson et al. [32] and Christodoulou et al. [33]. Due to the difference in the chemical compositions, different values for material constants C and n were obtained.

Table 4.2: Chemical composition of the different steel grades (in wt%).

Steel grade	C	Si	Mn	P	S	Cr	Ni
R260 (standard) [33]	0.6-0.8	0.1-0.5	0.8-1.3	0.04 max	0.04 max	-	-
R260 [33]	0.68	0.35	1.11	0.01	0.02	0.02	0.02
R260 [32]	0.74	0.27	1.06	0.03	0.02	0.03	0.02
R370CrHT [32]	0.76	0.39	1.06	0.01	0.02	0.51	0.06

Figure 4.5 shows that the higher the value of C , the shorter the fatigue life, as is expected from Paris's law. Furthermore, the two RCF damage functions for R260 obtained from numerical experiments with stress ratio $R=0.1$ are closer to the RCF damage function for R220 as determined by Burstow [6] than the data set for $R=0.5$. This can be explained by the fact that in practice the stress ratio during wheel-rail

Figure 4.5: Reconstruction of RCF function for steel grade R260, stress ratio $R=0.1$ and $R=0.5$ ($\mu=0.4$ and $R_a=0.4 \mu\text{m}$). The WLRM curve, determined for steel grade R220, is plotted as a reference.

contact is equal to zero: the normal contact load exerted on the rail by the wheels is the maximum load and the minimum load is equal to zero (no contact condition).

The RCF damage function which is obtained from simulations by using various values for the surface roughness R_a and stress ratio $R=0.1$ [33] is plotted in Figure 4.6. This figure shows that, as expected, higher surface roughness leads to shorter fatigue life. The surface roughness plays an important role in the fatigue life estimation, as explained in subsection 4.2.3.

Besides the crack growth material properties and the surface roughness of the rail, the friction coefficient also has a significant influence on the RCF damage [12]. In order to investigate this influence, the RCF damage functions for each steel grade are obtained from 200 numerical simulations with fixed coefficient of friction value. Hence, for each fixed coefficient of friction value 200 simulations were performed and because this study considers four values for the coefficient of friction ($\mu=0.3, 0.4, 0.5$ and 0.6) a total of 800 simulations were performed for each type of steel.

The RCF damage functions obtained from numerical simulations by using the material constant values (C and n) from Maya-Johnson et al. [32] are plotted in Figure 4.7. It can be concluded that the RCF damage function constructed by using these constants is similar to the WLRM as developed by Burstow [6]. Furthermore, the RCF damage function is plotted for various coefficients of friction and it can be seen from Figure 4.7 that higher values for the coefficient of friction yield a decrease in fatigue life, as expected [12].

Figure 4.6: Reconstruction of R260 RCF function for different values of the surface roughness R_a .

Figure 4.7: Reconstruction of RCF function for steel grade R260 using various friction coefficients.

A similar plot is constructed for steel grade R370CrHT, as is shown in Figure 4.8. As can be seen from this figure, the slope of the WLRM with coefficient of friction of 0.3 is similar to the WLRM as obtained by [Hiensch and Steenbergen](#) [10], who used a coefficient of friction of 0.32 in the vehicle dynamic simulations. However, the starting point of the obtained WLRM is lower than the starting point of the WLRM from [Hiensch and Steenbergen](#) [10]. This starting point will be further referred to as the first threshold of the WLRM (point A in Figure 4.1) and represents the crack initiation limit that is based on the material properties, primarily the fatigue limit. Hence, fatigue development starts when the stress state exceeds the fatigue limit [33].

[Christodoulou et al.](#) [33] studied the fatigue and fracture behavior of steel grade 900A, which is comparable to R260, and found that due to the high fatigue resistance the value of the fatigue limit is slightly higher than the material's yield strength. The fatigue limit in that study is found to be equal to 533 MPa. Thus the first threshold of the WLRM for R260 is determined from the relation between the stress state and the wear number, see Figure 4.9, where both variables are determined from the numerical experiments and plotted for each scenario. The threshold represented by the wear number is obtained from Figure 4.9 as the value for which the applied normal stress range $\Delta\sigma$ equals 533 MPa, because crack initiation takes place only when the cyclic loading exceeds the fatigue limit. Individual plots like these are generated for each coefficient of friction and the obtained thresholds are summarized in Table 4.3. The threshold obtained for R260 in the range of 13-17 N corresponds to the threshold of [Burstow](#)[6], who assumed a threshold between 15 and 20 N.

Table 4.3: RCF function lower threshold wear number values for both normal (R260) and premium (R370CrHT) steel grade with varying coefficient of friction.

Wear number threshold [N]				
μ	R260 ($\sigma_{fl}=533$ MPa)	R370CrHT ($\sigma_{fl}=767$ MPa)	R370CrHT ($\sigma_{fl}=900$ MPa)	R370CrHT ($\sigma_{fl}=1200$ MPa)
0.3	13.79	19.97	25.03	38.30
0.4	14.48	23.35	30.02	45.51
0.5	17.11	23.58	31.39	46.42
0.6	17.33	26.96	38.38	58.48

The threshold for R370CrHT cannot be determined accurately as the fatigue limit of this steel grade is not available in the literature. The threshold for R370CrHT can, however, be estimated using the yield strength value given by [Maya-Johnson et al.](#) [32], which is equal to 767 MPa. As it is known that R370CrHT steel grade has a good fatigue resistance [10], it is assumed that the fatigue limit is slightly higher than the yield strength. Hence, using 767 MPa for the fatigue limit results in a conservative threshold value (25 N), which is lower the threshold from [Hiensch and Steenbergen](#) [10] for R370CrHT (40 N). However, from the manufacturers data given in [34, 35] it

Figure 4.8: Reconstruction of RCF function for steel grade R370CrHT using various friction coefficients.

Figure 4.9: Relation between equivalent stress and wear number for R260 ($\mu=0.4$ and $R_a=0.4\mu\text{m}$).

can be seen that the typical values for the yield strength range from 900 to 1200 MPa and using these values as a measure for the fatigue limit, higher threshold values close

to 40 N, are found, see Figure 4.9 and Table 4.3.

4.3.2 Wear rate function

Before proceeding with the reconstruction of the wear rate function in the WLRM, it is necessary to prove that the wear calculation is correct. This is done by comparing the calculated wear rate using Archard's law with the experimental results for the wear rate of Bolton and Clayton [27]. Figure 4.10 shows the wear rate results for various coefficients of friction along with the wear rate of Bolton and Clayton. Each data point for each friction coefficient is a representation of the wear rate for one single simulation (or scenario). Using the LHS method, a rather wide range of scenarios could be explored. From Figure 4.10 it can be concluded that the wear rate of Bolton and Clayton corresponds with the results obtained for friction coefficient $\mu=0.5$. This validation shows that the implemented wear model based on Archard's wear law correctly represents the experimental work of Bolton and Clayton, as the friction coefficient used during their experiments was between 0.5 and 0.6. It should be noted that the results plotted in Figure 4.10 represent the dominant wear regime 2 (e.g. severe wear).

Figure 4.10: Calculated wear rates for various coefficient of friction values compared with the empirical relation of Bolton and Clayton [27].

For the reconstruction of the wear function in the WLRM, the wear rate must be converted into the number of cycles to failure, as this quantity is on the vertical axis in the WLRM. In the original WLRM this issue is circumvented, as the wear

function is assumed to be a straight line from point B through C to D (see Figure 4.1). However, in this work a physical foundation for the different curves is proposed to enable generalization of the model. The physical interpretation of point C is that the wear rate at this condition is such that it exactly counteracts the RCF crack propagation, so the RCF life will be infinite. It is therefore proposed here to calculate the number of cycles (i.e. passing train wheels) it takes the wear process to remove the crack propagation by using an average fatigue crack. From literature [1, 21] it is known that cracks propagate at an angle between 15° and 30° into the rail. Therefore, in this study it is assumed that a typical RCF crack propagates under an angle (θ) of 20° into the rail, and has an average length (L) of 2 mm. It then requires a wear depth (h) of 0.68 mm ($h = L \sin \theta$) to fully remove this crack [1]. Knowing the wear rate (i.e. the wear depth per cycle or in this case per passing wheel), the number of cycles required to accumulate to the required wear depth can be calculated. The resulting number of cycles from the simulations already performed, which are needed to exactly compensate RCF for wear regime 2, are shown in Figure 4.11.

Figure 4.11: Wear function fit for R260 and $\mu=0.5$.

This figure shows the wear rate for all 200 simulations and the data points for these simulations are fitted by means of a linear function. This linear function represents the wear rate function in the WLRM. It can be seen that the obtained linear fit for the wear rate (i.e. the slope of the line) is similar to the wear rate of the WLRM as derived for R220 from the work of Burstow [6]. The position of the curve, however, deviates from Burstow's curve. This is because wear occurs only after exceeding a certain threshold value for the wear number ($T\gamma$), as for lower values of shear force

and creepage the wear mechanism is not activated [27]. This is also the explanation for the inflection point B in Figure 4.1: from that point wear is counteracting the fatigue crack propagation to such an extent, that it leads to a decrease in total damage level (and increase in lifetime). The actual threshold of the wear rate function in the WLRM is determined from the interception with the x -axis of the linear function in Figure 4.10. Bolton and Clayton [27] explained that the wear mode requires some activation energy to start the wear process; for example, for $\mu=0.5$ this activation energy per unit contact area is found at $T\gamma/A \approx 10 \text{ N/mm}^2$. Therefore, the interception with the x -axis was determined for each friction coefficient for a large set of simulated scenarios (see Figure 4.10) and then the corresponding wear number was found from the relation between the wear number ($T\gamma$) and the wear number per contact area ($T\gamma/A$) plotted in Figure 4.12. The data points in this figure are obtained from the numerical simulations.

Figure 4.12: Relation between frictional energy per contact area and wear number.

Finally, the estimated thresholds for both R260 and R370CrHT are summarized in Table 4.4. From this table it can be concluded that the required activation energy per unit contact area is higher for increasing friction coefficient. This is as expected because more energy is required to overcome the static friction coefficient in order to have motion and eventually wear. Finally, using the threshold determined for R260 in Figure 4.11 shows that the curve now coincides with Burstow's curve.

Table 4.4: Wear function threshold values for both normal (R260) and premium (R370CrHT) steel grade with varying coefficient of friction.

	μ	0.3	0.4	0.5	0.6
R260	Interception activation energy [N/mm ²]	2.82	5.78	9.21	12.19
	Threshold wear number [N]	12.97	46.21	62.61	85.32
R370CrHT	Interception activation energy [N/mm ²]	3.26	6.34	9.24	12.31
	Threshold wear number [N]	15.67	49.96	62.61	88.06

4.3.3 WLRM reconstruction

This section presents the final results of the WLRMs that are obtained by using only analytical formulas and numerical simulations as described in the methodology section. As mentioned before, the WLRM consists of two parts: the RCF damage function and the wear function. The individual results of both functions have already been presented in the previous subsections. Figure 4.13 shows an example of how these two functions are combined in order to construct the WLRM for $\mu=0.5$.

The final WLRMs, obtained by subtracting the wear function from the RCF function for varying friction coefficients, are given in Figure 4.14 for R260. From this figure it can be seen that the WLRM from [Burstow](#), which is developed for $\mu=0.3$, is positioned between the WLRMs obtained for the current study for $\mu=0.4$ and 0.5 . The reason for this is the threshold value for the activation energy in the wear rate function. The activation energy for the WLRM from the work of [Burstow](#) was estimated around 65 N from field observations and vehicle dynamic simulations with $\mu=0.3$.

For the WLRM obtained in this study the activation energy using physics-based models (i.e. Archard's wear law) is around 12 N for $\mu=0.3$ and due to this difference the wear domination starts at a lower activation energy. The RCF damage function starts around 15 N and no interaction is found between the two functions, as the wear rate is higher than the RCF damage rate, see Figure 4.15. Hence, it can be concluded that the obtained WLRM for $\mu=0.3$ does not seem at first sight to correspond with the WLRM from literature [6]. However, in other work of [Burstow et al. \[36\]](#), where the wear rate was calculated based on the ratcheting model, the activation energy was found to be around 10 N, which is significantly lower than the previously adopted value of 65 N. This was claimed to be attributed to an unknown mechanism besides RCF and wear.

From the current study it can be concluded that this other mechanism is not needed to explain the results, but that the divergence is caused by the friction coefficient. The WLRM of [Burstow \[6\]](#) is based on field observations with an assumed fixed friction coefficient, whereas due to environmental conditions the actual friction coefficient varies in practice. The results from the current study show that

different WLRMs are obtained for different friction coefficients and to validate the obtained WLRMs with field observation data, the operating friction coefficient needs to be monitored. Furthermore, similar plots and similar conclusions can be drawn for R370CrHT.

Figure 4.13: Wear rate versus RCF damage for R260 ($\mu = 0.5$). The thresholds (A to D) in this figure can be compared with Figure 4.1.

4.4 Conclusion

The objective of this study was to find a more fundamental background for the Whole Life Rail Model, avoiding field observations and using only analytical analyses and numerical simulations. It can be concluded that overall this goal has been achieved, as the derived RCF damage function and the wear rate function from the WLRM were compared individually with already existing models and good correlations were found. The combination of these two functions that form the WLRM appeared to be very sensitive for the specific values of two thresholds. As these thresholds are also unknown for the existing WLRMs, comparison of the proposed approach to WLRMs could not yet be fully completed. It is recommended to validate the obtained WLRMs for varying friction coefficient values with well-documented field data in order to fully validate the approach. These developed models can then be very useful for infrastructure managers, as they can replace look up tables presently used for specific vehicles to predict the RCF life of railway tracks for all possible scenarios. The information on

Figure 4.14: WLRM reconstruction for R260 using various coefficients of friction. (Compare with Figure 4.1)

Figure 4.15: Wear rate versus RCF damage for R260 ($\mu = 0.3$).

RCF life, e.g. prioritizing track sections dominated by RCF, can then be included in the maintenance planning for RCF prevention such as grinding or track replacement. Another interesting insight that was obtained from this study was the influence of different mechanical and surface related properties (such as material constants ΔK_{th} , C and n , and surface roughness R_a) and it can be concluded that for these variations as well the proposed approach can be used to construct the appropriate WLRMs .

References

- [1] B. Dirks, R. Enblom, A. Ekberg, and M. Berg. The development of a crack propagation model for railway wheels and rails. *Fatigue & Fracture of Engineering Materials & Structures*, 38(12):1478–1491, 2015. ISSN 8756-758x. doi: 10.1111/ffe.12318.
- [2] G. Donzella and A. Mazzu. Extension to finite life of a failure assessment diagram for contact fatigue loading. *International Journal of Fatigue*, 44:217–224, 2012. ISSN 0142-1123. doi: 10.1016/j.ijfatigue.2012.04.014.
- [3] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Phd thesis, University of Twente, 2010.
- [4] A. F. Bower and K. L. Johnson. The influence of strain-hardening on cumulative plastic-deformation in rolling and sliding line contact. *Journal of the Mechanics and Physics of Solids*, 37(4):471–493, 1989. ISSN 0022-5096. doi: 10.1016/0022-5096(89)90025-2.
- [5] K. Dang Van, G. Cailletaud, J.F. Flavenot, A. Le Douaron, and H.P. Lieurade. Criterion for high cycle fatigue failure under multiaxial loading. *Biaxial and Multiaxial Fatigue*, pages 459 – 478, 1989.
- [6] M. C. Burstow. Whole life rail model application and development: Development of a rolling contact fatigue damage parameter. Technical report, RSSB, 2003.
- [7] M. C. Burstow. Whole life rail model application and development for rssb (t115) - continued development of an rcf damage parameter. Technical report, RSSB, 2004.
- [8] F. J. Franklin and A. Kapoor. Modelling wear and crack initiation in rails. *Proceedings of the Institution of Mechanical Engineers Part F-Journal of Rail and Rapid Transit*, 221(1):23–33, 2007. ISSN 0954-4097. doi: 10.1243/0954409jrtrt60.
- [9] M. Zacher. Prediction of gauge corner cracking in rails for rail maintenance. In *Contact Mechanics*, pages 1–9, 2009.
- [10] M. Hiensch and M. Steenbergen. Rolling contact fatigue on premium rail grades: Damage function development from field data. *Wear*, 394:187–194, 2018. ISSN 0043-1648. doi: 10.1016/j.wear.2017.10.018.
- [11] Coenraad Esveld. *Modern Railway Track*. MRT-Productions, second edition, 2001. ISBN 90-800324-3-3.
- [12] C. Marte, G. Trummer, A. Aichmayr, P. Dietmaier, and K. Six. Sensitivity analysis: Main parameters causing wear and rolling contact fatigue in wheel-rail contact. In *International Symposium on Dynamics of Vehicles on Roads and Tracks*, pages 1–10, 2016.

- [13] Radu Popovici. *Friction in Wheel - Rail Contacts*. Phd thesis, University of Twente, 2010.
- [14] VI-Rail. 17.0 documentation. Technical report, 2016.
- [15] A. Meghoo, R. Loendersloot, and T. Tinga. Rail wear and remaining life prediction using meta-models. *International Journal of Rail Transportation*, 1:1–26, 2019. ISSN 2324-8378. doi: 10.1080/23248378.2019.1621780.
- [16] A. Meghoo, R. Loendersloot, R. Bosman, and T. Tinga. Rail wear estimation for predictive maintenance: a strategic approach. In *European Conference of the Prognostics and Health Management Society 2018*, pages 1–11, 2018.
- [17] C. Y. Li, W. B. Dai, F. Duan, Y. M. Zhang, and D. He. Fatigue life estimation of medium-carbon steel with different surface roughness. *Applied Sciences-Basel*, 7(4), 2017. ISSN 2076-3417. doi: ARTN33810.3390/app7040338.
- [18] Q. Y. Wang, C. Bathias, N. Kawagoishi, and Q. Chen. Effect of inclusion on subsurface crack initiation and gigacycle fatigue strength. *International Journal of Fatigue*, 24(12):1269–1274, 2002. ISSN 0142-1123. doi: 10.1016/S0142-1123(02)00037-3.
- [19] Jinlong Wang, Yuanliang Zhang, Qingchao Sun, Shujie Liu, Bowen Shi, and Huitian Lu. Giga-fatigue life prediction of fv520b-i with surface roughness. *Materials & Design*, 89:1028–1034, 2016. ISSN 0264-1275. doi: 10.1016/j.matdes.2015.10.104.
- [20] K. Tanaka and T. Mura. A dislocation model for fatigue crack initiation. *Journal of Applied Mechanics*, 48(1):97–103, 1981. ISSN 0021-8936. doi: 10.1115/1.3157599.
- [21] B. Dirks and R. Enblom. Prediction model for wheel profile wear and rolling contact fatigue. *Wear*, 271(1-2):210–217, 2011. ISSN 0043-1648. doi: 10.1016/j.wear.2010.10.028.
- [22] Y Murakami. *Metal fatigue: effects of small defects and nonmetallic inclusions*. Elsevier Science Ltd., 1 edition, 2002. ISBN 0-08-044064.
- [23] F. de C. Santos, A. A. dos Santos Jr., and F. Bruni. Evaluation of subsurface contact stresses in railroad wheels using an elastic half-space model. *J. of the Braz. Soc. of Mech. Sci. & Eng.*, XXVI, No. 4 / 421, 2004.
- [24] Shuangbiao Liu, Qian Wang, and Geng Liu. A versatile method of discrete convolution and fft (dc-fft) for contact analyses. *Wear*, 243(1):101–111, 2000. ISSN 0043-1648. doi: 10.1016/S0043-1648(00)00427-0.

- [25] R. Bosman. *Mild Microscopic Wear Modeling in the Boundary lubrication regime*. Phd thesis, University of Twente, 2011.
- [26] J. F. Archard. Contact and rubbing of flat surfaces. *Journal of Applied Physics*, 24(8):981–988, 1953. ISSN 0021-8979. doi: 10.1063/1.1721448.
- [27] P. J. Bolton and P. Clayton. Rolling—sliding wear damage in rail and tyre steels. *Wear*, 93(2):145–165, 1984. ISSN 0043-1648. doi: 10.1016/0043-1648(84)90066-8.
- [28] T. Jendel. Prediction of wheel profile wear-comparisons with field measurements. *Wear*, 253(1-2):89–99, 2002. ISSN 0043-1648. doi: 10.1016/S0043-1648(02)00087-X.
- [29] R. Enblom and M. Berg. Proposed procedure and trial simulation of rail profile evolution due to uniform wear. *Proceedings of the Institution of Mechanical Engineers Part F-Journal of Rail and Rapid Transit*, 222(1):15–25, 2008. ISSN 0954-4097. doi: 10.1243/09544097jrrt173.
- [30] R. Enblom and M. Berg. Simulation of railway wheel profile development due to wear - influence of disc braking and contact environment. *Wear*, 258(7-8): 1055–1063, 2005. ISSN 0043-1648. doi: 10.1016/j.wear.2004.03.055.
- [31] A. Ward, R. Lewis, and R. S. Dwyer-Joyce. *Incorporating a railway wheel wear model into multi-body simulations of wheelset dynamics*, volume Volume 41, pages 367–376. Elsevier, 2003. ISBN 0167-8922. doi: 10.1016/S0167-8922(03)80150-5.
- [32] S. Maya-Johnson, A. J. Ramirez, and A. Toro. Fatigue crack growth rate of two pearlitic rail steels. *Engineering Fracture Mechanics*, 138:63–72, 2015. ISSN 0013-7944. doi: 10.1016/j.engfracmech.2015.03.023.
- [33] P. I. Christodoulou, A. T. Kermanidis, and G. N. Haidemenopoulos. Fatigue and fracture behavior of pearlitic grade 900a steel used in railway applications. *Theoretical and Applied Fracture Mechanics*, 83:51–59, 2016. ISSN 0167-8442. doi: 10.1016/j.tafmec.2015.12.017.
- [34] Jfe steel corporation, 2018. URL <http://www.jfe-steel.co.jp/en/>.
- [35] Rail:steel grades, 2018. URL <https://britishsteel.co.uk>.
- [36] M. C. Burstow, D. I. Fletcher, F. J. Franklin, and A. Kapoor. Management and understanding of rolling contact fatigue: Wp1 mechanisms of crack initiation, final report. Technical report, 2008.

Chapter 5

A hybrid predictive methodology for head checks in railway infrastructure ¹

Abstract

This chapter presents a hybrid method to assess the rail health with the focus on a specific type of rail surface defect called head check. The proposed method uses physics-based and data-driven models in order to model defect initiation and defect evolution on a rail for a given rail traffic tonnage. Ultrasonic (US) and Eddy Current (EC) defect detection measurements are used to provide Infrastructure Managers (IMs) with insight in the current rail condition. The defect initiation results obtained from the first part of the hybrid method which consists of the physics-based model is successfully validated with the EC measurements. Furthermore, the US and EC measurements are utilized to derive a data-driven model for defect evolution. Finally, a set of robust and predictive Key Performance Indicators (KPIs) are proposed to quantify the future condition of the rail based on different characteristics of rail health resulting from the defect initiation and defect evolution analysis.

5.1 Introduction

Increasing train traffic and axle loads change the railway infrastructure condition more rapidly than in the past. Hence, demands for efficient infrastructure monitoring and

---

¹This chapter is based on: Meghoe, A., Jamshidi, A., Loendersloot, R. and Tinga, T. (2019). A hybrid predictive methodology for head checks in railway infrastructure. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit* (submitted)

performance improvement in infrastructure operations are among the major concerns of Infrastructure Managers (IMs). To satisfy those demands, the infrastructure condition should be monitored and analysed. Hence, to maintain the railway infrastructure at an efficient working level, a condition-based maintenance strategy is required [1].

Among all the railway infrastructure systems involved in train operation, the rail track has a critical role in the railway network performance. In an intensively used network, a considerable amount of the maintenance has to be allocated to the track. In the Dutch railway network, this amounts almost half of the annual maintenance budget [2]. As a high percentage of the failures occurring in the railway infrastructure are directly related to rail defects, rail condition monitoring focuses on detecting the rail surface defects that can potentially result in rail fracture and derailment in worst cases [3–5].

Different methods are available to detect and monitor the rail surface defects. These methods include Ultrasonic (US) measurements [6], Eddy Current (EC) testing [7], Axle Box Acceleration (ABA) measurements [8], Video Images (VI) [9] and guided-wave based monitoring [10]. An extensive review of the US, EC and VI method can be found in [11, 12] along with the advantages and disadvantages of each method. In general, these methods are not capable of predicting the initiation of new rail surface defects, nor are they able to detect defects with a crack depth between 3 and 5 mm.

Head checks are one of the most common types of rail surface defects and can lead to rail fracture when not treated in time [13]. They are triggered by repeated wheel-rail contact at high velocity and with high axle loads [14], and can be spotted on the outer rail (at the gauge side) of curved tracks with radii between 500 and 3000 metres, as a cluster of very closely spaced fine cracks, see Figure 5.1. It should be noted that each cluster of head checks will be further regarded as a single head check i and the crack depth is then defined as the maximum value of all the head checks within that cluster.

Early detection of head checks is important to mitigate induced maintenance costs as well as the consequences of unexpected rail failures. However, as mentioned before, rail surface defect detection at an early stage of growth can be challenging. It is possible to confuse the presence of early stage defects with non-defective rail objects. The objective of this study is to propose a method which can be used to predict the occurrence, size and number of rail surface defects (in this case head checks) not only in their early stage of growth but during the entire rail life. Accurate prediction of this will enable efficient maintenance planning as the IMs will be aware of the rail health due to the size and number of defects on the rail.

The total size of a head check (i.e. the crack depth) is the result of crack initiation and crack propagation. In this study, the initiation of a head check is predicted by using meta-models of a head check initiation model, the Whole Life Rail Model (WLRM) [15], adopted from Chapter 4. The advantage of this physics-based model is that it can be implemented easily in maintenance decision tools. On the other hand, currently available crack propagation models derived from physics-based mod-

Figure 5.1: Real and schematic view of head checks on the gauge corner of the outer rail [13].

els are not suitable for strategic applications of predictive maintenance [17]. These types of models require detailed information on initial cracks where Finite Element Models (FEM) play an important role [18, 19]. Therefore, a data-driven framework is proposed to model the crack propagation. This framework includes a rail anomaly detection approach based on rail measurement sources like EC and US. Thereafter, a set of predictive and robust Key Performance Indicators (KPIs) are proposed to quantify the condition of different sections of rail by using the combination of the results obtained from the crack initiation and from crack propagation models.

However, the deterministic nature of this newly proposed approach makes it meaningless for the IMs, unless a stochastic model is added for the head check initiation model. The drawback of the meta-model for head check initiation adopted from Meghoo et al. [16] is that it predicts the occurrence of only a single head check for a given time period, whereas from field observations it is concluded that multiple head checks can initiate in the same time on a specific rail piece [12]. Therefore, first an initiation model then a stochastic model is introduced in this study to predict the number of head check initiations along with their location on the rail track.

In conclusion, in this study a hybrid predictive methodology to assess head checks in railway infrastructure is proposed. The proposed hybrid predictive methodology can be a robust tool for the prediction of rail condition. Infrastructure managers will be aware of the rail health and rail degradation over a given maintenance time horizon. Thus, the proposed method can greatly help to improve rail maintenance planning.

The proposed hybrid method consist of three steps: a physics-based model, a data-driven model and a health assessment analysis based on KPIs, see Figure 5.2. This figure depicts the flowchart of the entire methodology which is described in more detail in Section 5.2, 5.3 and 5.4. Finally, the results and discussion are put forward in Section 5.5 and the conclusion is set out in 5.6 respectively.

Figure 5.2: Flowchart of the proposed hybrid predictive methodology.

5.2 Physics-based head check initiation model

A number of early-stage head check initiation models have been reviewed and are listed in [12]. Regarding the requirements for implementation of these models, which depend mostly on calculation efficiency and direct coupling with operational conditions Meghooe et al. [12] concluded that the Whole Life Rail Model (WLRM) developed by Burstow [15] is the most suitable model for the hybrid predictive methodology. An additional advantage of the WLRM is that it also takes into account the damage rate induced by the wear mechanism. However, the disadvantage of this approach is that for each scenario with specific operational conditions and track geometry a simulation needs to be performed in a multi-body dynamics software code, in order to calculate the time to failure (defined in this case as head check initiation). Typically infrastructure managers do not have access to complex software such as multi-body dynamic codes. Thus, to overcome this obstacle and assist the infrastructure managers, this chapter provides meta-models for the head check initiation, that do not require multi-body simulations. These meta-models are derived for a relevant set of different scenarios obtained by the Latin Hypercube Sampling (LHS) method. Hence, this section will give a short description of the WLRM (see also Chapter 4), followed by a description of the meta-models and the process of damage prediction.

5.2.1 Whole Life Rail Model

The WLRM, see Figure 5.3, shows how many cycles (in this case the number of wheel passages) are required until failure occurs given a specific loading condition. This loading condition is described by a loading parameter also known as the wear number ($T\gamma$) which is defined as the product of tangential forces (T) and slip (γ) in the wheel-rail contact:

$$T\gamma = T_x\gamma_x + T_y\gamma_y \quad (5.1)$$

where x and y are the moving and lateral direction respectively.

The wear number is an output of the vehicle dynamics simulation and determines which degradation mechanism (RCF or wear) is dominant. The loading conditions between line section A-B in Figure 5.3 represent the RCF dominant region, B-C the combination of RCF and wear and C-D the wear dominant region. Furthermore, the wear number is also chosen as the response value of the meta-model as described in Subsection 5.2.2.

Typically a railway track experiences different traffic conditions, leading to different loading conditions. Then the total damage index D can be calculated by using the Palmgren-Miner rule:

$$D = \sum_{i=1}^k \frac{n_i}{N_i} \quad (5.2)$$

where N_i is equal to the total number of cycles required until failure occurs at a specific loading condition i , n_i is the actual number of cycles (obtained from operational data) for the same loading condition and k is the total number of loading conditions. Failure occurs when $D = 1$. The WLRM in Figure 5.3 presents the damage number per cycle for a range of load conditions. The associated life times can be obtained by taking the inverse of this quantity.

5.2.2 Meta-model

Meta-models are approximation models which are used to describe complex models of physical and engineering systems in an efficient way by means of input and output parameters [20]. Computationally expensive calculations are basically replaced by meta-models that are constructed from a relevant set of data points that represent the actual behaviour of the system. This relevant set of data points is selected through experimental design methods such as Latin Hypercube Sampling [21]. Then the data points are used to construct the meta-models through the application of the Response Surface Methodology (RSM) [22]. RSM typically uses first and or second order polynomial functions. In this study, the second order polynomial function is applied [23]. An extensive description of the meta-model development process and the specified range for the input parameters can be found in previous work performed by Meghoo et al. [24] (see Chapter 3).

Figure 5.3: WLRM showing the RCF damage index as a function of the wear number for steel grade R260 and friction coefficient 0.3 [13].

There are eight input parameters in this study, including operational condition parameters like the vehicle speed, the axle load, the longitudinal and lateral stiffness of the primary suspension of the vehicle's bogie, track geometry parameters such as the rail cant, the vertical wear depth of the rail profile and the curve radius, and the environmental condition represented by the coefficient of friction. The output (response value) of the meta-model is the wear number, i.e. the load parameter that governs the head check initiation. In order to have sufficient degrees of freedom to fit the quadratic function, the minimum number of data points (e.g. simulations) for eight input parameters should be equal to 45, according to Cioppa [23]. Furthermore, as a rule of thumb, the minimum number of simulations should be equal to ten times the number of input parameters [21]. Therefore, 80 vehicle dynamic simulations have been performed to derive the meta-models. The multi-body dynamics software used in this study is VI-Rail [25]. The default template vehicle of the ERRI Wagon was used with either s1002 or HIT wheels (most commonly used wheels on Dutch trains) in their worn condition as explained in [26].

The accuracy and quality of the meta-models are assessed by two measures, namely the coefficient of determination R^2 and the Mean Squared Error (MSE):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5.3)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (5.4)$$

where n is the number of simulations, $\hat{y}_i$ is the value predicted by means of the fitted

meta-model, y_i is the (real) response value obtained from the simulation and $\bar{y}$ is equal to the mean of all y_i values.

5.2.3 Damage evaluation

Once the wear number is determined for each passing wheel (by using the meta-model), the damage index can be calculated by using the Palmgren-Miner rule given in Equation 5.2. This process is depicted in Figure 5.4 where three data sources are required, namely 1) the Quo Vadis data that provides information about the operational conditions, e.g. number of trains, number of wheels, type of train, velocity of each wheel and axle load, 2) the rail profile measurements data that provides the value for vertical wear depth of the rail profile and 3) the Geographic Information System (GIS) data which provides information about the track geometry, e.g. curve radius and rail inclination.

5.3 Data-driven head check evolution model

Using the method proposed in Section 5.2, the initiation of head checks in a specific track section can be predicted. However, the severity of the head checks (in terms of the crack depth) will increase over time. This section describes how the defect evolution model is developed. The aim is to achieve a model that represents the crack depth of the head checks as function of the traffic tonnage denoted by Mega Gross Tons (MGT). MGT is a unit of measurement representing the total weight of the trains that passed a specific track over a given period of time.

The crack depth data used to obtain the evolution model is retrieved from the US and EC measurements while the traffic tonnage information for the past ten years is provided by ProRail. An extensive description of both testing methods (US and EC) can be found in [12]. Furthermore, the EC measurement data is not only used for the defect evolution model, but also to validate the crack initiation model. These results will be presented in Section 5.5.

The crack depth growth of each individual head check is defined as the difference between the crack depth values of two consecutive measurements. Thereafter the MGT between these two consecutive measurements is obtained. For maintenance decision making purposes it is important to set a threshold for maintenance based on an absolute value rather than on damage increase. Therefore, the crack depth values of the measurements were plotted against MGT. However, for the initial measurement the MGT value is set to zero as the history of the track before the measurement period is unknown. For the second and all consecutive measurements the ΔMGT value is used. In this way a cumulative representation of the measurements is achieved which also reveals the importance of the initial crack depth. Finally, a regression model is fitted to this cloud of data.

Figure 5.4: Flowchart describing the head check prediction process [12].

Different crack growth scenarios are defined as different cracks can exhibit different crack growth rates depending on local material properties. Hence the different crack growth scenarios in a general way are defined as: $s = \{s_1, s_2, s_3, \dots, s_H\}$. Furthermore, different steps ($m = \{0, 1, 2, \dots, N - 1\}$) and the maintenance intervention ($\gamma(m)$) at step m are also defined [27]. Thus, the prediction model for the crack

growth of head check i at location x_i in track segment j can be expressed as:

$$d_i^s(m+1) = f^s(d_i^s(m), \gamma(m), M(m)), \quad x_i \in [x_j, x_{j+1}] \quad (5.5)$$

where $d_i^s(m+1)$ is an estimation of the crack depth of the head check i at the step $m+1$ considering scenario s and f^s is the fitted function (or regression model) for scenario s . It should be noted that the same initial condition applies for all different scenarios and all head checks:

$$d_i^{s1} = d_i^{s2} = \dots = d_i^{sH} \quad \text{for } m = 0 \quad (5.6)$$

Furthermore, the function f_s considers the effect of maintenance $\gamma(m)$ and the crack depth of the head check $d_i(m)$ at the previous step m , and $M(m)$ which is the total amount of MGT from step m to $m+1$. MGT is chosen instead of track geometry parameters, time and traffic (vehicle) type in order to develop a more generic model and it is already known by infrastructure managers. Each crack growth scenario with a given (constant) MGT gives a different evolution rate. The crack depth expression if no maintenance is performed becomes:

$$d_i^s(m+1) = f^s(d_i(m), M) \quad (5.7)$$

In this study three scenarios are utilized, where s_1 represents slow growth, s_2 average growth and s_3 fast growth. The average scenario corresponds to the fitted regression model and the slow and fast scenario correspond to the upper and lower bound of the fitted model which are determined with the 95% confidence bounds.

Furthermore, it is assumed that newly initiated head checks can occur anywhere within the rail section with a certain probability. The location and number of newly initiated head checks within this study are selected through a stochastic model based on field observations. This will further be elaborated in Section 5.4. The location of initiation is then within track segment j in the range of $[x_j, x_{j+1}]$.

Finally, from the maintenance point of view, monitoring the initiation and evolution of a single head check may not be practical. Railway track maintenance decisions are generally based on larger segments of the track rather than on single rail surface defects. Aggregated information about large segments can assist in the maintenance planning. This study proposes to represent the required information by means of KPIs, which will be further elaborated in the next subsection.

5.4 Health assessment

Due to the frequent occurrence of head checks at random locations, the initiation and evolution analysis of a single head check is not practical for asset management. Aggregated information of larger track segments facilitates rail maintenance decisions. If the IMs are able to monitor the number of defects evolving over a period of time

on a certain track segment, they can determine the health of the track. Besides the number of defects, the density of the defects (e.g. how close the defects occur from each other) is also an important aspect in determining the rail health [27]. Therefore, in the case of head checks, six types of KPIs are proposed. The first four KPIs consider the number of head checks on a specific track segment for four different crack depth severity levels (see Table 5.1) and the fifth and sixth KPIs are related to the density of head checks. The latter KPIs quantify the number of head checks per metre on a specific track segment, for all severity levels (fifth KPI) and for the heavy and severe defects only (sixth KPI).

5.4.1 KPIs for number of defects

Table 5.1 shows the crack depth severity classification of head checks in accordance with UIC Code 725 [11, 13]. The original severity classification is based on the surface crack length L but the classification in this study is defined in terms of the crack depth d . Therefore, the crack depth d is calculated as proposed by Dirks [17]:

$$d = L \sin \theta \quad (5.8)$$

According to the literature review performed by Dirks [17] cracks propagate at an angle θ between 15° and 30° . In this study an average angle θ of 22.5° for crack propagation is considered.

The KPIs expressing the number of head checks for severity level 1 to 4 (see Table 5.1) at segment j , step m , and scenario s can be expressed as:

$$y_{s,j}^{1,2,3,4}(m) = \sum_{x \in [x_j, x_{j+1}]} \delta_{s,j}^{1,2,3,4}(x, m) \quad (5.9)$$

where the function $\delta_{s,j}^{1,2,3,4}(x, m)$ is a binary equation that is equal to 1 when a head check with certain severity level at location x and step m exists for scenario s , otherwise it is equal to 0. Thus, by having this binary function, the corresponding KPI at each level of severity can be defined as $y_{s,j}^1(m)$ to $y_{s,j}^4(m)$.

Table 5.1: Severity classification of head checks.

Level	Defect severity	Description
1	Light (L)	Crack depth < 3.8 mm
2	Medium (M)	3.8 mm < Crack depth < 7.7 mm
3	Heavy (H)	7.7 mm < Crack depth < 11.4 mm
4	Severe (S)	Crack depth > 11.4 mm

5.4.2 KPIs for density of defects

A high potential safety risk for rails is not only caused by a high number of defects, but also depends on the location of defects, i.e. their space. Therefore, the aim of the KPIs for density are to see how densely rail defects (in this case head checks) are clustered so that infrastructure managers can decide not only based on defect severity and occurrence, but also in terms of defect closeness.

To estimate the density of the head checks two cases are considered: 1) for all severity levels $d_{s,j}^{LMHS}(x, m)$ and 2) for only heavy and severe defects $d_{s,j}^{HS}(x, m)$. The reason to consider two cases are the different choices IMs need to make with regard to the type of maintenance actions: a high density of heavy and severe defects may indicate track renewal whereas a high density of all severity levels does not necessarily have to indicate track renewal. In that case the rail can also be treated with grinding or milling to restore its effective rail condition.

For both cases, a window of 90 metres is defined around the coordinate x . Within this window the number of head checks is determined. Thereafter the window moves to the next 90 metres of the rail and the same process is repeated. Hence, the density function $d_{s,j}^{LMHS}(x, m)$ or $d_{s,j}^{HS}(x, m)$ equals the total number of head checks with different crack depth severity in the moving window within the range of $[x - 0.045, x + 0.045]$ km. Thus, the fifth and sixth KPI that consider the density of the defects per metre, for segment j , step m , and scenario s can be defined as follows:

$$y_{s,j}^5(m) = \frac{\sum_{x \in [x_j, x_{j+1}]} d_{s,j}^{LMHS}(x, m)}{x_{j+1} - x_j} \quad (5.10)$$

$$y_{s,j}^6(m) = \frac{\sum_{x \in [x_j, x_{j+1}]} d_{s,j}^{HS}(x, m)}{x_{j+1} - x_j} \quad (5.11)$$

In order not only to find the least healthy segment but also wants to monitor the segment locally, an additional KPI can be introduced which is defined as the ratio between the maximum density (determined from all moving windows) and the length of the segment. Furthermore, a global KPI can also be introduced as suggested by [Jamshidi et al. \[27\]](#), which takes both KPI types into account, namely KPI for numbers and KPI for density.

5.4.3 Stochastic KPIs

The previously defined KPIs for the number and density of defects are for the deterministic case. However, as mentioned before the crack initiation modeling is incomplete without a stochastic model. Although the crack initiation model predicts the occurrence of head checks, it is not capable of predicting the number of initiated head checks and their locations. Therefore, field observation data is used from which

stochastic models are developed. The histograms for the number of head checks and their locations obtained from field data are plotted in Figure 5.5. The relative position in a curve (x -axis of Figure 5.5b) is defined as the distance to the defect divided by the length of a curve track.

Figure 5.5: Number and location of initiated head checks derived from EC measurements.

After using the deterministic model to determine whether or not head checks occur in a specific track section (curve), the number of new head checks is determined with the stochastic model by performing N Monte Carlo (MC) simulations. Each MC simulation randomly generates a value such that it fits the user defined probability density function as depicted in Figure 5.5a. Thereafter, for each head check the location on the track is determined by again generating a random value for the relative position in the curve, using the probability density function depicted in Figure 5.5b.

In summary, MC simulations are carried out to predict a range of N possibilities based on both histograms depicted in Figure 5.5 and then the results of the N simulations are utilized to calculate the probability distributions of the six KPIs as defined in the previous subsections. Finally, the results of the KPIs are presented in box plots to conveniently examine the evolving KPIs, which are important for the health assessment of the rail.

5.5 Results and discussion

As depicted in Figure 5.2, the proposed method consists of three steps from prediction of crack initiation to health assessment. The results and discussion for each of those steps are presented in this section.

5.5.1 Hit rate and accuracy of meta-models for crack initiation

Three different meta-models for crack initiation for three coefficient of friction (cof) ranges were derived from a total of 200 simulations performed by Meghoo et al. [24]. The coefficient of friction used in this study for the head check evaluation is 0.3, which is the average friction condition on Dutch railway tracks [28]. Therefore, the meta-models in the cof range of 0.15 to 0.3, for wheels s1002 and HIT (both in their worn condition), are considered. The numerical validation of the meta-models has already been performed by Meghoo et al. [24] and a good agreement was found.

Besides the numerical validation, the meta-models were also validated with real track data from EC measurements in this study. A total of 22 case studies were carried out, see Table 5.2. Each case study is defined as a track section with a certain curve radius and rail inclination, where the outer rail of the track has a certain measured rail profile characterized by the vertical wear depth and the track experiences a certain amount of traffic expressed in MGT. For each case study, the crack initiation prediction according to the process depicted in Figure 5.4 is performed and the results are compared with EC measurements. For example, if the calculated damage index for a case study is larger than or equal to 1 ($D \geq 1$), head check initiation is predicted and crack occurrence on the track is expected. If the EC measurements confirm the existence of cracks on the piece of track considered for the case study, the prediction is considered to yield a hit, otherwise it is denoted a miss.

From the results presented in Table 5.2 it can be concluded that the damage indices for tracks with a large curve radius (e.g. $R = 1600$ m) are smaller than those for tracks with a small curve radius (e.g. $R = 1431$ m) when experiencing the same amount of traffic. Hence, damage index $D = 1$, which indicates failure (i.e. crack initiation), is achieved earlier for a track with smaller curve radius than for a track with larger curve radius. Furthermore, it can be observed that for the 22 case studies only five did not result in a hit. The latter are considered as false positives, e.g. the model yielded a damage index $D > 1$, but no defects were registered during the EC measurements. This is most probably due to maintenance activities such as grinding, which are not taken into account in the model.

5.5.2 Evolution model

In order to derive the data-driven evolution model for crack depth growth as a function of MGT, US and EC measurement data, and traffic tonnage data from 2012 until 2018 over the entire Dutch rail network are used. The obtained data points are plotted in Figure 5.6. In this figure two main groups of data points can be seen. The lower group with crack depth < 5 mm contains data points from the EC measurements and the upper group with crack depth > 5 mm is from the US measurements. The current distribution of the data points in Figure 5.6 does not allow an accurate regression model to be fitted for the crack depth growth. Thus the data is rearranged and the outliers are removed.

Table 5.2: Hit rate results for crack initiation model.

Case study	Curve radius [m]	Vertical wear depth [mm]	Rail cant [mm]	Total MGT	Total damage index D	hit/miss
1	1500	1.3	100	16.03	2.83	hit
2	1500	1.3	100	28.81	5.52	hit
3	1500	1.3	100	15.85	2.41	hit
4	1504	3.2	105	16.35	2.40	hit
5	1504	2.4	105	29.84	5.72	hit
6	1504	2.7	105	16.20	2.42	miss
7	1431	3.2	90	19.70	2.81	hit
8	1600	5.6	90	19.70	2.65	hit
9	2013	5.6	60	19.70	1.11	hit
10	2092	6.0	60	19.70	0.98	hit
11	1431	3.2	90	27.08	3.39	miss
12	1600	5.6	90	27.08	3.02	miss
13	2013	5.6	60	27.08	0.63	hit
14	2092	6.0	60	27.08	0.50	hit
15	1435	3.2	90	19.79	3.03	hit
16	1603	5.6	90	19.79	2.73	hit
17	2005	5.6	60	19.79	1.02	hit
18	2100	6.0	60	19.79	0.96	hit
19	1435	3.2	90	27.63	3.40	miss
20	1603	5.6	90	27.63	2.75	miss
21	2005	5.6	60	27.63	0.25	hit
22	2100	6.0	60	27.63	0.16	hit

First, all data points with $MGT < 1$ are removed, because crack initiation takes place prior to crack growth and the amount of MGT required to initiate a crack is larger than 1 MGT. According to Figure 5.3 the minimum number of cycles required for crack initiation at its earliest is equal to 100,000 for a wear number of 65 N. Furthermore, the minimum and maximum axle load according to [24] are 9.4 and 26.67 tons respectively. Therefore, crack growth is assumed to take place only beyond 1 MGT ($\approx 100\,000$ cycles $\times$ 9.4 ton).

Thereafter, the outliers in this data set are removed with the quantile method [29]. The quantile technique splits the data set into subsets with equal probabilities (in this case 100 subsets) and then determines the values, also called the quantiles (or percentiles in this case), that separate (i.e. are exactly in between) two subsets. The 99 quantiles of the data set obtained are plotted in Figure 5.7.

To have a robust model which can be applicable in practice, it is important to capture the mechanical nature of the crack growth. According to Jamshidi et al. [9], RCF defects can be defined in three stages of growth: crack development occurs faster at the early stage and last stage than the middle stage. In the latter stage the defect is neither light (only in the early stage) nor severe. Therefore, a cubic polynomial

Figure 5.6: Field data for crack depth of head checks versus accumulated MGT.

Figure 5.7: Head checks evolution model derived from quantiles of field data, showing three scenarios: s_1 , s_2 and s_3 .

equation is fitted to the obtained data points in order to describe the crack growth as observed by [Jamshidi et al. 2017](#). The obtained fit with 95% prediction bounds is depicted in Figure 5.7. Although this plot contains the lengths of many different cracks at different locations and different stages of growth, the obtained relation between accumulated MGT and crack length is assumed to be typical for any head check. Therefore, the curve can also be used as a crack evolution model, as the expected crack length increase between, for example, $\text{MGT} = 5$ and $\text{MGT} = 10$ can be retrieved easily from the plot. In Figure 5.7, the fitted model is considered as the average crack growth scenario (s_2) and the prediction bounds as the slow (s_1) and fast growth scenario (s_3) respectively.

Figure 5.8 depicts the results obtained with the proposed crack initiation and evolution model for the case study considering the route between the cities Weesp and Almere. The track starts at Km 2.40 and ends at Km 11.43. Furthermore, the track is segmented in straight, transition and curved sections, see Table 5.3. Therefore, for the Weesp-Almere track head checks are predicted only for the curved sections.

Figure 5.8: Head checks initiation and evolution model implemented for the Weesp-Almere route considering scenario s_2 and six consecutive MGT steps ($m = 0 - 5$).

From Figure 5.8 it can be seen when new cracks are initiated and how the existing cracks grow. The step $m = 0$ corresponds with the initial EC measurement. Hence, the first subplot shows the measured crack depths of the detected head checks versus the position (in km). From this subplot it can be seen that some cracks occur over a greater length (this is the measured cluster of head checks) and are plotted as blocks in Figure 5.8. As mentioned in Section 5.1 the proposed initiation model predicts single head checks instead of clusters. Therefore, the horizontal length of the predicted cracks in Figure 5.8 do not vary.

Table 5.3: Segmentation of the Weesp-Almere track.

Segment	Km from	Km to	Type	Curve radius [m]
1	2.40	2.49	straight	-
2	2.49	2.67	transition	-
3	2.67	3.61	curve	1500
4	3.61	3.79	transition	-
5	3.79	4.22	straight	-
6	4.22	4.32	transition	-
7	4.32	4.60	curve	3970
8	4.60	5.06	curve	4029
9	5.06	5.84	curve	3704
10	5.84	6.18	curve	3688
11	6.18	6.46	curve	3718
12	6.46	6.69	curve	3687
13	6.69	6.78	transition	-
14	6.78	7.17	straight	-
15	7.17	7.32	transition	-
16	7.32	8.51	curve	1802
17	8.51	8.66	transition	-
18	8.66	8.90	straight	-
19	8.90	9.06	transition	-
20	9.06	10.86	curve	2498
21	10.86	11.02	transition	-
22	11.02	11.42	straight	-
23	11.42	11.43	straight	-
24	11.43	11.82	straight	-

Thereafter the evolution of these existing head checks is predicted by means of the evolution model and then the newly initiated cracks are calculated over a fixed step of $\Delta M = 4.57$ MGT. It should be noted that the initiation model is applicable only to curved sections with curve radius between 1000 and 4000 metres. Furthermore, the number and location of the initiated cracks in each segment are determined with the stochastic model presented in Subsection 5.4.3.

Figure 5.8 shows that the crack depth of the measured head checks at $m = 0$ increased from a minimum of 0.5 mm to 3.8 mm in only one step, which is quite unusual. However, this can be explained simply from the difference in daily tonnage between the considered track and the average track in the Netherlands. Figure 5.9 shows a histogram of the daily tonnage in 2018 over the entire Dutch rail network. The Weesp-Almere track experiences 0.05 MGT of traffic on a daily basis, whereas the most common daily MGT is around 0.015 MGT. This explains why the evolution model depicted in Figure 5.7 predicts a rather large crack depth increase in only one

step. In the subsequent steps the crack depth increase is slower, because after the second step the crack enters the middle stage of the crack growth and as mentioned before (see Figure 5.7) the increase is slower here.

Figure 5.9: Histogram of the average daily traffic data in 2018 for the entire Dutch rail network.

5.5.3 KPI results

In order to perform a health assessment of the rail, a list of KPIs is proposed to study different characteristics of the problem. Two groups of KPIs were defined, namely the KPIs for the number of head checks and the KPIs for the density of the head checks. Figure 5.10 shows the bar plot for the first group of KPIs considering different severity levels in segment 3 of the Weesp-Almere track. This figure shows how new head checks are initiated over six steps and how for example light and medium defects grow into heavy and severe defects. The bar plot in Figure 5.10 is basically derived from segment 3 in Figure 5.8 where the crack depth predictions are plotted. The KPIs for the number of defects quantify the results from this figure.

However, as mentioned before the crack initiation model does not consider the uncertainty in the number of head checks initiated or their corresponding locations. Therefore, the prediction process is repeated in 100 MC simulations and the distribution of the KPI for the light defects is plotted in Figure 5.11. These box plots

represent the results for the 100 MC simulations after each step, where the red line represents the average value, the blue box shows the 75% confidence region and the dashed line shows the min and max value. It can be seen how the predicted number of new defects varies between one and four according to the probability distribution given in Figure 5.5a. Furthermore, the probability for the number of initiated head checks can be derived from the box plots. For example for $m = 3$ the minimum number of head checks to be initiated is equal to one and the maximum is equal to four, while the median is equal to three and for 75% of the cases the number of initiated head checks is two or three. Furthermore, for $m = 1$ and $m = 2$ no boxes are plotted as the number of initiated head checks is equal to two and zero respectively for all 100 MC simulations. The advantage of using the box plots is that these plots account for the uncertainty in the output that is required for maintenance decision planning and risk analysis.

Figure 5.10: KPIs for number of head checks in segment 3 and for scenario s_2 .

5.6 Conclusion

The objective of this study was to develop a hybrid prediction method that can be used for maintenance and inspection planning. Meta-models for the prediction of head check initiation and an evolution model for head check size were proposed. The

Figure 5.11: KPI distribution for number of head checks (severity level: Light) in segment 3 and for scenario s_2 , obtained from 100 MC simulations.

advantage of using meta-models is the reduction in computation time and convenience in implementation by IMs. The validity of the obtained meta-models was proved in two ways, namely numerically and practically. From the hit rate results it could be concluded that the predicted probability of head check initiation using meta-models corresponded rather well to the EC measurements.

The main challenge for the evolution model was the large amount of outliers in the data set obtained from EC and US measurements, which was then solved by using the quantile technique. Thereafter, the prediction model was implemented on a real track in the Netherlands and the results demonstrated the capability of the prediction model in combination with the proposed KPIs for number of defects. Even though the hybrid method could not be validated, the useful numbers obtained after implementation of the method for the case study Weesp-Almere already gives confidence in the proposed method. However, it is recommended to validate the hybrid method and the use of KPIs by collecting a large amount of data and performing consecutive measurements.

Furthermore, for newly initiated cracks the number of cracks and the specific location of crack initiation can not be determined deterministic by using the meta-models. This is identified as a limitation of the initiation model and the problem was solved by adding a stochastic model.

References

- [1] A. Jamshidi, S. Faghih Roohi, A. Núñez, R. Babuska, B. De Schutter, R. Dollevoet, and Z. Li. Probabilistic defect-based risk assessment approach for rail failures in railway infrastructure. In *Proceedings of 4th IFAC Symposium on Control in Transportation Systems (CTS)*, 2016.
- [2] Arjen Zoeteman, Rolf Dollevoet, and Zili Li. Dutch research results on wheel/rail interface management: 2001–2013 and beyond. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 228(6):642–651, 2014. doi: 10.1177/0954409714524379.
- [3] Xiang Liu, Christopher P. L. Barkan, and M. Rapik Saat. Analysis of derailments by accident cause: Evaluating railroad track upgrades to reduce transportation risk. *Transportation Research Record*, 2261(1):178–185, 2011. doi: 10.3141/2261-21.
- [4] E Jafarian and M A Rezvani. Application of fuzzy fault tree analysis for evaluation of railway safety risks: an evaluation of root causes for passenger train derailment. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, 226(1):14–25, 2012. doi: 10.1177/0954409711403678.
- [5] Dewan Md Zahurul Islam, Konstantina Laparidou, and Arnaud Burgess. Cost effective future derailment mitigation techniques for rail freight traffic management in Europe. *Transportation Research Part C: Emerging Technologies*, 70: 185–196, 2016. ISSN 0968-090X. doi: 10.1016/j.trc.2015.06.017.
- [6] Y. Fan, S. Dixon, R. S. Edwards, and X. Jian. Ultrasonic surface wave propagation and interaction with surface defects on rail track head. *NDT and E International*, 40(6):471–477, 2007. doi: 10.1016/j.ndteint.2007.01.008.
- [7] Zenglu Song, Tsutomu Yamada, Hideki Shitara, and Yasushi Takemura. Detection of damage and crack in railhead by using eddy current testing. *Journal of Electromagnetic Analysis and Applications*, 3(12):546–550, 2011. doi: 10.4236/jemaa.2011.312082.
- [8] M. Molodova, Z. Li, and A. Núñez. Automatic detection of squats in railway infrastructure. *IEEE transactions on intelligent transportation systems*, 15(5), 2014.
- [9] Ali Jamshidi, Shahrzad Faghih-Roohi, Siamak Hajizadeh, Alfredo Núñez, Robert Babuska, Rolf Dollevoet, Zili Li, and Bart De Schutter. A big data analysis approach for rail failure risk assessment. *Risk Analysis*, 37(8):1495–1507, 2017. doi: 10.1111/risa.12836.

- [10] Stefano Mariani, Thompson V. Nguyen, Xuan Zhu, Simone Sternini, Francesco Lanza di Scalea, Mahmood Fateh, and Robert Wilson. Non-contact ultrasonic guided wave inspection of rails: Next generation approach. (49675): V001T06A011, 2016. doi: 10.1115/JRC2016-5771.
- [11] Zdenka Popović, Luka Lazarević, Ljiljana Brajović, and Milica Vilotijević. The importance of rail inspections in the urban area -aspect of head checking rail defects. *Procedia Engineering*, 117:596–608, 2015. ISSN 1877-7058. doi: 10.1016/j.proeng.2015.08.220.
- [12] A. Meghoe, A. Jamshidi, R. Loendersloot, and T. Tinga. Towards the development of a hybrid methodology for monitoring of head checks in railway infrastructure. In *15th International Conference on Railway Engineering*, 2019.
- [13] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Thesis, 2010.
- [14] H. Grohmann and W. Schoech. Contact geometry and surface fatigue—minimizing the risk of headcheck formation. *Wear*, 253:54–59, 2002.
- [15] M. C. Burstow. Whole life rail model application and development: Development of a rolling contact fatigue damage parameter. Technical report, RSSB, 2003.
- [16] A. Meghoe, R. Loendersloot, and T. Tinga. Generic rail damage function based on physical models. *Wear*, under review, 2019.
- [17] Babette Dirks. *Simulation and measurement of wheel on rail fatigue and wear*. Phd thesis, 2015.
- [18] B. Trolle, M. C. Baietto, A. Gravouil, S. H. Mai, and B. Prabel. 2d fatigue crack propagation in rails taking into account actual plastic stresses. *Engineering Fracture Mechanics*, 123:163–181, 2014. ISSN 0013-7944. doi: 10.1016/j.engfracmech.2014.03.020.
- [19] W. Daves, M. Krácalík, and S. Scheriau. Analysis of crack growth under rolling-sliding contact. *International Journal of Fatigue*, 121:63–72, 2019. ISSN 0142-1123. doi: 10.1016/j.ijfatigue.2018.12.006.
- [20] Tushar Goel, Raphael T. Haftka, Wei Shyy, and Nestor V. Queipo. Ensemble of surrogates. *Structural and Multidisciplinary Optimization*, 33(3):199–216, 2007. doi: 10.1007/s00158-006-0051-9.
- [21] A. I. J. Forrester, A. Sóbester, and A. J. Keane. *Engineering design via surrogate modelling*. John Wiley and Sons Ltd., West Sussex, United Kingdom, first edition, 2008. ISBN 978-0-470-06068.

- [22] H. Fang, M. Rais-Rohani, Z. Liu, and M. F. Horstemeyer. A comparative study of metamodeling methods for multiobjective crashworthiness optimization. *Computers and Structures*, 83(25):2121–2136, 2005. ISSN 0045-7949. doi: 10.1016/j.compstruc.2005.02.025.
- [23] T.M. Cioppa. Efficient nearly orthogonal and space-filling latin hypercubes. *Technometrics*, 49:45–55, 2007.
- [24] A. Meghoe, R. Loendersloot, and T. Tinga. Rail wear and remaining life prediction using meta-models. *International Journal of Rail Transportation*, pages 1–26, 2019. ISSN 2324-8378/2324-8386. doi: 10.1080/23248378.2019.1621780.
- [25] VI-Rail. Vi-rail17.0 documentation. Technical report, VI-grade, 2016.
- [26] A. Meghoe, R. Loendersloot, R. Bosman, and T. Tinga. Rail wear estimation for predictive maintenance: a strategic approach. In *European Conference of the Prognostics and Health Management Society 2018*, 2018.
- [27] A. Jamshidi, A. Núñez, R. Dollevoet, and Li Z. Robust and predictive fuzzy key performance indicators for condition-based treatment of squats in railway infrastructures. *Journal of Infrastructure Systems*, 23(3):04017006, 2017. doi: 10.1061/(ASCE)IS.1943-555X.0000357.
- [28] M. Hiensch and M. Steenbergen. Rolling contact fatigue on premium rail grades: Damage function development from field data. *Wear*, 394:187–194, 2018. ISSN 0043-1648. doi: 10.1016/j.wear.2017.10.018.
- [29] Roger Koenker. *Quantile Regression*. Econometric Society Monographs. Cambridge University Press, Cambridge, 2005. ISBN 9780521845731. doi: 10.1017/CBO9780511754098.

Chapter 6

Evaluation of rail wear prediction uncertainty for maintenance decision support

1

Abstract

Rail wear management based on accurate rail wear prediction is the ultimate wish of rail infrastructure managers. Several rail wear prediction models can be found in literature. However, the implementation of these models in maintenance decision tools is not yet available due to detailed modelling and the absence of direct coupling with operational conditions. A wear prediction model previously developed in Chapter 3 which addresses these shortcomings has been implemented in the current study. The limitation of this model is that it is deterministic. The uncertainty in the output of the model needs to be quantified before it can be utilized for maintenance decision support. This will ease the work of maintenance decision makers as it provides them with possible outcomes of rail wear. This is realized by considering probability density functions for the input parameters in both numerical and analytical analyses. The results obtained from these analyses are then compared with field measurements and the mean values for the amount of wear removal are relatively close but the variance is rather large.

---

¹This chapter is based on: Meghoe, A., Loendersloot, R. and Tinga, T. (2019). Evaluation of rail wear prediction uncertainty for maintenance decision support. (in preparation)

6.1 Introduction

From literature and maintenance experience it is reasonable to state that the Remaining Useful Life (RUL) of tracks is determined mostly by the wear and Rolling Contact Fatigue (RCF) mechanisms [1–3]. Track replacement of a wear dominated track takes place when the amount of material removed from the rail exceeds a certain critical value and the RUL is equal to zero. Accurate prediction of this amount of wear and determination of the RUL by taking into account the varying operating conditions has the potential to improve the maintenance planning considerably and reduce the maintenance costs. Therefore, an accurate wear prediction model is required for maintenance decision support. In Chapter 3 an efficient wear prediction model is developed by replacing the time-consuming vehicle dynamic simulations with meta-models. However, these models are deterministic and in order to utilize them for maintenance decision support the uncertainty in their outcome needs to be taken into account.

Maintenance decision support tools assist infrastructure managers in assessing the impact of varying operating and environmental conditions on the system and in optimizing maintenance planning. By assessing the magnitude of the model parameter uncertainties, the prediction model can provide possible outcomes for the amount of material removed due to wear. Uncertainty is often represented by probability distribution functions (pdfs) which show the likelihood of each possible outcome [5]. Therefore, stochastic models based on these pdfs are very common to evaluate uncertainty propagation in black-box functions like meta-models [6]. The uncertainty propagation analysis is thus used here to study the influence of input uncertainty on the model output (response) variation. During this study it is further noticed that the problem is not directly solved by using pdfs: the efficiency of the numerical or analytical models should also be taken into account by reducing the number of evaluations without loss of accuracy (see Subsection 6.2.2).

Uncertainty analyses have been performed in various scientific research fields from healthcare [7] and environmental modelling [5] to engineering design [6, 8] and maintenance modelling [9]. Over the past decades, several uncertainty analysis methods have been developed [10]. These methods include perturbation methods using Taylor-series expansions, Monte Carlo (MC) methods and analytical methods using integrals and tensor product basis functions. The approximation with Taylor-series expansions predicts the mean and variance of the model response and is used frequently due to its simplicity [11], but this method is not sufficiently accurate for nonlinear response functions when the uncertainty in the input parameter is large [12]. On the other hand the MC method is able to handle both linear and non-linear models. Hills and Trucano [13] concluded that the MC method is a robust method when considering highly nonlinear models. However, the disadvantage is that the results are not always reproducible, fast and accurate. The computational expense can nevertheless be reduced when MC is used together with meta-models. Finally, for non-complex models that are represented by well-established meta-models such as polynomials, Kriging,

Radial Basis Function, etc., the analytical approach is suitable [14].

The objective of this chapter is to include the model parameter uncertainties in the wear prediction model in order to obtain a robust model which can be included in railway maintenance decision support tools. The uncertainty propagation in the wear prediction model is thus calculated using first the numerical and then the analytical approach. The next section will first illustrate the use of the sensitivity analysis (see Subsection 6.2.1) for determining the necessity to use probability density functions for the model parameters, followed by the uncertainty propagation using the MC method (Subsection 6.2.2). The uncertainty calculation process can become very time consuming if a large number of evaluations are required. Hence, in this subsection it is also shown how to improve computational efficiency without accuracy loss. Thereafter, the formulations for the analytical approach are presented in Subsection 6.2.3 and the case studies along with the utilized measurement equipment are discussed in Subsection 6.2.4. Finally, the obtained probability density function for the response using both the numerical and analytical approach is compared with field measurement data in Section 6.3 and conclusions are put forward in Section 6.4.

6.2 Methodology

In order to test the accuracy of prediction models the results of the predictions are compared with field measurements. Good agreement between the predicted results and the field data is found when the measured value is within the confidence bounds of the predicted results. The confidence bound is derived from the uncertainty in the predicted (response) value, which is obtained by considering stochastic input parameters. Both an analytical and a numerical approach can be adopted to predict the uncertainty in the response due to uncertainty in the input parameters. This section presents the formulations needed for both methods. But first the sensitivity analysis is discussed, as this step is essential in order to distinguish between the random and absolute input parameters, which can considerably reduce the computational effort. Finally, the case studies for the field measurements used to validate the wear model are introduced.

6.2.1 Sensitivity analysis

Typically, a sensitivity analysis should be performed prior to an uncertainty propagation analysis. In this way the number of random variables can be reduced, making the analysis time significantly shorter, since the computational efficiency depends on the number of random variables. The result of this analysis is thus used to determine which input parameters should be taken into account as random variables and which as absolute variables. The scatter in the input parameters of the first group is then represented by their probability distribution functions (pdfs).

The sensitivity analysis can be performed with rough approximations or simple pdfs e.g. uniform or normal distributions. In this step, accurate distributions are not strictly necessary, as the only objective is to determine the relative sensitivities, i.e. ranking the random variables according to their significance. Sensitivity indices and correlation coefficients are then determined in order to denote the most dominant input parameters.

First, the sensitivity index S_i is calculated from two analyses per input parameter i to determine its individual sensitivity factor [15]:

$$S_i = \frac{y_{max,i} - y_{min,i}}{y_{max,i}} \quad (i = 1, \dots, k) \quad (6.1)$$

where $y_{min,i}$ and $y_{max,i}$ represent the response values for each of the k parameters at their minimum and maximum setting, respectively.

Next, N different MC simulations are performed to determine the Pearson correlation coefficients, which are suitable when both the input parameter and the response value are normally distributed. The N different simulations are performed with different parameter settings such that each parameter has N different values. Then, the Pearson correlation for parameter x is calculated as [16]:

$$\rho_i(x, y) = \frac{\sum_{i=1}^N (x_i - \bar{x}) \sum_{i=1}^N (y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (6.2)$$

where x_i is the i^{th} value (out of N) of input parameter x , $\bar{x}$ is the average of the input parameter vector, y_i is the response value at the i^{th} simulation and $\bar{y}$ is the average of the response value.

The value of the correlation coefficient is between -1 and +1, where a correlation coefficient of 0 indicates that no correlation exists and a strong correlation is represented by a relatively high (absolute) value for the correlation coefficient, i.e. close to ± 1 . A high correlation indicates that an input parameter is important and has to be taken into account as a random variable.

The minimum and maximum value for each input parameter of the wear prediction model and the mean and variance of the normally distributed pdfs used to calculate the correlation coefficients are shown in Table 6.1. The input parameters given in this table have been selected through a One Factor At a Time (OFAT) method [4] for a generalized wear prediction model.

In this study the wear prediction is focused on a certain track, hence some of the parameters are exactly known and therefore fixed. For example the curve radius is known from the track geometry, and the vehicle velocity and the axle load are measured by a system developed by ProRail and Nedtrain, named Quo Vadis. Therefore, no distribution is provided for these three input parameters and they are considered as absolute variables (as demonstrated by a 0 standard deviation in Table 6.1). The

Table 6.1: Input parameters and their distributions.

Input parameters	Min	Max	Normal distr. SA ¹		Normal distr. NA ²		Unit
			Mean	Std	Mean	Std	
Vertical wear depth (initial value)	0	12	6	2	1.15	0.58	[mm]
Curve radius	1500	1500	1500	0	1500	0	[m]
Rail cant	90	110	100	3	100	3	[mm]
Friction coefficient	0.02	0.6	0.3	0.1	0.14	0.08	[-]
Vehicle velocity	33.33	33.33	33.33	0	QV data	QV data	[m/s]
Axle load	15	15	15	0	QV data	QV data	[ton]
Longitudinal stiffness	2.56×10^5	4×10^7	2×10^7	8×10^6	2×10^7	8×10^6	[N/m]
Lateral stiffness	2.56×10^5	4×10^7	2×10^7	8×10^6	2×10^7	8×10^6	[N/m]
Hardness	260	340	289	14.45	308	48	[HB]

¹ SA: Sensitivity Analysis² NA: Numerical Analysis

Quo Vadis system can also determine the passing vehicle type based on axle spacing, speed and length. One would expect that, thanks to the information about the vehicle type, the longitudinal and lateral stiffness of the primary suspension of the bogie are known and therefore it is redundant to include the pdf for these two parameters. However, the information could not be retrieved for all vehicle types and therefore for those vehicle types a pdf is used. For the remaining parameters a normal distribution is chosen such that the range between the minimum and maximum values is covered to the greatest possible extent.

6.2.2 Numerical uncertainty propagation analysis

For the numerical approach of the uncertainty propagation analysis the MC method is used to evaluate the wear prediction model. As stated before, the wear prediction model developed in Chapter 3 is utilized in this study. This model is in the form of a second order polynomial and is defined as follows:

$$y(\mathbf{x}) = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{k+i} x_i^2 + \sum_{i=1}^{k-1} \sum_{j>i}^k \beta_{i,j} x_i x_j \quad (6.3)$$

where y is the wear area in [mm²], x_i are the various input parameters and β_i are the model parameters or regression coefficients as given in Table 3.C.1.

The uncertainty in the input parameters is represented by pdfs (see Table 6.1), which have been derived from histograms of measurement data. These measurements are performed at random locations of a specific track (in this case the part of the track with curve radius $R = 1500$ metres which will be further denoted as the curved track), for general validity. The histogram for the vertical wear depth as obtained from the rail profile measured by a measurement train is depicted in Figure 6.1a.

The measured vertical wear depth is used to characterize the initial rail profile which influences the rail wear [4]. Furthermore, the histogram for the hardness was created from measurements taken by using a portable hardness tester, at random locations on the curved track, see Figure 6.1b. At each location three measurements were taken, one close to the running surface, one close to the gauge and one between these two points, and then the average value was taken as representative of the hardness at that specific location. Finally, the histogram for the friction coefficient is taken from [17], see Figure 6.1c. Popovici [17] measured the friction on Dutch railway tracks for a period of three months (mainly in autumn) at three different locations by means of a tribometer mounted on a vehicle bogie.

Figure 6.1: Histograms for stochastic input parameters.

As no measurements were performed for the rail cant a normal distribution was chosen based on expert knowledge with a mean of 100 mm and a standard deviation of 3 mm. Finally, for the vehicle types of which the stiffness values were unknown a uniform distribution is assumed for both the longitudinal and the lateral stiffness with lower and upper bound as given in Table 6.1. It should be noted that the pdfs for the input parameters in the numerical analysis differ from the pdfs used in the sensitivity analysis, because the goal of the sensitivity analysis was to evaluate all possible scenarios whereas the numerical analysis is for a specific case study.

In the ideal case a wear prediction is obtained by evaluating the second order polynomial in Equation 6.3 for each passing wheel. In total 12 wear prediction models (each with its own set of model parameters β , see Equation 6.3) are available: for two different wheel types, for three friction coefficient ranges and for each range the distinction between mild and severe wear. Hence, for a single wear prediction (i.e. for one passing wheel) the steps as depicted in Figure 6.2 should be followed [4].

However, in order to have significant wear on moderately curved tracks, e.g. on tracks with a curve radius larger than 1000 metres, about 1 million wheels need to pass the rail. The calculation would then take hours of computation time and including the randomness in the input parameters would even further increase the computational effort. Evaluating the 1 million wheels only (without considering the input parameters as random variables) results in one million evaluations of the process

Figure 6.2: Wear prediction process.

depicted in Figure 6.2. Thus, by considering the pdfs of the input parameters for each passing wheel, a Monte Carlo simulation with N samples would require N million evaluations. Therefore, the number of evaluations will be reduced from 1 million to 40. Instead of considering each wheel passage as a single event, 40 clusters of events are defined, based on the type of wheel, type of train and axle load. In this way the total number of evaluations is reduced from $1.10^6 \times N$ to $40 \times N$, see Figure 6.3. The damage in each of the 40 clusters is then obtained by multiplying the calculated wear depth by the number of wheel passings in that specific cluster.

Furthermore, from the case studies it was concluded that the vehicle velocity did not vary much for the 1 million wheels and it is therefore assumed to be a constant. This also reduced the computation time. Finally, the resulting uncertainty in the wear model prediction is calculated using the following steps, which are also presented in Figure 6.3:

1. Split the set of wheel passages based on the wheel type. In this case two groups are created: wheel types s1002 and HIT, both in worn condition.
2. For each wheel type split the data set into known and unknown longitudinal and lateral stiffness values. This yields two groups for each wheel type i.e. known stiffness and unknown stiffness.
3. Split the data in each of the four groups into ten bins (or clusters) based on the axle load, which results in a total of 40 bins. Determine the number of wheel passings in each bin.

4. For each bin, sample the input parameter distribution functions N times using the MC method, and based on the combination of the input parameters define N input vectors with values for the k parameters.
5. Follow the process in Figure 6.2 for each input vector in each bin. This process ultimately yields the probability density function for the wear area for each bin. Thereafter, scale the obtained pdf of the specific bin with the number of wheels in that bin.
6. Finally, accumulate all the results (i.e. pdfs) from the 40 bins in order to obtain the total response value, which in this case is the wear area pdf.

The results obtained from following these steps were compared with the detailed method of evaluating all 1 million wheels individually and the difference was 7.3%. The proposed method of clustering the wheel passages is thus considered to be an acceptable way to reduce computational efforts.

Figure 6.3: Reduction of number of wear evaluations.

6.2.3 Analytical uncertainty propagation analysis

In the analytical approach of the uncertainty propagation analysis the mean and standard deviation of the response are calculated [8]. This approach assumes the response to be normally distributed. Furthermore, the input parameters should also be given as a mean and standard deviation. Therefore, the mean and standard deviation of

the actual distributions for the vertical wear depth, the hardness and the friction coefficient given in Figure 6.1a to 6.1c, respectively, were calculated to approximate these pdfs as normal distributions (see Table 6.1).

Given a response $y = f(\mathbf{x})$ with $\mathbf{x}$ being the vector with all input parameters (which can be either stochastic or deterministic) and $\mathbf{z}$ being the vector with only the stochastic input parameters such that $\mathbf{z} \in \mathbf{R}$, the mean (μ) and variance (σ^2) of the response are defined as [8]:

$$\mu(\mathbf{x}) = \int f(\mathbf{x})p(\mathbf{z})d\mathbf{z} \quad (6.4)$$

$$\sigma^2(\mathbf{x}) = \int [f(\mathbf{x}) - \mu(\mathbf{x})]^2 p(\mathbf{z})d\mathbf{z} \quad (6.5)$$

where $p(\mathbf{z})$ is the probability distribution function of the stochastic input parameters.

Based on the concept of tensor product basis functions the formulations for uncertainty propagation for a second order polynomial meta-model and normally distributed input parameters are as follows [8]:

$$\begin{aligned} \mu(\mathbf{x}) = & \beta_0 + \sum_{i \in \mathbf{R}} \beta_i \mu_i + \sum_{i \in \mathbf{R}} \beta_{ii} \sigma_i^2 + \sum_{i \in \mathbf{R}} \sum_{j \in \mathbf{R}, j \geq i} \beta_{ij} \mu_i \mu_j \\ & + \sum_{i \notin \mathbf{R}} (\beta_i + \sum_{j \in \mathbf{R}} \beta_{ij} \mu_j) x_i + \sum_{i \notin \mathbf{R}} \sum_{j \notin \mathbf{R}, j \geq i} \beta_{ij} x_i x_j \end{aligned} \quad (6.6)$$

$$\begin{aligned} \sigma^2(\mathbf{x}) = & \sum_{i \in \mathbf{R}} \beta_{ii}^2 \sigma_i^4 + \sum_{i \in \mathbf{R}} \sum_{j \notin \mathbf{R}, j \geq i} \beta_{ii}^2 \sigma_i^2 \sigma_j^2 + \sum_{i \in \mathbf{R}} (\beta_i + \beta_{ii} \mu_i \\ & + \sum_{j \in \mathbf{R}} \beta_{ij} \mu_j + \sum_{j \notin \mathbf{R}} \beta_{ij} x_j)^2 \sigma_i^2 \end{aligned} \quad (6.7)$$

where $\beta_{ji} = \beta_{ij}$ if $i > j$, x_i represents the values of the deterministic input parameters and the β 's are the model parameters from Equation 6.3.

The following expression for the mean and standard deviation is used to calculate a representative mean and standard deviation for a single bin and per wheel type:

$$\mu(\mathbf{x}) = \sum_{i=1}^6 n_i \mu_i(\mathbf{x}) \quad (6.8)$$

$$\sigma(\mathbf{x}) = \sum_{i=1}^6 n_i \sigma_i(\mathbf{x}) \quad (6.9)$$

where n_i is the percentage of the wheels covered by the i^{th} wear prediction model, and $\mu_i(\mathbf{x})$ and $\sigma_i(\mathbf{x})$ are the associated mean and standard deviation. The resulting

mean and standard deviation values can be compared with the numerical approach and the field measurements.

6.2.4 Field measurements

In order to check the validity of the wear prediction model, a case study between the Dutch cities of Weesp and Almere is selected. This case study consist of a curved track with curve radius $R = 1500$ metres and is based on two measurement sets from two different time periods, namely from March 2018 to October 2018 and from November 2018 to March 2019. These cases will be further regarded as case study 1 and 2, respectively. For the measurements in the first period the Railmonitor was used to measure the rail profiles while for the measurements performed in the second period the MiniProf was used. In the second measurement period also the rail hardness was measured using a portable hardness tester.

The advantage of the Railmonitor and MiniProf is that they enable the inclusion of a specific reference point on the rail which is not prone to wear. On the other hand, the main disadvantage is that the manual operation allows for only a very limited number of measurements to be taken from a track section [18]. For this reason manual devices cannot be used to measure rail profiles for longer tracks. For longer tracks the UFM120 measuring train with a vehicle speed of 120km/h is used in the Netherlands. Figure 6.4 depicts the rail profile measuring devices mentioned in this study, namely the Railmonitor, MiniProf and the measuring train UFM120.

The rail profile measurements are performed to determine the amount of rail material lost over a certain time period. The amount of wear (in mm^2) that is worn off (in a 2D cross sectional view) is determined by calculating the deviation of the measured rail profile with regard to the nominal profile. This can be done after fitting the measured profile to the nominal or standard profile (obtained from the manufacturer) on the reference point. Figure 6.5 shows the cross sectional shape of the measured rail profiles using the devices depicted in Figure 6.4. From this figure it can be seen that the measured rail profile obtained from UFM120 could not be properly fitted to the nominal profile, see Figure 6.5c. The reason for this is that the UFM120 measuring system does not have a specified reference point at a non-wearing location, which makes a unique fit (especially in vertical direction) impossible. This can lead to inaccurate wear estimates and even to negative wear loss for two consecutively measured rail profiles when the last measured profile is positioned higher than the first measured profile. The Railmonitor and MiniProf on the other hand have a robust method to align the measured rail profile on the nominal profile which assures an accurate calculation of the wear area and is therefore used in this study.

As mentioned before, UFM120 is suitable for longer tracks, thus if one wants to measure rail wear area, this approach is more efficient than Railmonitor and MiniProf. Therefore, it is recommended to improve the measurement technique of UFM120 such that a proper reference point can be defined.

(a) Railmonitor (source: Schmid Elektronik)

(b) MiniProf (source: Greenwood Engineering)

(c) Measurement train UFM120 (source: Eurailscout)

Figure 6.4: Rail profile measuring devices.

6.3 Results and discussion

The calculated sensitivity indices and correlation coefficients, which are required to determine which of the input parameters are dominant and which parameters should be treated as random variables, are presented in Table 6.2. The sensitivity indices show that the friction coefficient and the hardness are the most dominant parameters, whereas the correlation coefficients indicate rather high values for the friction coefficient and the lateral stiffness. Therefore, different simulations are performed with fixed input parameters and these are compared with the MC simulation for case study 1 where the actual distributions of the parameters are considered. The results are

Figure 6.5: Comparison between measured and nominal rail profiles for different measuring devices.

presented in Table 6.3 along with the absolute error with respect to the obtained wear area for the simulation with the actual pdfs. It can be concluded that the friction coefficient has the highest influence when it is not considered as a pdf, followed by the hardness and lateral stiffness.

Table 6.2: Sensitivity indices and correlation coefficients for wheeltype s1002.

Input parameters	Sensitivity index S_i	Pearson correlation coefficient ρ_i
Vertical wear depth	-0.07	0.24
Rail cant	-0.03	-0.10
Friction coefficient	0.98	0.37
Longitudinal stiffness	0.07	0.13
Lateral stiffness	-0.03	0.55
Hardness	-0.28	-0.24

Furthermore, the correlation coefficients in Table 6.2 also show which parameters are positively or negatively correlated with the response value. For example, an increase in the friction coefficient leads to an increase in rail wear area and an increase in the material hardness leads to a decrease in rail wear area. This is as expected since according to Archard's wear law the wear area is inversely proportional to the material hardness. Further, a higher friction coefficient leads to an increase in both slip velocity and contact pressure, which are both proportional to wear according to Archard's wear law.

Table 6.3 also shows the results for the numerical simulations when considering the input parameters to be normally distributed (see Table 6.1 for the corresponding mean and standard deviation). It can be seen that the mean and standard deviations obtained for the response value when using the normal distributions are close to the results when using the actual pdfs for the input parameters. The difference between

Table 6.3: Wear area results [mm²] for actual distribution, normal distribution and fixed parameters for case study 1 and 100 MC simulations.

Input parameters	Mean	Std	Absolute error mean [%]
MC100 (actual distribution all parameters)	20.62	12.15	0.00
MC100 (normal distribution all parameters)	23.18	11.62	12.96
MC100 (normal distribution with weight factors)	21.62	11.20	5.36
Vertical wear depth = 1.3 mm	21.00	11.88	2.34
Rail cant = 100 mm	19.12	10.86	6.82
Friction coefficient = 0.3	44.52	13.15	116.96
Longitudinal stiffness = 4×10^7	19.93	12.62	2.88
Lateral stiffness = 4×10^7	17.02	11.04	17.06
Hardness = 260 HB	29.95	12.05	45.96

the two methods is only 12.96%. These results can further be improved as follows:

1. As the stiffness of more than 60% of the vehicles is known for the considered case study, the pdf for the stiffness of only the remaining 40% is considered.
2. Instead of using a single pdf for the random variables, multiple pdfs with weight factors can be used, see Figure 6.6. The weight factors then represent the percentage of evaluations in each pdf.

Table 6.3 shows that by including the weight factors for the friction coefficient the difference is reduced to 5.36%. If one wants to further improve the results it is recommended to do the same for the other random variables. It has already been shown in Table 6.2 and 6.3 it is already shown that the friction coefficient has the highest influence on the wear area, hence using multiple pdfs for the friction coefficient already reduced the error significantly.

Table 6.4 presents the results for the numerical uncertainty propagation analysis with 100, 500 and 1000 MC simulations along with the measured and analytically calculated wear area. The measured wear area results are also presented in terms of the mean and standard deviation as the measurements were performed at randomly selected locations of the curved tracks such that every section was taken into account. The predicted wear area for a track with a certain curve radius is assumed to represent the average wear over its entire length.

The results in Table 6.4 show that for an increasing number of MC simulations the predicted wear area is closer to the measured wear area. However, the change is relatively small, so 100 simulations is considered to be an adequate number. Furthermore, the numerically and analytically predicted results for both case studies are in agreement with the field measurements. Figure 6.7 shows the pdfs of the wear area for case study 1 and 2 for both the numerical and the analytical approach compared

Figure 6.6: Single and multiple pdfs for the friction coefficient.

with the field measurements. This demonstrates that the actual and predicted distribution functions are not identical but do have a considerable amount of overlap. The standard deviation values in Table 6.4 show a large variation in both predicted and measured wear area. The reason for the variation in the measured wear area is that rail wear is not uniform in the real world, as has been assumed in this study. This is due to velocity variations in the curve radius, braking, traction and hunting oscillation of the vehicle while entering and leaving the curve. Thus, improving the prediction model will still result in large variation in the wear area, but this time closer to the measured values. The improvement of the prediction model can be achieved by considering the actual pdf for the friction coefficient and including the above mentioned usage variations in the curved track.

Table 6.4: Wear area results in $[\text{mm}^2]$.

Method	Case study 1		Case study 2	
	Mean	Std	Mean	Std
MC100	20.52	12.15	6.47	3.97
MC500	19.38	12.08	6.39	3.80
MC1000	19.49	11.21	6.01	3.73
Measurement	14.31	5.97	5.04	2.18
Analytical	20.81	11.77	6.83	3.59

Finally, it can be concluded that the analytical evaluation is ten times faster than the numerical evaluation. Hence, for maintenance decision purposes the analytical approach should be followed due to its computational efficiency. Coupling with

Figure 6.7: Wear area results comparison.

maintenance decision support can be achieved by proposing new Key Performance Indicators (KPIs) [19] for the mean and standard deviation values of the wear area. These two KPIs can then be compared with a certain threshold set by Infrastructure Managers for the wear area. Based on the outcome of the comparison the IMs can update their track maintenance planning.

6.4 Conclusion

The objective of this study was to obtain a robust wear prediction model by including model parameter uncertainties such that the resulting output (in this case wear area)

can be utilized in the process of maintenance decision making. The uncertainties have been evaluated through a numerical and an analytical analysis. It can be concluded that the results from both analyses are in overlap with the measured data. However, it is recommended to choose the analytical approach above the numerical approach for maintenance decision support tools, as the evaluation by means of the analytical approach is ten times faster. Furthermore, from the comparison with field measurements it could be seen that for both approaches the mean of the predicted wear distribution is relatively close to the field measurements but the variance is rather large. In order to minimize the variance it is recommended to use actual pdfs for the friction coefficient as this input parameter is highly correlated with the response value. Friction coefficient values from the literature were used in this study .

References

- [1] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Thesis, 2010.
- [2] B. Dirks and R. Enblom. Prediction model for wheel profile wear and rolling contact fatigue. *Wear*, 271(1-2):210–217, 2011. ISSN 0043-1648. doi: 10.1016/j.wear.2010.10.028.
- [3] B. Dirks, R. Enblom, A. Ekberg, and M. Berg. The development of a crack propagation model for railway wheels and rails. *Fatigue & Fracture of Engineering Materials & Structures*, 38(12):1478–1491, 2015. ISSN 8756-758x. doi: 10.1111/ffe.12318.
- [4] Annemieke Meghoe, Richard Loendersloot, and Tiedo Tinga. Rail wear and remaining life prediction using meta-models. *International Journal of Rail Transportation*, pages 1–26, 2019. ISSN 2324-8378/2324-8386. doi: 10.1080/23248378.2019.1621780.
- [5] Laura Uusitalo, Annukka Lehtikoinen, Inari Helle, and Kai Myrberg. An overview of methods to evaluate uncertainty of deterministic models in decision support. *Environmental Modelling & Software*, 63:24–31, 2015. ISSN 1364-8152. doi: 10.1016/j.envsoft.2014.09.017.
- [6] O. Nejadseyfi, H. J. M. Geijselaers, and A. H. van den Boogaard. Evaluation and assessment of non-normal output during robust optimization. *Structural and Multidisciplinary Optimization*, 59(6):2063–2076, 2018. ISSN 1615-147X/1615-1488. doi: 10.1007/s00158-018-2173-2.
- [7] D. Barchiesi, S. Kessentini, and T. Grosjes. Uncertainty analysis of nanoparticles for cancer photothermal therapy. In Antoine Grall & Carlos Guedes Soares Christophe Bérenguer, editor, *In Advances in Safety, Reliability and Risk Management: Proceedings of the European Safety and Reliability Conference (ESREL 2011)*, page 2197–2204, 2011.
- [8] Wei Chen, Ruichen Jin, and Agus Sudjianto. Analytical variance-based global sensitivity analysis in simulation-based design under uncertainty. *Journal of Mechanical Design*, 127(5):875, 2005.
- [9] Lu Gao and Zhanmin Zhang. Robust optimization for managing pavement maintenance and rehabilitation. *Transportation Research Record*, 2084(1):55–61, 2008. ISSN 0361-1981. doi: 10.3141/2084-07.
- [10] Reinout Heijungs and Manfred Lenzen. Error propagation methods for lca—a comparison. *The International Journal of Life Cycle Assessment*, 19(7):1445–1461, 2014. ISSN 1614-7502. doi: 10.1007/s11367-014-0751-0.

- [11] A. Parkinson, C. Sorensen, and N. Pourhassan. A general approach for robust optimal design. *Journal of Mechanical Design*, 115(1):74–80, 1993. ISSN 1050-0472. doi: 10.1115/1.2919328.
- [12] Y. T. Wu, H. R. Millwater, and T. A. Cruse. An advance probabilistic analysis method for implicit performance function. *AIAA Journal*, 28:1663–1669, 1990.
- [13] Richard G. Hills and Timothy G Trucano. Statistical validation of engineering and scientific models: background. Report, 1999.
- [14] Wei Chen, Lusine Baghdasaryan, Thaweepat Buranathiti, and Jian Cao. Model validation via uncertainty propagation and data transformations. *AIAA Journal*, 42(7), 2004.
- [15] D.J. Pannell. Sensitivity analysis of normative economic models: Theoretical framework and practical strategies. *Agricultural Economics*, 16:139–152, 1997.
- [16] M. M. Mukaka. Statistics corner: A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal*, 24(3):69–71, 2012.
- [17] Radu Popovici. *Friction in Wheel - Rail Contacts*. PhD thesis, University of Twente, 2010.
- [18] G. Grabner, O. Polach, and B. Eickhoff. A multi-national survey of the contact geometry between wheels and rails. *Journal of Rail and Rapid Transit*, 229(6): 691–709, 2015.
- [19] A. Jamshidi, A. Núñez, R. Dollevoet, and Li Z. Robust and predictive fuzzy key performance indicators for condition-based treatment of squats in railway infrastructures. *Journal of Infrastructure Systems*, 23(3):04017006, 2017. doi: 10.1061/(ASCE)IS.1943-555X.0000357.

Chapter 7

Discussion

7.1 Current status

The objective of this thesis was to solve a relevant problem that Strukton Rail and other infrastructure managers in the world are facing. This problem concerns the increasing number of failures and maintenance costs. The proposed solution to this problem is to shift from reactive maintenance and calendar time-based maintenance to predictive maintenance such as condition-based maintenance. In this chapter the contribution of the thesis to this shift in both the practical and scientific field is discussed. Furthermore, the applicability of the model in other fields and to other components are discussed, along with the corresponding limitations.

7.1.1 Contributions

This scientific contributions to the **current research field** are as follows:

- For the first time in the railway domain, the coupling of environmental and operating conditions with material level physics-based failure prediction models is realized by means of meta-models. (Chapter 3)
- A method has been proposed to predict the damage probability in a certain track section with a considerably lower computational effort than with existing methods. (Chapter 3 and 5)
- The Whole Life Rail Model which is an empirical model that combines the two dominant mechanisms in rail degradation (i.e. wear and RCF), has been reconstructed using physical formulations of wear (i.e. Archard's wear law), Low Cycle Fatigue initiation and crack propagation (i.e. Paris's law). (Chapter 4)

- The dependency of the WLRM on material type, as expected from literature, has been confirmed and new insights about WLRM dependency on surface roughness and friction coefficient have been revealed. (Chapter 4)
- An approach to determine the wear and RCF threshold in the WLRM is proposed based on the wear activation energy and fatigue limit. (Chapter 4)
- A hybrid method combining a physical degradation model with a data-driven damage evolution model has been developed, which enables the prediction and monitoring of head checks (one the most frequently occurring rail RCF defects). (Chapter 5)

This thesis contributes to the **current practice** as follows:

- A procedure has been proposed to fully characterize the rail profile by using one parameter instead of five. (Chapter 3)
- A list of most influential parameters in terms of geometry, material properties and operational conditions for both wear and RCF is provided. (Chapter 3)
- New KPIs to determine the estimated amount of RCF damage in a specific track, based on information on usage, have been proposed. These KPIs can be used for maintenance decision making by infrastructure managers. (Chapter 5)
- The proposed RCF model with the focus on crack initiation has successfully been validated with field measurements, which demonstrates that the model is ready for practical application. (Chapter 5)
- The developed hybrid method can be used for maintenance decisions like deciding which maintenance activity to perform e.g. grinding or milling. (Chapter 5)
- A robust model is developed for wear prediction by taking into account the variability in input parameters. This model is beneficial for infrastructure managers, especially in maintenance decision making and risk analysis. (Chapter 6)

7.1.2 Limitations and application

Besides the relevant contributions of this thesis to science and the practical field there are still some limitations of the developed model that should be addressed in future research:

- The hybrid method cannot yet quantify the amount of wear removal.

- The accuracy of the RCF crack evolution model has not yet been validated due to time constraints and the limited amount of data available.
- In the models, wear is assumed to be uniform on a curved track. However, the measurements have revealed that in practice considerable variation in wear occurs along a curve.
- The RCF crack initiation model in the hybrid method is based on data-driven techniques and is stochastic in terms of determining the location of crack initiation and the numbers of initiated cracks. Although this leads to damage prediction with certain confidence bounds, physics-based models, being deterministic, are still relatively more accurate.

Despite the limitations of the developed models, the RCF damage initiation model has successfully been implemented by Strukton Rail. Validation of this model can also be found in Chapter 5. The wear prediction model is also ready to be implemented in practice. The only disadvantage is that the accuracy in the prediction is still lower than required. The recommendation on how to improve the accuracy will be presented in Chapter 8. Finally, the inputs required for both wear and RCF models are similar and can be extracted from existing data sources, with the exception of the friction coefficient.

Furthermore, the results and findings in this thesis do not only add new knowledge to the current application, i.e. straight and curved rail tracks, but can also be used for other components like wheels, switches, joints, bolts or overhead wires. The approach followed in this work can even be applied in other application domains such as military systems, wind turbines and bridges. The experience from the present work has taught that the following aspects need to be taken into account when using the developed approach for other applications:

- Check whether any correlation exists between the main degradation mechanisms or whether one mechanism is dominant.
- If the main degradation mechanisms are interacting make sure to define the output of both mechanisms in terms of a common variable such that a combined model can be developed.
- Take material dependency of the mechanisms and model parameters into account.
- Consider the effect of environmental and weather conditions on the degradation mechanisms.

7.2 Outlook to future development

This section presents the discussion on the possibilities for the further development of the models proposed in this thesis.

7.2.1 Link between design and predictive maintenance

Two main degradation mechanisms are found acting as dominant mechanisms on the rail, namely wear and RCF. These two mechanisms interact, in the sense that surface cracks are constantly being removed by wear if the wear rate is higher than the crack propagation rate. Due to the interaction between wear and RCF and between vehicle and track the ultimate prediction model for infrastructure managers and vehicle operators is a model which combines both wear and RCF and optimizes the design of both track and vehicle. The main difficulty in this ambition is to establish collaboration between the two parties (i.e. infrastructure managers and vehicle operators) as there is a separation between track and vehicle ownership. The advantage of the optimization is a major reduction in maintenance costs in both track and vehicle operation and safer systems.

Dirks [1] proposed a wheel-rail life prediction tool with regard to both wear and surface-initiated RCF which included vehicle-track dynamic simulations and continual updating of wheel and rail profiles. The idea was to take into account many different wheel rail contact conditions. As mentioned in Chapter 3 this approach is very time consuming and cannot be implemented easily in maintenance decision tools. Therefore, the study presented in this work proposed the use of meta-models for rails. Similar meta-models can be developed for the wheels as the vehicle dynamics simulations have already been performed. For this, two things needs to be reconsidered:

1. The varying wheel profile should be defined in one or more parameters [2].
2. For the wear accumulation on the wheel the amount of distance travelled needs to be taken into account rather than the number of cycles [1] .

An example of track optimization with regard to rail profile can be found in [3], where the rail profile was optimized such that it prevents the formation of RCF. Furthermore, one of the common wheel types used in the Netherlands, also known as the HIT wheel profile, is designed in such a way that the amount of wear removal is kept to a minimum. However, these optimizations consider only one degradation mechanism either on the track or vehicle side and not in a combined sense, and only for a single vehicle type.

The optimization of the combined model could be realized by means of robust optimization of the meta-models via uncertainty propagation as proposed by Nejadseyfi et al. [4]. In this approach a distinction is made between design variables and noise variables. The design variables in the combined model can represent for example the wheel profile, bogie stiffness, rail profile, rail cant, etc. An optimum for these parameters is found such that minimum damage is induced. The noise variables are related to parameters which cannot be controlled, e.g. the friction coefficient which can vary based on weather conditions.

7.2.2 Railway switch

Initially the railway switch was determined to be the most critical system, but for this study the rail of the track system (second most critical system) was selected due to its simple structure (Chapter 2). It can be argued that the approach that is followed for the railway track can also be followed for the railway switch. This applies for both the mechanical and electrical part of the railway switch. However, some changes are required as the geometry, contact conditions, contact forces and degradation mechanisms of the railway switch are different from those of the railway track [5]. These changes include:

1. Introduction of new parameters to describe the rail profiles as the rails of the switch system consists of varying rail profiles [6].
2. Study of other degradation mechanisms as the rails of the switch system also suffers from plastic deformation, rail head cracking and rail web cracking, besides wear and RCF [7].

Based on the discussions presented in this chapter regarding the contributions, limitations and future outlook of the developed models, the conclusions and recommendations will be put forward in the next chapter.

References

- [1] Babette Dirks. *Simulation and measurement of wheel on rail fatigue and wear*. Phd thesis, KTH Royal Institute of Technology, 2015.
- [2] K. Karttunen, E. Kabo, and A. Ekberg. Estimation of gauge corner and flange root degradation from rail, wheel and track geometries. *Wear*, 366-367:294–302, 2016. ISSN 0043-1648. doi: 10.1016/j.wear.2016.03.030.
- [3] R.P.B.J. Dollevoet. *Design of an Anti Head Check Profile Based on Stress Relief*. Phd thesis, University of Twente, 2010.
- [4] O. Nejadseyfi, H. J. M. Geijselaers, and A. H. van den Boogaard. Evaluation and assessment of non-normal output during robust optimization. *Structural and Multidisciplinary Optimization*, 59(6):2063–2076, 2018. ISSN 1615-147X 1615-1488. doi: 10.1007/s00158-018-2173-2.
- [5] Anders Johansson, Björn Pålsson, Magnus Ekh, Jens C. O. Nielsen, Mats K. A. Ander, Jim Brouzoulis, and Elias Kassa. Simulation of wheel–rail contact and damage in switches & crossings. *Wear*, 271(1-2):472–481, 2011. ISSN 00431648. doi: 10.1016/j.wear.2010.10.014.
- [6] P. Wang, J. M. Xu, K. Z. Xie, and R. Chen. Numerical simulation of rail profiles evolution in the switch panel of a railway turnout. *Wear*, 366:105–115, 2016. ISSN 0043-1648. doi: 10.1016/j.wear.2016.04.014.
- [7] Seyedahmad Jalili Hassankiadeh. *Failure Analysis of Railway Switches and Crossings for the purpose of Preventive Maintenance*. Phd thesis, Royal Institute of Technology, 2011.

Chapter 8

Conclusions & recommendations

8.1 Conclusions

The conclusions of this study are obtained by answering the main research question. To be able to answer this main question first the **Sub Research Questions (SRQ)** are answered:

***SRQ 1:** What are the most critical components (cost drivers, performance killers) within rail infrastructure that are also suitable for predictive maintenance modelling?*
The most critical component based on the highest value of failure frequency and maintenance costs is the rail of the track system. (Chapter 2)

***SRQ 2:** What are the dominant degradation mechanisms that causes the critical components to fail?*
The degradation mechanisms that were identified to cause the rail to fail are wear and RCF. (Chapter 2)

***SRQ 3:** Which physics-based models should be selected for the most critical components with single or multiple degradation mechanisms?*
For the wear mechanism the Archard's wear law was selected due to its popularity in tribology and for the RCF mechanism the Whole Life Rail Model (WLRM) was selected as it also takes the wear into account (Chapter 2). Furthermore, for the RCF part of the WLRM a Low Cycle Fatigue (LCF) initiation model and a crack propagation model according to the Paris law were considered (Chapter 4).

***SRQ 4:** How to implement physics-based models for the most critical components*

with single or multiple degradation mechanisms?

The implementation of the physics-based models can be very detailed and time consuming. Therefore, a particular process has been followed during this study, starting from a sensitivity analysis and leading to the development of meta-models. (Chapter 3)

SRQ 5: *What sensing strategy, inspection and processing methods are available to capture the relevant monitoring parameters or do new ones need to be developed?*

For the inspection methods of wear and RCF the UFM120, Eddy Current testing and Ultrasonic testing are used in practice, but they are insufficient as they cannot capture the crack depth range from 3 to 5 mm (Chapter 5). For the monitoring of the parameters the Quo Vadis system is used for input parameters related to operational conditions (Chapter 5). To obtain accurate and representative friction coefficient and material hardness values, new techniques or strategies need to be developed (Chapter 6). Finally, the amount of wear can be estimated from the measurements performed by using UFM120, MiniProf and the Railmonitor. UFM120 is the most practical method among these three as it can be used for longer tracks. However, the accuracy of the measuring devices on UFM120 needs to be improved as discussed in Chapter 6.

SRQ 6: *How to couple the physics-based models with appropriate monitoring techniques at component and system level?*

The coupling between physics-based models and monitoring methods can be achieved if the input data are collected and processed such that they can easily be fed into the meta-models that represent the physical mechanisms. The process from collecting the data, evaluating the meta-model and plotting the results in terms of KPIs can be implemented in a user interface. In this way the KPIs for RCF damage and rail wear can be monitored over time or usage (Chapter 5).

The **main research question** of this study is:

How to apply physics-based models for appropriate monitoring and optimized predictive maintenance of critical components within rail infrastructure?

The work presented in this thesis has provided an answer to this question at two different levels:

1. Generic conclusion: the process to use physics-based models for predictive maintenance has been revealed. The required steps include the selection of the most critical component, determination of failure mechanism and governing loads, development of the life prediction model and the integration with relevant monitoring data (both input and output parameters). This work describes the challenges encountered in each of these steps and provides the associated solutions.

2. Application specific conclusion: the prediction of railway track maintenance is achieved by solving the detailed modelling problem (which includes local contact and vehicle dynamics modelling) by means of meta-models based on physical relations for both wear and RCF. These models have been combined with monitoring systems such as Quo Vadis and inspection methods such as Eddy Current and Ultrasonic testing (Chapter 3, 5 and 6).

Furthermore, some more specific conclusions from the previous chapters can be clustered in two categories: 1) Model development and 2) Model application.

Model development

1. A simple relation (in the form of a second order polynomial) between wear, which is one of the most dominant mechanisms, and operational parameters is shown to be effective. (Chapter 3)
2. The developed meta-models enable RUL predictions due to wear and RCF for various usage profiles of railway tracks. (Chapter 3, 5 and 6)
3. A more fundamental background for the Whole Life Rail Model has been established based on analytical and numerical formulations of the wear and RCF mechanism. (Chapter 4)
4. The existing WLRM in the literature is for friction coefficient 0.3. From the results obtained in this thesis it is concluded that different WLRMs need to be developed for different type of steel grades and friction coefficients using analytical and numerical formulations. (Chapter 4)
5. A robust wear prediction model is obtained by including model parameter uncertainties. (Chapter 6)

Model application

1. The developed meta-models are beneficial for infrastructure managers as they can predict the RUL quantitatively with a very limited computational effort and limited requirements on input data. (Chapter 3)
2. The meta-models are developed such that the required input parameters are those that are already monitored by infrastructure managers. (Chapter 3)
3. The developed WLRMs can be used as look up tables for specific vehicles to predict the RCF life. (Chapter 4)
4. Prioritizing track sections dominated by RCF can be included in the maintenance planning for RCF prevention (e.g. grinding or milling) and track replacement using the hybrid method. (Chapter 5)

8.2 Recommendations

In line with the discussion presented in Chapter 7 and the conclusions in the previous subsection, the recommendations are clustered in three categories: 1) model validation, 2) model application and 3) model improvements.

Model validation

1. In order to validate the wear model for other cases, a large amount of accurate data regarding the input parameters and wear measurements has to be collected.
2. Newly developed WLRMs should be validated with field experiments.
3. The crack propagation part of the hybrid method needs to be validated.

Model application

1. The Quo Vadis data information could be replaced with train time schedules.
2. Friction coefficient and material hardness should be measured in order to decrease the variation in the response value of the wear model. If the friction coefficient cannot be measured, friction coefficient determination can be related to weather conditions.
3. The developed meta-models should be implemented in maintenance decision making tools.
4. A user interface should be developed which extracts the input data from monitoring techniques, feeds the input data in the meta-model and yields the amount of predicted damage or remaining useful life.

Model improvements

1. Wheel parameters should be defined that can characterize any worn wheel profile in order to exclude the wheel dependency in meta-models and reduce the total number of meta-models.
2. The influence of maintenance activities such as grinding and milling should be included in the developed meta-models and hybrid method.
3. A fully physics-based RCF model can be established by developing meta-models for crack propagation. Detailed modelling of crack propagation is typically performed by means of Finite Element Methods (FEM). By using the Latin Hypercube Sampling method and the approach proposed in Chapter 3, a number of FEM simulations can be performed in order to develop meta-models for crack propagation.

4. The crack evolution model can be improved by adding more data points and using multiple consecutive measurements in order to eliminate the dependency on the quantile regression technique.
5. The WLRM takes the interaction between wear and RCF into account qualitatively. Therefore, wear and RCF models should be combined such that the crack size can be determined along with the amount of wear removal quantitatively.
6. RCF detection methods needs to be improved such that RCF defects with crack depth between 3 and 5 mm can be detected. This implies the development of other or better Non Destructive Inspection techniques.

Research deliverables

Journal articles

- Meghoe, A., Loendersloot, R. and Tinga T. (2019). Rail wear and remaining life prediction using meta-models. *International Journal of Rail Transportation*, 1-26, doi:10.1080/23248378.2019.1621780
- Meghoe, A., Loendersloot, R. and Tinga T. Generic rail damage function based on physical models. *Wear* (under review, revision submitted)
- Meghoe, A., Jamshidi, A., Loendersloot, R. and Tinga T. A hybrid predictive methodology for head checks in railway infrastructure. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit* (submitted)
- Meghoe, A., Loendersloot, R. and Tinga T. Evaluation of rail wear prediction uncertainty for maintenance decision support. (in preparation)

Conference papers

- Meghoe, A., Loendersloot, R., Bosman, R. and Tinga T., Rail wear estimation for predictive maintenance: a strategic approach. *European Conference of the Prognostics and Health Management Society 2018*. Utrecht, The Netherlands
- Meghoe, A., Jamshidi, A., Loendersloot, R. and Tinga T., Towards the development of a hybrid methodology for monitoring of head checks in railway infrastructure. *Railway Engineering 2019*. Edinburgh, Scotland

Presentations in conferences/symposia

- Meghoe, A., Loendersloot, R., Bosman, R. and Tinga T., Physics Based Wear Model for Predictive Maintenance of Rail-infrastructure. *Maintenance Research Day 2017*. Utrecht, The Netherlands

- Meghoe, A., Loendersloot, R., Bosman, R. and Tinga T., Rail Wear Prediction for Different Wheel-Rail Profile Combinations based on VI-Rail simulations. *VI-Grade user conference 2017*. Turin, Italy
- Meghoe, A., Loendersloot, R., Bosman, R. and Tinga T., Influence of wheelset dynamic behavior on rail wear prediction for different wheel-rail profile combinations. *Engineering Mechanics Symposium 2017*. Arnhem, The Netherlands

Poster contributions

- Engineering Mechanics Symposium, the Netherlands, 2016, 2017 and 2018

Acknowledgements

This thesis would not have been possible without the help and encouragement of many people. Therefore, I would like to thank all the people that have helped, supported and motivated me not only during my PhD but also during my life.

Firstly, I would like to express my deepest gratitude to my promotor Tiedo Tinga and my daily supervisor Richard Loendersloot for their guidance, support, patience and encouragement during these four years. Thank you Tiedo and Richard for always being available whenever I had questions and for the insightful discussions. I am very grateful that I had the opportunity to work with you. Secondly, I would like to thank the members of the graduation committee: Prof. dr. ir. A. de Boer, Prof. dr. ir. L.A.M. van Dongen, Prof. dr. M.I.A. Stoelinga, Prof. dr. ir. R.B.J.P. Dollevoet and Prof. M. Berg for their time and effort in evaluating my thesis.

This research is performed in collaboration with Strukton Rail and therefore I would like to thank David Vermeij, Marc de Wolf and Arjen van Leuven for their help and support in gathering real track data and giving me the opportunity to experience the working environment within the industry. I would also like to thank Corné van de Kraats and Majid Sawri from Strukton Rail for their help in performing field measurements. My gratitude also goes to Ali Jamshidi for his contributions and collaboration on data-driven models used in this research. I also express my gratitude to Anthonie Boogaard, Niels Lange, Niels Sturkenboom, Edin Hadzic, Robert Schuil, Eelco Westerveld, Tom Wessels, Bekir Koncak and Sravanthi Murali for providing me real track data.

I would also like to express my gratitude to my colleagues in the Dynamics Based Maintenance group. Thank you for your valuable feedback during the DBM meetings. Special thanks to my officemates: Farshad, Neda, Erkan and Nubia for creating a pleasant working environment. I would also like to thank my previous office mates: Flavilene, Amin and Mohammed. Furthermore, I would like to thank the colleagues from the Nonlinear Solid Mechanics group and the Structural Dynamics, Acoustics and Control group for the coffee/cake breaks and group activities. To all my female colleagues: thank you for the ladies nights.

I would like to thank Bert Geijselaars and Omid Nejadseyfi for sharing their knowledge on meta-models and Axel Lok for arranging all the software and license issues. I would also like to thank Rob Bosman for his guidance during the first years of my

PhD and the fruitful discussions that we had.

I am very grateful for the help, care and support I received from Debbie. Thank you Debbie for being so kind and supportive and organizing all the paperwork. I would also like to thank Belinda for her help whenever Debbie was not available.

I would like to extend my gratitude to my family and friends in Suriname and the Netherlands. To my friends in the Netherlands: thank you for making me feel home while being away from home by celebrating Surinamese holidays and organizing events with delicious Surinamese foods. A special thanks goes to my paranympths Jina Bhagwandas and Ranisha Sitlapersad for their assistance.

I am extremely grateful for the infinite love and support from my parents. I would like to thank them for believing in me and my dreams and for always standing by my side. A special thanks goes to my grandfather Poniman Sokarijo who always motivates me to achieve my goals. I would also like to thank my parents in law for their support especially during my first years in the Netherlands.

Last but not least, I would like to thank my best friend, my soulmate, my husband Viren for his love, support and patience not only during the last four years but the last twelve years. I feel blessed to have you in my life. Thank you for being my biggest critic and encouraging me to excel in both my professional and personal life.