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Executive Summary

This report is about the feasibility validation of the developed concepts and models for, asset management framework, track and switch maintenance, maintenance planning and, last but not least, tamping method. All work undertaken in the context of work package 6 of In2Rail.

Work package 6 is related to the technical demonstrator (TD) 3.8 of Shift2Rail and In2Rail WP6 dealt with several aspects of this TD. This included 1) an asset management framework, 2) for both track and S&C introducing dynamic modelling, 3) condition and risk-based maintenance planning (CRMP) and last but not least, 4) improved tamping methods as an example for new working methods.

The objective of WP6 is to demonstrate the possibility for a sound, consistent and holistic approach towards asset maintenance making a difference, not only to the reliability of the railway system/infrastructure, but also in the reduction in recurrent maintenance tasks and cost. Improving individual maintenance approaches or tasks are necessary but in isolation are not enough; instead an integrated approach is required. To illustrate this, the project took track and switches (S&C) as.

In this WP we have developed an internationally accepted common language for an Asset Modelling Framework and KPI's, illustrated in chapter 3. The asset management framework includes a framework for KPI decision making and a framework for performance prediction, modelling and decision support. The result fills the need for a structured KPI decision framework (see diagram) and includes a KPI definition guide.

In chapter 4, a dynamic model for track wear is described, based on ongoing regular track measurements. Chapter 5 digs into the functional model of the switch and outlines how the statistical approach from current measurements by POSS already allow the possibility to pre-empt mechanical failures on switches with a high degree of confidence.

Integrated modelling is the subject of chapter 6 in which the use of Petri-nets versus other models is discussed, and some optimisation using PEM. Both the dynamic model for track and respectively dynamic model for switch maintenance have chosen a similar approach. Innovative modelling combining functional and maintenance effectiveness models is tested based on real life data and expert knowledge. Multiple factors degradation models are used for local assessment of status indicators In order to provide decision support. The deliverables present concepts, prototypes and tests for these improved and innovating modelling approaches. The results show the potential and lay the foundation for future work.

Condition and risk-based maintenance (CRM) is now widely accepted as the way to efficiently use resources to maintain infrastructure, however Condition and risk-based maintenance planning (CRMP) is necessary to cash-in on this concept. First steps are described in chapter 7. The CRMP linked the theory of the planning concept to the railway practice using real-world use cases. Use cases involve day-to-day planning with a rolling time horizon and focus on an optimal usage of track possession windows. The results show that the relevance and usage.

Finally in chapter 8 we have described a use case of High Performance Tamping that combines examples from the previous chapters to give a perspective of the LEAN maintenance of the future. Besides that the requirements have been developed, a first test has been performed as well. 1700m of track has been tamped based on the data directly from the measurement train.

Links to Shift2Rail

Work Package 6 of In2Rail is directly related to the Shift2Rail's In2Smart member (CFM) project. See diagram below for the links with the work packages in In2Smart. Work on the optimized tamping is continued. The planning building blocks, optimized degradation modelling and asset management framework are the basis for the decision support tools in In2Smart.

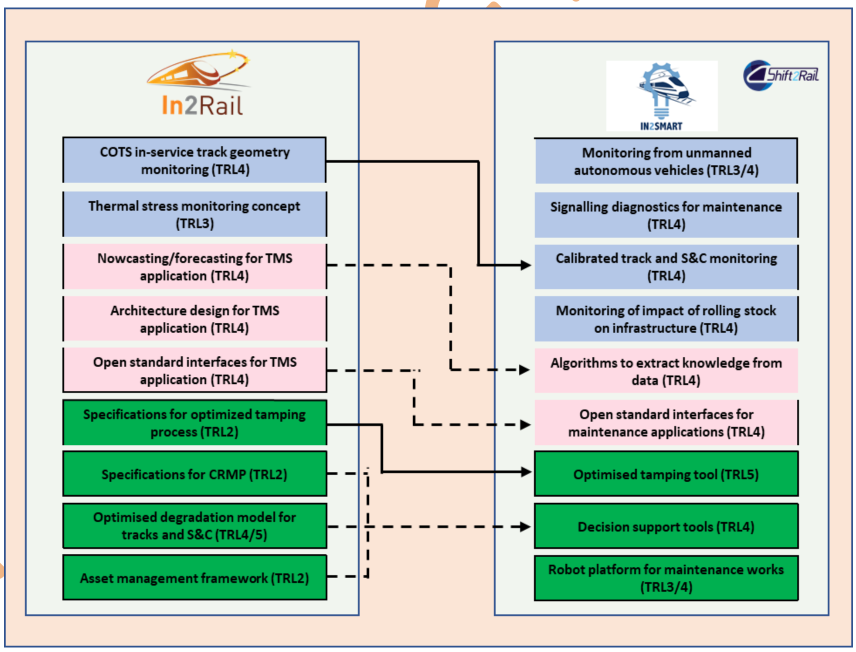

Figure: 1. Links between In2Rail and In2Smart

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Abbreviations and acronyms

Abbreviation / Acronyms	Description
AM	Asset Management
AMP	Asset Management Plan
CFM	(Shift2Rail) Call for Member
COST	Commercial off-the-shelf
CRM	Condition and risk-based maintenance
CRMP	Condition and risk-based maintenance planning
CWR	Continuous Welded Rail
DOE	Design of Experiments
FM	Functional Model
FMEA	Failure mode and effects analysis
FMECA	Failure mode, effects, and criticality analysis
IM	Infrastructure Manager
KPI	Key Performance Indicator
LCC	Life-Cycle-Cost
PEM	Point Estimate Method
RAMS	Reliability, Availability, Maintainability, and Safety
RCA	Risk and Control Assessment
RCF	Rail Contact Fatigue
RCM	Risk Control Measure
RTK	Real Time Kinematic
S&C	Switches & Crossings
SAMP	Strategic Asset Management Plan
SFT	Stress-free temperature
SPC	statistical process control
TMS	Traffic Management System
UIC	International Union of Railways

1. Background

Rail is a strategically, socially and economically essential mode of transport in Europe. Due to its efficiency and its city centre to city centre right of way it is the only way that passenger traffic and goods transport can viably and durably expand in the next century. As rail transportation and its required infrastructure is very capital intensive and components typically have a long life span, its Asset Management (AM) requires a long term vision and a sustainable strategy.

Strategic infrastructure and maintenance planning involves collecting information, setting up structures and goals, translating those strategic goals to specific tactical objectives and setting up activities to achieve the operational targets. This requires an accepted, consistent and holistic approach to asset management in general and maintenance in particular for improving the reliability of the railway system while reducing recurring maintenance interventions and costs. It is therefore that WP6 is constituted with its focus on an accepted and validated asset maintenance framework, an adaptive and dynamic model for track system maintenance, and Condition and Risk based Maintenance Planning (CRMP). By using CRMP it is possible to focus maintenance activities on targeted assets that need extra attention. Last but not least: also an example for the LEAN execution of maintenance is included in the shape of the improvement of the tamping process.

The objective of WP6 is to demonstrate the possibility for a sound, consistent and holistic approach towards asset maintenance making a difference, not only to the reliability of the railway system/infrastructure, but also in the reduction in recurrent maintenance tasks and cost. Improving individual maintenance approaches or tasks are necessary but in isolation are not enough; instead an integrated approach is required. To illustrate this approach the project took track and switches (S&C) as specimen for the combined application of these developments as they are the major cost drivers and performance killers in rail infrastructure. In a graphical structure representation:

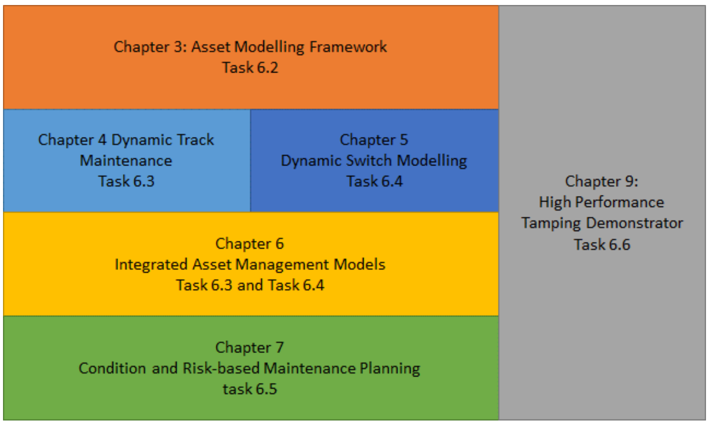


Figure: 2. Relationship chapter 5/10 to the tasks in WP6

The more detailed objectives are:

- To develop the initial concepts of an asset modelling framework aimed at achieving operational excellence and conceptual acceptability whilst being fully compliant with ISO 55000. The new approach supports decision-making on a whole life, whole system basis. (Task 6.2). This includes issues such as designed-in reliability and maintainability in combination with LCC to ensure cost effective maintenance strategies and its execution;
- To enhance maintenance approaches for track and switches (Task 6.3.) on local characteristics and place them in the above described asset modelling framework. To identify new opportunities offered by train borne and wayside monitoring systems for predictive maintenance decision-making (in conjunction with WP5);
- To identify possibilities and explore solutions for fruitful application of the Condition- and Risk-based Maintenance Planning concept (CRMP) which is the base for the shift towards the maintenance concept postulated in SHIFT²RAIL. To define dynamic and real-time planning capabilities leading to models for maintenance logistics and a concept for integration with rail service (CRMP and TMS) Task 6.4;
- To define a substantial improvement of the current way of maintain, in this case tamping and related tasks (track alignment), to illustrate the new and advanced working methods contributing to a higher availability and lower cost (Task 6.5).

This document constitutes the deliverable D6.8 “report on technical validation of concepts and models” in the framework of the Project titled “Innovative Intelligent Rail” (Project Acronym: In2Rail; Grant Agreement No 635900).

This document has been prepared to provide (1) an assessment of the feasibility and practicability of the results in WP6 and (2) give information about the next steps of the results within the Shift2Rail background. It is underpinned by numerous peer-reviewed publications and international presentations, allowing feed-back and acceptance from the wider rail community.

2. Objective / Aim

The objective of this task, according to the In2Rail proposal and grant agreement, is to present and validate the results of:

- the previous tasks in context of each other;
- as well as in the context with 5.2 and 5.3 (track geometry monitoring) and 5.4 and 5.5 (rail temperature stress monitoring).

Two general comments concerning how we interpreted the above objective and approached the work in this task 6.7:

- besides the link with 5.1 and 5.3, we have also looked at the relationship with other WP's, especially WP2 (Innovative S&C Solutions), WP3 (Innovative Track Solutions) and WP9 (Nowcasting and Forecasting);
- concerning validation, we have to take into account that In2Rail is a lighthouse project and it should lay the foundation for further work in Shift2Rail. More specific for WP6, this means that further work is carried out in the Shift2Rail member project In2Smart. Depending on the kind of result, the validation is in some case less a technical validation but more focussed on indicating the relevance and validity for the work in In2Smart and how the results are used.

As an overview of additional work carried out the work presented in this deliverable:

1. Task 6.2 is described and presented in chapter 3 (Specification of Asset Management framework). Results are summarised and relevance for future work is described;
2. The work of task 6.3 (track) is dealt with in chapter 4. This includes additional work around rail defects;
3. The work of task 6.4 (Switches & Crossings) is dealt with in in chapter 5. This includes also additional work: switch failure detection model and validation of the Functional Model Switches;
4. For both task 6.3 and 6.4 the integrated modelling is of importance. In the context of this task 6.7 some additional work has been carried out for the integrated modelling.
5. Results are presented chapter 6;
6. For task 6.5, condition and risk based maintenance planning, a summery is give in chapter 7. since work in task 6.5 already included initial validation work and the work is already adopted and continued, no additional work has been undertaken in the context of this task 6.7;
7. Extra work has been done in concerning validation for task 6.6 (high perfoamce tamping). Work is presented in chapter 8;

3. Specification of Asset Management framework

Deliverable D6.2 presents In2Rail's requirements and input for an asset management framework. The deliverable includes a framework for KPI decision making and a framework for performance prediction, modelling and decision support.

In this chapter we give a brief summary of both parts and describe the link with the future work.

3.1. KPI decision framework

3.1.1. Overview

Several projects are concerned with the identification of railway KPIs, for example PRIME and LICB (see D6.2). The results from such projects show that identifying common indicators across organisations is cumbersome, as IMs and supply chains differ vastly between countries in their strategic planning and operation. At the same time, however, IMs and supply chains commonly lack mutual KPIs, leading to the development and use of different KPIs, not just across companies but also within companies at various organisational levels and units. Often such developed KPIs are similar to each other but they lack structured definitions, making internal benchmarking hard. Therefore, as there was a lack of a structured KPI decision framework, this has been addressed in D6.2 (see Figure: 3 Developed KPI decision framework connected to AM framework).

The KPI framework also includes a KPI definition guide, including 36 questions for defining indicators and 10 questions for evaluation, as well as two case studies (Appendix E-F of D6.2). The case studies are on risk matrix KPI and the KPI availability (availability performance), with data from the Swedish railway. In both cases, all questions for defining and evaluating the KPIs are answered.

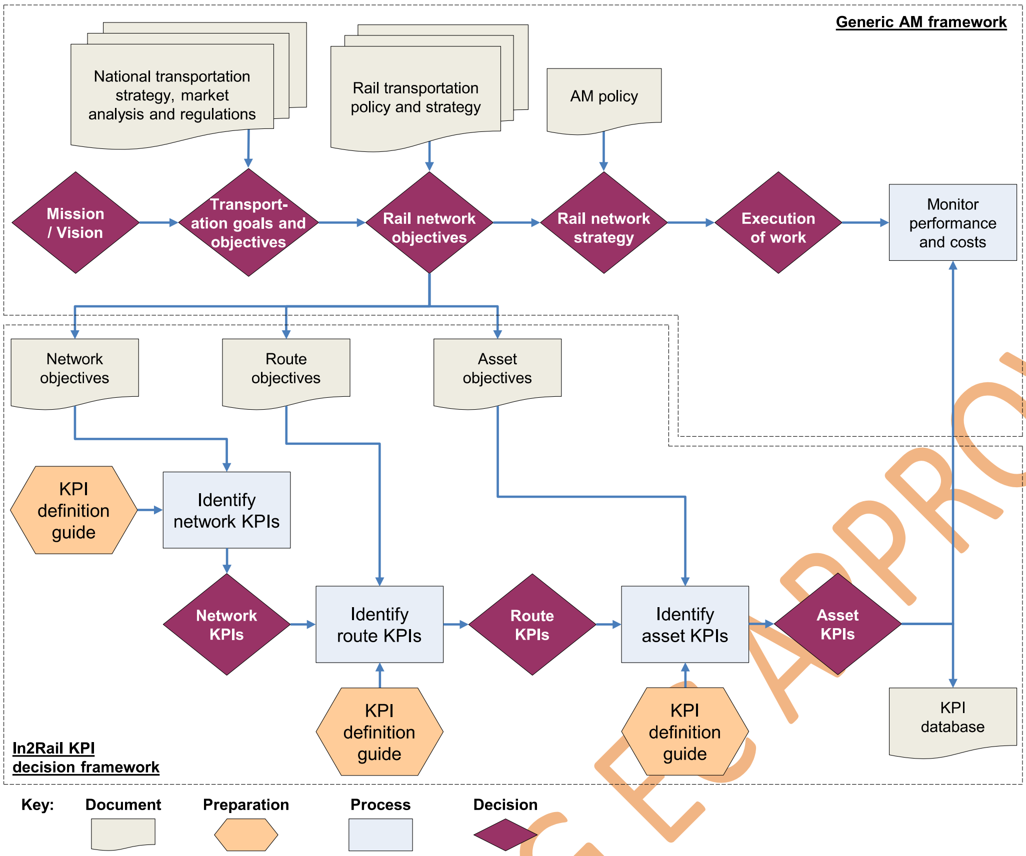


Figure: 3. Developed KPI decision framework connected to AM framework

3.1.2. Link with In2Smart

For demonstration and continuation of the work, The KPI framework has been connected to the asset management decision framework developed in In2Smart D2.1 (Figure 4.3 of D6.2).

3.2. Framework for prediction, modelling and decision support

3.2.1. Overview

IMs across Europe adopt their own procedures to manage railway assets and decisions are often taken for individual assets regardless of the dependencies and effects on the wider network. There is currently a lack of a structured approach for planning, scheduling and prioritising maintenance activities on a whole-system/whole-life basis. Furthermore, decisions should be based on conditions, performance, risks and cost profiles associated with each intervention plan, and focus on reliability and safety as well as cost efficiency. The work performed in D6.2 has contributed to fill such gaps by defining a framework for modelling the flow of decisions, activities and processes to predict railway assets' performance and support the decision making process. This is an important step towards the development of a unified approach to a safe, reliable and cost effective European railway system.

The necessity for an asset management framework for railway organisations has been long recognised, and in 2016, the UIC published the UIC Railway Application Guide, a document providing guidelines for the practical implementation of asset management based on ISO 55001. The modelling framework developed here is fully compliant with ISO 55001 and is complementary to the UIC Asset Management Framework for Railway Infrastructure Organizations (UIC, 2016).

The developed framework defines the modelling template for describing, analysing and optimising asset management decisions on a whole-life, whole-system basis. It offers a systematic approach to the analysis of the effects of any intervention plan and produces performance, risk and cost profiles based on which decisions can be made. The scope of the modelling framework currently includes the definition of the models, information/data flow and procedures to support the SAMP and initial phase of the AMP processes which are key components of the ISO 55001. With the structure of a library of models and data, the framework includes information/data and models with different levels of detail, from individual assets to the entire network, as well as their interaction for the prediction of assets/routes/network level KPIs (Figure: 4)

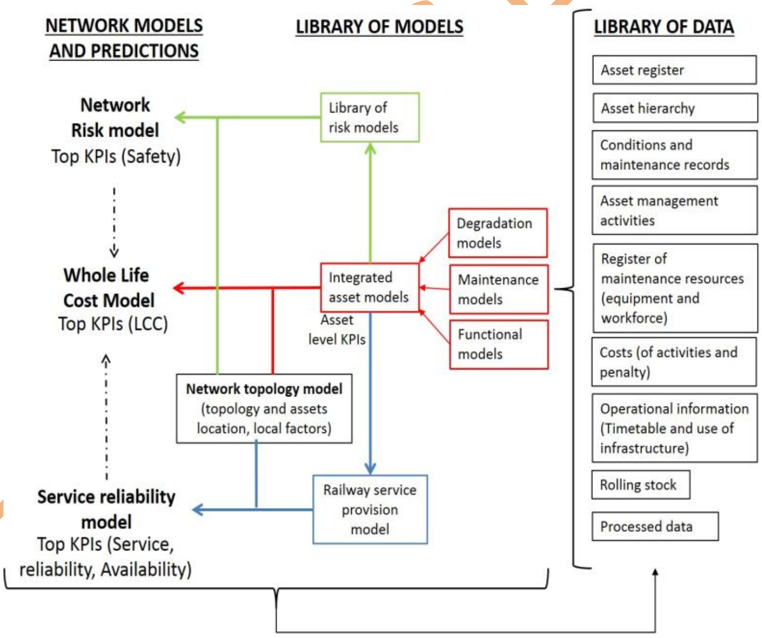


Figure: 4. Modelling framework general structure.

A key role within the modelling framework is played by the integrated asset models. These work at the interface between component-level models such as degradation and maintenance models, and higher-level models for predicting routes/network KPIs. The integrated models simulate the assets response to the interventions that can be performed in terms of assets KPIs thus enabling what-if analysis of a wide range of potential intervention strategies (Figure: 5).

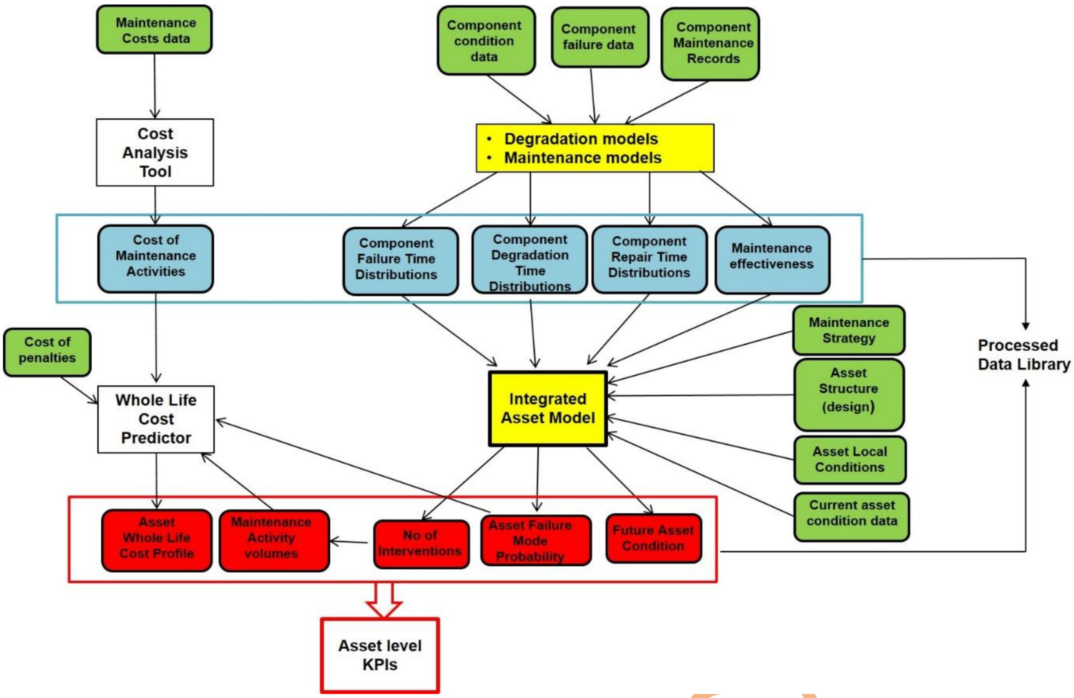


Figure: 5. Flow of input-output for integrated asset model

3.2.2. Link with In2Smart

The models described above have been regarded as relevant and the starting point for work in WP9 of In2Smart.

4. Dynamic model for track maintenance

This chapter refers to the results of task 6.3. The main results are presented in D6.3.

The first paragraph summarizes the results of task 6.3. The second paragraph puts task 6.3 in the context of the In2Rail project as a whole and highlights the main links with other work packages.

The last paragraph of this chapter reflects the additional results of the rail defect modelling (validation work). In the appendix some confidential results are included. A full paper will be presented at the 2018 Annual Conference of the Prognostics and Health Management Society.

For further work on integrated modelling we refer to chapter 6 Integrated modelling of this document.

4.1. Summary task 6.3

The research activities carried out in task 6.3 of In2Rail concerning the dynamic Track behaviour modelling. The results and prototypes developed on three main topics:

- Track functional modelling;
- Track components behaviour and maintenance modelling;
- Integrated Track geometry modelling.

Modelling activities enabled to propose, develop and test new modelling approaches. For each topic, this project leaded to go a step forward and provides better insights about the potential benefits and the limits of these approaches. First prototypes have been developed and enabled testing on realistic use cases.

These results correspond to a first and essential step for the integration of these approaches within Infrastructure Managers and Industrials tools. They must be seen as inputs forIn²Smart project, where work packages will be able to pursue their development and improvement.

This concerns especially the integrated Track geometry modelling results and prototype, as a first existing contribution for LCC and RAMS modelling activities to be performed in In2Smart project.

4.2. Link with other WP's

4.2.1. WP3 Innovative Track Solutions

WP3 of In2Rail Fast and efficient railhead repair methods, optimised ballast track system, solutions to decrease noise and vibration, and a radical hybrid track system will be areas of research. The track system has significant safety, efficiency and costs implications for European railways. WP3 targeted key aspects to deliver cost effective solutions.

WP6, task 6.3, looked into new concepts for track (geometry) maintenance based on risk assessment and improved sets of inputs: asset condition data (including train-born monitoring systems and actual (way-side monitoring systems) and forecasted usage information. Development of prediction models for optimized maintenance scenarios.. Besides the new data mining techniques in order to combine the various data sets, the framework of task 6.2 was used. For WP 6, track was used as specimen to illustrate this new approach.

Techniques developed in WP6 can be used for the by WP3 proposed new solutions.

4.2.2. **WP5: COTS Monitoring (thermal stress and track geometry)**

WP 5 is related to TD3.7 of the masterplan and MAAP of Shift2Rail. TD3.7. This TD is focussed on data acquisition. WP5 has two new forms of data acquisition:

- Track geometry monitoring using COTS (commercial off-the-shelf) sensors targeted to be implemented on in-service trains
- Thermals stress monitoring

Both developments are interesting data sources in future for the in WP6 developed model of dynamic behaviour of track including track usage.

4.2.2.1. Link to Task 5.2 'Track geometry monitoring'

Task 5.2 develops the new concept of equipping in-service trains with COTS (commercial off-the-shelf) sensors to build a large track condition data set, focusing on a more efficient evaluation of track geometry by means of innovative methods, ready to be integrated into a predictive maintenance procedure.

By combining high frequent data coming from COTS sensors mounted on in-service trains, with, low frequent data from measurement trains, improved track degeneration models can be achieved.

In particular, Task 6.3 'Dynamic model for track maintenance' using as input new data coming from COTS, shows that integrating in the loop of continuous track condition monitoring, less accurate data sets collected through high frequent in service vehicle rides, can help the development of efficient track degradation models.

Therefore, a track condition data-base system is created to perform short-term and long-term analysis of the track condition in order to allow (data-driven) predictive maintenance.

The considered track geometry parameters are the longitudinal level and the alignment. By measuring the dynamic behaviour of a railway vehicle by a set of accelerometers installed on different parts of the rolling stock, the information about the track geometry quality and isolated defects is extracted. The COTS sensors, chosen for the measurement of Car-body and bogie vertical and lateral accelerations, are mono-axial type, MEMS technology based. Even if their cost is low, the sensors are characterized by both static and dynamic response, with stable output over a wide operating range by integral temperature compensation.

The measurements are correlated to the geographical position by odometer, Satellite Localization system and Smart Phone based Localization System.

Indeed, the alignment between the data from different runs needs to be carried out accurately by detecting:

- position measurement;
- speed measurement;
- running direction.

The results show that the integration of this technology in the predicted maintenance process allows, to optimize the prediction models, due to the increased number of data sets and to better monitor the impact of maintenance actions (e.g. tamping). Moreover, by continuous monitoring track condition, defects can be detected at an earlier stage.

4.2.2.2. Link to Task 5.3 'Thermal Rail Stress Monitoring'

The aim of Task 5.3 is to design and develop a new methodology for thermal stress monitoring to decrease existing drawbacks in current monitoring procedures by introducing a technique that may provide continuous monitoring of stress-free temperatures (SFT) with significant less traffic disruptions and need for workforce in track.

This innovative monitoring concept, which includes the continuous on-board measurement of rail temperature, track geometry and stress-free temperature, equipping in-service trains with COTS (commercial off-the-shelf), makes available new data for the development of track degradation models, that can be used in Task 6.3 'Dynamic model for track maintenance'.

Moreover, the collected data allows the continuous improvement of the threshold values of rail temperature and stress-free temperature, refining the probability distributions of probabilistic risk models.

These models provide an important support for a more efficient maintenance decision-making process, contributing to Task 6.5 'Condition and Risk-based Maintenance Planning'.

In particular, Task 5.3 studies how thermal stresses influence the risk of track buckling (and rail breaks) and how this risk is related to the current temperature of the rail, the current stress-free temperature of the rail and the track resistance towards track buckling.

Simulations are performed to evaluate the relative influence of different parameters on track buckling resistance. In particular, the influence of ballast and fastening stiffness, curves and hanging sleepers have been investigated. The decreased track resistance is translated into an equivalent increase in temperature. This allows comparisons towards operational limit values.

The risk model considers probability distributions of SFT, lateral track resistance and track geometry alignment, in addition to other data such as traffic, climate/historic rail temperatures, and calculates one or more risk indicators (e.g. probability of buckling/rail break).

The results have shown the possibility:

- of adopting a risk-based approach to traffic and maintenance management decision-making as opposed to the traditional empirical approaches;
- of identifying a maintenance decision model, possibly risk-based, and compatible to the asset management approach of WP6.

The ability to measure SFT continuously from a track-recording car, or from an ordinary vehicle represents a large step forward to avoid track buckling and to improve maintenance both for jointed and CWR-track.

A maintenance decision-making procedure, referred to decisions regarding maintenance work intended to restore the track to an adequate condition for thermal stability, is developed demonstrating the link to Task 6.5.

4.3. Rail Defects: Model validation and testing

4.3.1. **Wear model**

In the previous deliverable of D6.3 the method for calculating rail wear using multi-body dynamics simulations, local contact and wear model is described. As already known, vehicle behaviour has a large influence on the wheel-rail interaction forces and contact points. Multi-body dynamics simulations enable to calculate slip and normal contact forces between wheel and rail which serve as input for the wear model. Preliminary simulation results of various wheel-rail combinations in both new and worn condition showed that, considering normal operating conditions, a higher wear rate is expected on the outer rail compared to the inner rail and the first wheel of the bogie is dominant. Furthermore, the minimum wear is predicted for new rail – new wheel combination, as expected. Whereas, new wheels running over worn rails lead to the highest wear rate. In the case study performed hereafter it is proposed to neglect the rail profile update iteration step, use variable measured rail profiles and calculate the wear only for one train passage and then accumulate for the number of passages and make a correction on the amount of axle loads.

4.3.2. **Case study**

For the case study the track line between the cities Weesp and Almere has been chosen. Track characteristics of three curves from this route were modelled in the multi-body dynamics software package VI-Rail, namely curves with radii of 1500, 1800 and 2500 meters, see Figure: 6. The minus sign before the curve with a radius of 1800 meters indicates that this is a left-hand side (LHS) curve. Furthermore, the rail profile is 54E1 and steel grade of the rails installed at this site is R260Mn.

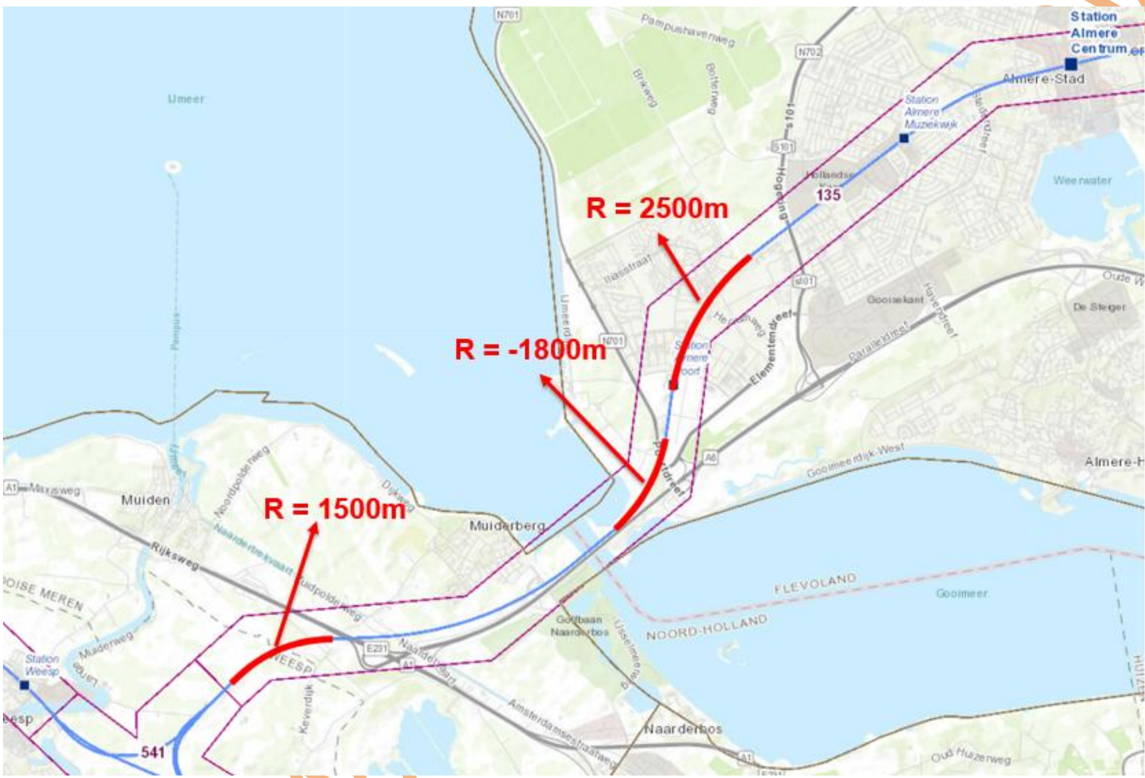


Figure: 6. Topographic representation of track line between Weesp and Almere.

The majority of the trains passed on this track are mainly the "Sprinter Light Train" (SLT) and the "Verlengd InterRegio Materieel" (VIRM) trains, see Figure: 7. The wheelsets of SLT trains consist of s1002 wheel profiles and the wheelsets of VIRM consist of HIT wheel profiles. Two simulations were carried out, in the first one only new wheels were considered to pass the track and in the second one only worn wheels. For each case the cumulative wear was calculated and compared with field measurements. An extensive explanation of the proposed method and its results are found in the appendix.

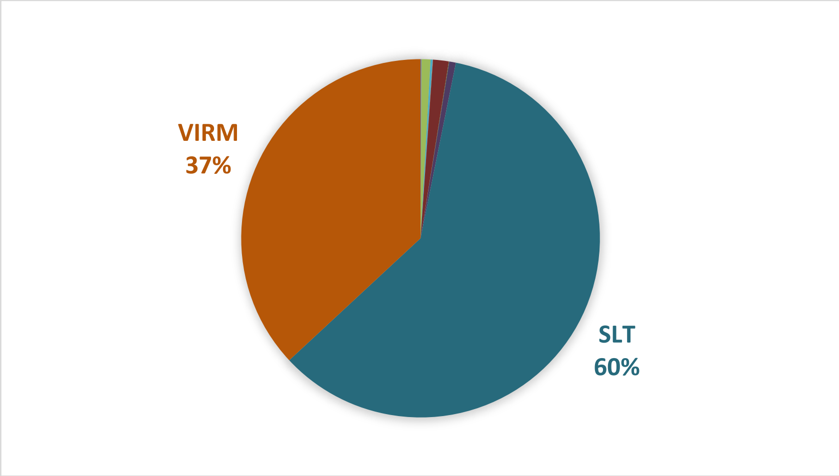


Figure: 7. Pie chart for the number of trains in percentages.

4.3.3. Measurements

Rail profiles are measured with the UFM 120 recording car of Eurailscout which runs with a maximum vehicle speed of 120 km/h [1]. The data sampling of the rail profile measuring system on this car/train is equal to 1/3 meter, meaning that every 3 meters two rail profiles (from both sides) are recorded. Data samples were collected from 2014 until 2016 and a total of six measurement sets were available. In order to determine the increase in wear area (of the cross sectional rail profile), the results from a measurement were subtracted from the results of the previous measurement. However it turned out that in some cases up to 50% of the data (of an individual dataset) is not directly usable for analysis, as the margin of error in the measurement system (e.g. due to sampling rate, moving reference profile) is in the same range as the difference measured between two consecutive measurement runs. In case of comparison with the simulation results a lower-bound for the measured wear area was defined using another analysis method. This method doesn't takes into account the vertical height of the rail profiles and only calculates the minimum amount of wear loss [2]. However, the simulation results do agree with this lower-bound but as long as the absolute wear values are not available a validation of the proposed method remains a challenge. In order to justify the findings with the proposed method measurements of rail profiles are performed with the measurement system RailMonitor which has a fixed reference point during the measurements and therefore is argued to be more accurate. The measurements from the RailMonitor were supposed to be compared with the UFM120 measurement, but unfortunately the data could not be delivered on time to be integrated in this report.

4.3.4. Sensitivity analysis

From the results of the case study it can be concluded that at least the minimum amount of wear area can be justified by performing simulations with measured rail profiles and discarding the profile update iteration strategy. Although the required computation time is reduced, Infrastructure Managers (IM) still need to perform simulations at least for every curve radius with measured rail profiles to determine the predefined wear rate. The goal of the research is to develop a damage accumulation index based on operating conditions and also to advise IM's which operating conditions to monitor in order to manage rail wear on moderate curves. Therefore, a sensitivity analysis is performed to investigate the dominant influence parameters related to operational conditions. The results, which are described in annex 2, show that rail profile, vehicle speed, rail cant, axle load, curve radius, material hardness, coefficient of friction and the longitudinal and lateral stiffness of the train bogie are relevant for rail wear prediction. Parameters related to underground conditions like ballast and sleeper stiffness are not considered in this analysis due to the rigid nature of the track model.

4.3.5. **Further steps**

The next step is to perform a Design of Experiments (DOE) to determine relative changes in rail wear for various scenarios and to provide insights into possible bandwidths. In this DOE the parameters which will be varied are the ones that are regarded as dominant from the sensitivity analysis. Furthermore, a transfer function will be developed from the results of the DOE which will serve as the base of the decision support tool for IM's. Thereafter the influence of track geometry irregularities on rail wear and their relation to vehicle frequencies will also be investigated. Finally, the wear model based on the Archard's wear law will be coupled to the Rolling Contact Fatigue (RCF) damage function in order to establish a hybrid model.

4.4. Link with Shift2Rail work

In the previous section of this chapter some extra validation work is given for the rail defects and also the next specific steps for the work around rail defects.

However, It is important to mention that all work around the models being developed for track are handed over for further development to the In2Smart project. Work is there allocated in work package 8. Models are integrated in the various use cases.

5. Dynamic model for switch maintenance

This chapter relates to task 6.4, Dynamic model for switch maintenance. The first paragraph of this chapter is a summary of the results as captured in deliverable D6.4 – Switch behavioural model.

The second paragraph describes links between other work packages in In2Rail. These identified links will be taken into account in future steps.

The third paragraph the specific validation of two modelling activities is documented. The last paragraph is about the work in Shift2Rail.

The work related to the integrated modelling for both switches and track (previous paragraph) is documented in the next chapter.

5.1. Summary of the results

This document defines the project approach of the In2Rail stakeholders for current and future dynamic switch modelling needs.

After a short reminder of background and objectives of this task, Chapter 3 presents a State of the Art and Gap Analysis regarding switch maintenance models which is based on the root causes and research needs identified in Deliverable D6.1 (In2Rail, Prioritised Relevant Input, 2017). In Chapter 0, the main part of the deliverable, the development and the characteristics of the selected switch maintenance sub-models is described. The basic concept for the integration of the sub-models in an integrated switch behavioural model to be placed in the asset modelling framework is outlined in Chapter 5.

The aim of this work is to provide the basis for a dynamic model for switch maintenance as part of the asset modelling framework. The following sub-models have been developed and investigated:

- switch functional model;
- switch failure detection model;
- switch settlement model;
- crossing transition geometry degradation model.

The sub-models have been tested and partly validated by means of a large amount of data provided by the partners.

Further, an integrated whole system model has been created in a Petri Nets modelling environment considering the required interfaces (input and output parameters) in order to integrate the developed sub-models. The benefit of this modelling approach will be demonstrated within In2Rail in the adjacent Task 6.7 by means of an illustrative use case.

5.2. Links other WP's

5.2.1. WP2 Innovative S&C Solutions

WP2 of In2Rail focussed on S&C: to create solutions for a radical redesign of the S&C system and deliver improvements to the existing S&C system, whilst embracing "state of the art" technologies.

WP6, task 6.4, looked at the development of switch behavioural models to predictive maintenance concepts for switches and insulation joints. The new aspect for these models was to use data from several sources and combine the data to be analysed and processed with new data mining techniques. Besides the new data mining techniques. The framework of task 6.2 was used.

For WP 6, S&C were used as specimen to illustrate this approach. This approach can be used in future work around enhanced and next generation of S&C.

The other way around (what can results for WP2 for WP6):

1. concepts for additional redundancy within S&C points operating equipment (either through actuation, locking and / or detection): This will affect the build-up of the S&C functional modelling that then feeds into the integrated model. While the structure of the integrated model should not change, this element on S&C predicted failures will allow the redundancy to influence in a positive way the intervention requirements of skilled resources to access the track during down time. It will also affect the Mean Time Between Failures (as WP2 predicts) and thus increase reliability.
2. a wide range of different sensor / monitoring technology for whole S&C system RCM. Data from these new sensor technology should be integrated in the modelling techniques developed by WP6.

Work done in WP2 of In2Rail, and possibly in the CFM project In2Track, around FMEA at component level of the different types of S&C units under different POE & switch size, provide WP6 modelling work the opportunity to utilise this data to refine the validation process of the various S&C failure models.

5.2.2. WP3, Innovative track solutions

Although task 6.3 looked at S&C as a specimen, part of the modelling went into more detail about the correlation with measured noise emissions on crossings.

WP3, with focus on innovative track solutions, had also a close look and noise and vibrations.

Results should be combined in the next steps.

5.3. Validation of individual modelling work

The validation of individual models is undertaken for the switch failure detection model, first paragraph, and secondly to the Functional Model Switches in de second paragraph

5.3.1. **Switch failure detection model**

In this deliverable the switch behavioural model for failure detection from task 6.4 described in deliverable 6.4 (D6.4) is validated by comparing its output parameters to the alerts triggered by the state-of-the-art monitoring system POSS®, which is currently in use by Strukton Rail. The purpose of the validation is to assess the model capabilities to reproduce POSS® alerts (in what follows called just alerts) and to reduce the number of false alerts. The validation is done for seven switches and found to provide temperature-robust anomaly detection.

5.3.1.1. POSS alerts

Strukton Rail uses POSS® to monitor switch engines. POSS® measures the engine current (proportional to the engine power consumption (Stoll and Bollrath, 2002)) during the switch blades movement. Switch malfunctioning can lead to irregularities in the power consumed during this movement. When these irregularities exceed certain thresholds defined by maintenance experts from manually selected reference curves, alerts are triggered (see In2Rail WP 6 D6.4, WP 9 D9.3 and D9.4, as well as (Dutschk et al., 2017)). These alerts indicate that the current state of the switch is different than expected. Moreover, weather conditions such as temperature and precipitation also play a role on the typical profile of such current measurements. Reference curves in POSS® are updated about every half a year to prevent false alerts due to seasonal temperature variations. In case of alert, maintenance experts assess the weather conditions and corresponding measured current, and decide on the urgency of inspection. Detailed scenario descriptions are given in In2Rail deliverables D 6.4 and 9.4.

Frequent manual selection of up-to-date reference curves for every switch and every direction of blade movement represents a significant work load for the condition monitoring operators. A conservative selection of thresholds avoids false alerts but likewise hampers the early detection of degrading switch condition and emerging switch failures. The objective of the data-based model for anomaly detection presented here is to significantly reduce the work load by disposing the need for manual reference curve selection, reducing the amount of false alerts and enhancing early detection capabilities for failure forecasting.

5.3.1.2. Switch failure detection model

The data-based model (see In2Rail deliverable D 6.4) exploits engine current during blades movement measured by POSS®. Every switch behaves in a unique way in each direction;

therefore the model is switch- and direction-specific. The model is trained with features extracted from a selection of current curves (so-called training set) that are assumed to predominantly represent normal switch behaviour.

Features are derived from each current curve. Feature selection considers: 1) area under the curve, 2) maximum, 3) median, 4) kurtosis, 5) skewness, 6) duration, 7) mean value during switch blade movement, and 8) standard deviation during switch-blade movement. The switch behaviour temperature dependence is reflected in the features. For example the area under the curve (or total power consumed) and the total duration of the curve systematically decrease with increasing temperature, up to a certain limit (see In2Rail D6.4, D9.3 and D9.4, as well as (Böhm and Doegen, 2010)). The model consists of applying the Principal Component Analysis (Jackson and Mudholkar, 1979; Sotiris and Pecht, 2017), which is sensitive to the different feature ranges. Thus each feature is scaled to have zero mean and standard deviation equal to one; see (Kuhn and Johnson, 2016). This transformation is separately applied to feature values from current curves, which were measured at a temperature within the same 1 Kelvin bin. With this scaling the temperature dependence is removed from the features (see In2Rail D6.4). In what follows we refer to the scaled features as features.

The selection of the training set is a non-trivial aspect of the model development, as it defines the model output and is the base for detecting abnormal switch behaviour. Different approaches for selecting samples predominantly representing normal operation are possible. The method applied here consists of identifying beforehand a timeframe in which it can be assumed that the switch predominantly functioned normally (e.g. the time between a pair of consecutive reported failures). This is possible since information on historical reported failures is available. Current curves measured in this timeframe are analysed in order to remove current curves that are statistical outliers from the training set based on two criteria: total duration of switch blade movement and area under the curve. Other possible training set selection methods include the use of clustering, and identify current curves belonging to the largest cluster as normal behaviour.

The model output consists of two positive parameters (square prediction error (SPE) and Hotelling's parameter (T^2)) associated to each current curve (Böhm et al., 2016). The SPE and T2 parameter values of the training set are typically chi-squared distributed. Quantiles corresponding to 1% and 99% (i.e. the probability that the parameter takes a value less than or equal to the given percent) are computed and used to define the range of normal switch behaviour. The trained switch-specific model is then applied to the same features extracted from current curves outside the training set (from the same switch and in the same direction). The output parameters corresponding to these curves are evaluated and identified to be abnormal whenever their values are outside the normal switch behaviour range. A preliminary set of four rules based on statistical process control was applied to both SPE and T^2 parameters, showing the potential of the approach to identify systematic abnormal behaviour on an early stage of an emerging failure (see In2Rail D9.5). This approach will be further explored in the In2Smart project for failure forecast and prevention.

5.3.1.3. Input data

The data considered consists of current curves measured with a frequency of 50 Hz at seven switches for blades movement in direction 1 only, given that for direction 0 there were less alerts observed for the analysed switches. The current curves were acquired between January 2012 and February 2017. The air temperature at the relay house (located about 1 km away from the switches) at the time each current curve was measured is available. Table 1 contains an overview of the available data for each switch identified with an ID.

Table 1. Data set overview.

Switch ID	Total number of current curves	Number of current curves in training set	Training set in duration months	Number of alerts with available temperature (alerts in total)
2604	5543	1041	12	42 (42)
2606	14326	1766	12	12 (76)
3015	2535	444	12	38 (38)
3069	9617	1810	12	24 (24)
3076	10653	1801	12	73 (189)
3083	10213	2239	12	125 (125)
3090	4968	729	9	39 (39)

POSS® provides a status description for each measured current curve. The large majority of curves have the status “okay”. However, when one or more of the set thresholds based on the reference curve are exceeded the status is different than “okay”. There are four alert types. Two are based on the total power consumed by the engine and can lead to “power too high” or “power too low” status. Another type is related to the total duration of the current curves and leads to “time too long” or “time too short” type of alert. Some curves may lead to both “time too long” and “power too high” alerts, since these quantities are correlated. However the status only provides one or the other alert type. When the measured current reaches high values and exceeds corresponding thresholds a “current too high” alert is triggered.

Furthermore historical data sets of all reported failures and planned maintenance actions provided to each switch are available. The first data set contains time and date when failures were reported by the network operator and when the switch was made available again, and additional remarks provided by the maintenance team on site. Maintenance activities related to each maintenance campaign, as well as planned execution date are contained in the second data set.

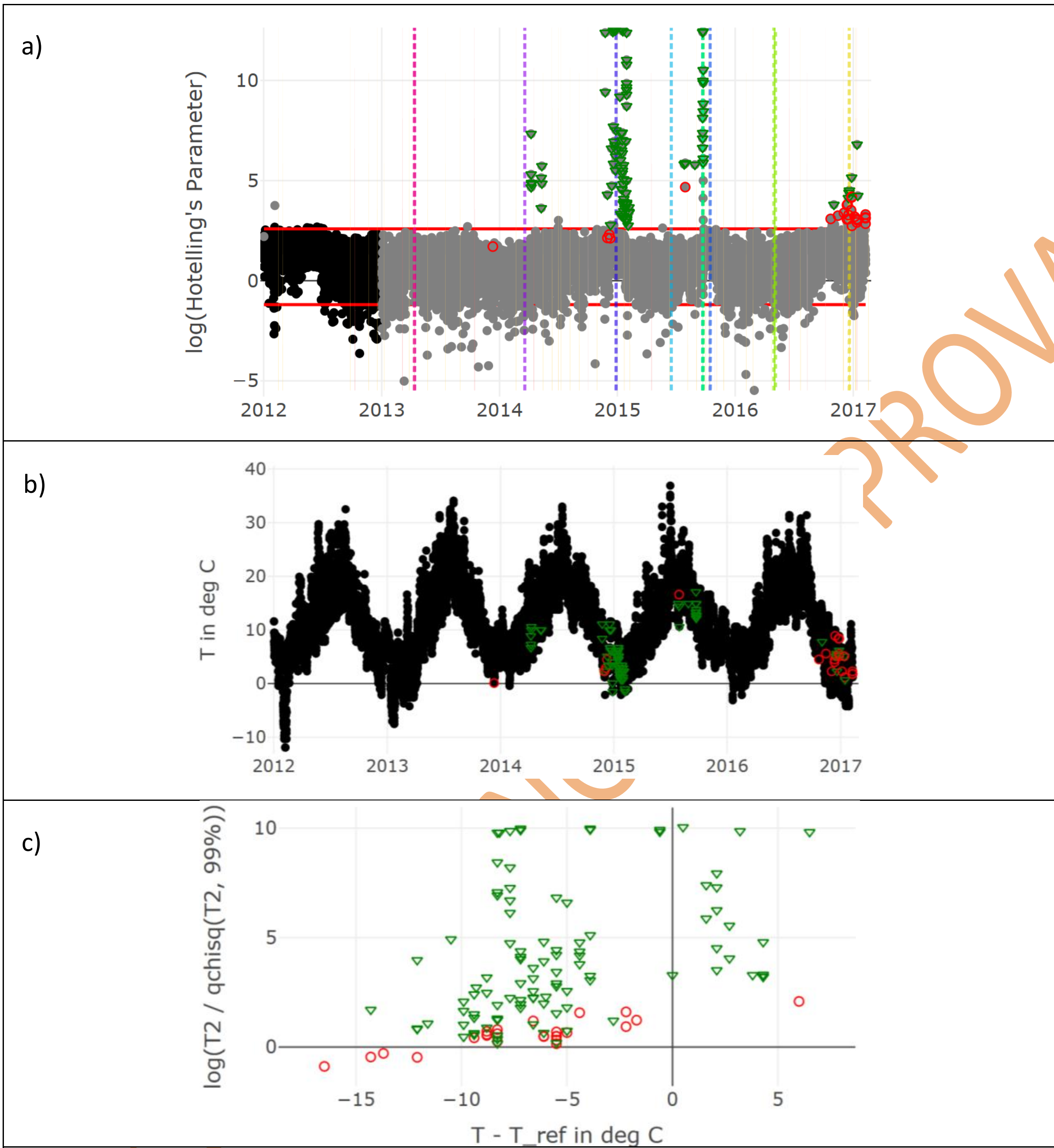
5.3.1.4. Results

Figure: 8a and Figure: 9a show the Hotelling's parameter (in log scale) over time for two switches. Data points larger than the 99% quantile of the assumed chi-squared distribution qchisq(T2, 99%) of the training set are considered to identify current curves outside the range of normal behaviour, thus called anomalies here. Data points smaller than the 1% quantile qchisq(T2, 1%) are, strictly seen, also anomalies. However anomalies with T2 values very close to the quantiles defining the range of normal behaviour are sensitive to how well the assumed chi-squared distribution represents the (finite sample of) data-values. Further research is necessary to address the validity of assuming the distribution of the T2 parameter. Nevertheless results so far indicate that the critically of values smaller than qchisq(T2, 1%) is very low in comparison to the criticality of anomalies with very large T2 values; that is, no POSS alert has been identified to have a T2 value smaller than the 1% quantile of the distribution. Therefore in what follows only the latter type of anomalies is discussed.

Switch 3083 (Figure: 8) experienced many more switchblades movements than switch 2604 (Figure: 9). The training set, spanning a whole year in both cases, consists of 2239 and 1041 current curves (see Figure: 10), respectively.

In Figure: 10 a most anomalies detected by the data-based model coincide with POSS® alerts of two types. Only a few "power too high" alerts are not detected as anomalies, however they are close to qchisq(T2, 99%). Some alerts and anomalies occurred shortly before a failure was reported, indicative that they were serious. In spite of the fact that the seasonal temperature variation (see Figure: 10 b) is compensated through the scaled features (see section 5.3.1.2), T2 values tend to be slightly smaller in the winter than in the summer times, except for years with reported failures in the winter (2015 and 2017).

In Figure: 9 a all alerts, which incurred in the cold months (Figure: 9 b), are inside the range of normal behaviour. In fact, none of these alerts seem to have been crucial, as there is no failure reported after they were triggered and their shape was identified as quite normal by experienced POSS® operators (see Figure: 12). That is, no vertical dashed-lines are close to the alerts, except for one in 2015, where a loose bolt was reported and fixed, which eventually prevented the complete failure. T2 values for this switch do not show a particular tendency for cold/warm months.



a) Logarithmic value of Hotelling's parameter (T2) as a function of time for switch 3083 in direction 1. Black and grey dots respectively correspond to current curves used to train the model, and curves to which the model was applied. Horizontal lines: 99% (upper) and 1% (lower) quantiles of training set distribution delimit the range of assumed normal behavior. Dashed vertical lines: reported switch failures. Thin solid vertical lines: maintenance (width corresponds to one day). POSS® alerts: "time too long" (triangles) and "power too high" (circles).

b) Temperature at the time of current curve measurements (and alerts when triggered) shown in a) as a function of time.

c) Logarithm of T2 values from alerts divided by qchisq(T2, 99%) as a function of the difference between temperature at the time of measurement from current curve (T) and reference curve (T_ref).

Figure: 8. Switch 3083

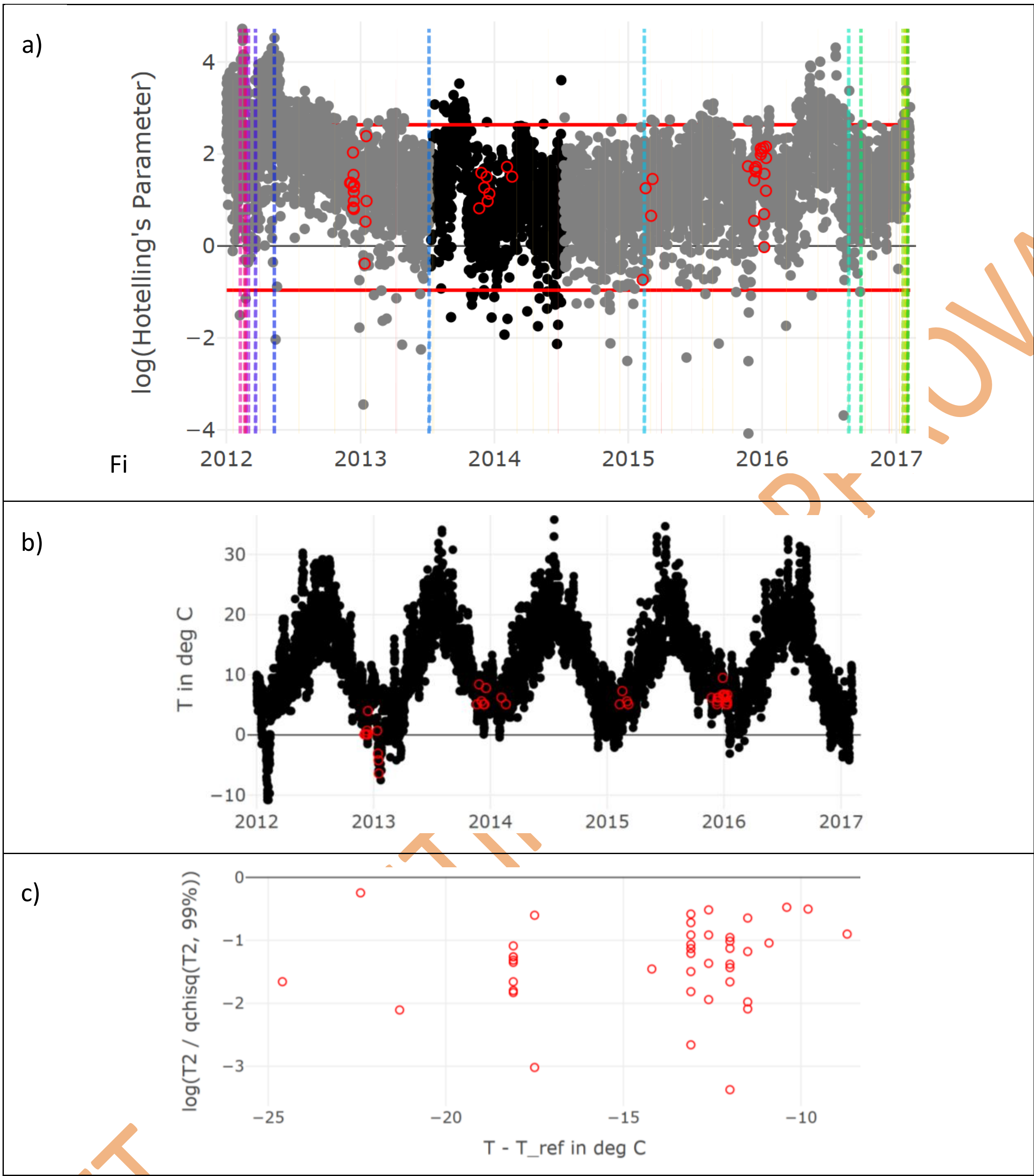


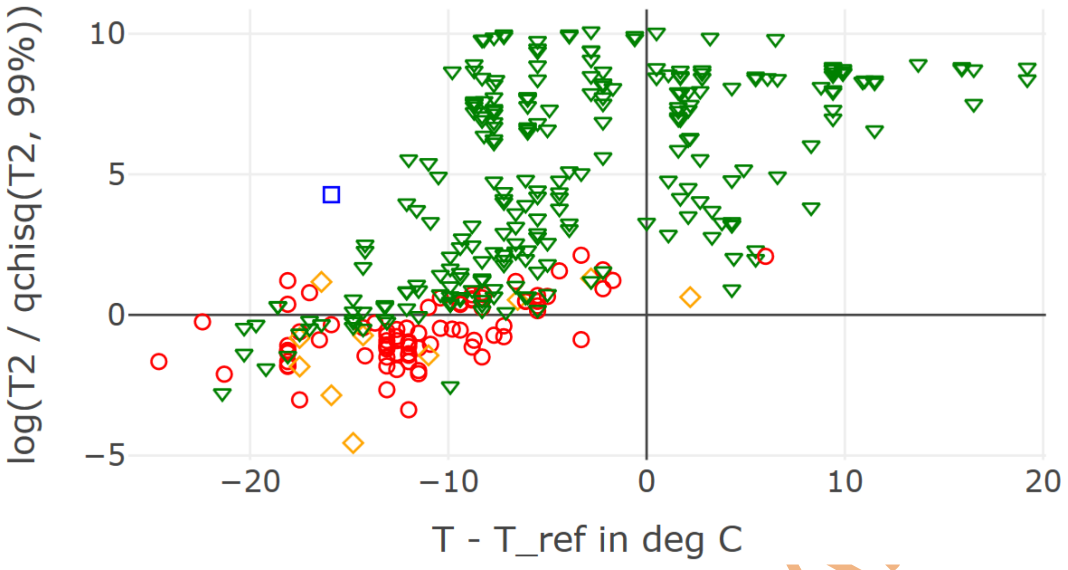
Figure: 9. Switch 2604

Figure: 8 c and Figure: 9 c present the difference between log(T2) values of alerts and log(qchisq(T2, 99%)) plotted as a function of the difference between the temperature when the alert-triggering curve (T) was measured and the one of the reference curve associated to that alert (T_ref). Thus positive y-values correspond to anomalies and negative ones to normal switch behaviour, according to the failure detection model.

The results for switches 3083 and 2604 exemplify two extremes cases. In the first case anomalies detected by the model coincide with alerts detected by POSS®. In the second case none of the alerts are detected as anomalies. To gain insight into this apparent contradictory capability of the model to detect abnormal behaviour it is crucial to consider the temperature at which the alerts were triggered. The state-of-the-art system is known to raise false alerts if the current temperature differs significantly from the temperature when the applied reference curve was measured (T_ref). As previously mentioned, total power consumed by the engine, maximal current value during switchblades movement and total current curve duration, are features that decrease with increasing temperature until they reach their temperature-independent nominal value. This is the motivation behind the current practice of manual selection of current curves per switch and direction twice a year for summer and winter times.

For switchblades movements under normal operation measured at a temperature T < T_ref, it is clear that these features are larger than the corresponding values of the reference curve. Thus even if the switch is behaving normally, the thresholds derived from the reference curve can be exceeded, triggering "power too high", "current too high" and "time too long" alerts in POSS®. In this context, such alerts are referred to as 'false' alert. The probability that an alert is false in such circumstances increases with increasing T - T_ref.

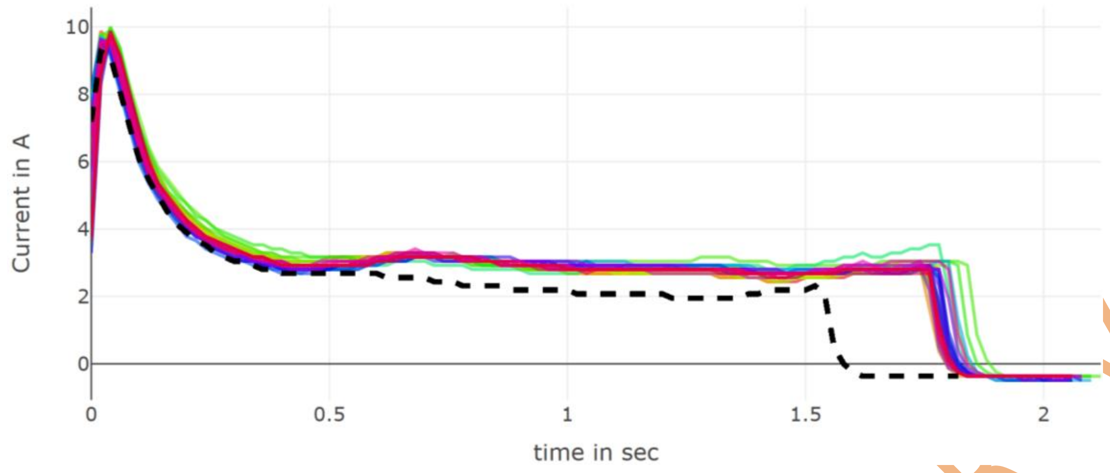
POSS® "power too high", "current too high" and "time too long" alerts triggered when T < T_ref can also point to a real problem with the switch. To differentiate between a real problem and a false alert when T < T_ref, one would have to consider how much the thresholds in POSS® (reference-curve-based) are exceeded. Based on a similar argument, a "power too low" alert triggered when T < T_ref is highly likely related to a problem with the switch. For cases where T_ref < T, "power too high", "time too long" and "current too high" alerts are to be treated as serious warnings, while "power too low" alerts could be false.



See **Error! Reference source not found.** b. POSS alerts of seven switches in direction 1: “Time too long” (green triangles), “power too high” (red circles), “current too high” (orange diamonds), “power too low” (blue square, only a single observation for all analysed switches).

Figure: 10. alerts from seven switches

Adding to Figure: 8 c and Figure: 9 c, shows all alerts from seven switches provided the corresponding T_ref was available (for some years and switches it is not). It is observed that temperatures at the time of switch movements were up to 20 Kelvin larger or smaller than T_ref used in POSS® to detect alerts. These large temperature differences can be expected to have triggered false alerts. In Figure: 11only one alert meets both conditions “power too high” and T > T_ref, pointing to a real problem, which is corroborated by the model by detecting it as anomaly. The majority of “power too high” alerts with T < T_ref (and all alerts in figure 10 c) were detected by an expert analysis to show normal behaviour (seefigure 10), which proves that these were false alerts originated due to an invalid reference curve. The remaining “power too high” alerts with T < T_ref were detected as anomalies by the model. All “time too long” alerts triggered when T_ref < T are likely related to real problems, as confirmed by the model. Even for T < T_ref “time too long” alerts are mostly identified as anomalies by the model, and the relatively few ones that are not are found for T-T_ref < -10 deg C. Only one “current to high” alert is certainly related to a real problem as T_ref < T, and additionally detected as anomaly. The others could be false and even though three of them are detected as anomalies, their y-value in figure 10 is quite close to zero. The “power too low” is identified as anomaly and related to a real problem with the switch.



All 42 current curves of switch 2604 that triggered “power too high” alerts in POSS® (solid colourful curves) and their corresponding reference curve (dashed black). These curves show no abnormal behaviour but triggered ‘false’ alerts due to T – T_ref < -10 deg C.

Figure: 11. Current curves triggering power too high

5.3.1.5. Discussion

POSS® alerts can be differentiated between likely ‘false’ and indicative of switch anomalies based on their T-T_ref value. The single “power too low” alert as well as all alerts in the upper right quadrant of figure 11 can be certainly considered to be pointing out to a real problem with the switch. The switch failure detection model is validated against these alerts and found to detect all of them as anomalies. The model is found to be temperature robust and capable of reducing the number of false alerts without the need to manually select reference curves and corresponding thresholds for each switch and in each direction. The implementation of the model for anomaly detection could improve the reliability of switch condition monitoring systems, such as POSS®.

Furthermore the model can detect anomalies that are not necessarily reflected in deviations from expected total power, even if the reference curve used in POSS® is valid for the measurement. For example, if one considers a sinusoidal curve, its area under the curve over one period is equal to zero. If a current curve would show fluctuations described by a sinusoidal curve, this abnormal behaviour would not be reflected in the total power and thus no alert would be triggered in POSS®. However since the model considers current standard deviation during switchblades movement, this example curve would be picked out by the model as abnormal.

The pattern recognized for switch 3083 in Figure: 8 a for summer and winter T2 values could be due to seasonal variations of other weather variables. For example precipitation evaporates faster in a warm sunny day than in a cold and cloudy one. Thus even when the model is temperature robust, this does not imply that other factors, which are temperature-correlated, affecting the switch behaviour, are being accounted for. Additionally the model is trained with one-year data and applied over the next 4 years. The way a switch reacts to temperature (and other weather conditions) might change with time. Therefore questions about model validity as well as under which conditions to re-train the model are of major importance for the model accurate output and are addressed in the Shift2Rail project In2Smart.

Results for switch 2604 (Figure: 9 a) are a good example to show how crucial is the definition of normal behaviour for the model. In the training period chosen here T2 values have large deviations and there is much structure in the data points contained in it. This is also reflected in the T2-distribution of the training set and thus on the limits of normal switch behaviour, ultimately affecting anomaly detection and leading to the detection of too many anomalies. The way to overcome this issue is not by simply taking a different training set, but by finding more and more adequate features representing switch behaviour. Ideally, the training set T2 values do not present structure as all parameters influencing the system are accounted for.

T2 and SPE values indicating an anomaly are of concern but further investigation is needed to categorize them and provide degrees of abnormal behaviour and criticality of the anomaly. Moreover, for condition-based maintenance support, detection anomaly needs to be accompanied by a diagnosis. The link between the switch functional model, which relates switch sub-functions to its components, and the data-based model output, are the features. Domain knowledge can further provide features that are directly linked to switch components. In this way, when an anomaly is detected, the features can be traced back to identify the components that are compromised.

5.3.1.6. Conclusions and outlook

The data-based switch failure detection model is verified against POSS® alerts from seven switches over more than five years; given that it identifies all alerts that certainly point to abnormal switch behaviour as anomalies. The model does not rely on manual reference and threshold selection, while it already produces reliable detections. Further research on feature engineering is necessary to enable more accurate modelling of switch behaviour, which will increase the model accuracy and reliability when anomalies are detected. Additionally, other weather variables and actions performed on the switches which modify their normal behaviour need to be accounted for. The research is continued in Shift2Rail IP 3 (In2Smart project).

5.3.2. **Technical validation Functional Model Switches**

5.3.2.1. Introduction

The purpose of the functional model is gaining new insights in relation to usage, maintenance activities, performances and costs. The functional model describes the “main” functions of a system and its components. By defining these functions, the model can be used as a key integrator for different data inputs and are linked with functions of the model. By doing this new insights will be gained, and could be used as a decision support tool.

Domain knowledge and the availability of data is the key for bringing the theory into a practical model which can be used in daily operation. Strukton Rail brings in its knowledge and experience on maintenance and reliability engineering (FMECA/RCA/…) , and has access to data from its maintenance contracts. Strukton is familiar with the functional breakdown of systems and can analyse the failure data/ costs, maintenance activities and maintenance costs to determine cost-drivers and performance killers. To verify the model Strukton Rail developed a use case as a proof of concept.

Strukton Rail uses several systems for collecting and analyse data. For the use case it is considered only to failure data, costs and maintenance activities. Risk analyses, monitoring data, environmental data and load conditions are part of the In2smart project.

5.3.2.2. Failures

Table 2 shows the average number of failures per sub function and switch engine. If no failure data can be linked to one or more sub functions, this results in empty cells.

Due to the way in which the failures are registered, it is difficult to link data to a sub function. Therefore, at sub function (99. Switch general) we see a higher ratio number than in the other sub functions.

The ratio numbers and differences between them say something about the performance of the contract or between them.

Table 2. failures per contract / sub function

		Guiding and change direction of trains										
		Steering	Steering	Movement	Movement	Movement	Movement	Controlling	Controlling	Controlling	Controlling	Other
Contract	No. of switch engines	10. IL-S interlocking steering	99. General	20. Converse energy into rotating	30. Protection and motion	40. Guiding and change direction trains	99. General	50. Allocate position switch blades	60. Switch control circuit	70. IL-C interlocking control	99. General	99. Switch general
Contract area 1	543	-	-	0,06	0,07	0,49	-	0,10	0,08	-	-	1,66
Contract area 2	177	-	-	0,07	0,03	0,33	-	0,13	0,37	-	-	2,18
Contract area 3	286	-	-	0,06	0,06	0,36	-	0,10	0,07	-	-	1,34
Contract area 4	432	-	-	0,07	0,06	0,32	-	0,18	0,03	-	-	1,27
Contract area 5	212	-	-	0,05	0,09	0,11	-	0,06	-	-	-	1,31
Contract area 6	208	-	-	0,04	0,05	0,29	-	0,13	0,00	-	-	1,07
Contract area 7	168	-	-	0,04	0,05	0,32	-	0,13	0,02	-	-	1,48
Contract area 8	197	-	-	0,04	0,01	0,20	-	0,08	-	-	-	0,96
Contract area 9	140	-	-	0,04	0,01	0,20	-	0,05	0,01	-	-	0,83
Contract area 10	217	-	-	0,02	0,05	0,29	-	0,06	0,03	-	-	0,76
Contract area 11	181	-	-	0,06	0,02	0,30	-	0,08	0,02	-	-	0,85
Contract area 12	250	-	-	0,04	0,07	0,27	-	0,13	0,02	-	-	1,24
Contract area 13	93	-	-	0,04	0,09	0,44	-	0,19	0,02	-	-	1,83
Contract area 14	117	-	-	0,05	0,10	0,44	-	0,17	0,03	-	-	1,43

All the information gives an idea of whether the quality of the failure registration improves and shows a better result across all contracts (less failures).

Another advantage is the ability to compare contracts with the knowledge that the same maintenance concept is being implemented.

Improvement potential of the failure registration is 69% as can be seen in the graph

5.3.2.3. Maintenance data

It should be noted that these repairs do not include repairs related to failures. The table only shows repairs that are generated by inspections or maintenance activities. All the repairs that were extracted from SAP best related to "maintain windows stiffness" or "transferring load". For that reason the other functions are filled out with question marks.

Directly is visible that contract numbers 1, 4 and 6 have the most repairs. This relates to the failures, because these contracts also have a high number of failures.

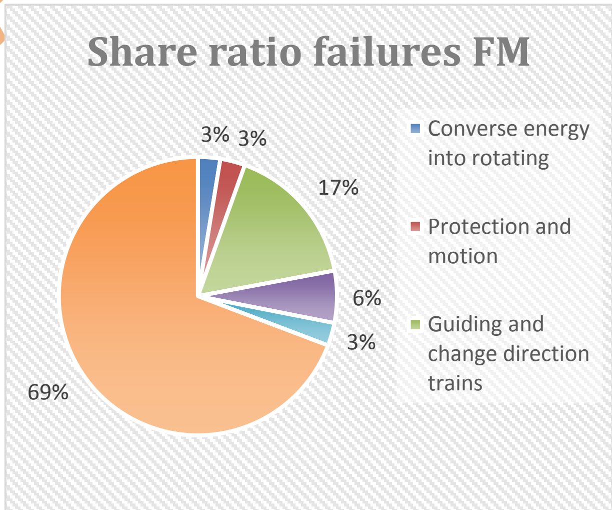


Figure: 12. Ratio failures for each sub function

The most interesting question is: how do these failures and repairs relate to each other? it is not possible to make direct conclusions, but a lot of indications are available and can facilitate decision making.

Combining failures and repairs is just an example what is possible with Functional Modelling. It is clear that a lot of information can be gained by combing the right sources of data. This modelling is pragmatic and could be greatly improved, but the possibilities look very promising.

5.3.2.4. Data driven switch failure detection and forecasting tools

The Functional Model will be integrated in in2rail WP 9.1 and 9.2 Asset status nowcasting and forecasting for TMS dispatching system.

The approach of a data-driven unsupervised machine learning approach in combination with the switch FM. They are expected to jointly provide information to identify both patterns associated to asset failures and their cause, leading to failure forecast and current asset technical status. In practice the shift from (current) preventive to predictive maintenance implies developing algorithms that:

- set dynamical thresholds (adapted to environmental information),
- detect abnormal switch behaviour in an early stage,
- forecast failures,
- recognize the failure origin and allocate the corresponding switch component,
- provide insight into unique asset behaviour

A switch failure detection model concept is described, which builds on the existing domain knowledge formalized in a FM and an unsupervised data-driven approach, namely the statistical process control (SPC) model. The SPC model is presented through a case study showing its ability to detect the development of failures, see (Böhm et al., 2016). The SPC model is trained with available current curves during 'normal' functioning of a given switch. The link between the FM and the SPC model will be further explored in two directions. First, the FM will be used to extend the heuristically selected features such that they are directly related to switch units and their functions. Second, based on these specialized features the SPC model will identify abnormal switch behaviour and relate it to potentially affected units and/or functions, see (Yue and Qin, 2001). In this way, the detections provided by the SPC failure detection model will be enriched with diagnostic information to improve the asset now- and forecasted status.

5.3.2.5. Conclusion

The use case shows the very first benefits of Functional Modelling for maintenance activities, as a tool for performance and criticality analysis. The first use case shows that the development method is an effective way which ensures Functional models are designed in a consistent manner. The first results of the use cases look very promising. By only combing two bits of data, Failures and Repairs, there is already a lot of information and insight gained.

The functional switch model shows where the most problems are in each of the sub functions, but the fact that a lot is reported at the generic level shows that the failure registration needs to be improved.

- Fault registration will improve as a result from the detailed model;
- Insight in were most failures occur -> input for improvement;
- Benchmark systems on contracts and countries independent of supplier and brand;
- Combine with output analysis like machine learning, detection models, big data etc.;
- Uniform interpretation of the system throughout the organization.

It is clear that a lot of work still has to be done. Performing these use cases enabled to underline the impact of the quality of the data on the usability of the modelling. A clear and efficient data structure is also an important condition and has a big influence on the possibilities of functional models. Improvement of the quality and registration of the data should be a big focus in order to improve the practicality of functional models.

With proper development of data quality and functional models, both use cases show that there are great opportunities to be gained. Functional modelling has the prospect to mature into an efficient decision support tool.

6. Integrated modelling

6.1. General overview – strategy testing and validating integrated models

This paragraph gives a general overview and expresses thoughts for a strategy for testing and validating integrated models for Asset Management decision-making,

6.1.1. **Context and issues**

Validating an integrated modelling is a difficult task due to the heterogeneity of the inputs, elementary models and parameters to be implemented. Classical approach shall be based on a direct comparison between provided results and real-life data. This strategy is not sufficient for validating integrated models proposed for supporting Asset Management decision-making, as:

1. These models are developed in order to represent the mean behaviour of assets (of interest) and related Asset Management processes. By definition, the behaviour of a specific asset is particular (e.g. due to local context) and do not correspond strictly to the mean expected behaviour.
   Comparing the outputs of an integrated model with real assets and processes life shall require to use consolidated indicators (based on representative assets and contexts)
2. These models integrate different modules (i.e. Assets and components degradation and reliability, Maintenance activities, Maintenance decision-making, etc.), consolidated on different level of granularity (different groups of assets, operated in different contexts and over different time horizons).
   The figure below illustrates this diversity of models to be implemented and connected within the proposed integrated model

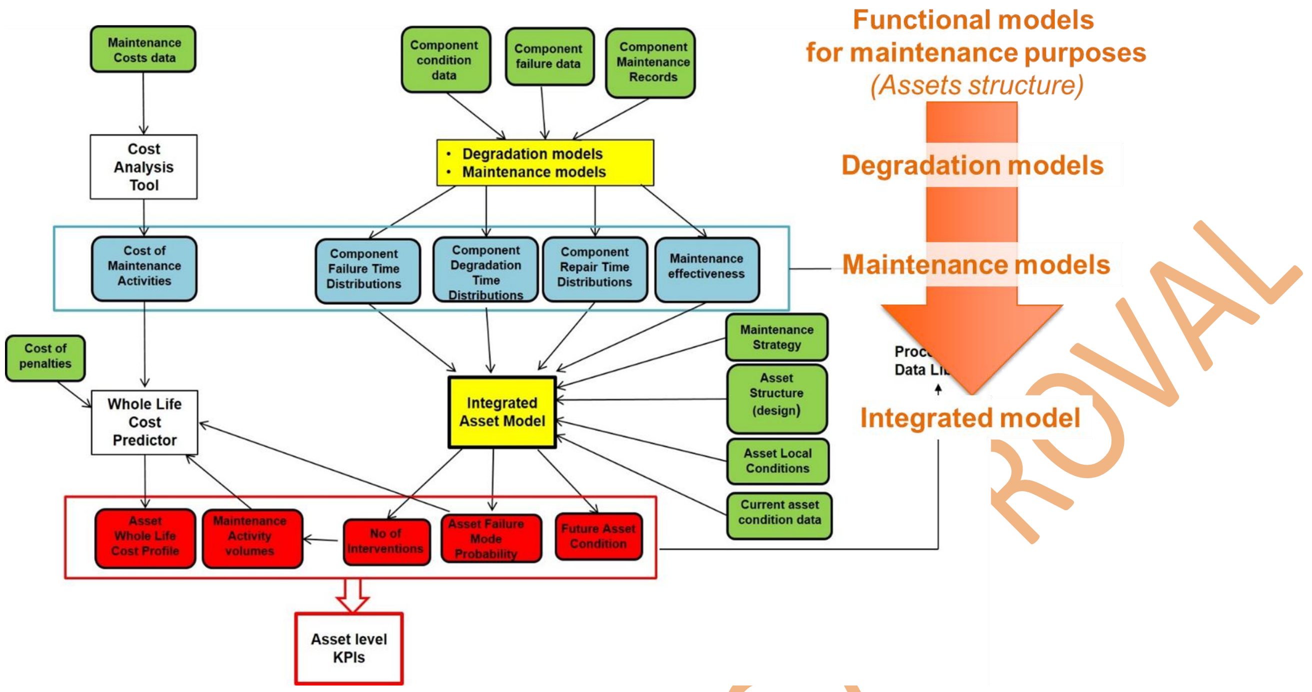


Figure: 13. Modelling Framework for Asset Management (see D6.2 – In2Rail project)

In this context, **validating an integrated model would require a structured strategy** in order to ensure that:

- **Each specific elementary model** is integrated in the right way
- **Links and interfaces between these models**, required within the integrated models, are relevant and functional

Qualitative approach is generally implemented for achieving this validation. This enables to identify the contribution of each sub model in the final results of the integrated model, and then isolate those contributing to unexpected deviation

1. Asset Management decision-making requires to take into account 2 major types of events (see D6.2 – Asset Management KPIs) :
   - Recurrent events, i.e. dynamic changes of assets status over time and Maintenance operations
   - rare events, which correspond mainly to events related to Safety and Performances issues

By definition, these rare events are very seldom met along the lifecycle of components, assets and routes. All the Asset Management processes, implemented in reality, contribute to minimize the risks related to such events.

Integrated models are based on probabilistic modelling of the reality. By definition, in this context, these events do not present a null probability of occurrence and have an impact on the outputs.

2. Integrated models are mainly used for testing and simulating Asset Management "what-if" scenarios
    - Changes within the Asset Management processes and decision rules (e.g. Maintenance policies, investment decision criteria, etc.)
    - Changes within the design of assets and/or choice of assets along routes

    This leads to simulate new technical and processes configuration, which are usually not met in reality.

    - In this context, **validation and testing shall focus on the gradient assessed between integrated model outputs for the current configuration and those for the alternative one** (i.e. represented by each scenario).

6.1.2. Strategy proposed for testing and validating an integrated model

In this context, a generic approach based on 3 main steps has to be implemented for testing and validating of integrated models:

- Qualitative and quantitative validation of the elementary parts of the modelling:
    - ⇨ Elementary models representing assets degradation and reliability
    - ⇨ Asset Management activities and decision-making processes

  This testing and validation phase has to be done before integration within the whole model. In the case of assets reliability and degradation models, Goodness-of-the-fit testing is one of the most suitable and used approaches.
- Qualitative validation of the structural part of the modelling : control of the interfaces and links between subparts of the model (inputs/outputs/priorities), comparison with the expected share of structural parameters / variables, validation of the elementary outputs of these models (regarding sets of fixed elementary inputs);
- Qualitative and quantitative validation of the final outputs provided by the whole modelling. As it is difficult to compare this directly to real life observations, the validation shall be based on :
    - ⇨ **Gradient analysis** between outputs provided for different scenarios. In this case, current configuration is used as a basis for this comparison
    - ⇨ **Sensitivity analysis**. For each significant parameter and input of the integrated model, the impact of standard deviation is analysed regarding the related outputs.

The 2 first steps of this strategy are strongly linked to each use case, based on the data and knowledge and data available within organisation. This validation is under the only responsibility of modelling teams, and shall assess how they simplified reality when they produced such models.

Section 6.2 focuses on a specific point related to these 2 steps. D6.3 proposed a mathematical improvement (namely P.E.M.) when developing integrated models based on Petri Net approach. This section illustrates how testing and validating the implementation of such improvement, based on an example.

The 3rd step is performed jointly with Asset Management decision-makers. Fixing scenarios has to be done regarding the future usage of the integrated models. Section 6.3 focuses on this last step and provides on illustrative example based on comparison between realistic scenarios.

6.2. Exemplary validation of the combination of Petri Nets and PEM

Railway asset management usually requires tools for monitoring and predicting the health states of the rail infrastructure. These tools can rely on physical (i.e., model-based) and/or statistical (i.e., data-driven) approaches, for instance.[1] Moreover, causes of failure need to be identified effectively (diagnosis) in order to optimize maintenance processes whenever malfunctions occur.

Regarding railway track sections, Andrews[2,3] (cf. In2Rail Deliverable D6.3) proposed a quite complex Petri net model for simulating the interaction between all relevant processes in track asset management in terms of an integrated model. His model includes parts for deterioration, inspection, intervention and renewal. A similar Petri net model, by the way, is available for bridge maintenance,[4] for instance. Figure 1 shows the degradation part of the model in an extended version with five instead of four health states (i.e., $P_1, \dots, P_5$) as proposed in In2Rail Deliverable D6.3. In this context, the transitions $T_1, \dots, T_4$ describe the durations in time [in days] after which the system switches to the corresponding next health state. They are considered to be stochastically independent random variables having Weibull distributions $\mathcal{W}(\beta_r, \eta_r)$ for $r = 1, \dots, 4$ with parameters as in Table 3.

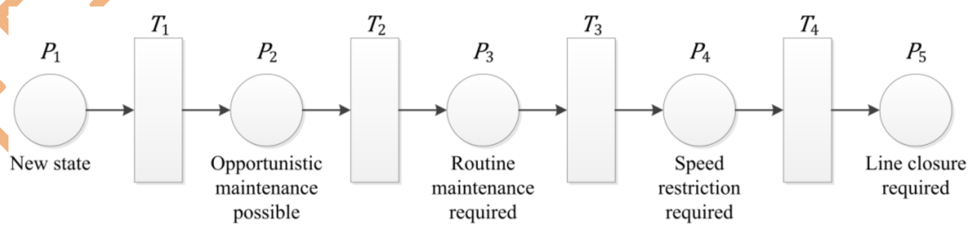


Figure: 14. Petri net model for track degradation (cf. In2Rail Deliverable D6.3).

Table 3. Expert guess of the Weibull parameters of the degradation model (cf. In2Rail Deliverable D6.3).

	T_1	T_2	T_3	T_4

β_r (shape)	1.5	1.5	1.6	1.7
η_r (scale)	600	500	370	280

Starting from state P_1 (i.e., directly after renewal or new construction), the duration before the system reaches the state P_{s+1} for $s = 1, \ldots, 4$ is defined then by $\tilde{T}_s \coloneqq \sum_{r=1}^{s} T_r$. Thus, the expectation and standard deviation of $\tilde{T}_s$ [in days] are given by

$$(1) \quad \mathbb{E}(\tilde{T}_s) = \sum_{r=1}^{s} \mathbb{E}(T_r) = \sum_{r=1}^{s} \eta_r \Gamma\left(1 + \frac{1}{\beta_r}\right)$$

and

$$(2) \quad \sigma(\tilde{T}_s) = \mathrm{Var}(\tilde{T}_s)^{\frac{1}{2}} = \left(\sum_{r=1}^{s} \mathrm{Var}(T_r)\right)^{\frac{1}{2}} = \left(\sum_{r=1}^{s} \eta_r^2 \left[\Gamma\left(1 + \frac{2}{\beta_r}\right) - \left(\Gamma\left(1 + \frac{1}{\beta_r}\right)\right)^2\right]\right)^{\frac{1}{2}}.$$

In comparison to these analytical solutions, Table 4shows the numerical results as obtained by a standard MC simulation of the distribution of $\tilde{T}_s$ with 10,000 samples and as alternatively based on the PEM approximation from In2Rail Deliverable D6.3 for $\mathbb{E}(\tilde{T}_s)$ and $\mathrm{Var}(\tilde{T}_s)$ with an additional application of the transformation for Weibull input distributions. The corresponding relative errors Δ_{rel} referring to the exact (i.e., analytical) values from equations (1) and (2) are given in Table 5.

Table 4. Comparison of the results for $\mathbb{E}(\tilde{T}_s)$ and $\sigma(\tilde{T}_s)$ [in days].

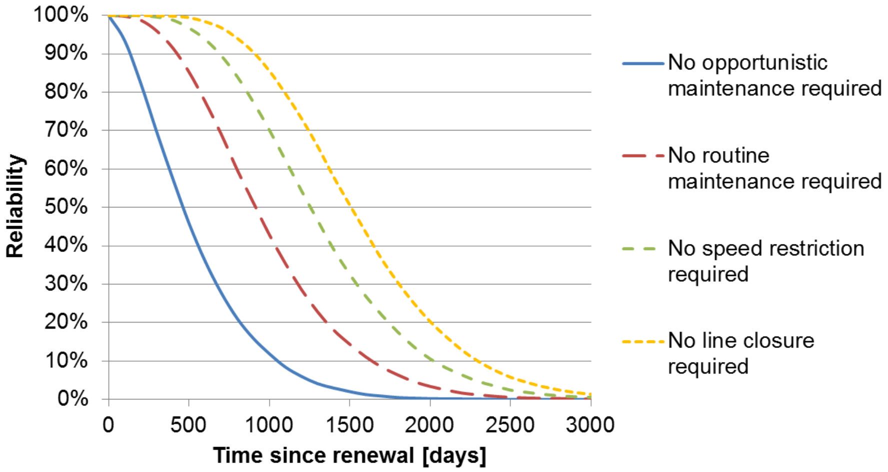
	$\mathbb{E}(\tilde{T}_1)$	$\sigma(\tilde{T}_1)$	$\mathbb{E}(\tilde{T}_2)$	$\sigma(\tilde{T}_2)$	$\mathbb{E}(\tilde{T}_3)$	$\sigma(\tilde{T}_3)$	$\mathbb{E}(\tilde{T}_4)$	$\sigma(\tilde{T}_4)$
Analytical	541.6	367.8	993.0	478.7	1324.8	523.7	1574.6	545.1
MC	538.0	369.6	983.1	478.6	1317.3	526.3	1566.8	548.7
PEM	541.7	367.6	993.1	478.6	1324.8	523.4	1574.7	544.7

Table 5. Relative errors of the MC approach and PEM for $\mathbb{E}(\tilde{T}_s)$ and $\sigma(\tilde{T}_s)$.

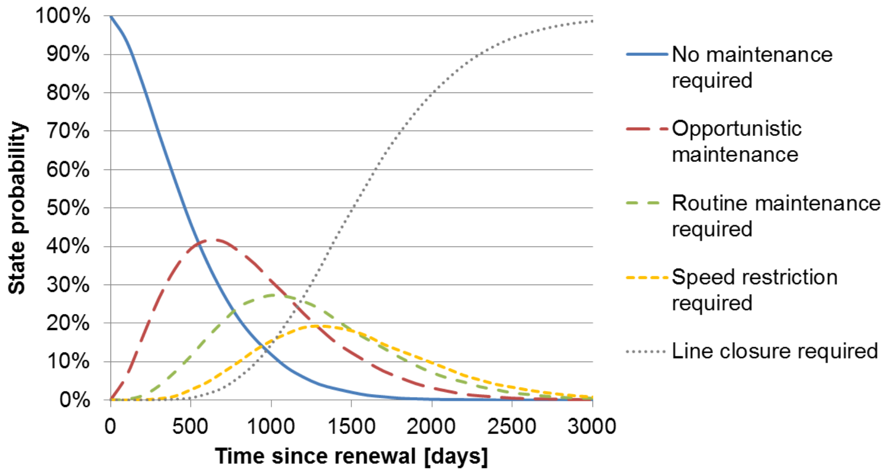
Δ_{rel}	$\mathbb{E}(\tilde{T}_1)$	$\sigma(\tilde{T}_1)$	$\mathbb{E}(\tilde{T}_2)$	$\sigma(\tilde{T}_2)$	$\mathbb{E}(\tilde{T}_3)$	$\sigma(\tilde{T}_3)$	$\mathbb{E}(\tilde{T}_4)$	$\sigma(\tilde{T}_4)$
MC	−0.68%	+0.50%	−1.00%	−0.03%	−0.56%	+0.50%	−0.49%	+0.67%
PEM	+0.00%	−0.03%	+0.00%	−0.03%	+0.01%	−0.05%	+0.01%	−0.07%

The full (approximate) distributions of $\tilde{T}_s$ for $s = 1, \ldots, 4$ – as derived from the MC simulations – are depicted in Figure 2(a) in the form of the corresponding reliability functions $t \mapsto R_{\tilde{T}_s}(t) \coloneqq 1 - F_{\tilde{T}_s}(t)$ where $F_{\tilde{T}_s}$ is the cumulative distribution function of $\tilde{T}_s$.

Moreover, Figure 2(b) shows the simulated probabilities for the states $P_1, \ldots, P_5$ depending on the time since renewal.



(a)



(b)

Figure: 15. (a) Simulated track reliability with regard to the modelled degradation levels and (b) Simulated state probabilities depending on time since renewal [in days].

As can be seen, the PEM and the MC simulations both provide good results for the degradation model. In fact, the PEM approximations are even nearly exact (cf. Tables 2 and 3) which is not that surprising in this case because $\tilde{T}_s$ is a simple linear combination of the input variables T_r. Moreover, the function $\left(\tilde{T}_s - \mathbb{E}(\tilde{T}_s)\right)^2$ which is used for computing the variances via the PEM is quadratic then. Consequently, as the PEM scheme used is exact for polynomials up to a degree of 5, the only source of error results from the (more or less) exact Weibull transformation needed. In contrast, the MC approach shows relative errors up to $\pm 1\%$ despite the use of a large sample number (i.e., 10,000 evaluations). This result is quite striking when noting that the (nearly exact) PEM in this case effectively requires 25 (!)

distinguished sample points only. However, the PEM is not directly able to reconstruct the full distributions of $\tilde{T}_s$ for $s = 1, \dots, 4$ as depicted in Figure 2 as already discussed in In2Rail Deliverable D6.3.

6.3. Validation of integrated modelling

The validation of the integrated models developed for track geometry and railway switching and crossing is based on an expert knowledge approach. The structure of the models relies on the knowledge of the asset behaviour and the rules implemented by the IMs to perform inspection and maintenance. Validation based on real data is difficult due to the lack of ready to use real data to input into the models. The main input data required are the statistical distributions of the times to degrade and/or fail of the components of interest. Although such statistical distributions are not currently available because they are not use in current maintenance practices, conditions data and maintenance records are currently collected by infrastructure managers and only require a statistical analysis in order to extrapolate the distributions of time to degrade to different level of interest for maintenance purposes. In order to overcome such issue at this stage, model validation can be supported by scenario analysis. Following discussion with domain experts, degradation parameters have been assumed which are considered to be close to real values. Then asset response as simulated through the developed models have been analysed for different values of the maintenance parameters. This scenario analysis has two main purposes:

- to show the model capabilities in terms of the type of output that can be generated and how these can be used to compare the effects of different maintenance strategies,
- to determine, based on expert knowledge, whether the response of the asset provided by the model to the variation of the maintenance parameters reflects the expected behaviour.

6.3.1. **Integrated track geometry model**

In subtask 6.3.5 an integrated track geometry model has been developed to represent the ballast degradation process and its interaction with the interventions that can be performed. The model is representative of the behaviour of a 200 metres track section and is aimed at evaluating the asset response to a wide range of potential maintenance strategies. By simulating the model it is possible to predict the future track geometry conditions, the probabilities of occurrence of the different failure modes and the number of interventions performed over a given time horizon, following the implementation of a variety of intervention options.

The modelling approach adopted is the Petri net (PN) method. This is a state-based stochastic modelling technique widely used to represent discrete-event systems characterised by dependencies and concurrencies between different processes. Through the

PN, the asset behaviour in terms of degradation and maintenance can be represented as a graph with two type of nodes: *places* (circles) represent possible states and *transitions* (rectangles) represent events that cause a change in the asset state. Tokens are used to mark places to indicate which state is currently active. The transitions govern the movement of the tokens from one place to another thus representing the change in state due to the occurrence of events such as failures, degradation or maintenance interventions. Figure 1 depicts the PN representing the integrated track geometry model.

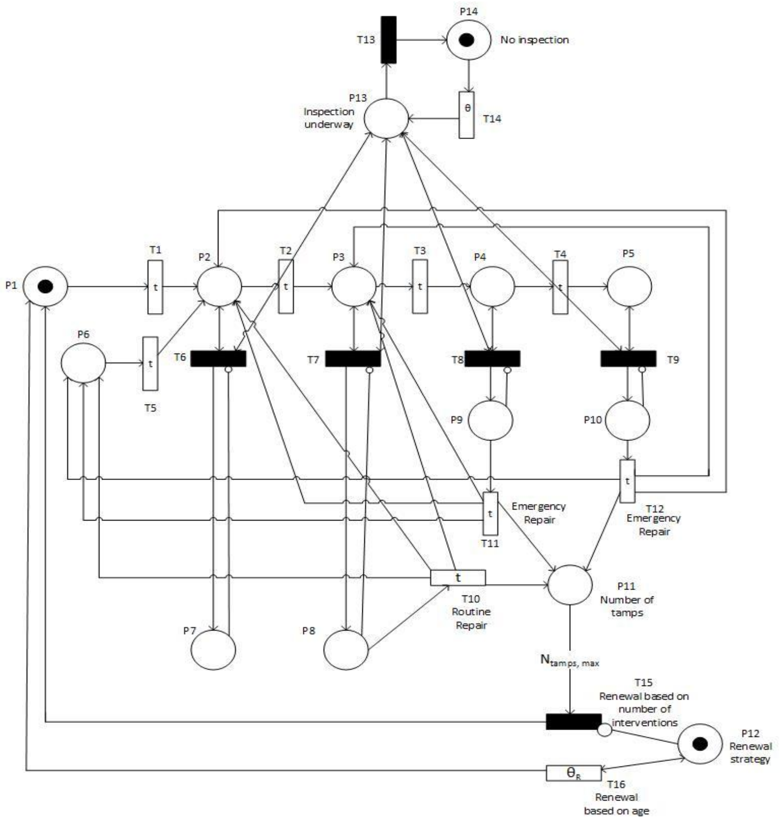


Figure 1 PN representation of the integrated track geometry model.

The integrated track geometry model which includes four main processes:

- Degradation;
- Inspection;
- Maintenance (tamping);
- Renewal.

This is a state-based model where the conditions of the track are described by a finite number of possible states. The Standard Deviation (SD) of the vertical top over 35 metres wavelength is used as an indicator of the geometry quality, as in common maintenance practice. A number of discrete degraded states are distinguished in the model to represent the track geometry conditions, each defined in terms of the values of SD of the vertical top that are representative of geometry conditions requiring maintenance. The number of such states depends on the Infrastructure Manger’s practice. In a condition-based approach, maintenance actions are scheduled only once degraded conditions has been discovered through inspection. Therefore it is necessary to distinguish between degraded conditions which are still unknown, and degraded conditions that are revealed upon inspection. Table 6 summarises the different states and corresponding places in the PN model.

Table 6. Different states represented in the PN model and corresponding places.

States		Places
New (following renewal)		P1
Degraded	Opportunistic maintenance possible	P2
Degraded	Routine maintenance required	P3
Degraded	Speed restriction and emergency intervention required	P4
Degraded	Line closure and emergency intervention required	P5
Good conditions (following effective maintenance)		P6
Revealed	Opportunistic maintenance possible (revealed)	P7
Revealed	Routine maintenance required (revealed)	P8
Revealed	Speed restriction imposed and emergency intervention required (revealed)	P9
Revealed	Line closure imposed and emergency intervention required (revealed)	P10

Additional places which do not represent the track condition but are essential to represent and understand the behaviour of the asset are detailed in Table 7.

Table 7. Additional places

P11	Keeps track of the number of interventions performed
P12	Determine the renewal strategy (maintenance-based or age-based)
P13	Asset currently under inspection
P14	Asset not currently inspected

Relevant events that cause a change in the state of the asset are modelled through transitions which govern the degradation, inspection, maintenance and renewal process. These are summarised in Table 8.

Table 8. Transitions and corresponding meaning.

Events		Transitions
Degradation from one degraded state to the next		T1, T2, T3, T4, T5
Inspection	Inspection revealing current state	T6, T7, T8, T9
	Start inspection cycle/End inspection cycle	T14/T13
Maintenance	Routine maintenance	T10
	Emergency intervention from speed restriction	T11
	Emergency intervention from line closure	T12
Renewal	Based on maintenance history	T15
	Based on age	T16

6.3.2. **Model specification and analysis**

The PN model simulates the behaviour over time of the track in terms of degradation and maintenance and it is therefore necessary to know the time when degradation, failure and maintenance events occur. However, the time of occurrence of such events is not known a priori and is not deterministic because both the degradation and maintenance are intrinsically random processes. The stochastic nature of the track behaviour along with the complexity of the interaction between degradation and maintenance, make stochastic simulation via the Monte Carlo method the most suitable approach for the analysis of the system. The Monte Carlo method consists of running a number of simulations duplicating the system behaviour. This process can be seen as a statistical experiment where each simulation is one observation of the system. This approach requires the knowledge of the distributions of times of occurrence of all the significant events which determine the evolution of the system state over time. In the PN, the occurrence of events is represented by firing of transitions. Distributions of times to degrade to the different levels of SD of the vertical alignment are used to sample the time at which such levels of degradation are reached. Distributions of times to schedule and perform maintenance are used to sample the time at which an intervention is performed. Inspection is supposed to be carried out at regular intervals and it is therefore reasonable to assume that its time of occurrence is deterministic.

The input necessary to the model are therefore:

- The initial asset state (new if the asset has just been renewed)
- The parameters of the statistical distributions associated to each stochastic transition. These are the transitions representing the event of scheduling and performing maintenance (T10, T11, and T12), and the transitions representing the degradation of the track geometry from one SD level to the next (T1 to T5);
- The deterministic time interval associated to the deterministic-not immediate transition representing the start of the inspection process (T14).

The parameters of the statistical distributions of times to degrade, are the results of a statistical analysis on the degradation and maintenance data collected during inspection. Literature contributions such as [..] have shown methods to extrapolate the distributions of times to degrade based on the statistical analysis of the values of SD of the vertical alignment obtained from the track measurement trains and maintenance records (time of interventions). Although such statistical distributions are not currently available because they are not use in current maintenance practices, conditions data and maintenance records are currently collected by infrastructure managers and only require a statistical analysis in order to extrapolate the distributions of time to degrade to different level of interest for maintenance purposes.

6.3.2.1. Use of stochastic distributions to sample events times.

It has been shown that the distribution of times to reach such threshold values of SD of the vertical alignment follow a 2-parameter Weibull distribution [Ref] with the cumulative distribution function given by

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}. \qquad (1)$$

The parameters of the Weibull distribution have a recognisable physical meaning: the shape parameter β is representative of the degradation rate, while the scale parameter η represent the time at which 63.2% of the population has reached the specified threshold. Values of β >1 indicates that the degradation rate increases with time; this is typical of components subject to wear and ageing. For calculation of firing times, a random number X uniformly distributed in the range [0, 1] is generated and equated to the cumulative probability (1)

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} = X \qquad (2)$$

This gives the sample time

$$t = \eta[-\ln X]^{\frac{1}{\beta}}. \qquad (3)$$

During each simulation, occurrence times for each stochastic distribution are sampled every time the transition is enabled. Each simulation represents one life-cycle of the track system. A big enough number of independent simulations are run to ensure convergence of results starting from the same initial conditions. During each simulation the value taken by the variables of interest are recorded either by counting the number of firing of specific transitions or keeping track of the marking of specific places. The distributions of the key performance characteristics of the system can be extrapolated, analysed and interpreted to better understand the behaviour of the system. The data recorded during simulations are:

- number of interventions,
- number, probability and duration of line closures,
- number, probability and duration of imposed speed restrictions,
- probability of being in each of the 5 states.

Once the marking of the PN has been initialised according to the system initial conditions (initial state), the simulation starts following the sequence below:

- Given the current marking (current state), determine the set of enabled transitions (events that can occur),
- For all stochastic transitions currently enabled, sample the firing time from the corresponding distribution,
- Fire the transition with minimum firing time (imminent transition),
- Determine the new marking (new state),

By varying the frequency of inspection, the thresholds triggering opportunistic and routine maintenance and the time to repair, different strategies can be investigated by running the model for the desired time horizon.

6.3.3. **Case studies**

In order to demonstrate the capability of the model, two case studies have been analysed.

- Case study 1: Scenario analysis performed on an individual 200 metres section in a mass transit and a regional line.
- Case study 2: scenario analysis performed on a line section with multiple adjacent sections linked through inspection and opportunistic maintenance.

The statistical distributions for the times to degrade to the different levels of interest based on real data are not currently available. Therefore, for the purpose of this analysis, the parameters used to simulate the integrated track model have been assumed and, following discussion with IMs, they are considered to be close to real values.

The threshold values of SD of vertical top defining the different degraded states are summarised in Table 9.

Table 9. SD threshold values for each degraded state.

Line type	SD_{op}	SD_{rm}	SD_{sr}	SD_{lc}
	opportunistic maintenance is possible (associated to place P2)	routine maintenance is required (associated to place P3)	SR and emergency repair required (associated to place P4)	LC and immediate repair required (associated to place P5)
Regional	2	2.5	3	4
Mass transit	1.5	1.8	2.5	3.5

Table 10 details the parameters of the Weibull distributions associated to each stochastic transition representing the degradation between different degraded states. The parameters of the statistical distributions representing the time to degrade reflect that the section of track in a mass transit line degrades faster than a section of track in a regional line with less traffic.

Table 10. Weibull parameters associated to each stochastic transition representing degradation.

Line type	T1		T2		T3		T4		T5	
	β	η	β	η	β	η	β	η	β	H
Regional	1.2	1500	1.2	740	1.2	600	1.3	500	1.4	1100
Mass Transit	1.5	600	1.5	500	1.6	370	1.7	280	1.8	740

For both case studies, the response of the asset to different maintenance strategies has been analysed. The maintenance parameters are given in Table 11. The following assumptions are considered:

- Inspection is performed at regular intervals. This correspond to transition T14 being deterministic and firing with frequency θ.
- The transitions T10, T11 and T12 represent the scheduling and execution of maintenance - routine (T10), emergency from speed restriction (T11) and immediate from line closure (T12) respectively. These transitions are stochastic with time distributed according to a lognormal distribution.

Table 11. Maintenance parameters.

Inspection period (**T14**)	Mean time to perform routine maintenance (**T10**)		Mean time to perform maintenance from SR state (**T11**)		Mean time to perform immediate repair (**T12**)	
Θ (days)	μ (days)	σ^2 (days^2)	μ (days)	σ^2 (days^2)	μ (days)	σ^2 (days^2)
15	20	5	5	1	1	0.1
30	40	10	10	2		
90						

Twelve different maintenance strategies are obtained by combining the maintenance parameters in Table 11. Details of each strategy is provided in Table 12. Renewal is based on age, and it is assumed the track section lifetime is 40 years.

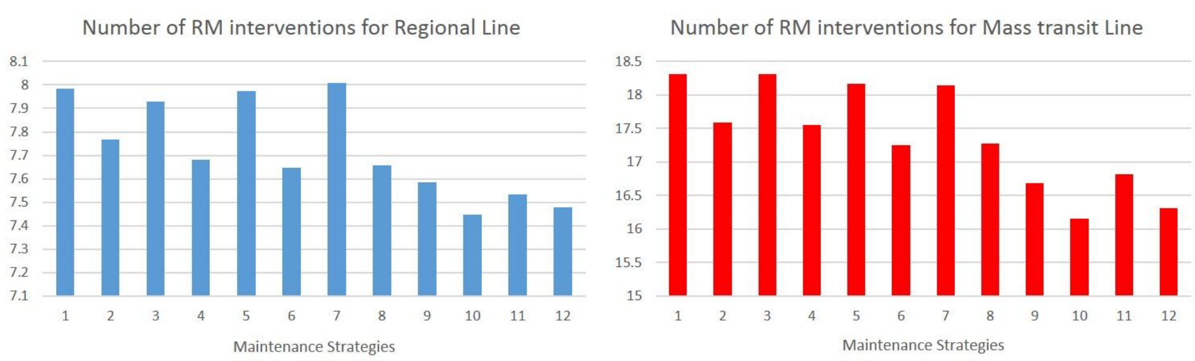
Table 12. Maintenance strategies analysed.

Strategy	Inspection frequency	Mean time to perform routine maintenance		Mean time to perform emergency intervention from SR	
	Θ (days)	μ (days)	σ^2 (days^2)	μ (days)	σ^2 (days^2)
1	15	20	5	5	2
2	15	40	5	5	2
3	15	20	5	10	2
4	15	40	5	10	2
5	30	20	5	5	2
6	30	40	5	5	2
7	30	20	5	10	2
8	30	40	5	10	2

Strategy	Inspection frequency	Mean time to perform routine maintenance		Mean time to perform emergency intervention from SR	
	Θ (days)	μ (days)	σ^2 (days^2)	μ (days)	σ^2 (days^2)
9	90	20	5	5	2
10	90	40	5	5	2
11	90	20	5	10	2
12	90	40	5	10	2

6.3.3.1. Case study 1: Individual track section on Regional line and Mass Transit line.

The track behaviour throughout its 40 years lifetime has been simulated and results are reported in this section. Analysis of the simulations results enable to evaluate the impact of the different maintenance parameters on the asset response. Figures 16 shows the average number of routine maintenance interventions per lifetime for both regional and mass transit line, obtained for each of the 12 maintenance strategies, while Figure 173 depicts the number of speed restrictions imposed. The frequency of inspection appear to have a major effect the number and type of intervention performed. By decreasing the inspection frequency, we notice a decrease of the number of routine maintenance interventions and an increase in the number of speed restrictions and consequent emergency interventions. As expected, both the average number of routine interventions and the number of imposed speed restrictions are bigger for the section on the mass transit line, where heavier traffic and higher speeds result in higher rates of degradation.



(a) (b)

Figure: 16. Average number of routine maintenance intervention per lifetime, registered for each maintenance strategy.

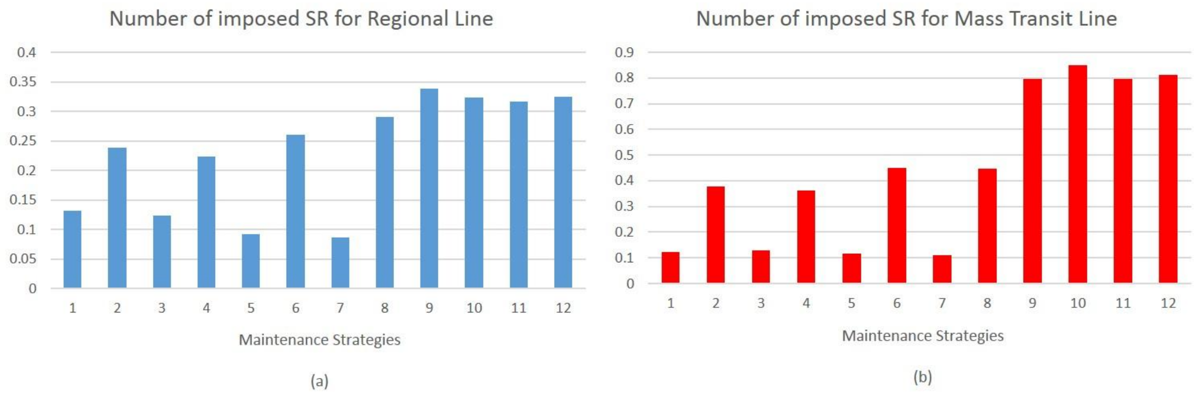


Figure: 17. Average number of speed restrictions (SR) imposed and consequent emergency interventions

Figures 18, 19 and 20 depict the probability of being in good conditions, the probability of a speed restriction and the probability of a state requiring a speed restriction not yet discovered, respectively. Results show that the probability of the track being in good conditions decreases for lower inspection frequencies, while the probability of a speed restriction being imposed as well as the probability of being in a condition requiring a speed restriction not yet revealed by inspection, increase with a consequence impact on both service and safety. The probability of being in good conditions is in general higher for regional line than mass transit. Furthermore, the section on the mass transit line shows a sharper decrease then the regional line, when the mean time to perform routine maintenance and the inspection period increase.

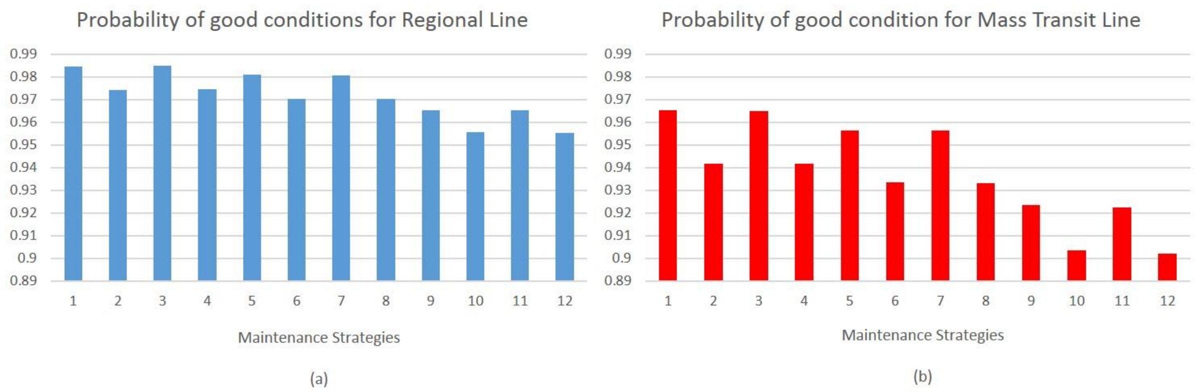


Figure: 18. Probability of being in good conditions.

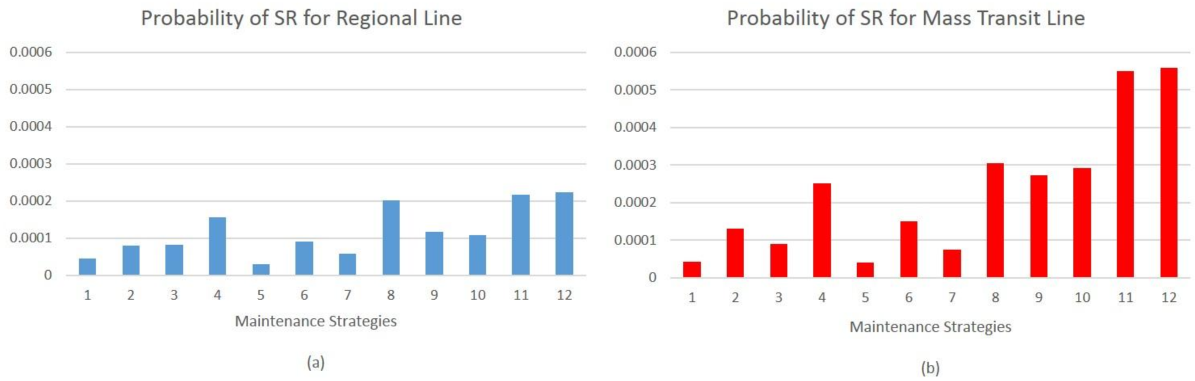


Figure: 19. Probability of speed restriction (SR)

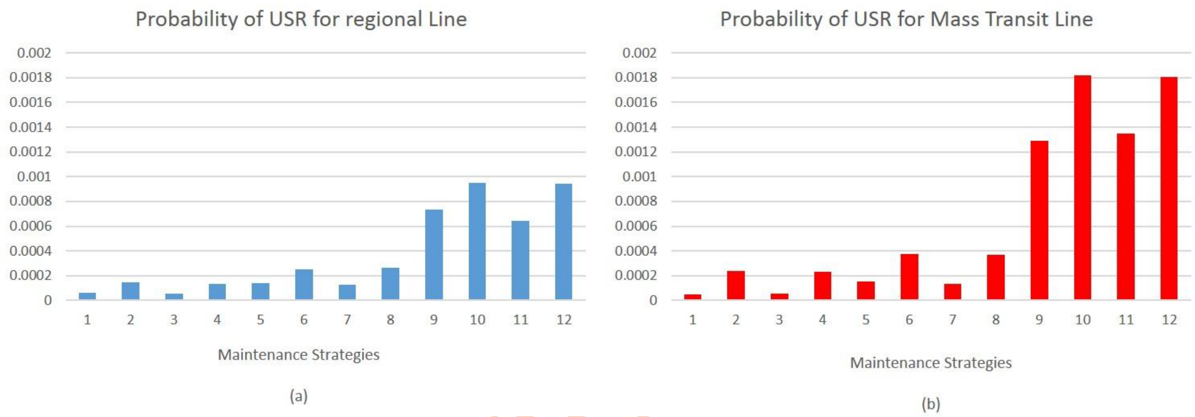


Figure: 20. Probability of being in a state requiring a speed restriction which has not been yet revealed by inspection.

6.3.3.2. <u>Case study 2: Multiple tracks section on Mass Transit line.</u>

The integrated track geometry model has been developed to represent an individual 200 metres section of plain line track. In order to form a line section model, multiple instances of the integrated track geometry model are generated and linked together according to the dependencies between adjacent sections. Two types of dependencies have been considered here in order to build the line section model: the inspection process and the opportunistic maintenance. An example of line section model is shown in Figure 7.

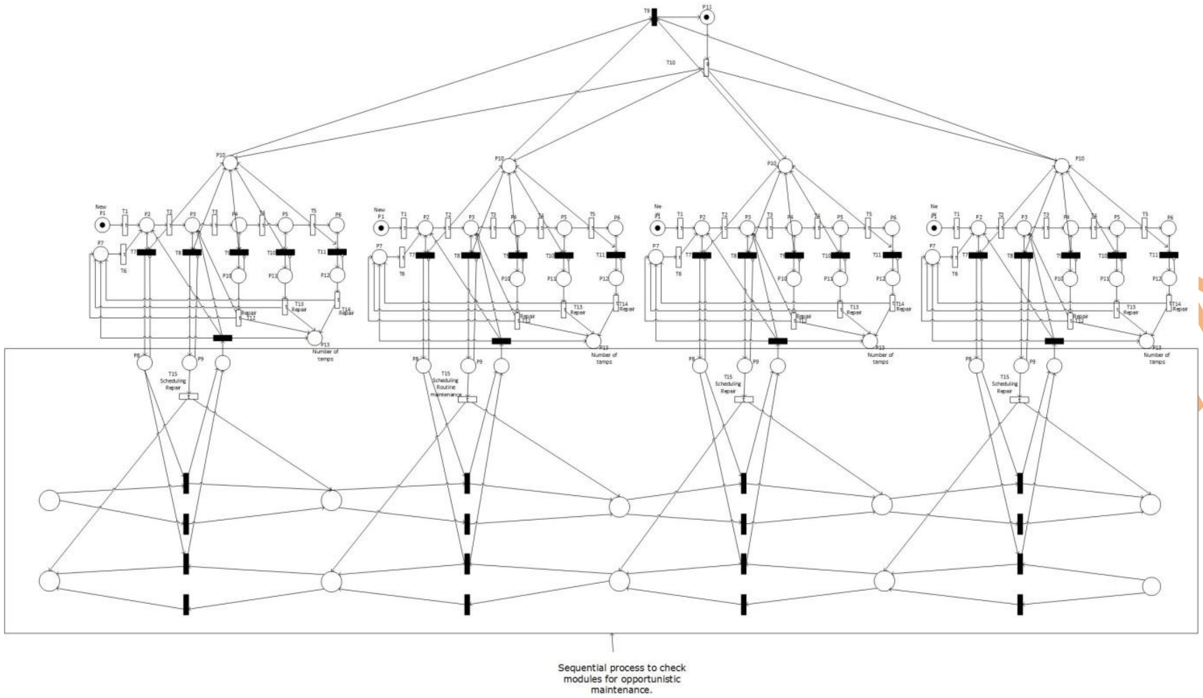


Figure: 21. Petri net for a line section.

When the state requiring routine maintenance is revealed in one of the track geometry degradation and maintenance modules (1/8 mile section), the state of the adjacent modules within a given distance is checked. If any of the adjacent modules is found to be in a state where opportunistic maintenance is suitable, then an intervention for routine maintenance will be performed on such modules too. The chain of places and transitions at the bottom of Figure 21 represents the process of sequentially checking the state of the modules adjacent to the one currently needing routine maintenance.

The analysis of a line section enables the investigation of the effects of opportunistic maintenance, which it is not otherwise possible when considering each of the 200 metres sections individually. Below, results for a 10 miles line section within a Mass Transit line are discussed. The line section is considered homogenous; therefore, the degradation parameters given in Table 5 for Mass Transit line have been applied throughout the 10 miles. Simulations have been performed for the 12 maintenance strategies listed in Table 7.

Figure 8a shows the total number of interventions performed for each individual 200 metres section of track, while Figure 8b depicts the number of opportunistic interventions.

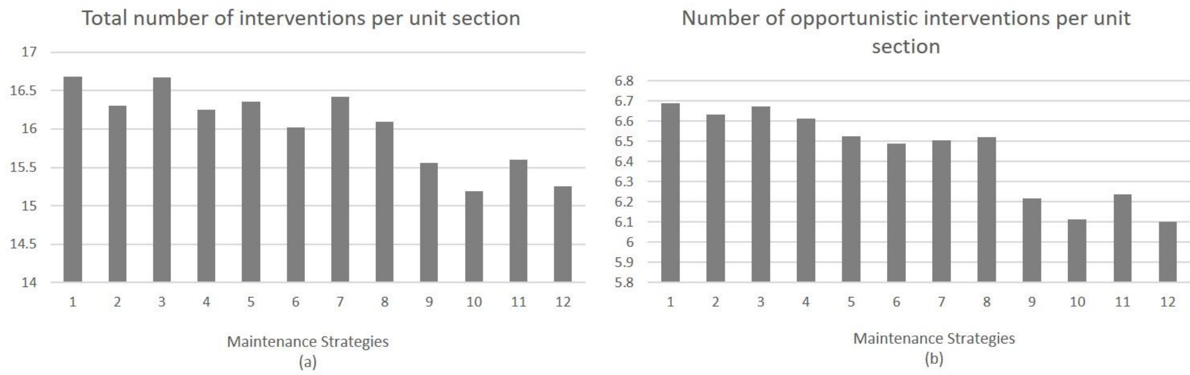


Figure: 22. Total number of interventions per 200 metres unit (a), and number of opportunistic intervention per 200 metres unit (b).

For example, when maintenance strategy 1 is applied, the total number of interventions performed for an individual 200 meters section is 16.7, of which 6.68 are opportunistic interventions. Results also show that opportunistic maintenance results in a lesser number of interventions per lifetime. Indeed, when opportunistic maintenance is considered, the total number of interventions performed per each section within the line is lower compared to the situation when grouping of interventions for adjacent sections is not considered. This can be seen by comparing the values shown in Figure 2b and Figure 8a, representing the total number of interventions per section obtained when each section is considered individually (Figure 2a) with no opportunistic maintenance, and within a line (figure 8a) with opportunistic maintenance.

Figure 9 shows the probability that the line is in good conditions reported for each maintenance strategy. Such probability values are higher than the ones obtained when no opportunistic maintenance is considered (Figure 3b).

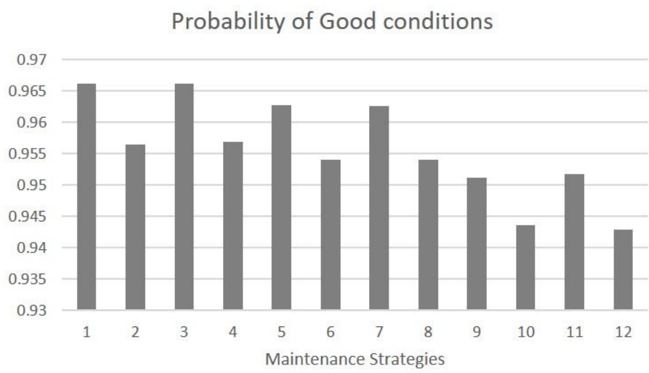


Figure: 23. Probability of the line section being in good conditions.

Figure 10a shows the values of probability that the line is subject to a speed restriction for each maintenance strategy, while Figure 10b depicts the probability that the line is in a state requiring a speed restriction which has not been yet revealed by inspection. The probability of an unrevealed need for a speed restriction increases sharply for the highest value of inspection period (90 days). The probability values obtained for the line section where opportunistic maintenance is considered, are lower than the corresponding values obtained in case study 1 where opportunistic maintenance is not part of the intervention strategies.

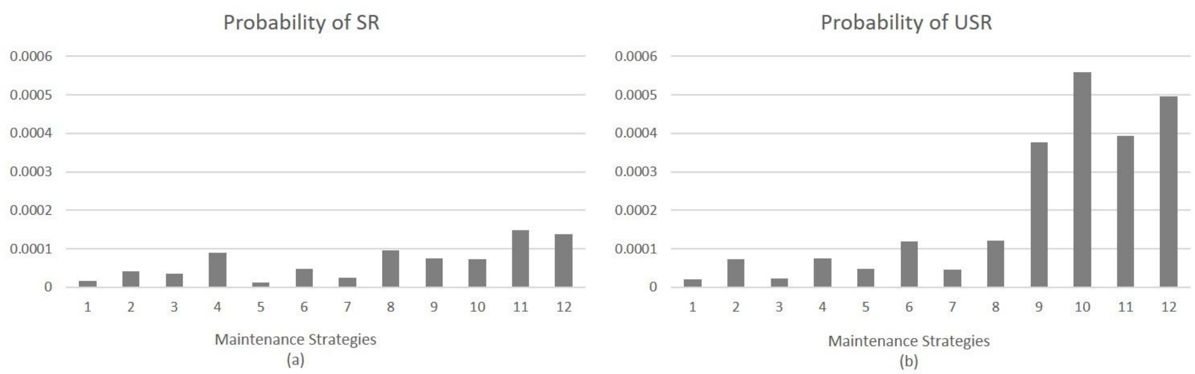


Figure: 24. Probability of the line section having a speed restriction (a), and being in a state requiring a speed restriction not yet revealed by inspection (b).

Overall, results have shown that opportunistic maintenance brings some positive effects. When the results obtained in case study 1 and 2 are compared, it appears that the grouping of maintenance interventions for adjacent sections of track results in: (i) a smaller number of interventions performed throughout the track lifetime, (ii) a higher probability of being in good conditions, (iii) a lower probability of a speed restriction is imposed.

6.3.4. **Integrated switch model**

The integrated switch model is build up in modules, each module describing the degradation/failure and maintenance processes for a component of an S&C. Figure 11 depicts an S&C layout with its constituent components.

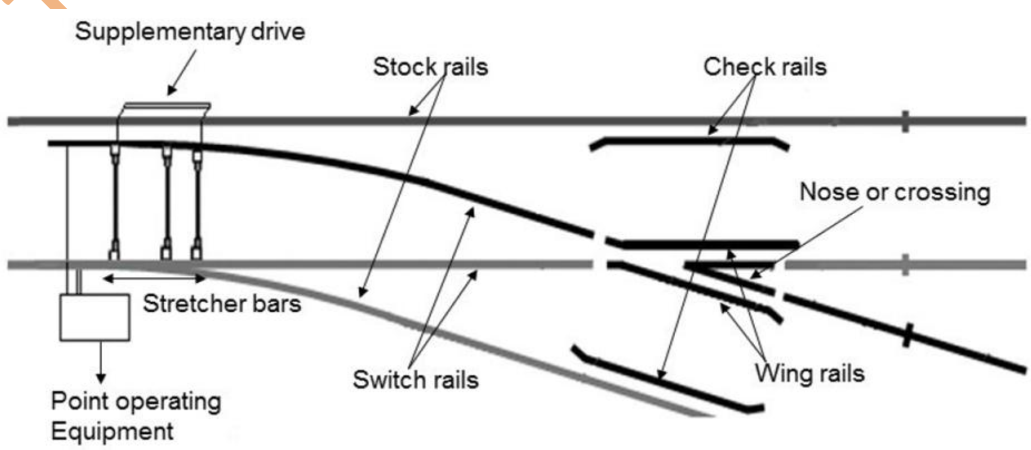


Figure: 25. S&C layout.

A Petri net module has been developed for each component:

- Rails: Stock rail, switch rail, wing rail, check rail and crossing nose (or frog)
- Fastening material: rail clip, rail pad, screw spikes, insulator and fish plate
- Rail support: slide chair or baseplate,
- Ballast (Geometry degradation considered here)
- Sleepers (or bearers)
- S&C drivers and locking device: stretcher bar, point operating equipment (POE) and supplementary drive.

The different modules are then combined to form the integrated switch model which is shown in Figure 12.

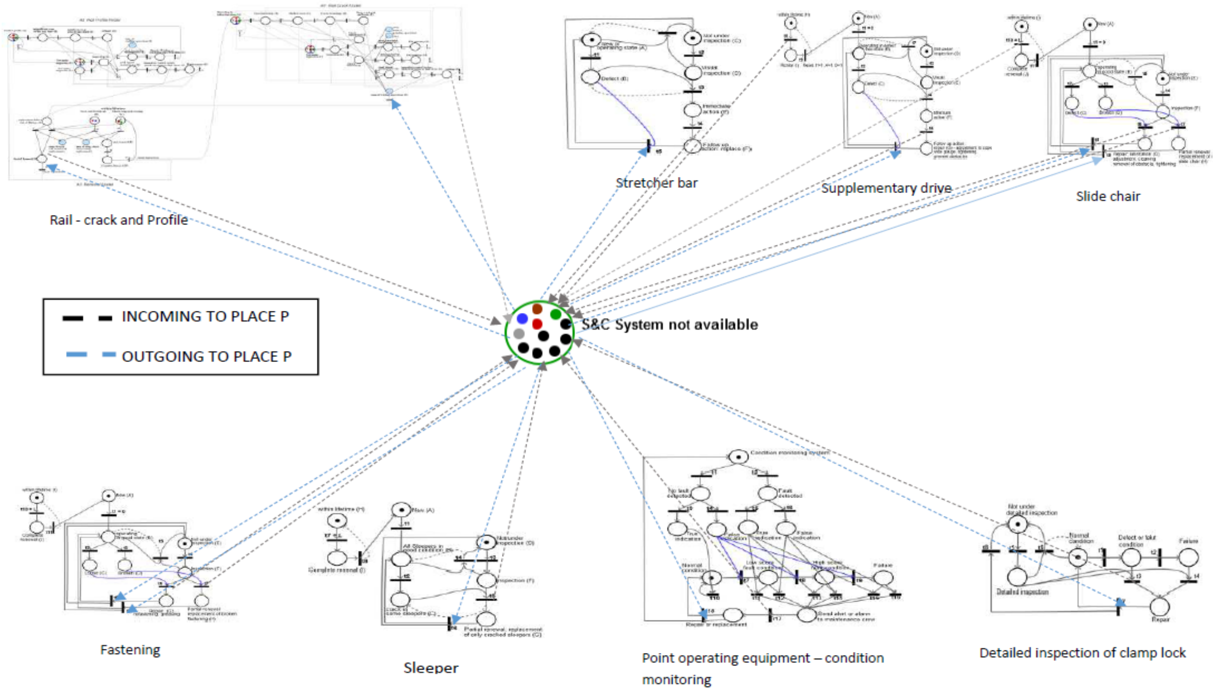


Figure: 26. Petri net integrated switch model

6.3.4.1. <u>Case study 3: Switching & Crossing on Regional and Mass Transit lines</u>

Failure, degradation and maintenance processes involving the S&C components over 35 years have been simulated for an S&C on a regional line and on a mass transit line. Figures 13 to 18 depict the cumulated number of interventions of different types (repair, partial and complete renewals) performed on each component. Scenario 1 and 2 differ for the frequency of inspections, equal to 30 and 90 days respectively.

Figure 13 shows the number of repair and replacement performed over time. As expected, the number of repair and replacement is higher when inspection is performed more frequently as this increases the chance to discover the need for maintenance. For the same scenario, the number of intervention is in general slightly higher for components on the mass transit line.

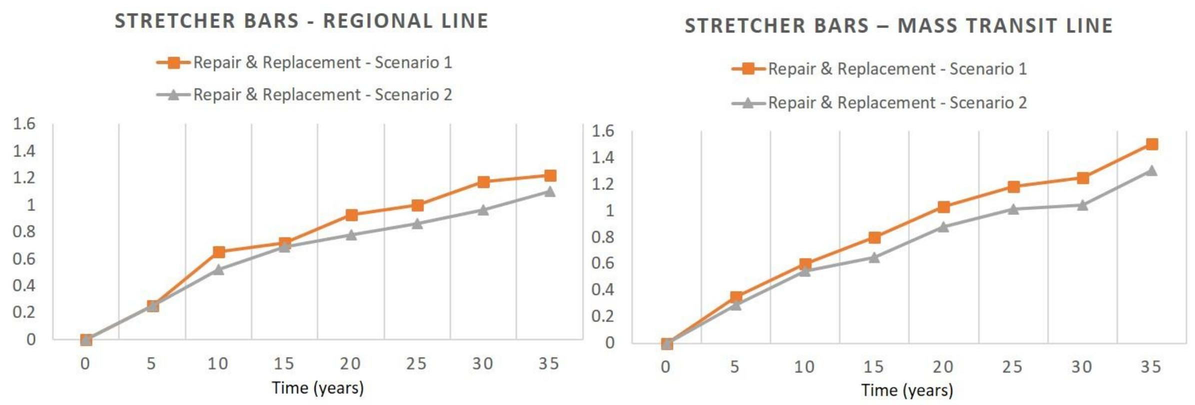


Figure: 27. Number of stretcher bar repairs and replacements.

Figure 14 depicts the number of interventions carried out on the supplementary drive. The number of control actions (for example speed restriction) is comparable between regional and mass transit line, as well as between the two scenarios (different inspection frequencies). The time to complete renewal instead is higher for regional line compared to the component on the mass transit line (25 and 20 years respectively).

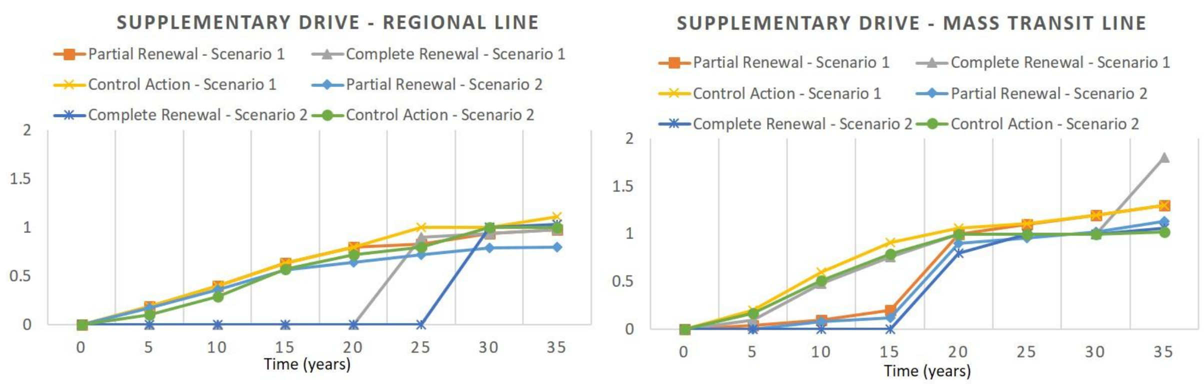


Figure: 28. Number of supplementary drive partial renewal, complete renewal and control action

The number of partial and complete renewals of sleepers is depicted in Figure 15. The number of partial renewals are higher for the sleepers on mass transit line. For the same line type the number of partial renewals are comparable between the two scenarios; this is due to the fact that the degradation process for concrete sleepers is slow, and the values of inspection frequency used in the two scenarios do not have much influence. Complete renewal is never reached as the sleepers lifetime is longer than 35 years.

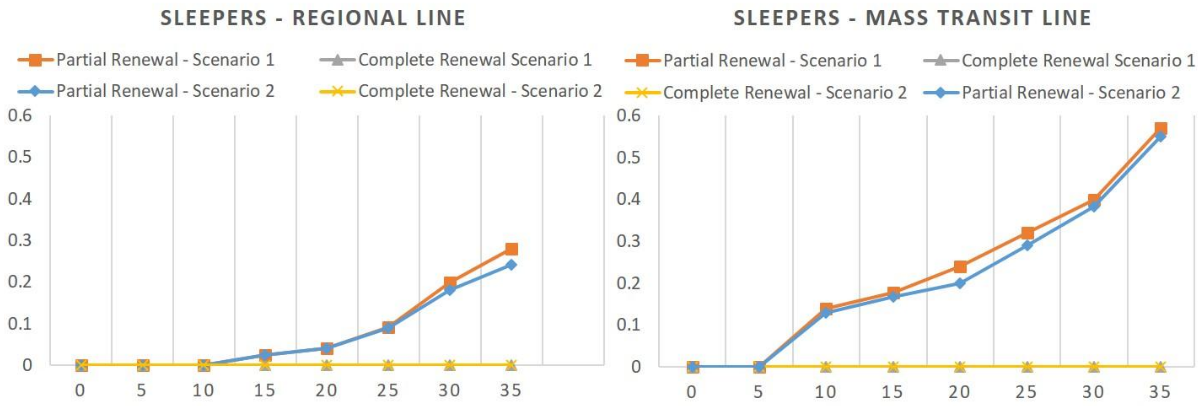


Figure: 29. Number of sleepers partial and complete renewals

Results for fastenings are shown in Figure 16. Complete renewal of fastenings occur after 25 years for regional line and 20 years for mass transit line. The number of repairs is comparable between the two line types as well as between the two scenarios, while the number of fastenings partial renewals is higher for mass transit line.

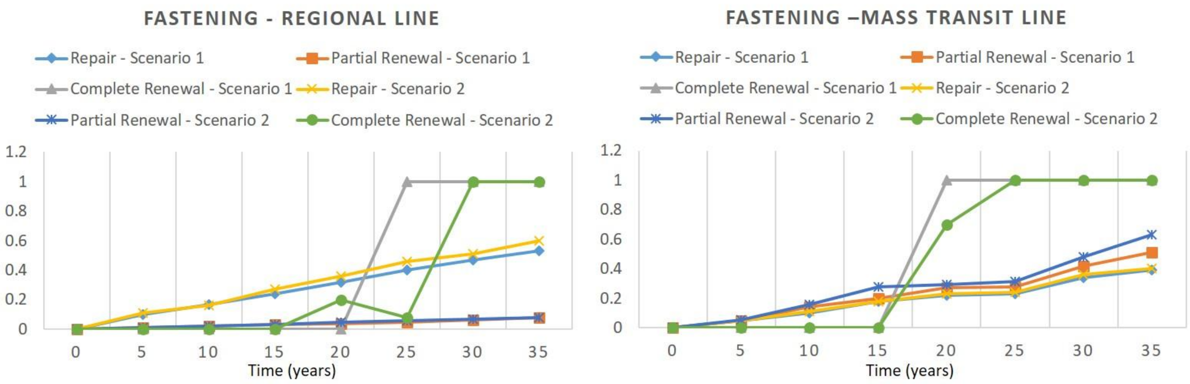


Figure: 30. Number of fastenings repairs, partial and complete renewals

A similar trend is observed for slide chair as shown in Figure 17. The number of repairs is comparable between line types and scenarios, while the number of partial renewals is higher on the mass transit line.

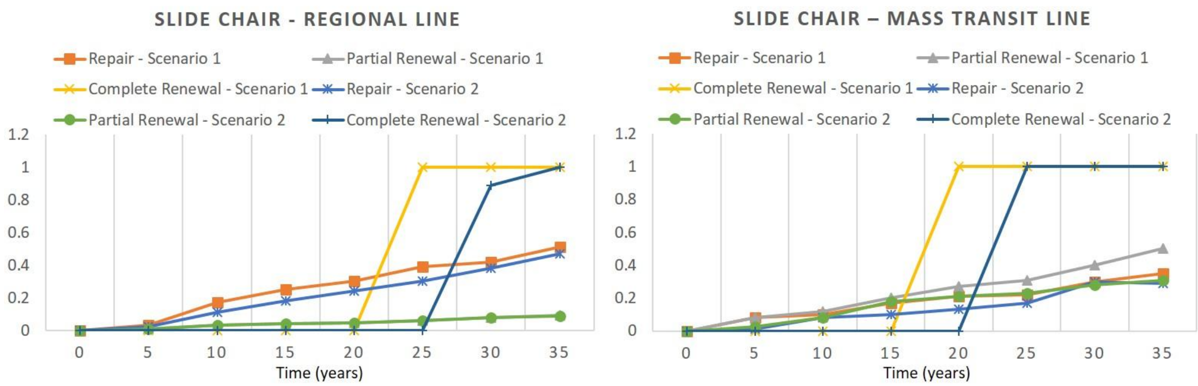


Figure: 31. Number of slide chair repairs, partial and complete renewals

For POE, condition monitoring to detect faults is implemented, along with detailed inspection performed periodically. Figures 18 shows the number of repair performed on POE for different inspection frequencies. Higher frequencies results in slightly higher number of repairs. Also, more repairs are carried out on the mass transit line than the regional line.

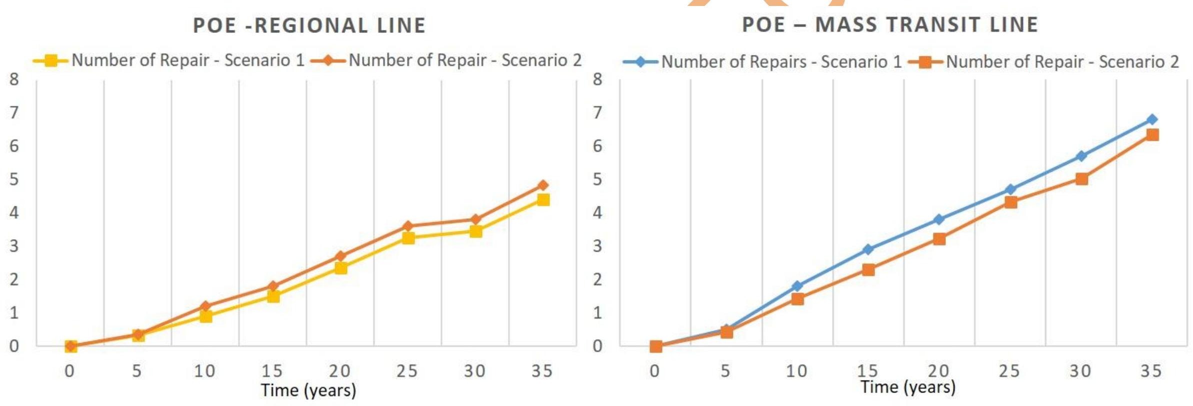


Figure: 32. Number of POE repairs

7. Condition and Risk-based Maintenance Planning (CRMP)

Task 5 of work package 6 focussed on the design of a concept for a new approach of Condition and Risk-based Maintenance Planning (CRMP), based on an analysis of challenges and requirements for using real-time diagnosis of asset conditions, prognosis of future condition from predictive models and probabilistic risk assessments. Dynamic and real-time maintenance planning with the integration of maintenance logistics into the CRMP concept to enable efficient work site management, including dynamic planning and adaption of maintenance schedules to real-time information or unforeseen events and situations, supporting a risk-based approach. This led to the deliverables:

- D6.5 –Condition- & Risk-based Maintenance Planning (CRMP) Concept
  A concept for Condition- and Risk-based Maintenance Planning (CRMP);
- D6.6 – Dynamic and real-time maintenance planning concept
  Integrated solution for maintenance logistics and TMS with the CRMP concept.

In the first section of this chapter a summary of the work undertaken is give. The work described in the two deliverables contained already consideration to the validation of the concepts as such. Since work is directly continued in In2Smart, a brief overview of how the work is handed over is given in the second section of this chapter. To be complete in covering all task of work package 6, this chapter is included, although no direct work has been undertaken in the context of task 6.7 of this work package.

7.1. Summary of the work undertaken

The defined concept for Condition- and Risk-based Maintenance Planning provides the theoretical framework to address the above-mentioned practical issues, as it contains modelling approaches to integrate both asset condition information and risk assessment. The concept is capable to deal with uncertainties occurring in the planning process with the help of stochastic modelling on the one hand and robust optimisation techniques as solution approaches on the other hand. The feasibility of the concept has been demonstrated and proofed by linking use cases to the concept, in the follow up research program In2Smart the concept will be made more practical resulting in a working demonstrator based on the continued use-cases.

The current weakness in the long-, mid- and short-term maintenance planning process are that real-time monitoring and prognostic algorithmic information is not an integrated part of the current business and processes. Another issue is the planning of workspace and resources, that are planned in a very traditional manner (filling timeslots with work) and could be performed with more intelligence. There is a business need for more precise predictive modelling that predicts the optimum moment for maintenance.

In a heavy used railway the optimum interval is not only the moment of need for physical maintenance, but also a broader context. The moment of minimal disturbance of train movements combined with availability of (critical) resources like a (safe) workplace and the right equipment.

A decision support tool simplifies these analyses and would be used as a decision support for maintenance teams in long-, medium- and short-term maintenance and planning activities. The specific tamping use case made clear that still some level of expert judgement would be involved this decision support tool.

Use cases proved that the concept should take account of:

- Budget;
- offer a platform to present the state of the art real time / prognostic information which is coming rapidly to railway companies, outcomes of datamining, algorithms end-user platform etc.;
- the maintenance concept (activities and intervals);
- geometric and dynamic monitoring;
- resources (human resources and machinery);
- available maintenance windows;
- prediction input (for example as executed in other In2Rail work packages);
- monitoring information;
- have an open architecture so it can run individually on different platforms;
- degradation & taking into account effects for example caused by tamping;
- thresholds to be met like track quality to be achieved.

User requirements are given in the report after each use case.
The output should be towards an integrated dashboard in the process which helps with (link with Tasks 6.2 "Asset Management framework"):

- long-term predictions in reliability & availability, input for long-term planning;
- cost estimations of the given advices / decisions;
- smart combinations of mid- and short-term maintenance activities;
- residual reliability & availability;
- applicable resources, resource planning.

In a second step the concept was extended for maintenance planning in a dynamic and real-time context which is capable to integrate aspects related to maintenance logistics and to interact with Traffic Management Systems (TMS). The described concept (deliverable D6.6) is an extension of the CRMP concept presented in Deliverable D6.5.

Dynamic and real-time planning can be solved by using a nested and adaptive planning approach, where the different planning levels – strategic, tactical and operational – are linked to each other through feedback loops with input and output variables. Furthermore, the planning horizon is defined in a rolling manner, i.e. there are overlapping time windows from each planning step to the next one, so that information and results from one step (planning instance) will influence the following ones. This enables to adapt maintenance plans from time to time, depending on available data and knowledge.

Maintenance logistics as well as traffic management issues can be included in maintenance planning models in several ways: Either in the form of well-defined constraints that restrict the decision space accordingly, i.e. that restrict maintenance activities in a way that they have to be aligned with e.g. resource capacities, available material and staff, possession windows and train services. It is also possible to include objective functions that consider respective issues like optimal resources utilisation, minimum impact on train service, optimal use of track possession etc.

Three real-world use cases have been presented in which the modelling of the maintenance planning can make use of the developed concept: (1) Daily operational maintenance planning typically to be conducted by a maintenance contractor, where one has to take care about resources availabilities and penalty costs for using extra possession times due to delayed maintenance; (2) day-to-day tamping planning in a rolling time horizon, considering outputs from predictive track degradation modelling as an input for the required maintenance; (3) a similar model for optimal tamping execution with the additional challenge of minimising train delays. Conclusion; the concept fits the use cases in a dynamic and real-time environment.

7.2. Continuation in Shift2Rail

In2Rail laid the foundation: building blocks of next generation maintenance and asset management were developed individually. In2Smart will make the next steps by putting the building blocks in context and provide a more holistic expected view. The work will reach higher TRL levels in order more realistic demonstration is possible.

The work of the Asset Management framework (task 6.2 In2Rail) will become of importance in the next steps. Where the now- & forecasting techniques of WP9 in In2Rail were focused predominantly on the use in a TMS context.In2Smart will focus on the prediction of current and future asset performance in respect of maintenance. This would lead to enhance the CRMP process for which it was originally intended to be: including the risk aspect.

To continue the work in In2Samrt, various parts of the In2Rail project become relavant:

- the Asset Management framework (In2Rail 6.2, In2Smart WP2);
- now- and forecasting outcomes (In2Rail WP9, In2Smart WP8);
- next level monitoring solutions to enable now- and forecasting (In2Smart WP3/4/5/6);
- condition- and Risk based Planning information (CRMP In2Rail Task 6.5, In2Smart WP9).

8. High performance tamping

The objective of task 6.6 (high performance tamping) was to define a substantial improvement of the current way of tamping and the related task for track alignment. Idea was by doing this, to illustrate how LEAN thinking can lead towards new and advanced working methods and contribute to a higher availability and lower cost. So, besides working on the subject as such, the higher objective is to set an example how to approach other working methods in a similar way and to seek for substantial improvements by eliminating time consuming steps and apply technology to do so. This to boost improvement rather than seeking for small incremental improvements.

Although the work in In2Rail concentrated on the specification of requirements for improved tamping methods, also initial test runs were performed under the umbrella of this project.

The main work is documented in deliverable D6.7 – Requirements for improved tamping methods [TRL 3-5] Requirements and technological outline for improved tamping method.

In the first section of this chapter, a summery is provided of the work done in task 6.6 (High performance tamping). In the context of this task 6.8 (Technical validation), extra work has been undertaken to validate the technology for the exact positioning for both the measurement trains as well as the tamping machine. Actual validation has been done around the technology being used in the Strukton tests. Also discussions with experts of the University of Nottingham have been undertaken to see whether state of the art technology has been used and to discuss (possible) shortcomings. In this context the University of Nottingham has added some work to be considered in future in areas with bad GNSS reception, such as mountains areas and tunnels.

The last section of this chapter describes how the work is continued in Shift2Rail.

8.1. Summary work task 6.6

In this paragraph, first an overview of the work been done in task 6.6 (High performance tamping), followed by some additional considerations as part of the reviewing work undertaken in the context of task 6.7 (Technical validation).

8.1.1. Overview

The objective of In2Rail WP 6 task 6.6 was to look for requirements for improved tamping methods (based on the European project AUTOMAIN). Focus of the work was on the elimination of pre-measurements and use of track geometry inspection data for preparation of tamping operations.

The deliverable D6.7 and the associated requirements matrix are elaborated by the core group of the In2Rail WP 6 task 6.6: DB, Strukton Rail/Eurailscout and Acciona. It presents the vision on the development of maintenance tamping methodology with focus on the elimination of pre-run measurement and use of track geometry inspection data for preparation of tamping values. As pre-measurements need relevant possession time and relevant resources, the new approach will lead to more efficiency in the tamping process.

Task 6.6 of In2Rail was the preparation task for the following Europian project In2Smart WP10.1 (Shift2Rail). Requirements specifications for the new improved method as well as the gap analysis and the analysis of data to be used in the new process provide the basis for the necessary further work that has to be carried out in In2Smart WP10.1 (Shift2Rail) for the realisation of the new tamping maintenance method.

The requirement analysis and the prioritisation of In2Rail task 6.6 have pointed out two important requirements for the new method, which are related to safety:

- the accuracy of localisation of the recorded track geometry along the track axis, which must be between 0,1 m to 0,6 m and
- the reliability and completeness of the measured track geometry data.

The proposed solution for the required accurate positioning of recorded track geometry data is use of corrected Global Navigation Satellite System (GNSS) technology on the track recording car in combination with additional measurements (IMU and distance measurements e.g.). The correction of positioning results in the post-processing can deliver the required accuracy of longitudinal positioning on the track axis between 0,1 m and 0,6 m.

For identification of measuring failures and inspection data gaps, it will be necessary to develop and implement a quality management system: with installation of an auxiliary measurement system on track recording car and development of a quality check tool in post-processing of recorded inspection data.

Also the consideration of the absolute position of the track, which is usually measured within the pre-measurements, is an issue to address in further developments.

In2Rail task 6.6 has identified two approaches for tamping methods and addressed both of them to the following project In2Smart (Shift2Rail):

- "*relative tamping*" based on imitation of chord-measurement of tamping machine (with TRL 3-5) and
- tamping "*accurate to shape*" with or without combination of absolute measurements on reference points (with partly TRL<3, considering important requirements related to the absolute position of the track, according to the actual national regulations) .
- In In2Smart WP10.1 both approaches will be considered, developed and tested according to the user requirements.

For the approach "relative tamping" Strukton Rail has performed a proof of concept (TRL 5), which is documented in the annex of In2Rail D6.7. New tests performed on track site within

In2Smart WP10.1 verify the possibility of high accuracy of track inspection localisation using the GNSS with additional measurements and the post-processing technology.

8.1.2. **Additional comments towards the requirements**

Reviewing the requirements as expressed in the deliverable D6.7, the following requirements should be taken into account in the future prototype of the development of a high performance tamping methodology:

In terms of Requirements on the process "inspection -maintenance planning - tamping":

- Precise positioning output from post-processing must be checked for gross errors by comparing it to reliable auxiliary positioning system. (*Quality check of position results*)
- For any pair of km-axis positions, timestamp of the farthest to origin must always be posterior to timestamp of the closest. (*Quality check of position results)*
- Where available, geometric and inertial inspection data should be compared for coherence, questioning the reliability of defects registered by only one measurement system. *(Quality check of track geometry inspection data)*
- It is assumed that inertial measurements are a consequence of train response to geometric defects. It is also assumed that appropriate models to relate both exist or shall be developed.
- Tamping data calculation must consider both the impossibility of tamping fixed geometry and the need to provide smooth transition through the fixed points.(*Generation of tamping data)*

In terms of business requirements :

- By optimizing the use of available resources, more defects may be corrected, increasing the general quality of the track and minimizing speed reductions. "Scarce" scenarios assume that resources are given (possession time, tamping machines, personnel) and insufficient to maintain perfect track quality. (e*conomic advantages)*
- Less idle time on tamping machines and workers assigned to a track segment. (*Strategic advantages).*
- Recovered data, properly stored, will allow heuristic analysis, defect pattern detection and prognostics on track deterioration. (*Strategic advantages).*

8.2. Positioning: validation and outlook next steps

Exact positioning of the vehicle recording the data is essential. Within the In2rail project initial tests have been undertaken. The first part of this section is about the validation being undertaken by Strukton of the equipment used for the test runs.

The second part of this section is work undertaken

8.2.1. **Validation technology used by Strukton**

8.2.1.1. Technology used

The project we are currently working on is geographically extracting geometry (alignment, cant, level) measurements (5-5 chord, but D1 and D2 space curve and curvature are also possible) from the measurement vehicle.

The geometry measurements serve as input for tamping machine which it can geographically locate with its global navigation satellite system (GNSS) receiver with its virtual reference system (VRS) service. +/- 0.02m accuracy

The tamping machine is equipped with Plasser's ALC software which computes solutions to restore geometric deviations.

The maximum operational maintenance speed of a universal tamping machine is 1500 meters per hour.

The measurement vehicle is the UFM120 from Eurailscout. The position and geometry measurements are performed with a system supplied by Plasser America.

Plasser makes use of Applanix POS TG.

The Applanix POS TG reads signals from the Applanix Inertia measurement unit (IMU), Trimble GNSS antenna, Lenor Bauer distance measuring instrument (DMI) and optical gauge measurement system (OGMS).

The geometry measurements are generated on baord while driving. Geometry measurements are computed from the IMU, DMI and OGMS. The instruments are designed to measure at 200 Hz.

The position measurements are generated off board. Position measurements are computed wit Applanix POSpac Suite. The software program reads the IMU, GNSS and DMI data and combines it with GNSS correction data from surrounding the measurement area.

8.2.1.2. Conclusions

The following conclusion:

- Positioning system within system tolerances
  - UFM position vs reference (<0.01m) >1800 samples
  - UFM position vs GNSS RTK tamping machine (<0.02m) >65000 samples
- Geometry UFM
  - Geographic reproduction analysis showed that geometric deviations had a constant geographic position shift up to 0.5m
  - The reason for the shift still has to be determined
- Geometry tamping machine

    - Geometry reproduction surveys executed and remain to be analysed, difference between “reference rail” left or right
- Geometry UFM vs Geometry tamping machine
    - Analysis showed that geometric deviations had a geographic position shift up to 1.0m
    - The reason for the shift still has to be determined

8.2.2. **Positioning assessment with integration GNSS and IMU**

This is about the positioning assessment with the integration of the high performance GNSS and IMU. This is done in a non-rail environment. The use of this technology will be useful in future steps in more difficult areas with low reception of GNSS, such as mountains and tunnels.

The University of Nottingham has experience and performed following test.

8.2.2.1. Background

According to the project requirements, we tried to use the integration of the GNSS and IMU (Inertial Measurement Unit) to get the accurate position and assess the performance in different conditions including the village, motorway, country road and the city centre.

8.2.2.2. Integration Sensors

(1) Leica GS10 is a high performance GNSS, the accuracy information is listed in the below table:

- Differential phase in post-processing

Table 13. Accuracy in static and rapid static positioning

Static		Kinematic	
Horizontal	**Vertical**	**Horizontal**	**Vertical**
5mm+0.5ppm	10mm+0.5pp,	10mm+1ppm	20mm+1ppm

Table 14. Accuracy in static mode with long observations positioning

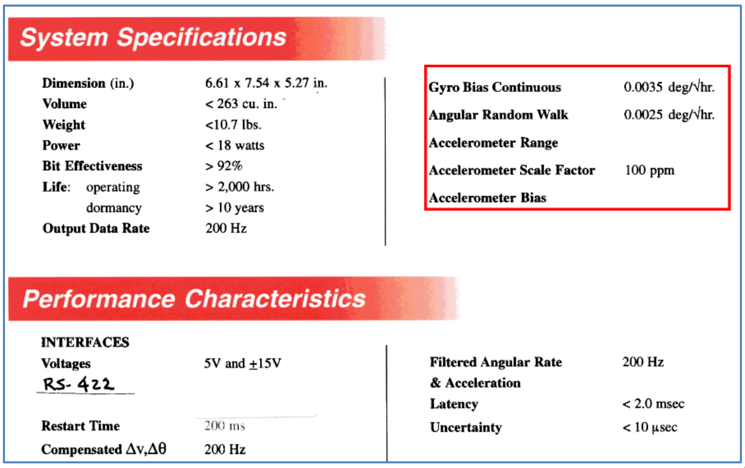
Static		Kinematic	
Horizontal	**Vertical**	**Horizontal**	**Vertical**
3mm+0.1ppm	3.5mm+0.4ppm	10mm+1ppm	20mm+1ppm

- Differential phase in real-time

Table 15. Accuracy in real-time positioning

Static		Kinematic	
Horizontal	**Vertical**	**Horizontal**	**Vertical**
5mm+0.5ppm	10mm+0.5ppm	10mm+1ppm	20mm+1ppm

(2) IMU is a commercial product made by Honeywell for survey, pipeline, and mining application. It includes digital laser gyro (GG1320) for angular measurement and accelerometers (QA2000 Quartz-Flex) for linear changes. Figure 1 shows the parameters.



System Specifications

Dimension (in.)	6.61 x 7.54 x 5.27 in.
Volume	< 263 cu. in.
Weight	<10.7 lbs.
Power	< 18 watts
Bit Effectiveness	> 92%
Life: operating	> 2,000 hrs.
dormancy	> 10 years
Output Data Rate	200 Hz
Gyro Bias Continuous	0.0035 deg/√hr.
Angular Random Walk	0.0025 deg/√hr.
Accelerometer Range	
Accelerometer Scale Factor	100 ppm
Accelerometer Bias	

Performance Characteristics

INTERFACES	
Voltages	5V and ±15V
RS-422	
Restart Time	200 ms
Compensated Δv,Δθ	200 Hz
Filtered Angular Rate & Acceleration	200 Hz
Latency	< 2.0 msec
Uncertainty	< 10 μsec

Figure: 33. The parameters of the POSRS

(a) (b)

Figure: 34. Leica GS10 (a) and Honeywell IMU (b)

8.2.2.3. Trials

For the performance assessment in different situations, four areas including city centre, motorway, village and country road are chosen to take the test.

Figure: 35. City centre (a), motorway (b) village (c) and country road (d)

According to the different accuracy, six position types were defined and they were listed in Table 4:

Table 16. Distribution of different accuracy position (Leica GS10+Honeywell IMU)

Quality Type	Percent	Accuracy
1	45.6%	<1.5cm
2	20.7%	<0.4m
3	18.4%	<1m

Quality Type	Percent	Accuracy
4	8.7%	<2m
5	5.6%	<5m
6	1.0%	<10m

Table 17. Time span for different condition

Different Condition	Time Span (GPS Time)	Time Span (UTC Time)
City Centre	224760-225240	14:26-14:34
Village	226200-226800	14:50-15:00
Country Road	226980-227520	15:03-15:12
Motorway	228000-228480	15:20-15:28

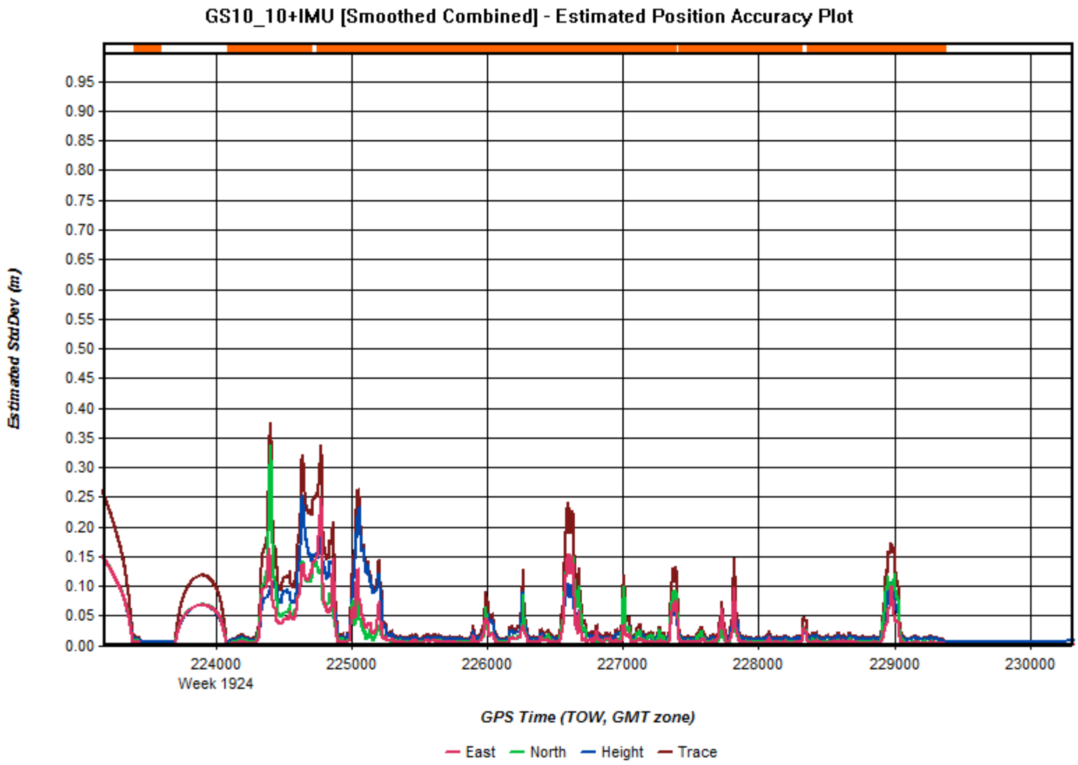


Figure: 36. Estimated STD of the GNSS/IMU solution

As can be seen in the Table 4, 5 and Figure 4 above, because of the good condition on the motorway, the accuracy is very good, but with the bad conditions in the city centre (GNSS signal was blocked), the accuracy decreases.

8.2.2.4. Signal Coverage Analysis

The rover station needs the correction information from the reference station to get the accurate position and Leica NRTK technology was used in the experiment. However the GSM signal was poor in some areas and this caused a delay in the correction information. In order to have a clear understanding of the impact to the position performance caused by GSM signal strength, we divided differential message latency into three classes and drew epochs with different colours as shown in Figure 5.

1. Low latency, 0-5 seconds, green colour;
2. Middle latency, 6-10 seconds, yellow colour;
3. High latency, over 10 seconds, red colour.

To illustrate the position performance, we draw epochs with different symbols in Figure 5.

1. Fixed solution, circle;
2. None fixed solution, rectangle.

Figure: 37. Fixes switch to unfixed solutions when the time latency increases (numbers closed to each epoch symbol are differential latency in second)

Table 18. Latency distribution

	Low latency (0-5s)	Middle latency (5-10s)	High latency (10s+)
Percentage	90.4%	3.4%	6.2%

According to the statistics, 10 epochs that switch from fix to unfix have large potential to be caused by the increase of differential message latency.

Table 19. Latency for the unfix positioning

No.	Time	Latency lead to unfix (s)
1	14:24:24	15
2	14:43:05	7
3	14:51:57	10
4	15:04:54	15
5	15:07:04	15
6	15:10:50	14
7	15:21:31	15
8	15:22:36	16
9	15:23:41	16
10	15:25:47	15

Therefore, we can conclude that for achieving reasonable positioning solutions the wireless connectivity latency needs to be:

1. At least: within 15 seconds
2. Better: within 10 seconds
3. Best: within 5 seconds

8.2.2.5. Leica GS 10 only performance

Table 20. Statistics for Leica GS 10 only positioning

Position Type	Percentage

None	1.9%
SPP	10.0%
DGNSS	16.2%
Float	0%
Fix	72%
Total	100%

Table 21. Error statistics for Leica GS 10 only positioning

	East	North	Height
RMS Error (m)	0.46	1.28	1.42

Table 22. Error statistics for Leica GS 10 only fixed solution positioning

	East	North	Height
RMS Error (m)	0.14	0.19	0.15

The statistics show a much larger error than we expected, this may be caused by a reference trajectory issue. Compared with the result from the integration with GNSS and IMU, the integration solution is more accurate, especially when the GNSS signal is blocked.

8.2.2.6. Conclusion

From the experiment we can conclude:

1. By the integration of high performance GNSS receiver and IMU, we can get accurate position and satisfy the positioning requirements for the tamping machine.
2. For the wireless connectivity using the GSM signals, according to our statistics, the performance of data latency is important to get the fixed positioning data, and the time latency should be:
    - At least within 15 seconds
    - Better within 10 seconds
    - Best within 5 seconds

8.2.3. Possible next steps

Following consideration for future work between Strukton and the University of Nottingham could be:

Currently the tacho and the GPS on the tamping machine are not connected to each other. The use of an IMU might be difficult on a robust environment such as a tamping machine (vibration). In areas with no 3g/4g data connection the tacho could be used to keep positioning the tamping machine. To do this successfully, it is important to know the GNSS positions of the track (UFM data). This would enable working in tunnels, stations with roof covering above platforms and in areas without 3g/4g coverage.

8.3. Next steps in Shift2Rail

Work is continued, and already being undertaken, in the Shift2Rail member project In2Smart. The work is part of work package 10 of In2Smart.

The objective of In2Smart task 10.1 is to develop the prototypes of a "Lean Inspection and Tamping Process" which avoids pre-measurements. The "direct" use of inspection data to determine the work of the tamping machines is the key issue and the innovation. The work of task 10.1 includes:

- detailed analysis of actual used pre-measurements and their interfaces to maintenance machines and relevant process steps
- development of technologies, evaluation tools, measurement equipment and quality management system to overcome the pre-measurements and to ensure required quality
- improvements of the inspection car and tamping machine used for the prototypes
- test and validation of the prototypes on test sites
- assessment of integrated process with respect to quality, capacity and cost

To eliminate the process step "pre-measurement" the inspection and perhaps the tamping process must provide the information gathered normally by the pre-measurements in identical format and quality.

Beside technical solutions the actual national and European standards should be revised to allow the implementation and use of the new more efficient tamping method. Best practice should lead to a harmonisation of the standards in Europe.

9. Conclusions

The results of this work package have indeed laid the foundation of the work being undertaken of Shift2Rail and are considered as valuable. To illustrate this, as a summary:

- Work of task 6.2 is being used in the Shift2Rail member project In2Smart. Interaction between In2Rail and work package 2 of In2Smart has resulted in the adoption of the process overview of the asset management;
- The KPI manual has been given as input to the CCA projects Impact 1 and Impact 2 as a consideration;
- The modelling work of both task 6.3 and 6.4 have been picked up in the use cases of work package 8 of the member project;
- The same for the integrated modelling using Petri Nets, included in work of In2Smart work package 10
- The CRMP concepts are also included in work package 10 of In2Smart;
- Further tests for high performance tamping are being undertaken, taking the defined requirements as a basis;
- The localisation technology for the high performance tamping

10. References

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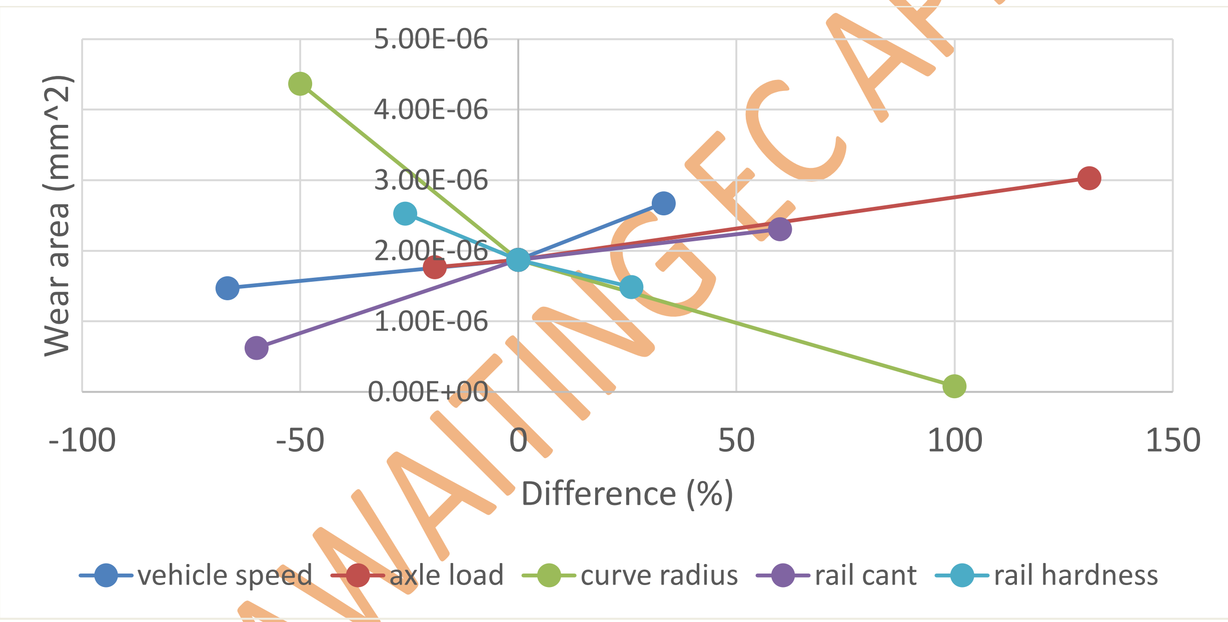
11. Appendices

Annex 1: Results of Sensitivity Analysis

Related to: 4.3 Rail Defects: Model validation and testing

The plots given below show the results obtained from the sensitivity analysis. The x-axis in these plots represents the change per parameter in percentages and the y-axis represents the wear (in mm^2) caused by the first wheel of the front bogie. Furthermore, the y-value at x=0 represents the wear area for the baseline case to which the other results are compared. It can be concluded that the parameters that did not change with respect to the baseline are the wheel diameter, and the vertical damping and vertical stiffness of the primary suspension of the bogie.



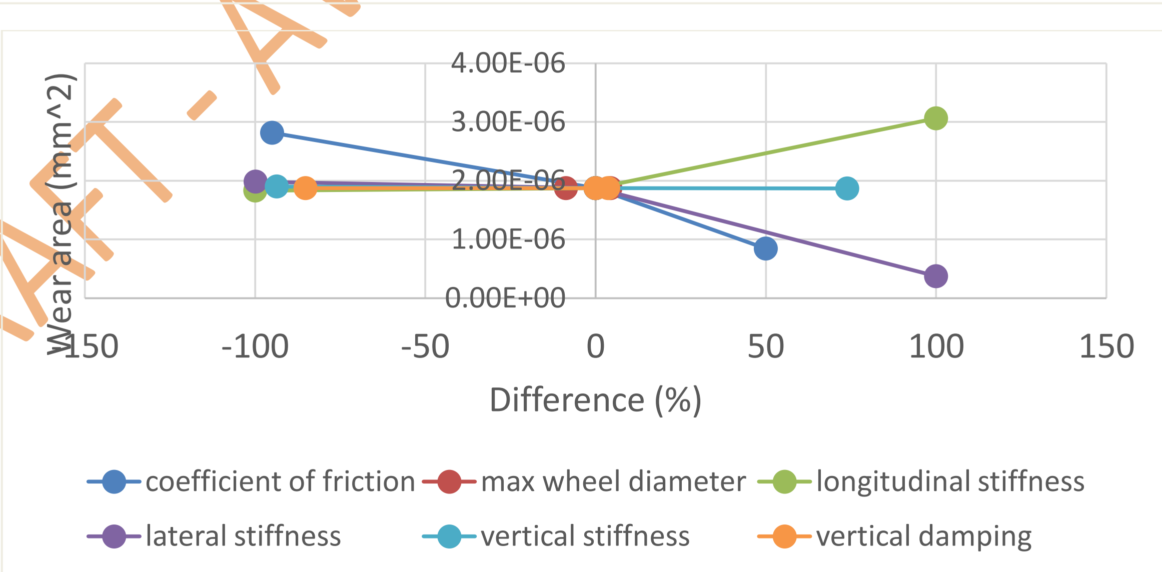


Figure: 38. results obtained from the sensitivity analysis