Wheel and Rail Maintenance Planning with Support of Digital Twins

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KTH Royal Institute of Technology, Railway Group
Swedens largest technical university

- Around 13,500 full-time students (one-third women).
- Close to 1,700 research students (one-third women).
- More than 3,700 full-time positions (one-third women).
- Five campuses in the Stockholm region.
KTH Railway Group – A Multidisciplinary Research Centre

Traffic and Logistics

Signalling

Structural Engineering and Bridges

Cost effective bridges

Electric propulsion and energy supply

Tribology

Rail Vehicles – Vehicle-Track interaction
Division of Rail Vehicles: Research focus

Vehicle-track dynamic interaction

- Vehicle dynamics simulation
- Ride comfort calculation
- Contact mechanics and wear/fatigue prediction
- Active suspension
- Tilting trains
- Crosswind stability
- Condition monitoring

Energy usage and environmental impact

Lightweight structures

Vehicle-catenary interaction
Since 2018 we have a Master program together with RailTec at the University of Illinois Urbana-Champaign
Outline

• Introduction – System Perspective
• Calculation of rail damage – Optimisation of grinding intervals
• Wheel life prediction – Planning of reprofiling intervals
• Machine learning tools to predict component failures
• Summary
Background

- About 40% of track maintenance / renewal costs in Sweden are attributed to rail wear and RCF [1]: Rail Surface Damage
- The maintenance activities associated with damage due to wear and RCF are interlinked
- The maintenance activities influence the wheel-rail dynamic interactions which in turn influences the damage process.

Wheel-rail damage prediction: A system tool

**Principles & processes**

- Advanced MBS models
- Contact mechanics
- Damage models
- Fast calculation methods
- Mathematical Optimization
- Optimized vehicle suspension design
- Wheel-rail interface management
- Modelling maintenance activities
- Validation of tools
- Differentiated track access charges

**A Digital Twin to predict & achieve outcomes**

**Outcomes**

- Higher infrastructure availability
- Reduced track maintenance
- Reduced costs due to delays
- Lower operating costs
- Reduced vehicle maintenance
- Higher vehicle availability
- Better ride comfort
- Less running instability
Wheel-Rail contact damage models

Evolution of the KTH Damage Model

- Jendel: wheel wear prediction algorithm (1999)
- Casanueva: simulation of damage in freight vehicles, switches (2011)
- Sichani: development of improved contact models (2016)
- Krishna: influence of track maintenance (2020)

- (2015) Dirks: advanced RCF modeling, wear and RCF interaction
- (2017) Hossein-Nia: stochastic variables, code restructuring, wheel life prediction
Examples discussed in the presentation

• Calculation of rail damage – Optimisation of grinding intervals (ongoing PhD work)

• Calculation of wheel damage – Wheel life prediction (finished PhD thesis)

• Calculation of rail damage – Influence of track gauge (recent master thesis)

• Using Machine Learning tools to detect vehicle hunting or to monitor track irregularities (ongoing PhD work)

• Identification of local rail defects with help of Machine Learning (recent master thesis)
Calculation of rail damage –
Optimisation of grinding intervals
Significance of maintenance interventions

*1* Schoech et al. (2006)

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**German Rail Cross Section Grinding Schedule (17 MGT/year)**

- **Year**: 2000 to 2018
- **Section [Km]**: 1525 to 1540
- **Curvature [m⁻¹]**: -500⁻¹ to 500⁻¹
- **R≤600 m**
- **Grinding**
- **Vehicle**

More frequent

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Rail Vehicle Dynamics based Rail surface damage prediction

- Rail surface damage calculation
- Vehicle
- Track
- Operation

Flange lubrication
MBS model
Dynamic Friction
Track Geometry
Track Layout
Rail Profiles
Traction and braking
Real speed
Stochastic inputs

Stochastic inputs
Calculating long term rail surface damage

- A MBS simulations-based method to assess long term accumulated rail surface damage due to
  - Vehicle passing
  - Intermediate maintenance actions
Comparing bogie designs

Elements of simulation modelling

Vehicle Designs
- Suspension elements
- Axle loads
- Wheel profiles

Track operation
- Track design geometries
- Friction levels
- Operating speeds
- Rail profiles

Maintenance
- Type (Grinding/milling)
- Intervals
- Depths

1. Cross bracing linkages
2. Double Lenoir links
3. Sidebearer longitudinal clearnance

Standard Y25

FR8RAIL
Rail surface damage evolution

- **Standard Y25 bogie**
- **FR8RAIL bogie**
- $R = 450 \text{ m}$
- Outer rail
- 100 MGT
- $\sim 4 \text{ years}$

Wear depth | Surface RCF | Accumulated RCF

- **Flange & head**
- Spread but mostly on head
Optimization of grinding intervals

- The RCF accumulation ($\Sigma N_r$) on the rail surface just before each grinding pass are plotted for
  - R450
  - R600
  - R1500
- Presents opportunity to modify grinding intervals w.r.t running gear behaviour for different curve radii.
Calculation of wheel damage – Wheel life prediction
Wheel life prediction

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Anders Ekberg, Chalmers
Rail Vehicle Dynamics based Wheel Life prediction

Wheel life model

Vehicle

Track

Operation

Flange lubrication

MBS Locomotive model

Dynamic Friction

Track Geometry

Track Layout

Rail Profiles

Traction and braking

Real speed

Stochastic inputs

2021-04-16
RCF Calculation

- Sim. set design
- *Veh.-trc. Sim.
- Wheel-rail contact response
- Wear & RCF calculation
- Profile updating
  - Desired distance?
  - New wear-step
- Finished
RCF calculation

1. Check the exceedance of the yield limit in shear in each element of the contact mesh
2. Count the amount of incidents where #1 occurs
RCF calculation

1. Check the exceedance of the yield limit in shear in each element of the contact mesh
2. Count the amount of incidents where #1 occurs
3. Correct the RCF-number (Nr) values by energy dissipation method (Burstow)

$$E_i = \frac{v_i \cdot A}{2\sqrt{3}} (\sigma_y + \sigma_U), \text{ for } i = 1, 2$$

$v_i$ are 0.3% and 1%

$\sigma_y$ and $\sigma_U$ are material yield limit and its ultimate tensile strength

$$E(x, y) = \tau_{zx}(x, y) \cdot (v_x - \phi \cdot y) + \tau_{zy}(x, y) \cdot (v_y + \phi \cdot x)$$
Simulated RCF results for various operational cases after 50 000km; maximum value for the colour-bar is set to 300 000 RCF number.
Wheel life prediction model

\[ y = 0.00013 \left( \frac{N_f}{1000} \right)^2 + 0.1 \left( \frac{N_f}{1000} \right)^{-0.3} \]

\( N_f \) Fatigue life
Wheel life prediction model

\[ N_f = \frac{10}{F_{I_{surf}}^{4}} \]

*Fatigue life: \( N_f \)

Wheel life prediction model: results

Cumulative Distribution Function

- Calculated average operational distance between reprofilings [1000km]

Measurements*

- Average operational distance between reprofilings [1000 km]
Wheel Life prediction: wear and RCF

Calculation of rail damage – Influence of track gauge
Machine Learning

• Computer algorithms that improve automatically through experience
  – Use a dataset in order to build a mathematical model that can make further predictions
  – Used where it is not feasible to develop conventional algorithms to perform the tasks
Machine Learning Algorithms for condition monitoring and fault diagnostics

Rail Vehicle Dynamics Informed Machine Learning Algorithms for onboard condition monitoring and fault diagnostics
Monitoring of track geometry irregularities

Identification of local defects

Identification of rail squats from axle box acceleration measurements using machine learning algorithms

Summary

The presented tools

• Show good agreement with field observations

and could be used to

• Optimise rail grinding or wheel turning intervals with respect to
  – Track section
  – Operational changes
  – Vehicle type
  – Changes of wheel or rail profile type
  – …

• Detect faults in vehicle and/or track with help of **Rail Vehicle Dynamics** Informed Machine Learning Algorithms