KTH ROYAL INSTITUTE
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Reduction of infrastructure maintenance costs using machine learning and digital twins

Carlos Casanueva, Rail Vehicles Unit, KTH Railway Group

KTH Railway Group Autumn Seminar

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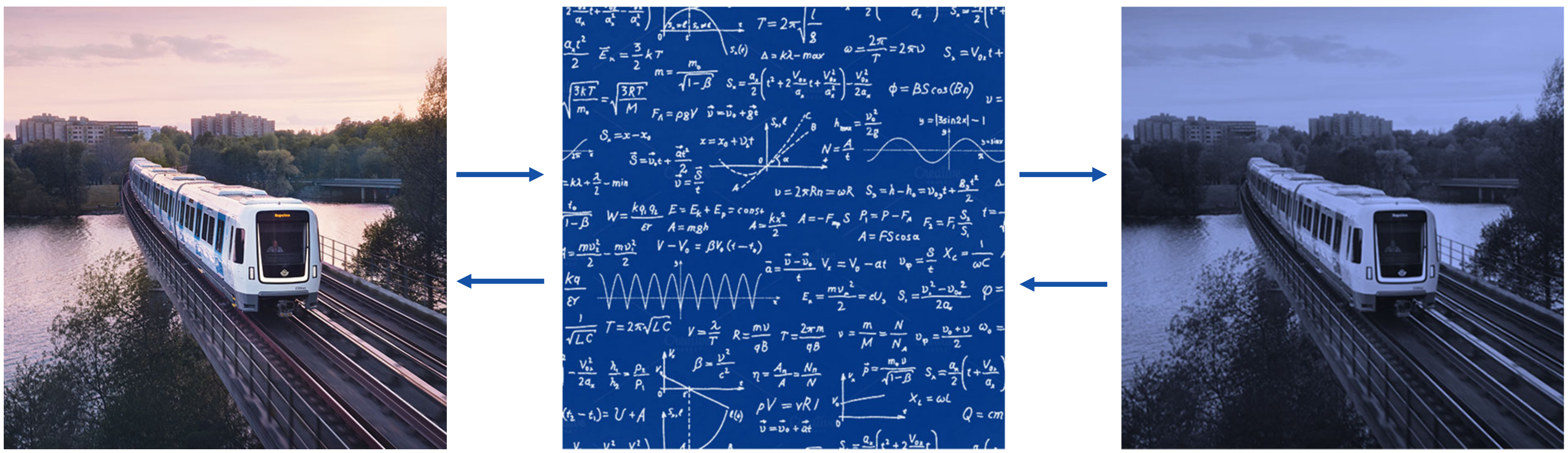
Digital Twin

- Digital replica of a specific physical system



sll.se

Digital Twin

- Digital replica of a specific physical system
  - It can include assets, processes, people, places…
  - It can be used for many purposes

Rail vehicles

Tracks

Timetabling

Passengers

Electrical system

Signalling system

Maintenance

Drivers

Digital Twin modelling

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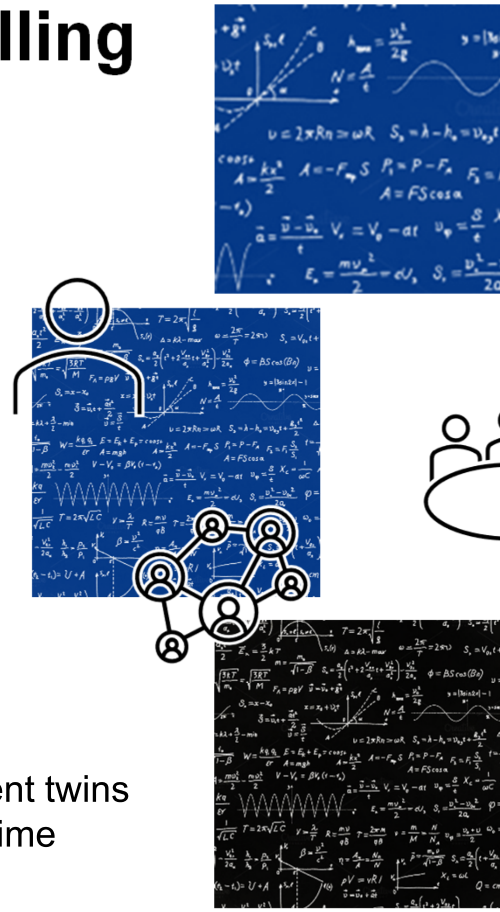
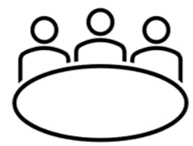
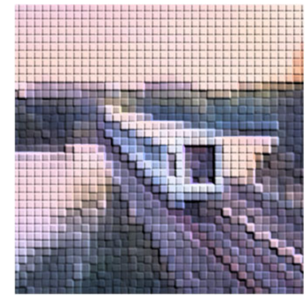
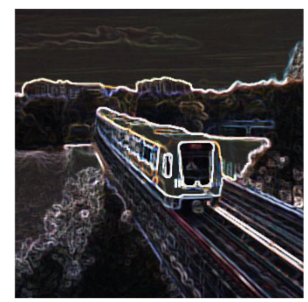






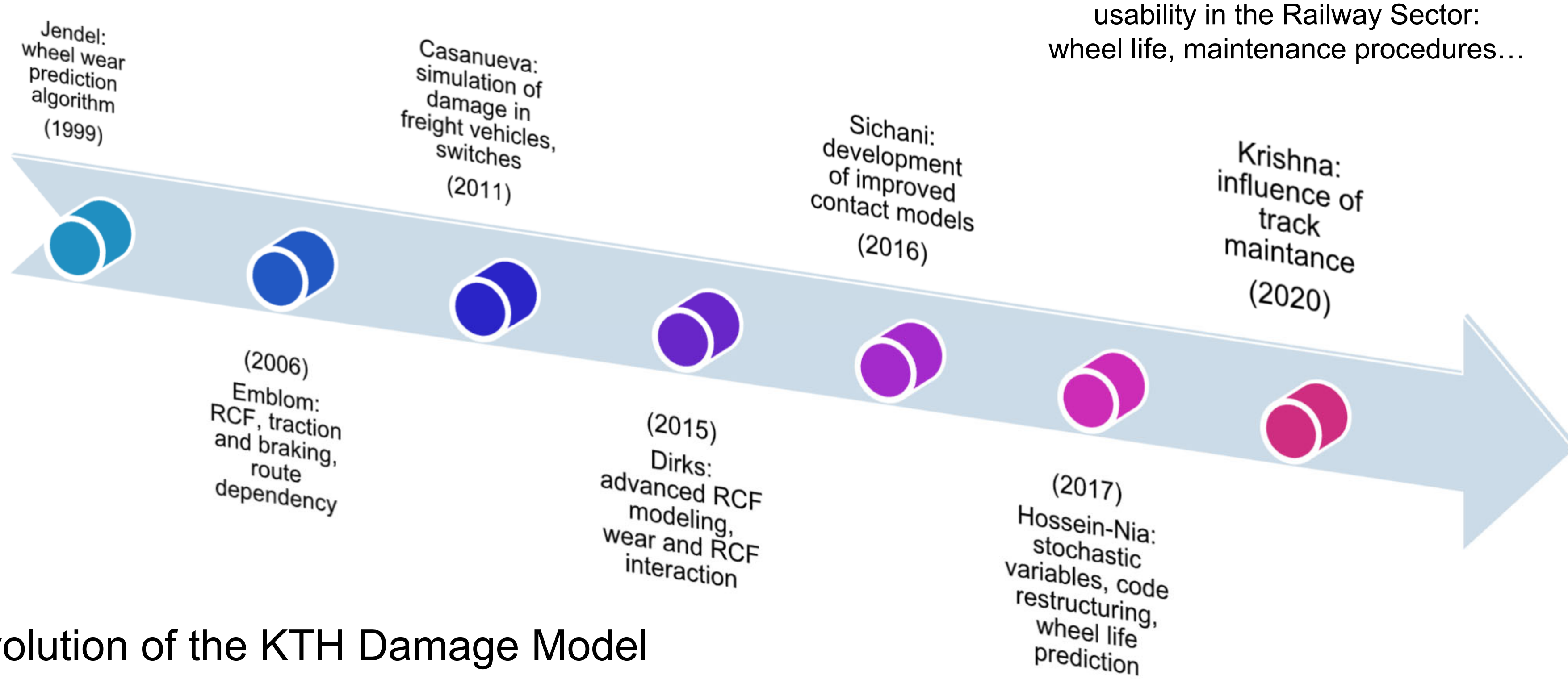


Modelling by <u>people</u>

- Usually subsystem focused
- Different modelling approaches give different twins
- The more precise, the more complex and time consuming

Wheel-Rail contact damage models

Latest developments focus on usability in the Railway Sector: wheel life, maintenance procedures…

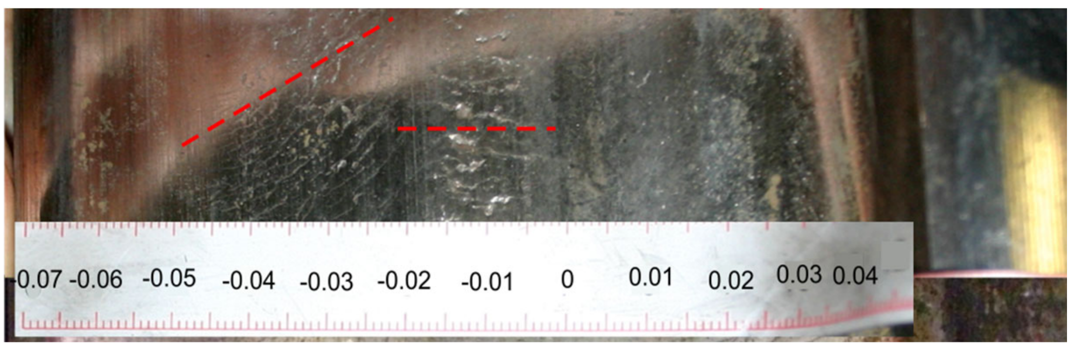


Evolution of the KTH Damage Model

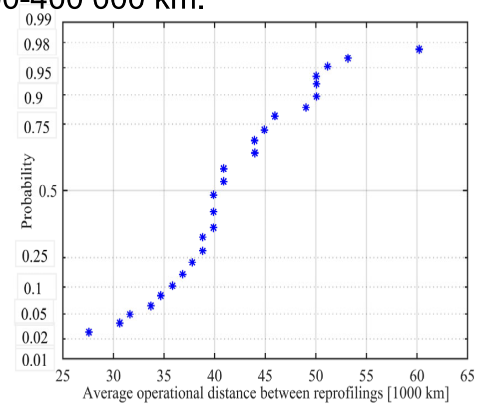
Wheel life prediction

Photo licensed under CC BY-SA

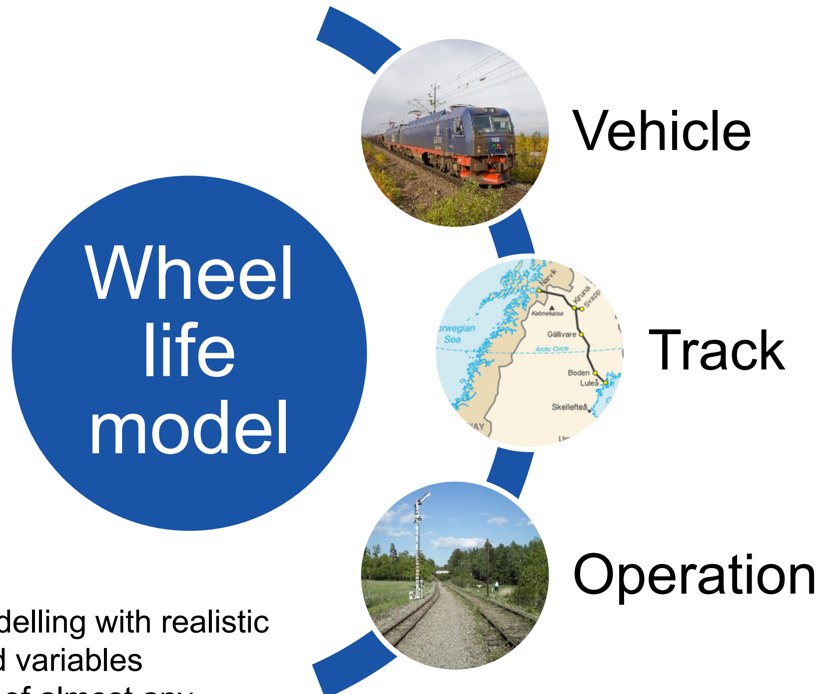
50% of the wheels must be reprofiled after 40k km.
Average wheel-life 300 000-400 000 km.

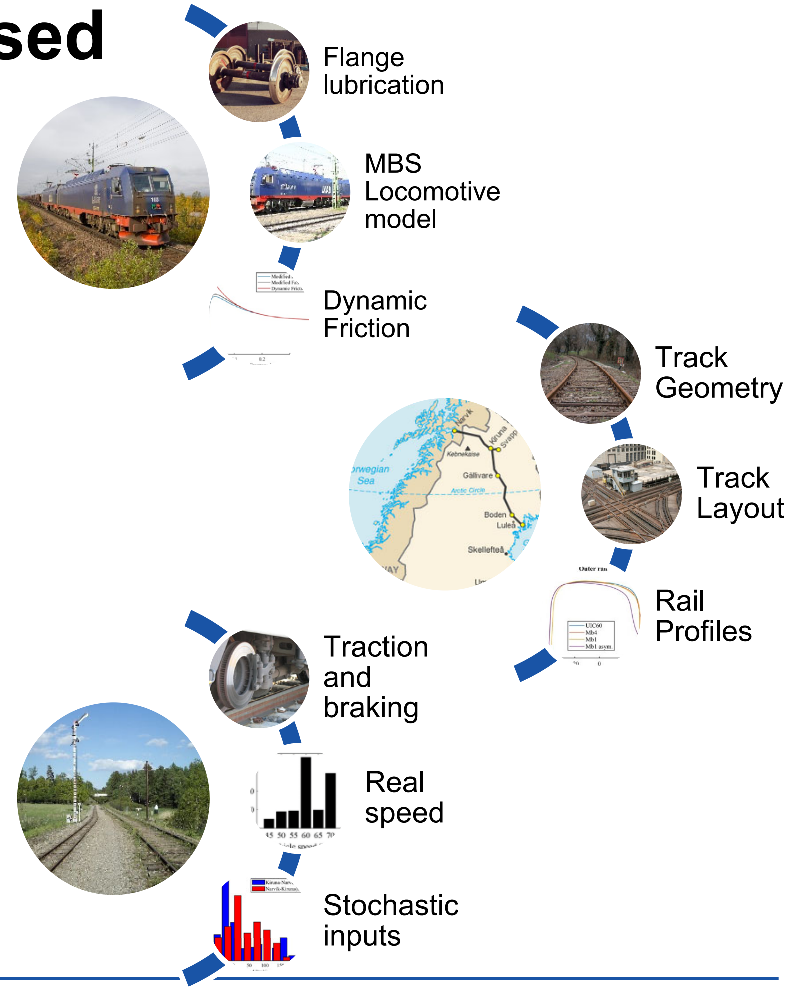


Anders Ekberg, Chalmers



Rail Vehicle Dynamics based Wheel Life prediction

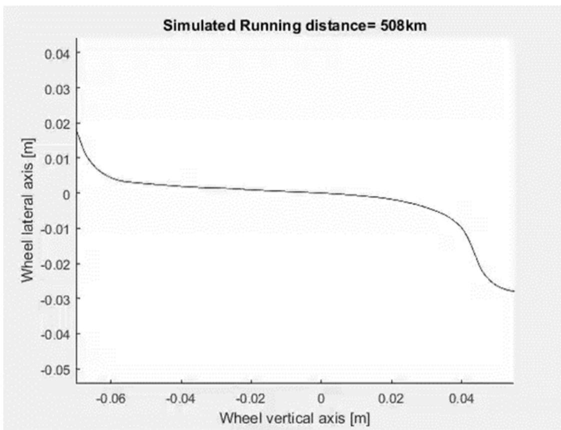


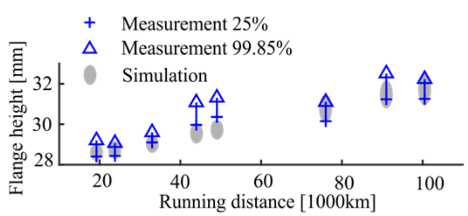


Extensive modelling with realistic and measured variables
The influence of almost any variable can be analysed

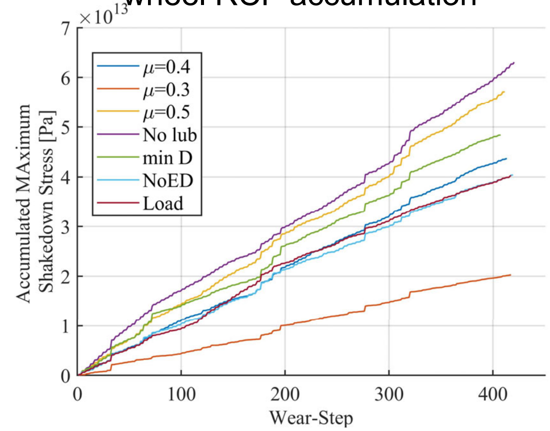
Wheel Life prediction: wear and RCF

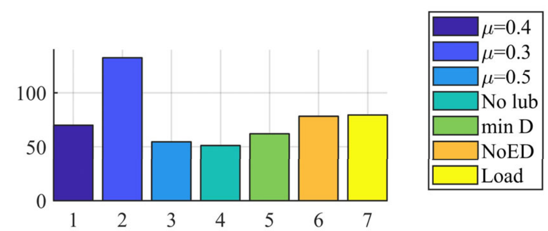
Wheel wear evolution





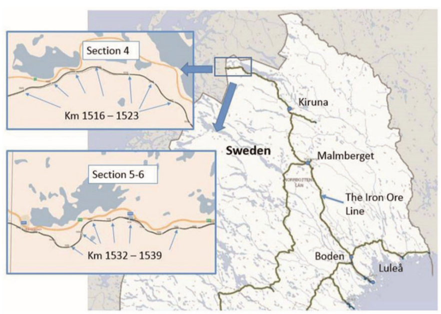
Influence of different parameters on wheel RCF accumulation

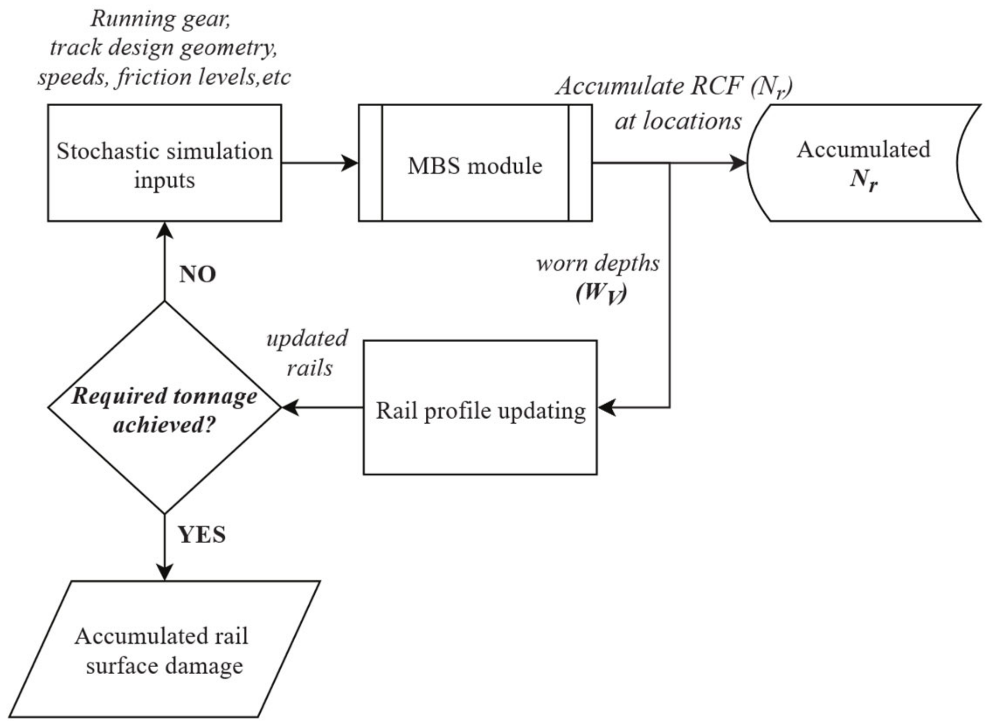




S Hossein-Nia, S Stichel, 2019, *Multibody simulation as virtual twin to predict the wheel life for Iron-ore locomotive wheels* International Heavy Haul Association Conference, IHHA 2019, Narvik

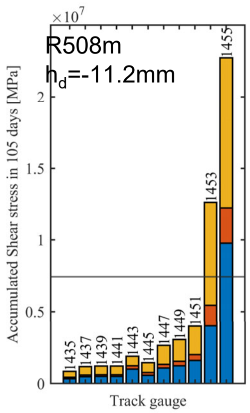
Rail Life prediction

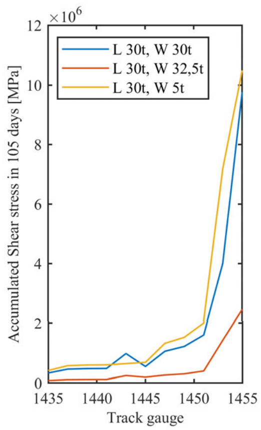




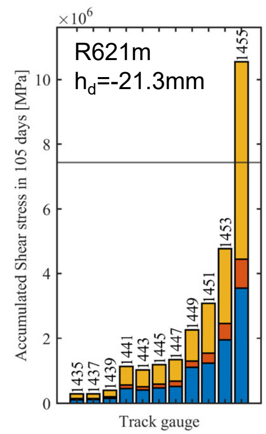
Rail Life prediction

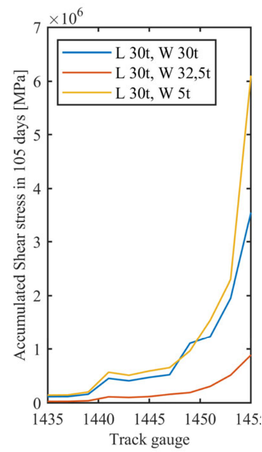
Baseline
Influence of track gauge

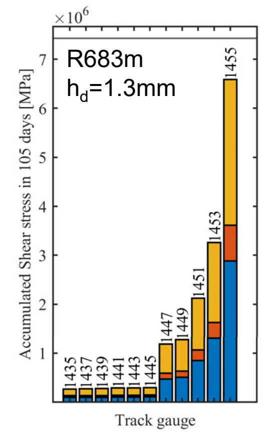


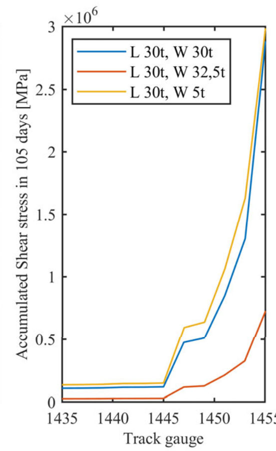


Influence of cant

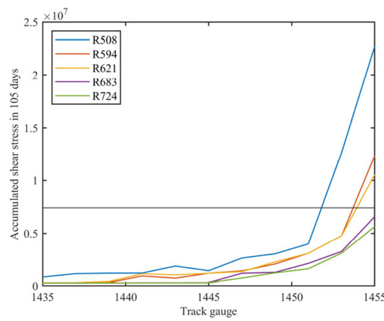






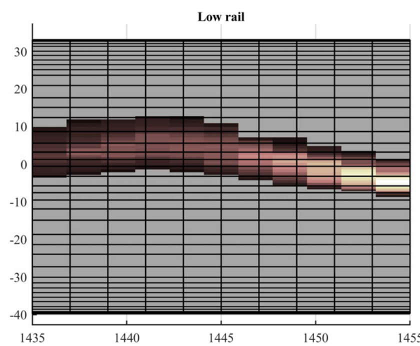


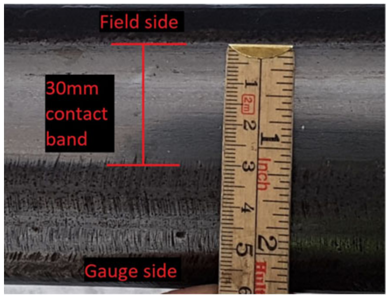
Influence of radius



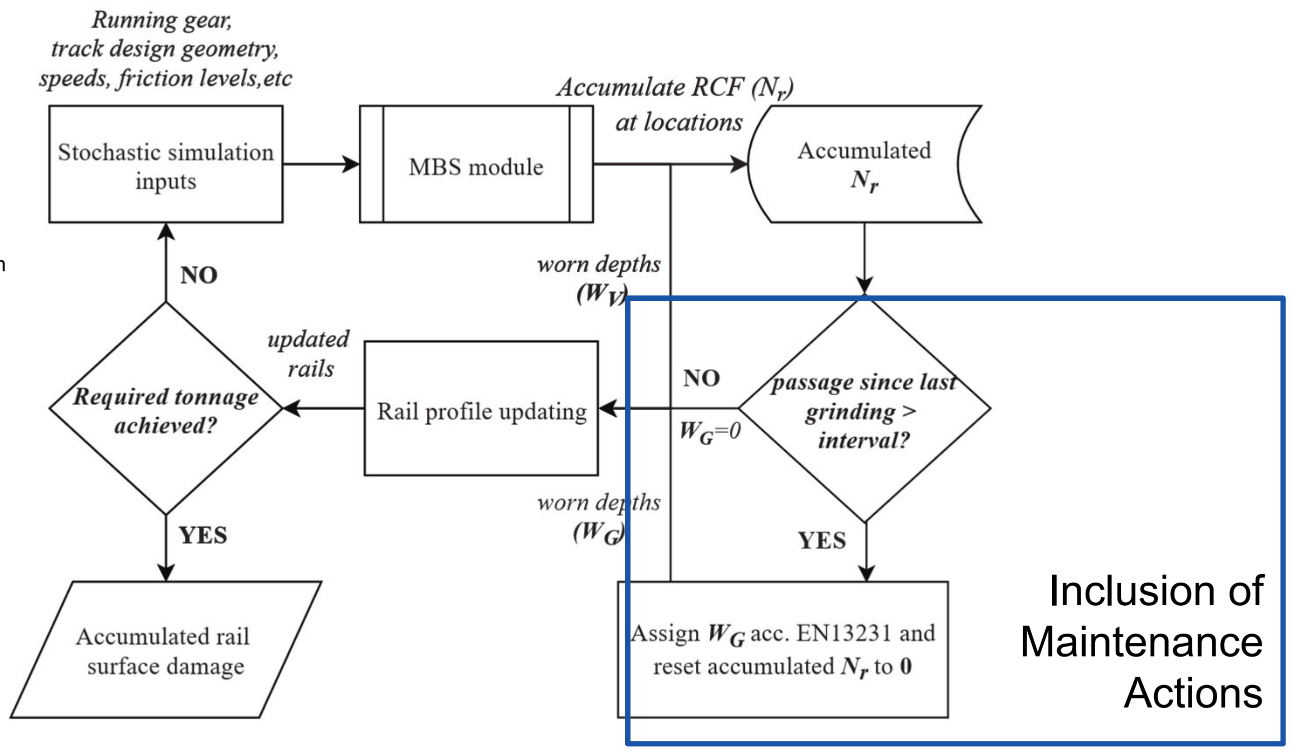
J. Flodin, 2020, *Investigate the track gauge widening on the Iron-ore line and suggest maintenance limits*, KTH Dissertation

Location of cracks

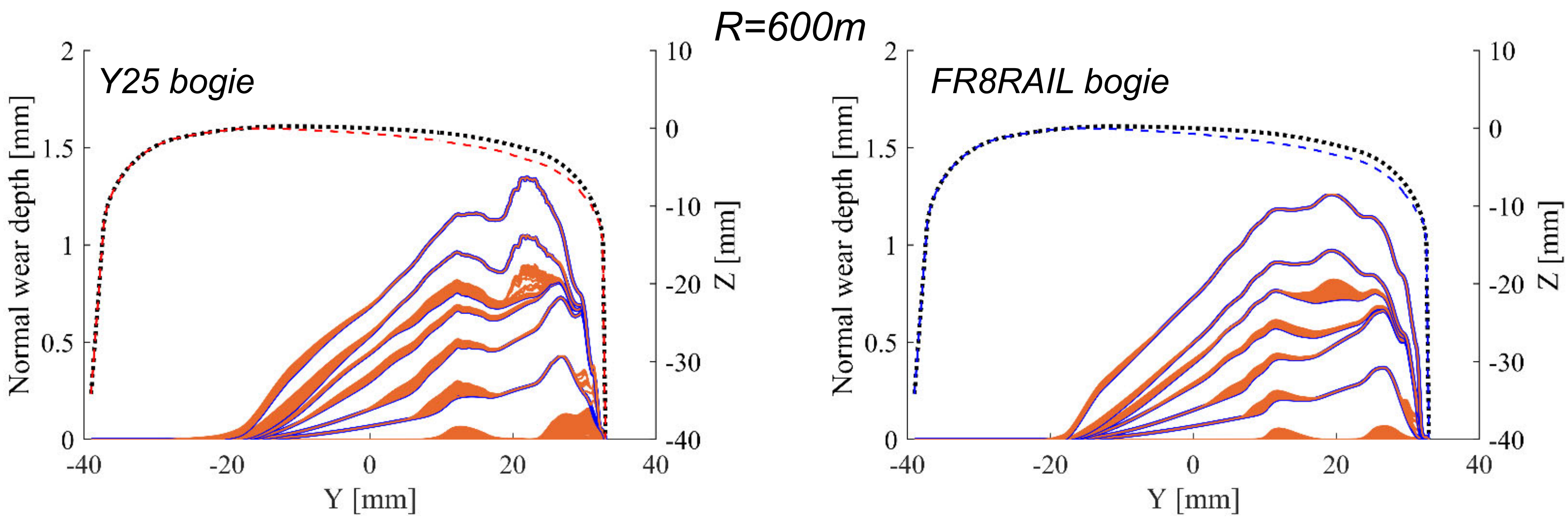




Rail damage modelling including maintenance



Wear evolution including grinding cycles



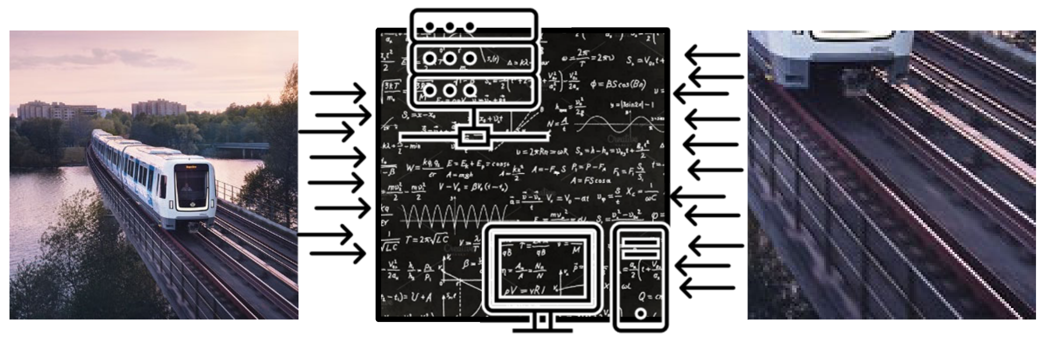
- 15 MGT grinding cycle
- Normal worn depths on the outer rail, vehicle induced (orange) and grinding (blue)
- Artificial wear (grinding) much higher – innovative vehicles need adapted maintenance to be effective

Shift2Rail – FR8RAIL2 – Krishna, V. V., Hossein Nia, S., Casanueva, C. & Stichel, S. (2020). *Long term rail surface damage considering maintenance interventions*. Wear, 460-461.

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

- Approaches
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning



- How is this useful?

NyTeknik

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ANNONS

FORDON

Fler tågtyper skakar genom Hallandsåsen

2016-02-08 09:34 Av: Linda Nohrstedt 0 kommentarer

Det är inte bara SJ 3000 som har drabbats av vibrationer genom Hallandsåstunneln. Även ombord på Öresundståg och godståg har kraftiga skakningar upplevts.

SYDSVENSKAN

Här skakar tåget genom Hallandsåsen

Edward Granville-Self var på väg hem från jobbet när Öresundståget plötsligt började skaka våldsamt inne i Hallandsåstunneln.

sverigesradio

Så mycket skakar tågen genom Hallandsåsen

2:00 min Min sida Dela

Publicerat fredag 5 februari 2016 kl 11.19

Sen en tid tillbaka går tågen med sänkt hastighet genom Hallandsåsen på grund av vibrationer.

NyTeknik

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ANNONS

TEKNIKNYHETER

Mysteriet med skakningar i Hallandsås-tunneln är löst

2016-06-14 10:40 Av: Linda Nohrstedt 14 kommentarer

Flera tåg drabbades av kraftiga vibrationer genom nybyggda Hallandsåstunneln. Orsaken var länge okänd. Men nu anser Trafikverket att mysteriet är löst.

- Solved after 5 months
- Not only a Swedish problem

stern

Double-decker IC of the Deutsche Bahn December 16, 2015 11:09 a.m.

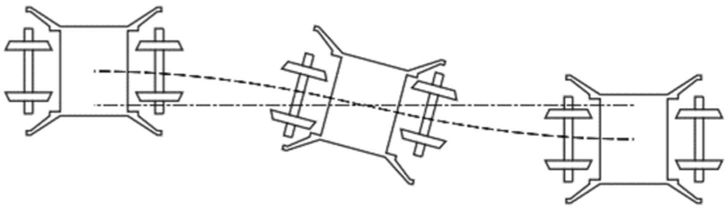
Passengers get sick on the new trains

Hardly in use, already problems: Due to a wobbling of the wagons, the railway wants to have the damping system revised in its new double-decker intercity. Travelers complain about other shortcomings.

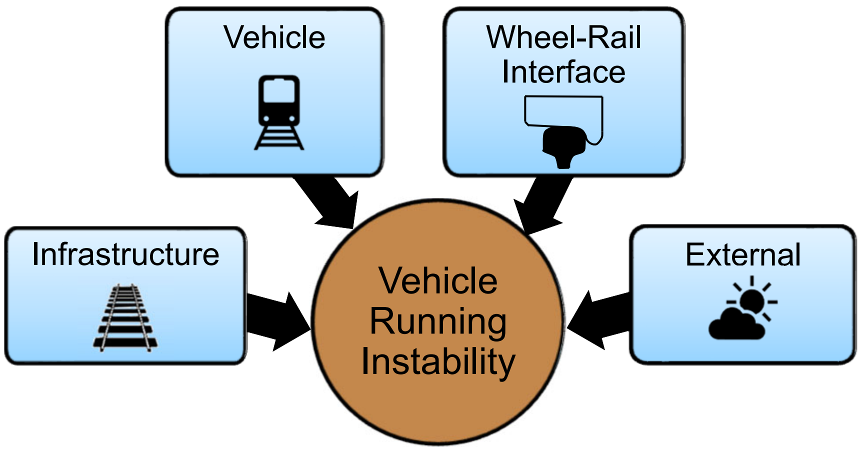
You have to go straight back to the workshop: on certain sections of the route, the wagons of the new double-decker IC start to falter.
© Jens Wolf / DPA

Jönsson L-O, Asplund M, Li M. *Vehicle vibrations at the Hallandsås tunnel: Collaborative investigation and results.* Proc. 25th Int. Symp. Dyn. Veh. Roads Tracks (IAVSD 2017). Rockhampton, Australia; 2018. p. 1059–1063.

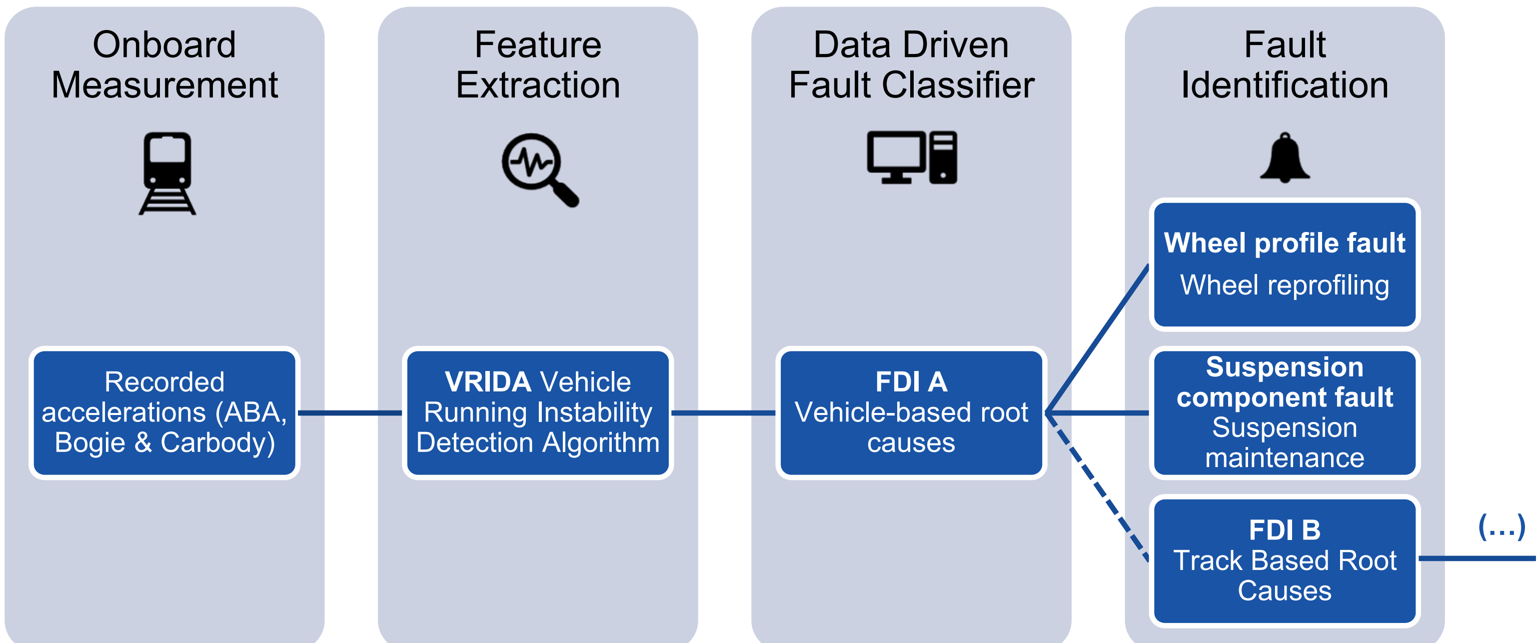
Vehicle Running Instability



- Sinusoidal motion is a natural phenomenon
- Instability influenced by many variables
- Can the responsible variables be detected faster?



Fault Diagnosis and Isolation (FDI) of Vehicle Running Instability



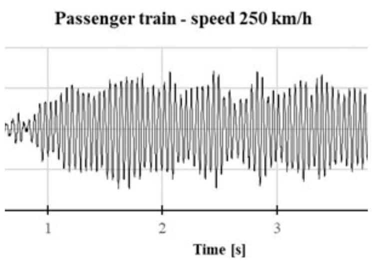
Shift2Rail – IN2TRACK2 – Kulkarni R, Qazizadeh A, Berg M, et al. Vehicle Running Instability Detection Algorithm (VRIDA): A signal based onboard diagnostic method for detecting hunting instability of rail vehicles. (manuscript under peer-review)

Shift2Rail – PIVOT-2 – Kulkarni R, Qazizadeh A, Berg M, et al. Fault Detection and Isolation Method for Vehicle Running Instability from Vehicle Dynamics Response Using Machine Learning. Proc. BOGIE'19. Budapest; 2019.

Machine Learning Algorithms for condition monitoring and fault diagnostics

Track geometry

Local track defects

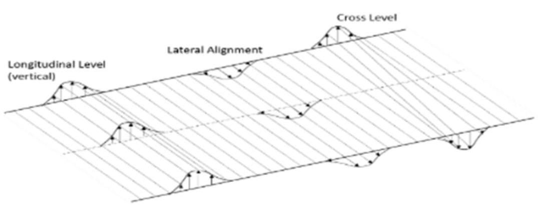


Running instability

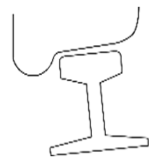
Component failure

Rail Vehicle Dynamics Informed Machine Learning Algorithms for **onboard** condition monitoring and fault diagnostics

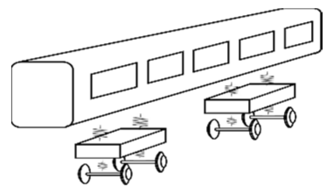
Monitoring of track geometry irregularities



Track irregularities

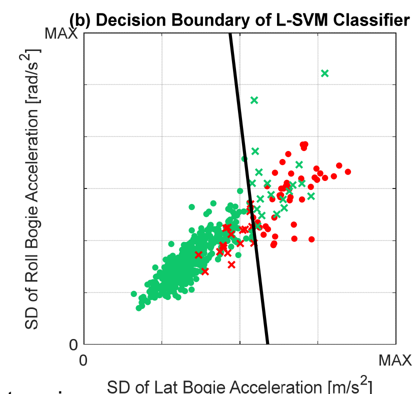


Wheel–rail contact



Vehicle dynamic response

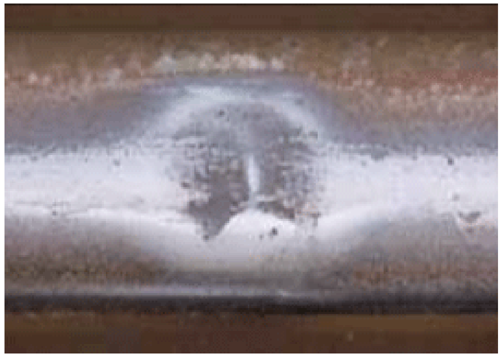
Onboard Vehicle Dynamic Measurement → Feature Extraction → Data Driven Fault Classifier → Monitoring of Track Geometry Irregularities



92% accuracy with ca. 500 simulation cases

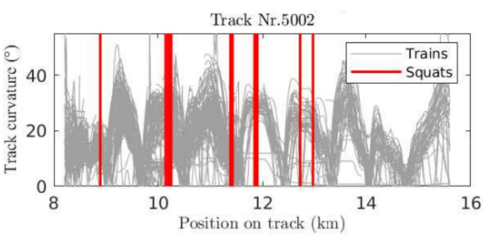
A. D. Rosa et al., 'Monitoring of lateral and cross level track geometry irregularities through onboard vehicle dynamics measurements using machine learning classification algorithms', Proceedings of the Institution of mechanical engineers. Part F, journal of rail and rapid transit, 2020.

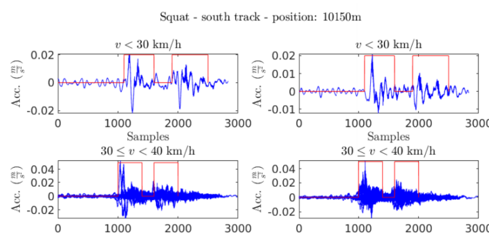
Identification of local defects

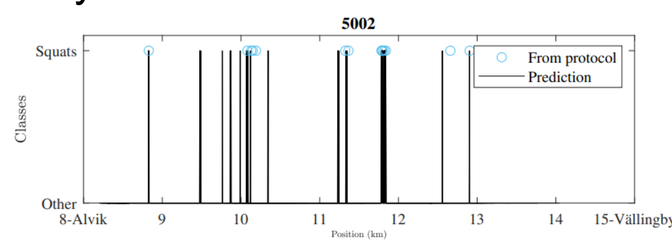


Identification of **rail squats** from axle box acceleration measurements using machine learning algorithms

In use in the Stockholm Metro system







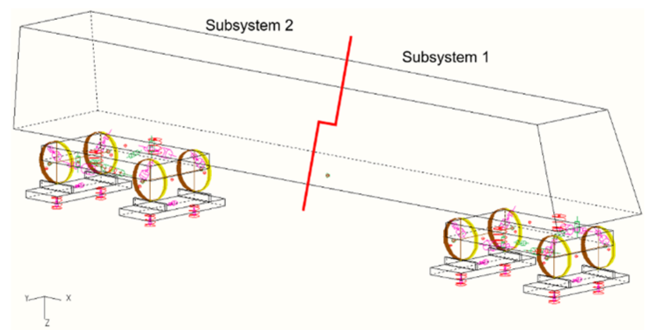
T. Niewalda, 'Deep Learning Based Classification of Rail Defects Using On-board Monitoring in the Stockholm Underground', KTH Dissertation, 2020.

Condition Monitoring of Vehicle Components

- Identification of degraded dampers
- Location of the failed damper

1-Nearest-Neighbour classifier without dim. red.

			Fault factor on damper	Training dataset 1: 0,1	0,25	0,6	Ref	Training dataset 2: 0,1	0,25	0,6	Ref	Training dataset 3: 0,1	0,25	0,6	Ref
Massfact 1	Track1	Straight	200	100	90	10	100	100	100	90	100	100	100	90	50
			180	100	100	100	100	100	100	100	100	100	100	90	65,6
			160	70	70	50	100	100	100	100	100	100	100	100	100
			Dyn	90	80	70	100	100	100	100	100	100	100	100	100
		Curved	200	90	90	0	100	100	100	60	100	100	90	90	100
			180	100	100	100	100	90	90	60	100	100	100	90	100
			160	70	70	40	100	100	100	80	100	100	100	80	100
			Dyn	90	90	70	100	100	100	70	100	100	100	100	100
	Track2	Straight	200	70	60	20	100	90	80	30	100	100	100	100	100
			180	80	80	30	100	100	100	90	100	100	100	90	100
			160	60	50	40	100	90	80	80	100	90	90	70	9,4
			Dyn	60	60	40	100	90	100	70	100	100	100	100	100
		Curved	200	80	60	10	100	90	80	30	100	100	90	50	100
			180	90	70	70	100	100	90	70	100	100	100	90	100
			160	60	60	40	100	80	80	60	100	100	100	90	100
			Dyn	60	60	60	100	100	90	70	100	100	100	100	100
Massfact 1.04	Track1	Straight	200	90	90	20	100	100	100	100	100	100	100	100	43,8
			180	100	100	100	100	100	100	100	100	100	100	90	15,6
			160	70	70	50	100	100	100	100	100	100	100	100	100
			Dyn	90	90	70	100	100	100	100	100	100	100	100	100
		Curved	200	90	90	10	100	100	90	70	100	100	90	90	100
			180	100	100	100	100	90	90	80	100	100	100	90	84,4
			160	80	70	50	100	100	100	90	100	100	100	80	100
			Dyn	90	90	70	100	100	90	80	100	100	90	100	100
	Track2	Straight	200	70	60	30	100	90	90	40	100	100	100	100	100
			180	80	80	50	100	100	100	80	96,9	100	100	90	100
			160	60	60	30	100	80	80	70	100	90	90	70	6,3
			Dyn	60	60	50	40,6	90	90	80	37,5	100	100	100	100
		Curved	200	70	60	20	100	90	80	30	100	100	100	50	100
			180	90	60	60	100	100	100	70	100	100	100	100	100
			160	60	60	40	100	90	80	70	100	100	100	90	100
			Dyn	60	60	60	37,5	100	100	70	100	100	100	100	100
	Average accuracy:			79,1	74,7	48,8	96,2	95,6	93,1	74,7	98	99,4	98,1	90	86,7



Accuracies higher than 74% in identification of extensively damaged dampers.

Good potential for being used in practice.

Concluding remarks

- A digital twin of the vehicle-track system is a powerful tool capable of correctly predicting the damage in the wheel-rail interface and enabling the optimization of maintenance actions.
- Machine learning can further improve the prediction quality when the analysed system is complex and extensive.
- Machine learning is, in principle, black box modelling. As such, it cannot replace the physical understanding of the system behaviour.
- Specific subsystem-focused tools are already in use by companies in different Swedish railway systems.

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Carlos Casanueva, Rail Vehicles Unit, KTH Railway Group

Thank you for your attention!