



Tecnun
Universidad
de Navarra



Avances en el diagnóstico de la calidad de vía ferroviaria mediante técnicas de Machine Learning

Adrián Sansiñena Rodríguez

Borja Rodríguez de Arana

Saioa Arrizabalaga Juaristi

Ceit - Grupo DAIM



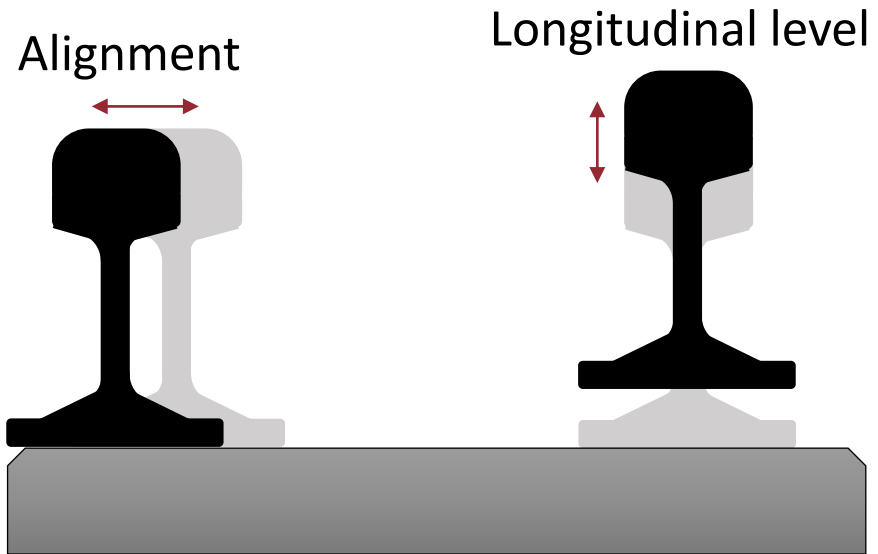
Co-funded by
the European Union



FP1 MOTIONAL
European Rail Network and Mobility Management



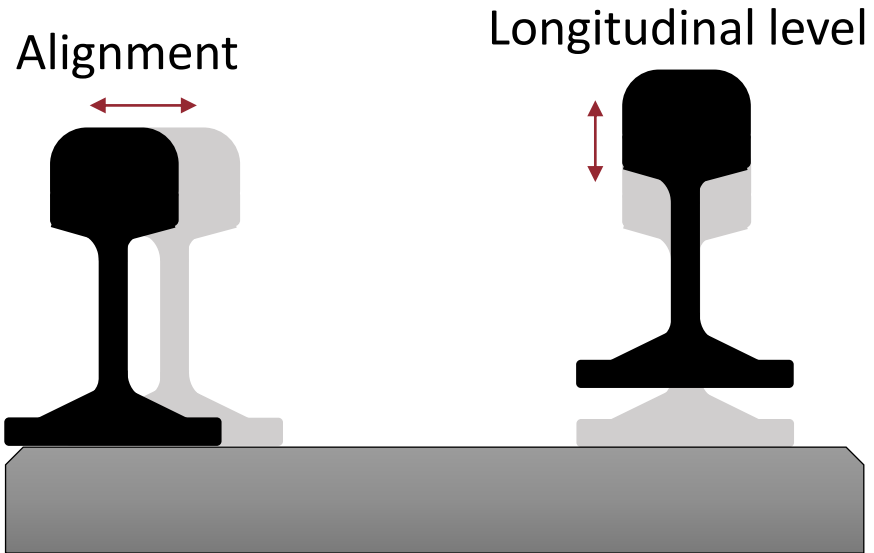
Track Irregularities



Track Irregularities



Track Quality Degradation

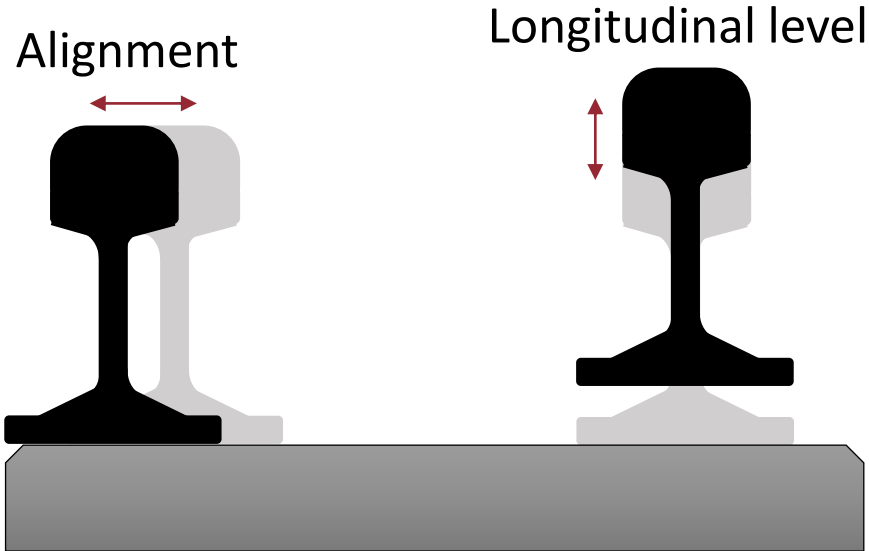


- Safety risk
- Comfort worsen (vibrations, noise)
- Maintenance costs

Track Irregularities



Track Quality Degradation



- Safety risk
- Comfort worsen (vibrations, noise)
- Maintenance costs

Traditional diagnostic methods

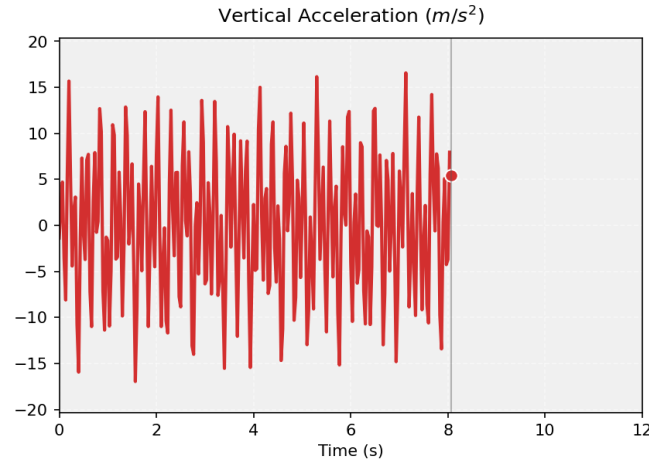


<https://www.pandrol.com/product/track-geometry-trolley/>



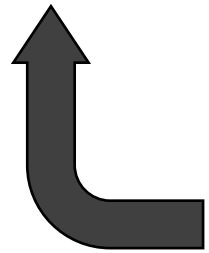
<https://www.spoorpro.nl/materieel/2021/12/20/nut-van-dynamisch-meten-besproken-tijdens-harmotrack-project-uic/>

Introduction

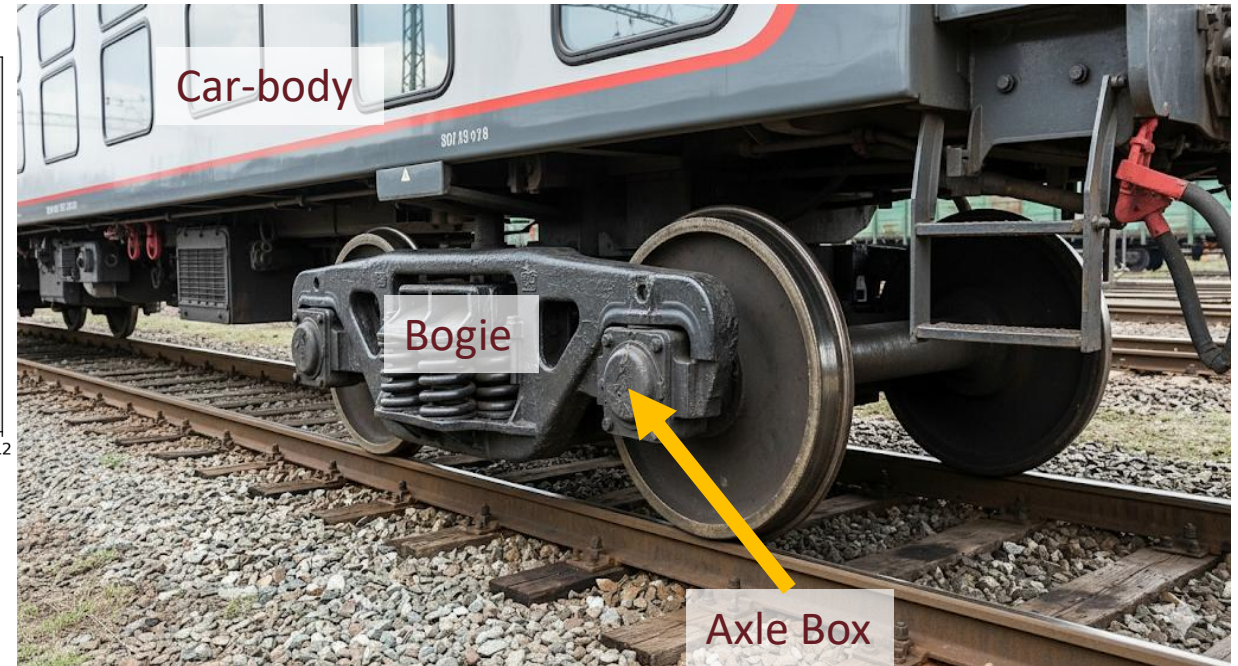
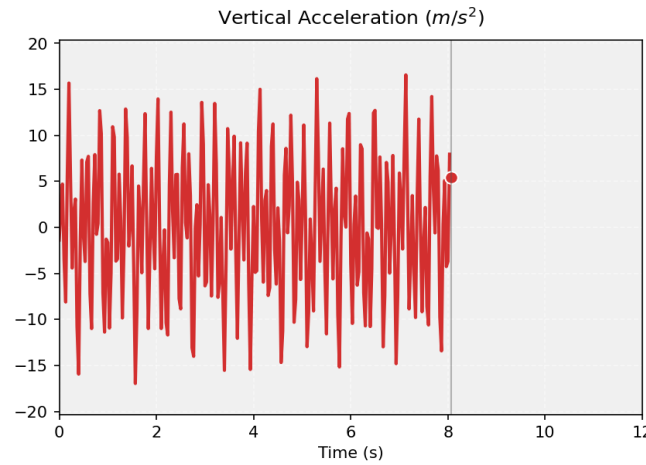


Track quality
assessment

Track Diagnostic
System



Introduction

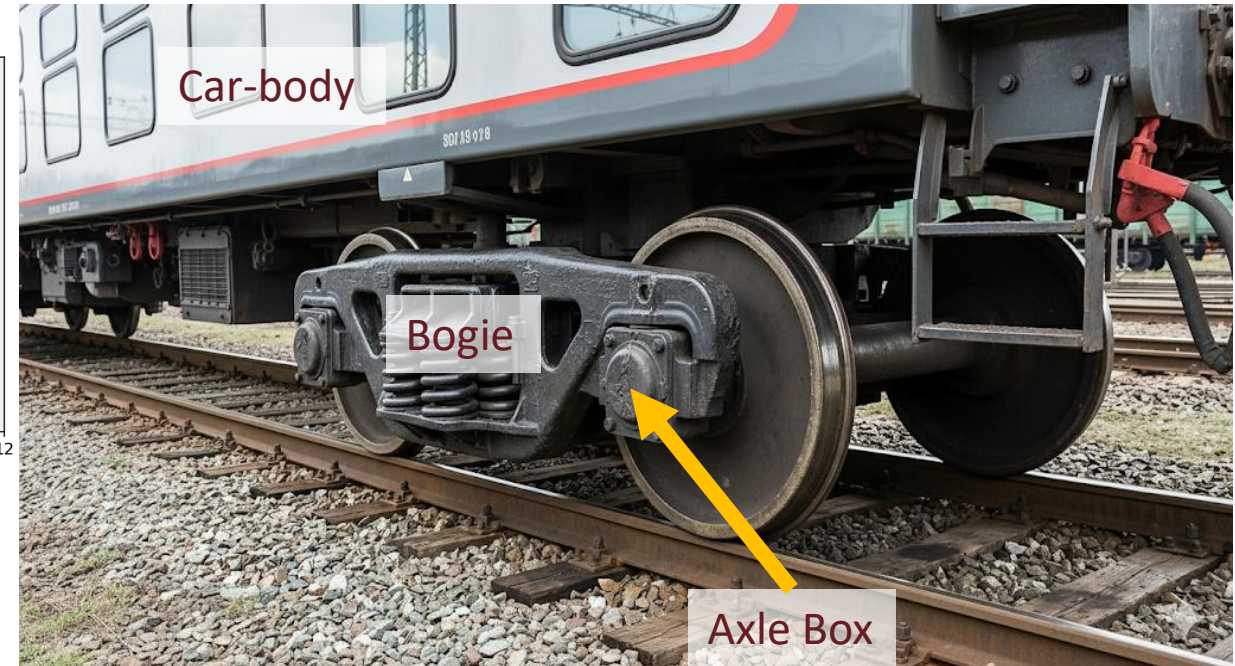
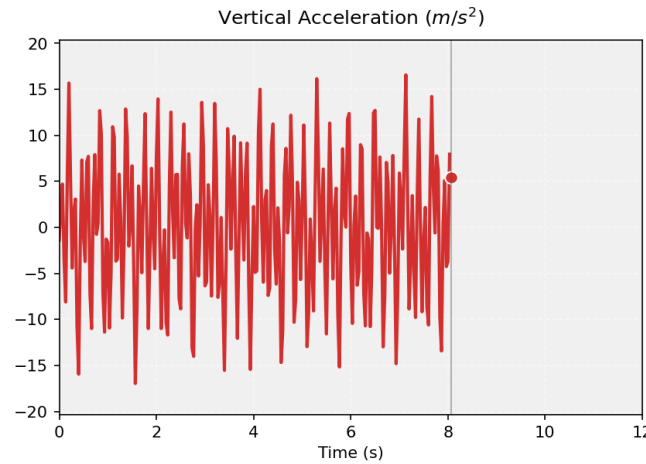


Track quality
assessment

Track Diagnostic
System

- ✓ In-service vehicles
- ✓ Cheap system
- ✓ Continuous monitoring (at least 1 measure per day)

Introduction



Track quality
assessment

Track Diagnostic
System

VEHICLE SYSTEM DYNAMICS
<https://doi.org/10.1080/00423114.2025.2483972>



Check for updates

A systematic review of acceleration-based estimation of railway track quality

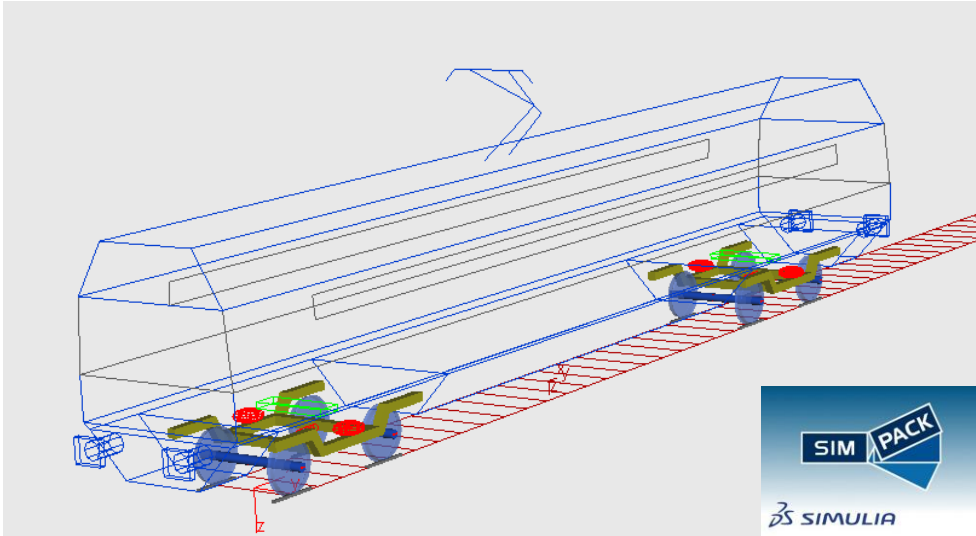
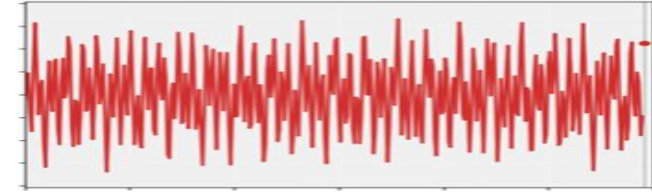
Adrián Sansiñena^{a,b}, Borja Rodríguez-Arana^{id a,b} and Saioa Arrizabalaga^{a,b,c}

From accelerations measured on board in-service vehicles:

- Propose a modular and flexible ML methodology for track quality diagnosis
- Integrate:
 - Data generation
 - Feature learning
 - Sensor selection
- Application to the estimation of two track-quality indices.

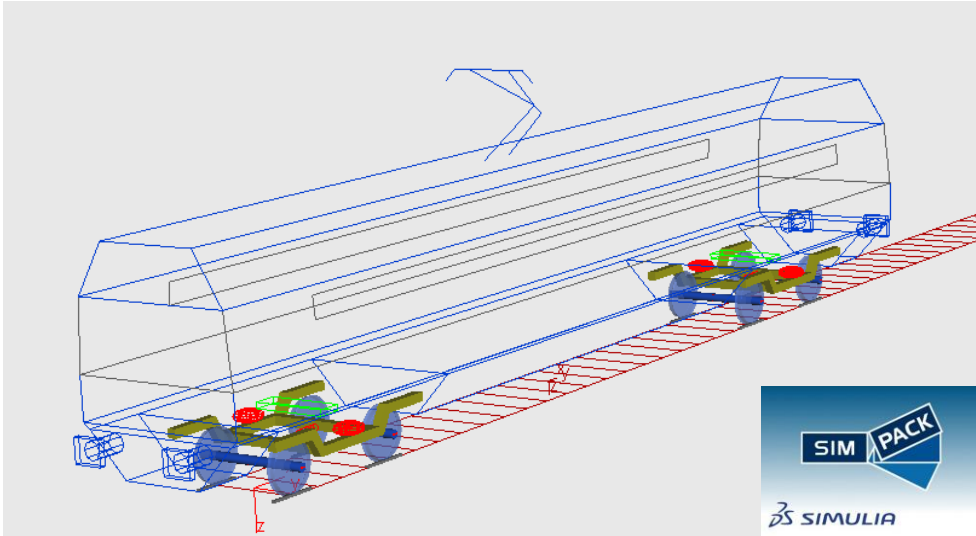
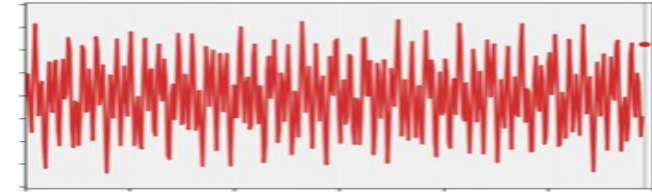
Generation of synthetic data

SIMPACK Multibody simulations software  Raw acceleration time series



Generation of synthetic data

SIMPACK Multibody simulations software  Raw acceleration time series



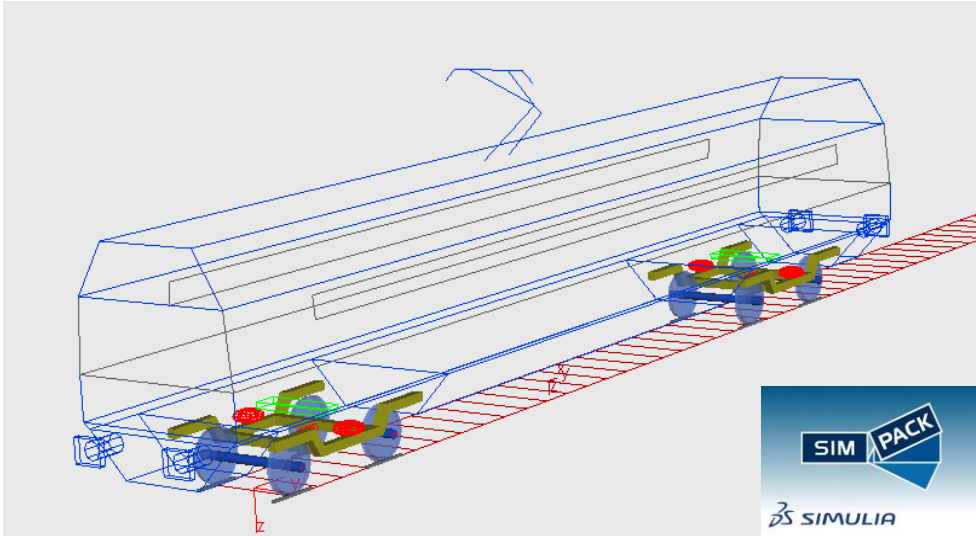
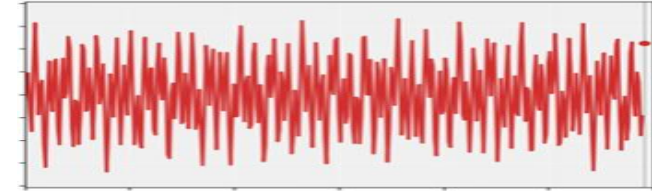
Several simulation parameters:

- Speed
- Load
- Track layout
- ...



Generation of synthetic data

SIMPACK Multibody simulations software  Raw acceleration time series



Several simulation parameters:

- Speed
- Load
- Track layout
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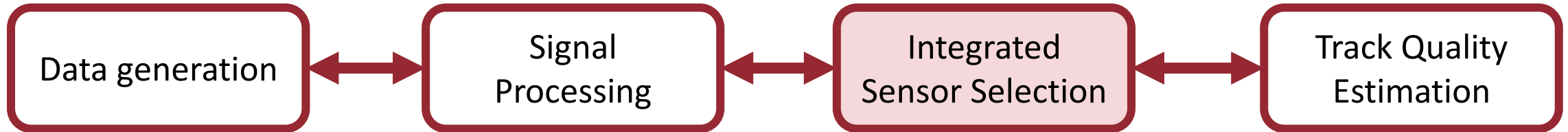


Simulations represent a regional train with a maximum speed of 80 km/h under a wide range of scenarios.

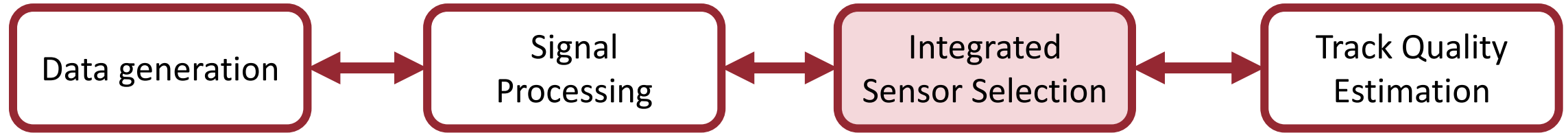


Representative and general for this type of vehicle.

General methodology for track assessment

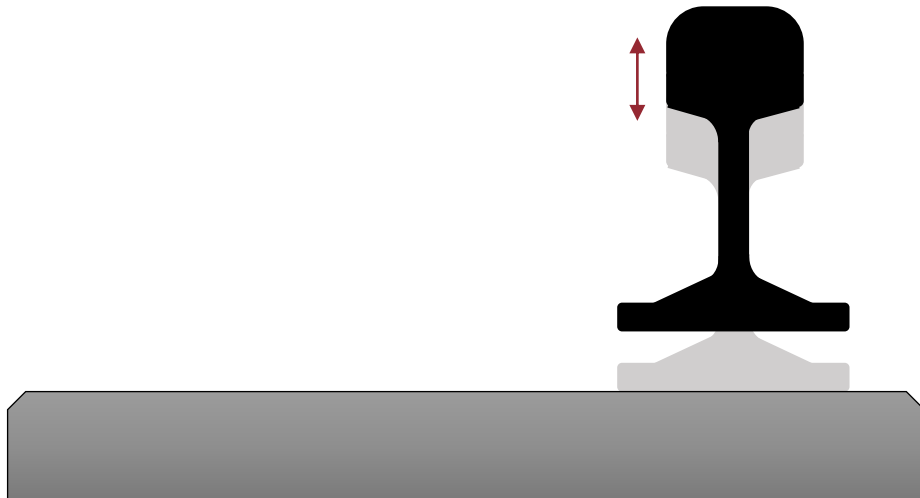


General methodology for track assessment

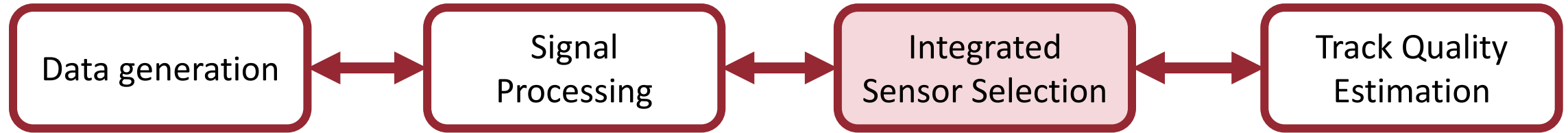


Two application cases studied:

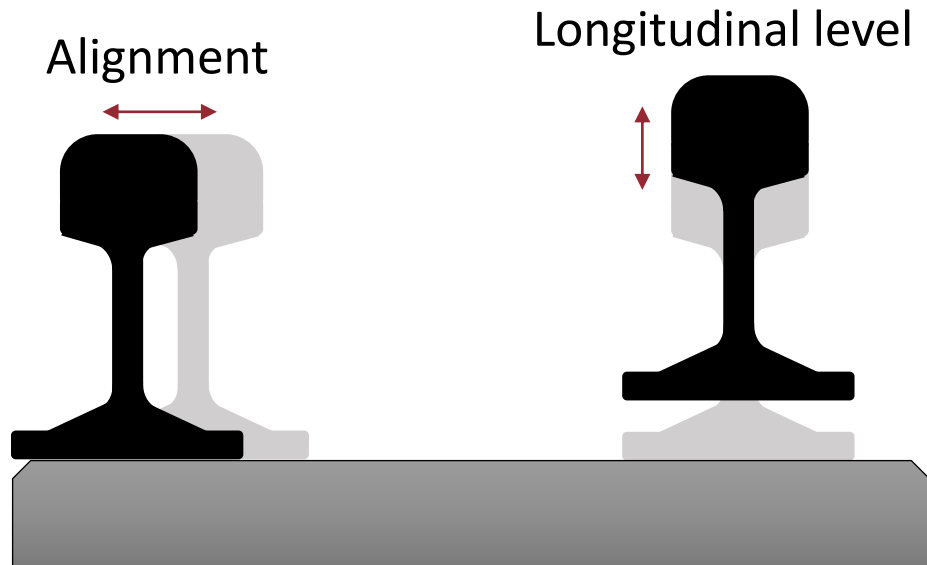
Longitudinal level



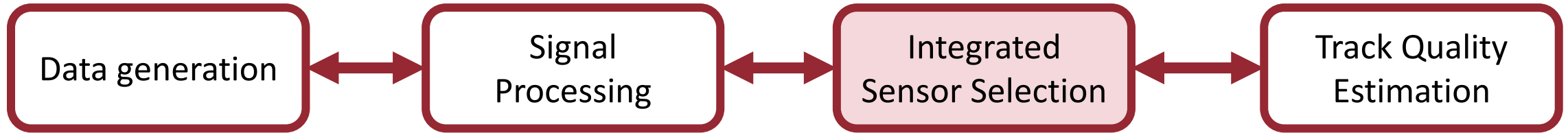
General methodology for track assessment



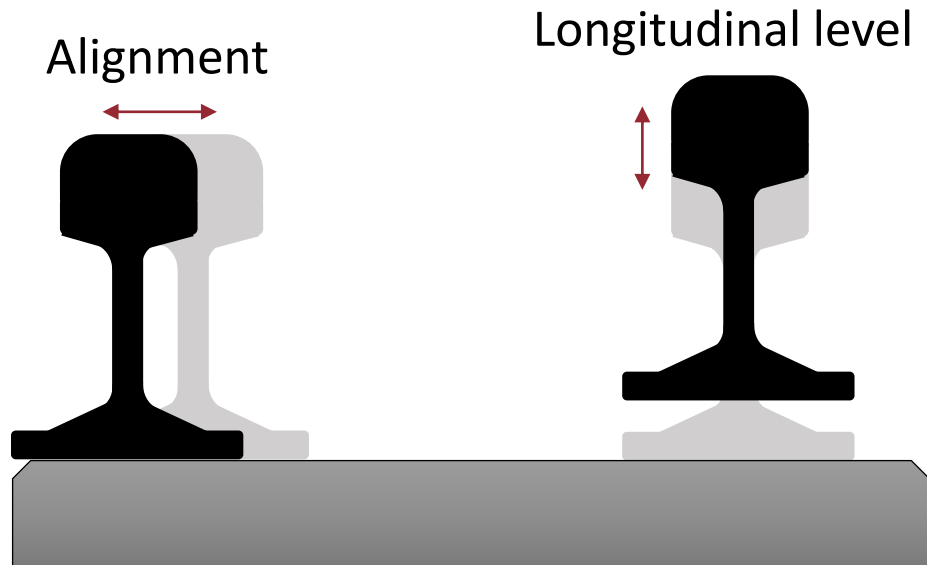
Two application cases studied:



General methodology for track assessment



Two application cases studied:



We use the **EN-13848** track quality definition:

Standard deviation of irregularities in a **200 m section**.



Regression of a single value from
acceleration time series

Longitudinal Level Quality Estimation

“Easy” case. Vehicle-track interaction is simpler



We prioritize compact models and tabular data

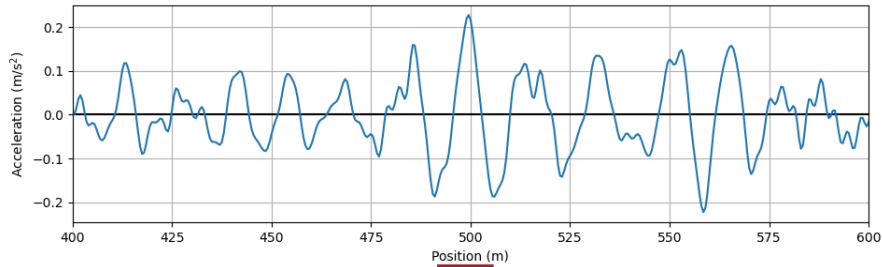
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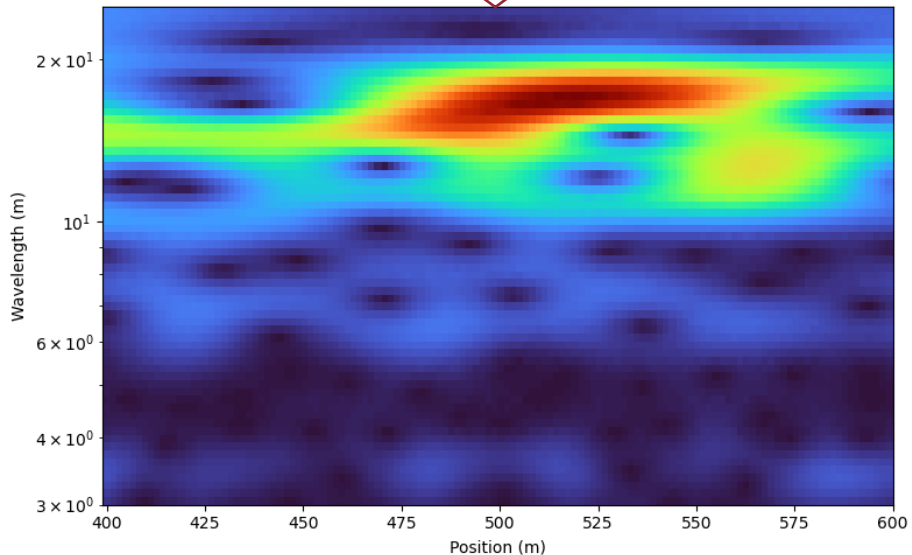
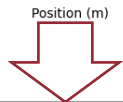
Signal Processing:



Ad-hoc features



- RMS
- peak-to-peak value
- Dominant frequency
- ...



PCA



First 10 principal components

Input
Dataset

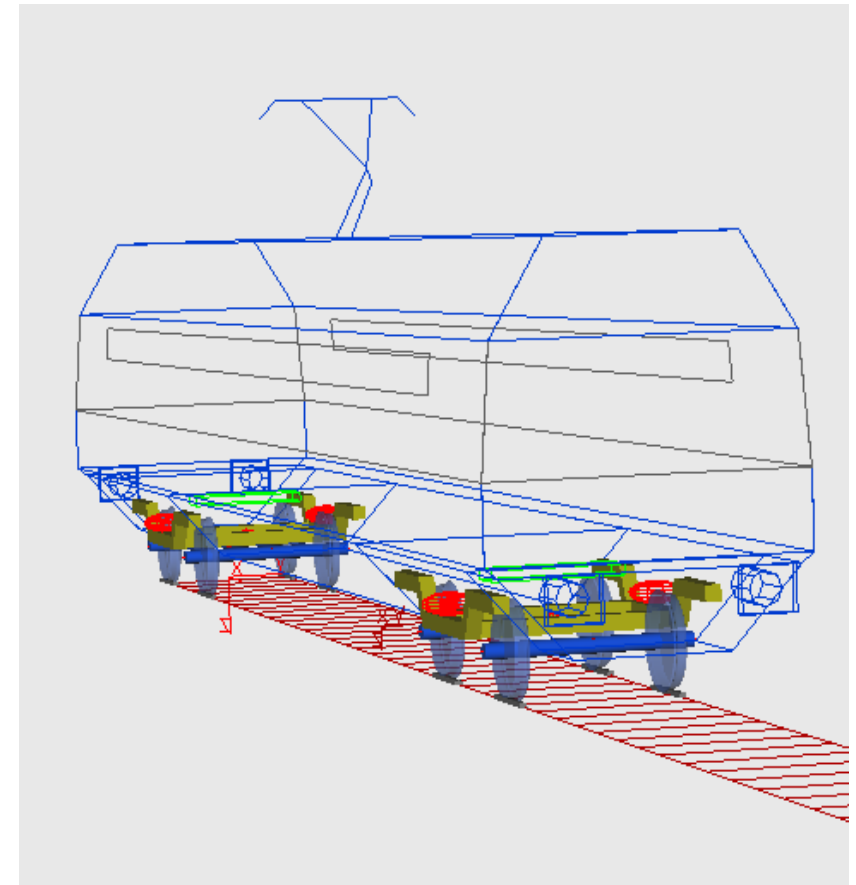
Longitudinal Level Quality Estimation

Sensor selection:

NSGA-II for multi-objective optimization:

Estimation RMSE

Number of sensors

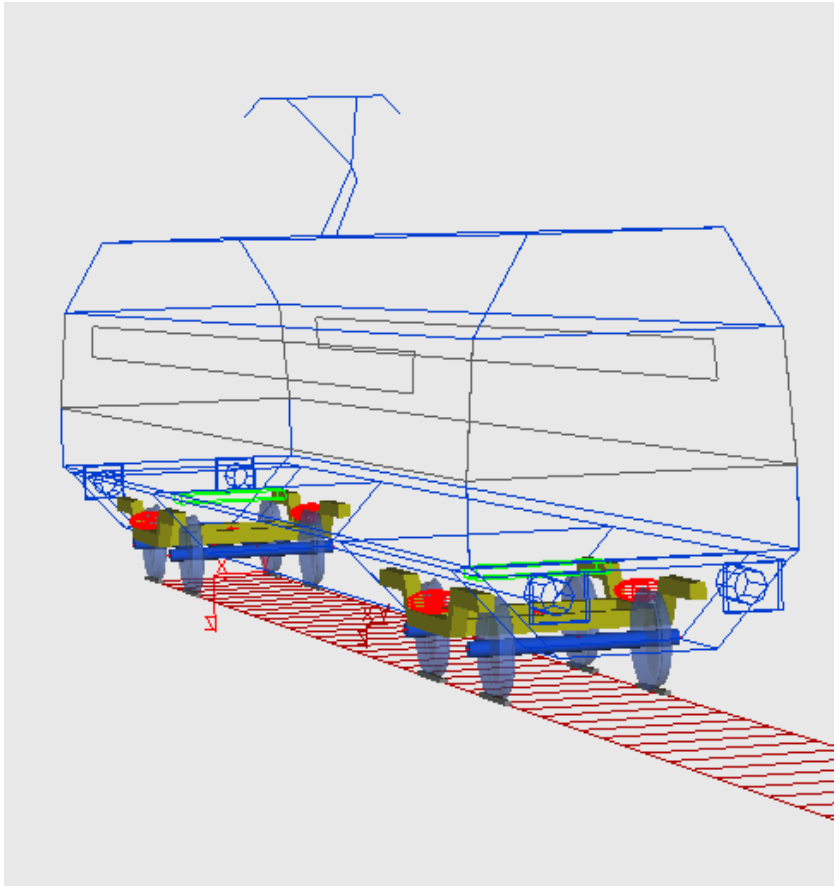
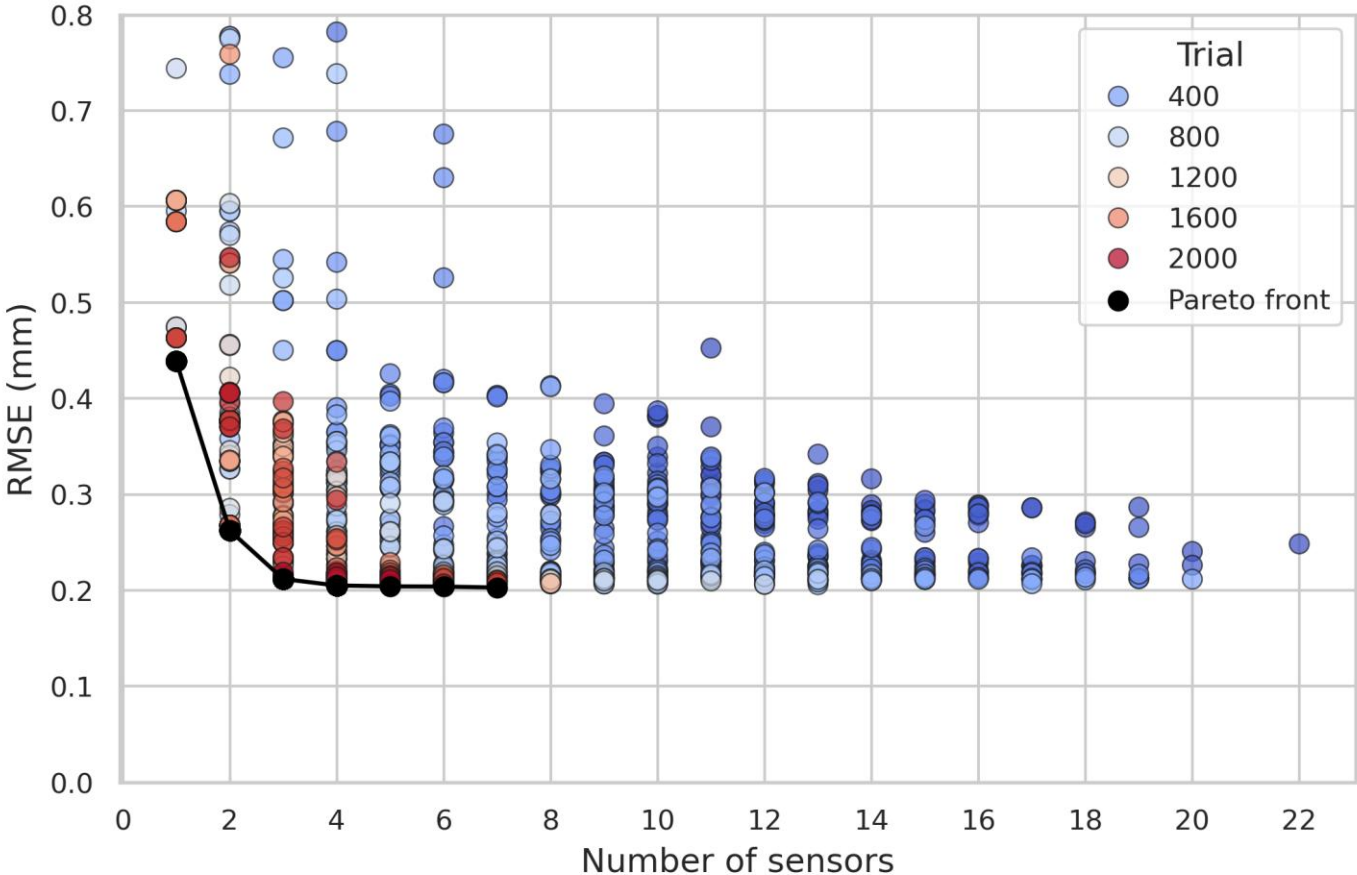


Longitudinal Level Quality Estimation

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Longitudinal Level Quality Estimation

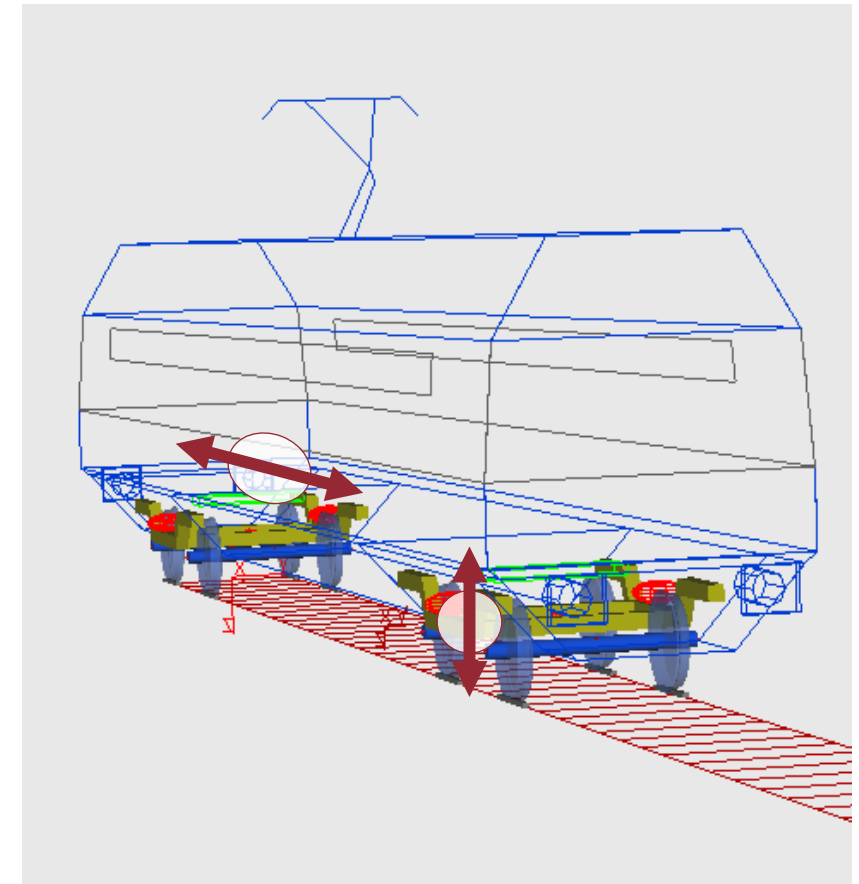
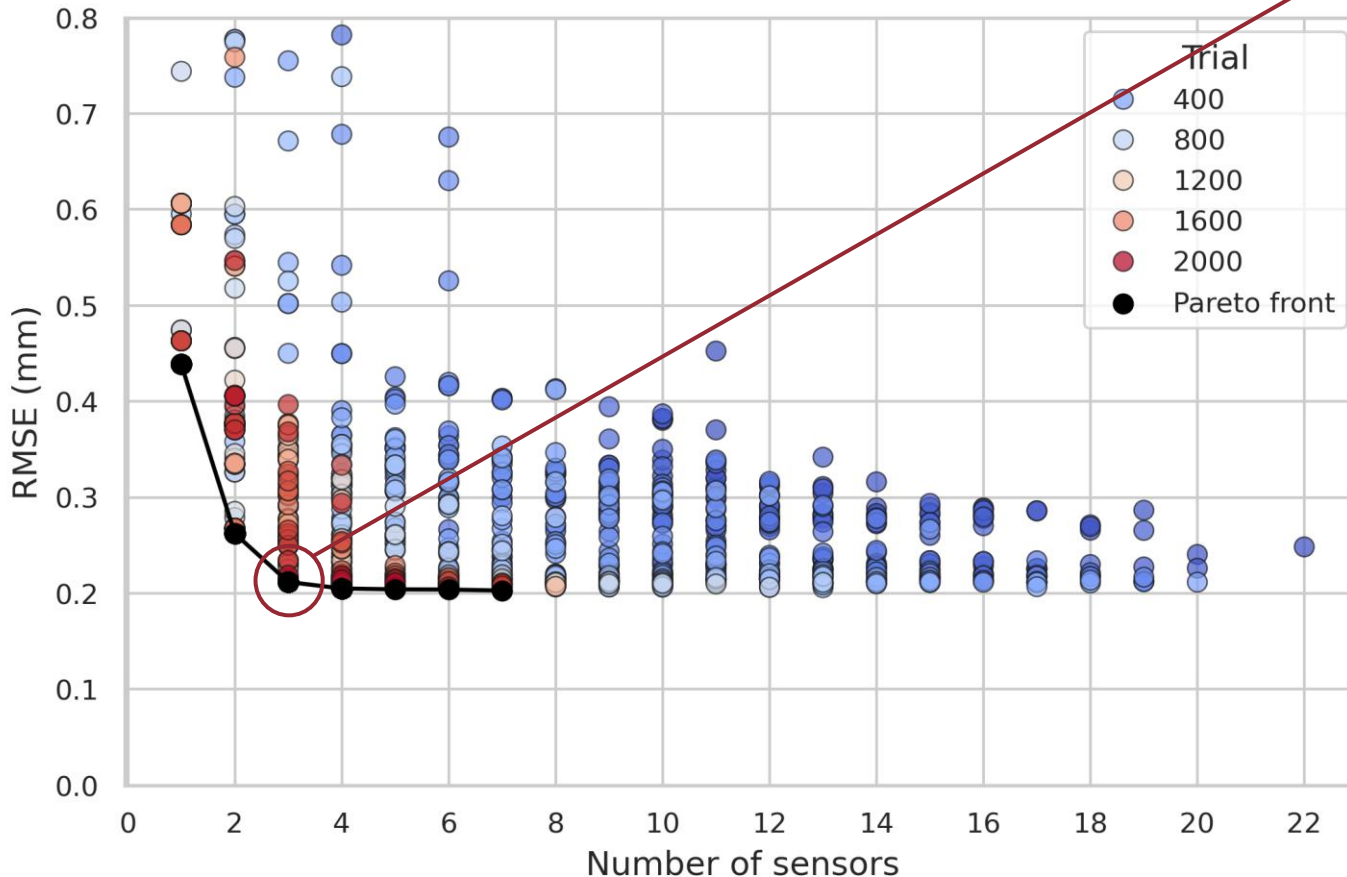
Sensor selection:

NSGA-II for multi-objective optimization:

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Number of sensors

Train speed
Acc. Vertical Front Bogie
Acc. Long. Back of the Car-Body



Longitudinal Level Quality Estimation



Track Quality Estimation:

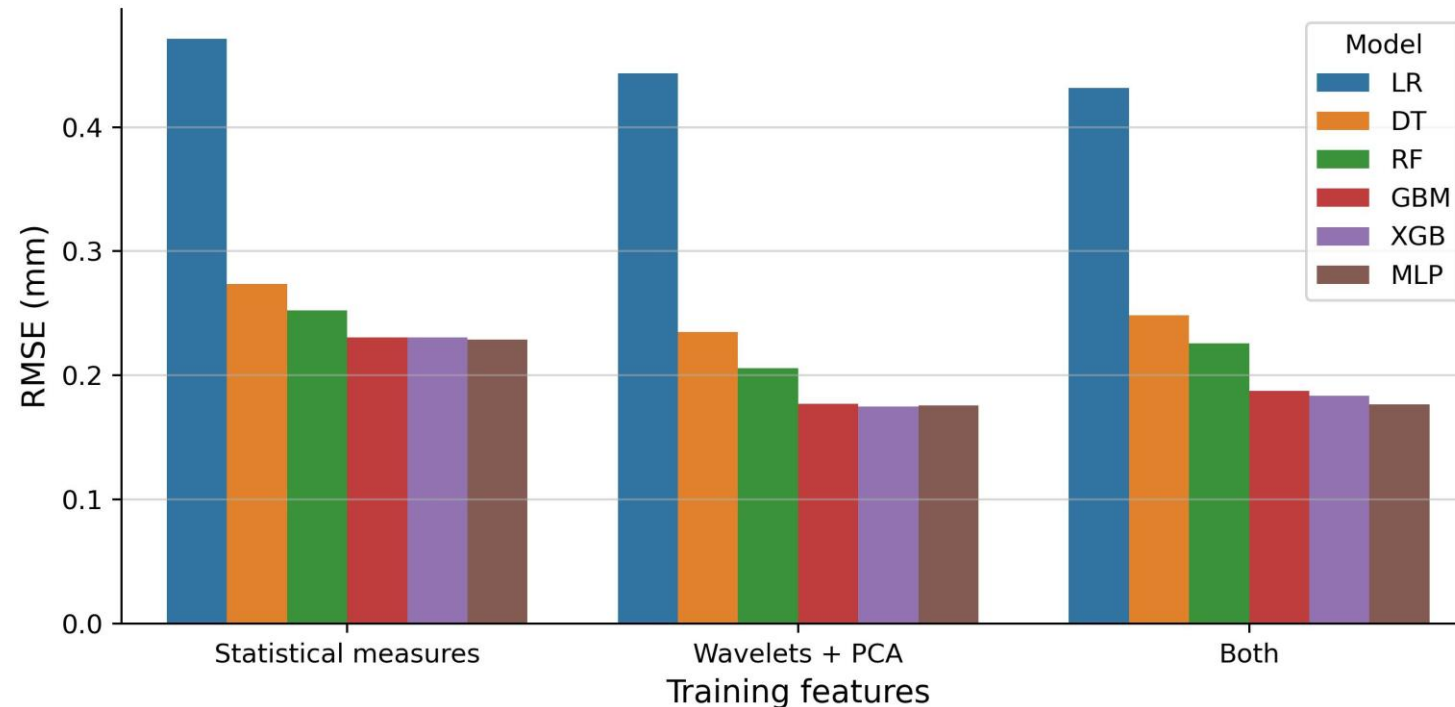
With data coming from the selected sensor configuration:

Track Quality Estimation:

With data coming from the selected sensor configuration:

Train several baseline models: linear regression, Decision Tree, Random Forest, **GBM, XGBoost and MLP**

 Use XGBoost because of its training speed



Longitudinal Level Quality Estimation

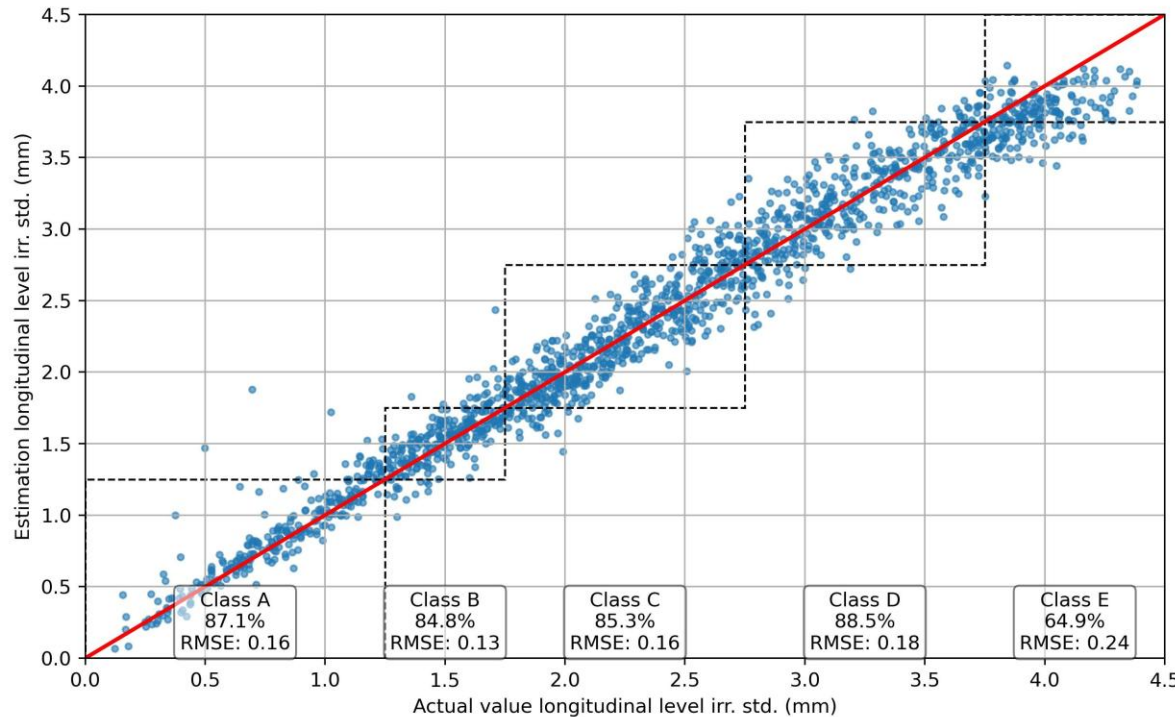
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RMSE:
0,175 mm



Actual Class	A	B	C	D	E
A	87.1%	12.4%	0.4%	0.0%	0.0%
B	5.5%	84.8%	9.7%	0.0%	0.0%
C	0.0%	5.2%	85.3%	9.5%	0.0%
D	0.0%	0.0%	6.8%	88.5%	4.7%
E	0.0%	0.0%	0.0%	35.1%	64.9%
Predicted Class	A	B	C	D	E

Longitudinal Level Quality Estimation

Track Quality Estimation:

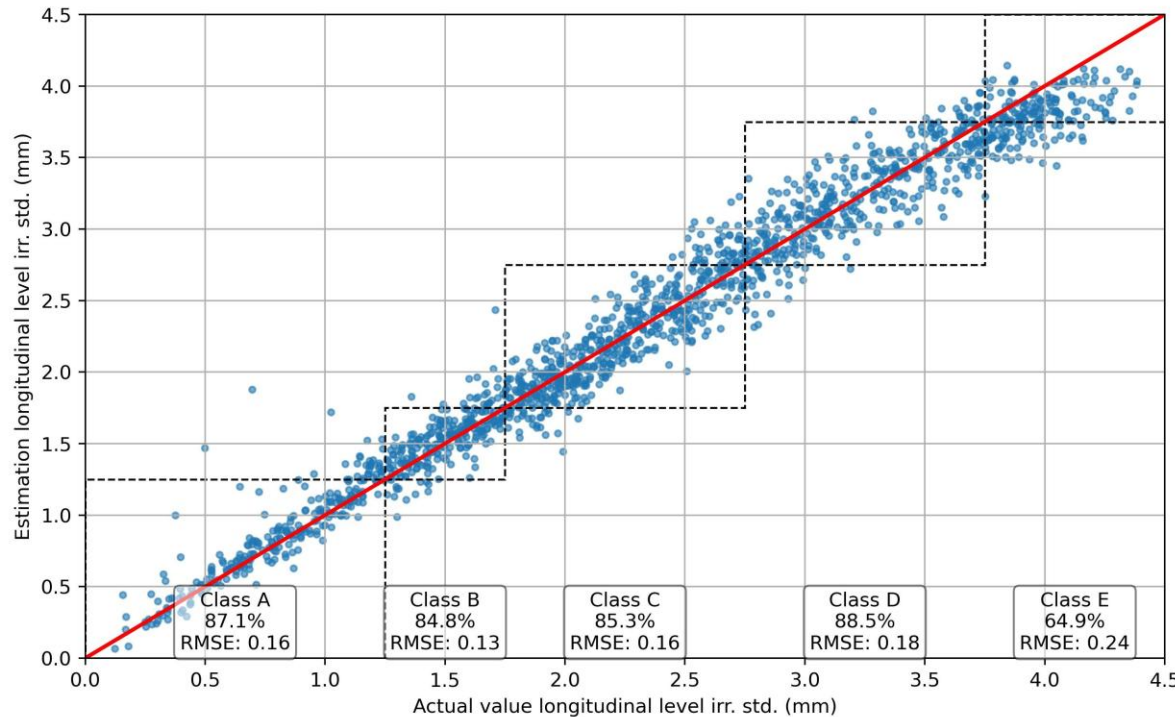
With data coming from the selected sensor configuration:

Train several baseline models: linear regression, Decision



Use XGBoost because of its training speed

RMSE:
0,175 mm



applied sciences



Article

An Integrated Machine Learning and Optimization Framework for Railway Track Quality Assessment: Application to Longitudinal Level

Adrián Sansiñena ^{1,2,*}, Borja Rodríguez-Arana ^{1,2} and Saioa Arrizabalaga ^{1,2,3}

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Alignment Quality Estimation

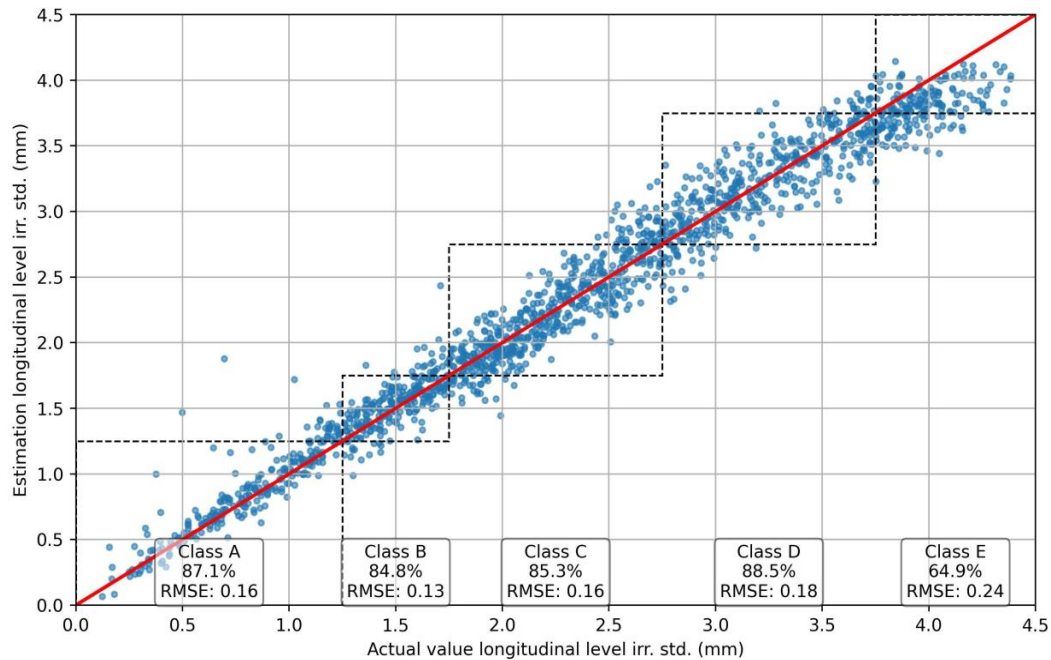
Longitudinal level

Vertical movement in consonance with vertical irregularities

Simpler dynamics

High correlation irregularities - accelerations

RMSE = 0,175 mm



Alignment Quality Estimation

Longitudinal level

Vertical movement in consonance with vertical irregularities

Simpler dynamics

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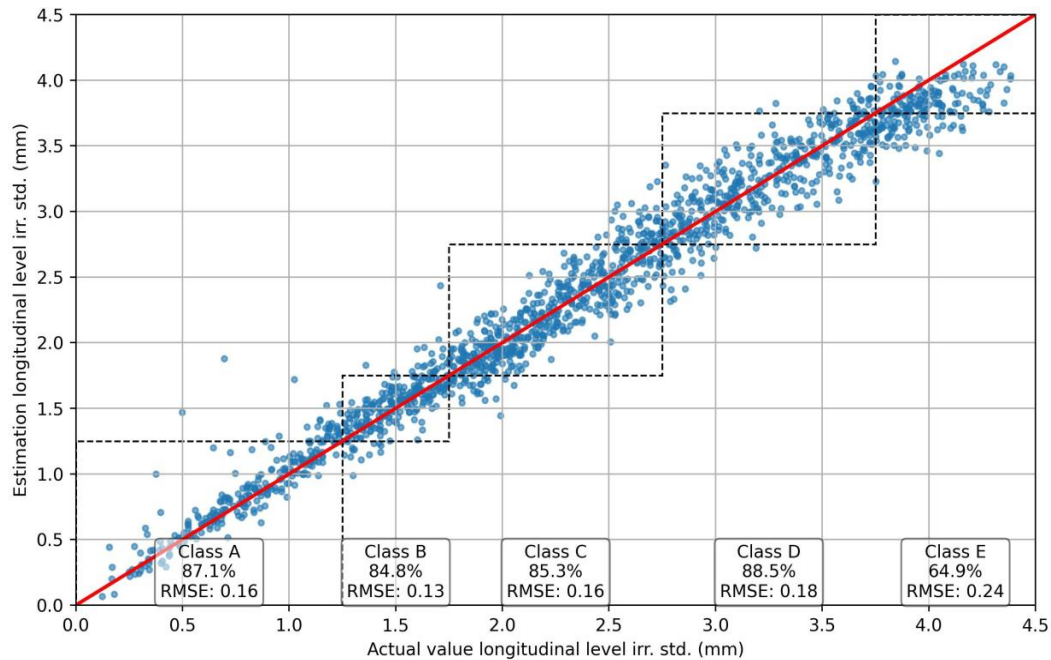
Alignment level

Wheels conicity

More complex dynamics

Low correlation irregularities - accelerations

RMSE = 0,175 mm



Alignment Quality Estimation

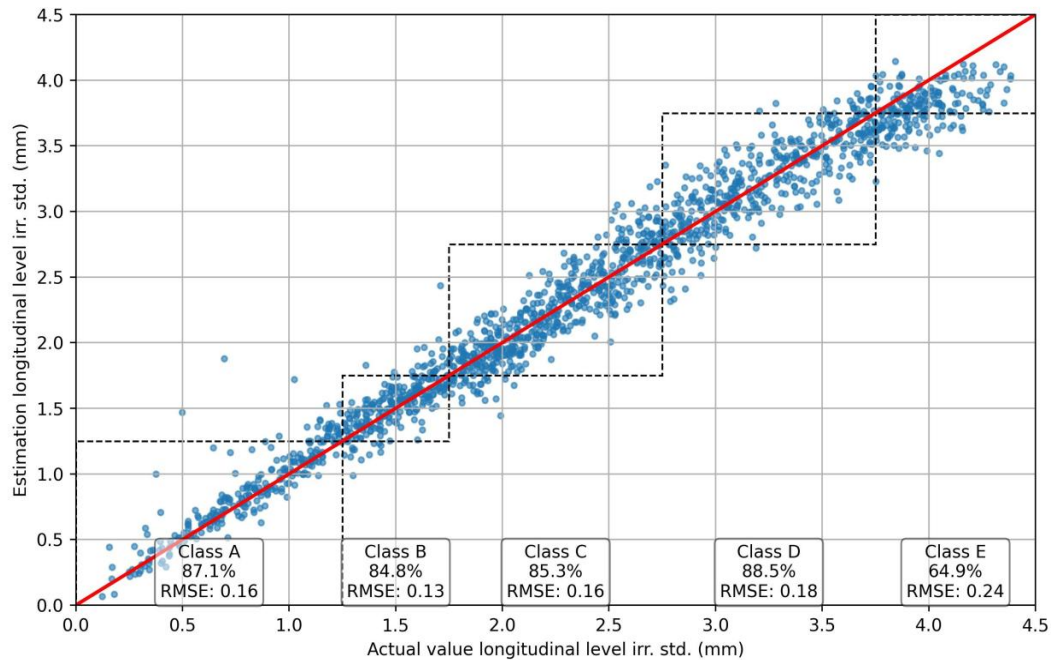
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Vertical movement in consonance with vertical irregularities

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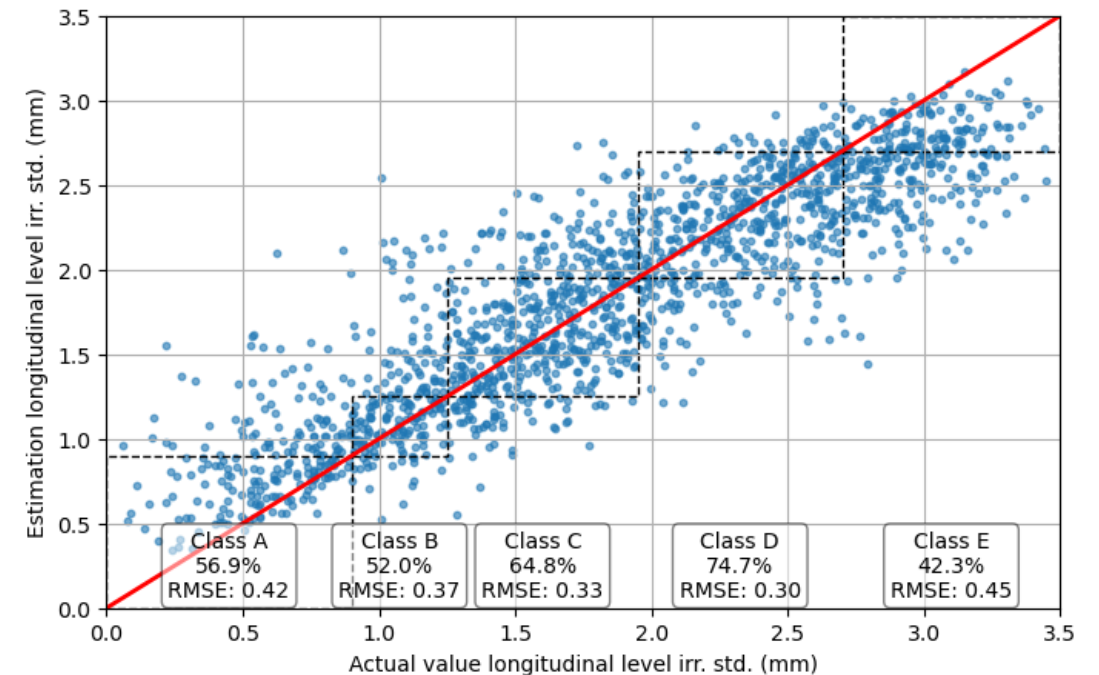
Alignment level

Wheels conicity

More complex dynamics

Low correlation irregularities - accelerations

RMSE = 0,360 mm



Alignment Quality Estimation



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de Navarra

New methodology implementation is required:

Alignment Quality Estimation

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Features

Wavelet Spectra

~~ML models for tabular data~~

Deep Learning

Alignment Quality Estimation

New methodology implementation is required:

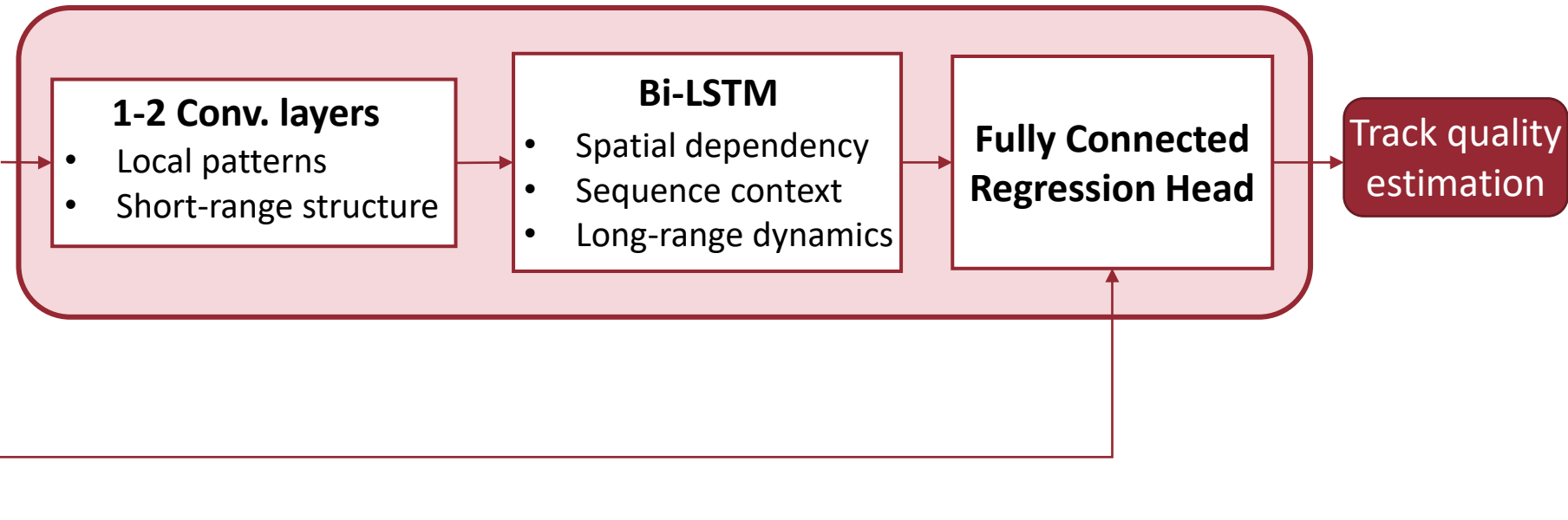
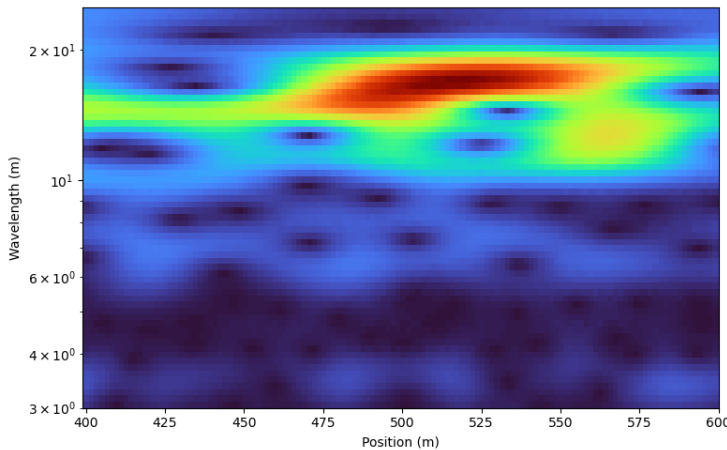
Features

~~ML models for tabular data~~

Wavelet Spectra

Deep Learning

Wavelets (one channel per sensor)



Alignment Quality Estimation

Sensor selection:

! Not a specific adaptation yet.

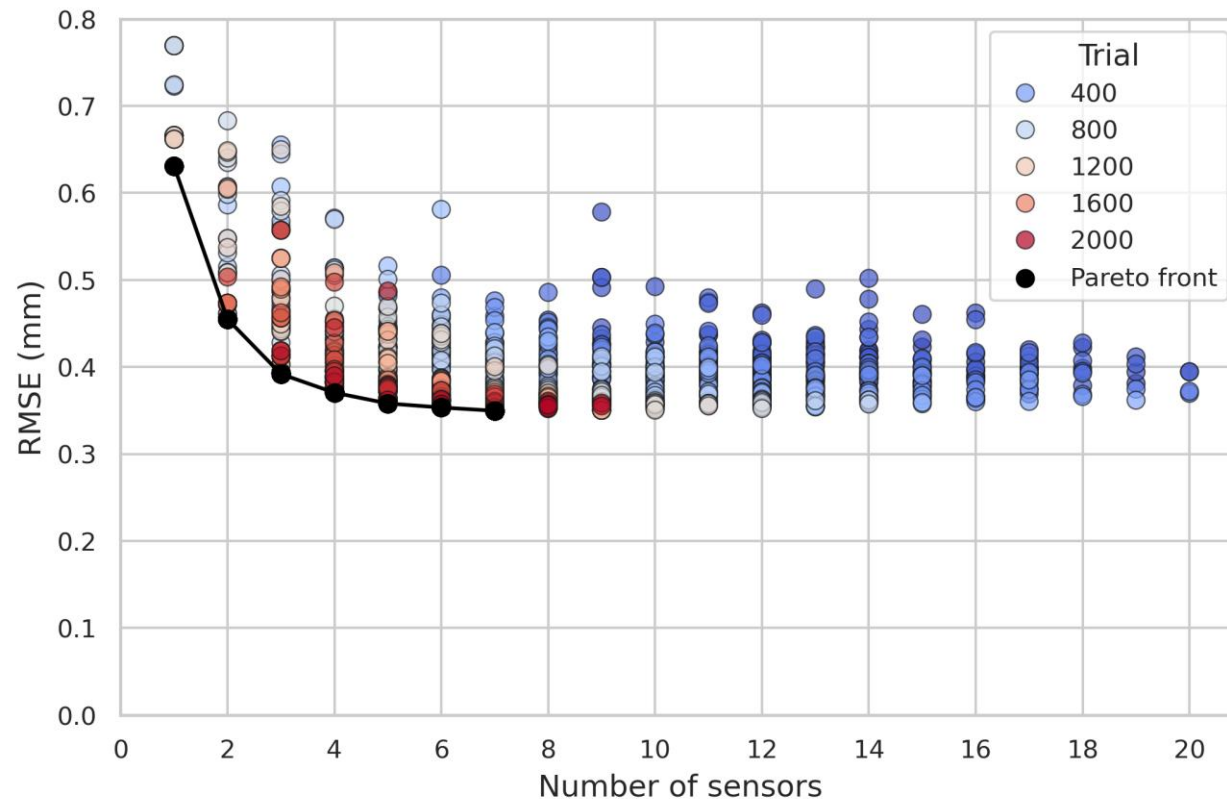
Similar to longitudinal level case: XGBoost and features

Alignment Quality Estimation

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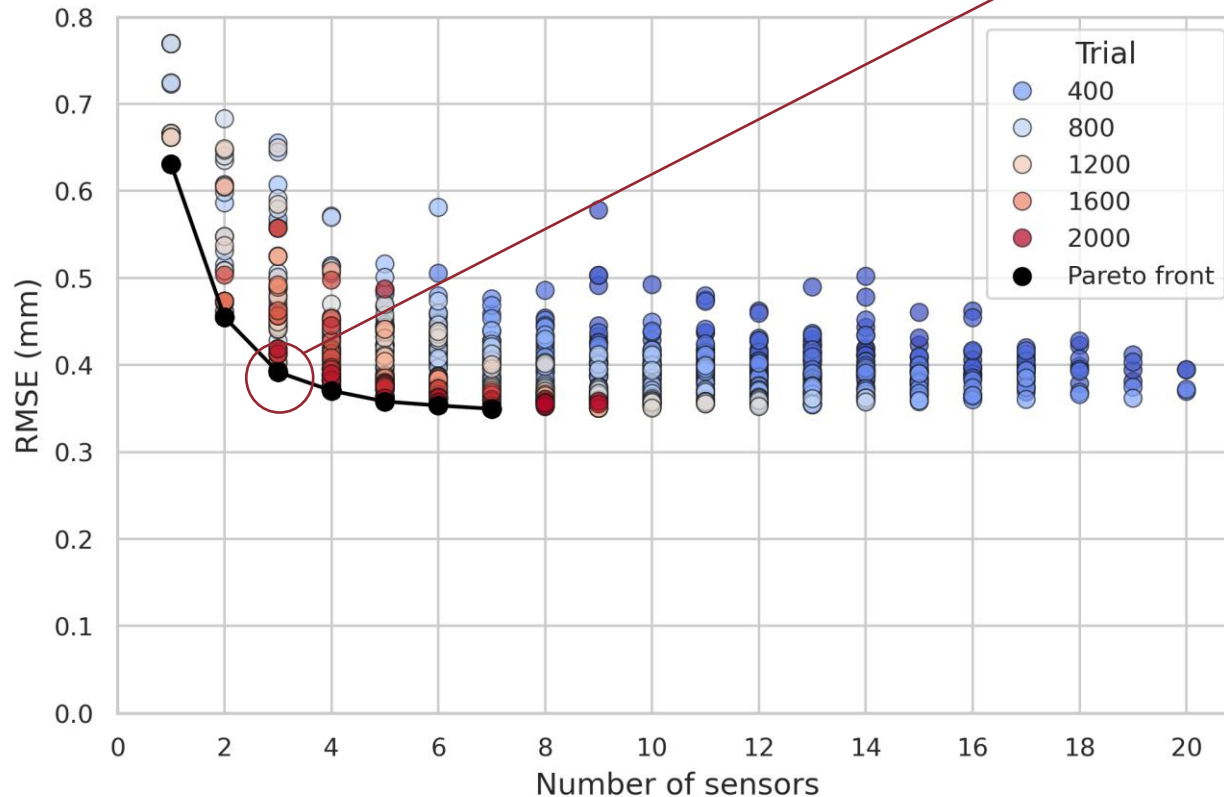


Alignment Quality Estimation

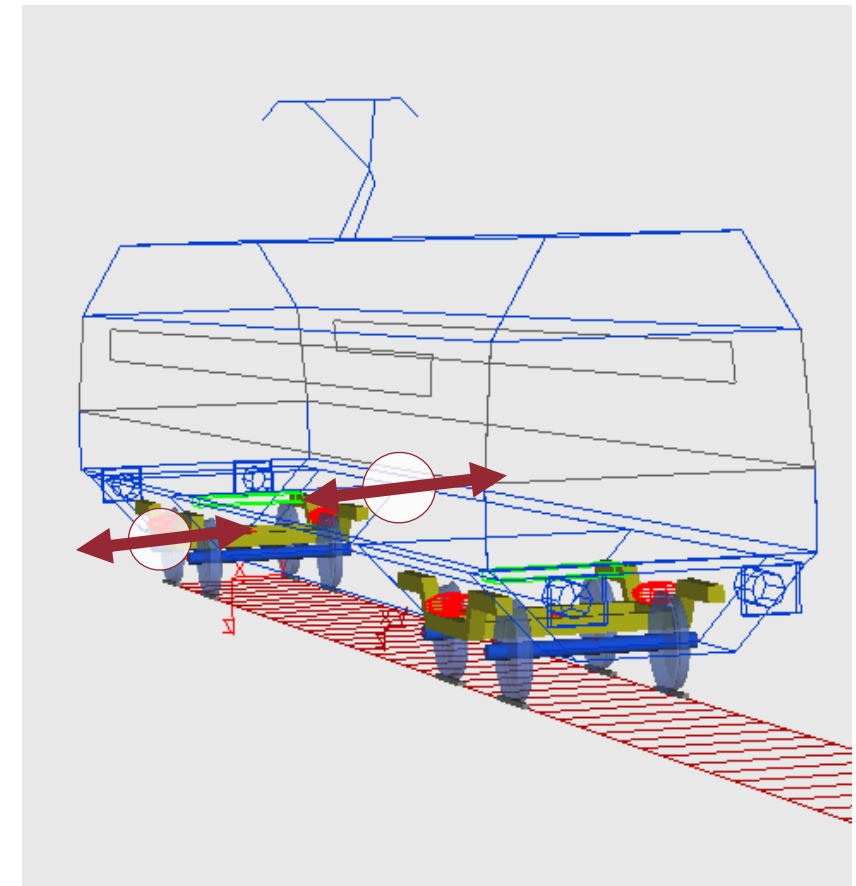
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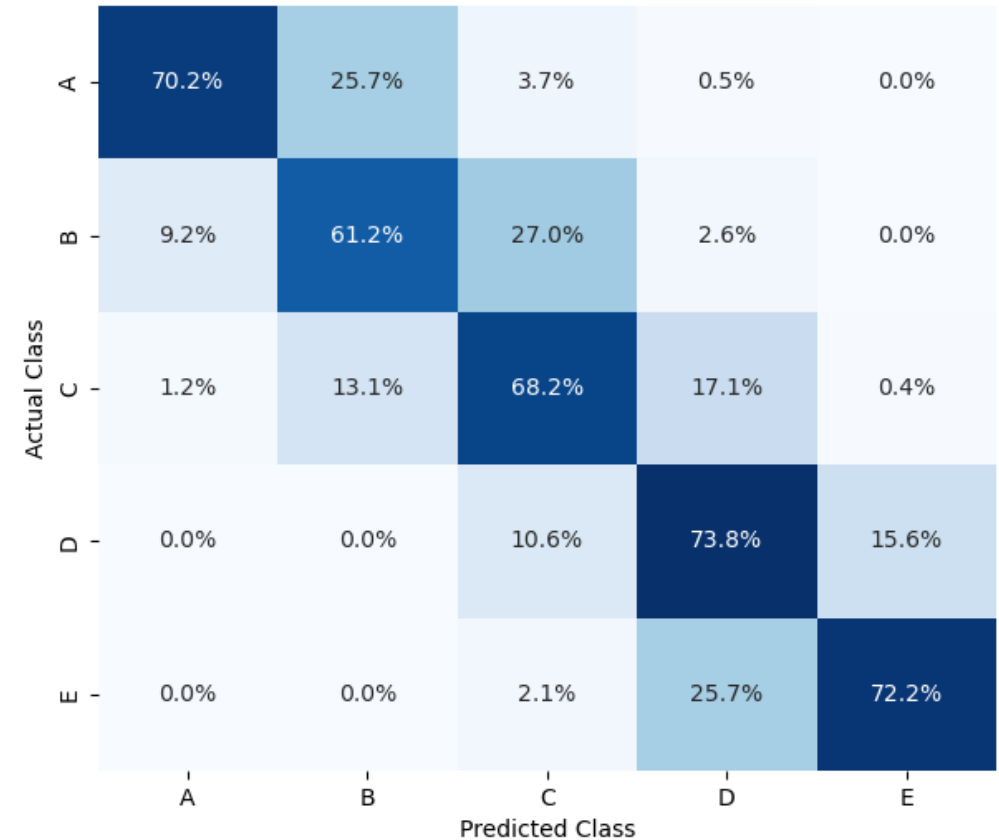
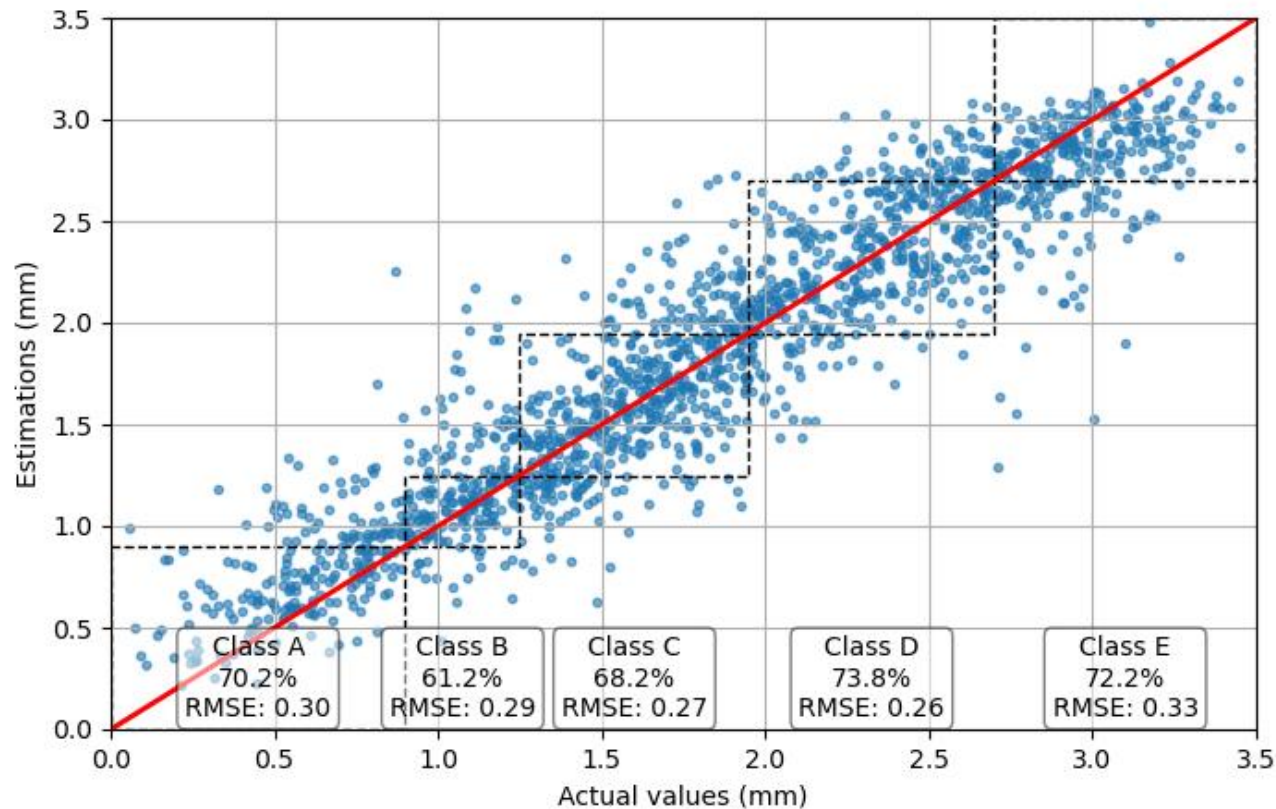
Train speed
Acc. Lateral Rear Bogie
Acc. Lateral Center of Car-Body



Alignment Quality Estimation

Track Quality Estimation:

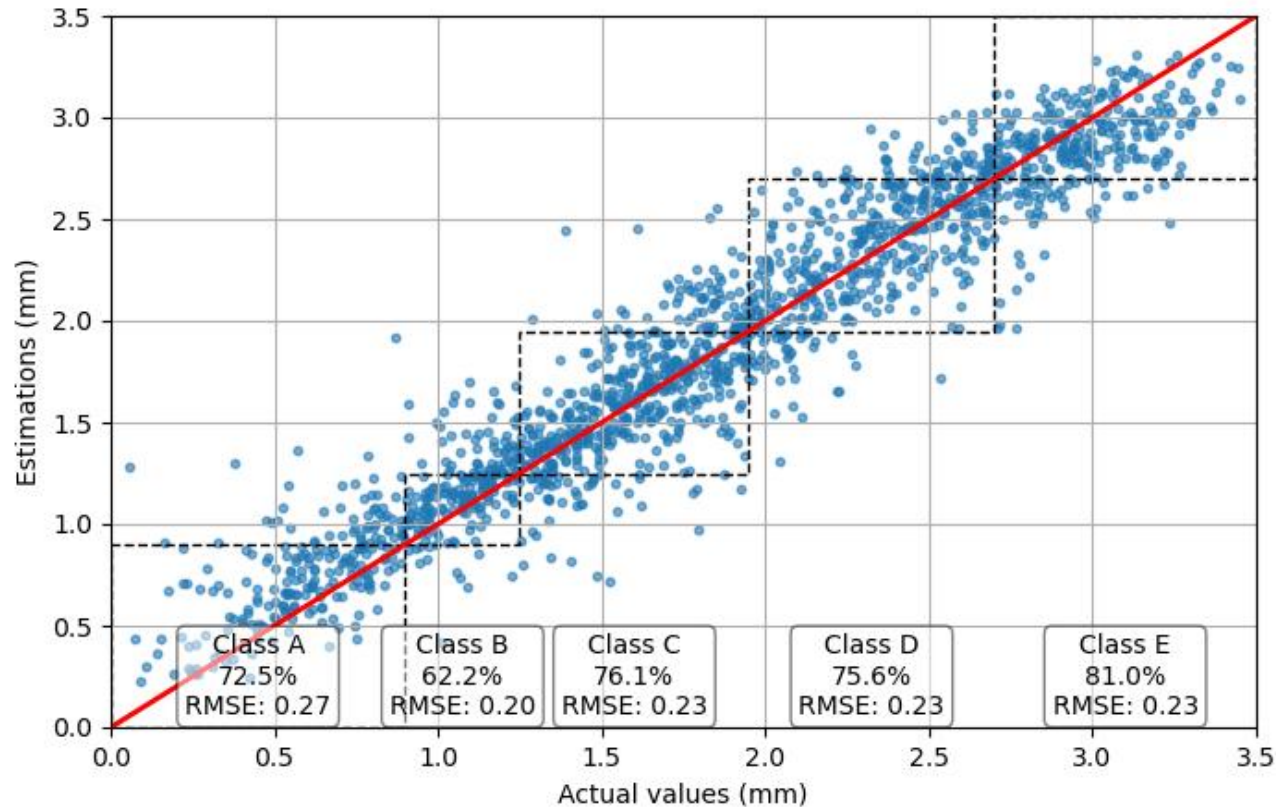
3 sensors combination: RSME = 0,29 mm



Alignment Quality Estimation

Track Quality Estimation:

5 sensors combination: RSME = 0,23 mm



Confusion matrix showing Actual Class (A-E) on the y-axis versus Predicted Class (A-E) on the x-axis. The matrix displays the percentage of data points for each combination of actual and predicted classes.

Actual Class	A	B	C	D	E
A	72.5%	25.2%	2.3%	0.0%	0.0%
B	6.1%	62.2%	31.6%	0.0%	0.0%
C	1.0%	8.9%	76.1%	14.1%	0.0%
D	0.0%	0.0%	9.5%	75.6%	14.9%
E	0.0%	0.0%	0.0%	19.0%	81.0%

Conclusions

- General and modular systematic methodology leveraging simulations
- Focus on sensor selection
- Longitudinal level: mature and validated
- Alignment: harder, richer, more interesting

Conclusions

- General and modular systematic methodology leveraging simulations
- Focus on sensor selection
- Longitudinal level: mature and validated
- Alignment: harder, in progress

Next Steps

- Alignment estimation:
 - Model refinement.
 - Integration with sensor selection.
 - Physical-mechanical interpretation of the results.
- Transfer learning to other environments with scarce data.
- Ideally, validation on real data.

Thank you for your attention!



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