High Speed Rail Suspension System Health Monitoring Using Multi-location Vibration Data

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Introduction

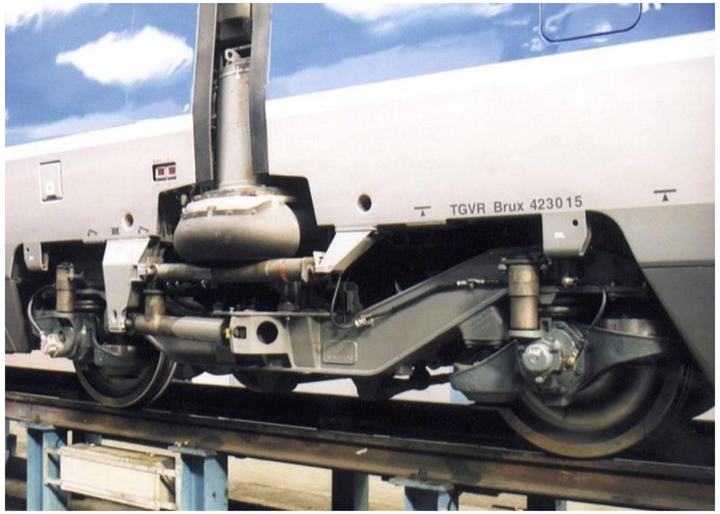
- China has the longest HSR system in the world, reached 29,000 km in total length, accounting for about two-thirds of the world's high-speed rail tracks in commercial service, by the end of 2018
- The safety concerns are accentuated for high-speed trains. The possible failure of train systems may cause immense loss of life or monetary damage, resulting in irretrievable and catastrophic consequences
- The current maintenance is scheduled based on fixed intervals that include a large safety margin, causing increased operational cost
- Shifting towards proactive maintenance and real-time health monitoring - maintaining a high standard of safety while reducing cost

CRH

CRH2A-2260&2011 at Xiamen railway station, image source: wikipedia.org

Introduction - suspension system health monitoring

- Suspension system is fundamental in rail vehicles and its reliability is directly related to safety
  - Consists of **<u>primary suspension</u>** and **<u>secondary suspension</u>**
  - Failures of suspensions may lead to accelerated wear of wheels and rails, in extreme cases, may increase risk of derailment

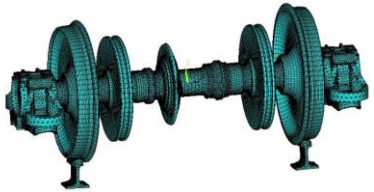


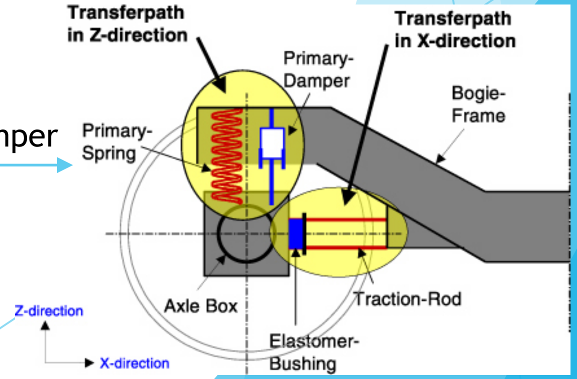
Secondary Suspension

air spring

Primary Suspension

spring & damper



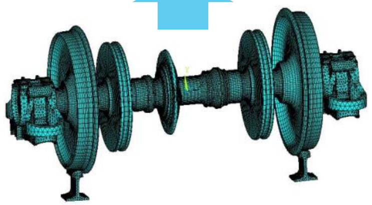


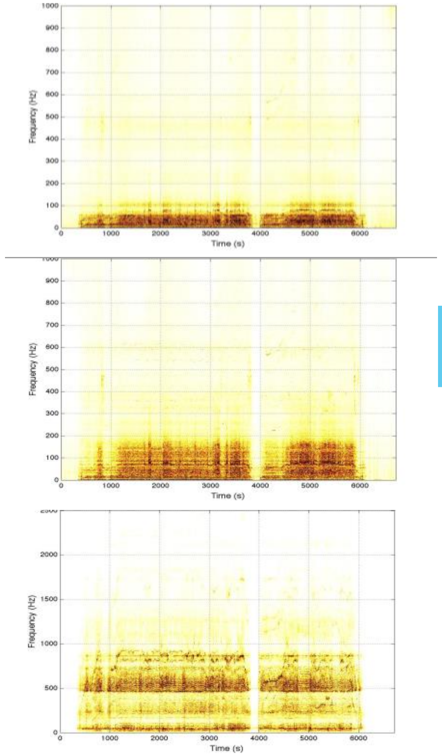
Existing methods

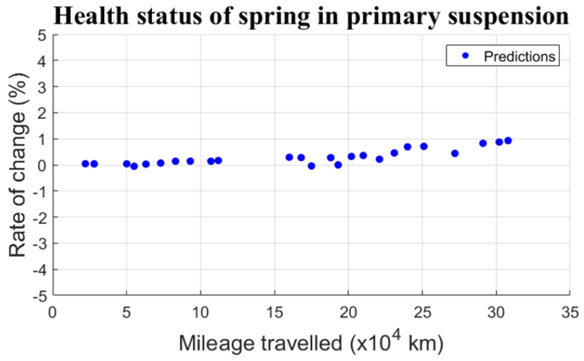
- Two distinctive approaches are primarily applied for the condition monitoring or fault detection of railway suspension systems:
  - **Model-based approach: Kalman filter detection** (Jesussek M., 2014; Goda K.,2004), **non-Kalman estimation** (Liu X. Y., 2016; Wu Y., 2015; Xue P., 2015; Wei X., 2014), **multiple-model approach** (Gu X., 2015; Tsunashima H., 2010, 2008)
    - Require precise suspension and inertial parameter values
    - Highly depended on accuracy of the vehicle model
    - Need a significant computational effort
  - **Data-driven approach: relations between specific motions of a vehicle's bogie** (Kojima T., 2013; Mei T. X., 2009, 2008), **multivariate statistical methods** (Wei X., 2014; Yin S., 2010; Lee C., 2006), **stochastic ARX-type model** (Sakellariou J. S., 2015)
    - The results are less interpretable than the results from the model-based approaches – only fault categories
    - Few of studies used large-scale real operational data of high-speed trains

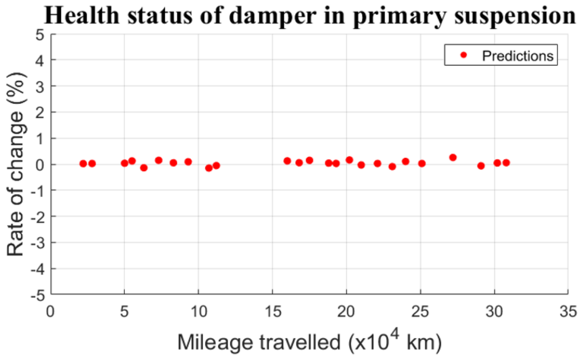
Research Objective

- This study develops a novel domain-knowledge guided data-driven framework to monitor the health status of suspension systems based on multi-location vibration data
  - ***Data-driven:*** easy to implement; do not reply on sophisticated physics-based models
  - ***Domain-knowledge guided:*** interpretable model, reflecting system actual features



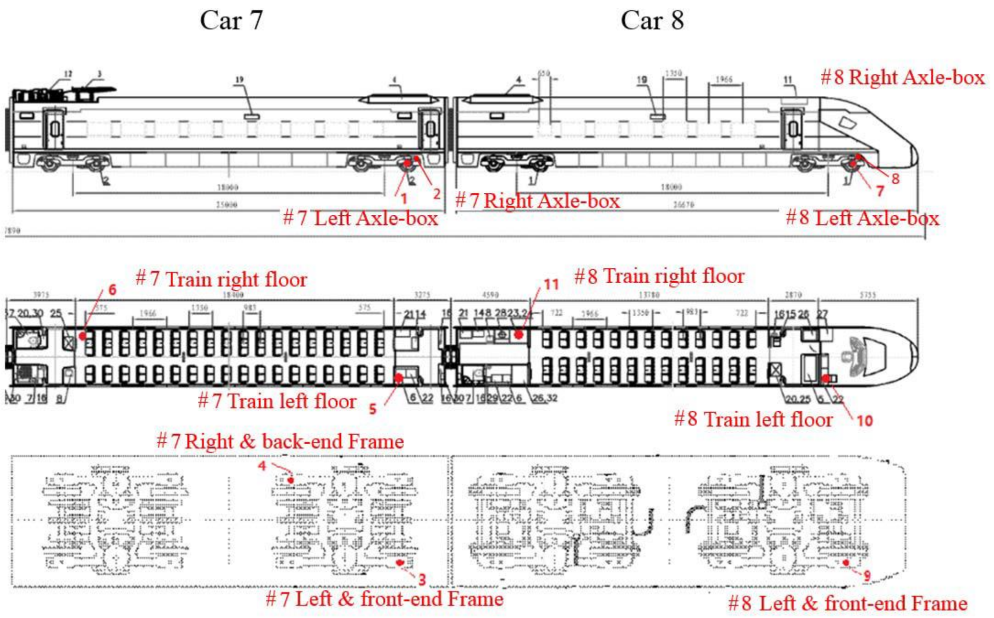






Data

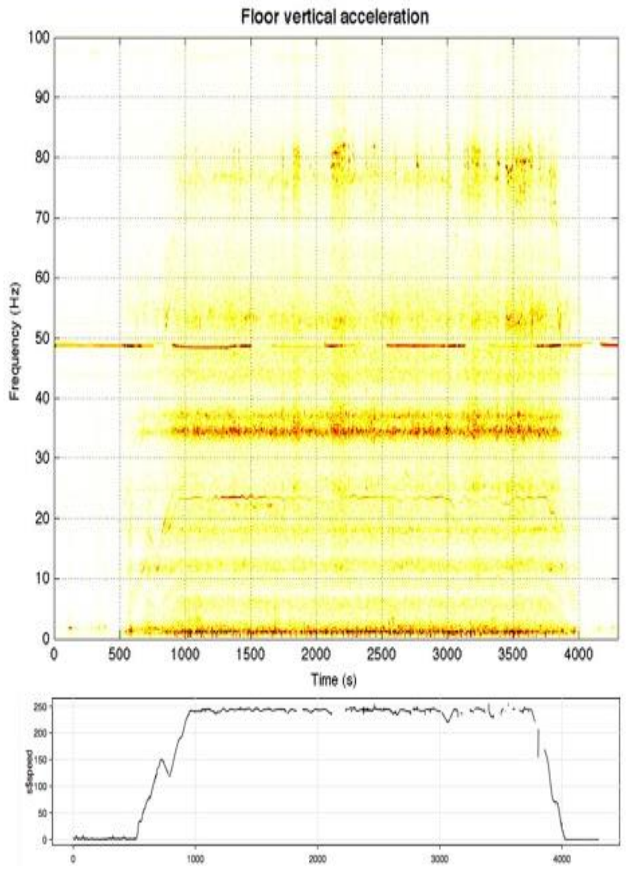
- In-field sensor data from 30 trips in 10 months
  - August 2015 - June 2016
  - 3 routes: Changsha–Huaihua line; Guangzhou–Zhuhai line; Sanya–Haikou loop line
  - Train type: CRH1A (Bogie-AM96)
- Vibration signals via 11 onboard acceleration sensors (2000 – 5000 Hz)
- Speed data of the train collected via GPS (1 Hz)

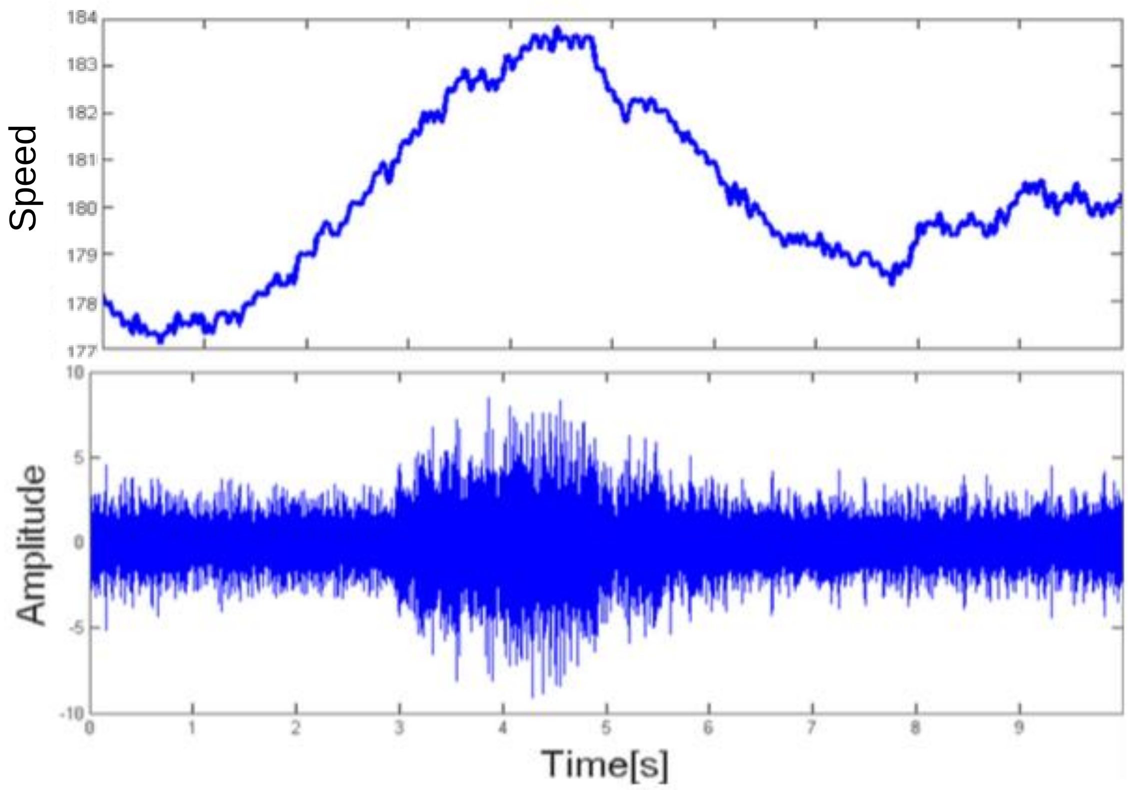


CAR	Sensing Point			Sampling Frequency
Car-7 (Trail Car)	Axle box	Left	**1**	5000 Hz
		Right	2	
	Bogie frame	Left	**3**	2000 Hz
		Right	4	
	Car body	Left	**5**	
		Right	6	
Car-8 (Motor Car)	Axle box	Left	7	5000 Hz
		Right	8	
	Bogie frame	Left	9	2000 Hz
	Car Body	Left	10	
		Right	11	

Non-stationary vibration process

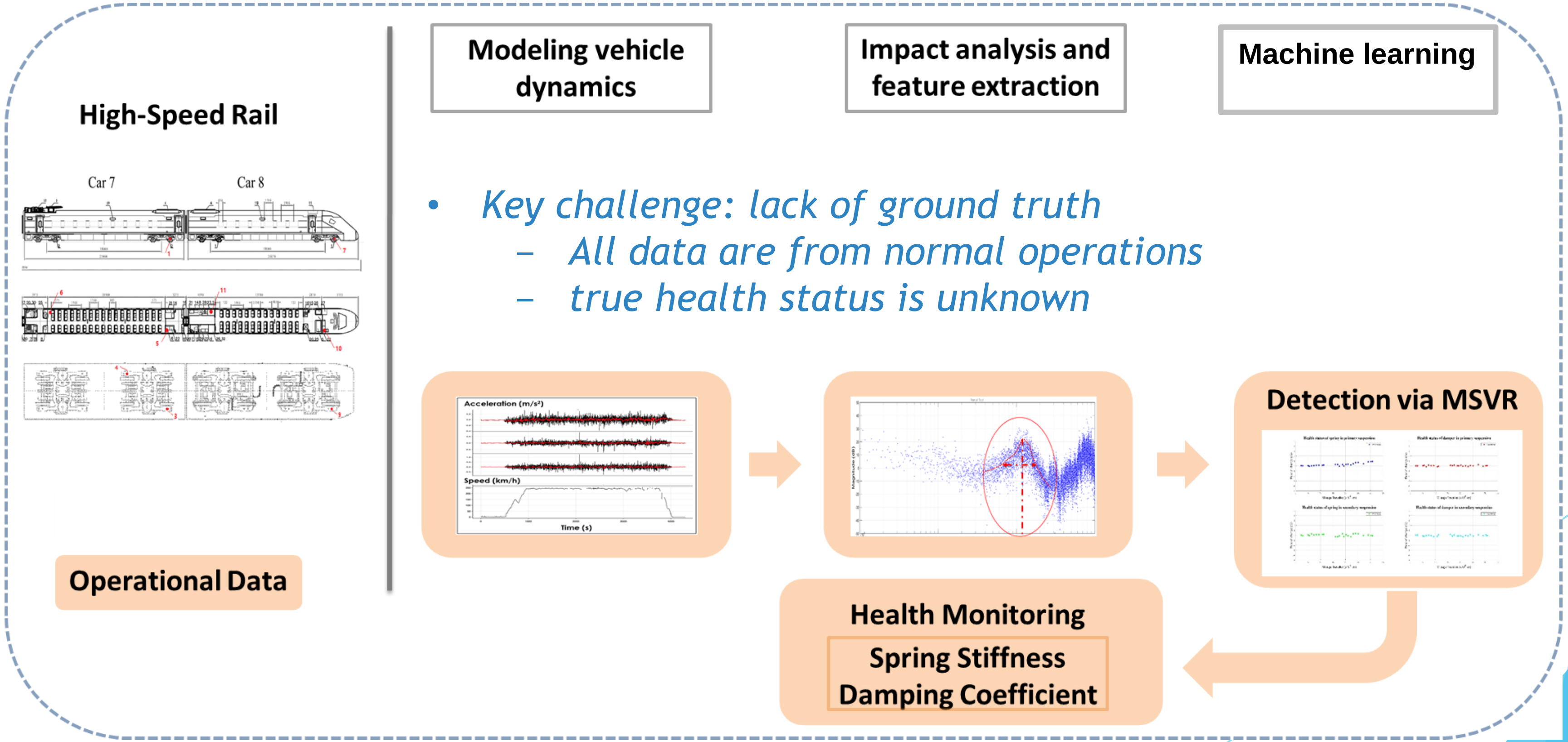
- Frequency components smeared around central frequency
- Amplitude affected by operating conditions (speed, load)





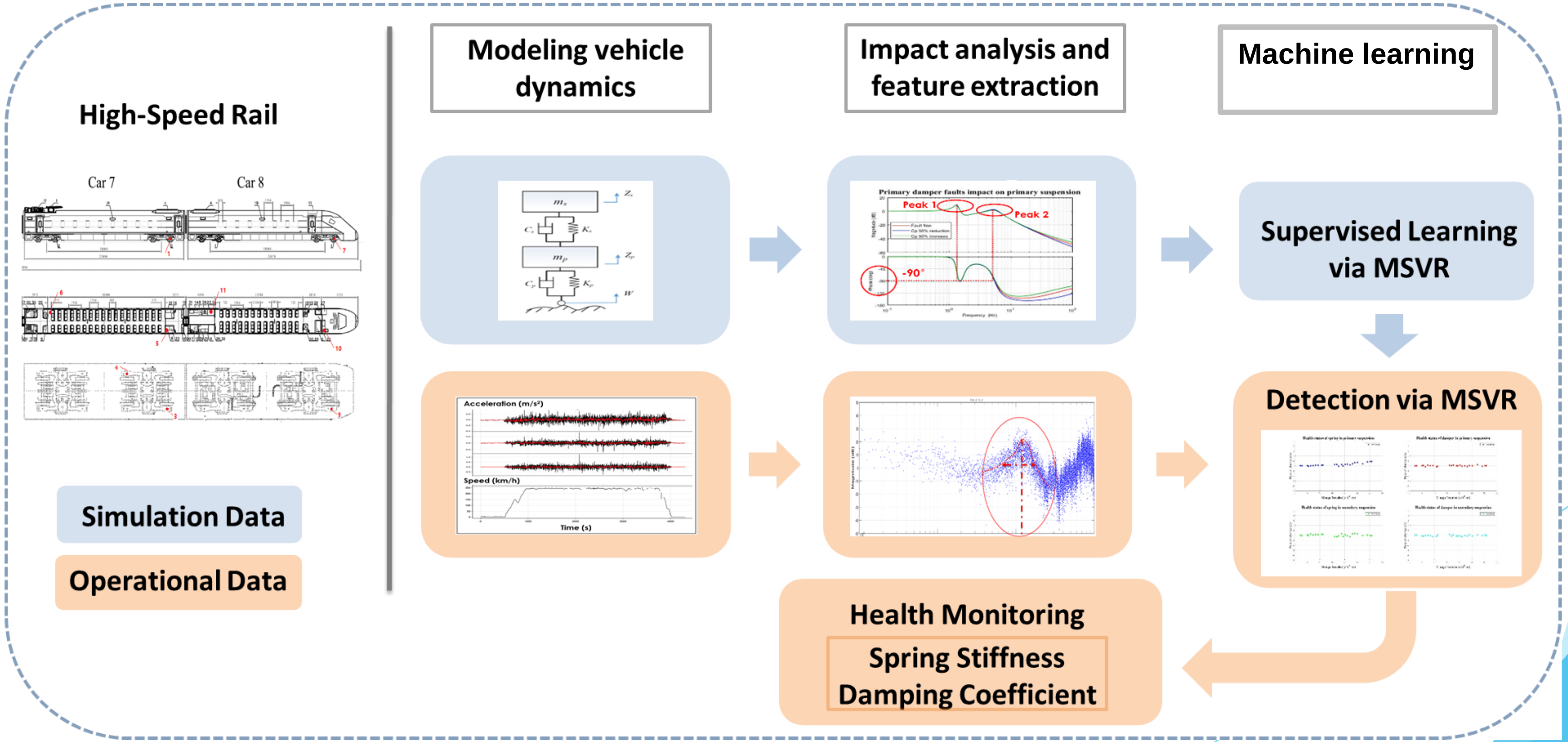
Method – 1/2

- A data-driven framework to predict of the health status of high-speed rail suspension systems
  - Inputs: vibration signals collected on trains during its operation
  - Outputs: stiffness and damping coefficients of train suspension systems



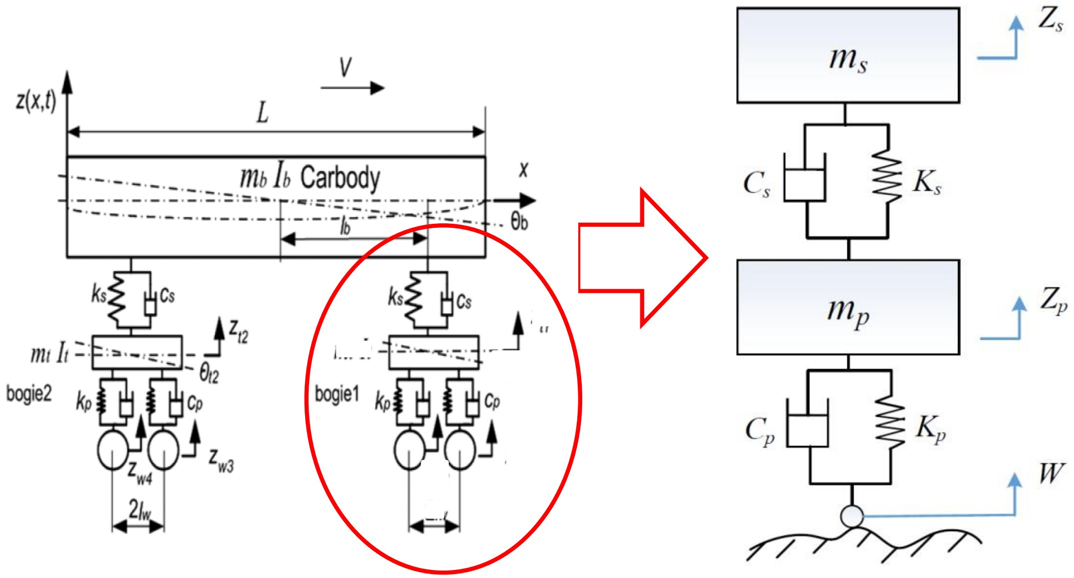
Method – 2/2

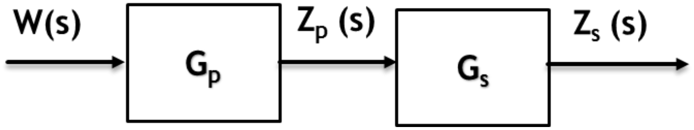
- A data-driven framework to predict of the health status of high-speed rail suspension systems
  - Inputs: vibration signals collected on trains during its operation
  - Outputs: stiffness and damping coefficients of train suspension systems



A. Modeling Vehicle Dynamics

- Build a simple dynamics model that can provide insights into how vibration signals change because of suspension system degradation
- The suspension system is simplified as a 2-DOF model to obtain its transfer function





$$Set : \Delta = \frac{C_s s + K_s}{m_s s^2 + C_s s + K_s}$$

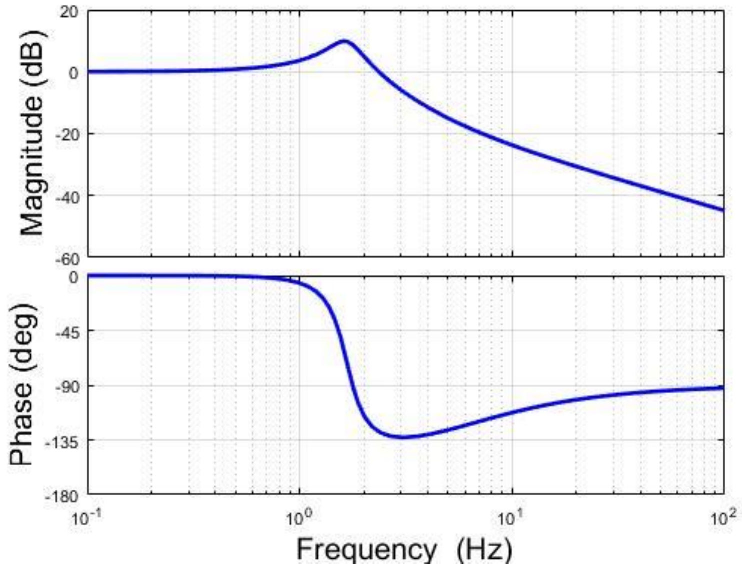
$$G_S(s) = \frac{Z_s(s)}{Z_p(s)} = \frac{C_s s + K_s}{m_s s^2 + C_s s + K_s}$$

$$G_P(s) = \frac{Z_P(s)}{W(s)} = \frac{C_P s + K_P}{m_P s^2 + [C_P + C_S(1-\Delta)]s + [K_P + K_S(1-\Delta)]}$$

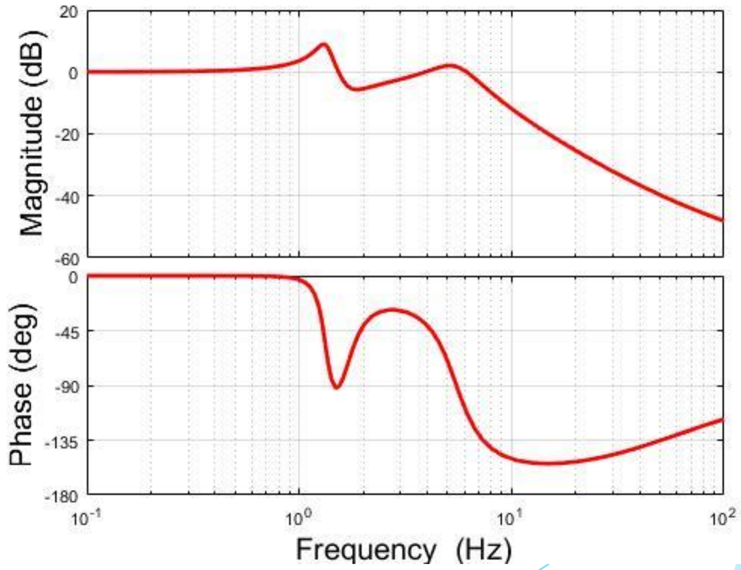
B. Impact Analysis and Feature Extraction

- Generate the Bode plots and investigate the impact of spring and damper degradation to guide feature construction
  - 1) Generate the Bode plots

$G_S(s)$ - Secondary Suspension System



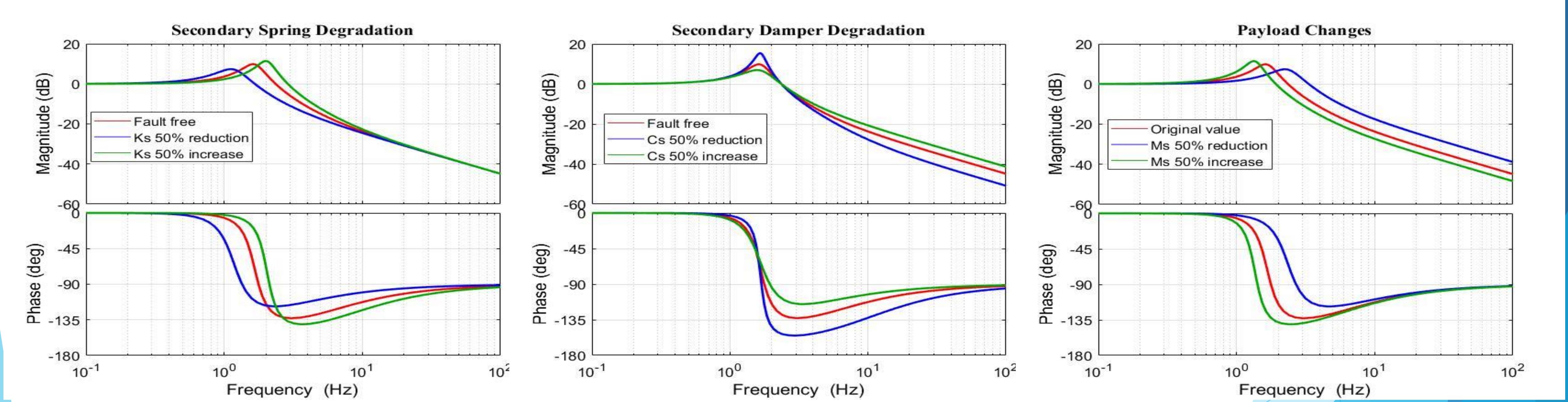
$G_p(s)$ - Primary Suspension System



B. Impact Analysis and Feature Extraction

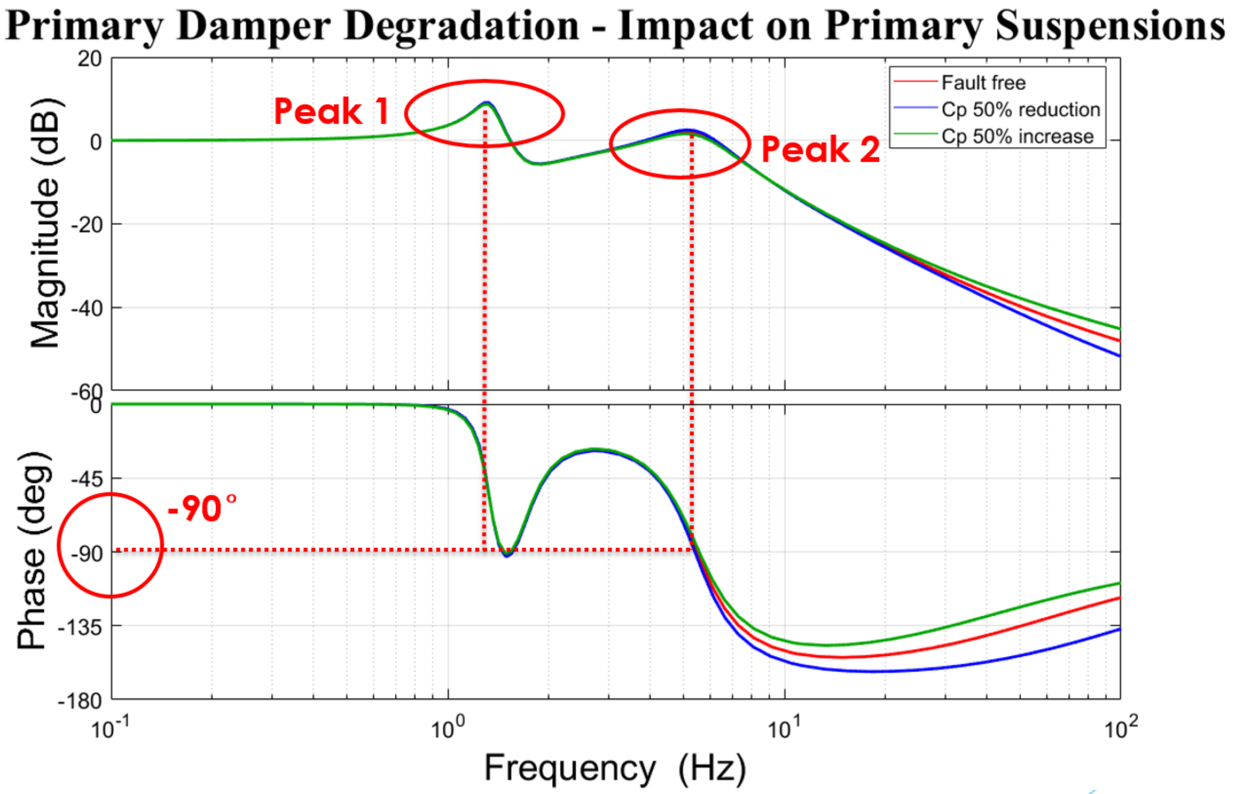
– <u>2) Investigate the impact of degradation:</u>

  - **<u>Secondary suspension system</u>**



B. Impact Analysis and Feature Extraction

- Characteristics of the resonant frequency are linked to intrinsic parameters of suspension system
- Extracted features: Position, Height and Width of the largest peak (resonant frequency) in magnitude frequency response curves

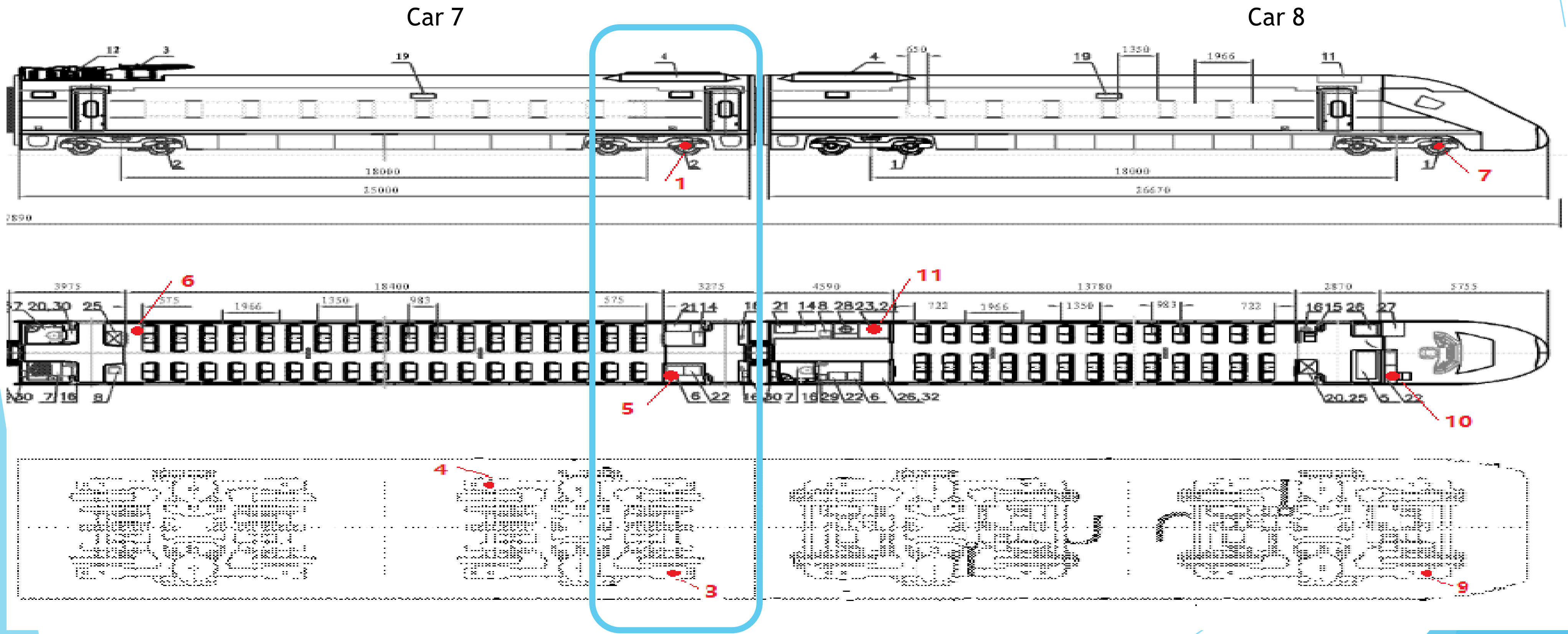


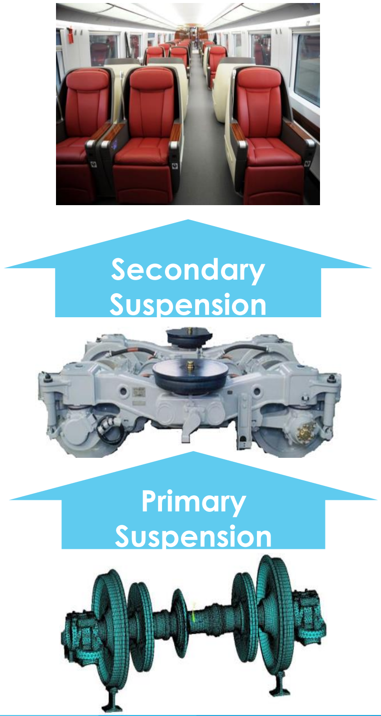
C. Supervised Learning via MSVR

- Develop multioutput support vector regression (MSVR) models to predict the health status of suspension systems
  - Two MSVR models: 1) primary suspension system, 2)secondary suspension system
  - Input vector: $x_i = \begin{bmatrix} position_i \\ width_i \\ height_i \end{bmatrix}$ the relative changes of position, width, and height of resonant frequency
  - Output vector: $y_i = \begin{bmatrix} spring\ stiffness_i \\ damping\ coefficient_i \end{bmatrix}$ the relative changes of spring and damper parameters
- Why MSVR?
  - support vector regression (SVR) is the **most accurate and reliable** among advanced regression methods
  - SVR requires less training data and is relatively easier for others to reproduce the results
  - MSVR is chosen over SVR because our model has multiple outputs

Evaluation and Testing

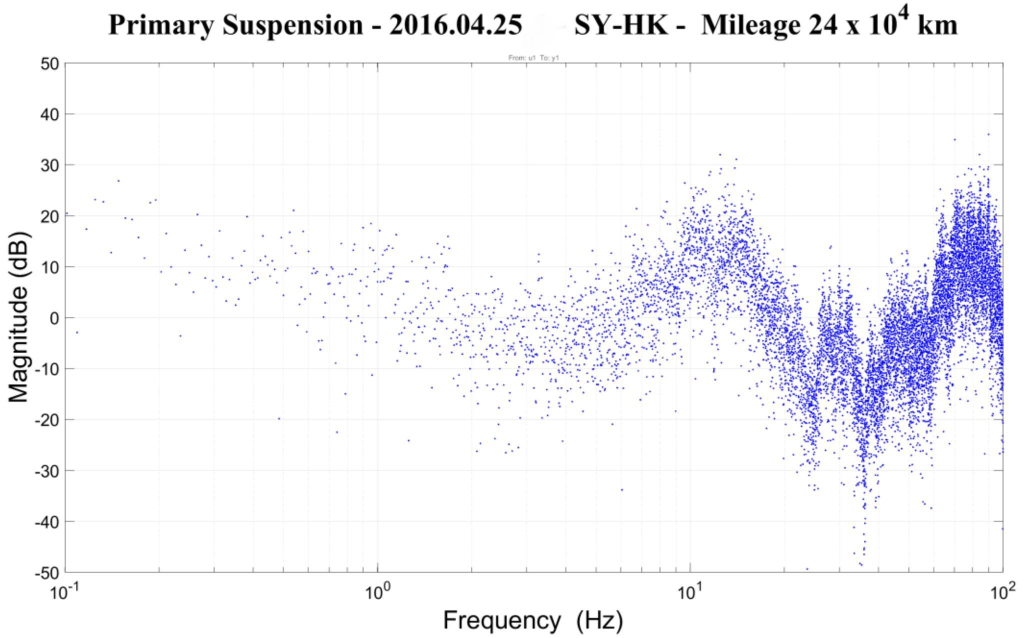
- HSR operational data processing:
  - **sensor selection (Car 7)**
    - Primary suspension: Axle Box (Sensor 1) & Bogie (Sensor 3)
    - Secondary suspension: Bogie (Sensor 3) & Floor (Sensor 5)

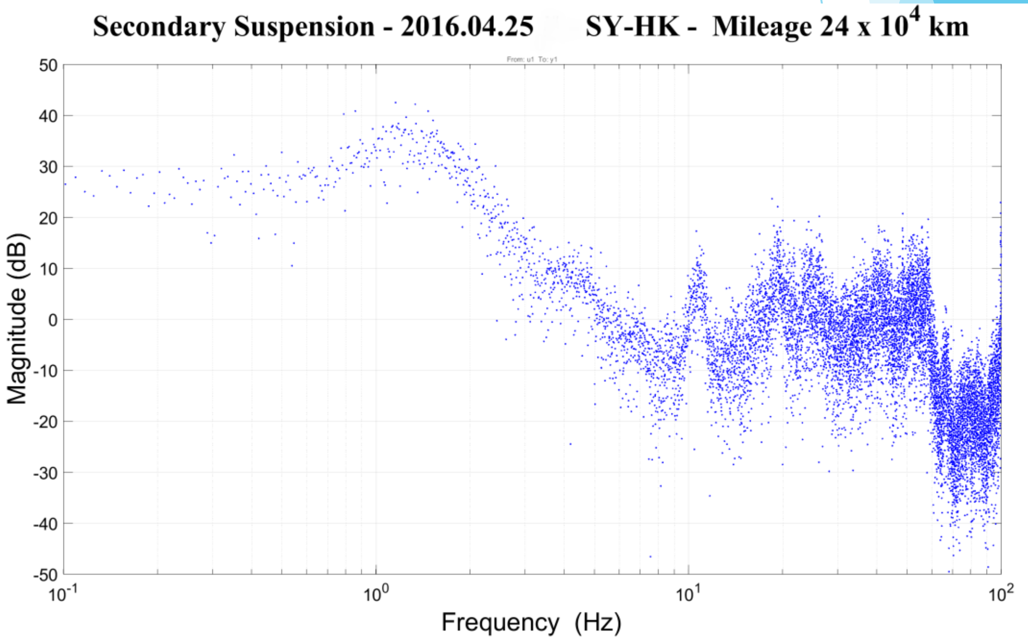




Evaluation and Testing

- **Pre-processing**
  - Normalization (divided by sample standard deviation)
  - Synchronization (‘Union’ 5000Hz with 2000 Hz)
- **Generate amplitude response curves:** Transfer function via ‘**TFESTIMATE**’ algorithm
- **Feature Extraction:** Peak finding and measurement via ‘**findpeaks**’ algorithms





Samples of magnitude frequency response curves

Evaluation and Testing

- Compare performance of MSVR, SVR, MV-GPR and MV-LS models

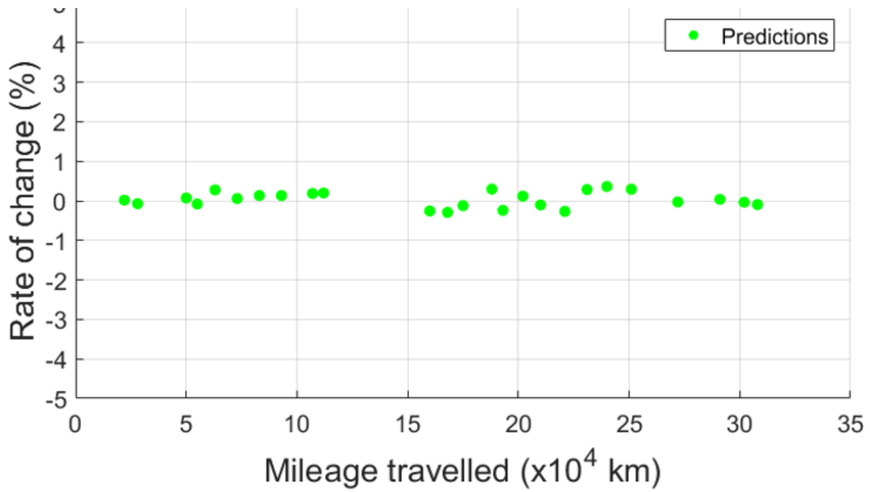
Group	Output	Metrics	MSVR	SVR	MV-GPR (MEAN)	MV-LR
I	Primary Spring Stiffness	MAPE (%)	5.89	7.34	14.76	19.69
		RMSE	0.0579	0.0721	0.1438	0.1953
	Primary Damper Coefficient	MAPE (%)	8.97	10.29	17.26	21.71
		RMSE	0.0871	0.1013	0.1703	0.2151
II	Secondary Spring Stiffness	MAPE (%)	4.37	6.96	13.27	18.06
		RMSE	0.0426	0.0673	0.1311	0.1791
	Secondary Damper Coefficient	MAPE (%)	7.53	9.92	16.43	20.84
		RMSE	0.0739	0.0972	0.1632	0.2073

MSVR: multioutput support vector regression
SVR: support vector regression
MV-GPR: multivariate Gaussian process regression
MV-LR: multivariate linear regression

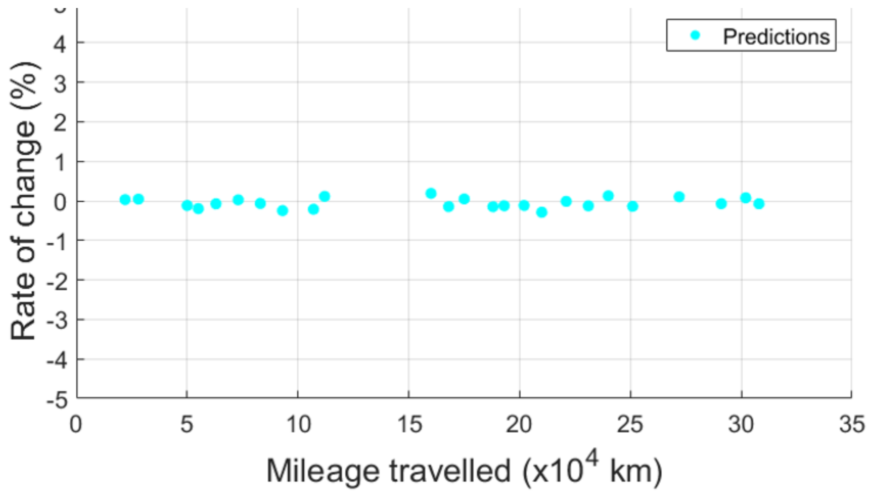
Evaluation and Testing

Prediction Result: Secondary Suspension System

Stiffness coefficient change



Damping coefficient change

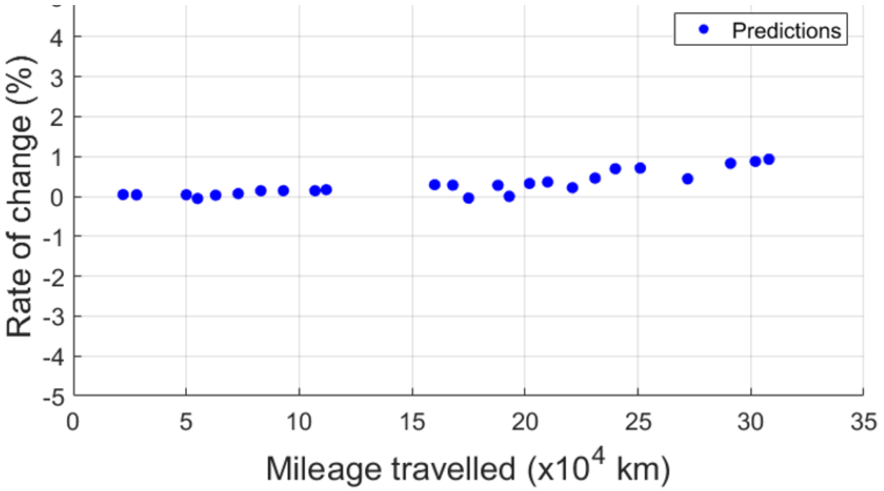


- There is no obvious change for damping & stiffness coefficients
  - **Current maintenance regulation:** the components should be replaced when the train has traveled **360 ± 10 x 10^4 km;** While, the CRH1A train in our study merely traveled **30.8 x 10^4 km**, which is approximately **1/12** of the designed mileage, during the signal tracking period
  - **Air spring & anti-yaw damper**: longer useful life, less load and less wear

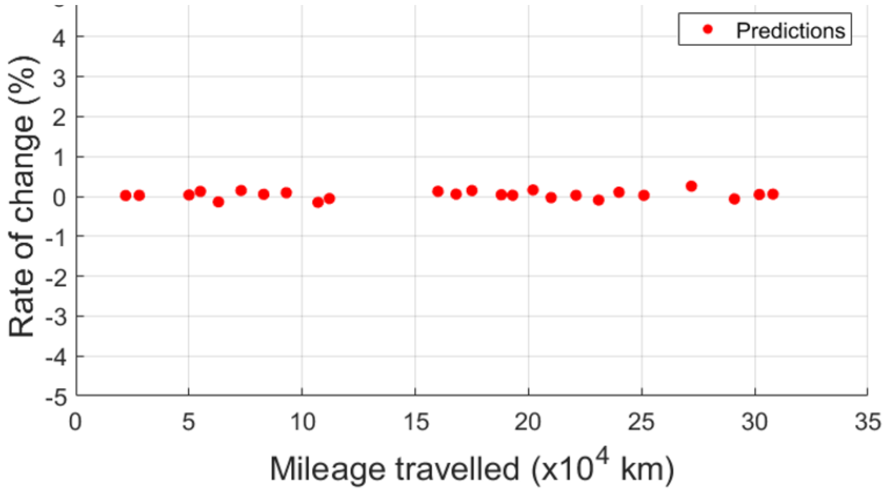
Evaluation and Testing

Prediction Result: Primary Suspension System

Stiffness coefficient change



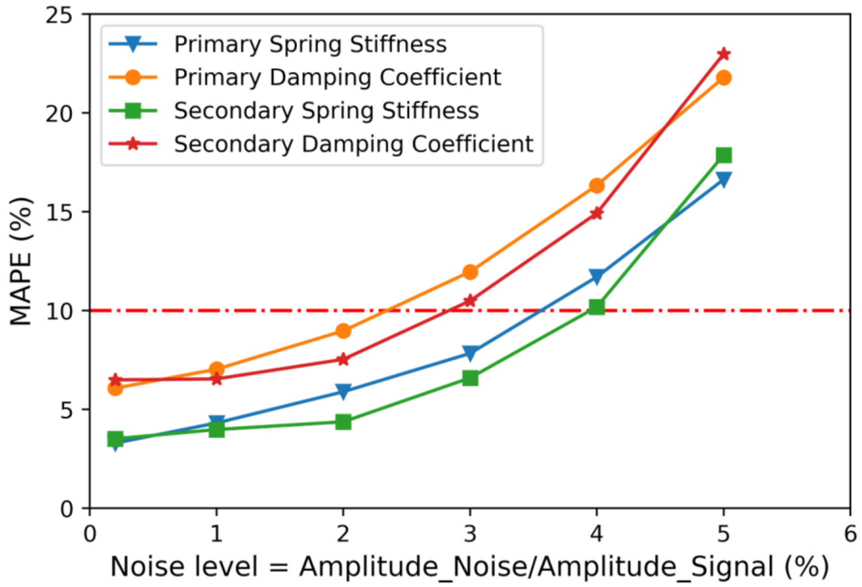
Damping coefficient change



- A slight change (~ 1%) occurred for stiffness; no obvious change in damping coefficients
  - This is consistent with the studies (J. Luo et.al, 2008, 2003) that reported the degradation rate of the suspension spring health of approximately **1%** when the operational time is approximately **1/12** of the designed lifetime

Sensitivity Analysis

- Because the performance and cost of specific accelerometers vary significantly, a sensitivity analysis to evaluate the robustness of the method



- The specification of the sensors used in this study

ZW9609A-2 integrated circuits piezoelectric accelerometers

TYPE	RANGE	PRECISION	SENSITIVITY	FREQUENCY RESPONSE	POWER	PRICE
ZW9609A-2	± 2g	0.1%	Vertical: 993.7 mV/g Lateral: 992.6 mV/g Longitudinal: 1003.3 mV/g	DC-2500 Hz (-3dB)	+8 ~ +20 V_{DC}	~700 USD

Conclusion

- Developed a data-driven framework for the prediction of the state of integrity of primary and secondary suspension systems, adopting a hybrid procedure that uses a simplified model and vibration measurements (indirect indicators)
- Main advantages
  - Easy-to-implement and adaptable to other systems
  - Interpretable results – reporting health indicators with physical meanings, not a few fault labels, compared with pure data-driven methods
  - Unbound to the availability of real-world labeled data
  - Support the current trend of replacing planned (more expensive) maintenance with predictive maintenance

Publications

1. Hong, N., Li, L., Yao, W., Zhao, Y., Yi, C., Lin, J., & Tsui, K. L. (2019). High-Speed Rail Suspension System Health Monitoring Using Multi-Location Vibration Data. *IEEE Transactions on Intelligent Transportation Systems, 1-13*.
2. Xu, P., Yao, W., Zhao, Y., Yi, C., Li, L., Lin, J., & Tsui, K. L. (2018). Condition monitoring of wheel wear for high-speed trains: A data-driven approach. In *2018 IEEE International Conference on Prognostics and Health Management (ICPHM)* (pp. 1–8). Seattle, WA.

Future Work

- Future extensions of this research work includes the following:
  - Modification of the framework to enable real-time online monitoring
  - Estimation of the remaining useful life and the design of the corresponding maintenance strategy;
  - Extension of the application of the proposed approach to the suspension systems of other types of vehicles, such as metros, trucks, and sedans, as they can be subjected to similar vehicle system dynamics and monitored using similar types of features

- Currently working on an Innovation and Technology Fund (ITF) proposal in collaboration with MTR Corporation Limited

Wheel Wear Monitoring

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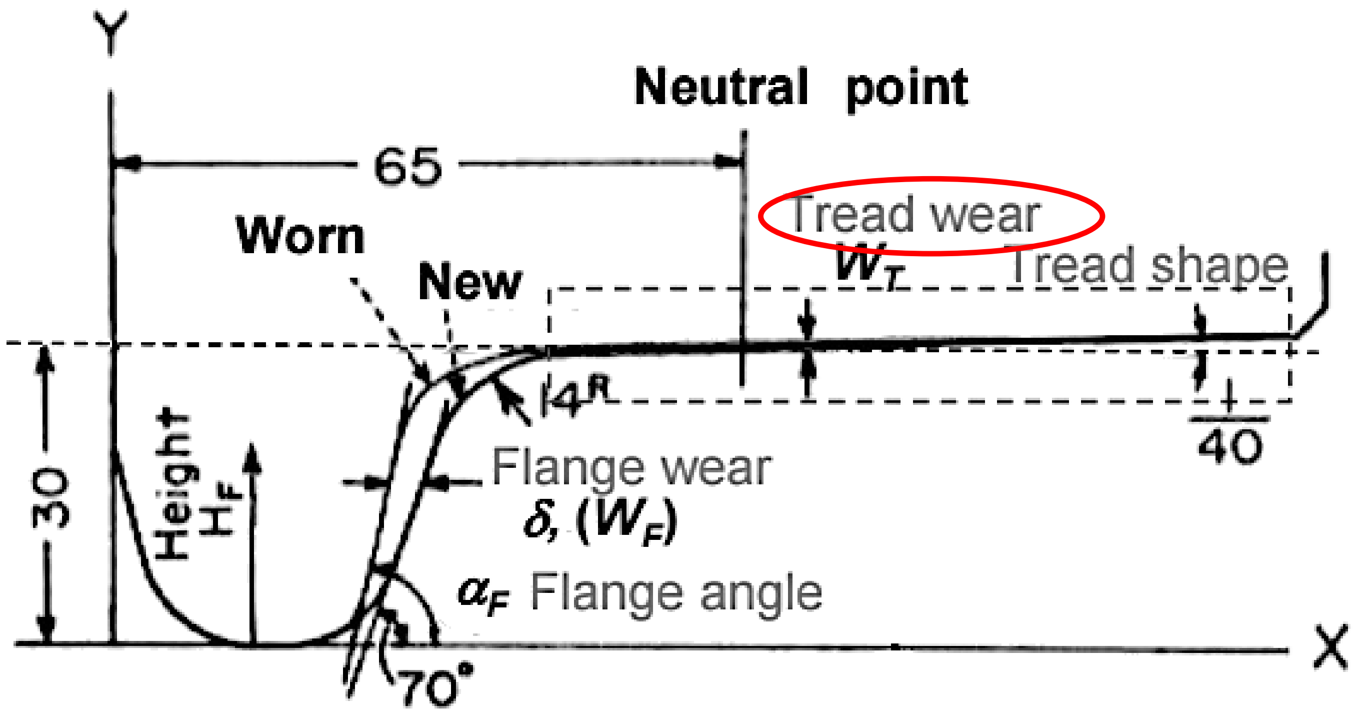
Wheel Wear

- Wheels of trainsets are subjected to wear due to wheel-track contact
- When the worn state of the profiles reaches the limit values defined by the regulations, the wheels need to be re-profiled
- Current re-profiling strategies in China are based on fixed schedule
- Real-time wheel profile monitoring could reduce maintenance cost while improve safety



Focus of this study

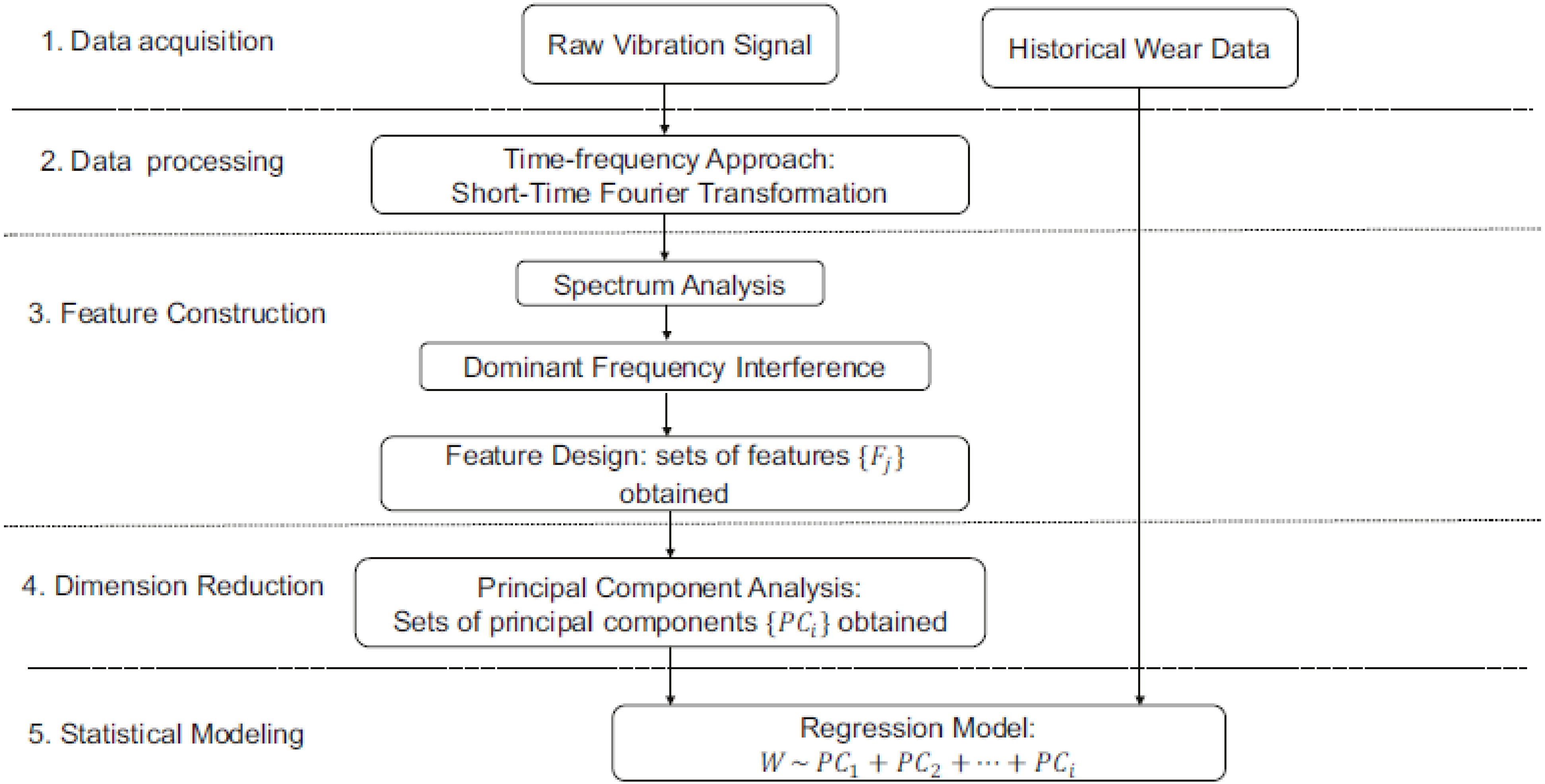
Existing methods

- Existing models are dependent on specific vehicle system dynamics. wheel-rail contact characteristics and the wear properties of wheels.
  – The Archard wheel wear model (Archard, 1953) is one of the oldest; commonly used to estimate a wear depth due to sliding
  – Many extensions based on this model have been proposed during the past decades (Arizon et al., 2007)
  – Simulation software such as SIMPACK (Rulka, 1990) are used to build the wheel-rail dynamic interaction system and validate wheel wear prediction models,

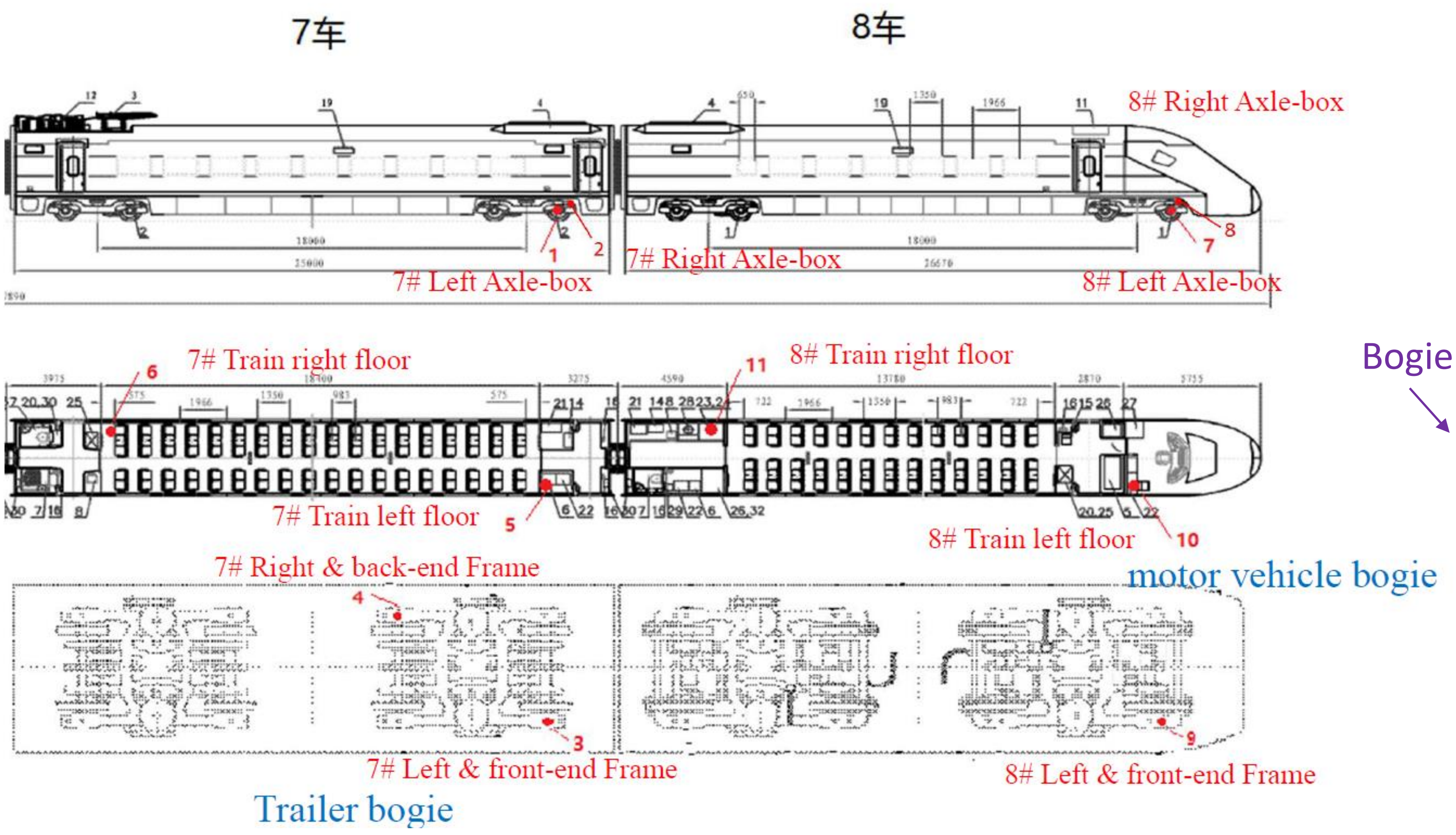
- Alternatively, few statistical methods have been proposed to monitor and predict the wear of the wheel. Han and Zhang (2015) proposed a binary wheel wear prediction model. However, real time monitoring can’t be achieved if using profile data.

Our approach

- A new method to monitor the wheel wear using vibration data based on ***statistical modeling*** and ***signal processing***



Vibration Sensors Locations

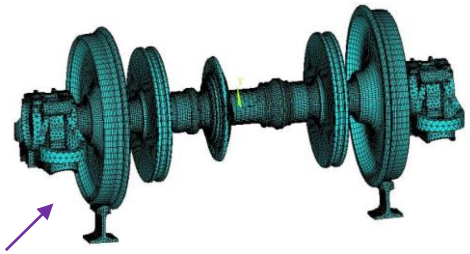


Floor

2nd Suspension
(air spring)

Bogie

1st Suspension
(spring &damper)



Axle Box

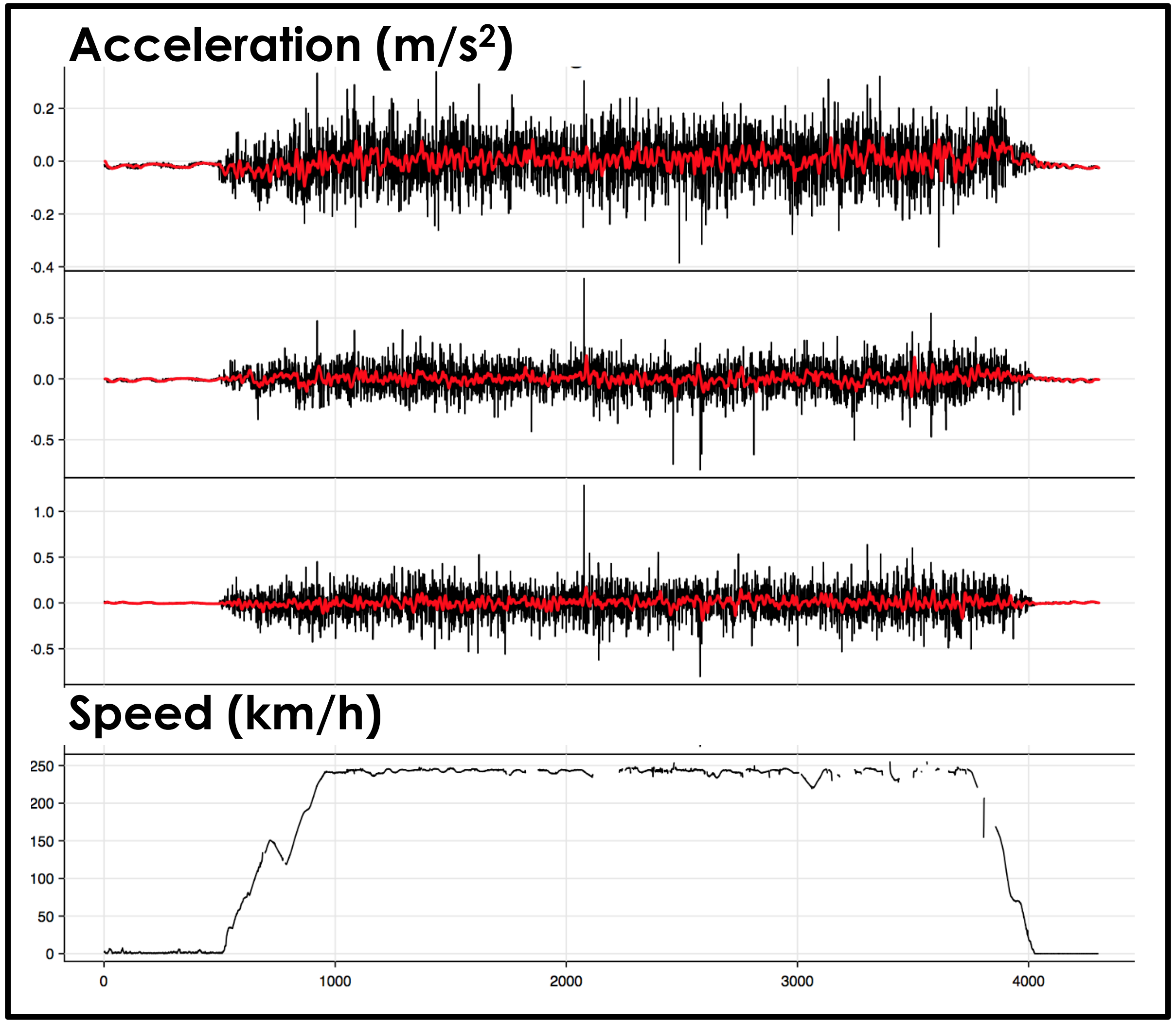
Z

Data

- Continuously tracking one train's three dimensional vibration for 8 months
  - Data contain 30 entire trips collected along 3 different routes: 11 trips on Changsha-Huaihua line (CH), 3 trips on Guangzhou-Zhuhai line (GZ), and 16 Hainan-Sanya loop line (HS)
- GPS speed data (1HZ)
- Maintenance event data (2 maintenance events)
- Wheel profile data: Shape (x,y), Treat wear, Flange wear

Car #	Location	L/R	Sensor #	Sampling frequency
7 (Trail car)	Axle box	Left	1	5000 Hz
		Right	2	
	Bogie frame	Left	3	2000 Hz
		Right	4	
	Car body	Left	5	
		Right	6	
8 (Motor car)	Axle box	Left	7	5000 Hz
		Right	8	
	Bogie frame	Left	9	2000 Hz
	Car Body	Left	10	
		Right	11	

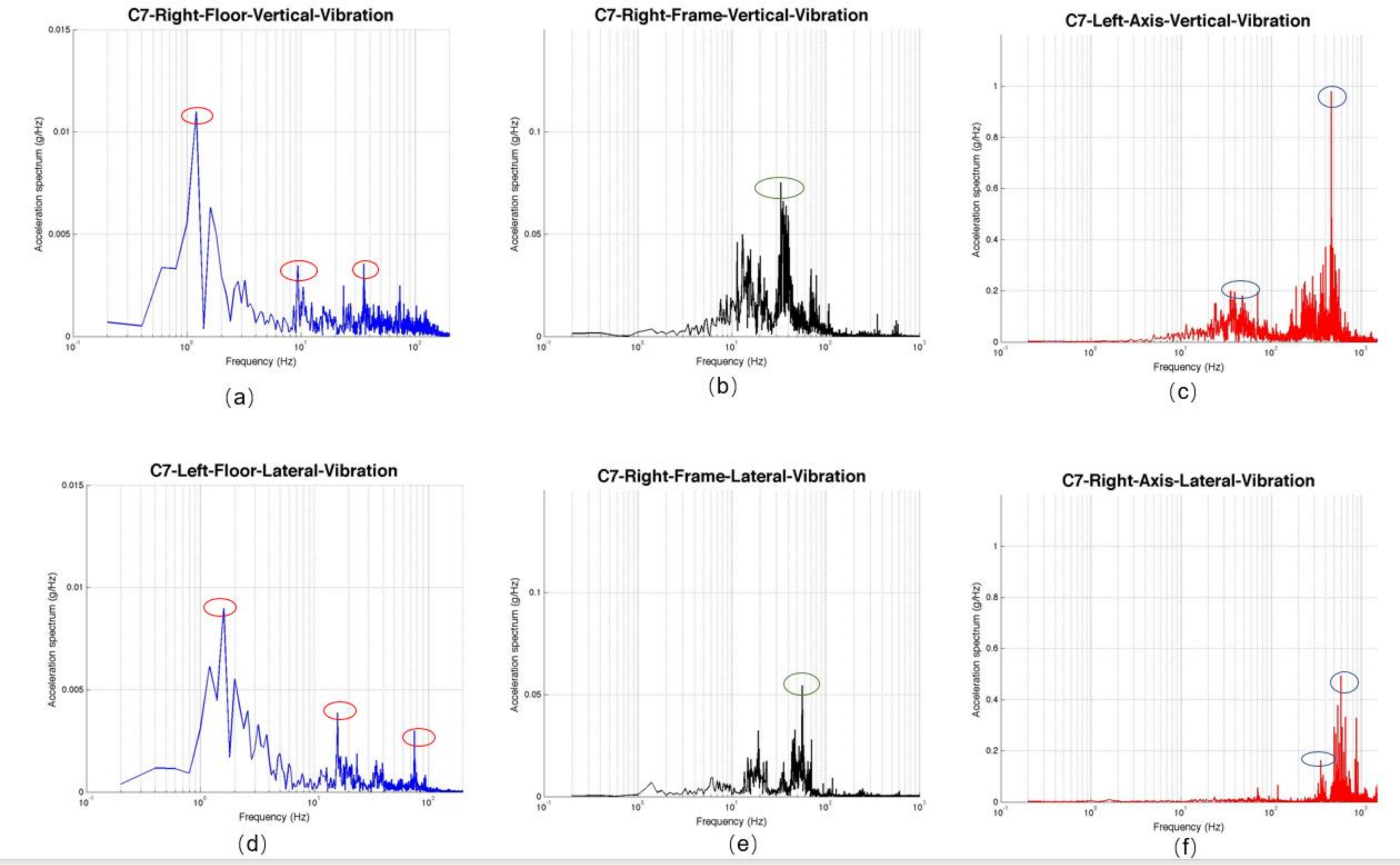
Raw Data Example



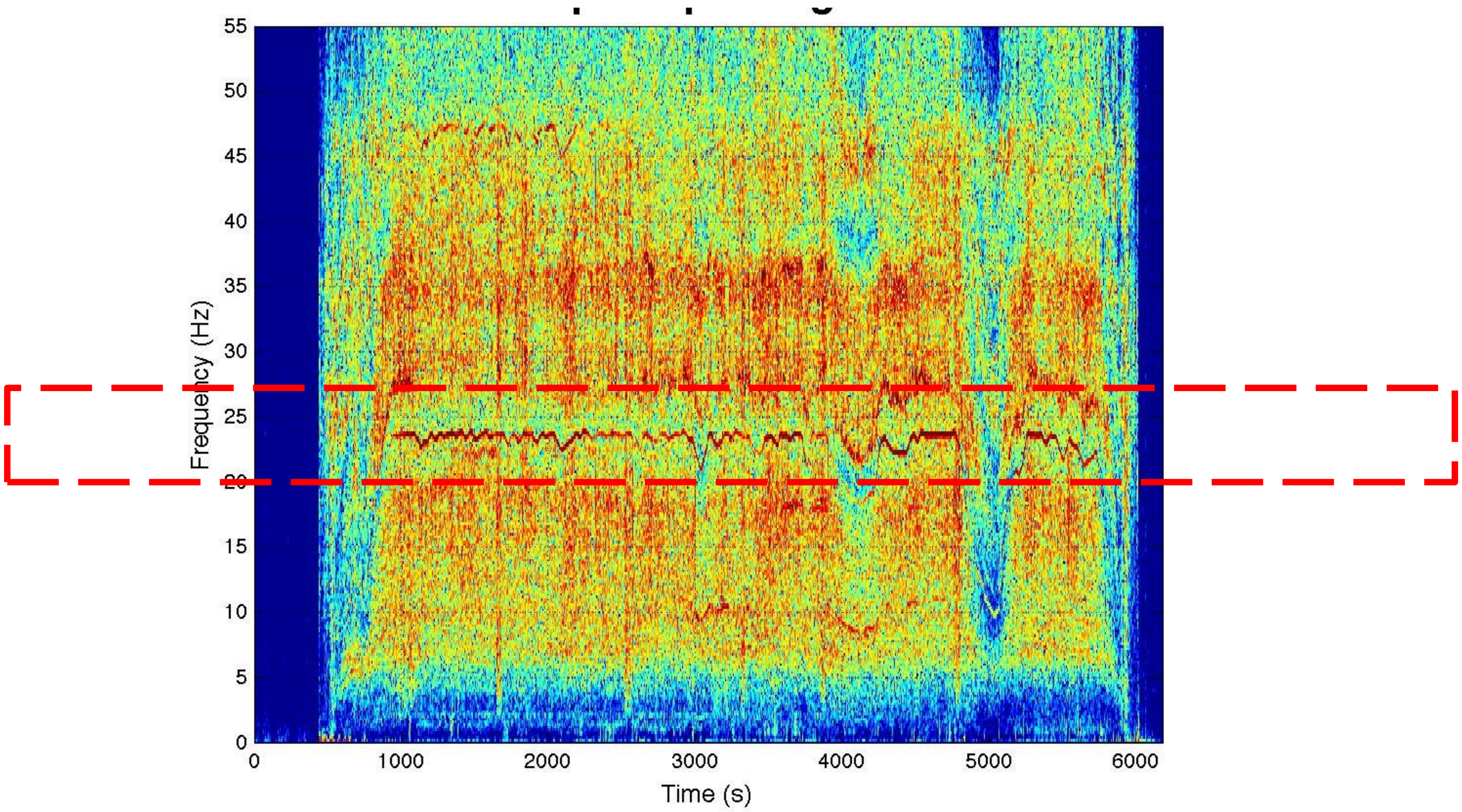
- Vertical acceleration
- Lateral acceleration
- Lateral acceleration
- Speed data collected from GPS

Feature Construction - Spectrum Analysis

- Floor Vibration
  - 1 Hz: Natural vibration frequency of car body's vertical suspension
  - 10 Hz: First-order natural vibration frequency of car body vertical bending
- Bogie Frame vibration:
  - 20-50 Hz: the low-order elastic modal frequencies
- Axle box vibration:
  - 30-50 Hz : induced vibration related to wheel perimeter and the elastic vibration of bogie frame.
  - 400-450 Hz: high-frequency Hertzian contact occurring in the wheel-rail interface.

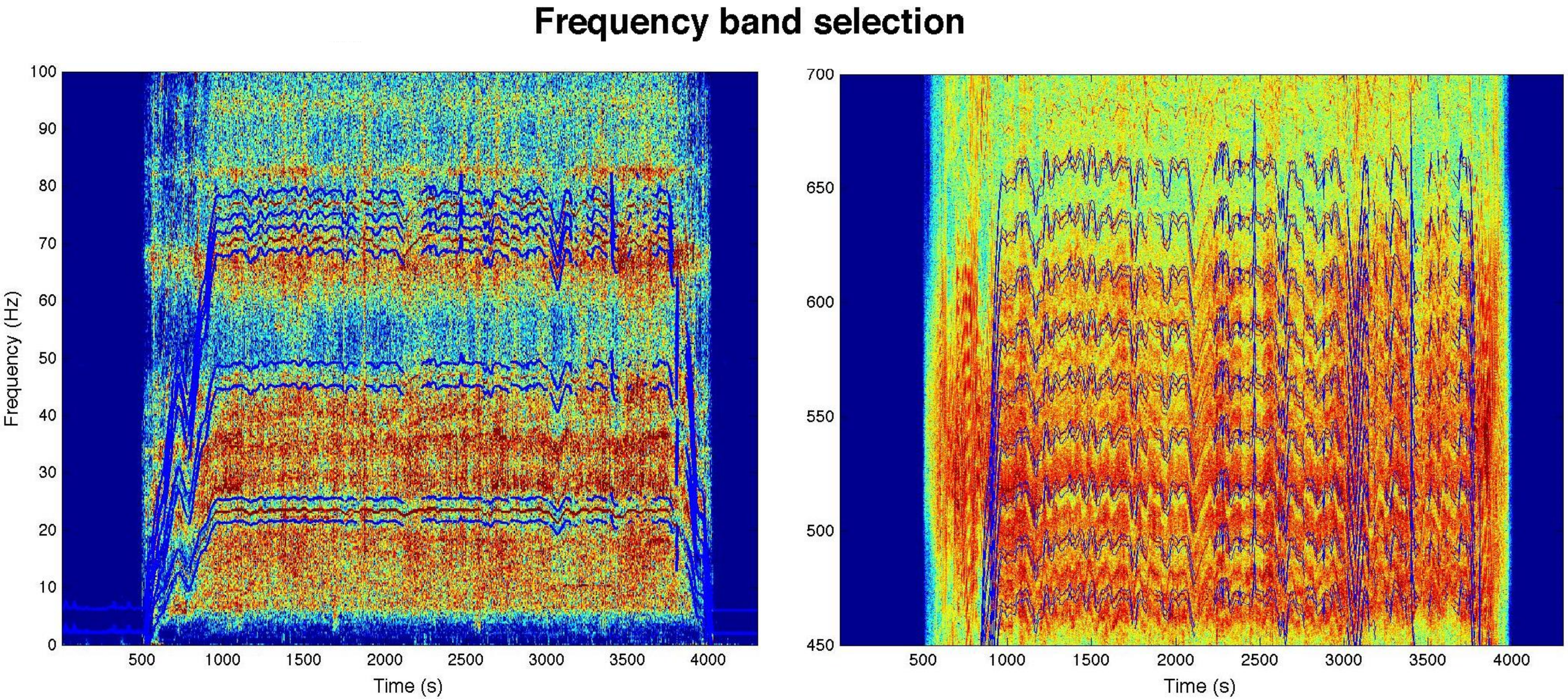


Feature Construction—— Dominant Frequency Inference



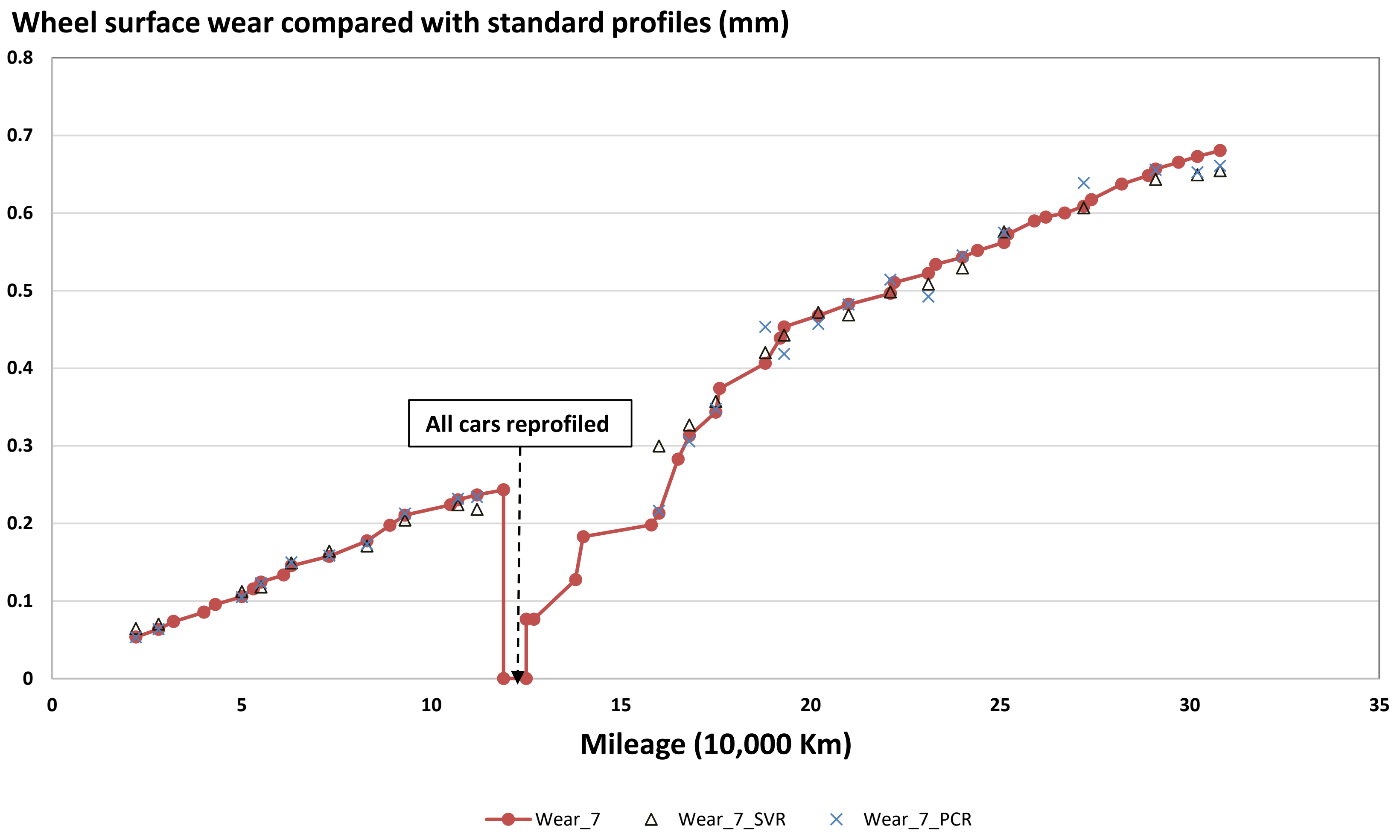
- Extract wheel-induced frequency band with frequencies varied by speed

Feature Construction - Design frequency features

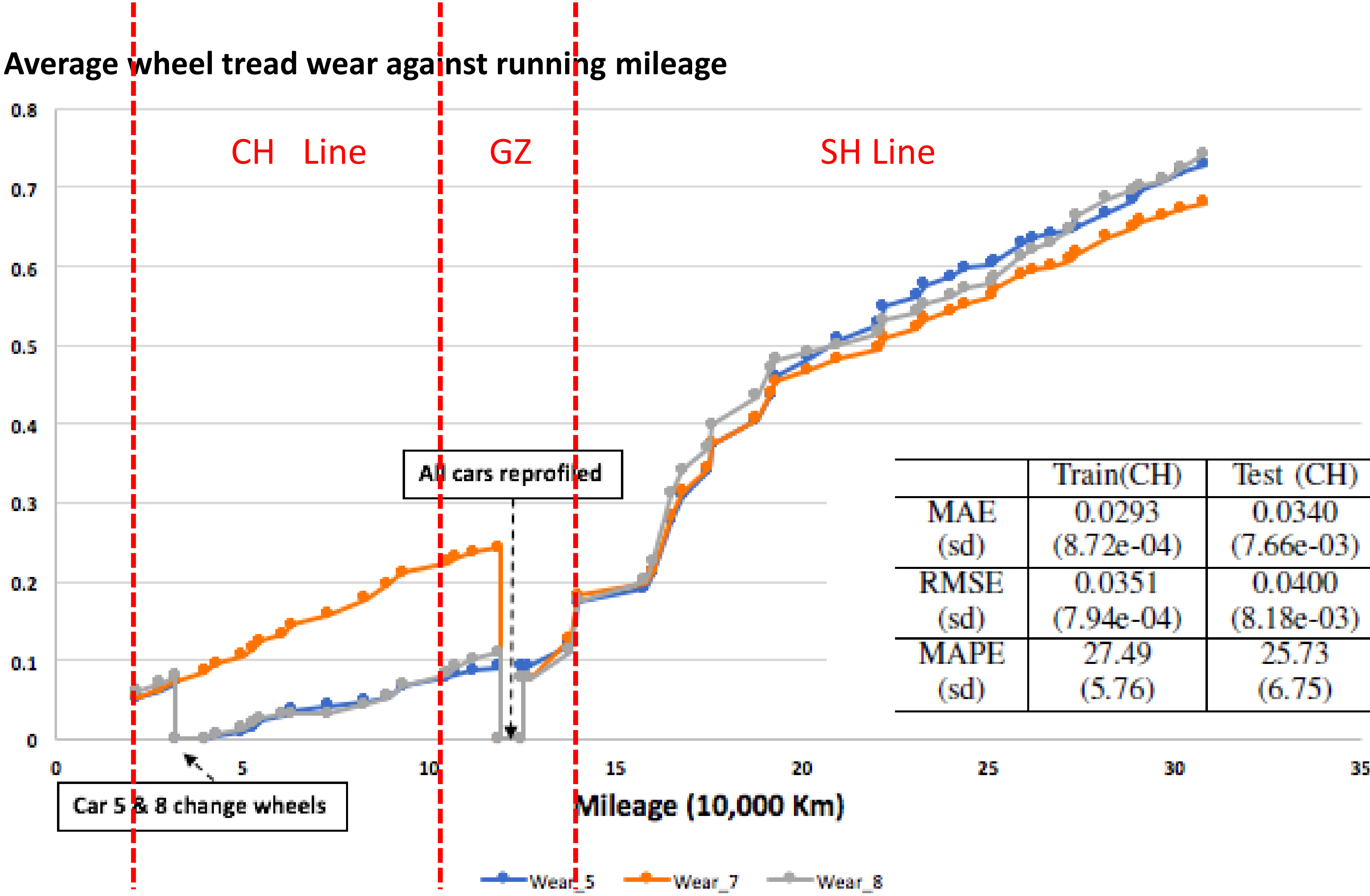


- Induced vibration band (∓2HZ around f=kv, k in [1, 40])
- Frequency bands between induced frequency (hertizian contact)
- Extract the energy in and between induced frequency bands

Results: tread wear against travelling mileage



Results: tread wear against travelling mileage



	Train(CH)	Test (CH)	Train(SH)	Test (SH)
MAE (sd)	0.0293 (8.72e-04)	0.0340 (7.66e-03)	0.0266 (6.8e-05)	0.0265 (6.94e-03)
RMSE (sd)	0.0351 (7.94e-04)	0.0400 (8.18e-03)	0.0326 (8.76e-05)	0.0311 (8.40e-03)
MAPE (sd)	27.49 (5.76)	25.73 (6.75)	8.422 (4.38)	6.274 (2.39)

Conclusion

- Two case studies show that it is promising to use ***data-driven methods*** for health monitoring of high speed rail systems using vibration sensor data

- ***Domain knowledge*** is important to construct features and build interpretable models

- More research is needed on how to integrate the models for monitoring different components and use them for ***integrated system monitoring***

- More research is needed on how to design ***better maintenance strategies*** based on these new monitoring methods

The Research Grants Council (RGC)
Theme-based Research Scheme 2015/16

Safety, Reliability, and Disruption Management of High Speed Rail and Metro Systems

[T32-101/15-R]

Co-(Principal) Investigator

Lishuai Li (City University of Hong Kong)

THANK YOU!

Q & A

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