Physikalisch-Technische Bundesanstalt
Braunschweig und Berlin
Nationales Metrologieinstitut

ComTraForce Project

Advanced practical model for describing dynamic forces

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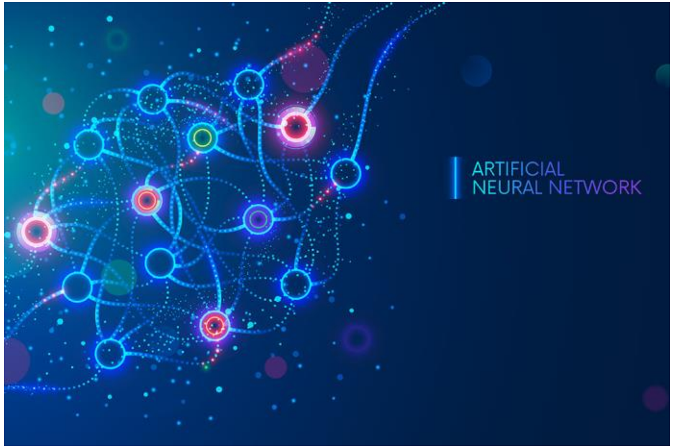
EURAMET

ComTraForce

Advanced practical model for describing dynamic forces

Outlines

1. Motivation: Kelvin-Voigt model
2. Developing a new measurement approach
3. Examination and understanding of the generated data :
   - ➢ Frequency domain
   - ➢ Time domain
4. Artificial Neural Networks (ANN) for signal modeling:
   - ➢ Recurrent Neural Networks (RNN)
   - ➢ Long Short-Term Memory (LSTM)
   - ➢ Gated Recurrent Unit (GRU)
   - ➢ Bidirectional Recurrent Neural Networks (BRNN)
5. Recommendations and further work



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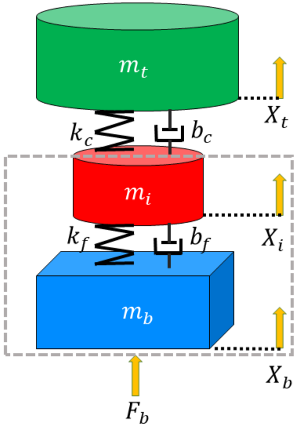
1) Motivation:

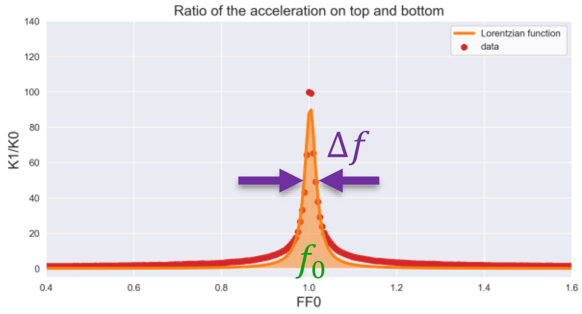
- Sinusoidal-based calibration according to DKD 3 -10
- Kelvin-Voigt model
- Transducer is modeled as a head mass which is connected to its base mass by a spring of constant k_f, and a damper b_f.
- Low-resolution, low speed
- Unstable model parameters
- rocking motion, the dominant source of uncertainty
- Solution: Averaging over all points on the surface ???



$$S_f = \frac{U_f}{a_t(f).[(m_a + m_i) + (m_t.k_0)]}$$

$$K_f = (2\pi.f_0)^2.[m_a + m_i + (m_t \cdot K_0)]$$

$$b_f = \frac{\Delta f}{f_0}\sqrt{k_f.[m_a + m_i + (m_t \cdot K_0)]} = \frac{1}{Q}\sqrt{k_f.[m_a + m_i + (m_t \cdot K_0)]}$$



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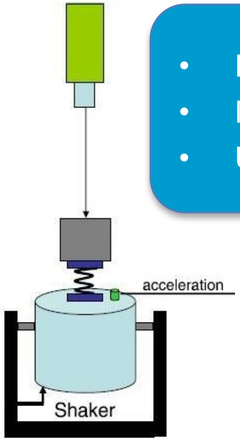
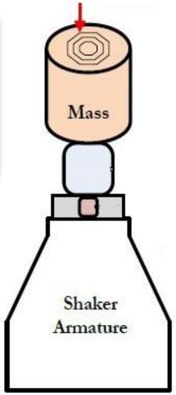
1) Motivation:



- Excitation signal: Sinusoidal
- No information about the rocking motion
- Unstable model parameters

Acceleration Measurement: sided
Sensor: Laser / Piezoelectric
No. of signal: 1 Top / 1 Bottom



- Excitation signal: Periodic chirp
- ARMAX and Box-Jenkins for fitting
- Special setup configuration
- Significantly better results

Acceleration Measurement : axial
Sensor : Laser / Piezoelectric
No. of signal : 24 Top / 1 Bottom

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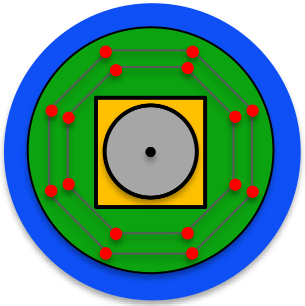
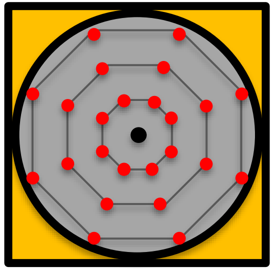
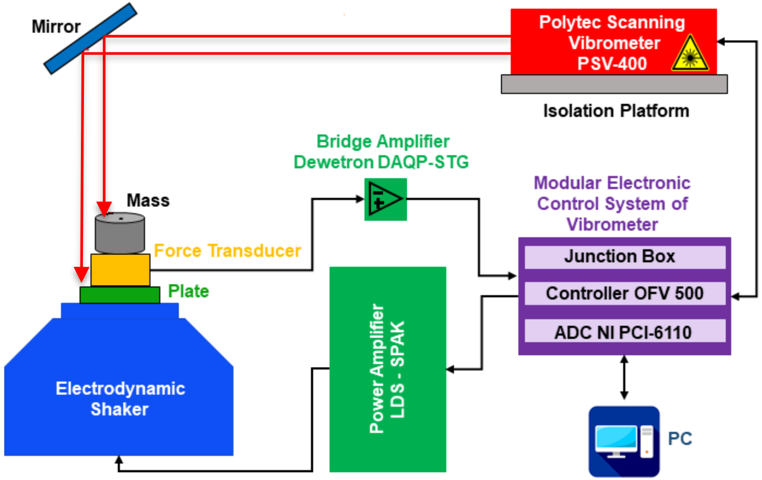
2) Developing a new measurement approach

- Applicable to all types of the calibration assembly
- Good understanding of the rocking motion
- High-resolution, high speed
- Periodic chirp excitation as an alternative to sinusoidal
- High amount of generated data
- Data can be fed into ANN
- Calibration with higher degree of the automatization







Acceleration Measurement : sided
Sensor : Laser / Laser
No. of signals : 24 Top / 16 Bottom

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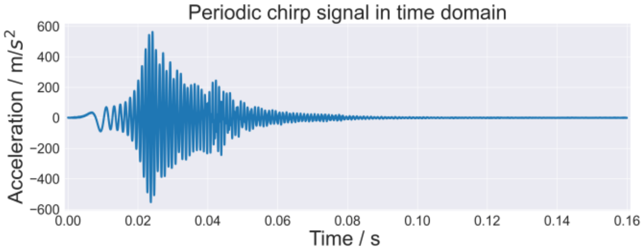
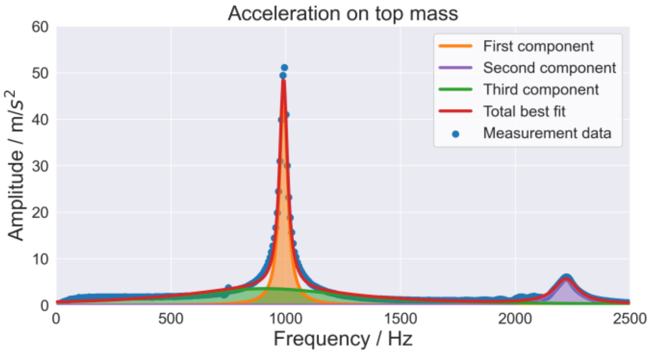
3) Examination and understanding of the generated data
Frequency domain

- Fitting model selection
  - Akaike Information Criterion (AIC)
  - Bayesian Information Criterion (BIC)



Curve of best fit: weighted Linear sum of three Lorentzian functions with different parameters



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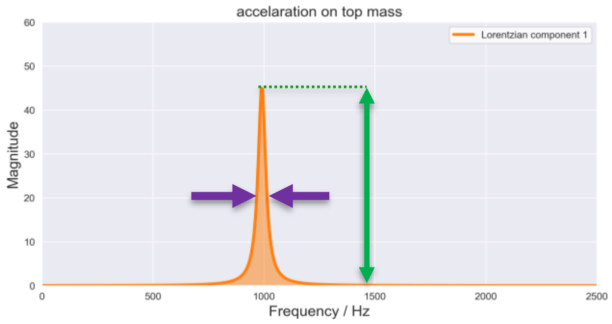
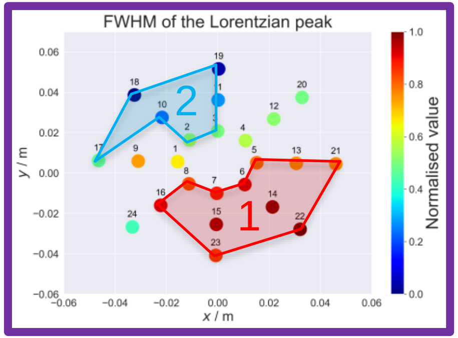
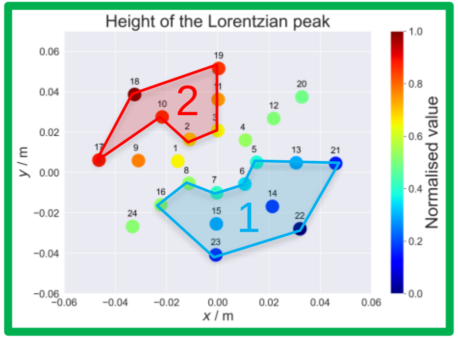
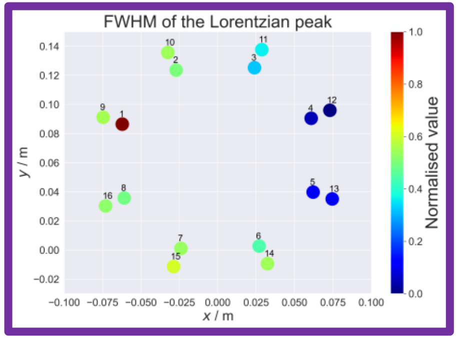
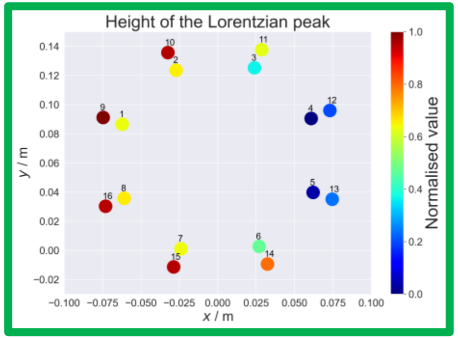
3) Examination and understanding of the generated data
Frequency domain











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3) Examination and understanding of the generated data

Investigations in the frequency domain:

- Subject to leakage effect
- Initialization of the values in the fitting model
- Fitting model gets stuck in local minima instead of global minima
- Weakness to generalization for all recorded signals

Investigations in the time domain:

- Using **RMSE** (Root Mean Square Error) and **MAE** (mean absolute error) metrics to calculate deviations for each signal in comparison to the average acceleration on each surface

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(a_t - \hat{a}_t)^2} \qquad MAE = \frac{1}{n}\sum_{t=1}^{n}|a_t - \hat{a}_t|$$

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3) Examination and understanding of the generated data
Time domain

n = 4096

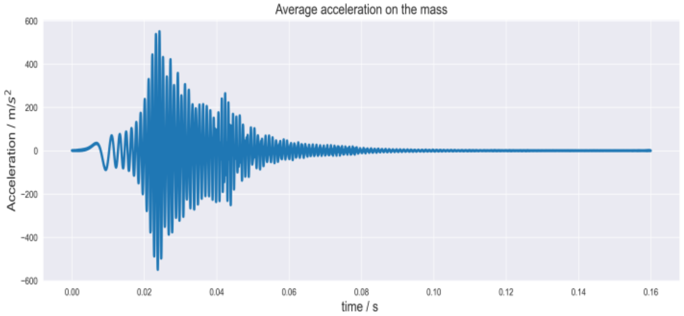
a_t : acceleration for a grid point at given time t

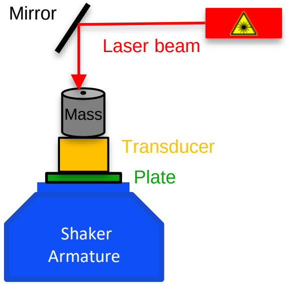
$\hat{a}_t$: average acceleration of all grid points at given time t

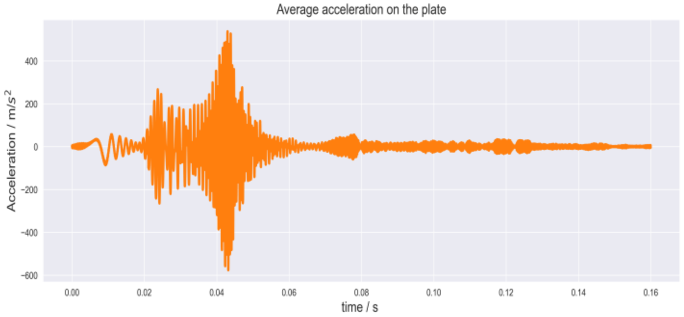
$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(a_t - \hat{a}_t)^2}$$

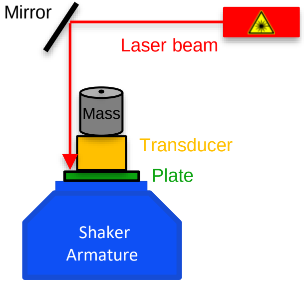
$$MAE = \frac{1}{n}\sum_{t=1}^{n}|a_t - \hat{a}_t|$$

Disadvantage:
Mean values include outliers









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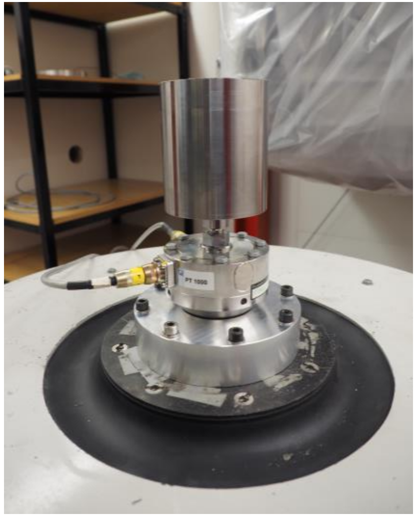
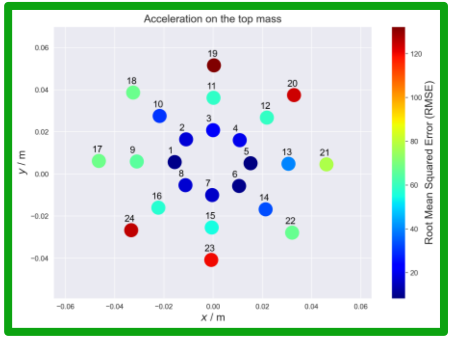
3) Examination and understanding of the generated data
Time domain

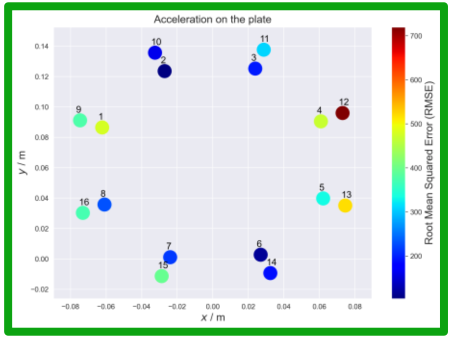
Top Mass: 7 kg



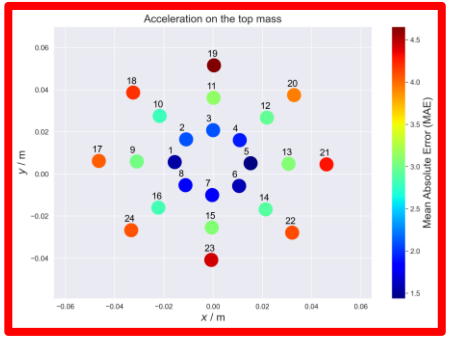
25 kN HBM Force Transducer

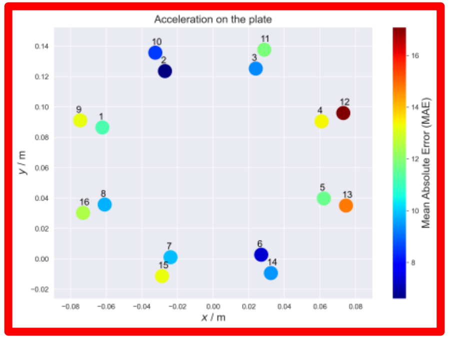
RMSE

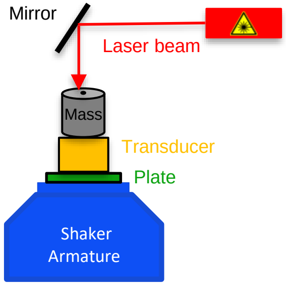


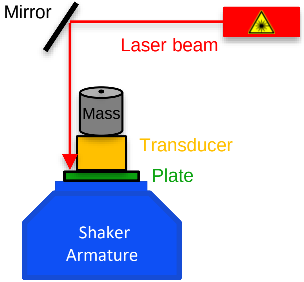


MAE









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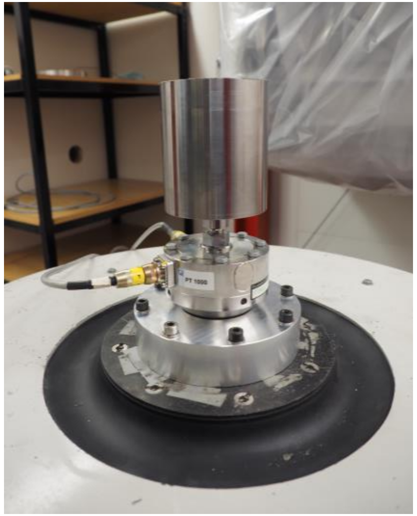
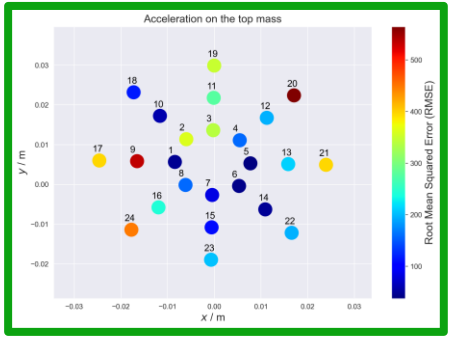
3) Examination and understanding of the generated data
Time domain

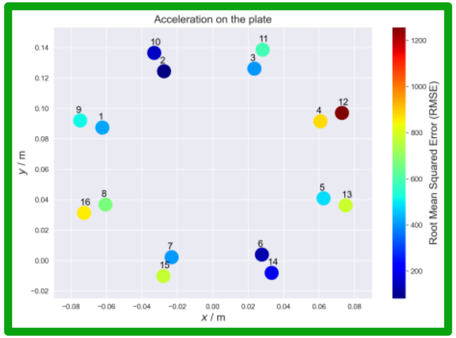
Top Mass: 1 kg



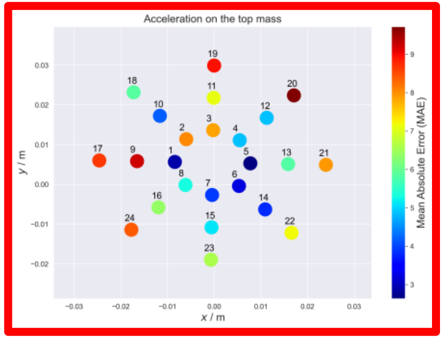
25 kN HBM Force Transducer

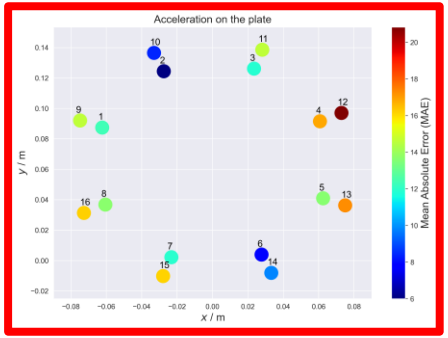
RMSE

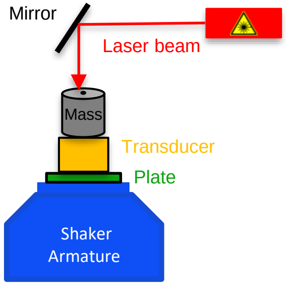


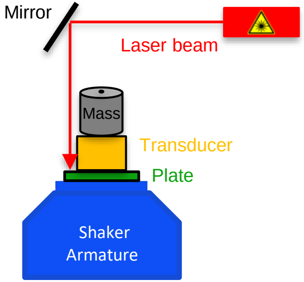


MAE









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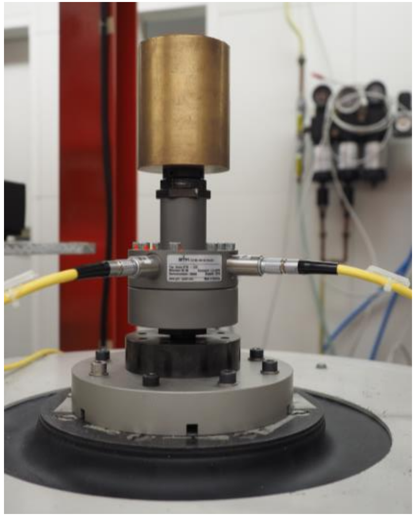
3) Examination and understanding of the generated data

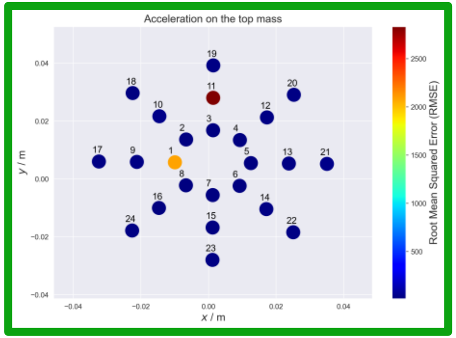
Time domain

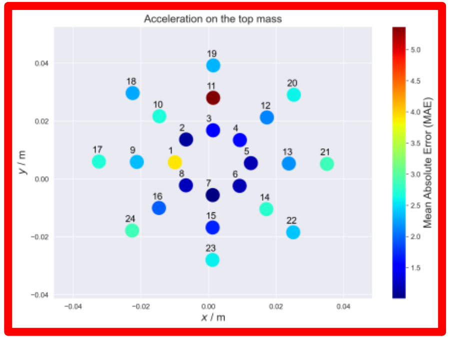
RMSE **MAE**

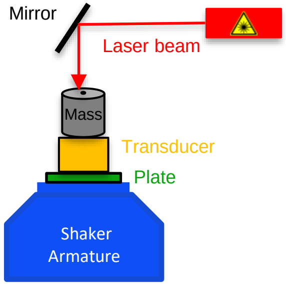
Top Mass: 4 kg

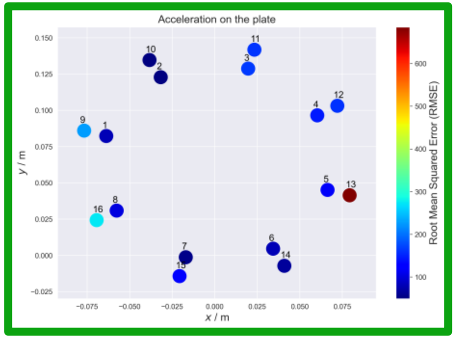


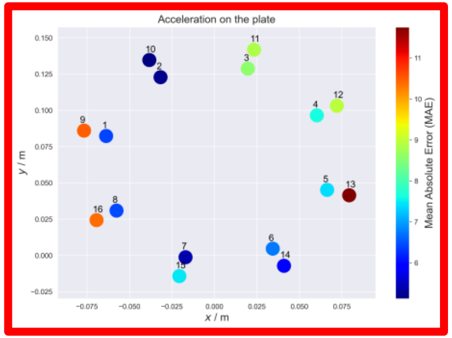
20 kN GTM Force Transducer

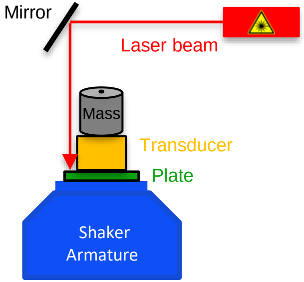












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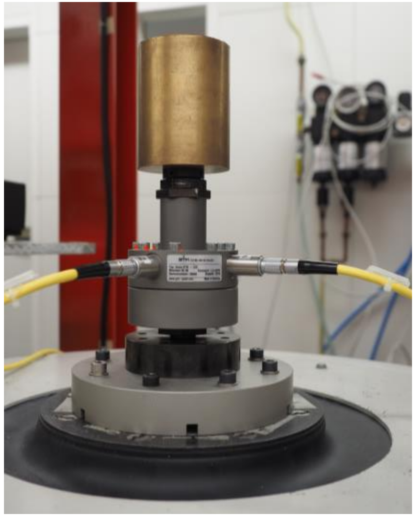
3) Examination and understanding of the generated data
Time domain

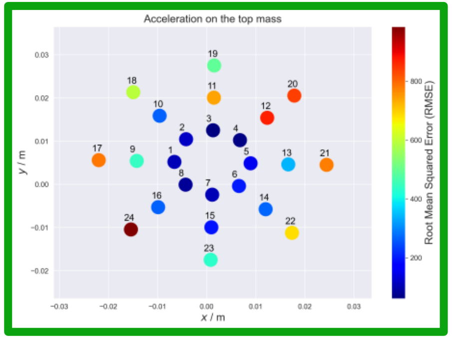
RMSE

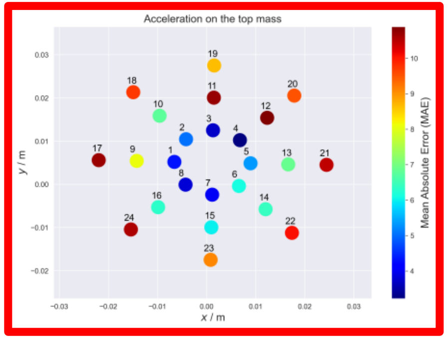
MAE

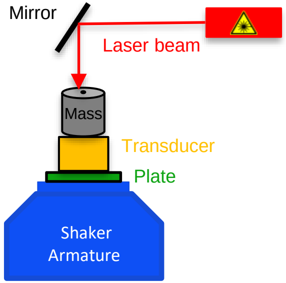
Top Mass: 1 kg

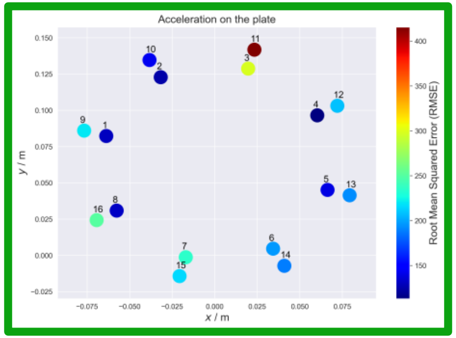


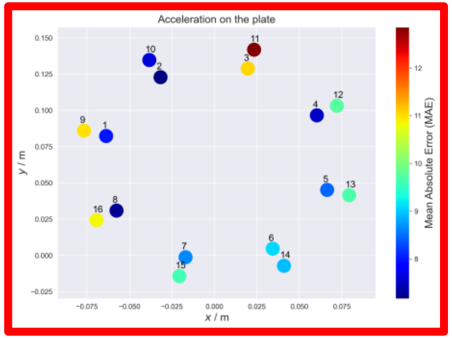
20 kN GTM Force Transducer

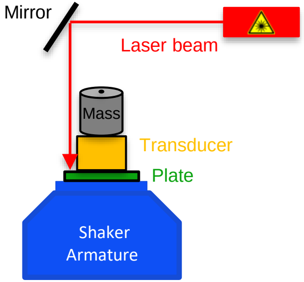












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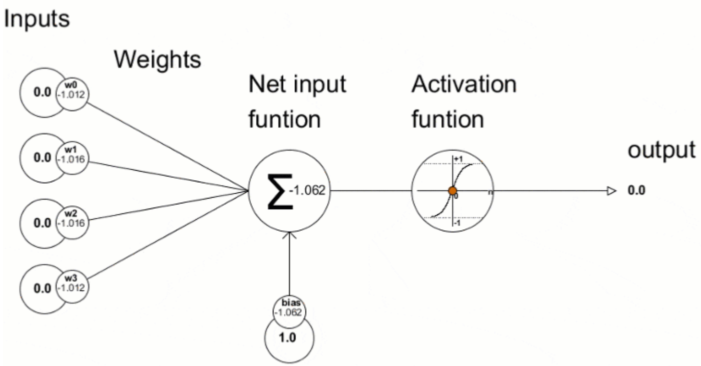
4) Artificial Neural Networks (ANN) for signal modeling

- Alternative to traditional approaches
- ANN outperform other Machine Learning ML methods
- Infer knowledge from the data without explicit programming
- Ability of artificial neural networks ANN
  - Anomalies detection in signals
  - Filtering anomalies arithmetically

$$\hat{y}\,(X) = \sigma(WX + b)$$

- $\hat{y}$ network prediction
- X is the matrix of input features
- W matrix of weights
- b bias vector
- σ is a nonlinear activation function



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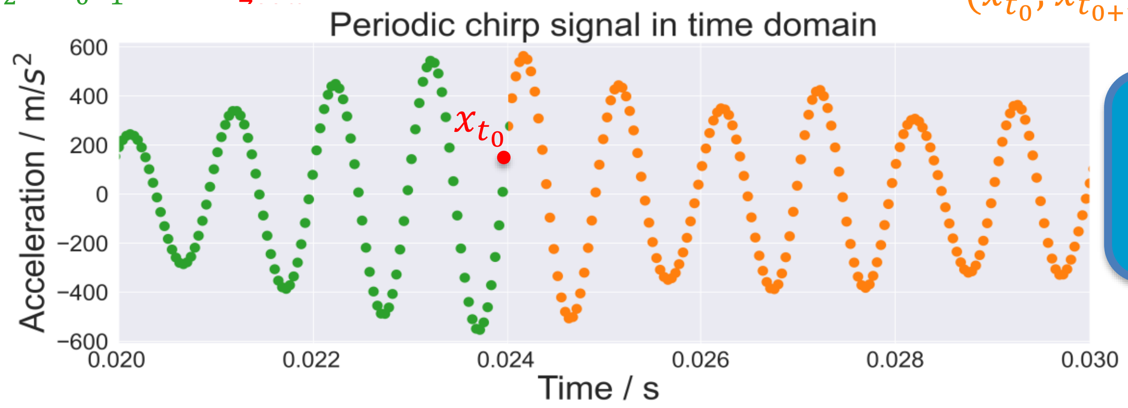
4) Artificial Neural Networks (ANN) for signal modeling

- Choice of an appropriate network architecture
- Acceleration values in the time domain over the time T can be considered as a sequence data

$$x = (x_1, x_2, x_3, \dots x_{T-1}, x_T)$$

$(x_1, \dots x_{t_{0-2}}, x_{t_{0-1}})$

$(x_{t_0}, x_{t_{0+1}}, \dots, x_T)$



Doing so for all acceleration signals recorded at each surface, a general model should be learned by ANN

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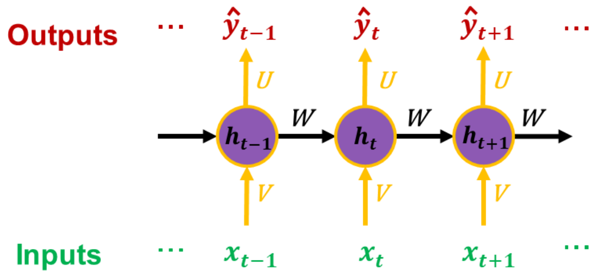
4) Artificial Neural Networks (ANN) for signal modeling
Recurrent Neural Networks RNN

- Chain-like structure (looping mechanism in hidden layers)
- Good at modelling the temporal sequence of the data
- Data transformation (from t to the $t+1$)

$$h_t = \sigma(Vx_t + Wh_{t-1} + b_h)$$

$$\hat{y}_t = \sigma(Uh_t + b_y)$$

- Hidden states are a function of all previous hidden states.
- Vanishing gradient during back-propagation



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4) Artificial Neural Networks (ANN) for signal modeling

Long Short-Term Memory LSTM

- Variant of the RNN networks
- Mitigation of the short-term memory problem using gating mechanisms
- Information are transmitted through the LSTM cells-chain via the cell state C_t
- Information can be optionally added / removed by input gate / forget gate
- Sigmoid neural layers enable the cells to optionally let data pass through or dispose.
- Output gate decides which data should be sent to the next cell
- Learning long-term dependencies
- Deleting irrelevant information

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4) Artificial Neural Networks (ANN) for signal modeling

Gated Recurrent Unit GRU

- Implement the gating mechanism to eliminate the vanishing gradient
- Two gates control the data flow
- Update gate keeps information from time steps long ago
- Update gate determines how much of them needs to be passed to the future
- Reset gate removes irrelevant information
- GRUs outperform LSTM on some tasks in terms of speed and generalization

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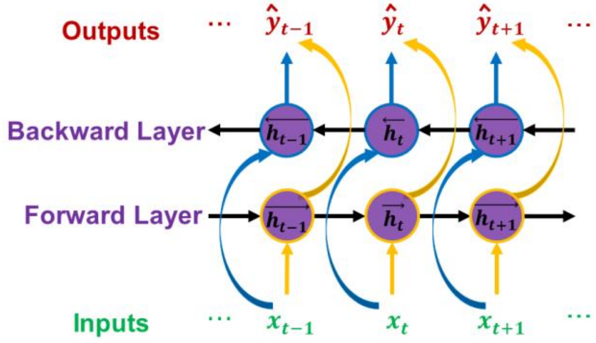
4) Artificial Neural Networks (ANN) for signal modeling
Bidirectional Recurrent Neural Networks BRNN

- ❖ Recorded acceleration signal includes whole data also in the future
- ❖ Future values exploitation
- ❖ Training simultaneously in the positive and negative time directions
- ❖ Using all available input information
- ❖ Robust against anomalies and outliers
- ❖ Combining RNNs (LSTM and GRU)
- ❖ Accessing long-range data in both input directions



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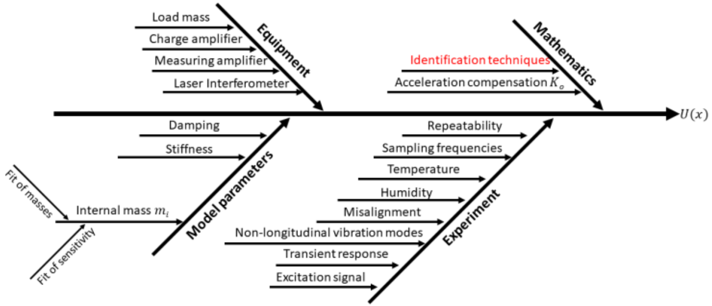
5) Recommendations and further work

- Rocking movement of the dynamic force measurement setup as a dominant source of uncertainty must be investigated precisely
- Simple averaging models can not be applied to all calibrations assemblies
- New evaluation method based on utilizing ANN can be used to better characterization of force transducers and reduce measurement uncertainty

- Black-Box nature of the ANN introduces a new uncertainty contribution
  - Imperfect training
  - Systematic errors
  - Sampling noise
  - Unexpected shifts in the data

- Uncertainty quantification of ANN is motivated for further work
  - Bayesian neural networks
  - Dropout-based methods
  - Ensemble techniques



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