Professorship of Data Mining and Analytics
Department of Informatics
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Virtual Sensors Machine Learning Lab Course

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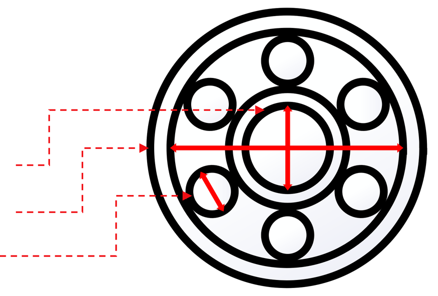
in cooperation with SIEMENS

Motivation

- Bearings are a critical part of electric motors and require a reliable online monitoring
- Real use of sensors is complex and expensive
- Simulation tools (FEM) are computationally expensive due to extensive non-linearity
- Machine Learning can potentially substitute the expensive simulation process, while still yielding accurate results

Data

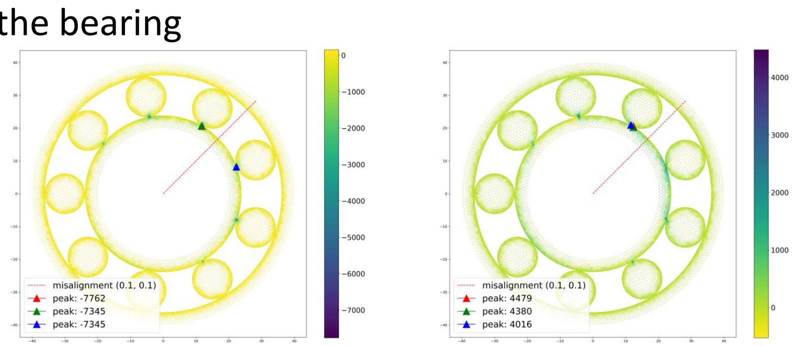
Bearing characteristics
- Number of balls
- Radius of cage
- Diameter of inner race
- Diameter of outer race
- Diameter of balls



Each bearing is associated with a set of 2D coordinates.

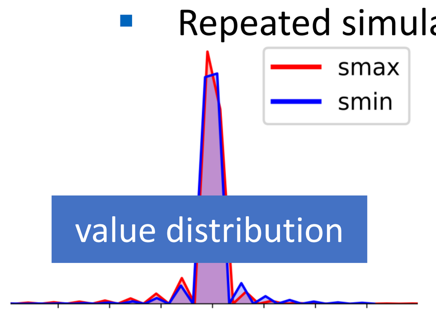
Scenarios, which consist of
- Revolutions per minute (RPM)
- Direction of force acting on the inner race
- Strength of the force

Simulation results obtained from a static FEM for each bearing and scenario
- Each coordinate has two values: smax and smin, which are the lowest and highest eigenvalues of the Cauchy stress tensor at that position
- High smax and low smin values indicate an overload of the bearing



Overall, there are **7** bearings with **25500 to 59836** coordinate points and **216** different scenarios.

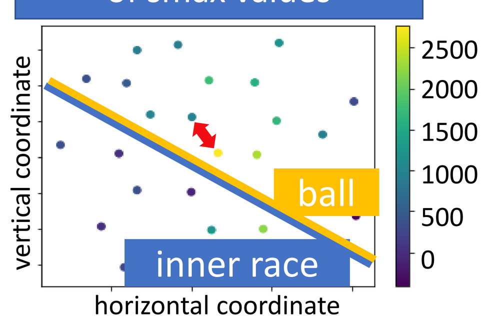
Further properties
- The force is only applied to certain directions
- Only a small amount of data is available
- Coordinates are constant for a certain bearing
- Few points with very high values, many with small values
- Points with high value differences are close by
- Some scenario results seem unreliable
  - High stress values are far away from force direction
  - Repeated simulations show very different extrema



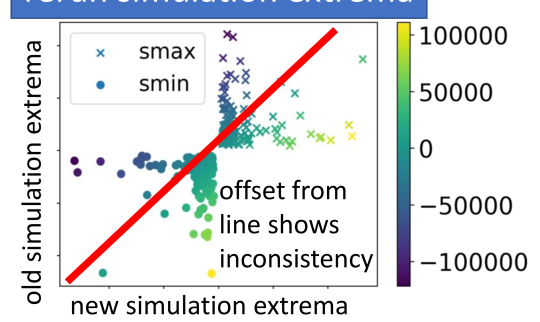
value distribution

force directions

Small picture clipping of smax values



Difference of original and rerun simulation extrema



Challenges of the problem

- Non-standard problem and little existing research
- Generalization to unseen force directions
- Generalization to unseen bearing geometries
- The 2D coordinates have no rotational invariance

or

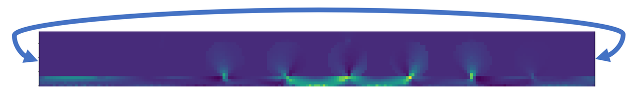
or

Custom polar grid representation

Convolutional models use the polar grid representation internally ⑥

- Wrap padding

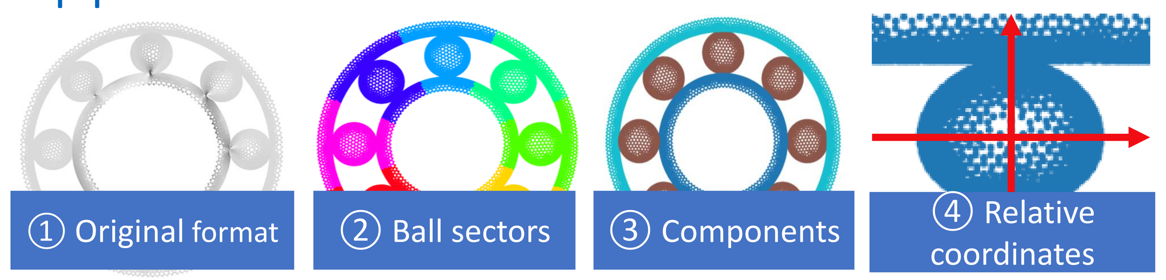
  Angles are **2π-periodic**. The horizontal axis of ⑥ describes an angle. Standard convolutions do not take this into account. To comply with the periodicity, the angle dimension is padded with values from the opposite border



- Point interpolation Layer

  The ground truth values are scattered to **continuous coordinates**, whereas the intermediate representation is a **grid** ⑥. The custom point interpolation layer applies bilinear interpolation from the grid to the continuous coordinate points taking the periodicity into account. To ensure learning, the layer enables gradients

Applied data transformations



① Original format ② Ball sectors ③ Components ④ Relative coordinates

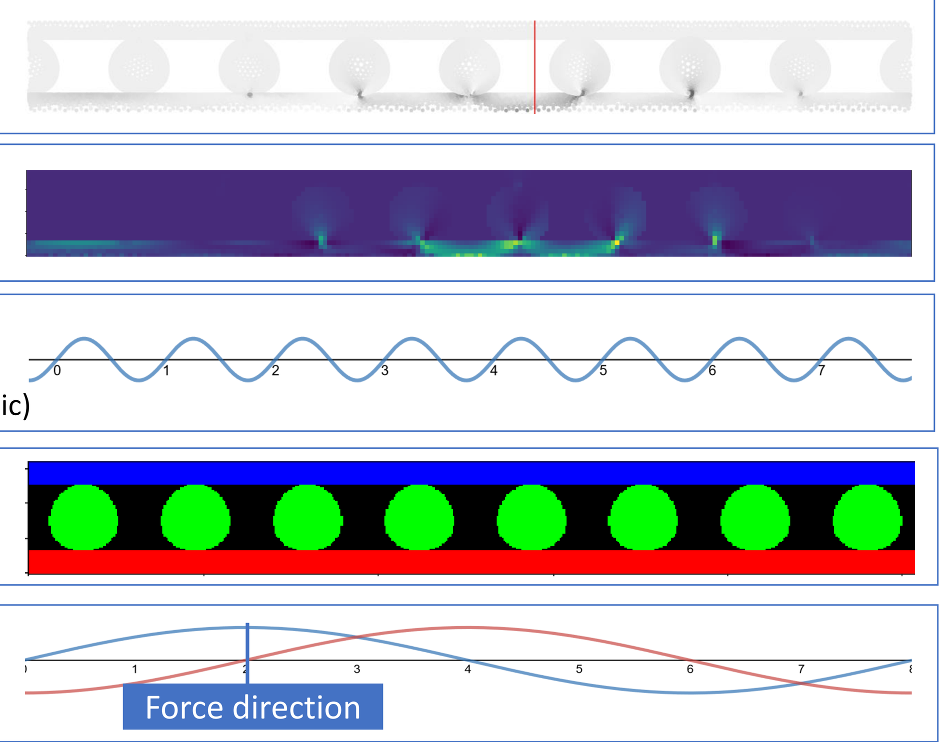
⑤ Polar coordinates

⑥ Polar grid representation

⑦ Ball 1D grid encoding (cos / any periodic)

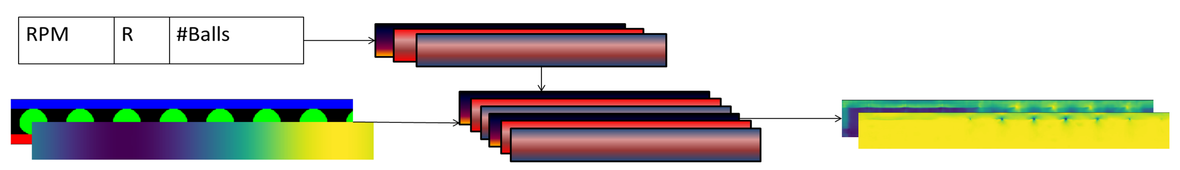
⑧ Ball 2D grid encoding

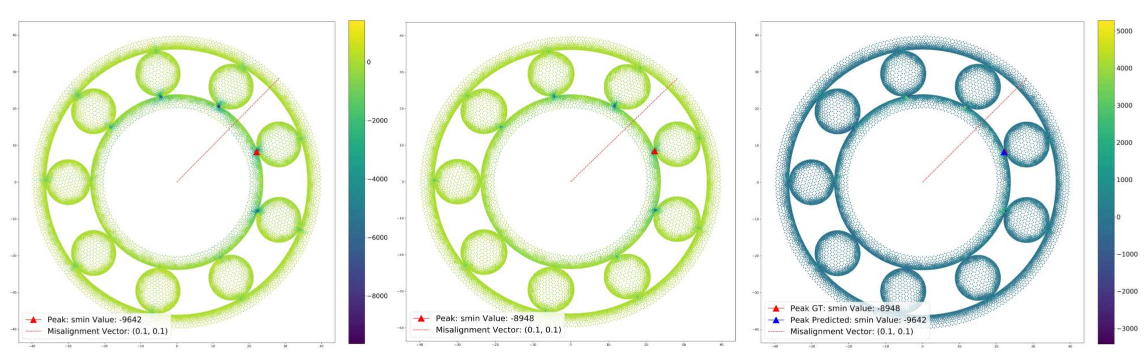
⑨ Force 1D grid encoding (sin / cos)



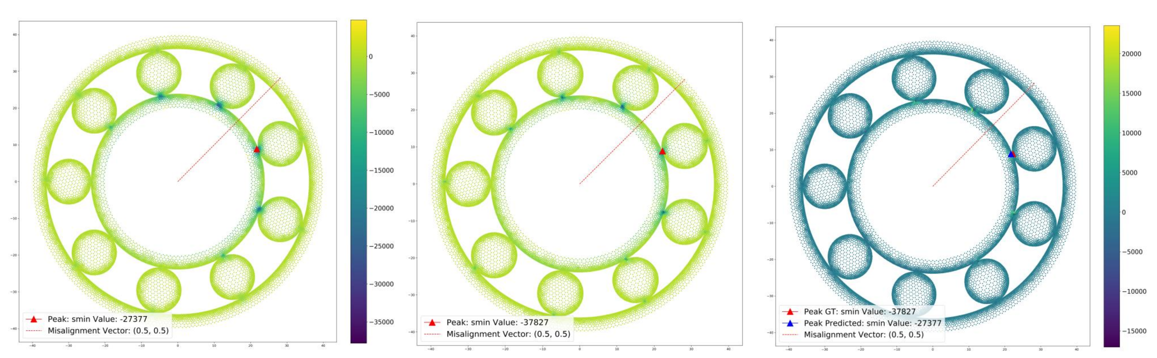
2D Convolutional Model

- Input:
  - Ball 2D grid encoding ⑧
  - Force 1D grid encoding ⑨ broadcasted to 2D
  - Scenario (rpm, misalignment magnitude) broadcasted to 2D
- Intermediate:
  - Stress grid representation ⑥
  - Use standard techniques from Image Processing, such as 2D convolutions, inception layers and residual blocks
- Output:
  - Interpolated smin/smax for each coordinate



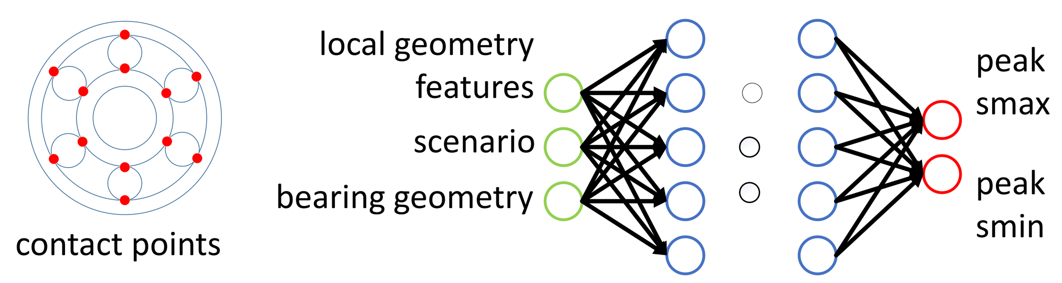


best prediction (top), worst prediction (bottom)
Prediction (left), ground truth (middle), difference (right)

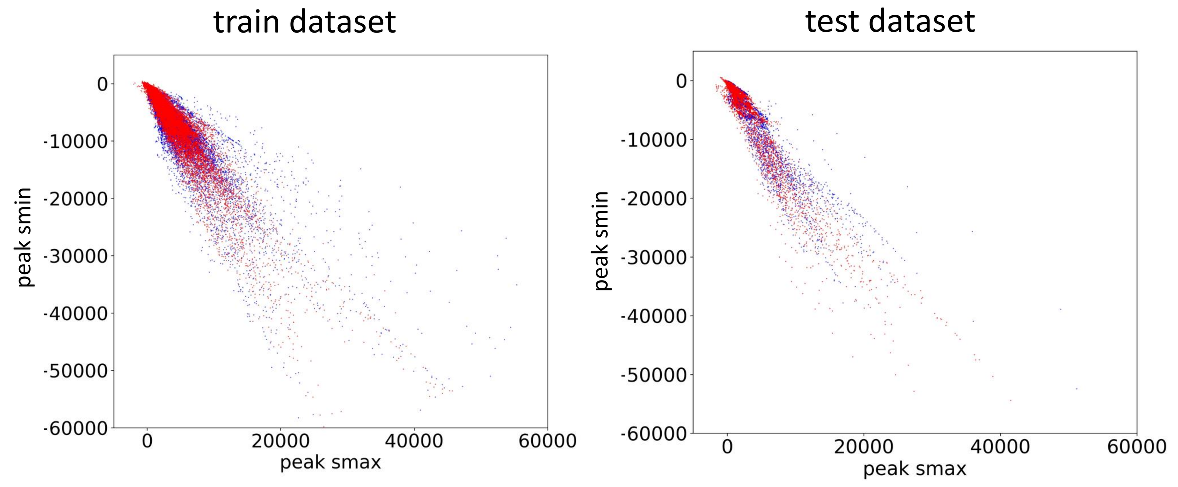


Peak Prediction + Propagation

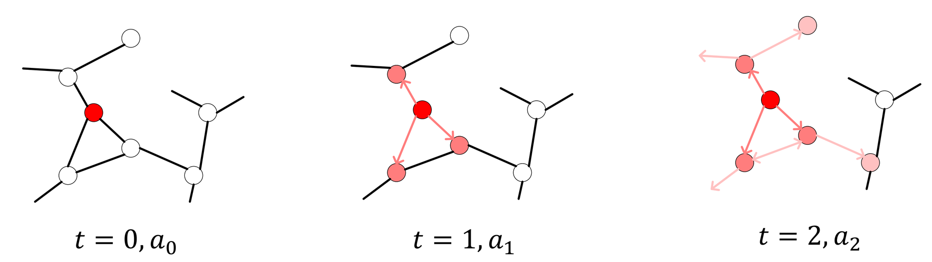
- Predict the peaks (highest for smax, lowest for smin) near the contact points of the balls and the inner/outer ring using dense neural networks (3 layers, 76 hidden units, ReLU, L2 regularization: 3e-07, obtained with hyperparameter optimization)



- Blue points show the ground truth peaks and red points the prediction by the model



- Construct a graph for each bearing by connecting coordinate points if their distance is below a fixed threshold. We normalize the corresponding adjacency matrix. Predict the stress at the peaks



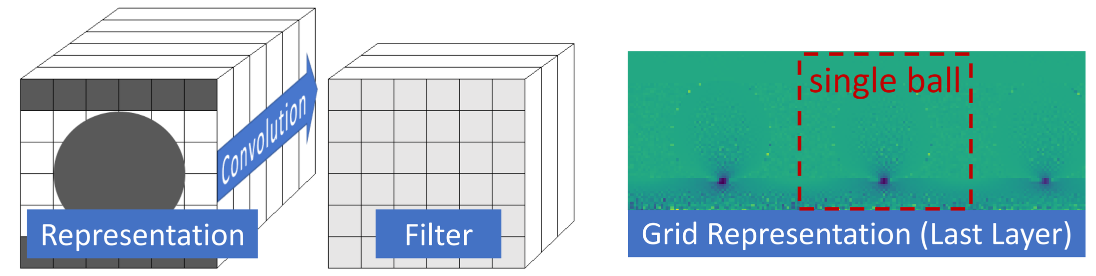
- Simulate flow from the peaks to the other nodes for 40 timesteps. The flow from vertex i to vertex j at time t depends on the normalized adjacency matrix, the incoming flow on j and is proportional to a_t, which is a learnable parameter

Naïve Dense Model

- Input: naïve scenario
- Output: smin/smax for each coordinate

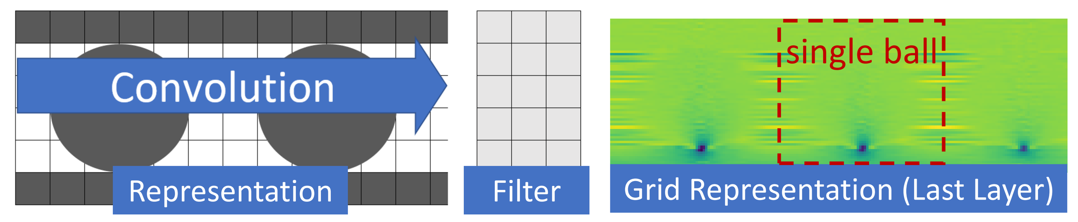
1D Ball Convolution

- Input: ⑨, scenario
- Intermediate: modification of ⑥ to tensor:
  - Squared ball matrices stacked along 3rd axis
  - Convolution with wrap padding along 3rd axis
  - Reshaping to ⑥ after last convolution
- Output: interpolated smin/smax for each coordinate



1D Angle Convolution

- Input: ⑨, ⑦, scenario
- Intermediate: ⑥, 1D convolution with wrap padding along 2nd (angle) axis
- Output: interpolated smin/smax for each coordinate

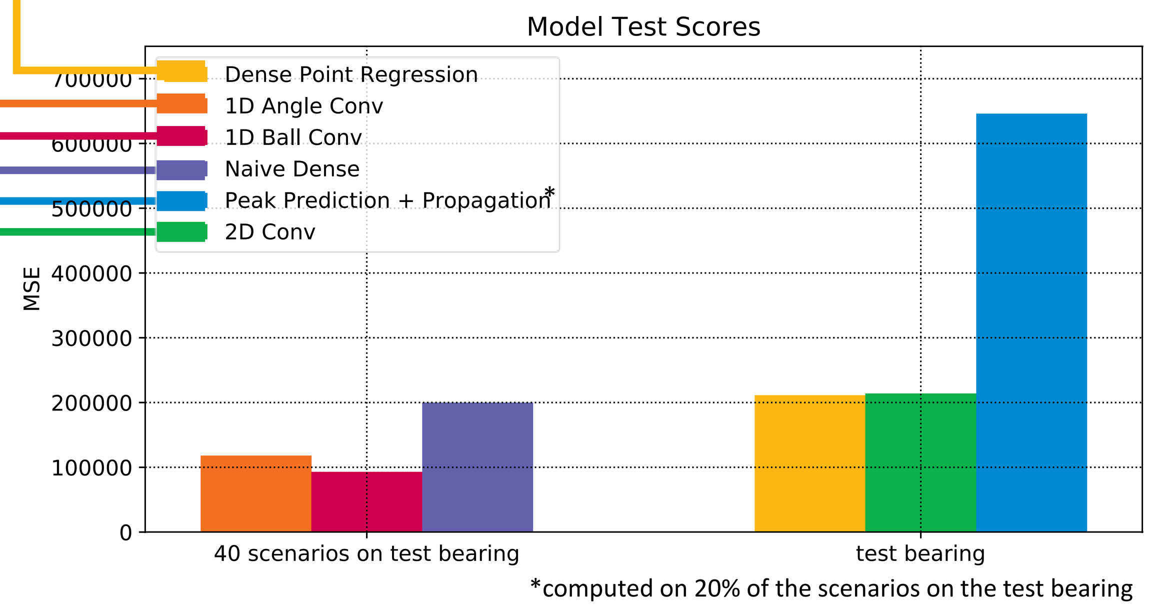


Dense Point Regression

- Input: ③, ④, geometry, scenario, relative force angle to ball center, one sample consists of one smin/smax pair
- Intermediate: dense network
- Output: smin/smax for a certain point

Evaluation

- We compare models, which generalize over multiple bearings by comparing the MSE on all coordinates and scenarios on an unseen test bearing
- The models that do not generalize over multiple bearings are trained on the test bearing and compared to each other on 40 selected scenarios on the test bearing



*computed on 20% of the scenarios on the test bearing

- The models that are trained on a specific bearing outperform the models, which generalize over multiple bearings on scenarios from that specific bearing