An Industry 4.0 example: real-time quality control for steel-based mass production using Machine Learning on non-invasive sensor data

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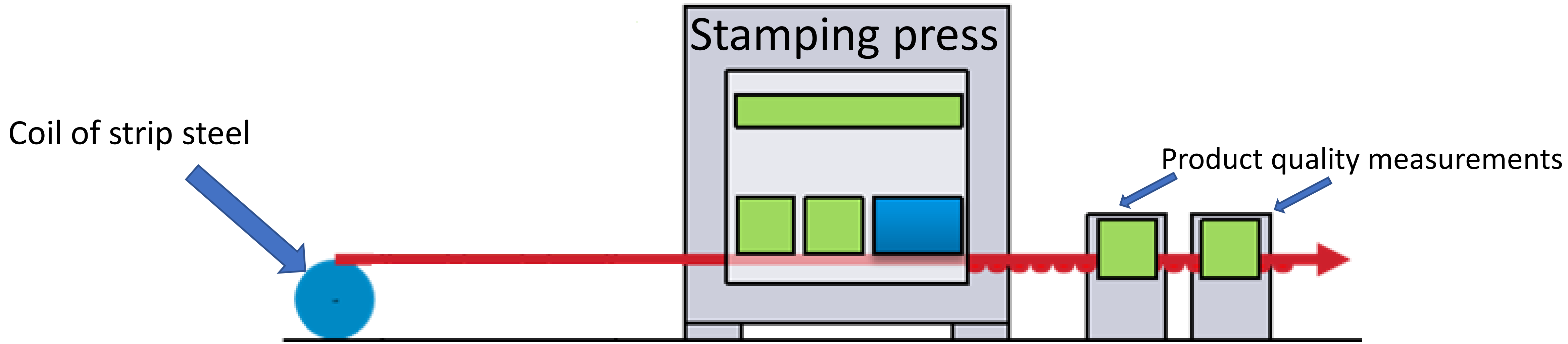
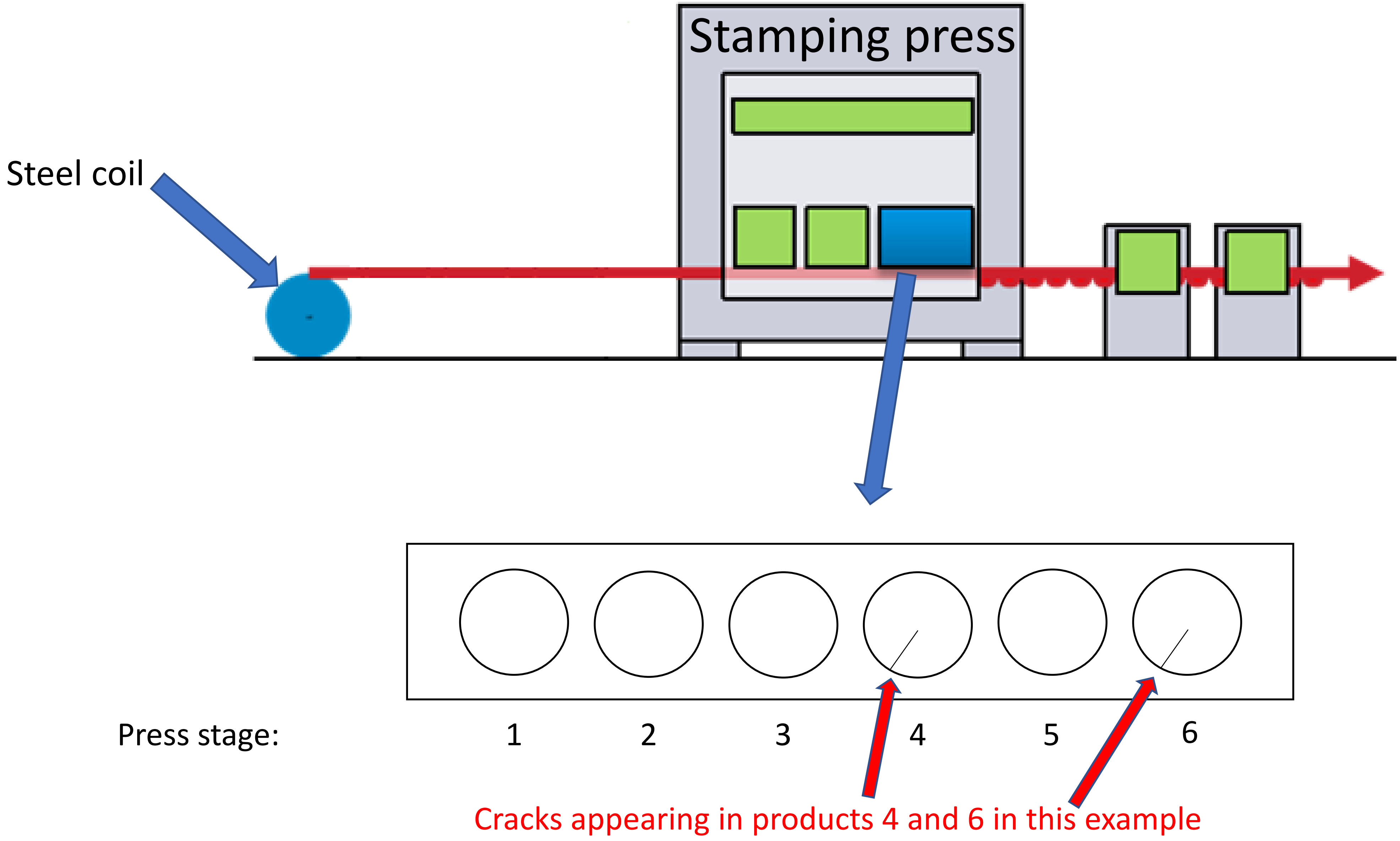
Problem overview

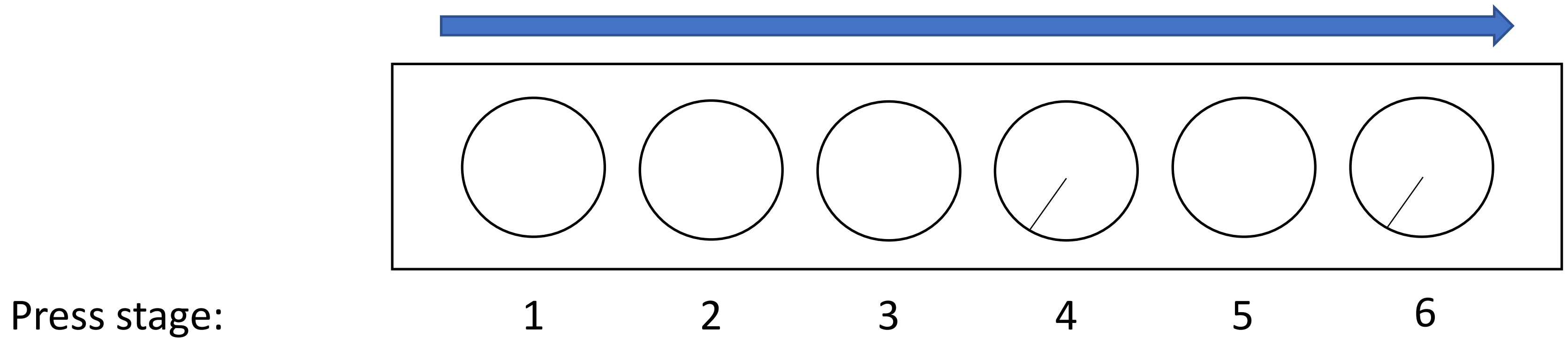


- Progressive stamping @ 180 strokes per minute.
- Tens of thousands of products per day.

Problem overview



Problem overview



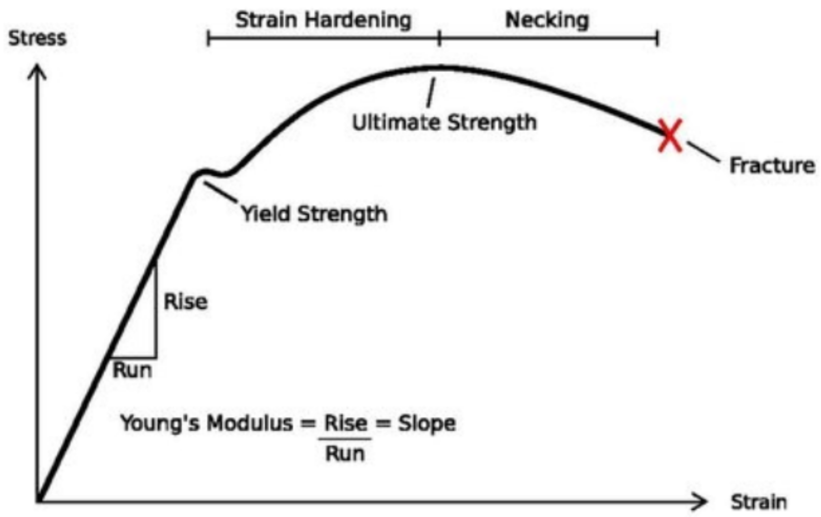
Consequences product faults:

- costly damage to tooling.
- production down time.
- When undetected: low quality products at final stage.

Hypothesis: the faults are caused by material that does not conform to specifications.

Testing the material

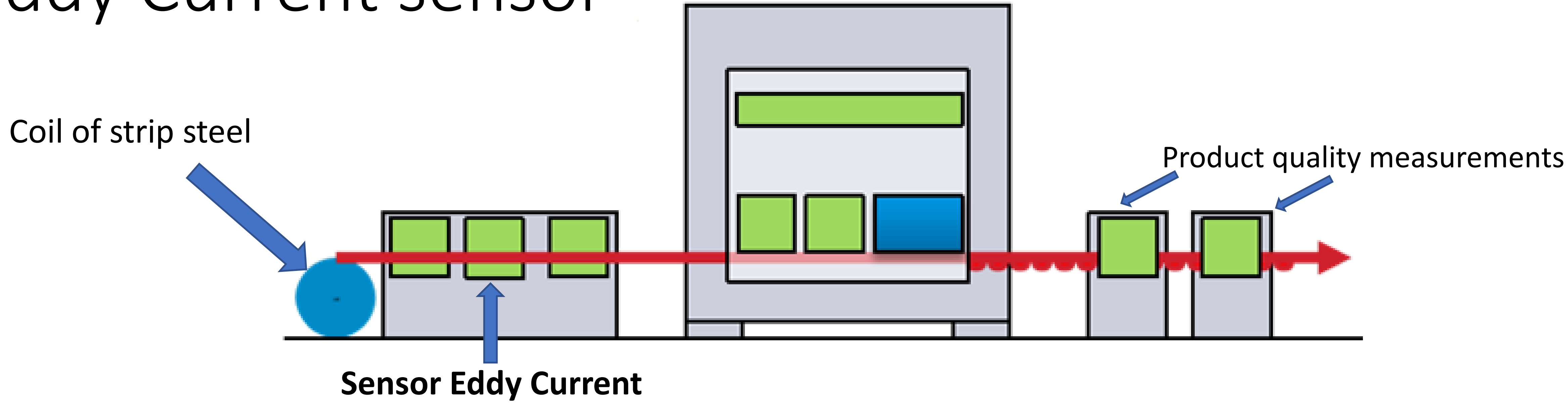
- Tensile tests on sampled steel
- Interpolation over large amount of steel
- **Cannot detect quickly changing material properties**

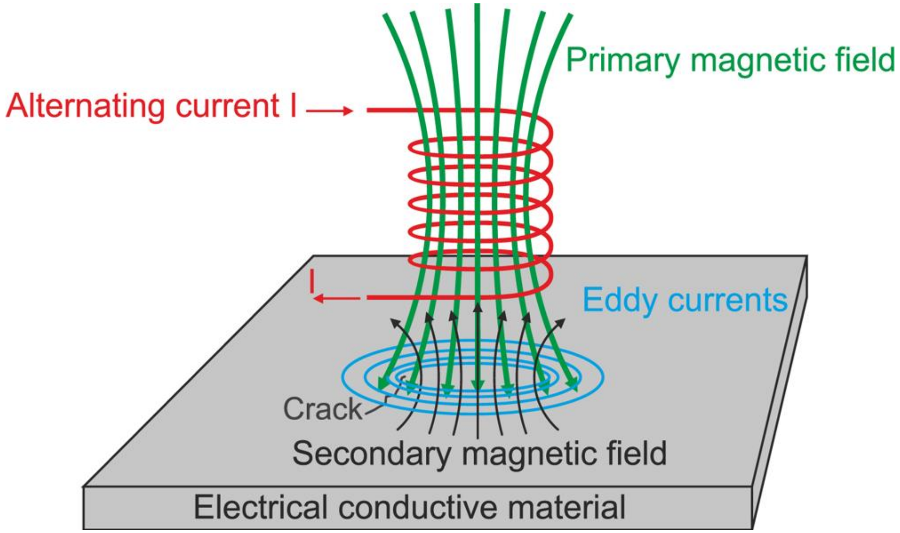


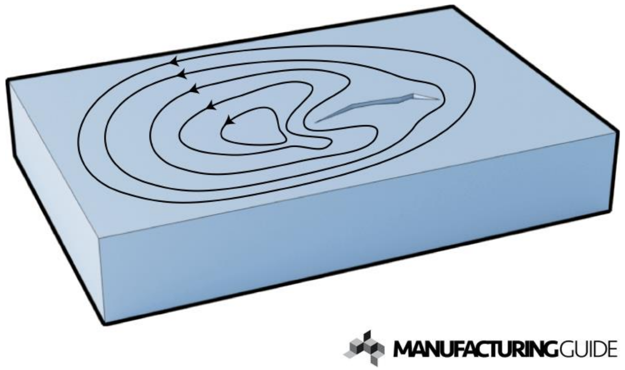
https://nl.wikipedia.org/wiki/Trekproef
https://www.smalley.com/blog/tensile-strength-hardness-importance-tensile-strength-wave-spring-and-retaining-ring-design

Solution: real-time quality control based on in-line sensor measurements

Eddy Current sensor



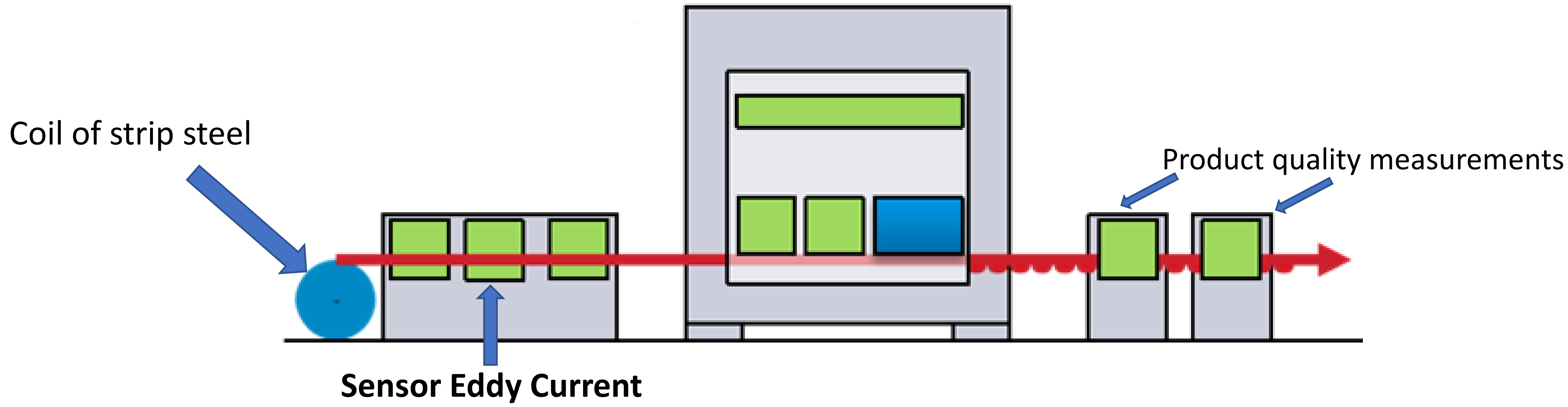




García-Martín, J.; Gómez-Gil, J.; Vázquez-Sánchez, E. Non-Destructive Techniques Based on Eddy Current Testing. *Sensors* **2011**, *11*, 2525-2565.

https://www.manufacturingguide.com/en/eddy-current-testing-et

Goals

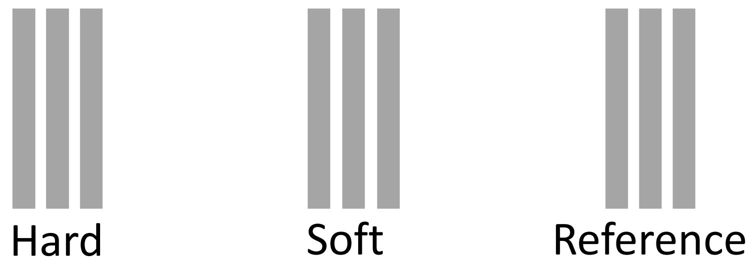


- Goal 1: relate Eddy Current measurements to material properties.
- Goal 2: relate material properties to product faults.

Dataset 1

- **Altered material**

- Sensor measurements on deliberately altered material:

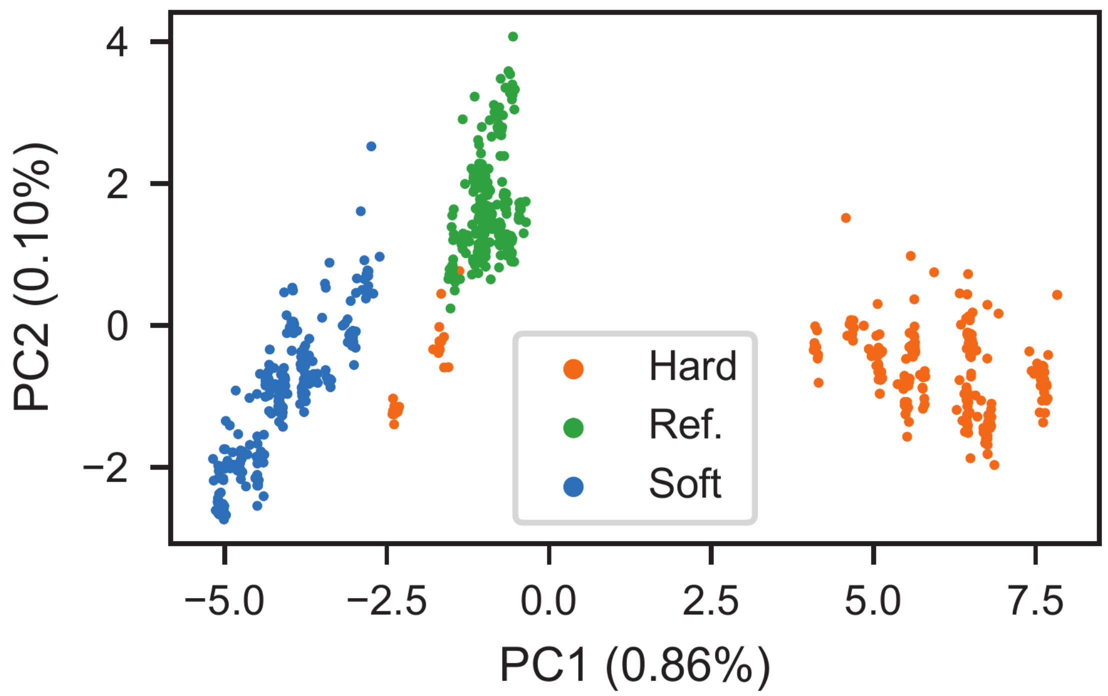


- Verify that sensor can differentiate these groups
- Lower/upper bound of values

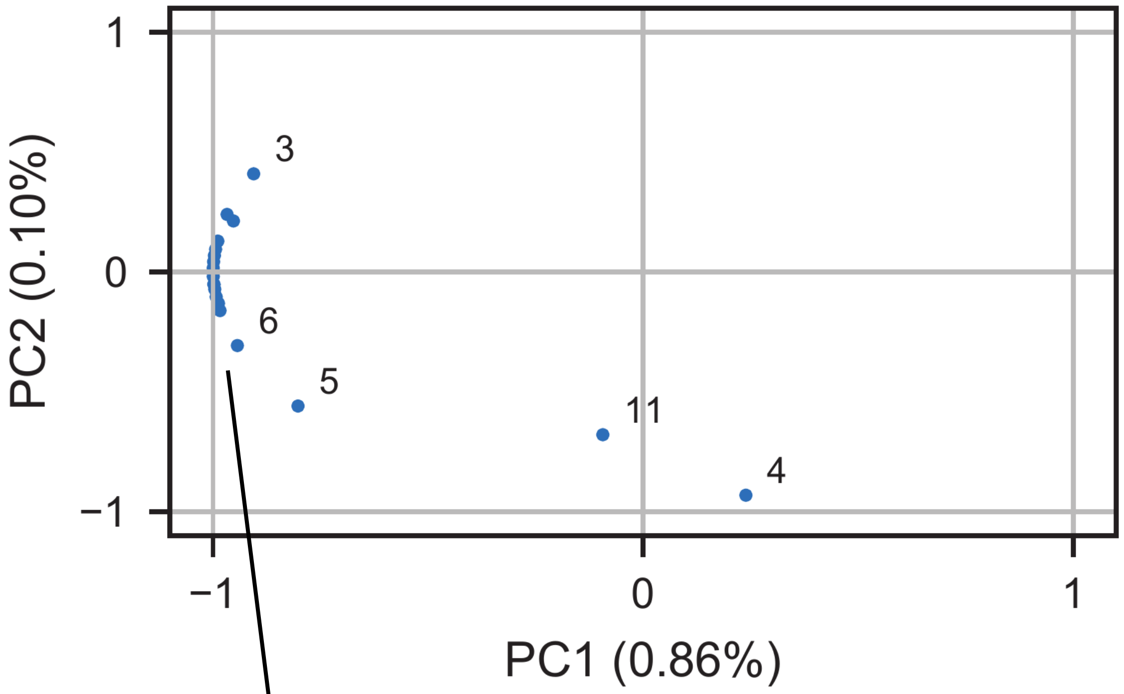
Altered material

Principal Component Analysis on sensor measurements

Projection of data points on Principal Components



Variable loadings on Principal Components

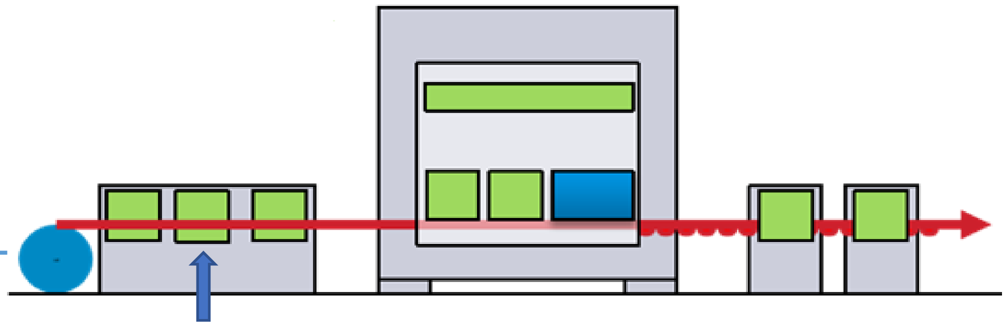


The different material properties are clear in the sensor data on PC 1

Large positive correlation between variables

Dataset 2

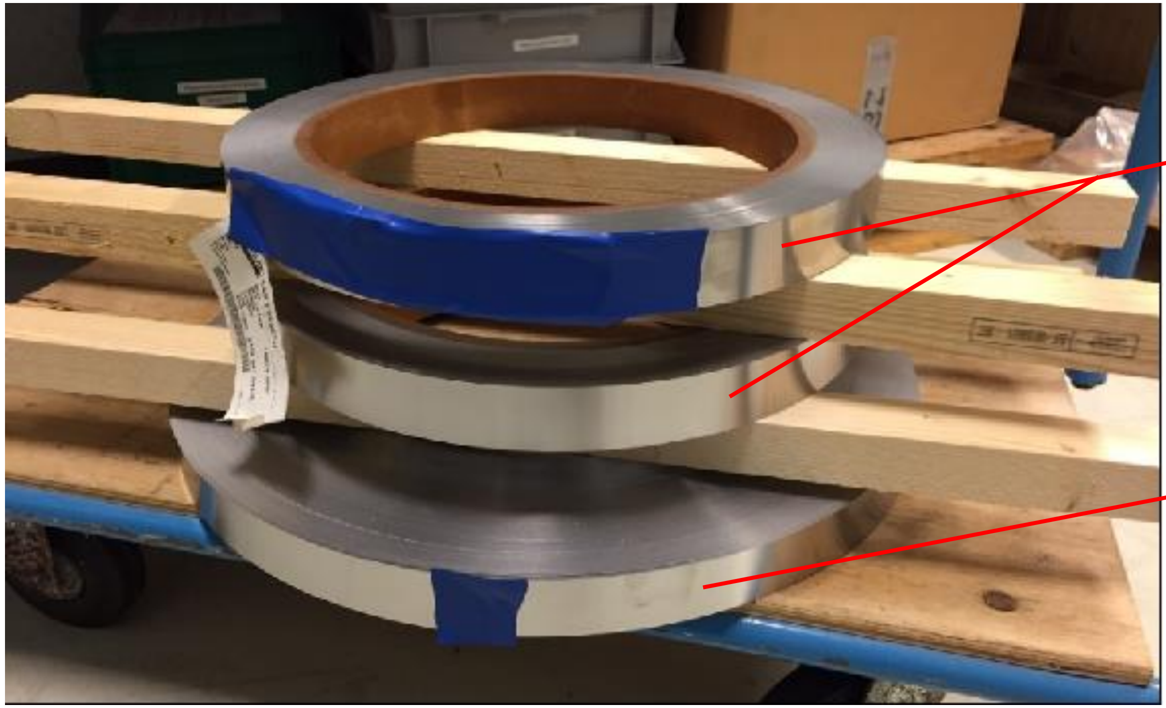
- Altered material
- **Tensile tests and Eddy Current of production coils**



- Tensile test samples at start of the coil
- Eddy Current measurements while producing with the coil

Dataset 2

- Altered material
- **Tensile tests and Eddy Current of production coils**

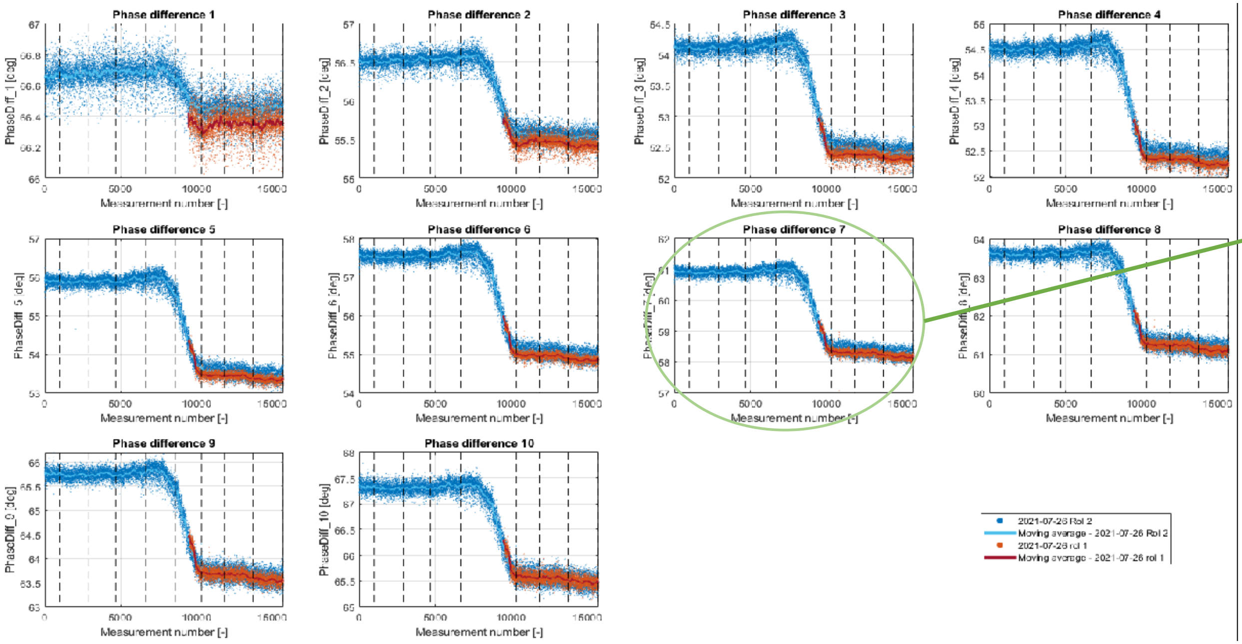


Coils rejected halfway due to cracks in products

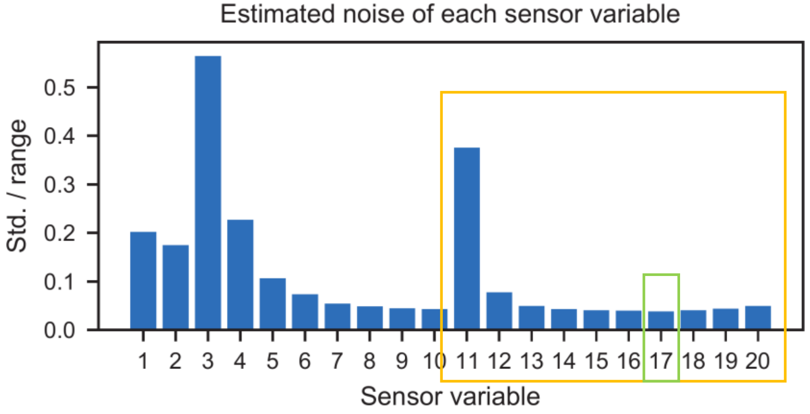
Coil rejected preventively and labeled “testcoil”.
-> Measure this coil with the sensor and take 9 tensile tests over the full length of the coil.

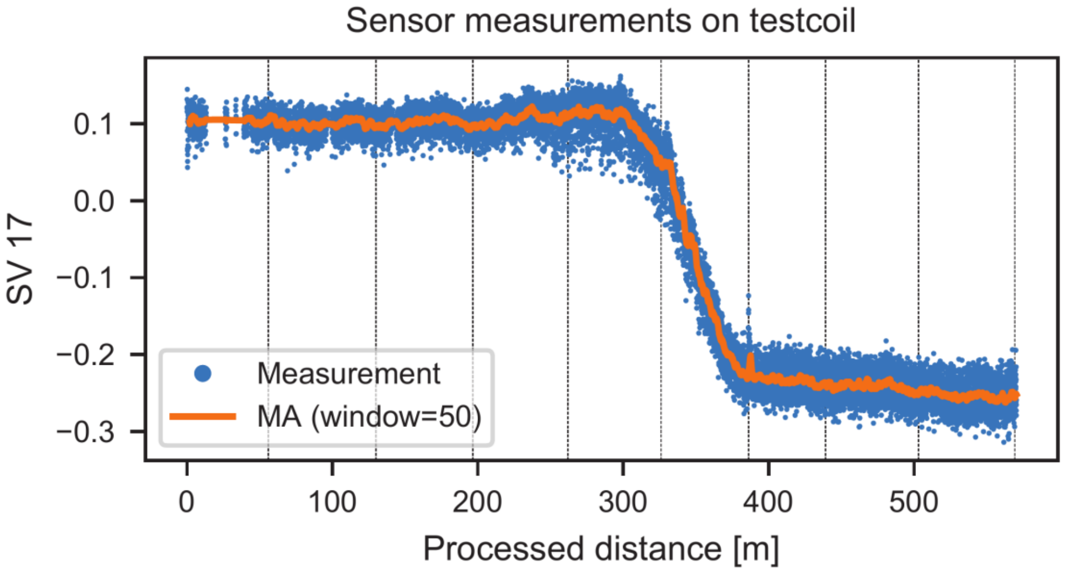
Tensile tests and Eddy Current

Eddy Current phase variables for the testcoil



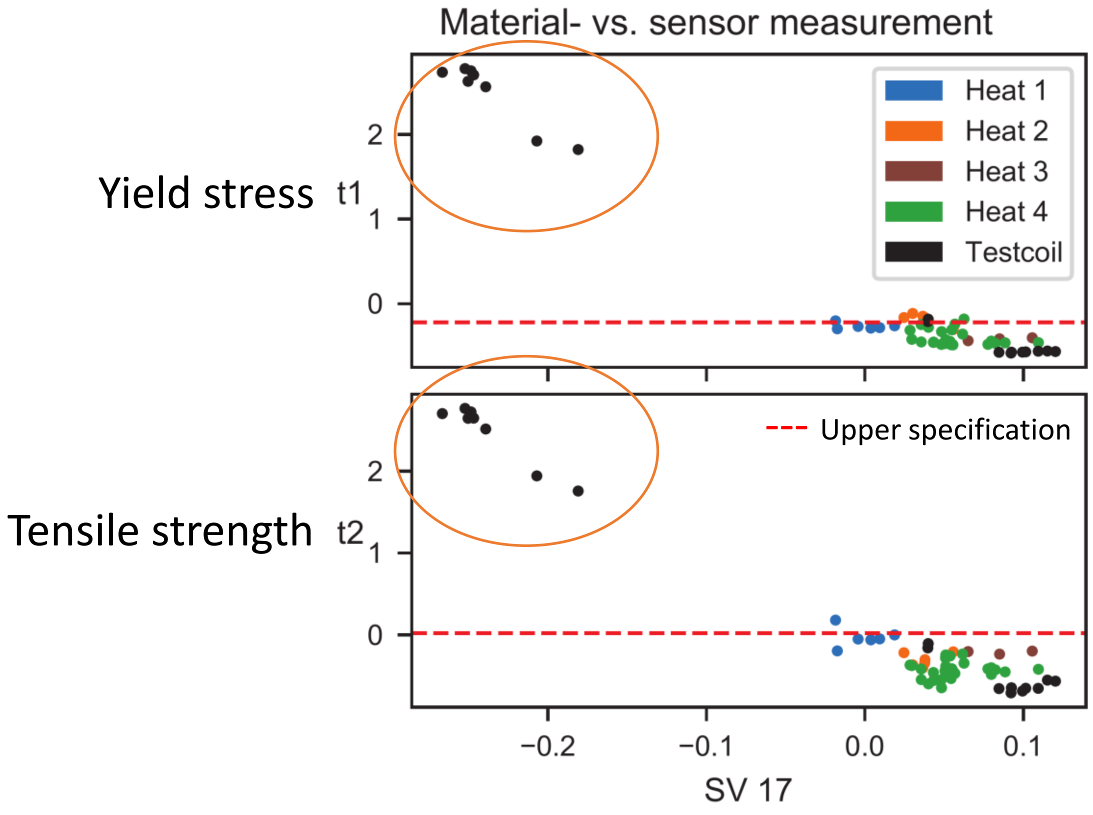
-> highly correlated, but different noise





TODO: resultaten tensile tests testcoil

Tensile tests and Eddy Current



- Correlations appear linear
- Material properties of testcoil are far exceeding the specifications

Tensile tests and Eddy Current

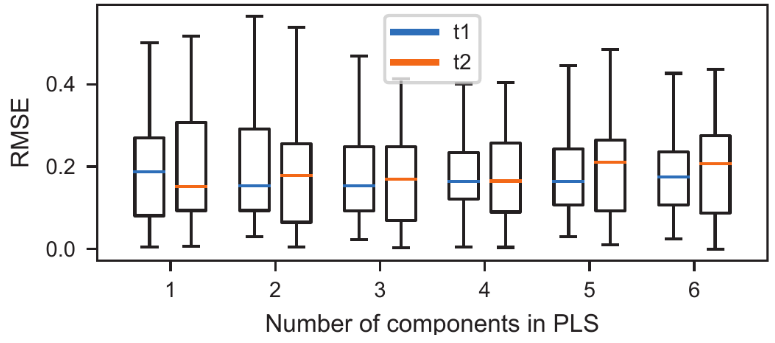
Fit *Partial Least Squares* regression model relating sensor data $\boldsymbol{X} \in \mathbb{R}^{N\times 20}$ to material properties $\boldsymbol{Y} \in \mathbb{R}^{N\times 2}$.

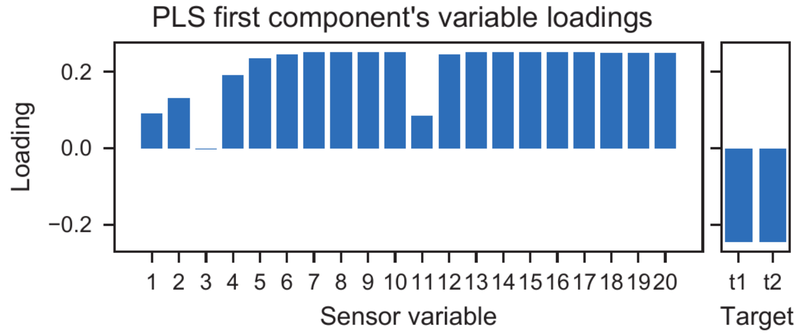
Model assumption: $$\boldsymbol{X} = \boldsymbol{T}\boldsymbol{P}^{\boldsymbol{T}} + \boldsymbol{E}\,,$$ $$\boldsymbol{Y} = \boldsymbol{U}\boldsymbol{Q}^{\boldsymbol{T}} + \boldsymbol{F}\,.$$

Optimization: find loadings $\boldsymbol{P}$ and $\boldsymbol{Q}$ so that the covariance between latent variables $\boldsymbol{T}$ and $\boldsymbol{U}$ is maximum.

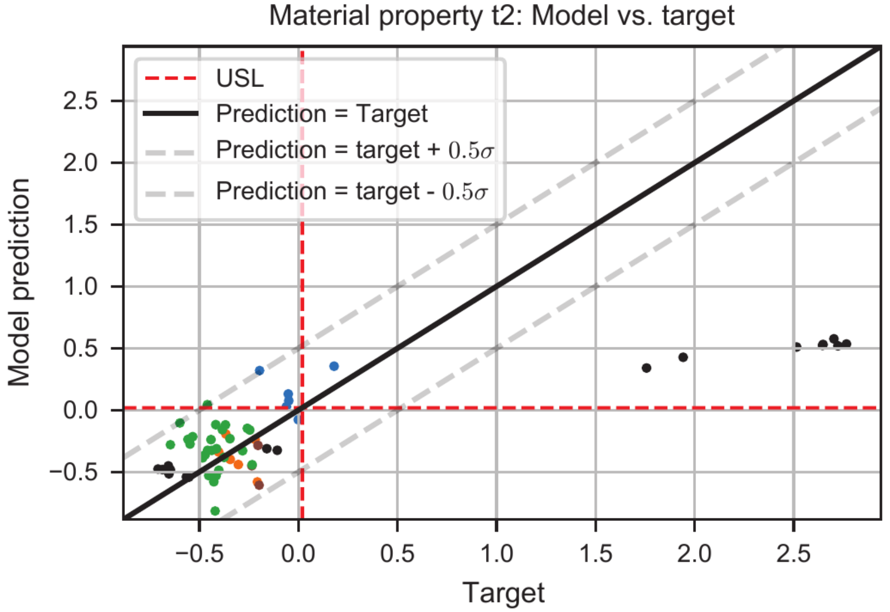
Partial Least Squares results

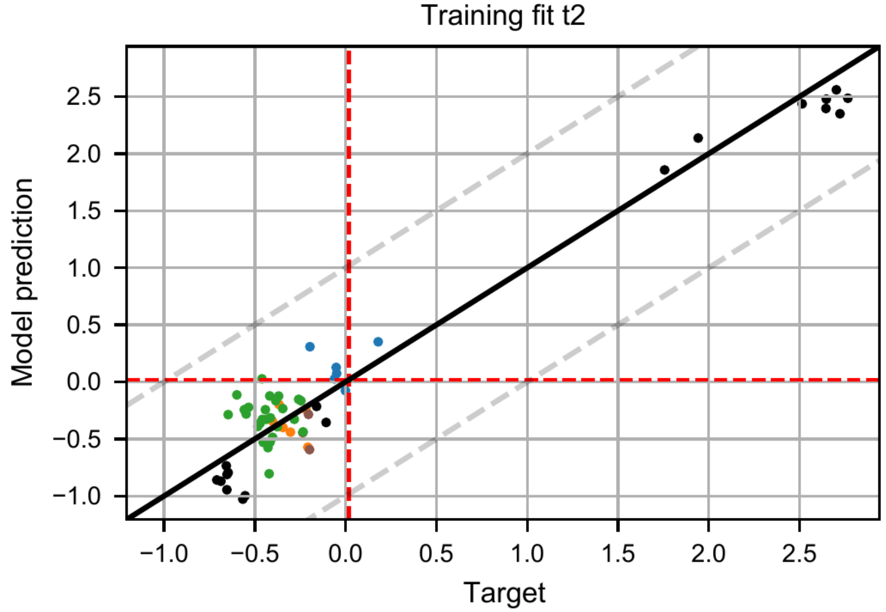
Average cross validation RMSE



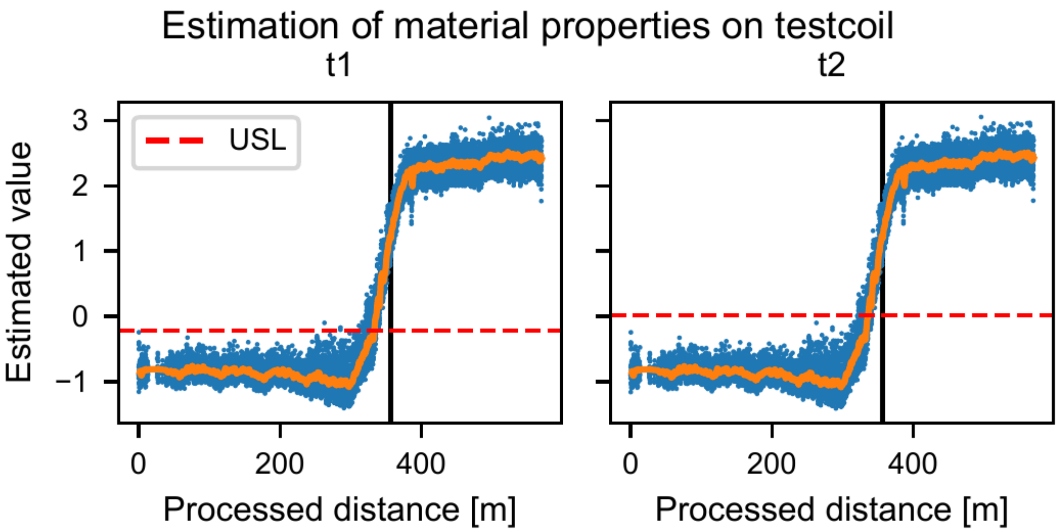


Cross-validation fit





Model predictions on testcoil



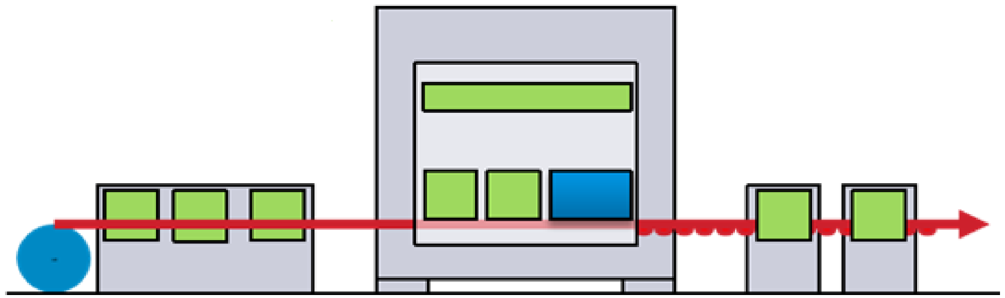
Dataset 1 and 2: conclusions

- The sensor can differentiate between the varying material properties.
- Partial Least Squares model fitted to the data which estimates material properties from the sensor readings.
- The model can detect quickly changing material properties, so that the line can be stopped preventively.

Dataset 3

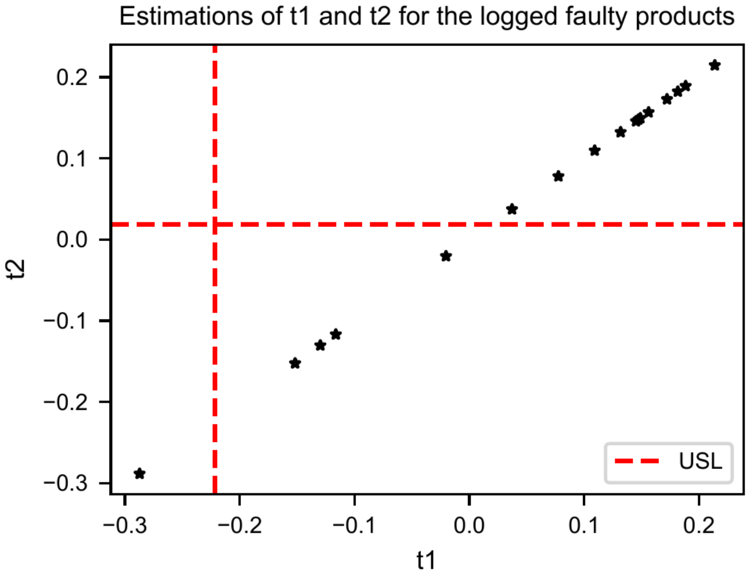
- Altered material and faulty material
- Tensile tests and Eddy Current of production coils
- **Logbooks of production covering 108 km of coil**

Logbooks of production covering 108 km of coil

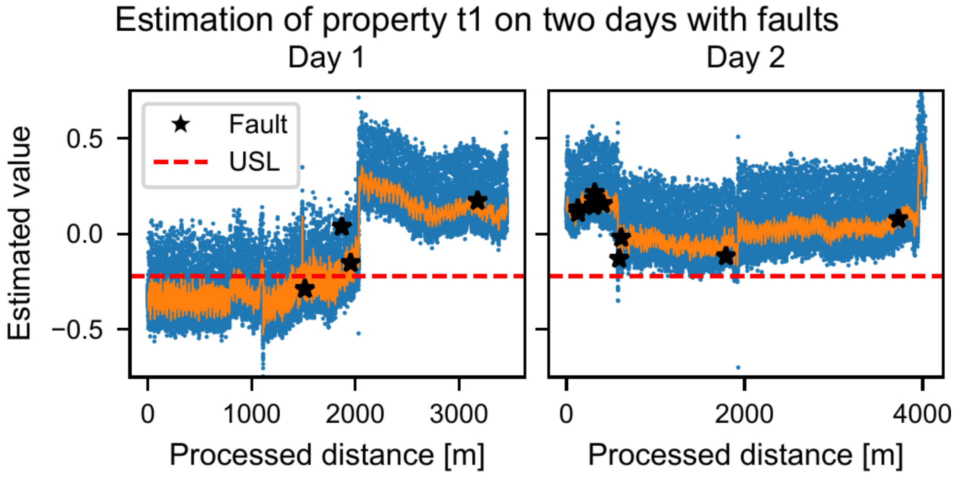


- Covers 108 km of processed steel measured with sensor
- Operators logged the time of product faults and in a few cases the product ID
- Can the model estimations help in the prediction of faults?

Dataset 3: Logbooks of production



- Of the 16 reported faults, 15 exceed the specification limit of t1



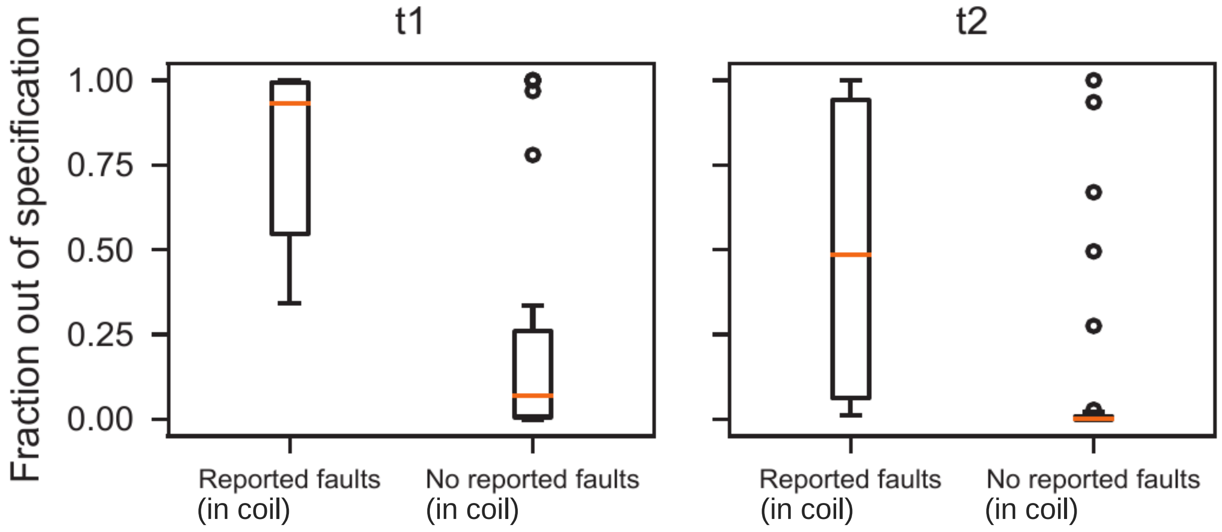
- However, many predictions exceed the specification limits on the corresponding production days.

- Moreover: supervised training of a fault classifier yielded an average ROC of 0.58.
- Hence no direct distinction possible between faults and no faults based on Eddy Current.

Dataset 3: Logbooks of production

So what can we do?

- Compare statistics of the estimations between coils: e.g. fraction of measurements not conforming to specifications



Product faults are associated with a large percentage of predictions that are out of the specifications.

Conclusions

- Relationship between Eddy Current and tensile tests exploited to develop real-time material property estimation
- Partial Least Squares model
- The model is able to detect quickly changing material properties -> automatic preventive product stops.
- Not in all cases were cracks detectable from Eddy Current measurement and material property estimation.
- Cracks always occurred in coils with a large fraction of estimated out of specification material -> risk factor.

Future work

- Measure more data of deviating material to validate the model.
- Interplay between material properties and the press -> incorporate the machine parameter settings in the model.
- Aim: Optimize the machine settings for the real-time measured material: