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

Michiel Straat\(^{[1]}\), Kevin Koster\(^{[2]}\), Nick Goet\(^{[2]}\), Kerstin Bunte\(^{[1]}\)

\(^{[1]}\)Bernoulli Institute, University of Groningen, The Netherlands
\(^{[2]}\)Philips Personal Health, MG Innovation DTN, Drachten, The Netherlands
Problem overview

- Made out of steel coils that are up to a kilometre long
- Tens of thousands of products per day.
- Progressive stamping @ 180 strokes per minute.

- Material properties need to conform to strict specification limits in order to be appropriate for the tooling

https://www.materials.sandvik/fr/products/strip-steel/strip-products/

https://www.hudson-technologies.com/blog/progressive-die-stamping-overview/
Problem overview

Cracks appear in the products at station 4 and 6 in this example (these cracks are usually not visible in the input material).

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 (e.g. too hard or brittle material)
Tensile tests of the material

- Tensile tests on samples of the strip steel, covering only a small fraction of the coil
- Requires interpolation over large amount of steel
- **Not a solution for detecting quickly changing material properties**

Goal of this work: predict yield strength and tensile strength for all material that is used in production, in order to prevent faults occurring in the press.

https://www.smalley.com/blog/tensile-strength-hardness-importance-tensile-strength-wave-spring-and-retaining-ring-design
In-line sensor

Coil of strip steel

Sensor Eddy Current

Stamping press

Product quality measurements

Non-Destructive Testing (NDT)

Alternating current I → Eddy currents

Primary magnetic field

Secondary magnetic field

Crack

Electrical conductive material

Responding coil

• 10 test frequencies, yields measurements $x \in \mathbb{R}^{20}$

• Very quick (2ms) contactless measurement

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

• Question 1: Can we predict material properties from the sensor measurements?

• Question 2: Can we prevent product faults using the inline sensor measurements?
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.

Dataset: measurements on outlier coil
Measurements on testcoil

Eddy Current phase variables for the testcoil

Sensor measurements of Phase variable 7 on testcoil

Material properties

Gain variables Phase variables

Estimated noise of each sensor variable

Material properties
(normalized)

Processed distance [m]

Gain variables Phase variables

Material properties
(normalized)

Processed distance [m]
Measurements production coils

For 40 production coils:
- Tensile test samples at start of the coil
- Eddy Current measurements while producing with the coil
- The product faults occurring by producing with these coils were logged by the operators

Operator reports the time of faults in the production logbook. In 16 consecutive cases, the measurement ID of the steel was recovered.
Tensile tests and Eddy Current

Material vs. sensor measurement

Yield stress (averaged)

Tensile strength (averaged)

SV 17 (averaged)

Upper specifications
Predicting material properties from Eddy Current

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

Model assumption: \[
X = TP^T + E,
Y = UQ^T + F.
\]

Optimization: find loadings \( P \) and \( Q \) so that the covariance between latent variables \( T \) and \( U \) is maximum.
Partial Least Squares results

Average cross validation RMSE

Tensile strength: Model vs. target

PLS first component's variable loadings
Model predictions on testcoil

![Graph showing model predictions for yield stress and tensile strength.](image-url)
Predicting faults from Eddy Current measurements

- Of the 16 reported faults, 15 exceed the specification limit of yield stress.

- Supervised training of a fault classifier yielded an average ROC of 0.58.
Are coils with reported faults different?

- Compute of the 40 coils the fraction of predictions exceeding the specifications.
- Compare these fractions between coils with reported faults to coils without reported faults.

A large percentage of predictions exceeding the specifications is a risk factor for product faults.
Conclusion and future work

- Developed real-time material property estimation based on inline sensor measurements.
- Preventive production stops in case of changing material properties.
- A large fraction of estimated out of specification material is a risk factor for faults.

Future work
- Measure more data of deviating material to validate the model further.
- Future aim: Optimize the machine settings for the real-time measured material to obtain the least faults and highest product quality.