eit Manufacturing

LMS
Laboratory for Manufacturing Systems & Automation

RIS Industry 4.0 Hubs

Predictive analytics/ maintenance & industrial applications

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- Predictive maintenance in steel production industry
- Application in steel part production industry
  - Data-driven predictive analytics
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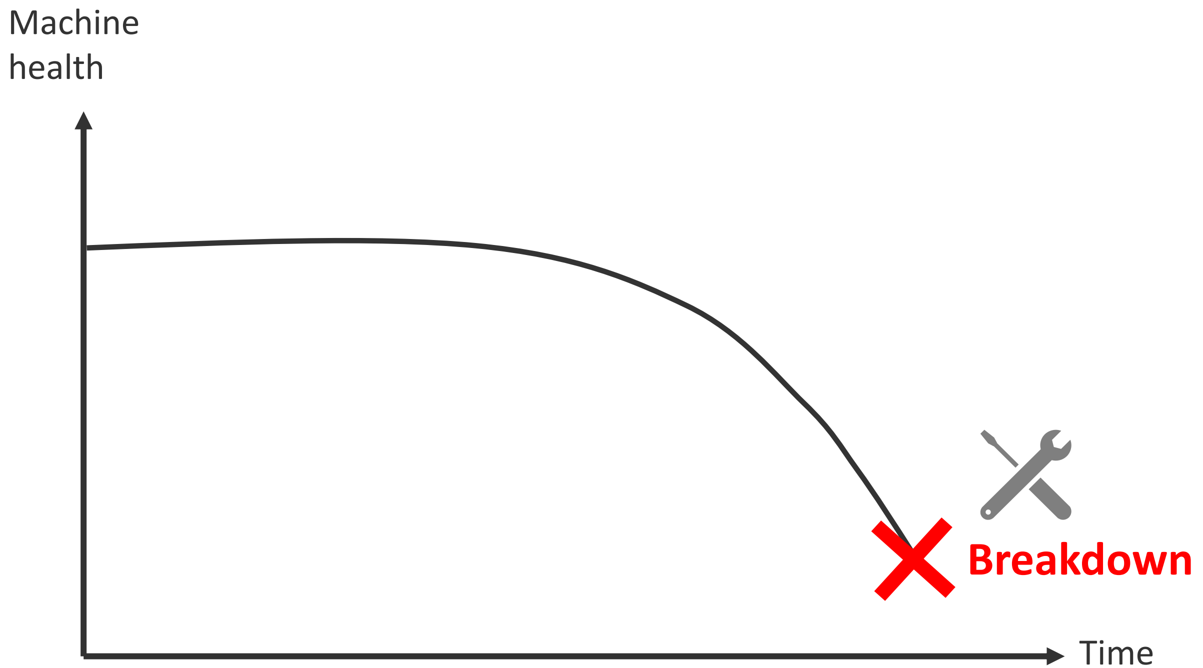
Maintenance strategies

- Reactive maintenance
- Preventive maintenance
- Predictive maintenance

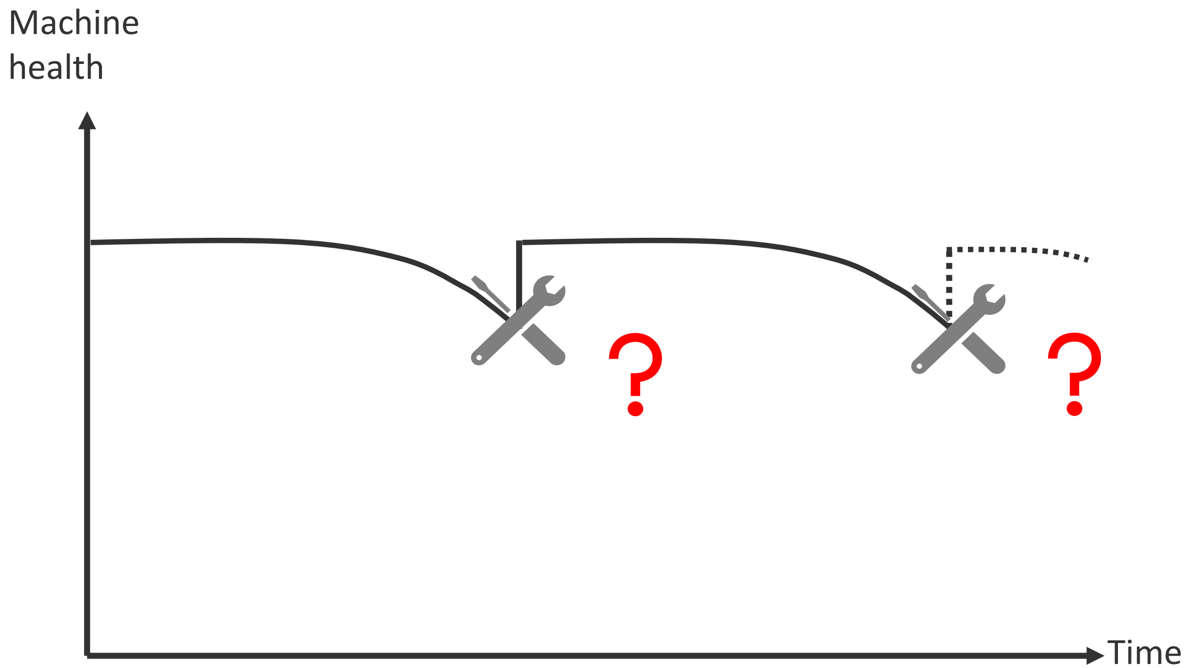
Maintenance strategies

- **Reactive maintenance:**
  - Repairs after machine's breakdown
  - No safe
  - Extremely costly



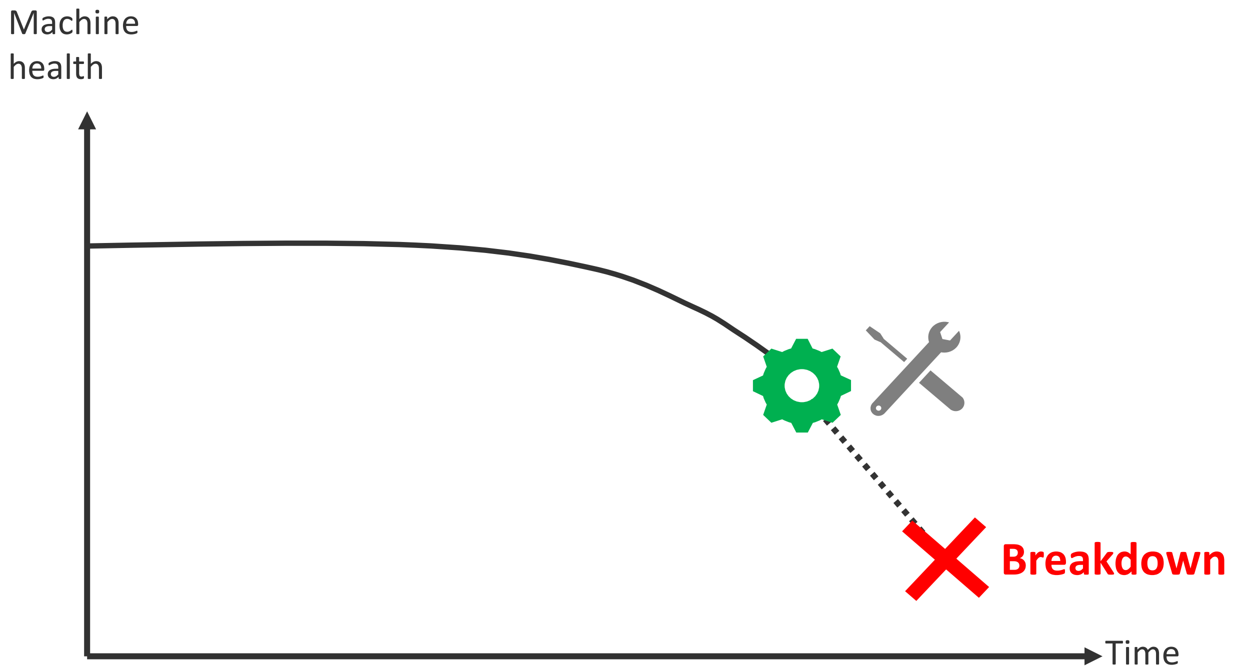
Maintenance strategies

- **Preventive maintenance:**
  - Repairs before machine's breakdown
  - Breakdown can not be predicted
  - Wasting machine's operational life
  - No cost savings



Maintenance strategies

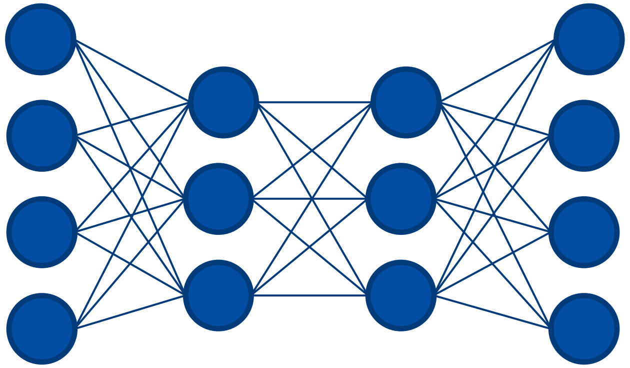
- **Predictive maintenance:**
  - Breakdown prediction
  - Avoid unnecessary maintenance activities
  - Save cost
  - Optimal exploitation of components’ lifecycle



Maintenance strategies

Predictive maintenance

- Data-driven predictive analytics
  - AI and Machine Learning(ML)
  - Neural Networks



- Model based predictive analytics
  - Mathematics/physics models

$$W = \int_{f_a}^{f_b} G_{FF}(f)\,df + \int_{f_a}^{f_b} G_{TT}(f)\,df - \int_{f_a}^{f_b} |G_{TF}(f)|\,df$$

$$E\left(\frac{dW}{dN}\right) = \frac{d\overline{W}}{dN} \approx \frac{\Delta W}{\Delta N} = \frac{\Sigma W}{N_t}$$

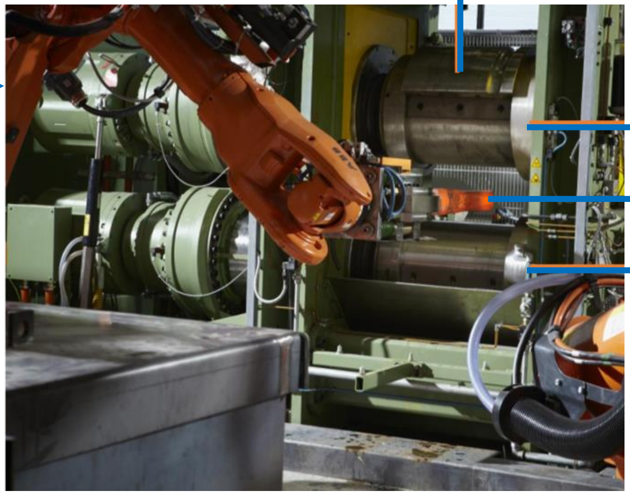
$$N = \left\lfloor \frac{W_p - W_N}{\left(\frac{d\overline{W}}{dN}\right)\Big|_{N=N_t}} \right\rfloor$$

Predictive maintenance in steel production industry

VDL-WEW case study:

Maintenance activities in a highly automated trailing arm production line – Predicting and scheduling the replacement of the coated segments of the machine

Heating → Rolling → Eye-rolling → Forming → Hardening



Preventive maintenance weaknesses:

- Interruptions in the production process
- Reduced productivity
- Unnecessary maintenance activities
- Machine's breakdown

Predictive maintenance in steel production industry

Problem Definition

- The scope of the current approach is the real-time prediction of the Remaining Useful Life (RUL) of the coating segments in a hot rolling mill.
- The segments degrade due to forces, friction and high temperatures during the process.
- The coating thickness cannot be measured during production – an indirect measurement must be applied to indicate their wear.

Hot Rolling Mill

- The rolling mill is composed of two rolling cylinders
- The lower rolling cylinder has a fixed position and only the upper can move linearly
- The segments have a wear-resistant coating that degrades over time.

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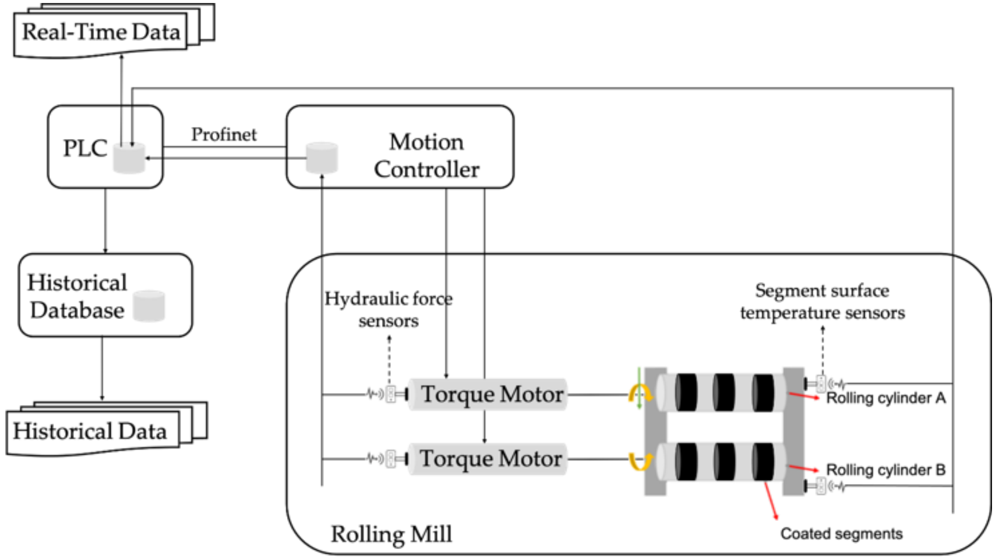
Predictive maintenance in steel production industry

Motivation

- Enabling Predictive Maintenance (PdM) for the coating segments of a hot rolling mill machine, through estimating in real-time their RUL.
- Monitoring the wear stage of machine components can lead to improved scheduling of maintenance activities.
- The occurrence of unscheduled maintenance can introduce costly delays and breakdowns.

Data collection

Timestamp	Segment Top Surface Temperature (Celsius Degrees)	Segment Bottom Surface Temperature (Celsius Degrees)	Cylinder Hydraulic A Force (kilonewtons)	Cylinder Hydraulic B Force (kilonewtons)
2020-01-22T09:26:09	[189, 189, ..., 102]	[548, 549, ..., 90]	[−29, −16, ..., −67]	[15, 3, ..., −30]
2020-01-22T09:26:37	[262, 260, ..., 158]	[542, 540, ..., 527]	[−43, −49, ..., −58]	[−18, 25, ..., −24]
2020-01-22T09:27:03	[199, 198, ..., 94]	[550, 550, ..., 95]	[−46, −67, ..., −61]	[−18, −9, ..., −24]
2020-01-22T09:27:31	[256, 251, ..., 147]	[548, 548, ..., 496]	[−31, −17, ..., −58]	[−2, 20, ..., −34]
2020-01-22T10:28:43	[191, 187, ..., 101]	[550, 550, ..., 93]	[−46, −27, ..., −61]	[−21, −6, ..., −30]
2020-01-22T10:29:11	[260, 256, ..., 157]	[544, 543, ..., 536]	[−46, −21, ..., −60]	[−21, −5, ..., −24]
2020-01-22T10:29:37	[197, 195, ..., 103]	[550, 550, ..., 95]	[−58, −31, ..., −61]	[−15, 13, ..., −18]
2020-01-22T10:30:05	[259, 252, ..., 152]	[550, 550, ..., 511]	[−49, −24, ..., −58]	[−21, −11, ..., −34]
2020-01-22T10:30:33	[197, 194, ..., 103]	[550, 550, ..., 496]	[−16, −18, ..., −61]	[12, 14, ..., −36]



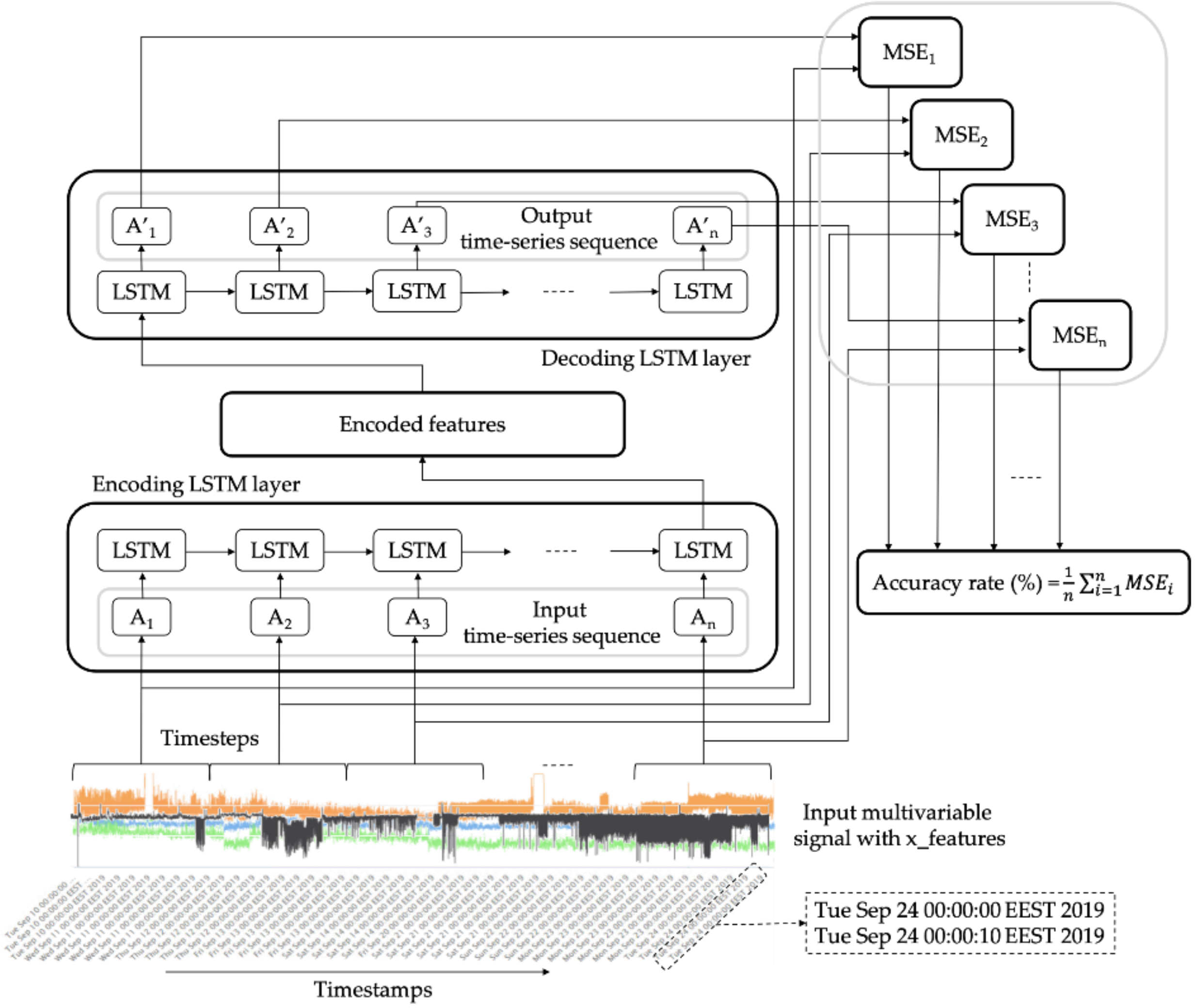
Data-driven predictive analytics

Approach - Overview

- Sensor data for monitoring different parameters of the production machine

- LSTM-autoencoders training for classification of incoming data to different operational status

- Estimation of the RUL value based on the input dataset's performance

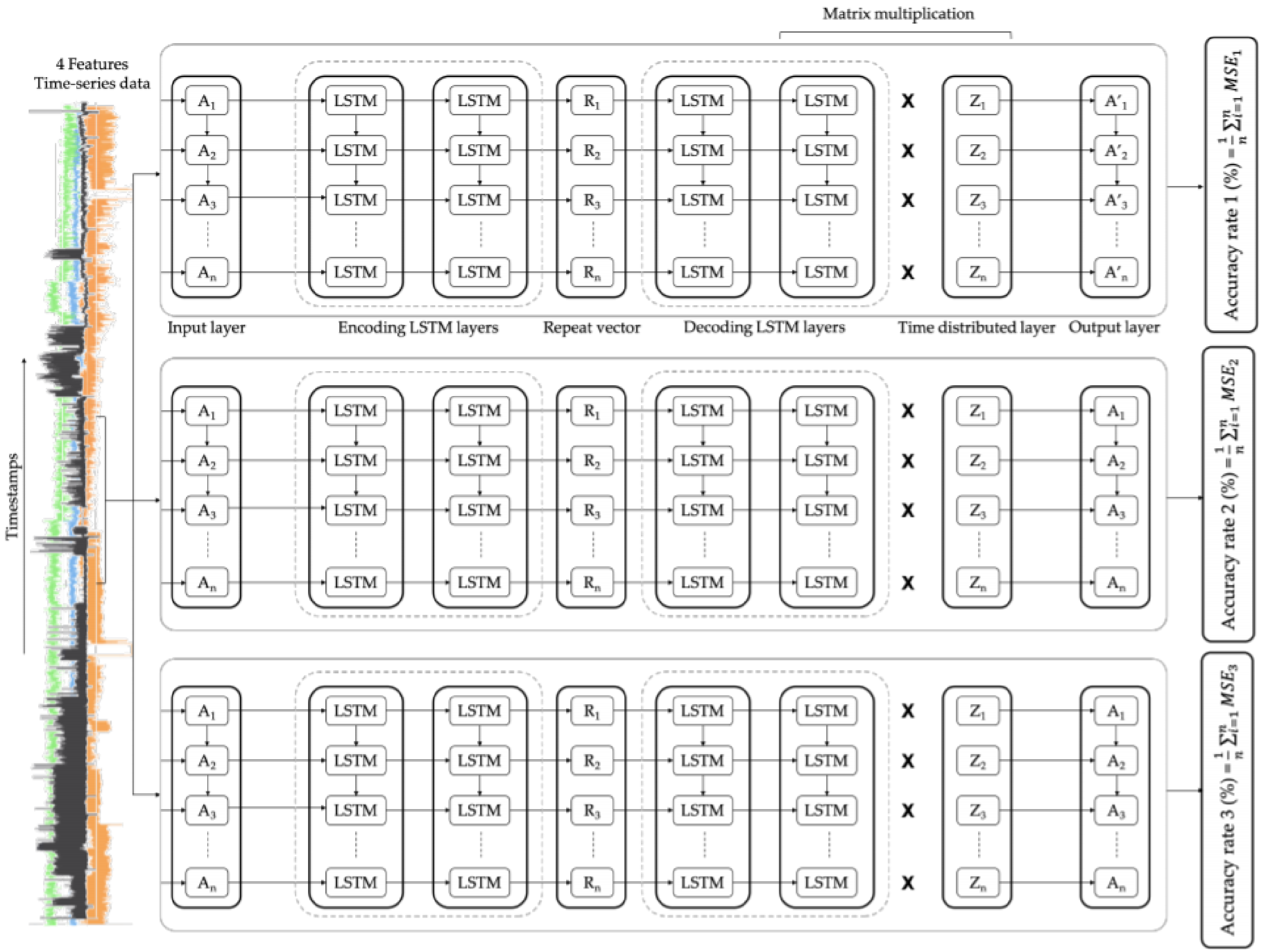


Bampoula, X.; Siaterlis, G.; Nikolakis, N.; Alexopoulos, K. A Deep Learning Model for Predictive Maintenance in Cyber-Physical Production Systems Using LSTM Autoencoders. Sensors ***2021****, 21, 972. https://doi.org/10.3390/s21030972*

Data-driven predictive analytics

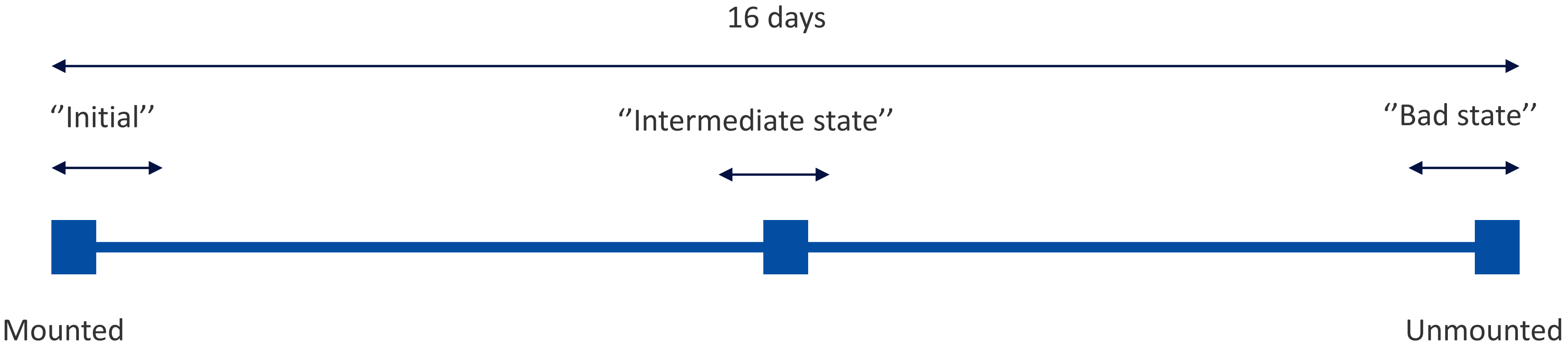
Architecture

- 3 LSTM-autoencoders
- 3 Labels:
  - ''initial''
  - ''Intermediate''
  - ''Bad''
- 3 Accuracy rates



Data-driven predictive analytics

Labeling



Data-driven predictive analytics

Results

Historical Maintenance Records		Accuracy Rates (%)		
Equipment State	Dates	Initial	Intermediate	Bad
Initial	2019-12-24 T 01:01:49–2019-12-25 T 02:42:55	90.09%	83.71%	85.51%
Intermediate	2020-01-10 T 00:38:54–2020-01-10 T 23:01:24	73.42%	82.28%	73.42%
Bad	2020-01-13 T 00:05:47–2020-01-13 T 23:38:20	82.43%	86.74%	91.21%
Initial	2020-02-20 T 00:46:49–2020-02-21 T 22:38:45	96.09%	72.91%	63.44%
Intermediate	2020-02-25 T 01:20:54–2020-02-26 T 03:46:30	75.31%	94.80%	80.15%
Bad	2020-03-01 T 01:53:56–2020-03-01 T 21:37:48	92.54%	82.59%	81.55%
Initial	2020-03-02 T 01:00:14–2020-03-02 T 23:15:53	93.22%	89.10%	88.05%
Intermediate	2020-03-08 T 00:10:24–2020-03-08 T 22:46:33	70.31%	87.80%	80.15%
Bad	2020-03-16 T 09:13:47–2020-03-16 T 21:37:48	89.65%	71.23%	70.41%

Data-driven predictive analytics

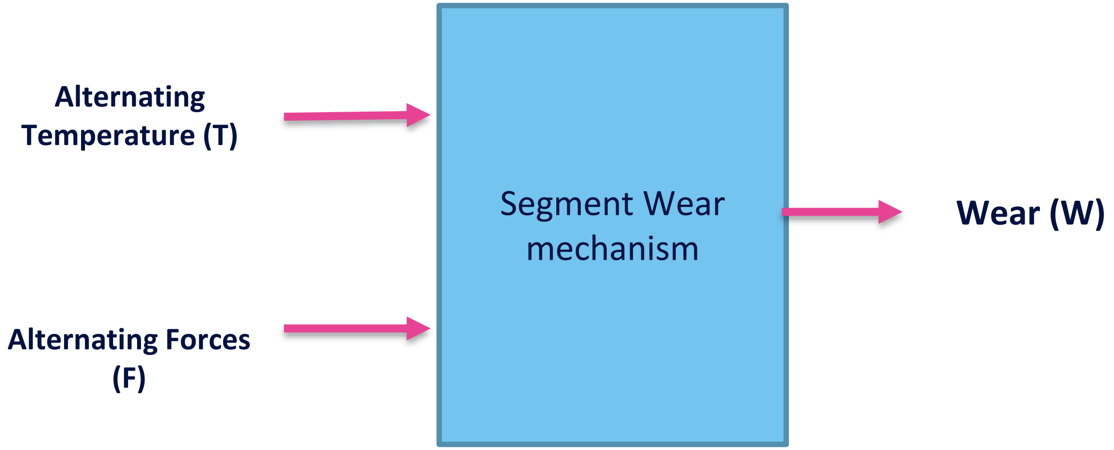
Results

Mounted	Unmounted	Cause	Suggested Unmounted Date	Days Gained
2019-12-23	2020-01-14	Broken	2020-01-13	-
2020-02-19	2020-03-02	Preventive maintenance	2020-03-04	approx 3
2020-03-02	2020-03-16	Preventive maintenance	2020-03-18	approx 5

- Approximately 96 more days of life
- 22.22% reduction in preventive stoppages

Model based predictive analytics

- Products charge the working tools with an excitation dynamic energy that causes wear.
- The working tools have a maximum embodied energy capacity that can withstand until they break or require replacement.
- After a product is processed, their remaining embodied energy capacity decreases.



Anagiannis, I.; Nikolakis, N.; Alexopoulos, K. Energy-Based Prognosis of the Remaining Useful Life of the Coating Segments in Hot Rolling Mill. *Appl. Sci.* **2020**, *10*, 6827. https://doi.org/10.3390/app10196827

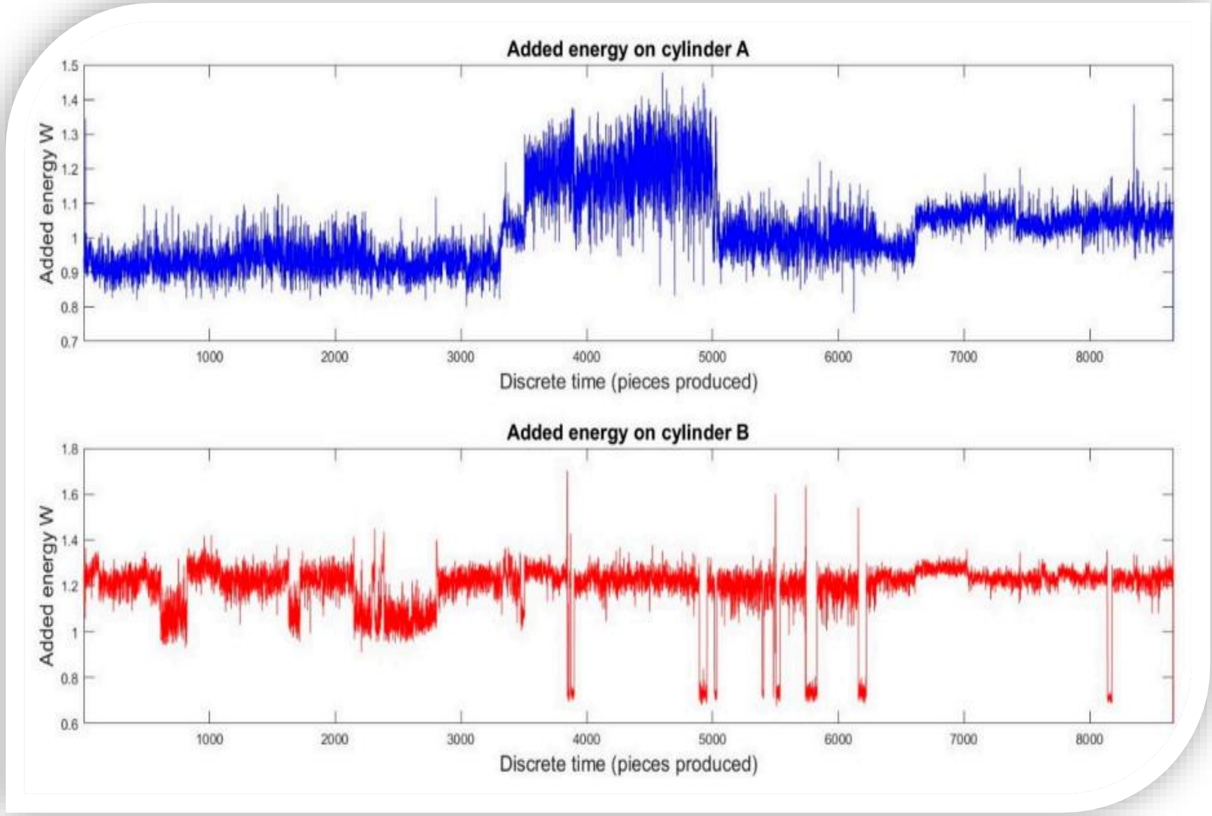
Model based predictive analytics

Excitation Energy to each Cylinder, according to Bendat & Piersol (Bendat and Piersol, 1986), per processed product:

$$W = \int_{fa}^{fb} G_{FF}(f)df + \int_{fa}^{fb} G_{TT}(f)df - \int_{fa}^{fb} |G_{TF}(f)|df$$

where:

- F: force time-series
- T: segment temperature time-series
- G(*f*): Welch based PSD
- [*fa*, *fb*]: frequency range (bandwidth)



Model based predictive analytics

- **Mean Rate of Wear Progress:**

$$E\left(\frac{dW}{dN}\right) = \frac{d\overline{W}}{dN} \approx \frac{\Delta W}{\Delta N} = \frac{\Sigma W}{N_t}$$

- **RUL Prediction (*N* remaining products to produce):**

$$N = \left\lfloor \frac{W_p - W_N}{\left(\frac{d\overline{W}}{dN}\right)\Big|_{N=N_t}} \right\rfloor$$

- **Interval Prediction:**

$$\begin{cases} [N-\Delta N, N+\Delta N] \;, & N-\Delta N > 0 \\ [0, N+\Delta N] \;, & N-\Delta N \le 0 \end{cases}$$

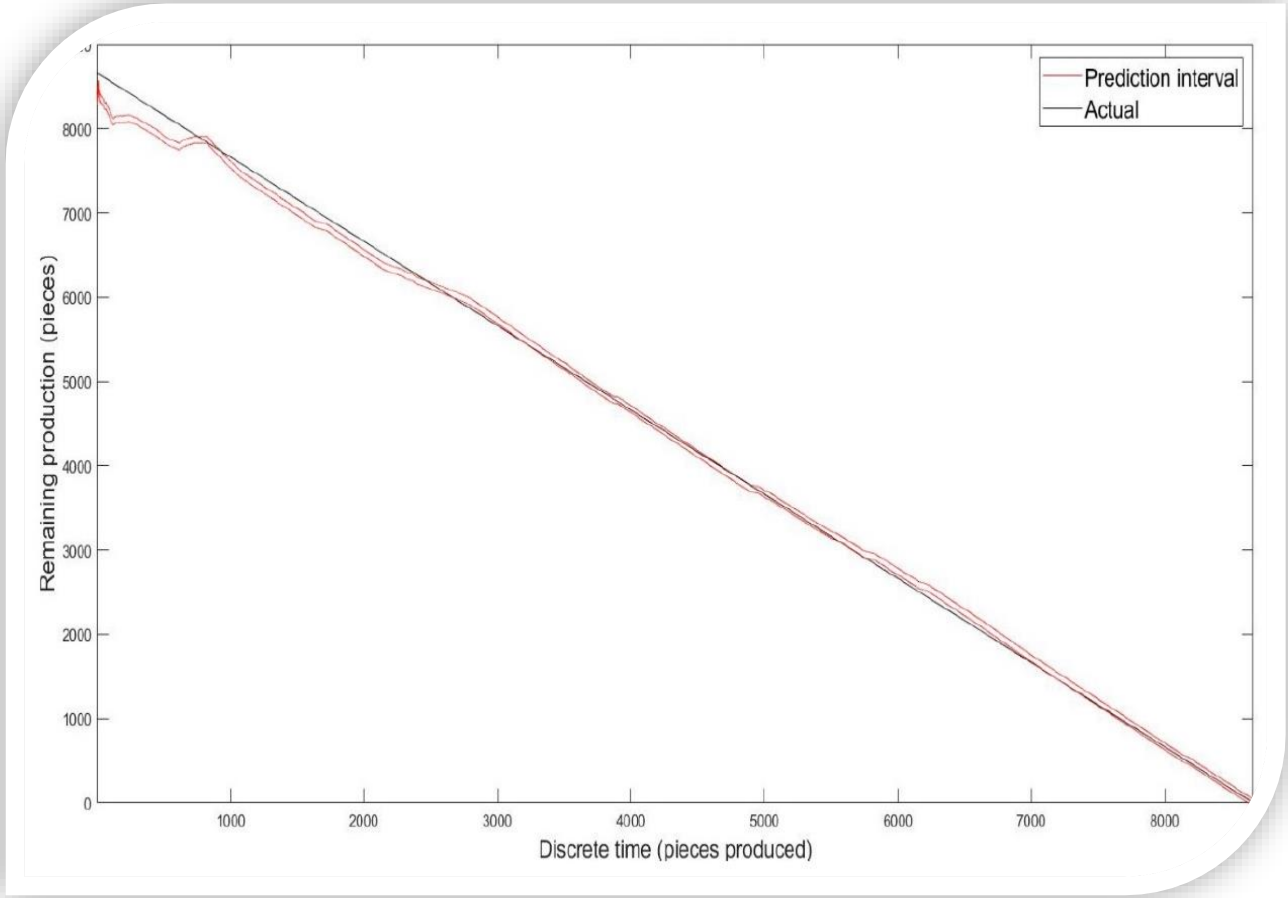
- **Prediction confidence:**
  The confidence of the predicted RUL interval in remaining products to proceed is estimated via **Maximum Likelihood Estimation (MLE)**.

- **Implementation:**
  Developed standalone app for running the RUL estimation in real time, providing GUIs indicating the current production, the RUL estimation, as well as the prediction Interval confidence.

```
Pieces produced: 7003
Remaining: 1671-1751 pieces
Confidence: 75.8 % (Very High)
```

Model based predictive analytics

- The proposed approach was tested through 9 Monte Carlo prediction simulations.
- RUL Prediction accuracy was evaluated via Mean Absolute Percentage Error.
- The prediction simulation results indicate a prediction accuracy higher than 97%.
- The proposed method is robust against product type variations and accurate enough to be used in industrial practice.



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Thank you!

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