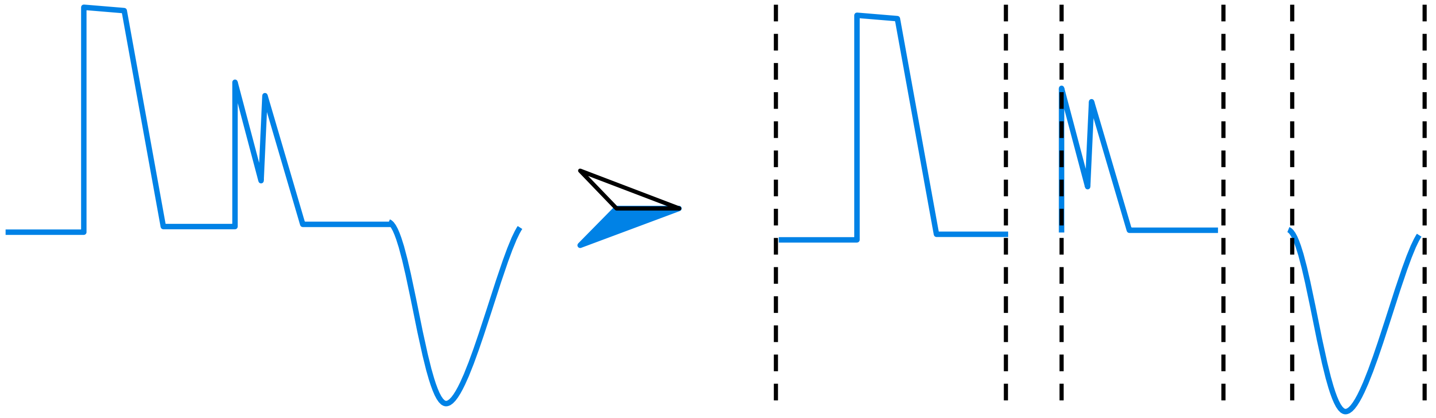

Predictive Maintenance using MATLAB: Pattern Matching for Time Series Data

Dr. Irina Ostapenko (Dr. Türck Ingenieurbüro GmbH),
Jessica Fisch (Daimler AG)

26.06.2018

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Collaboration partners

Mercedes-Benz

Jessica Fisch

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Focus:

- Digital Transformation
- Big Data
- IIoT

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Irina Ostapenko

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We provide

- Algorithms
- Signal Processing
- Measurement Systems Developing

Optical System Design

Outline

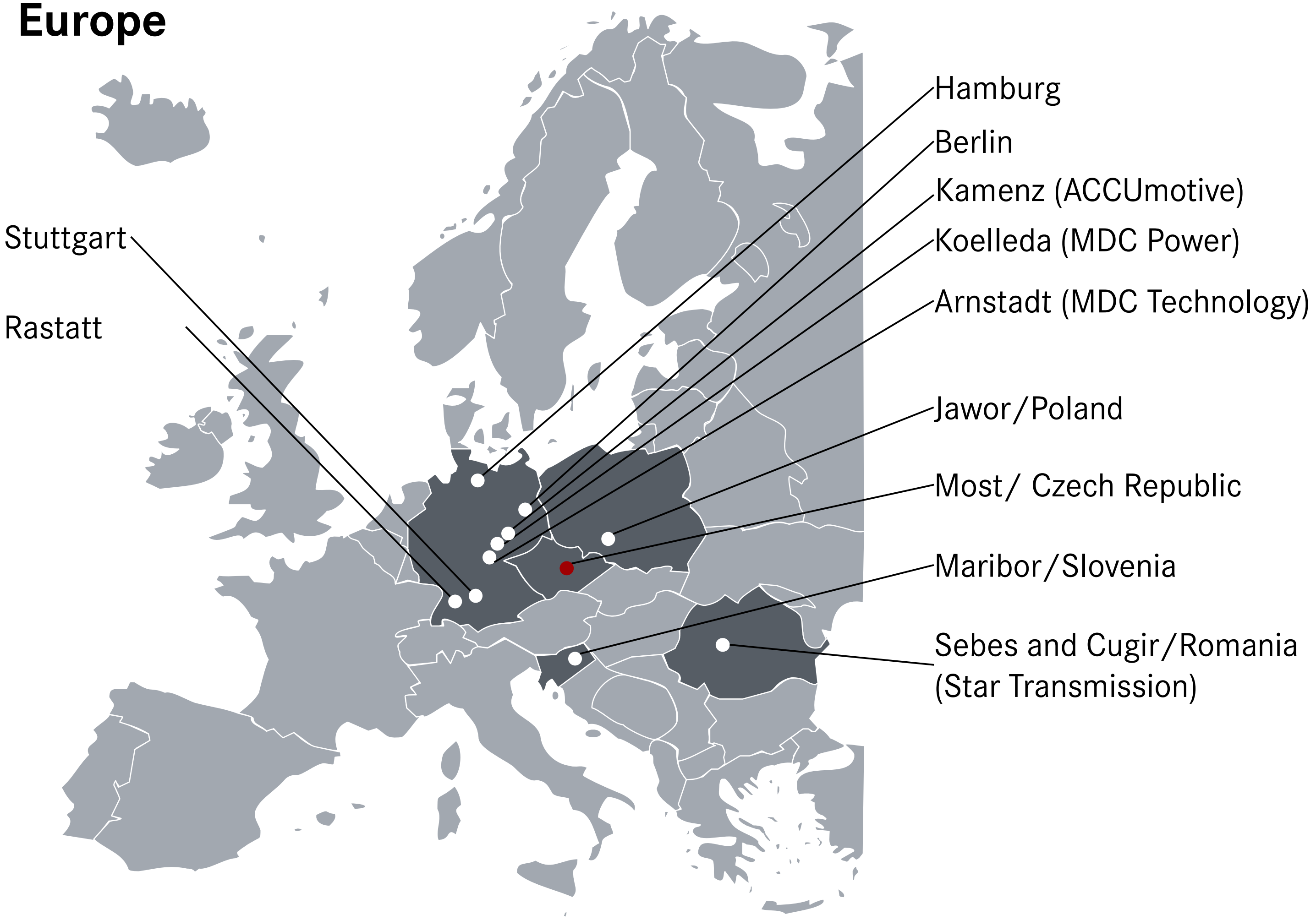
1. Project introduction
2. Task description
3. Solution/Algorithm
4. Summary

POWERTRAIN

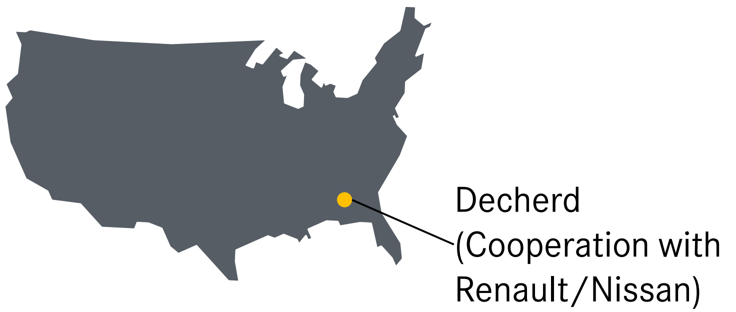
Five modules form
the core of our cars

The Powertrain production network is set up globally with lead plant in Germany

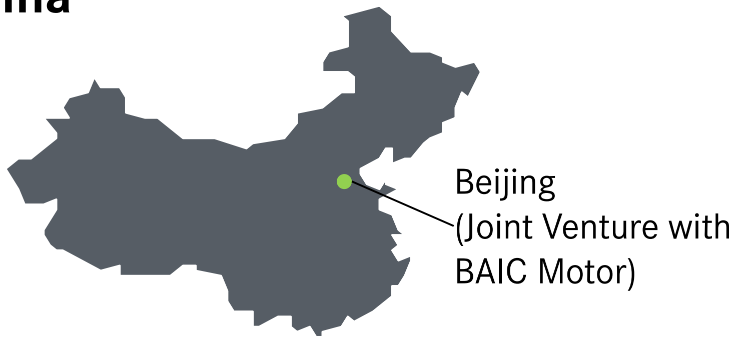
Europe



USA



China



Legend
- 100% Daimler
- Majority Holding
- Joint Venture
- Cooperation

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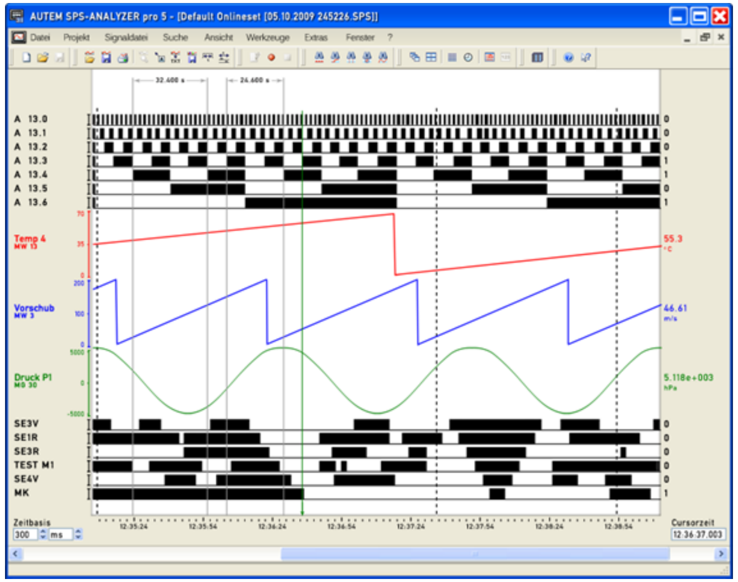
Data Science

Motivation for Anomaly Detection in the Projekt „iLL“

The goal is to detect anomalies in data

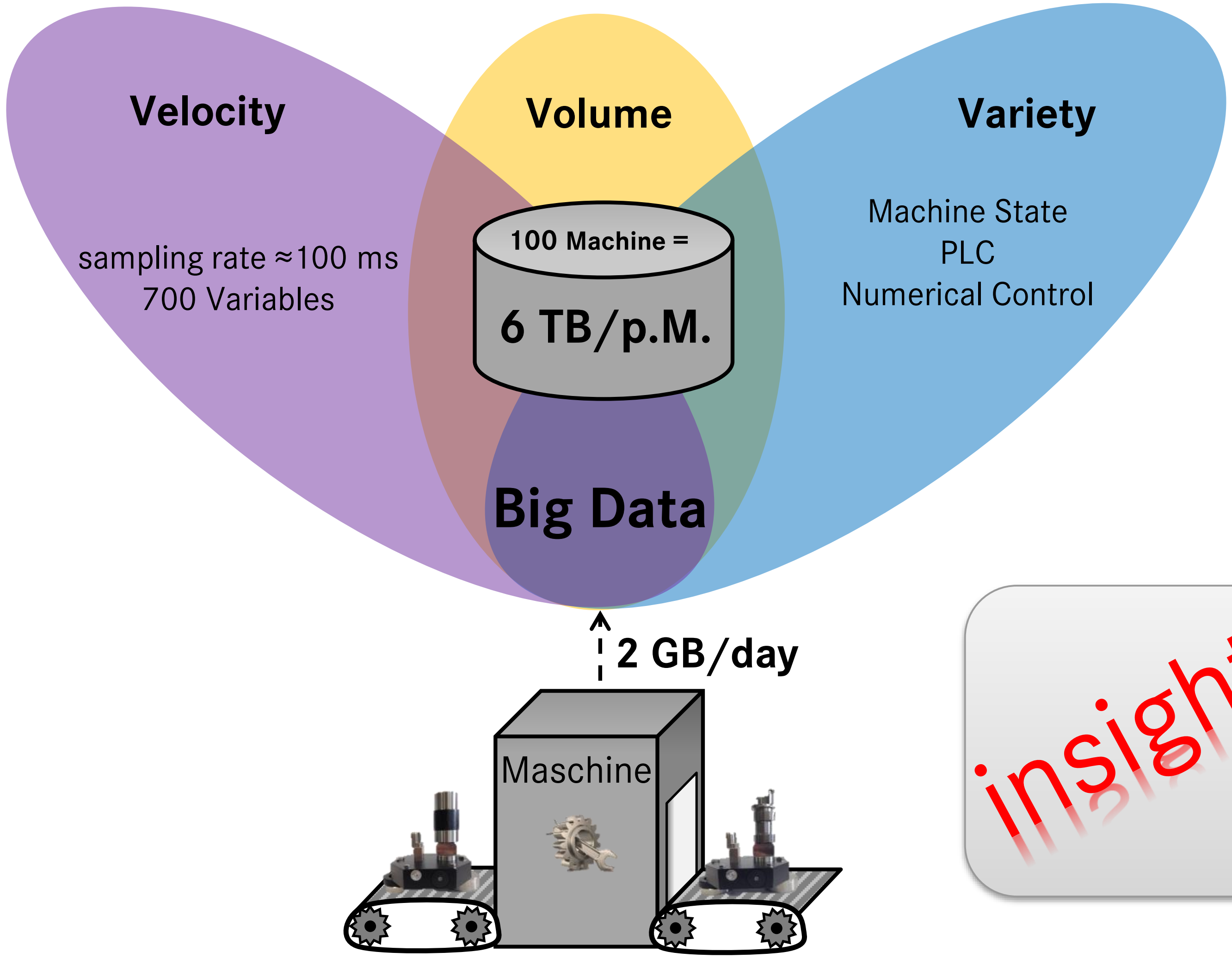
PLC-Data today:



Source: www.autem.de

Automatic Notification of the Deviation:

Data properties in the context of Big Data



The 3 basic V's of Big Data:

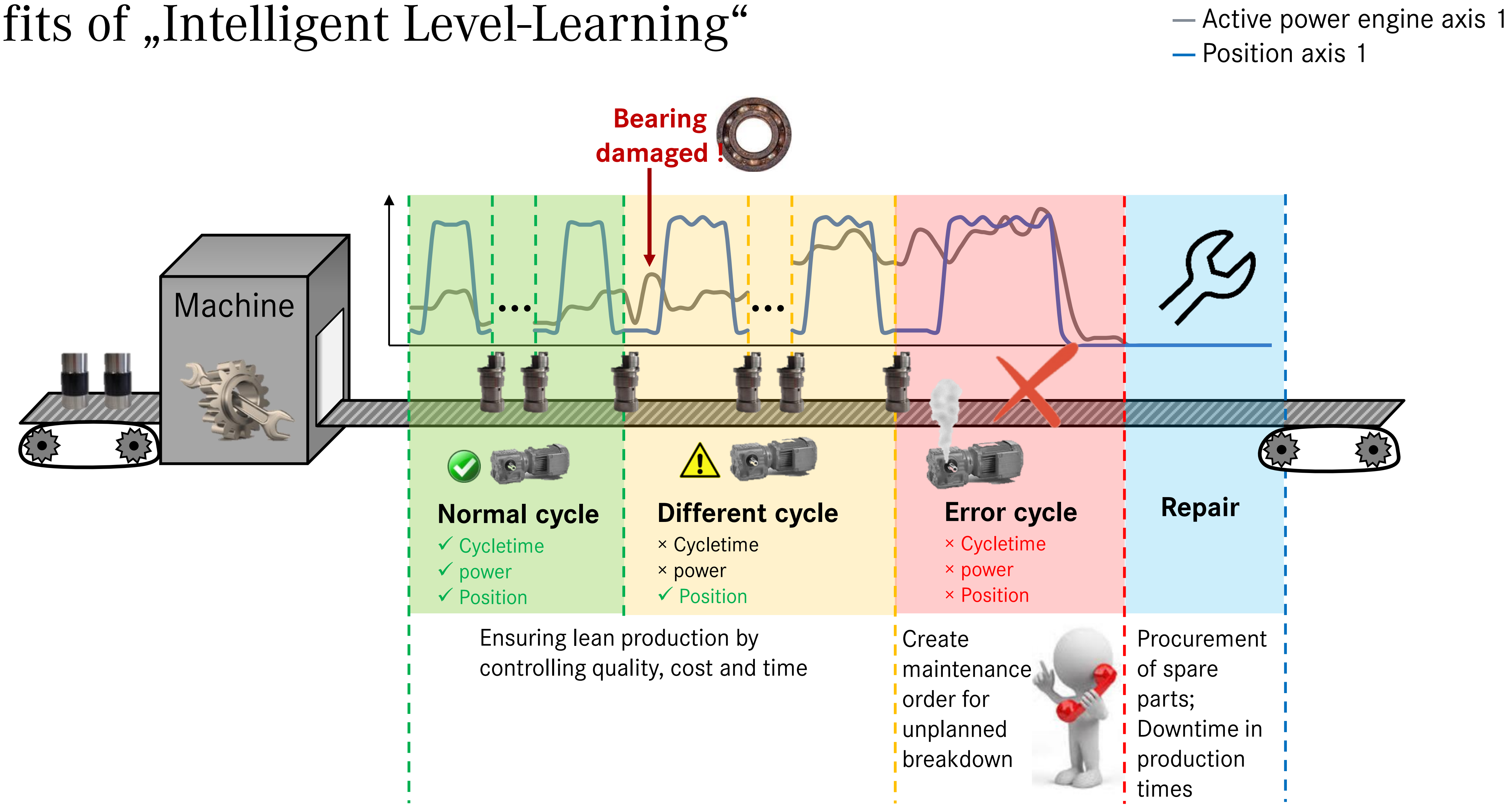
- **Velocity**: Speed with which data is generated and analyzed
- **Volume**: Amount of data that traditionally can not be analyzed
- **Variety**: Data diversity refers to unstructured data without a recognizable context

insight

The 2 additional V‘s:

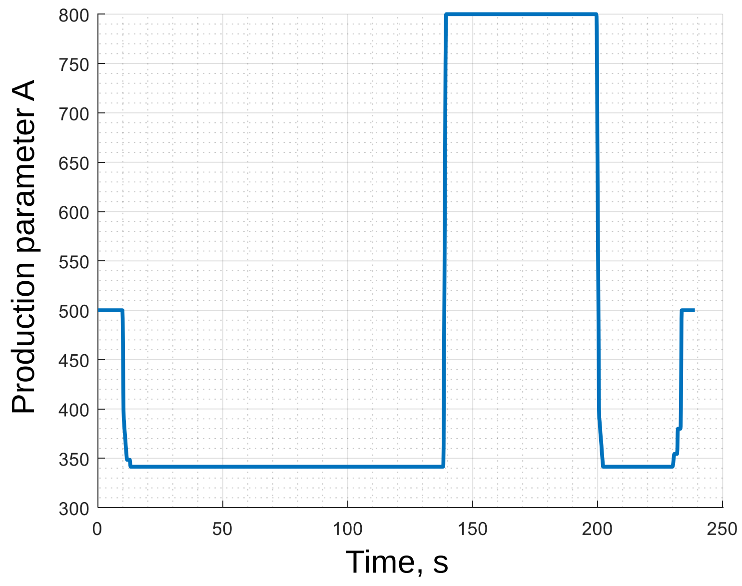
- **Validity**: Ensuring data quality
- **Value**: measurable benefits from the data

Benefits of „Intelligent Level-Learning“



Challenges

- About 700 parameters are continuously monitored in every production cycle yielding 700 individual time-series of about 2500 samples each



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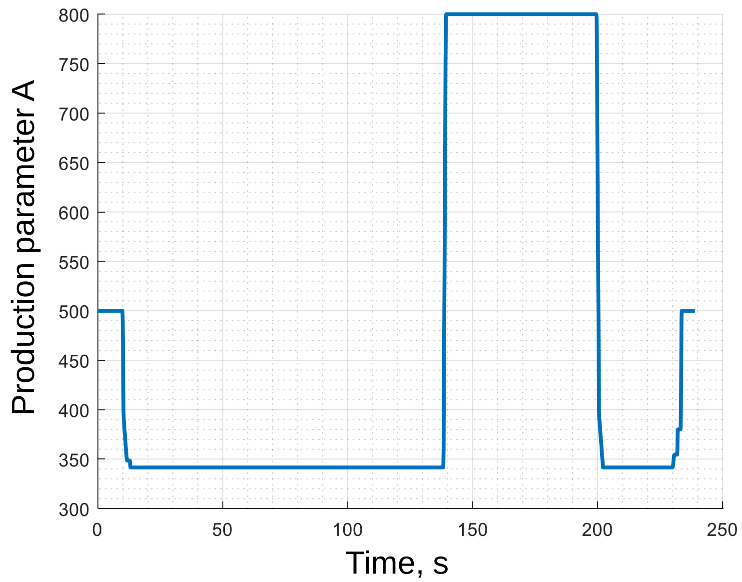
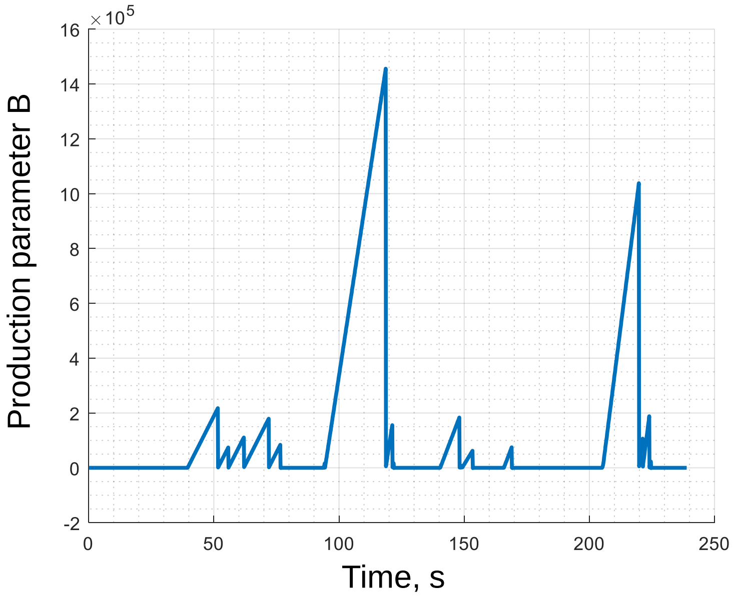
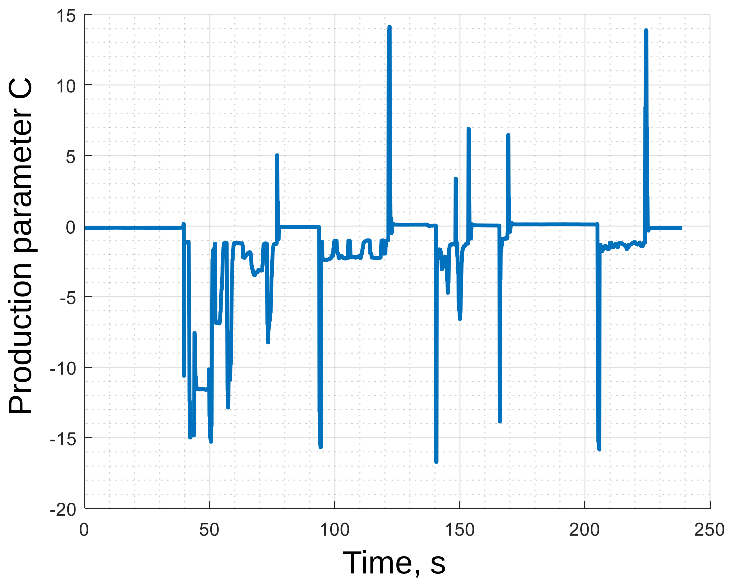


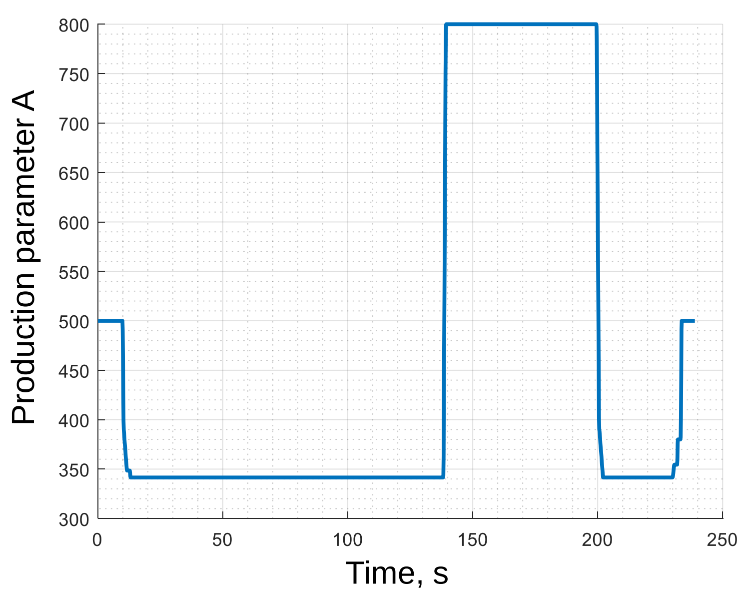


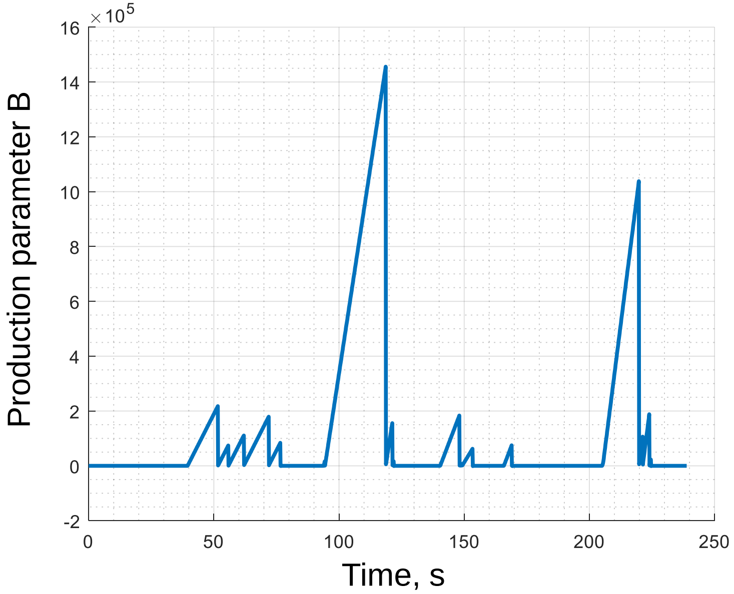


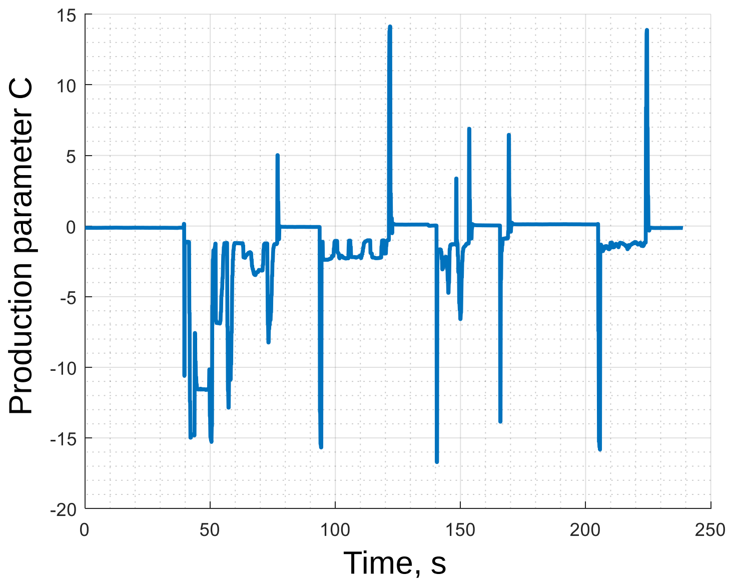
- Different parameters show very different and elaborate features

Challenges

- About 700 parameters are continuously monitored in every production cycle yielding 700 individual time-series of about 2500 samples each



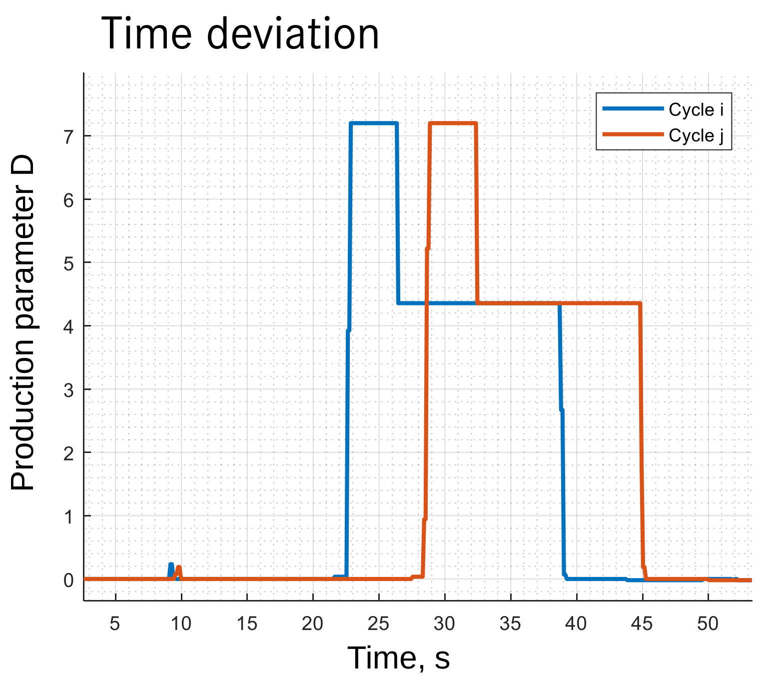




- Different parameters show very different and elaborate features

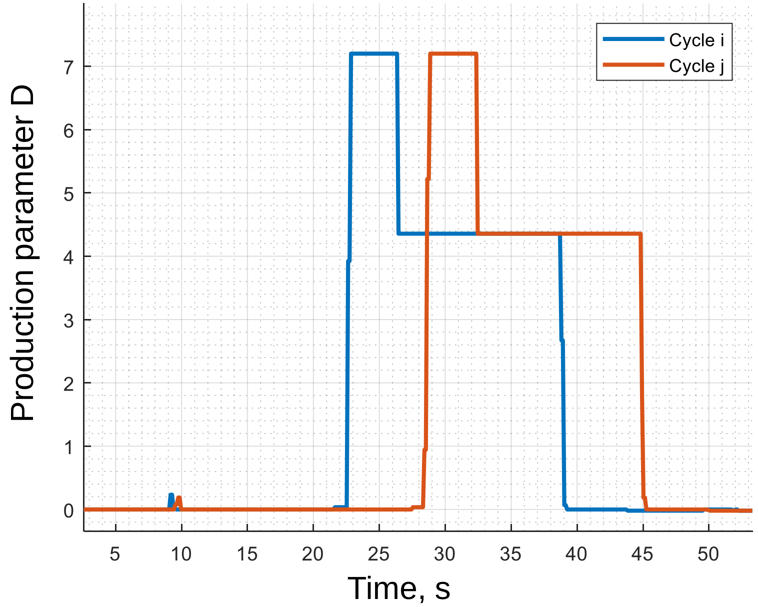
⇨ Task: Analyse these 700 time-series and find specific kinds of deviations

Requirements for algorithm

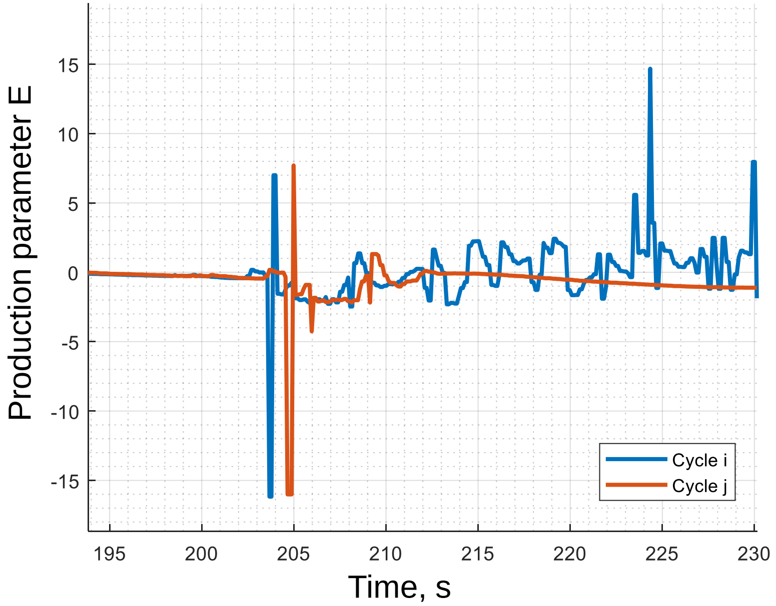


Requirements for algorithm

Time deviation

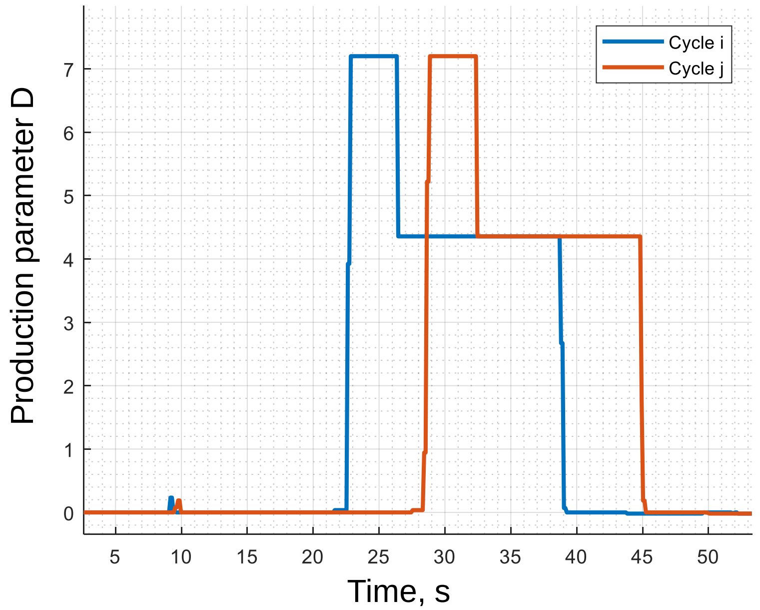


Pattern deviation

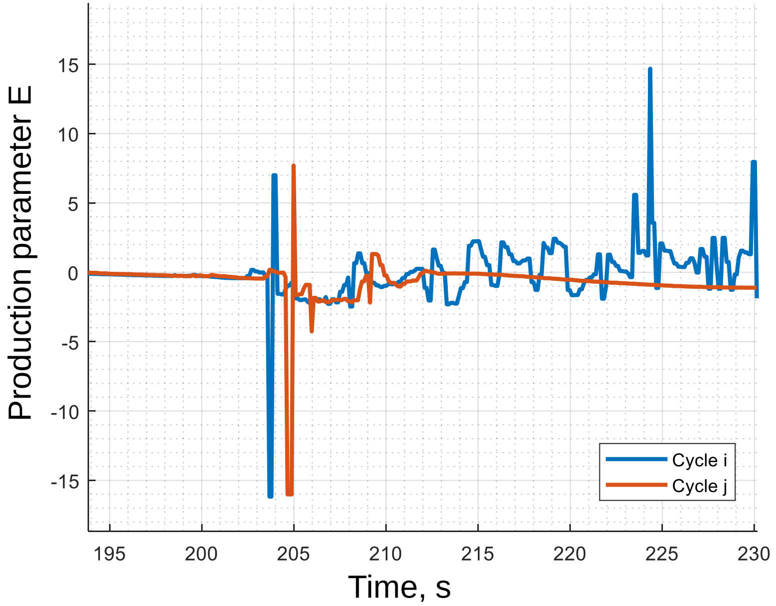


Requirements for algorithm

Time deviation might not be critical



Pattern deviation is critical



Requirements for algorithm

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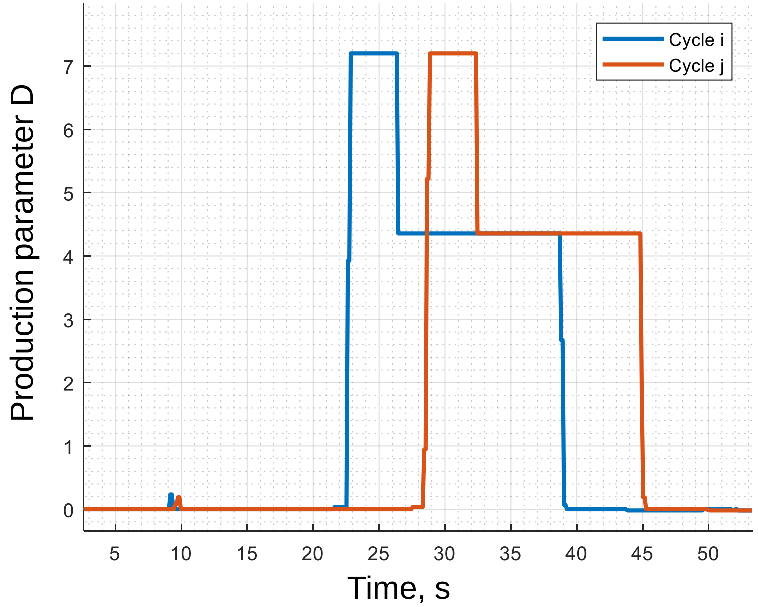
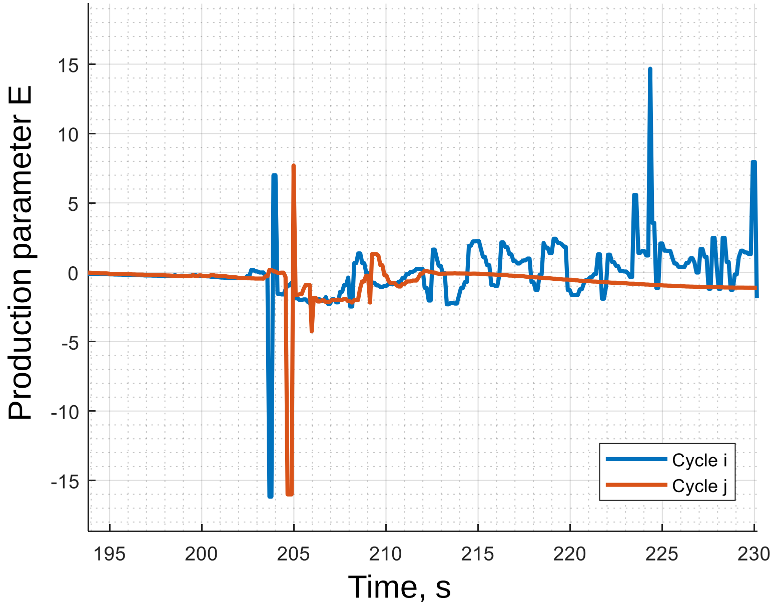


Pattern deviation is critical



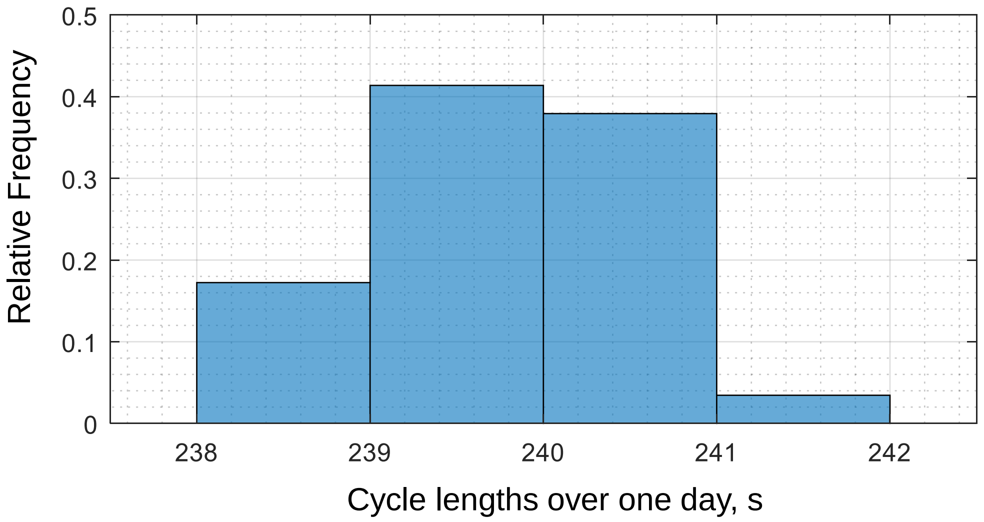
What the algorithm should do

- Time series analysis
- Find deviations from normal cycle and
- Distinguishing between time and pattern deviation

What is *normal*?

Delays in production cycles

- Length of time-series varies from cycle to cycle even for normal production



Delays in production cycles

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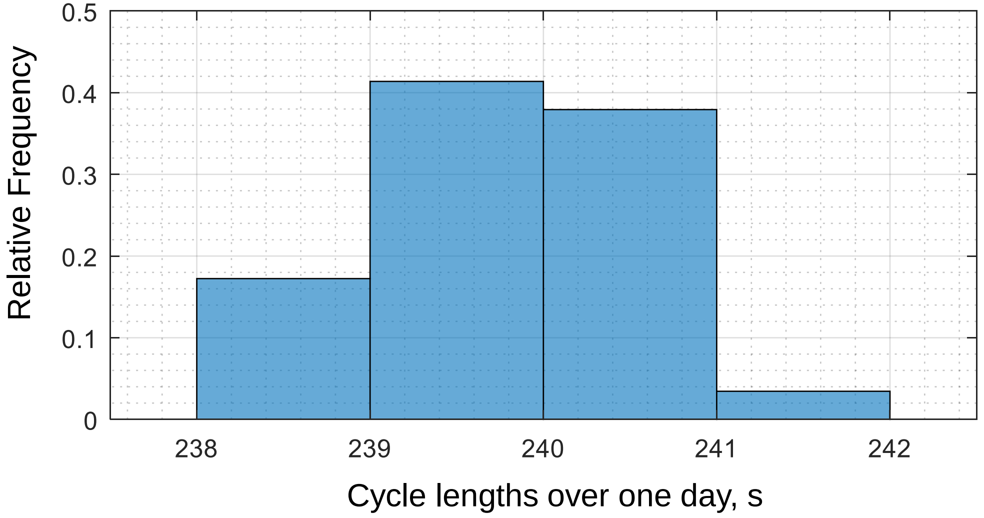

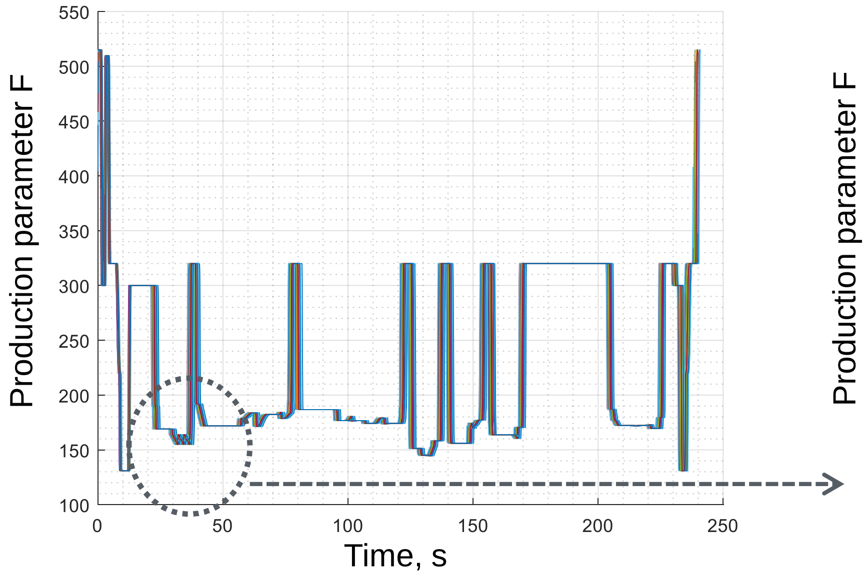

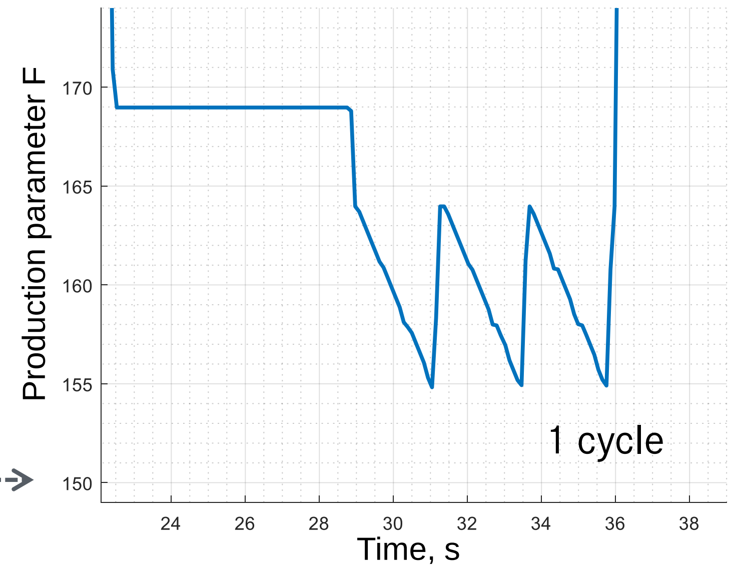

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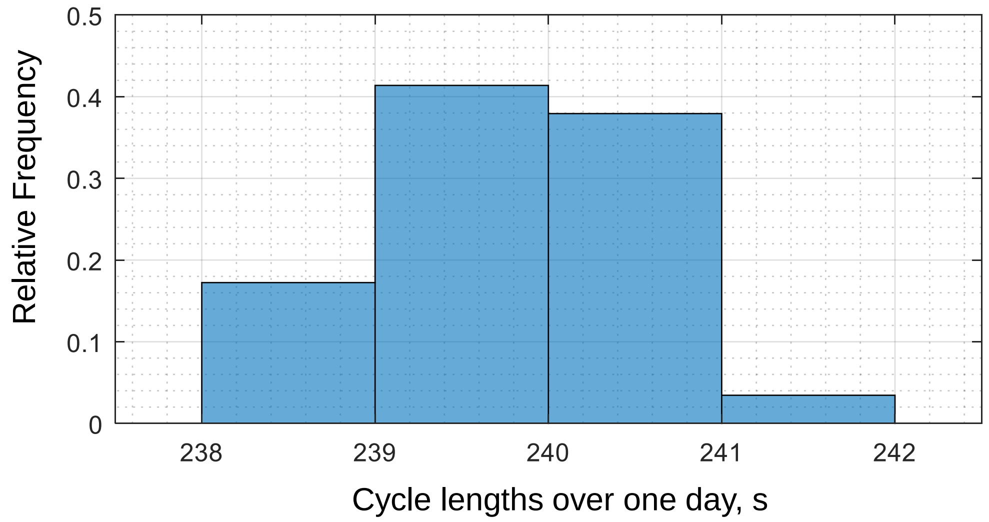

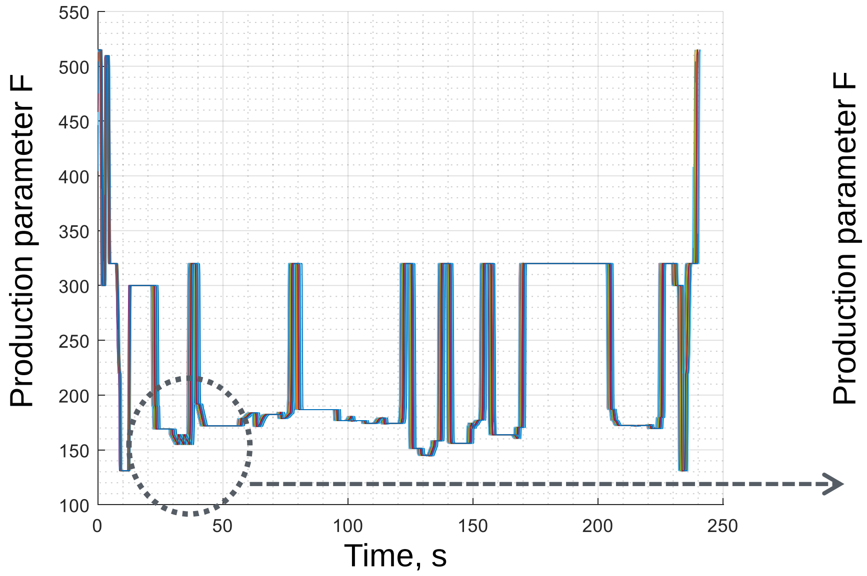

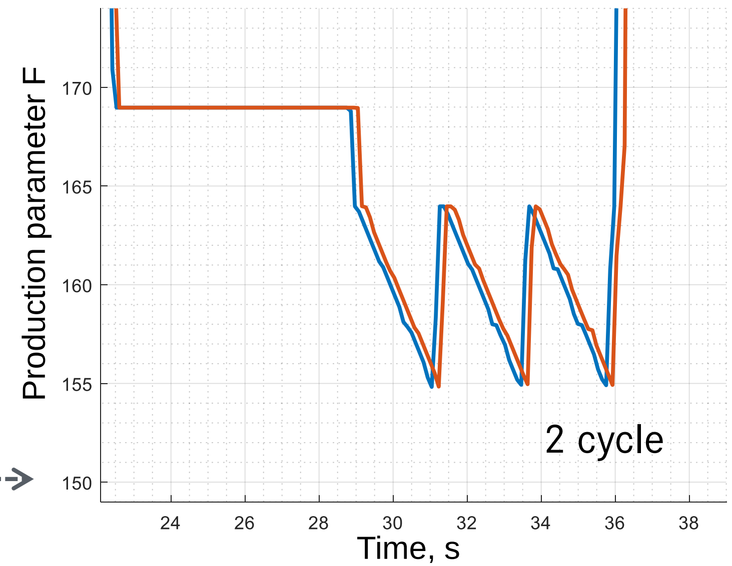

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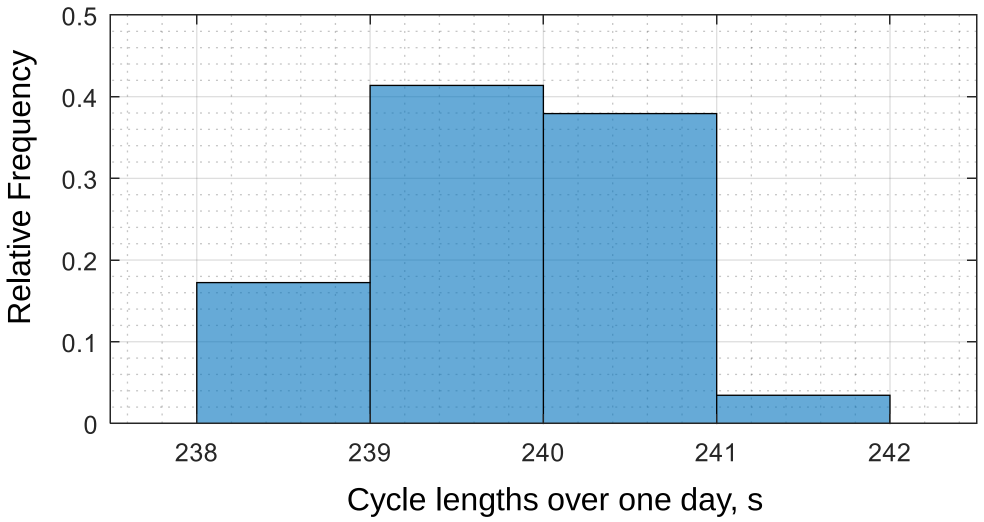

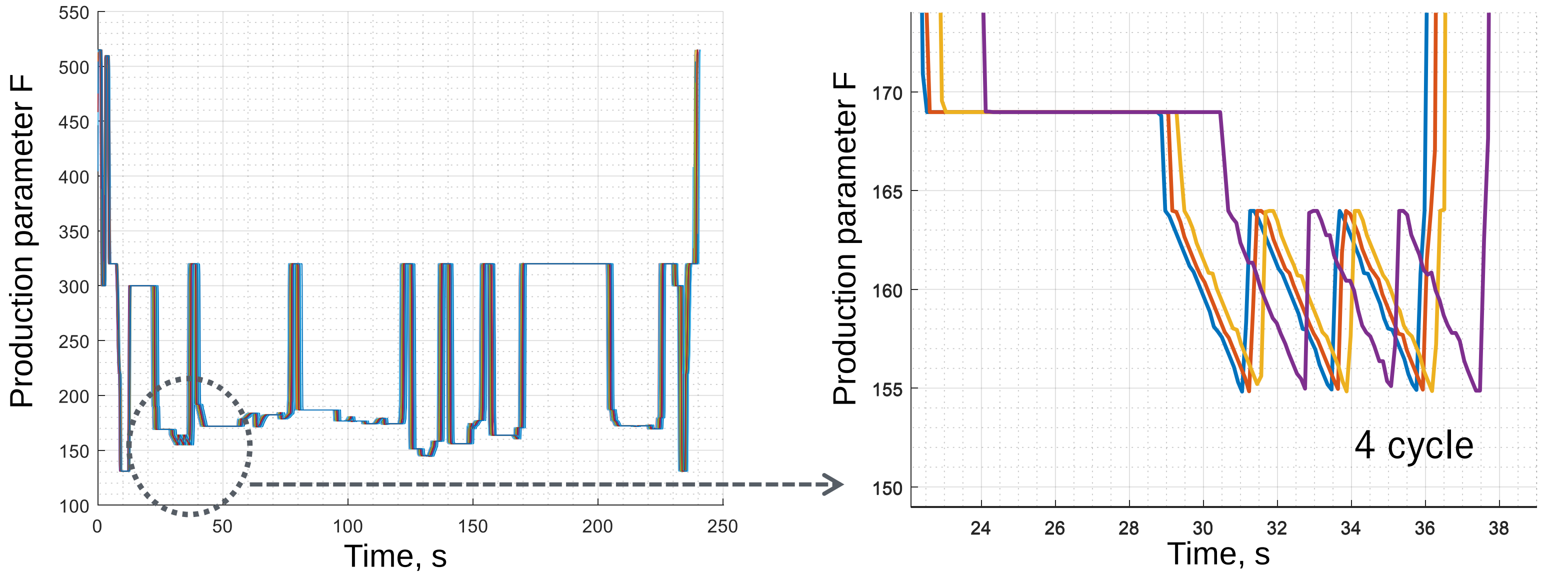

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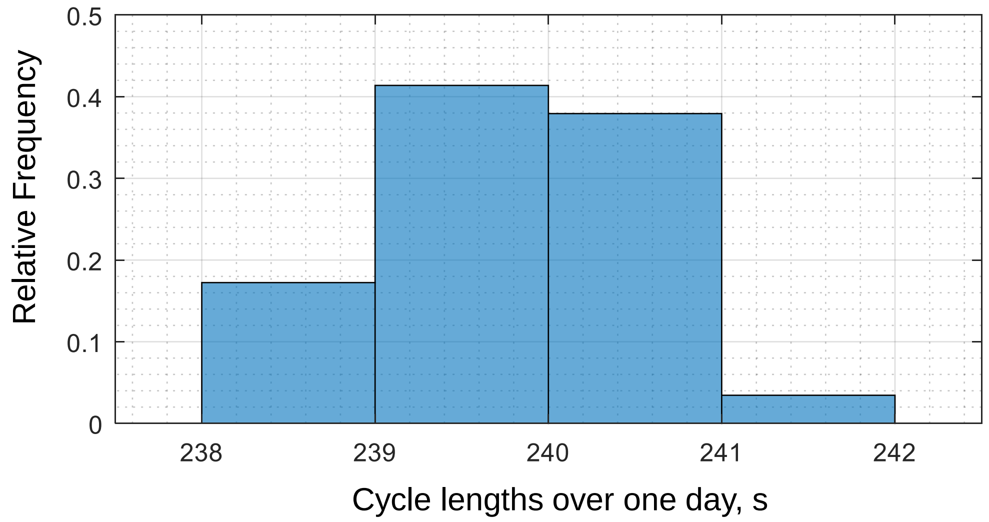
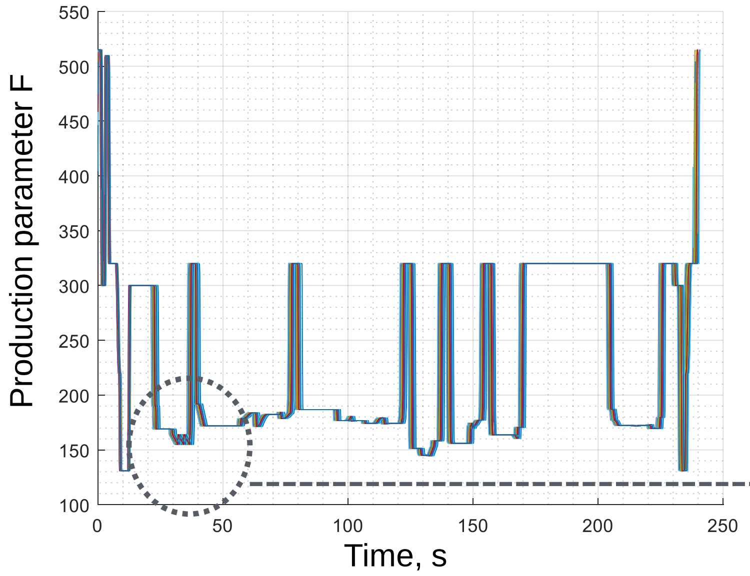
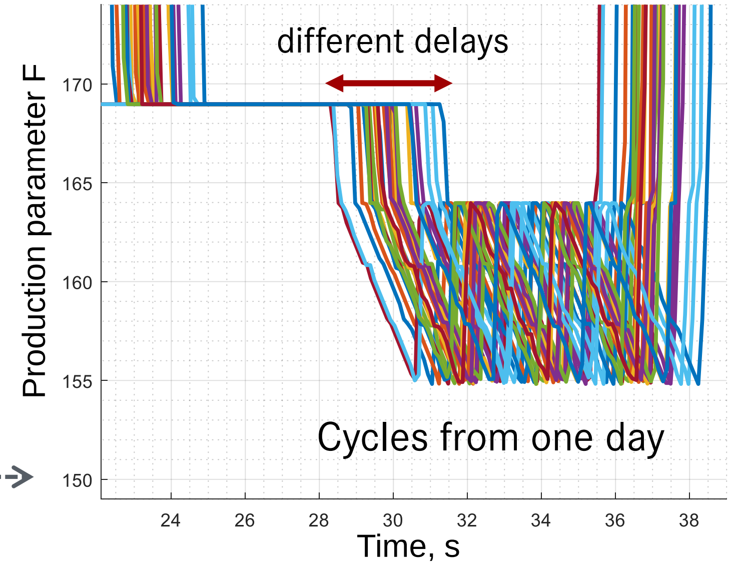


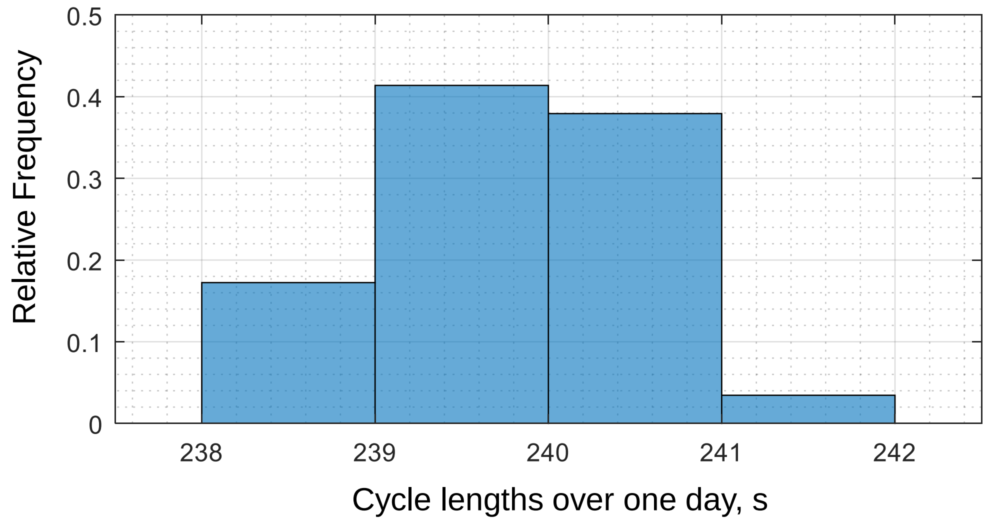


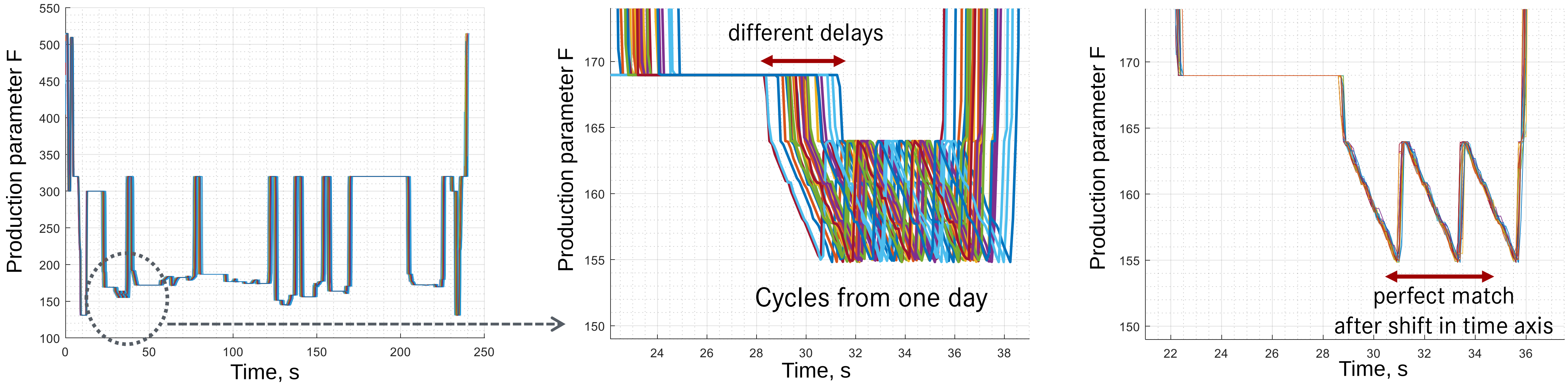


Delays in production cycles

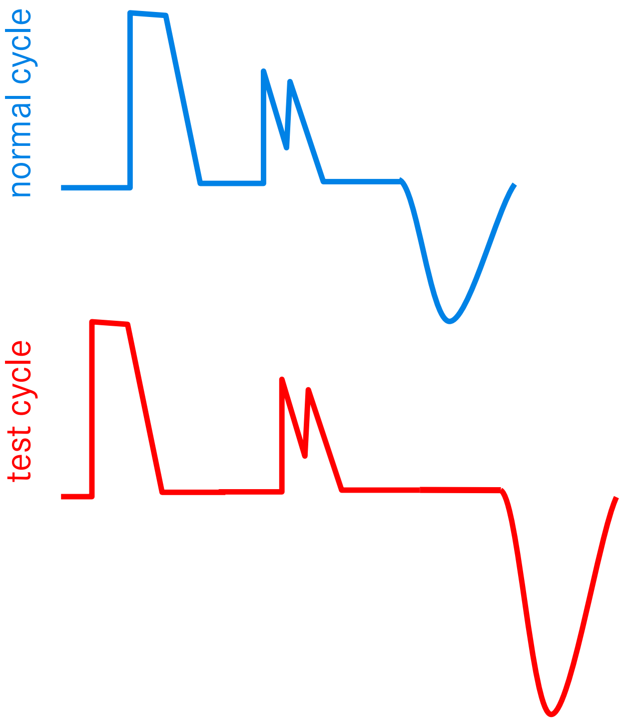
- Length of time-series varies from cycle to cycle even for normal production

⇨ Normal cycles can be matched to one another through shifting in time axis!

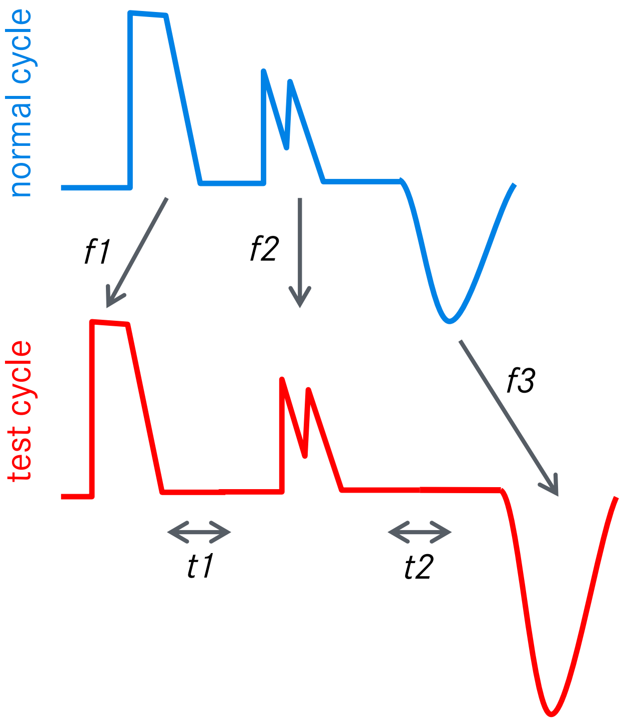




Algorithm principle

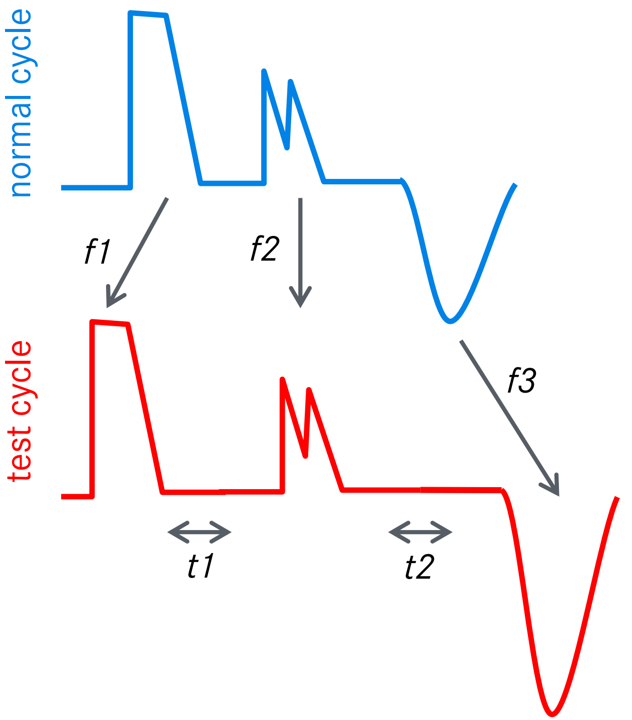


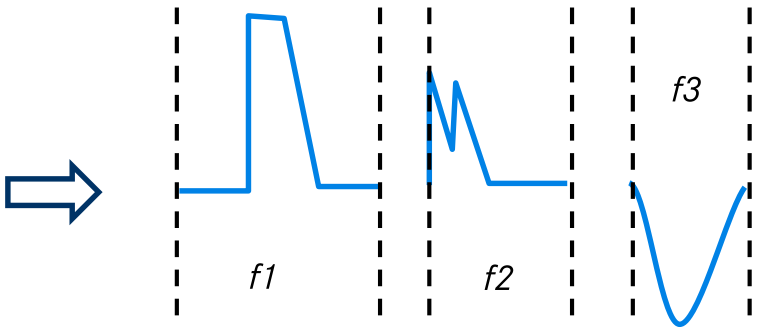
Algorithm principle



- Cycle can be described as sequence of features f1, f2, f3
- Each cycle can show some delays in time t1, t2

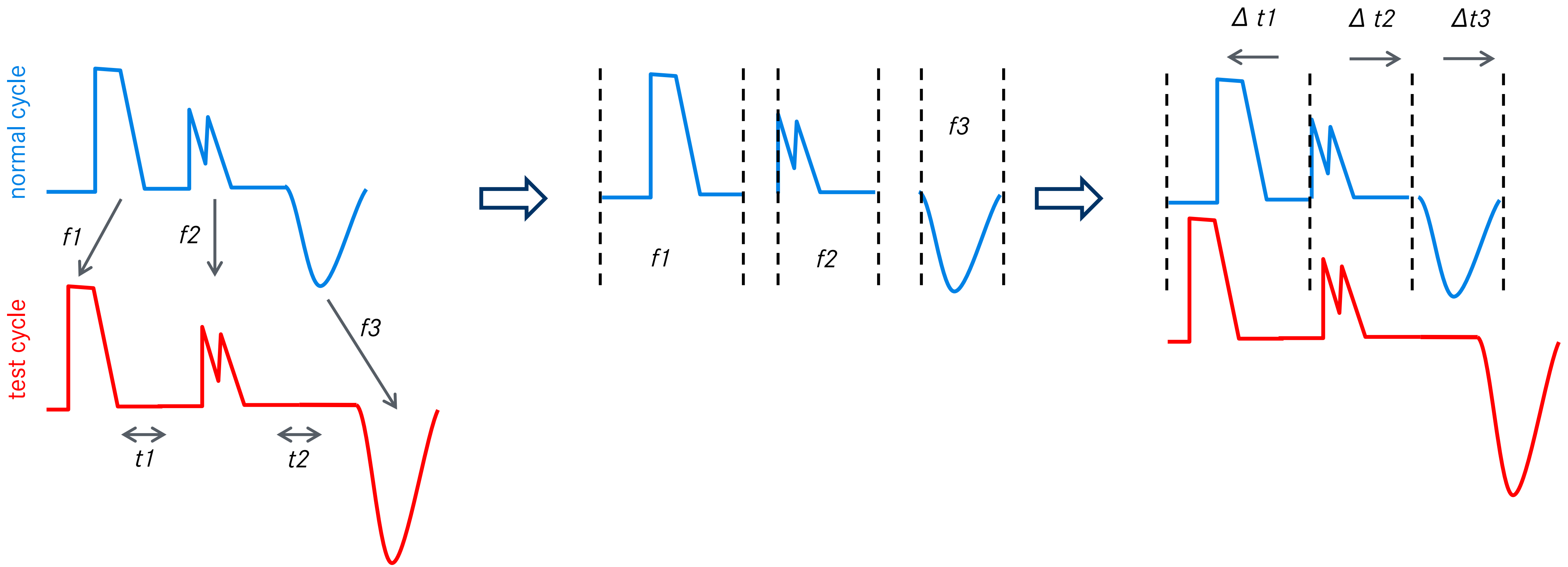
Algorithm principle





- Cycle can be described as sequence of features f1, f2, f3
- Each cycle can show some delays in time t1, t2
- Automatic feature detection *f1, f2, f3*

Algorithm principle



- Cycle can be described as sequence of features f1, f2, f3
- Each cycle can show some delays in time t1, t2

- Automatic feature detection *f1, f2, f3*

- Pattern matching through shift of feature along time axis (*Δt2, Δt2, Δt3*): least square fit (t_{shift} to minimize the Sum of Residual Squares of two signals)

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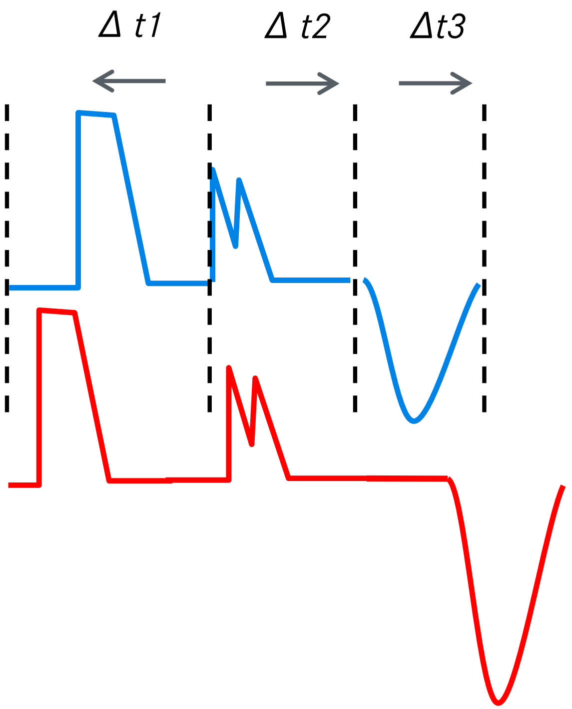
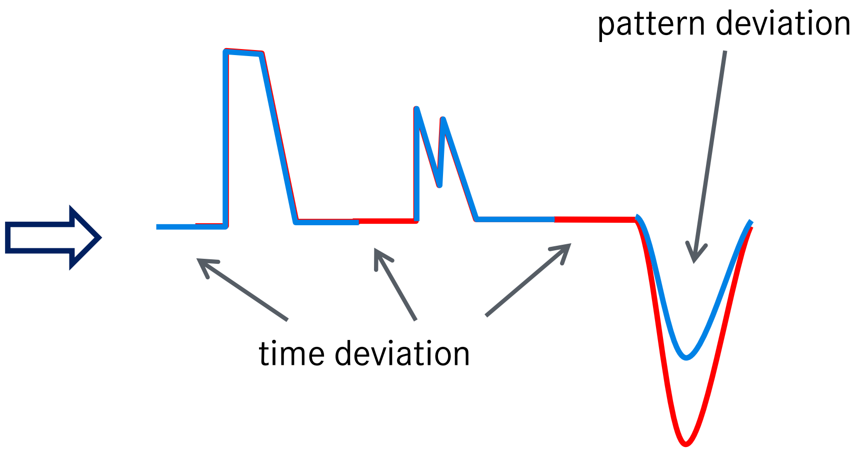
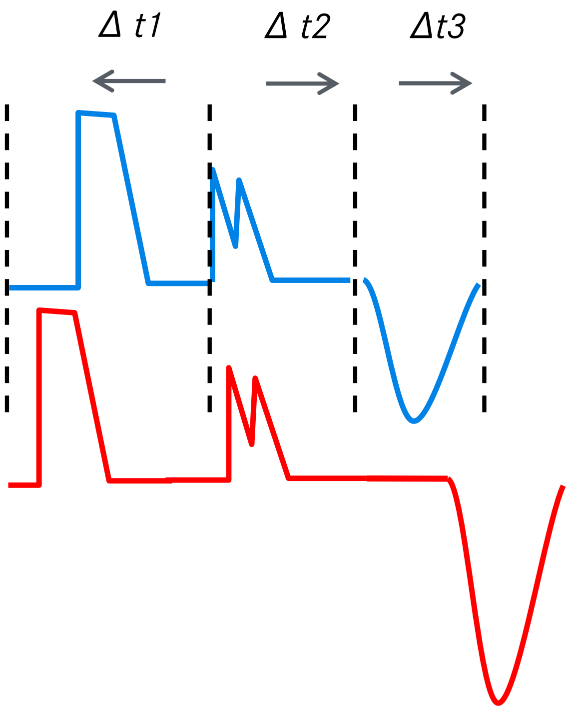
Algorithm principle

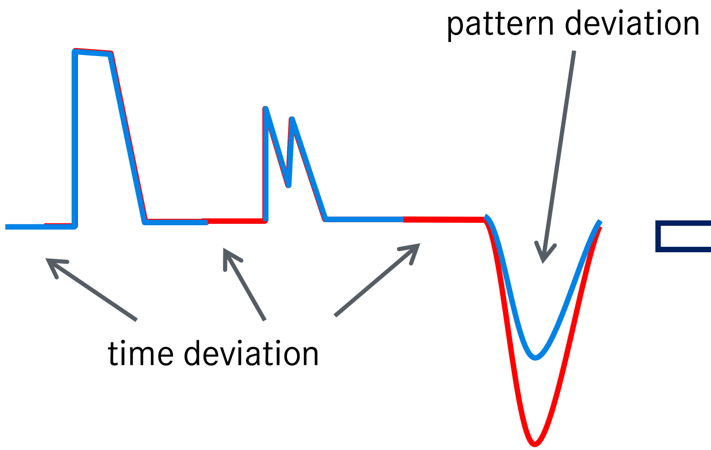




- Pattern matching through shift of feature along time axis (*Δt2, Δt2, Δt3*): minimization of SRS

Algorithm principle





f1	*f2*	*f3*	
Δt1	*Δt2*	*Δt3*	Time deviation
No	No	Yes	Pattern deviation

- Pattern matching through shift of feature along time axis (*Δt1, Δt2, Δt3*): minimization of SRS

- Decription of a cycle as feature sequence
- For each feature time and pattern deviation can be calculated

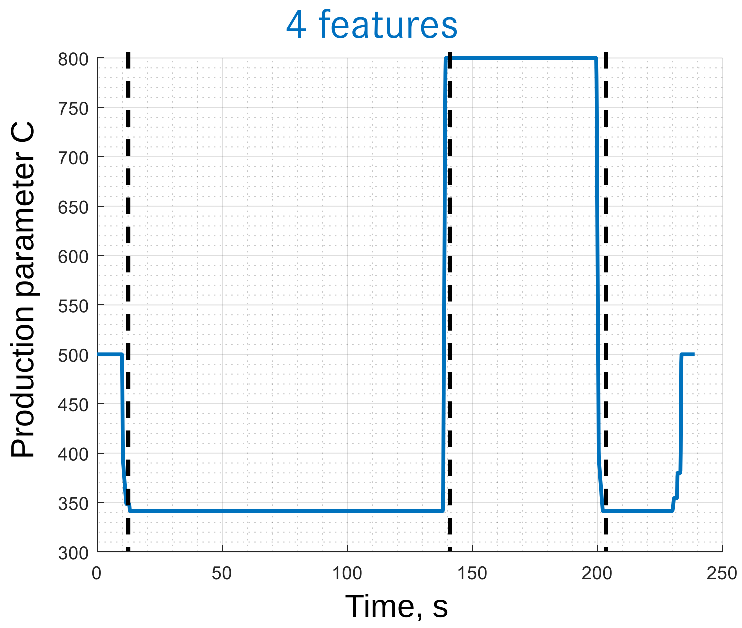
- Time and pattern deviation for each feature are used as characteristic numbers for test cycle

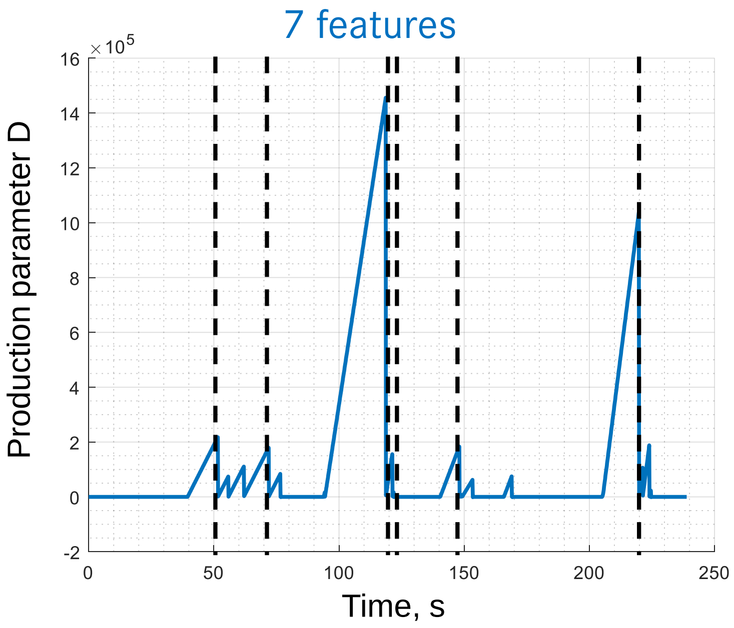
Data reduction!

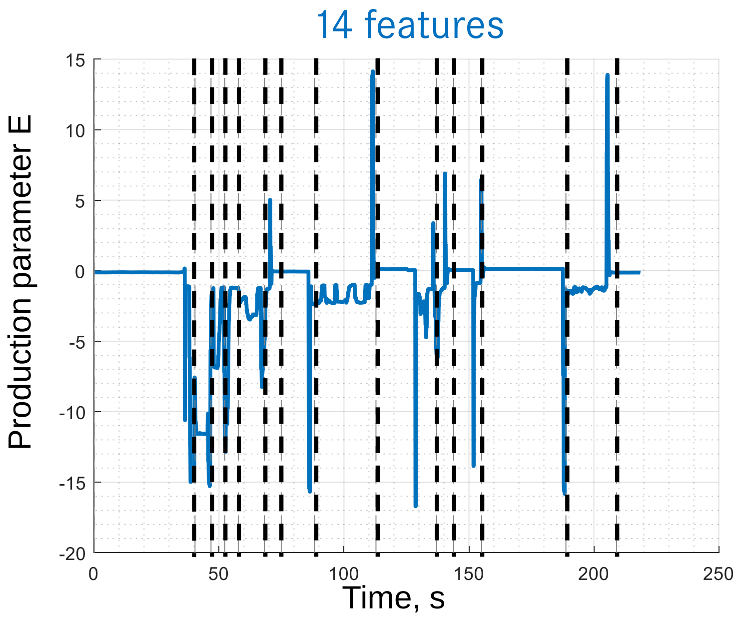
Automatic feature detection

Time series is split

- After a local extremum (maximum or minimum) or on a plateau
- After a given relative change







⇨ Data reduction of time series from 2500 datapoints to sequence of max. 60 features (typically 10)!

Algorithm implementation: machine learning approach in MATLAB

Training

Reference cycles ->

- Build „reference signal“ for each feature
- Limits for time and pattern deviation

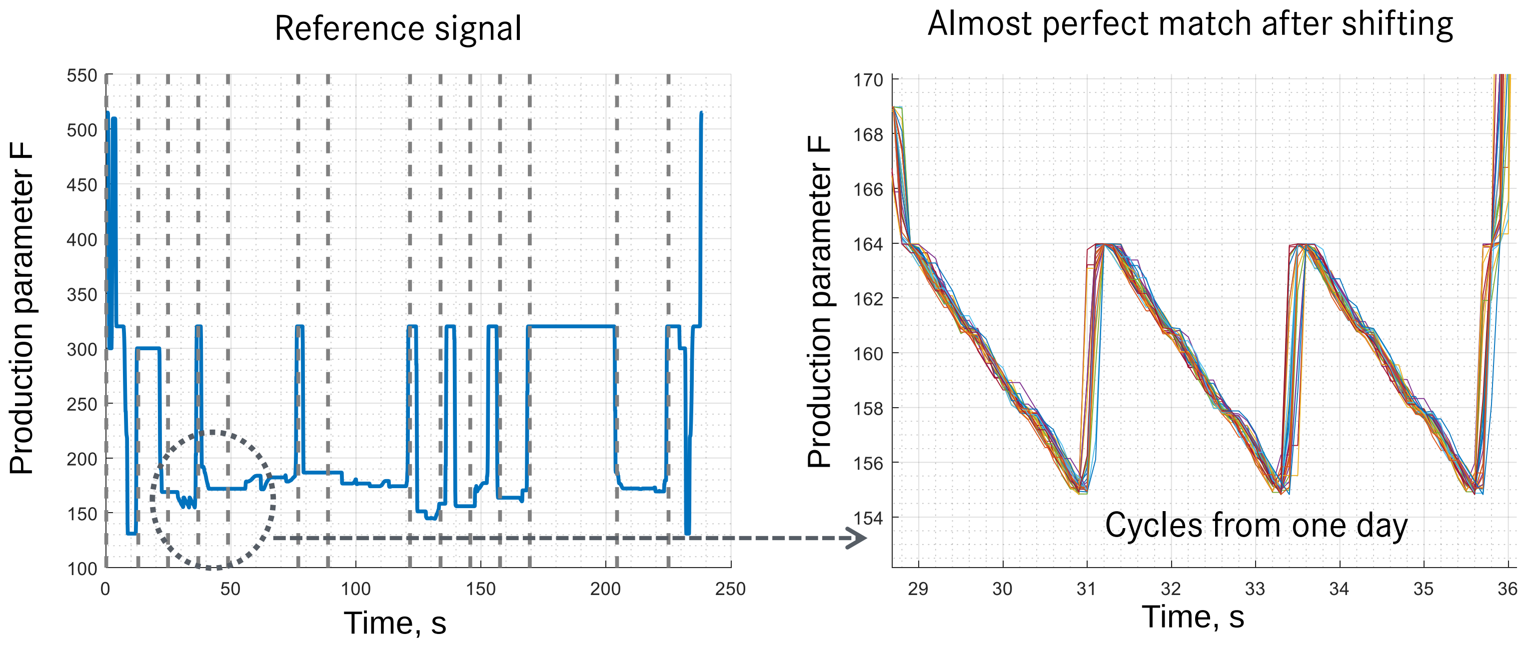
Testing

Test cycles ->

- Comparison of each feature in reference signal
- Is time and pattern deviation within the limits?

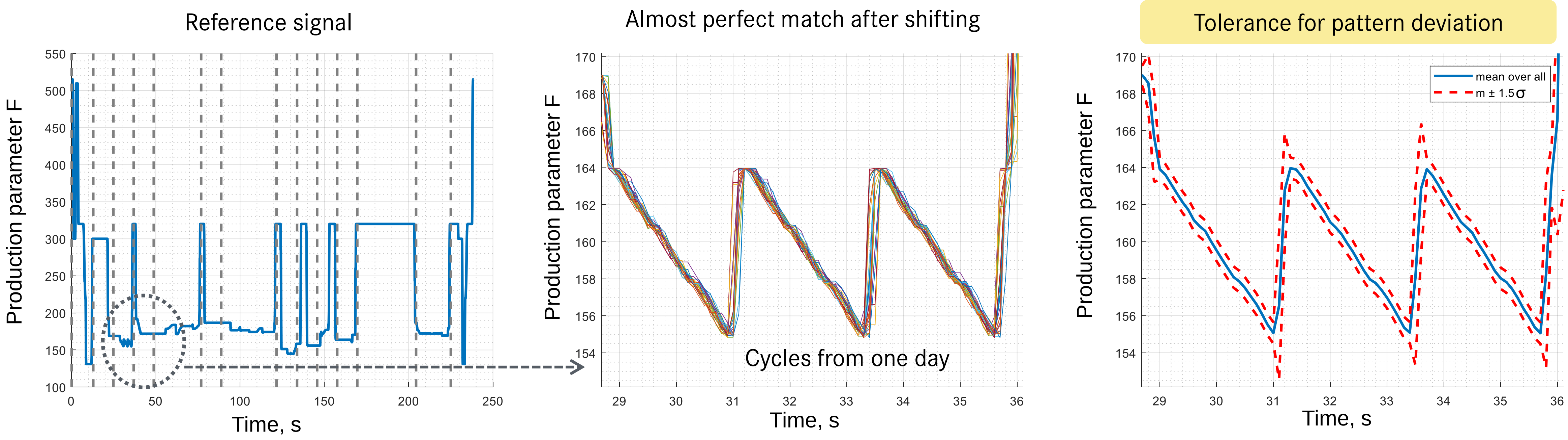
Create „reference signal“ for each produciton parameter

1. For all training cycles - matching to shortest cycle
2. Create „reference signal“ – mean over all matched reference cycles



Create „reference signal“ for each produciton parameter

1. For all training cycles - matching to shortest cycle
2. Create „reference signal“ – mean over all matched reference cycles
3. Possible pattern deviation - standard deviation over all matched reference cycles

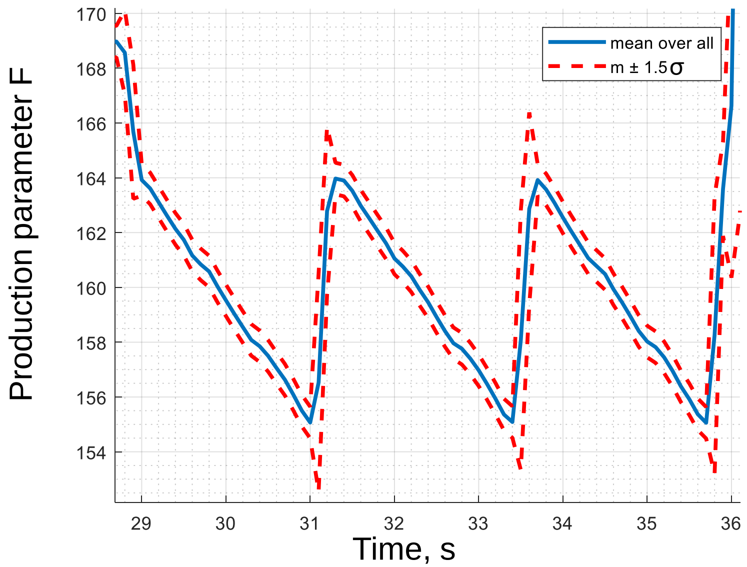


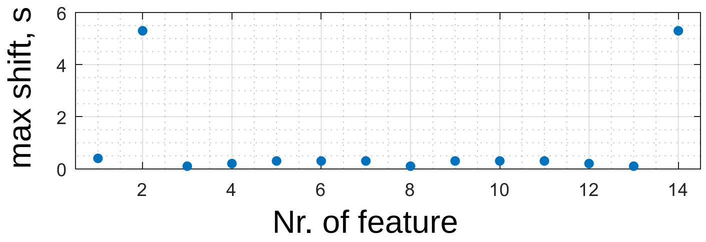
Create „reference signal“ for each produciton parameter

Training

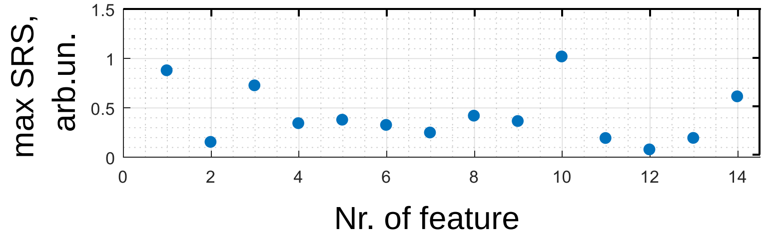
1. Create „reference signal“ – mean over all matched reference cycles
2. Possible pattern deviation - standard deviation over all matched reference cycles, limits for SRS
3. Possible time deviation – maximal absolute shift from matched reference cycles

Tolerance for pattern deviation



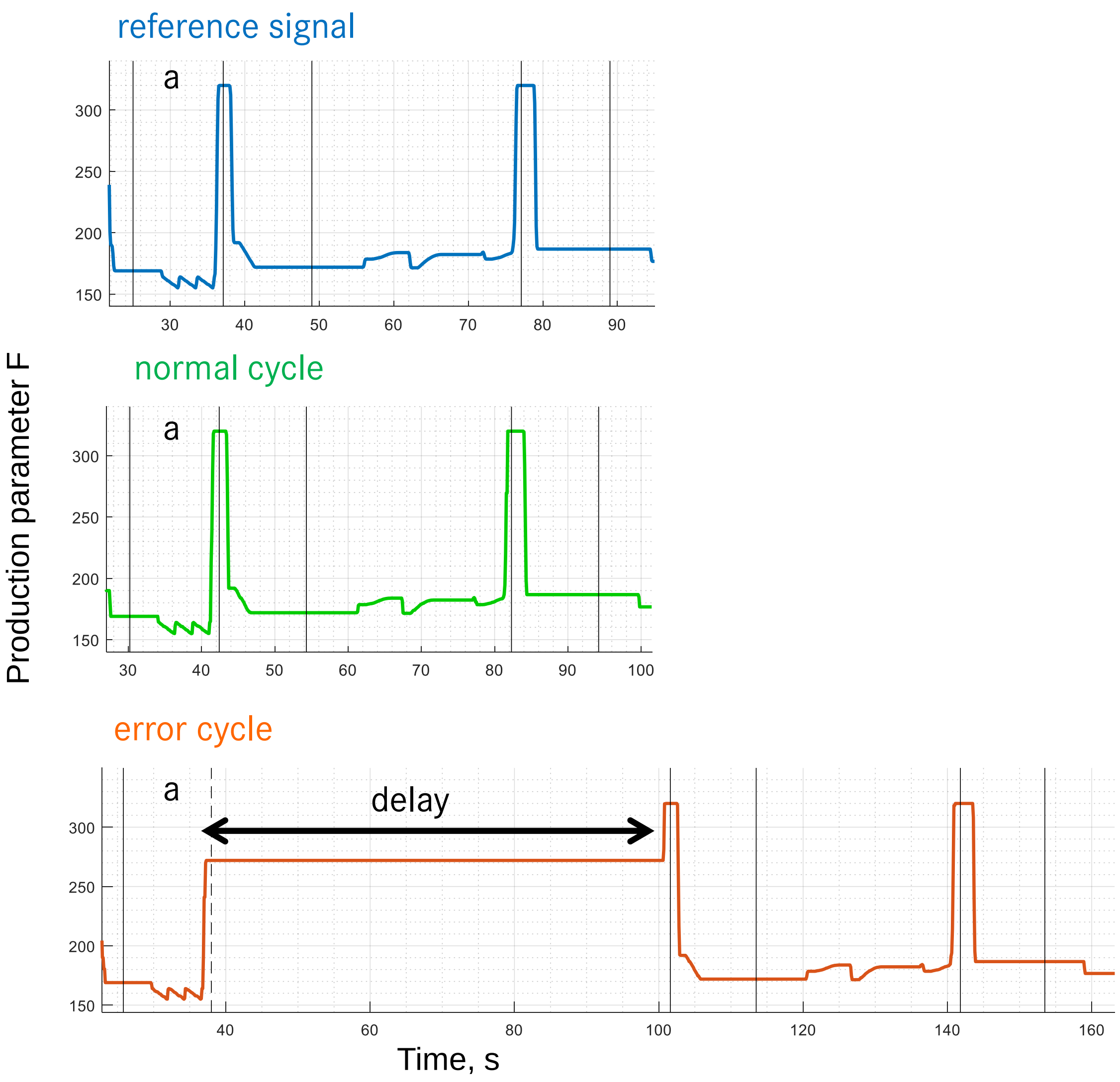


Possible time deviation



Possible pattern deviation

Testing: time and pattern deviation evaluation



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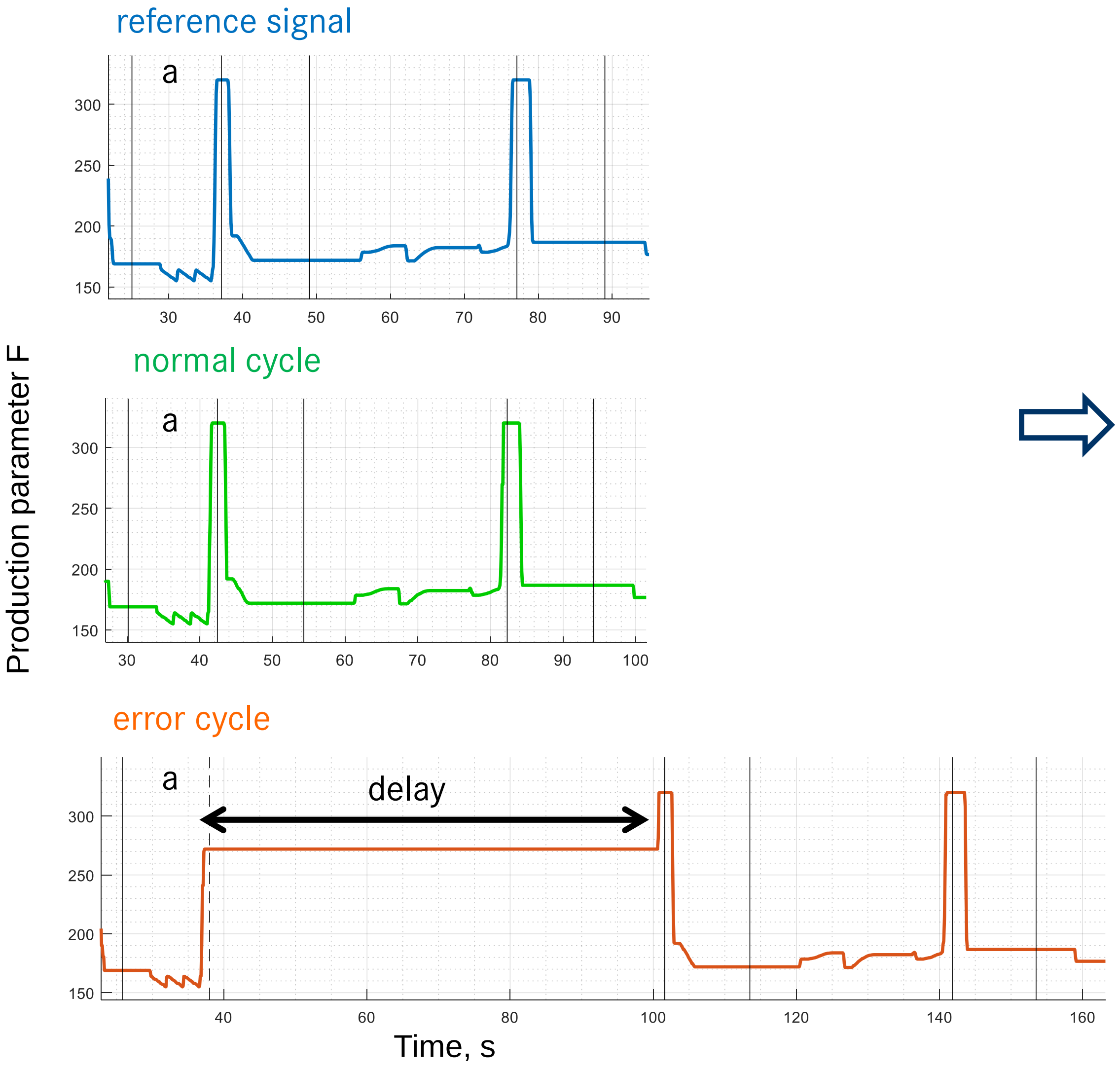
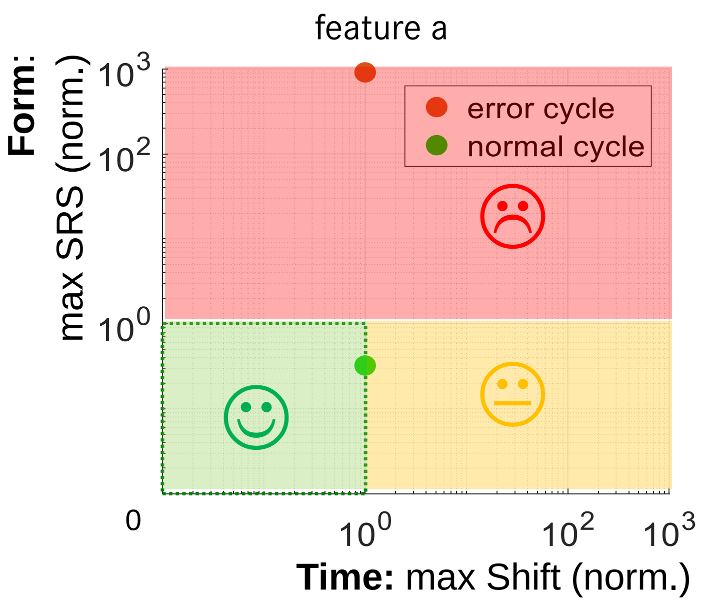
Testing: time and pattern deviation evaluation

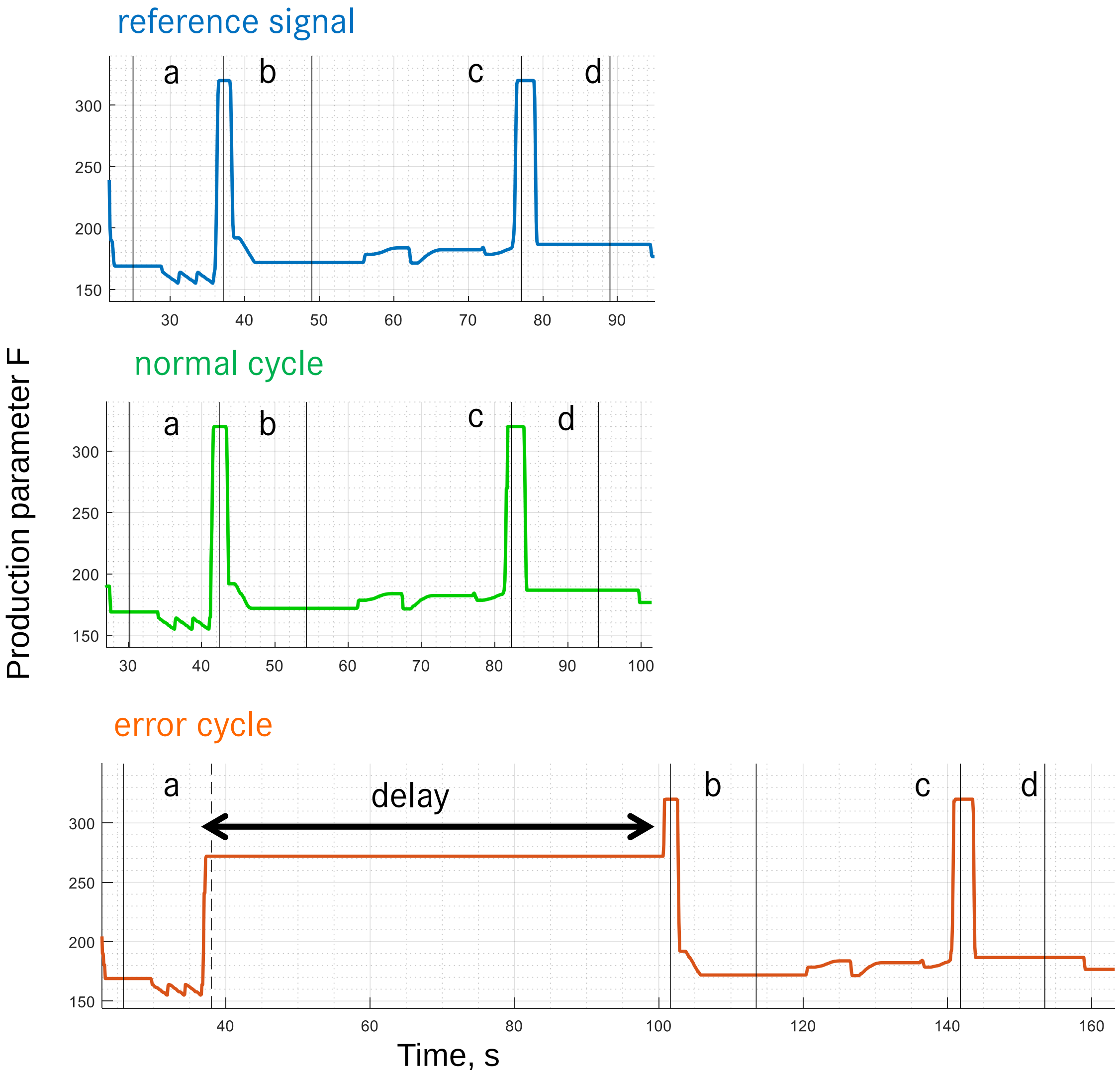


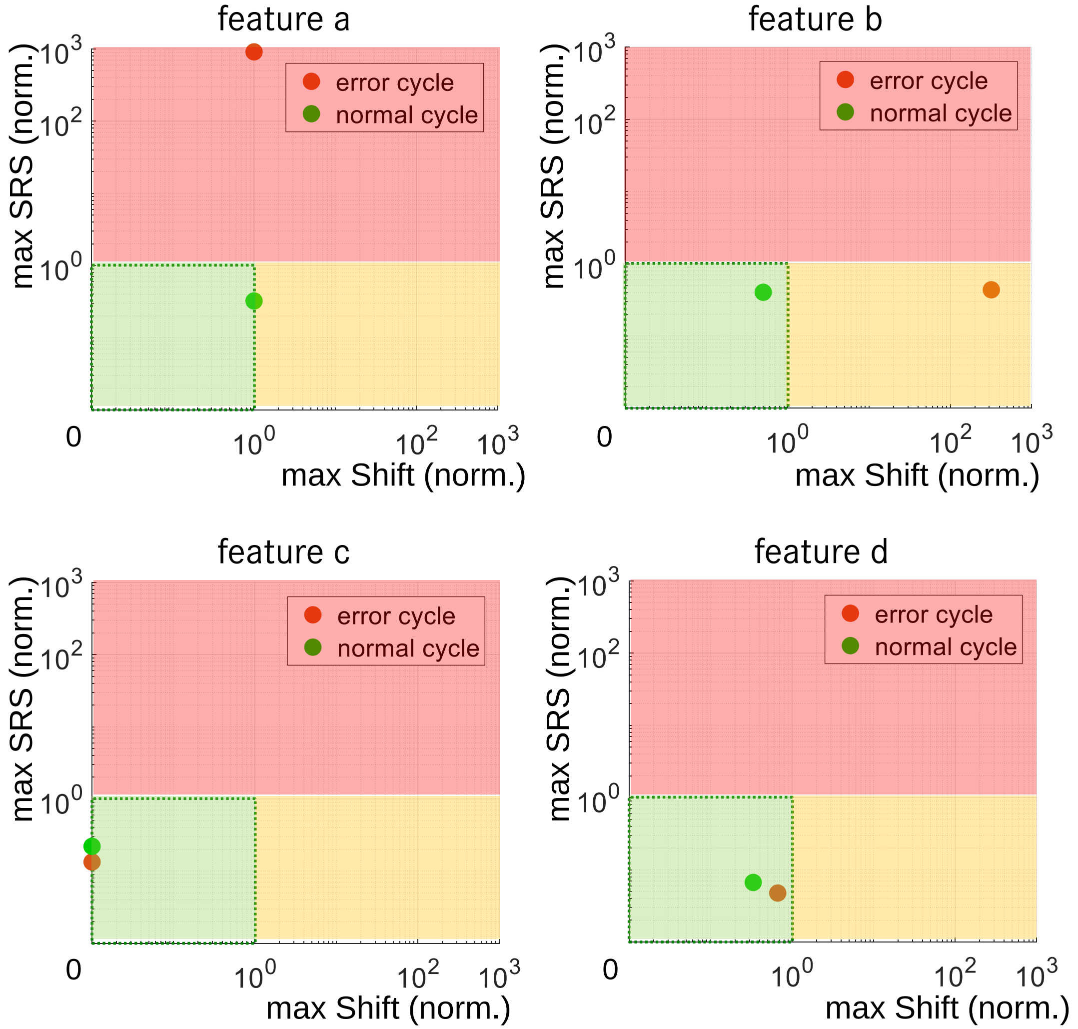
Is time and pattern deviation
for this feature within the limits?

- Tolerance window ($\Delta\ t$, *SRS*)
- Easy to spot a critical deviation



Testing: time and pattern deviation evaluation





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Algorithm: Summary

1. Quantitative and qualitative description of production failure
2. Independent of signal form -> universally applicable to other applications or machines
3. Signal description with characteristic numbers, which are easy to interpret
4. Data reduction with a factor **250** without significant loss of information!
5. Easy control of production: recognition of critical errors and non-critical delays online

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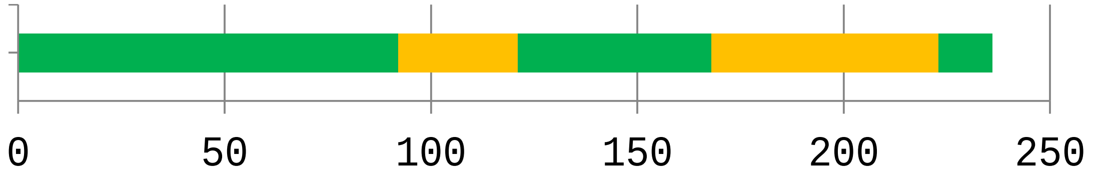
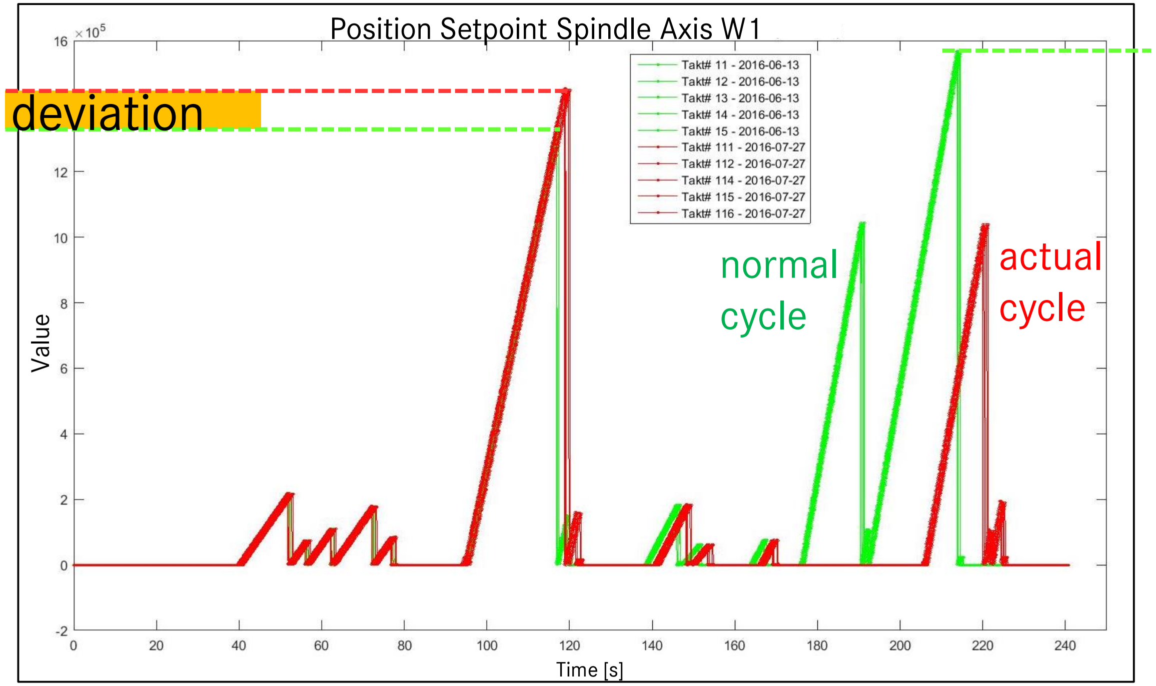
Example of the added value

Example: Change in code





Results:

- Transparency of the process
- Deviation for each Signal
- Reason of Cycletime increase found

➔ Time and Pattern deviation are recognized

Summary

Algorithm using pattern matching for time series developed and implemented for production data

Why MATLAB?

- easy algorithm implementation
- existing solution for data import
- very good support and broad use in universities

MathWorks products used:

- Signal Processing Toolbox
- Statistics and Machine Learning Toolbox

Outlook:

- Parallel Computing Toolbox for performance improvement

Prototyp intelligent Level-Learning (iLL) has a new function for anomaly detection

- Troubleshooting in case of failure (maintenance), Parts Planning, Influences on the quality
    - ➔ Optimization of repair time, spreaders amount, …

Thank you for your attention!

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