Selection and optimization of historical data for the training of artificial intelligence in power plant engineering

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Content of today's presentation

- **Introduction** to the lecture / Focus
- **Challenges** of "Big Data"
- **Theory** of predictions of process variables with NN
- Integral **prediction**
- **Selection** and **evaluation** of training and test data
- **Case study**

Introduction to the lecture / Focus

- Application of artificial intelligence (AI) in power plant process engineering
  ►Encounter with "Big Data"!
- Procedures for the selection and optimization of historical data for the training of AI
- Applications for predicting process variables:
  - Steamgeneration
  - Temperature boiler ceiling
  - CO
  - etc…
- High expenditure of time for selection of learning patterns
  ► > 64,0000 learning patterns corresponds to > 1.5 Gbyte of data

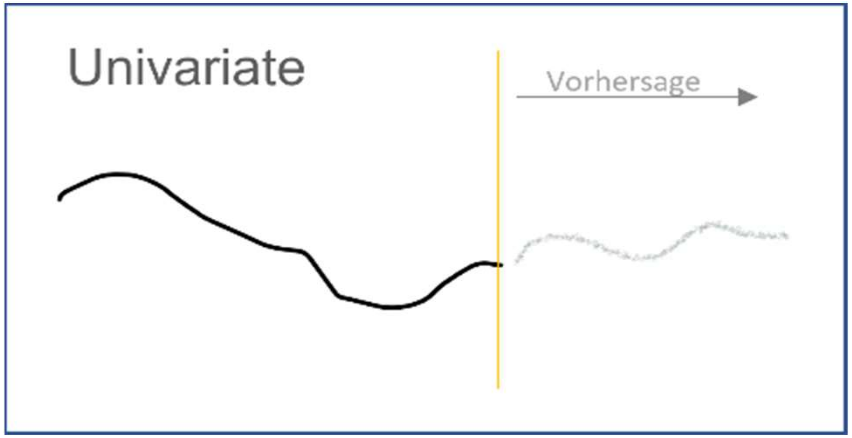
Challenges of "Big Data"

- Data amount
  - cannot be processed because, for example, there are upper limits on the number of rows in Excel
- Performance Issues
  - is available with e.g. Excel, if you want to open a file > 1 GByte
  - may mean several minutes of waiting time
- Search for alternatives is required
- Algorithms for preprocessing the training data very helpful!
  ► Professional processing required for cost-effectiveness!

Theory of predictions of process variables with NN 1v2

Different approaches and possibilities for predicting process variables:

- Dependence on only **one** variable:
  - Only one signal is used to predict future behavior, e.g. only steam
  - This dependence is called "univariate" in mathematics



- Dependence on **several** variables:
  - Several signals are used to predict future behavior, e.g. steam, temperature, CO, air, ...
  - This dependence is called "multivariate" in mathematics

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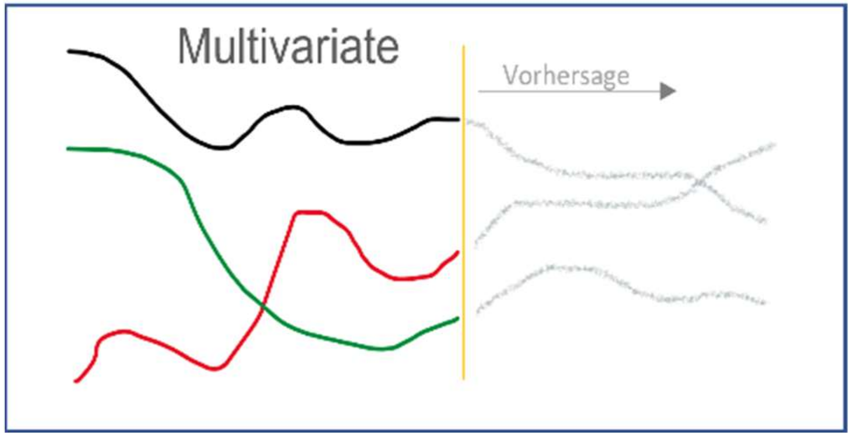
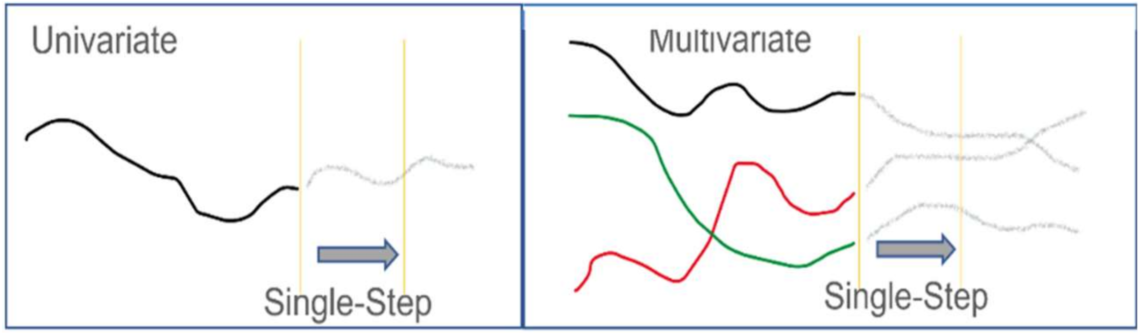


Theory of predictions of process variables with NN 2v2

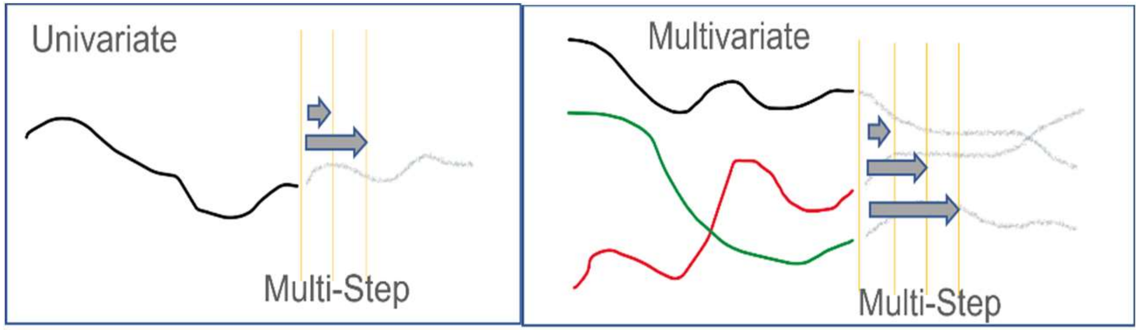
Forecast horizons

There are different forecast horizons for predicting process variables:

- Single-Step: only one forecast horizon, e.g. only 5 minutes:

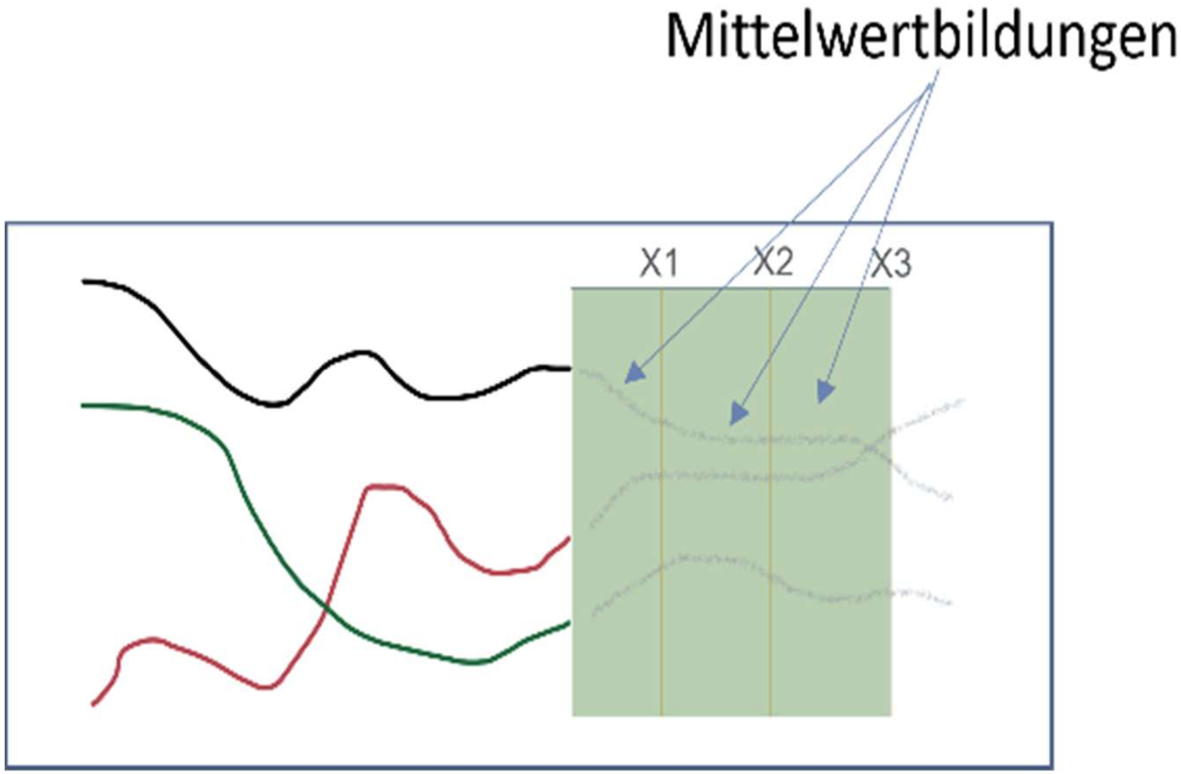


- Multi-Step: Predict multiple forecast horizons, e.g. 5 minutes, 10 minutes, ...



Integral prediction

- Multivariate and multi-level forecasting method
- Averaging over forecast horizon
- **Averages:**
  - easier to predict
  - contain the important process engineering information
- Confirmation by practice
  - ► Prediction of steam mass flows



Selection and evaluation of training and test data 1v5

- Training dataset
  - 4 to 6 months for predictive model, e.g. steam prediction
  - Elimination of plant downtimes and disruptive process events
  - Storage of as much data as possible
- Test dataset
  - Selection of a small test set of a few weeks

  ► These are the data that the neural network has not learned, i.e. does not know
- Overfitting
  - Typical strategies to avoid overfitting don't seem to work here
  - Large datasets are the key!
  - Practical confirmation of steam prediction and temperature prediction boiler ceiling

  ► Use of very, very large data sets required!

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Selection and evaluation of training and test data 2v5

Complexity optimization (with the same NN topology)

- **Large** data set
  - In case of underfitting (poor learning), the complexity of the NN is too low to model the complexity of the data set

  ► Solution: Reduce the number of trainable outputs to increase the available complexity per output or reduce variarity
- **Small** data set
  - With **Overfitting** the complexity of the NN is too great
  - The NN remembers each sample of the training data set, the generalization of test data will be poor in most of these cases

  ► Solution: Increase the number of trainable outputs or increase training dataset or variarity

Selection and evaluation of training and test data 3v5

Uneven distribution of data in a data set

- "Unbalanced regression"
- Large 6-month data sets reflect typical distribution of actual plant operation

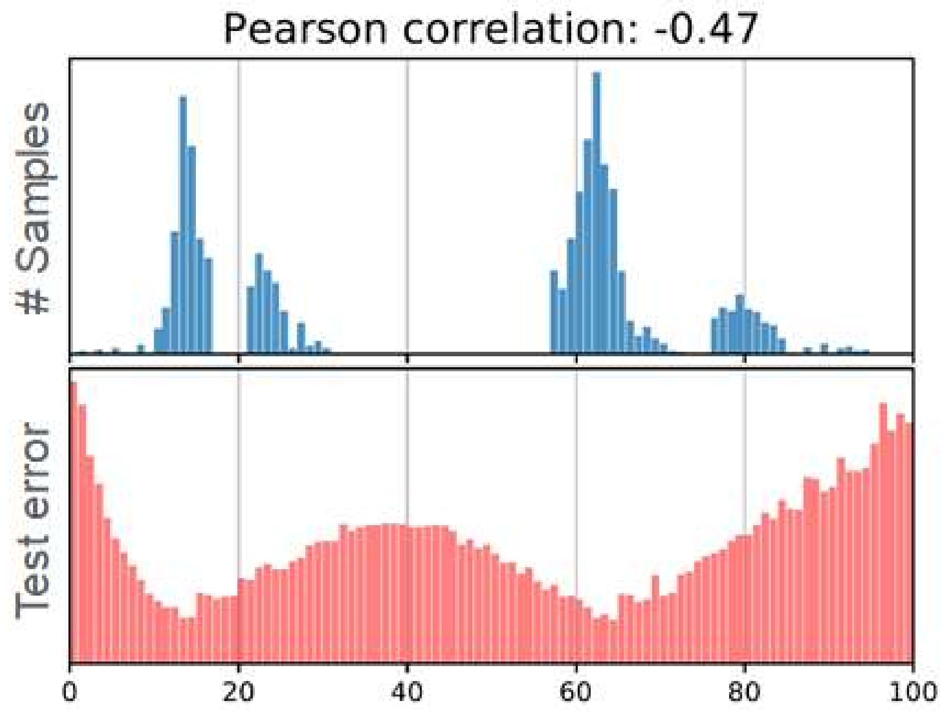
Number of input/output pairs	Spatial density	Probability of alternative similar input/output pairs
Accumulation	high	high
Shortage	low	low

Selection and evaluation of training and test data 4v5

Example of a data set distribution

► Negative correlation (-0.47) between the number of samples for a given operating behaviour and a test error

- **Frequent** data in a particular operating behavior results in a **small test error** for that behavior
- **Rare** data in a certain operating behavior leads to a **high test error** for this operating behavior

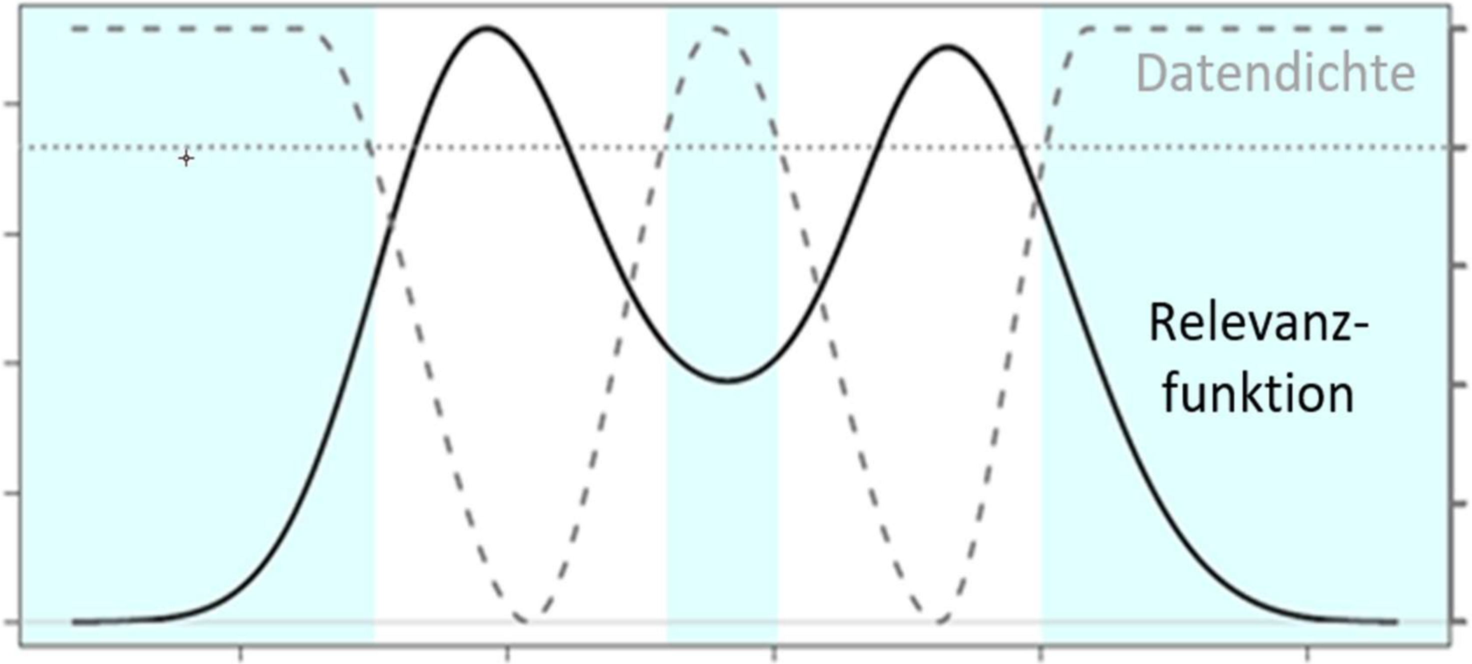


Selection and evaluation of training and test data 5v5

Relevance function

To improve the learning success of the NN:

► **Inverted** data density is used as a relevance function



There are many theoretical methods from the literature:

- SMOTER (2013)
- SMOGN (2017)
- **WERCS (2018)**
- Dense Loss (2021)

Steam prediction:

- Method WERCS
- Specific weighting of synapse weights
- Strong improvement
- Practical!

Practical example - Procedure 1v8

Standard procedure for balancing algorithms for balancing learning patterns according to the previous mentioned methods:

1. **Analysis** of the complete data set for common and rare data

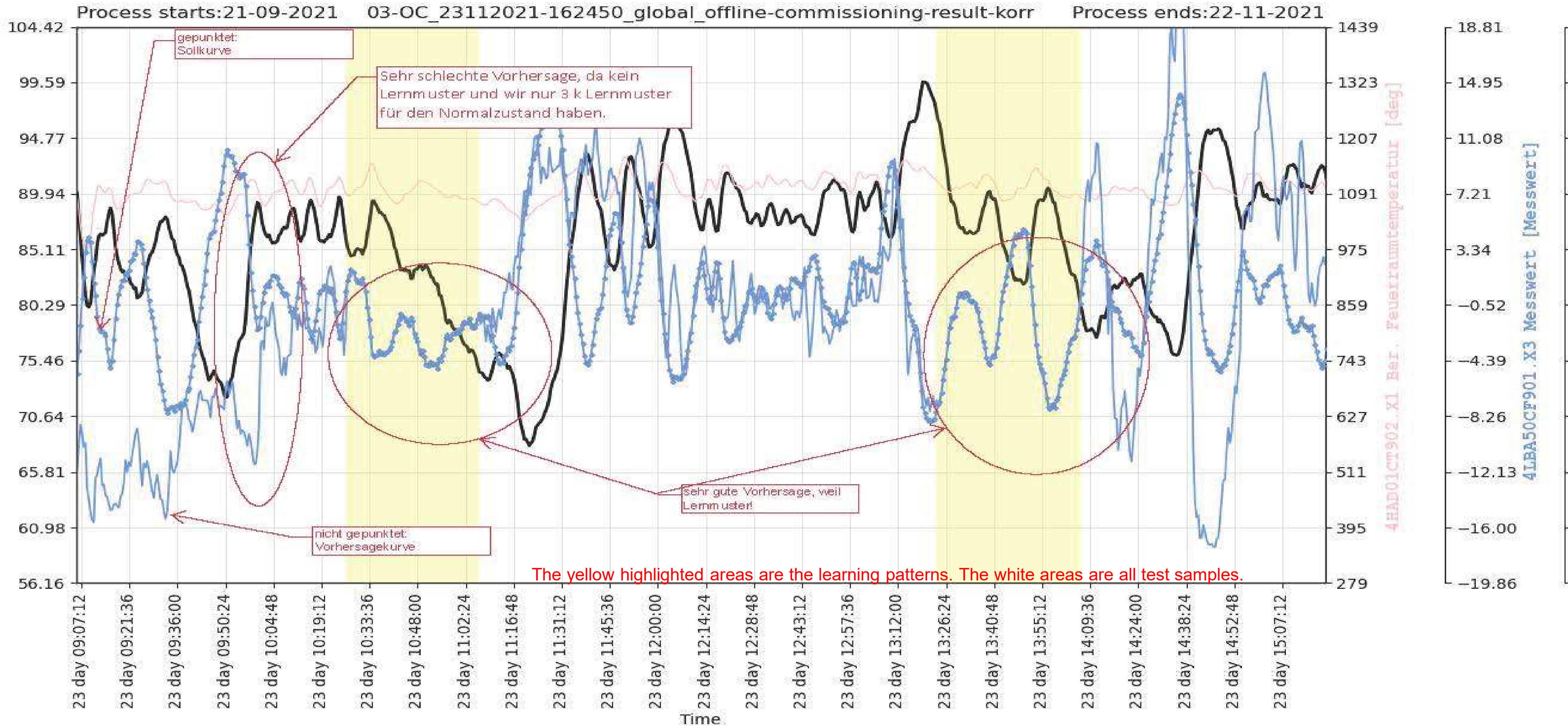
2. **Balancing** the common and rare cases by using a combination of:

   - **Oversampling rare** data by creating synthetic data, such as adding random noise to existing data
   - **Undersampling for data clusters by finding data that:**
     - are close to each other and therefore approximately the same
     - are staggered in time and similar

     and can therefore be deleted.

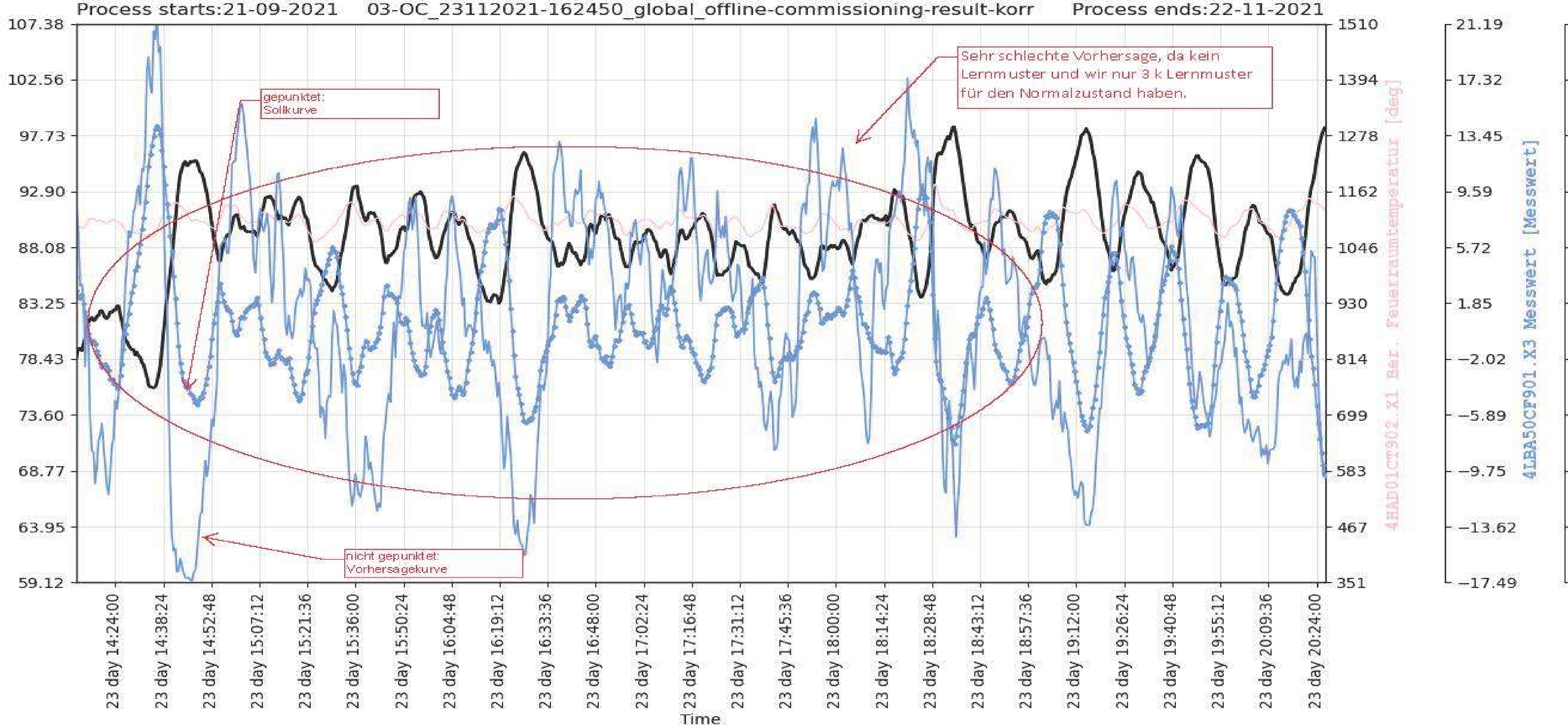
Practical example - steam forecast WIP (waste incineration plant) 2v8

4k-Learning-Pattern-3k-Normal-1k-Steamdrop



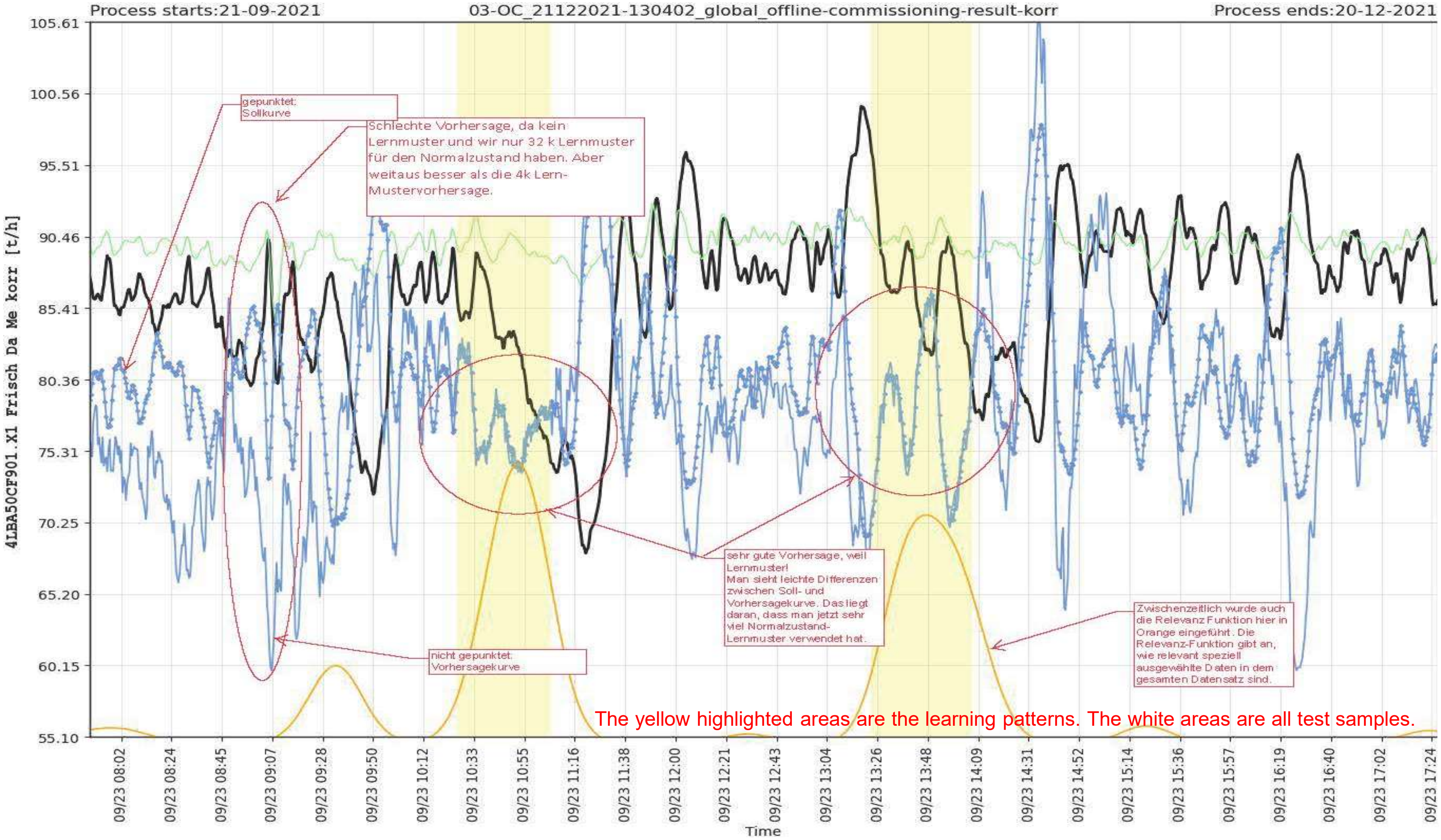
Practical example - steam forecast WIP (waste incineration plant) 3v8

The following test pattern was found for the normal state (no steamdrop)



Practical example - steam forecast WIP (waste incineration plant) 4v8

32k-Learning-Pattern-30k-Normal-2k-Steamdrop:

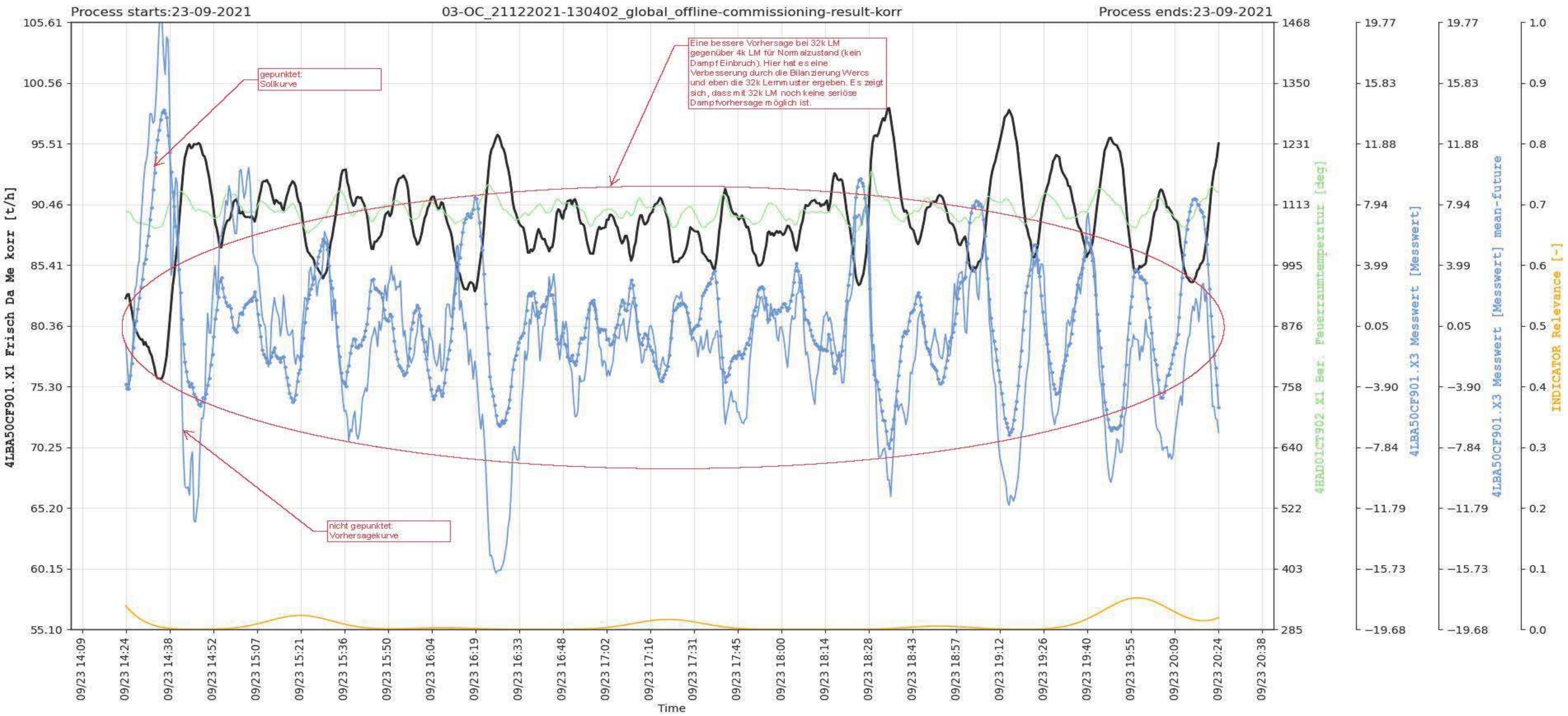


Relevance Function:

- Trend in Orange
- High relevance values lead to the reinforcement of learning patterns!

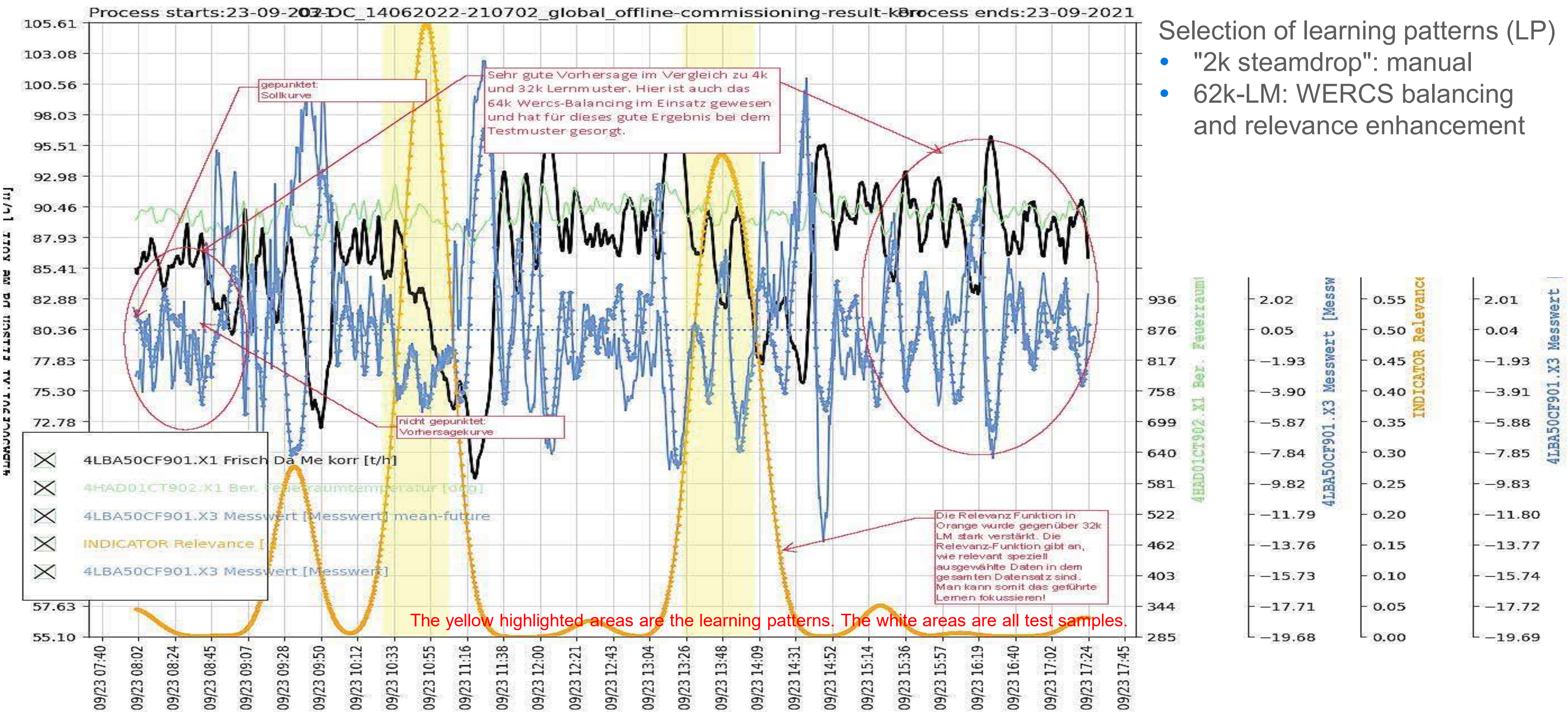
Practical example - steam forecast WIP (waste incineration plant) 5v8

The following test pattern was found for the normal state (no steamdrop)



Practical example - steam forecast WIP (waste incineration plant) 6v8

64k-Learning-Pattern-62k-Normal-2k-Steamdrop:

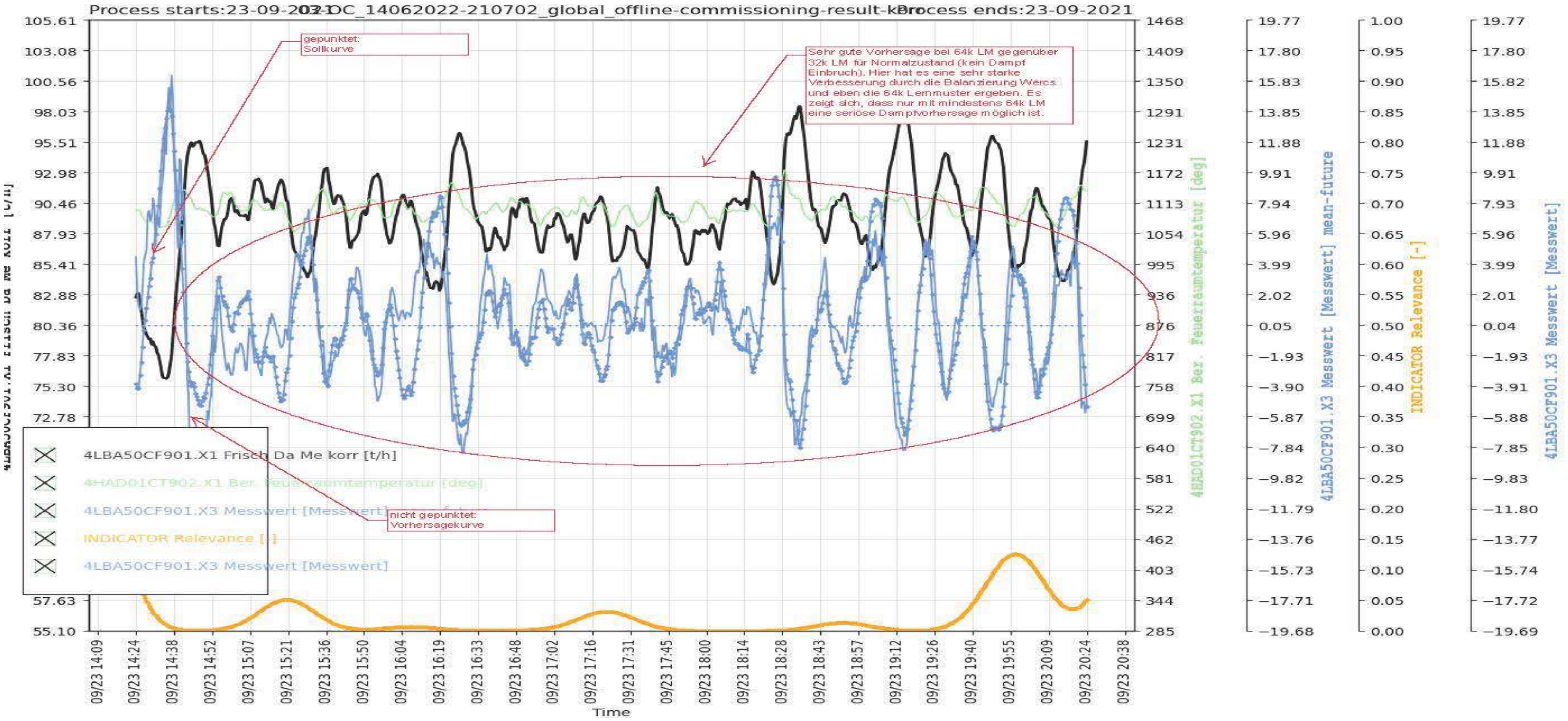


Selection of learning patterns (LP)

- "2k steamdrop": manual
- 62k-LM: WERCS balancing and relevance enhancement

Practical example - steam forecast WIP (waste incineration plant) 7v8

The following test pattern was found for the normal state (no steamdrop):



Practical example - steam forecast WIP (waste incineration plant) 8v8

Relevance / Process Engineering Indicator – Definition

- The relevance was also used as a process engineering indicator, which was called here "Process category 1: Waste grate overfill" (double function!)
- Trends in measurements:
  - Primary air pressures: trend upwards
  - Flue gas O2 content: trend upwards
  - Fire rate control grate feed: trend upwards
  - Combustion chamber temperature: trend downwards
  - Moisture measurement: trend upwards
- Future values of steam production
  - 5 minutes: Trend downward
  - 15 minutes: Trend downward
  - 30 minutes: Trend downward
- Calculation of relevance / process engineering indicator
  - Mathematical linking of:
    - Trends in measurements
    - Future values of steam production

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