COGNIPLANT

FORNACI Training – 9th of May 2023

STAM & Fornaci

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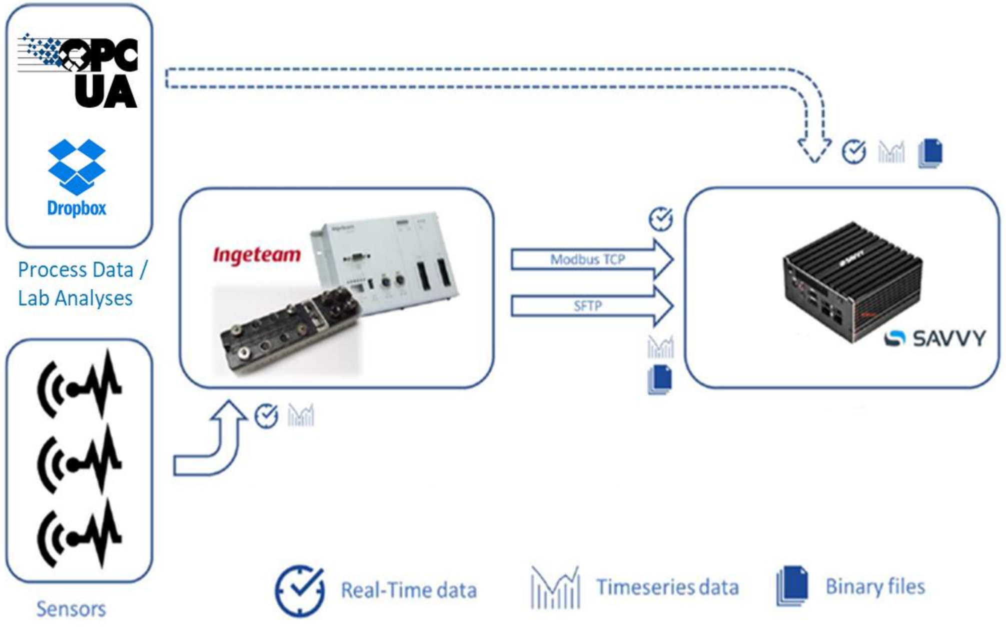
TRAINING ACTIVITIES

Technology deployed: SmartBox (Co-Digitize)

- AK 601 Process data collection from OPC UA gateway
  - Real-time process values
  - Cycle aggregated values
  - Alarms
- Integration with Ingeteam Edge Node for new sensor data (vibrations)
- Lab analysis data collection from shared Dropbox folder
  - Automated Excel file download and digestion
  - Data pre-process for increased resolution (required by Co-Analyse)
- Possibility to automatically write Cognitive suggestions back to OPC UA gateway (not currently used)

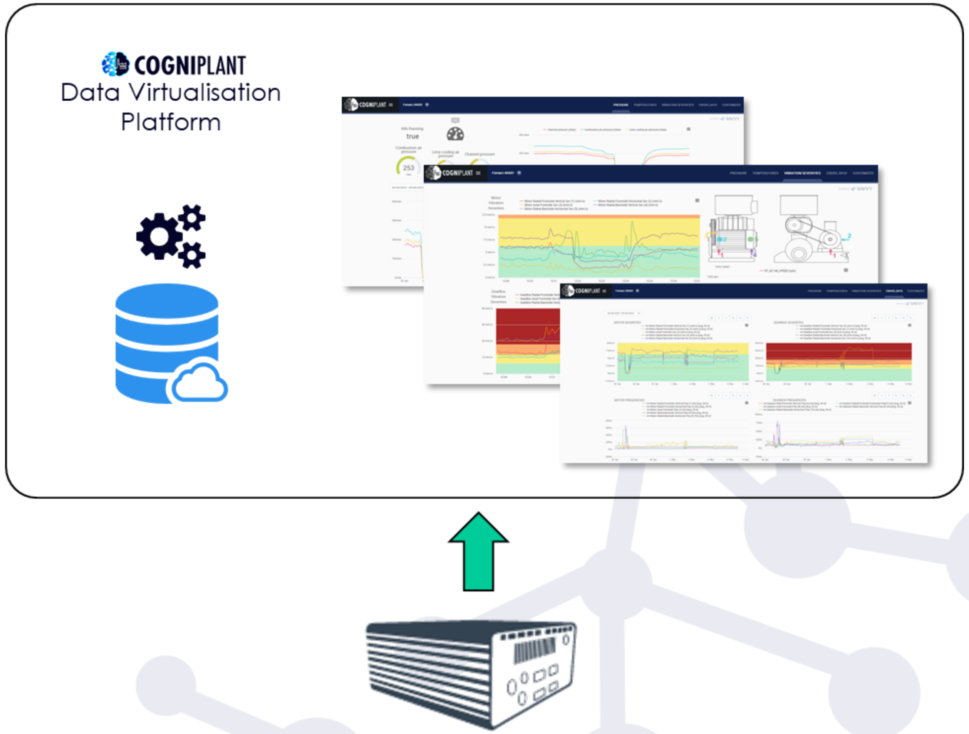


Demo expectations

- Seamless collection, refining and provisioning of lab analysis data
  - Suggested test: upload new version of lab analysis Excel file to Dropbox
  - Expected result: lab analysis data digested and available on Cognitive platform

Technology deployed: Datalake (Co-Digitize)

- Raw data (1 second resolution) provisioning over secure REST API
    - Real time data streams for online predictions on AVUBDI / Digital Twins
    - Historical data batches for in-depth analysis on AVUBDI / Digital Twins
    - Unbounded, long-term cloud storage
- Data aggregations by minute & hour
    - MAX, MIN, AVG, SUM, COUNT
- Process visualization and monitoring thanks to specialized dashboards
- Email notifications for specific machine alarms



Demo expectations

- Subscription to email-based alarm notifications for different roles / users
    - Suggested test: simulate distinct alarm conditions on AK601
    - Expected result: email notification received by operator or manager in timely fashion

SCCH Technologies for FORNA Plant

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Developed and Deployed applications

<u>Data preparing and preprocessing:</u>

1. FORNA_Data_Conversion
2. FORNA_Data_Preprocessing

<u>Machine learning models:</u>

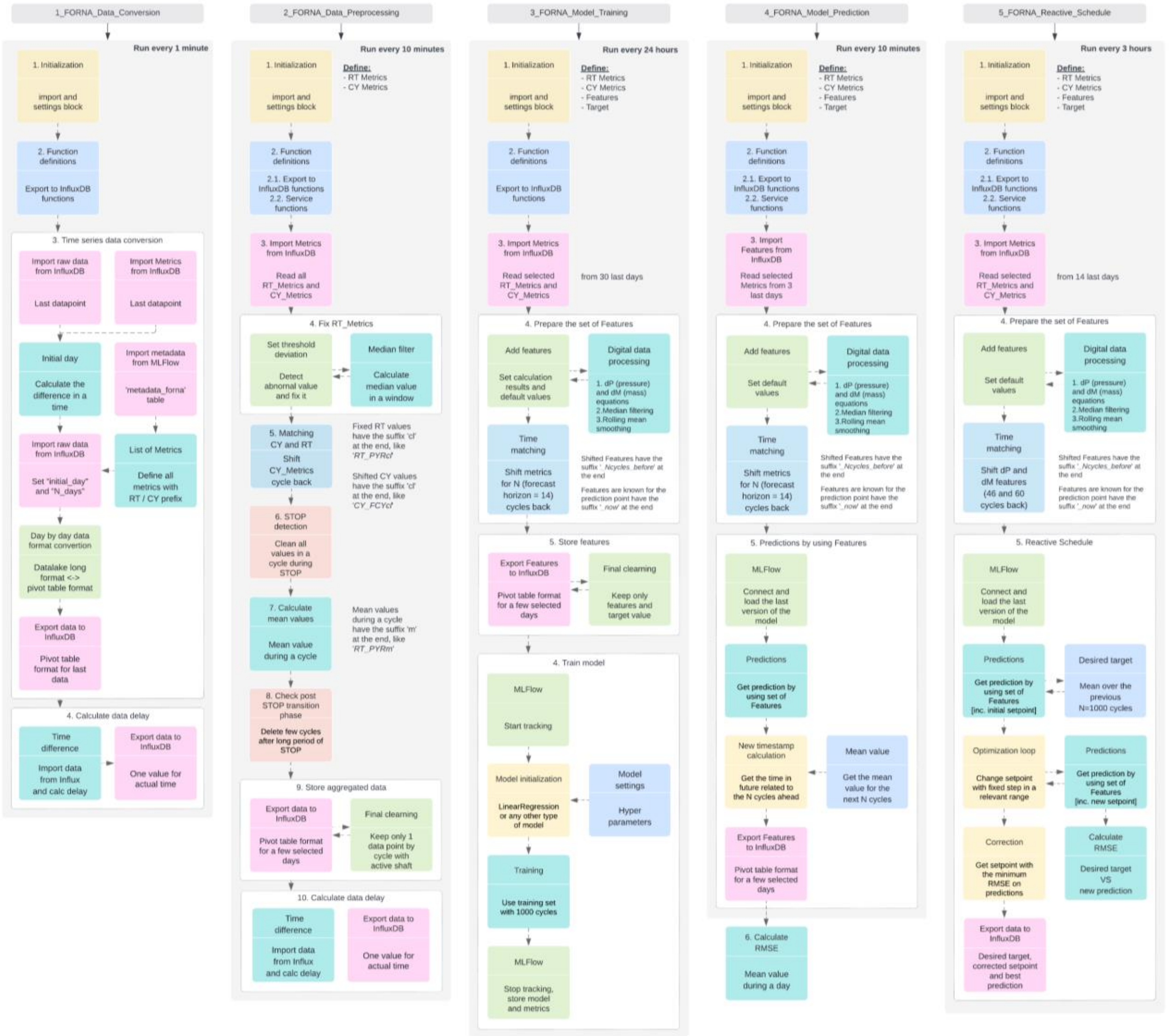
3. FORNA_Model_Training
4. FORNA_Model_Prediction

<u>Optimization:</u>

5. FORNA_Reactive_Schedule

<u>General features:</u>

- Low computation complexity
- Dockerized services
- Architecture based on parallel flows
- Each application runs in specific time



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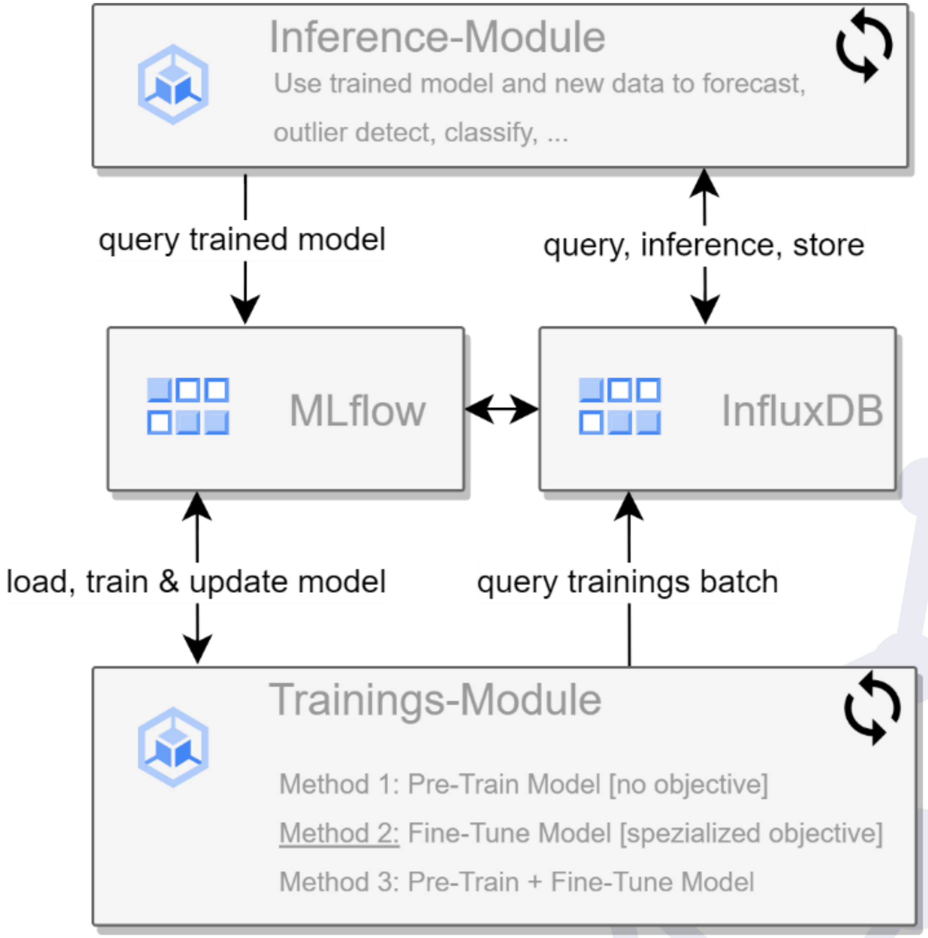
Developed and Deployed applications

<u>Pattern Abstractions and Virtual Layer Models:</u>

1. FORNA_Model_Trainings_Module
2. FORNA_Model_Inference_Module

<u>General features:</u>

- Dockerized services
- Global model
- Learns latent representations of the process
- Customizable architecture and objective



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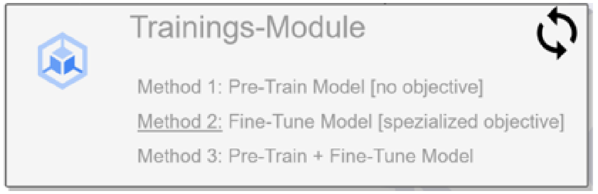
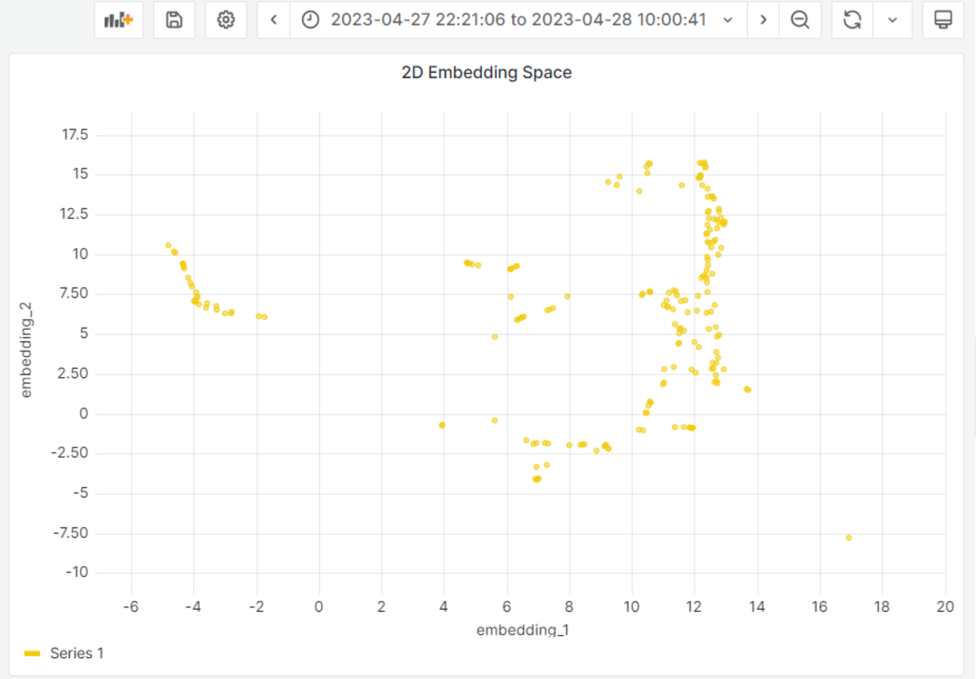


Pattern Abstractions and Virtual Layer Models - Training:

Key features and benefits:

- Trains a **global** model to **forecast** the next N timesteps of a customizable target (implemented for Channel Temperature with N=60) given M timesteps of **context length** (implemented with M=15).
- Possible to **retrain from scratch** or **update existing** model w.r.t. new data
- Uses (optionally lagged) pressure sensor, sawdust and limestone weight values
- Persists learned representations in InfluxDB
- Enables **a higher-level understanding** of the process and enables **complex historic similarity searches**, i.e., given a window of data points, which historical windows behave similarly?
- Higher context length possible when GPUs are available



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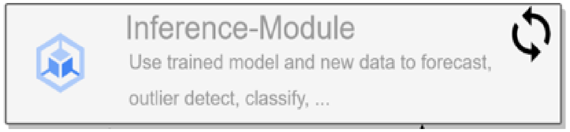
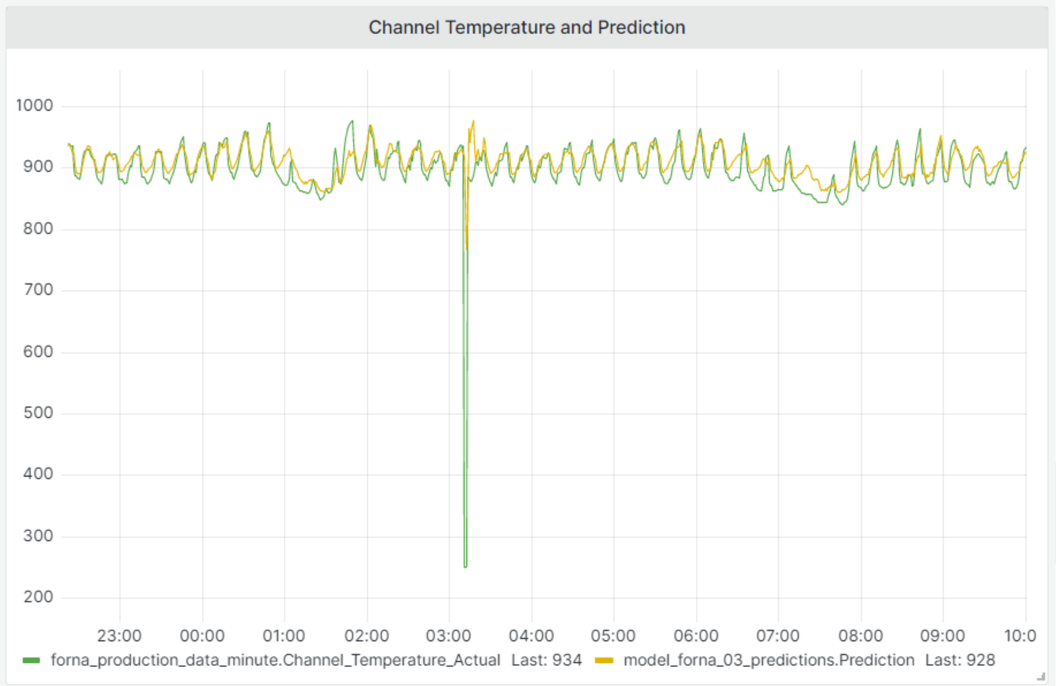


Pattern Abstractions and Virtual Layer Models - Inference:

Key features and benefits:

- Infers **knowledge about new data** based on the **training data** and objective (Forecast)
- Inference **conducted** on a **global model**
- Outputs a forecast of length N given a trained model and **unseen data**
- Generates and saves embeddings from **unseen data** to InfluxDB
- Enables **online inference** of the (current) behavior of the system and thus can query similar complex historic behaviors given the learned embeddings in InfluxDB.



Upcoming Alerts

Time	model_forna_03_predictions.Status
2023-05-05 09:36:00	low temperature alert
2023-05-05 09:37:00	low temperature alert
2023-05-05 09:38:00	low temperature alert
2023-05-05 09:39:00	low temperature alert
2023-05-05 09:40:00	low temperature alert

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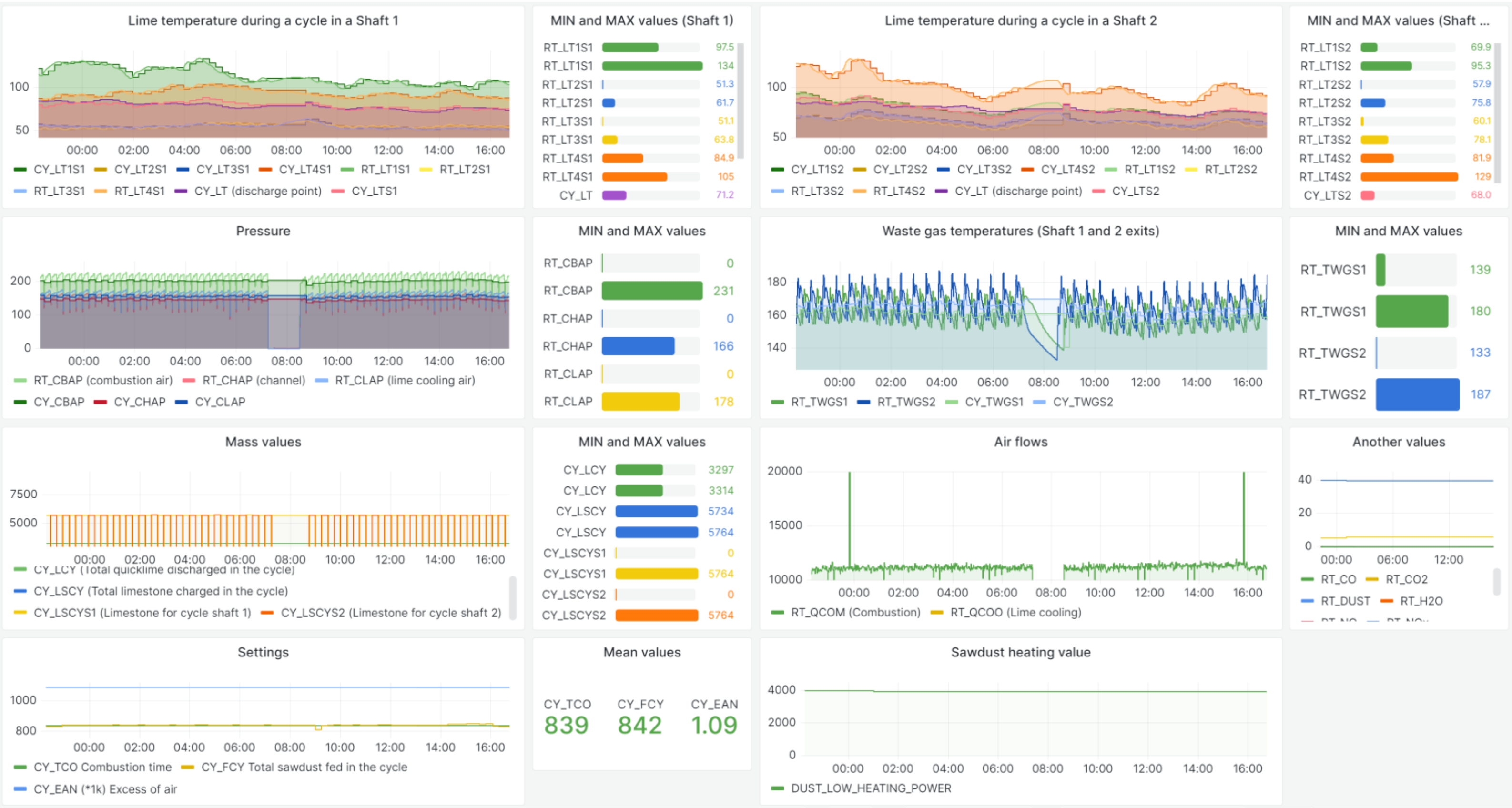
Data preparing and preprocessing:

1. FORNA_Data_Conversion

Key features and benefits:

- Online or history view of 46 metrics
- Real time and cycle aggregated data
- Process parameters with 1 minute granularity
- Calculate min and max values
- Display different time interval, like 1 hour, 3 hours, 6 hours, 12 hours, a day, a week, a month or any other



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<u>Data preparing and preprocessing:</u>
2. FORNA_Data_Preprocessing

<u>Key features and benefits:</u>
- Detect and fix anomalies in RT values
- Aggregate clean RT data by cycle
- Synchronize CY and RT by time
- Temperature in the channel (RT_PYR) is colored regarding the active shaft
- Plot cyclogram of the kiln operation
- Analysis RT_PYR variations
- Detect and reduce RT_PYR transition phases during post-stops
- Show time delay for raw and aggregated by cycle data

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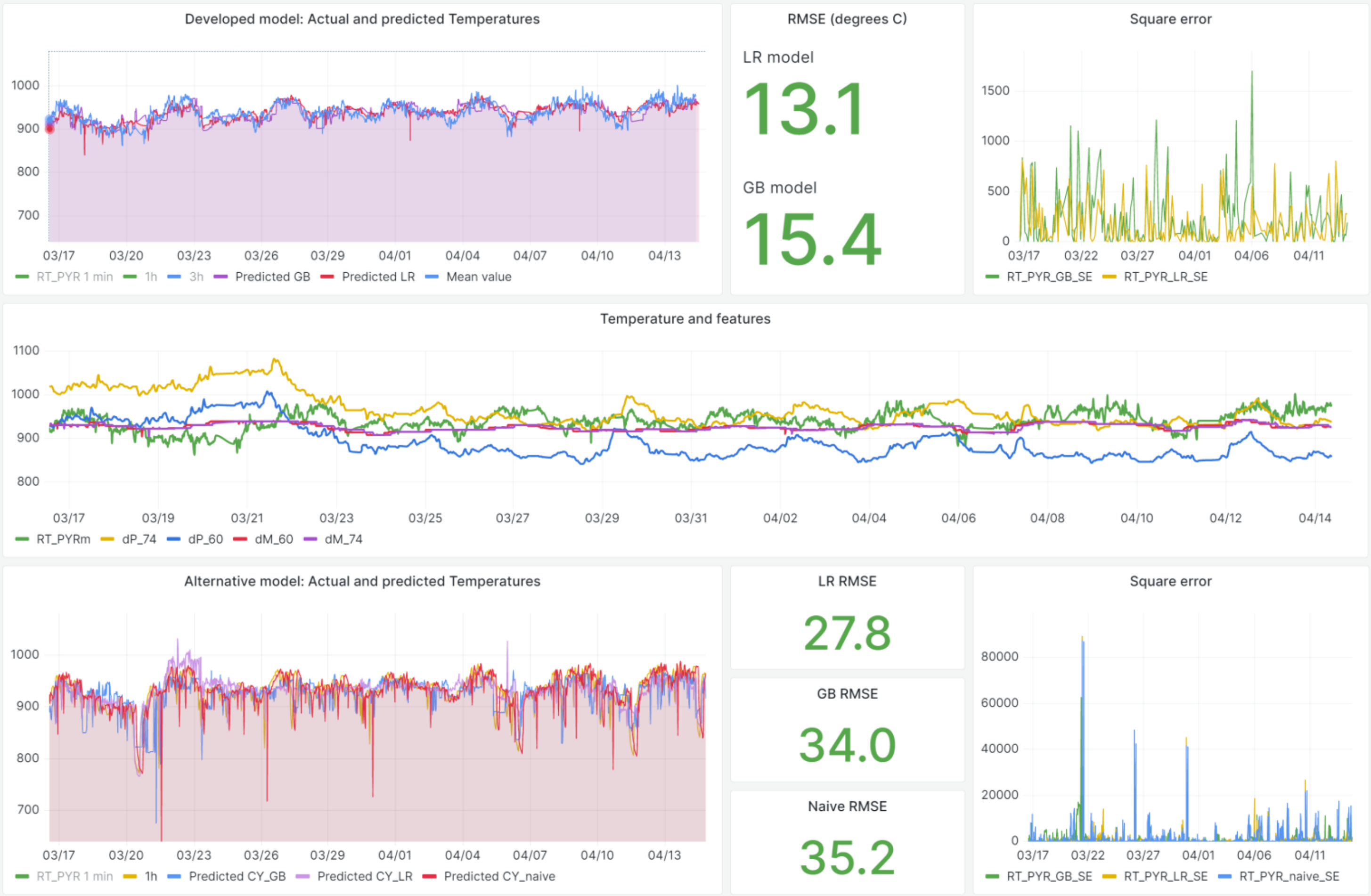
SCCH Technologies for FORNA Plant: Deployment & Benefits

<u>Machine learning models:</u>

3. FORNA_Model_Training

<u>Key features and benefits:</u>

- Process cycle aggregated data with linear regression and gradient boosting models for prev. 10 days
- Train model to predict RT_PYR for 14 cycles ahead (closed to 3h)
- Automatic retraining once a day
- Use pressure at various zones in the kiln, sawdust and limestone weights
- Detect the high inertia patterns by specific calculations on pressure and mass having 60 and 74 cycles delay



Developed model is better than:

1. Naïve model in 2.7 times
2. Basic LR in 2 times

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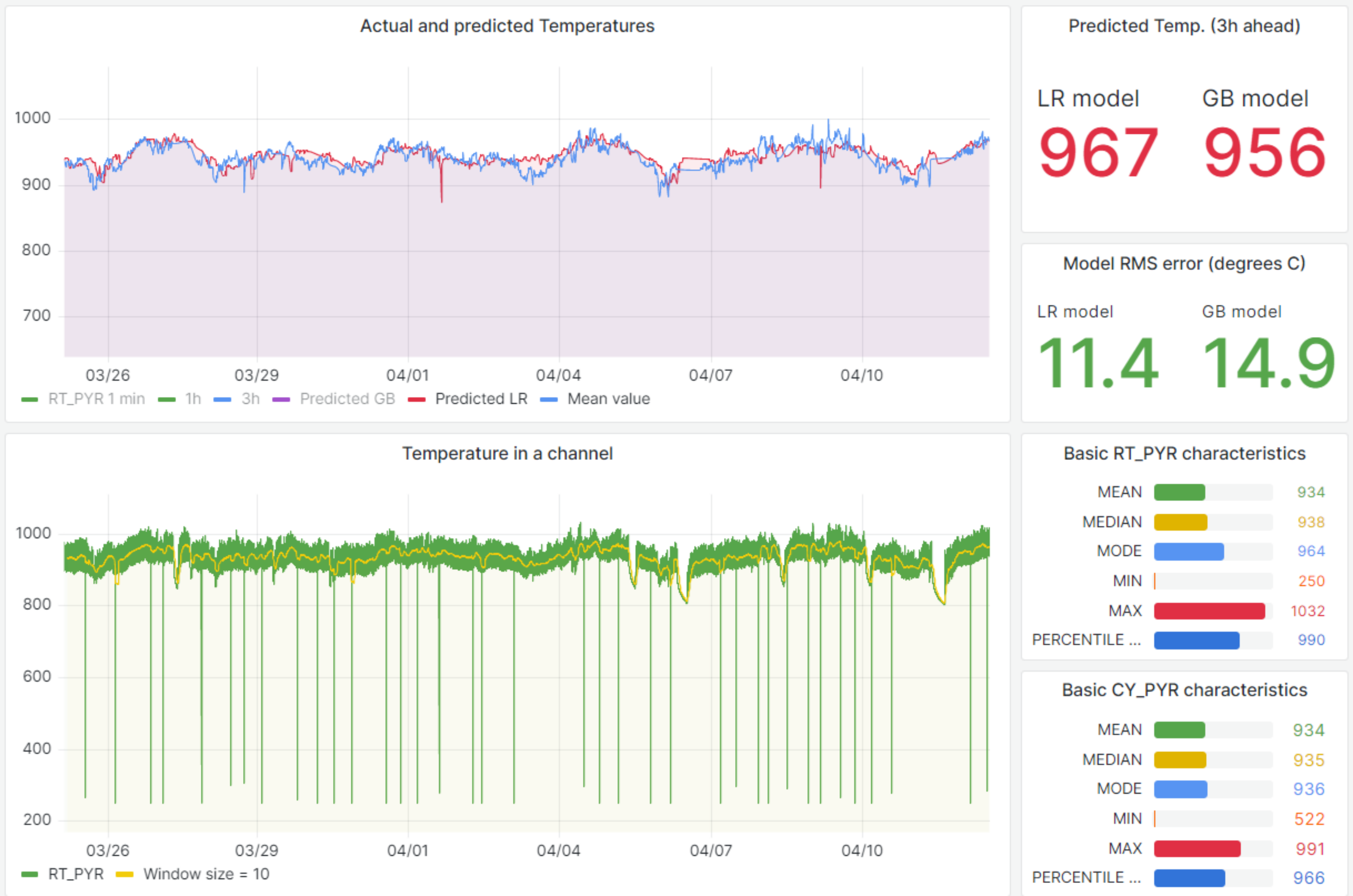
<u>Machine learning models:</u>
4. FORNA_Model_Prediction

<u>Key features and benefits:</u>
- RT_PYR predictions for 14 cycles ahead (about 3 hours) by LR and GB models
- Update values every 10 minutes
- Support time series and basic statistic panels
- Plot RT_PYR with aggregation by time: mean values during 1h and 3h
- Show moving average RT_PYR
- Use RMSE as an accuracy metric

Temperature predictions are more accurate if the statistics show small deviation around the mean (median) value

The operator can use this screen to obtain RT_PYR predictions and to estimate its relevance under real-time operation conditions



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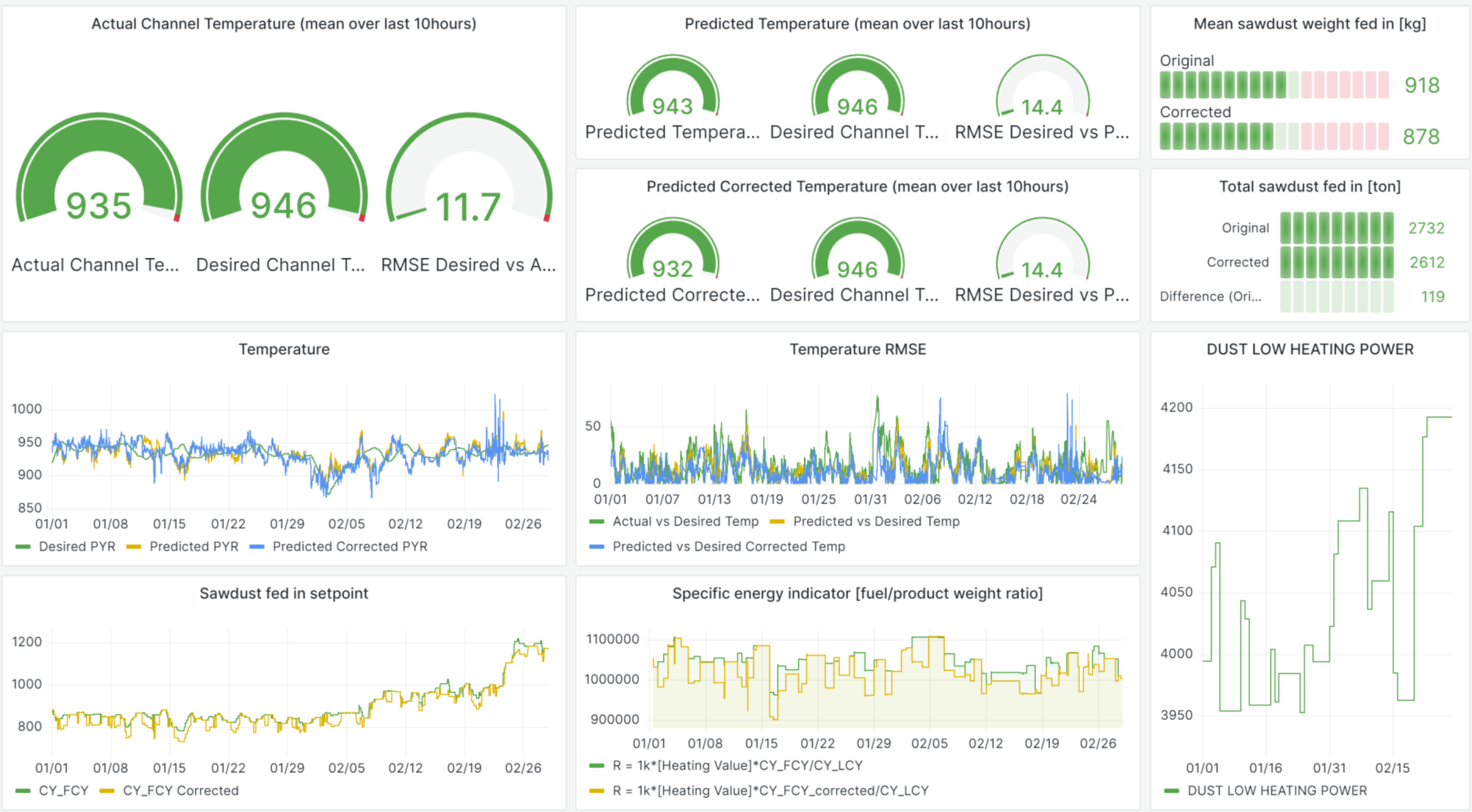
Optimization:
5. FORNA_Reactive_Schedule

Key features and benefits:

- Stabilize RT_PYR by smoothing within 48 hours
- Optimize the RT_PYR for 3h ahead by sawdust CY_FCY correction
- Calculate difference in sawdust weight after correction [in tons]
- Energy efficiency evaluation based on sawdust heating value

This app helps to analyze the impact of the sawdust feed to the channel temperature for the next 3 hours

Operator could use corrected setpoint values for the channel temperature stabilization, quicklime quality and kiln energy efficiency increasing



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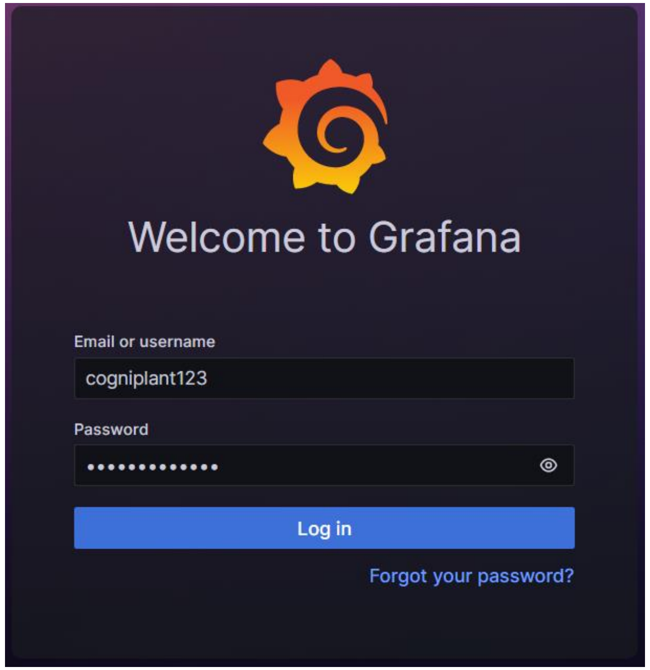
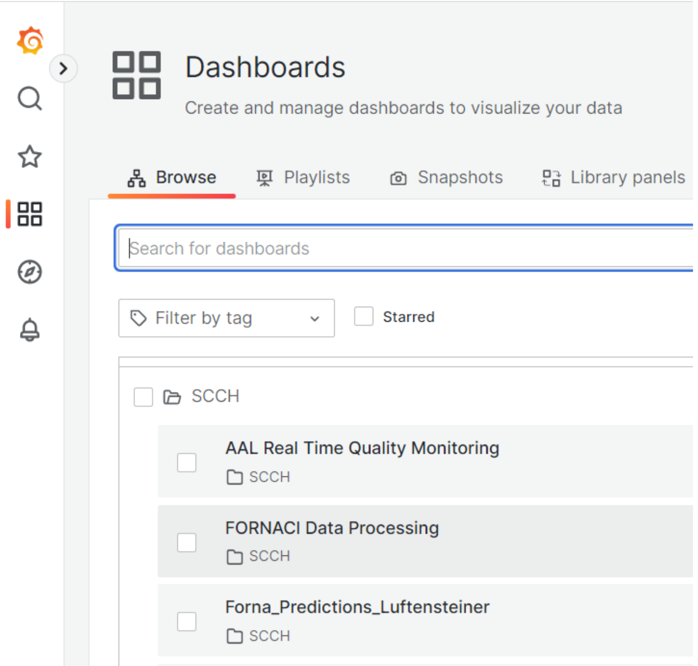
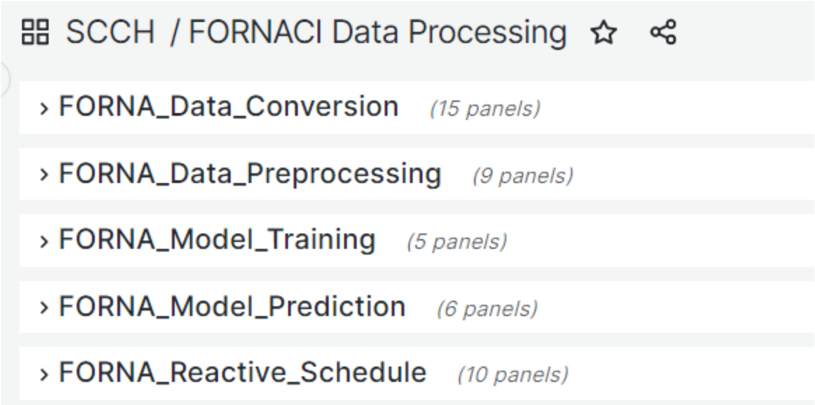
How to use applications?



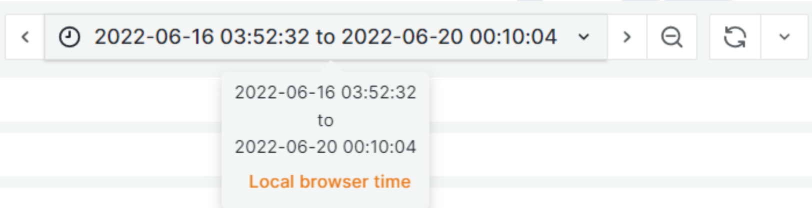
1. Login to Grafana visualization tool



2. Browse dashboards and select **FORNACI Data Processing** (SCCH folder)



3. Open required panel



4. Set the time interval

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F-KPI-3:
Temperature in the channel

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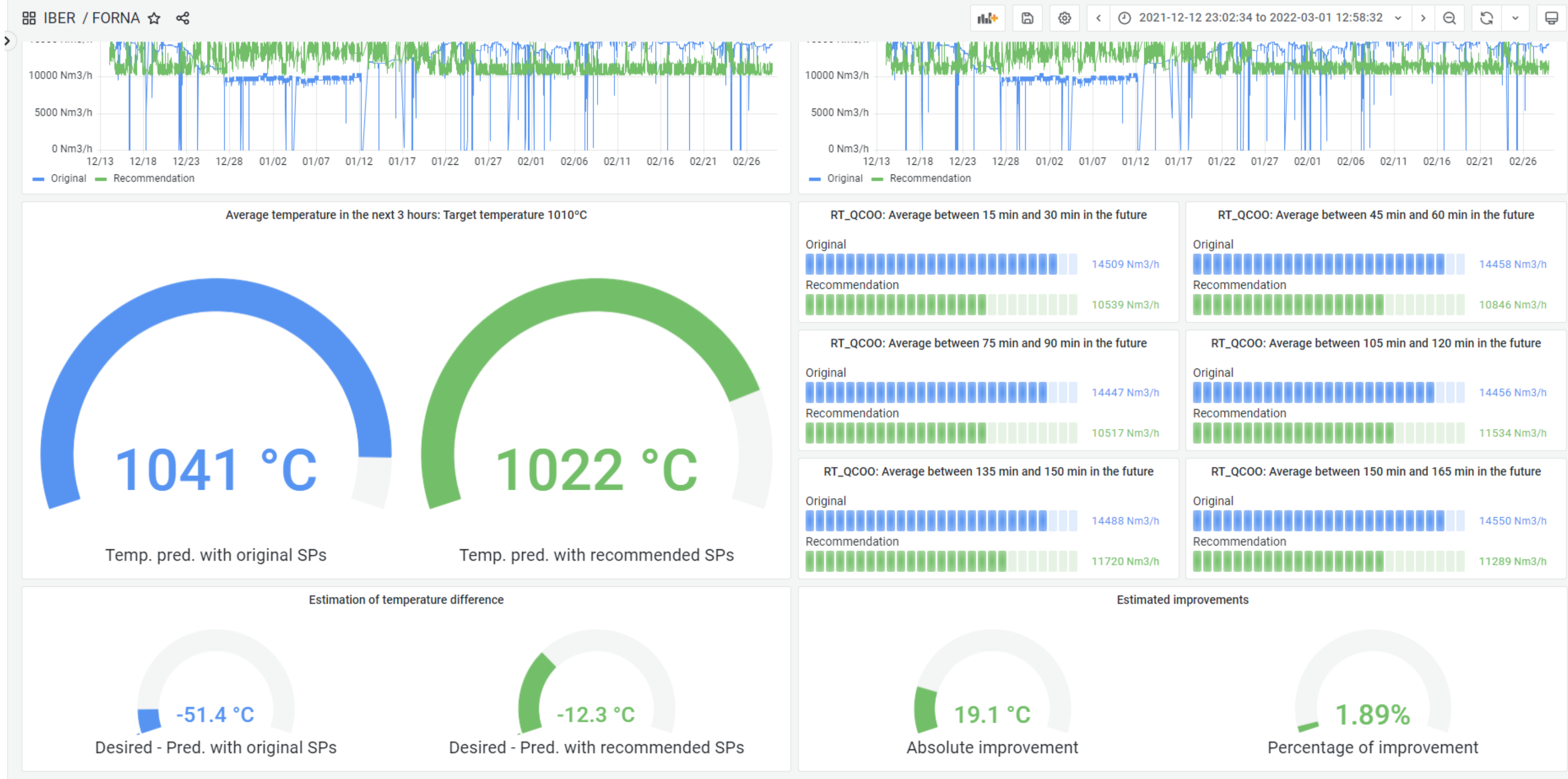
Introduction: on-demand optimization for channel temperature

- The temperature in the channel is a key indicator of the overall healthiness of the process, reflecting directly to the quality.
- **Ultimate goal**: given a real plant scenario, to generate future recommendations of setpoints (SPs) to maintain the channel temperature between 980-1000°C when working with small size limestone and between 1020-1030°C when working with large size limestone.

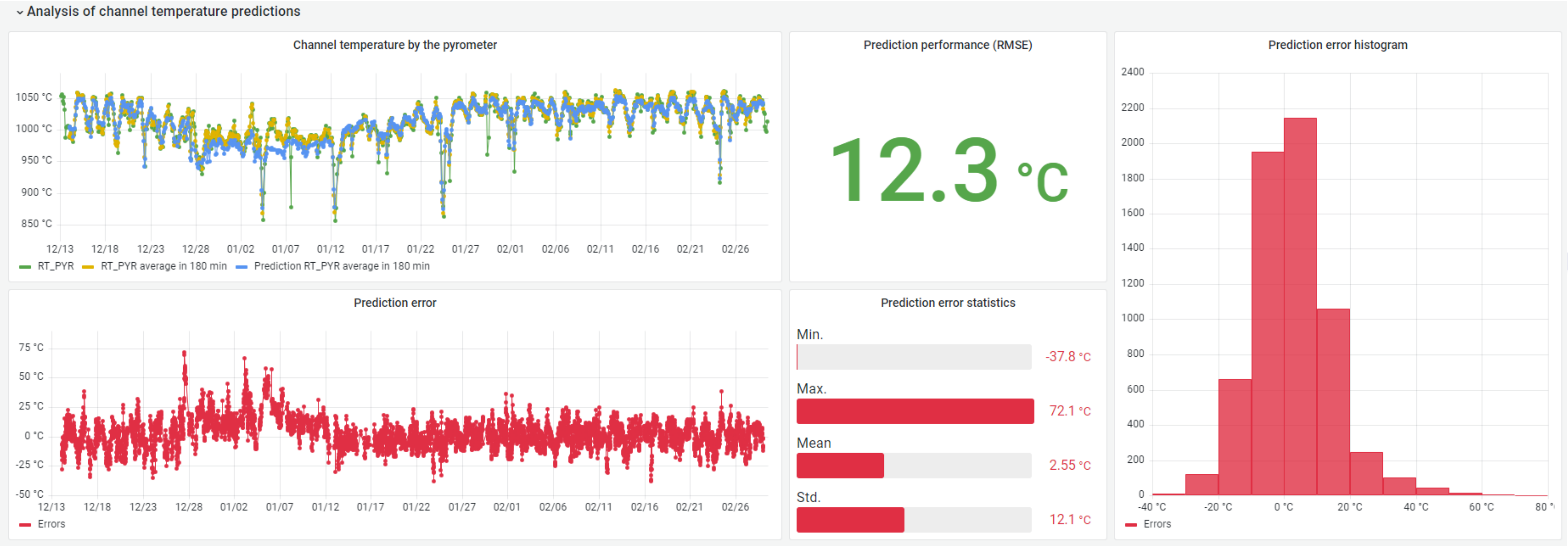


Development Description

- To address this KPI and develop an optimizer, the models developed in WP3 are used using a **simulation-based search approach**.

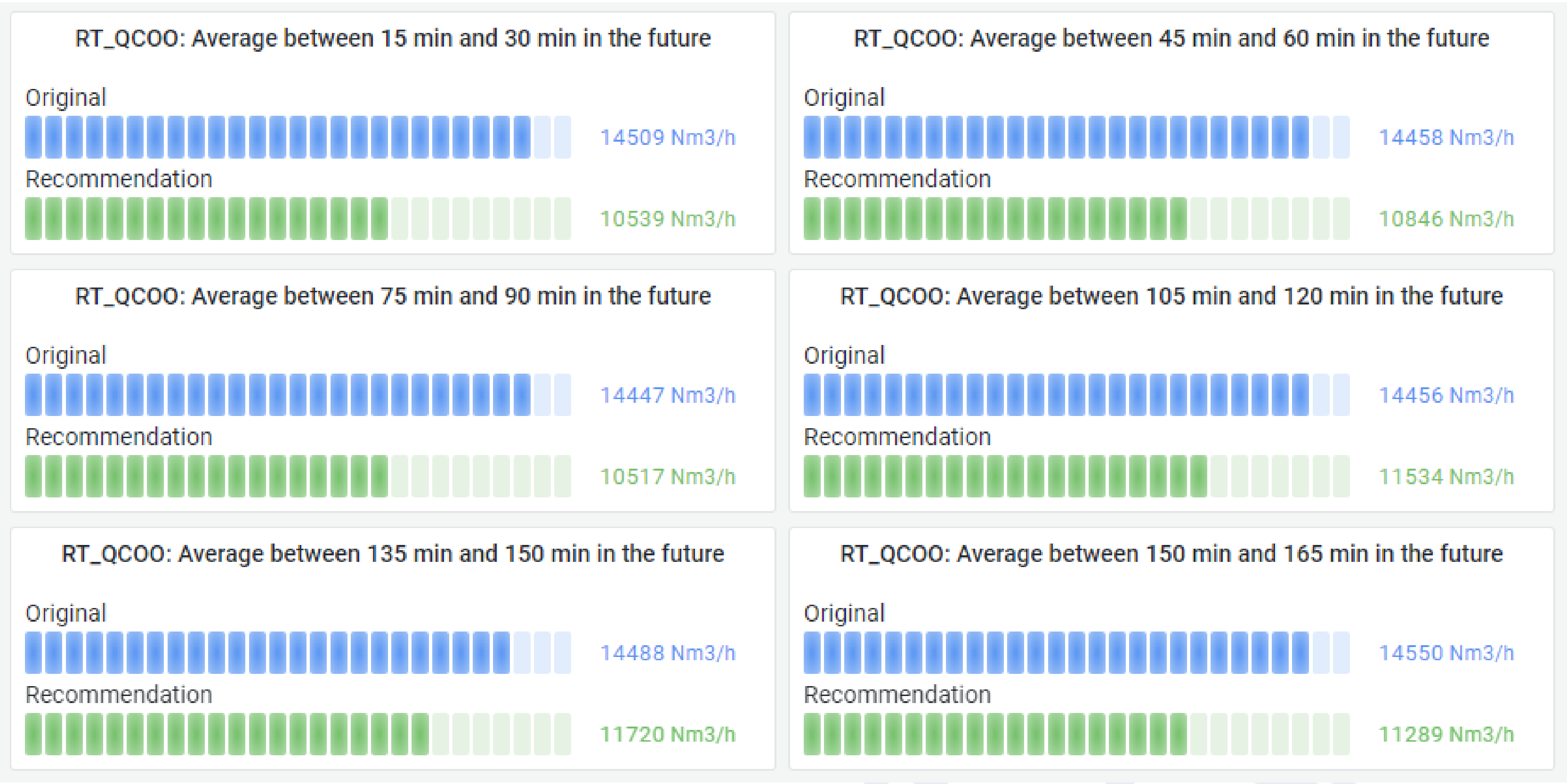
- A **genetic algorithm** has been chosen to optimize this case due to the need for an exhaustive exploration of the search space and the presence of complex constraints.

- **Objective function**: This is the ML model developed in WP3 in which the average of the temperature in the channel over the next 180 minutes is predicted.
  - Train: 5-TimeSeriesSplit RMSE = 10.49, 5-TimeSeriesSplit R2 = 0.74
  - Test: RMSE = 12.25, R2 = 0.81



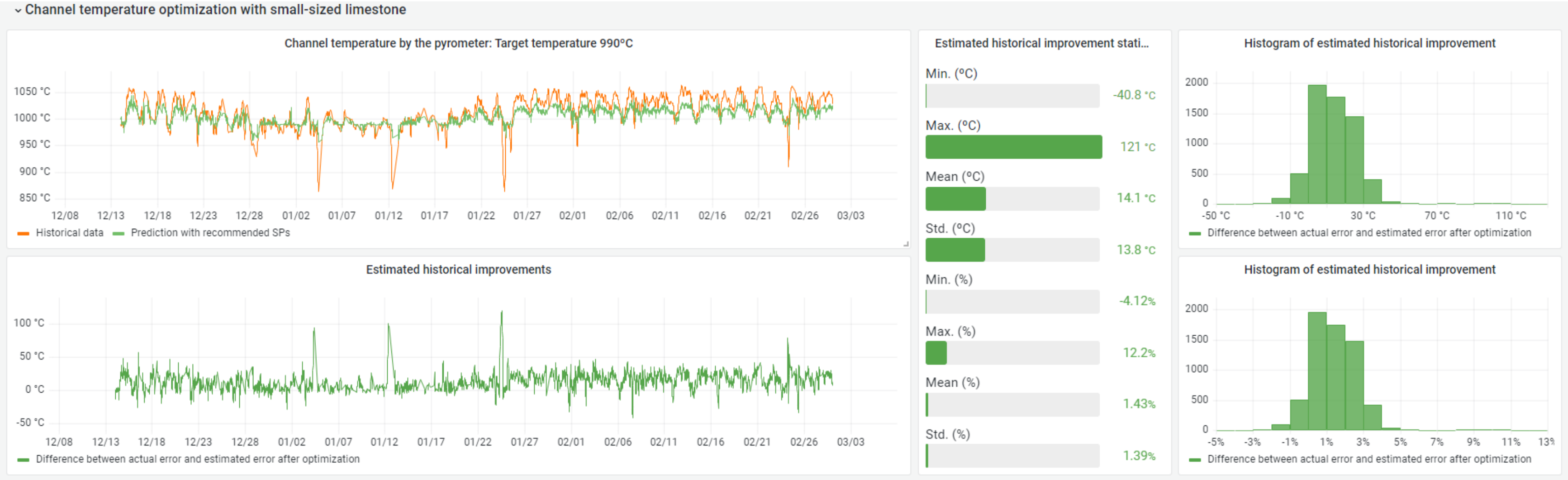
2. Development Description
2.1. The parts of the optimizer

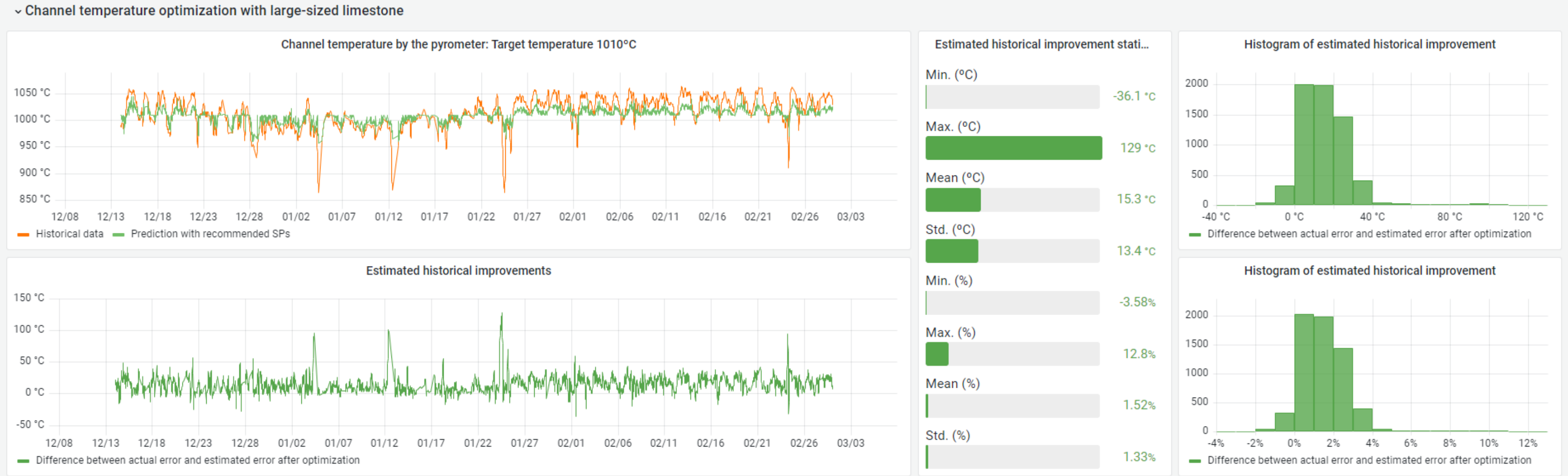
- **Setpoints (SP-s) and Boundaries**: The boundaries are defined based on the original value of the SP and the allowable change. The allowable change is established considering the past variability of that SP.
- **Constraints**:
  - An autoencoder is used as a constraint to rule out anomalous scenarios.
  - The SD of the future windows to be recommended does not exceed the P85 of the SD observed in the historical ones



3. Optimization results

- **Estimated improvements:** Using historical data, on average, the channel temperature improves 1.56% for small limestone and 1.66% for large limestone.





- **Predictive model performance testing:** verify the accuracy of the predictive model and its ability to generalize to different situations. It is necessary to perform tests comparing model predictions with actual temperature values for different production conditions.

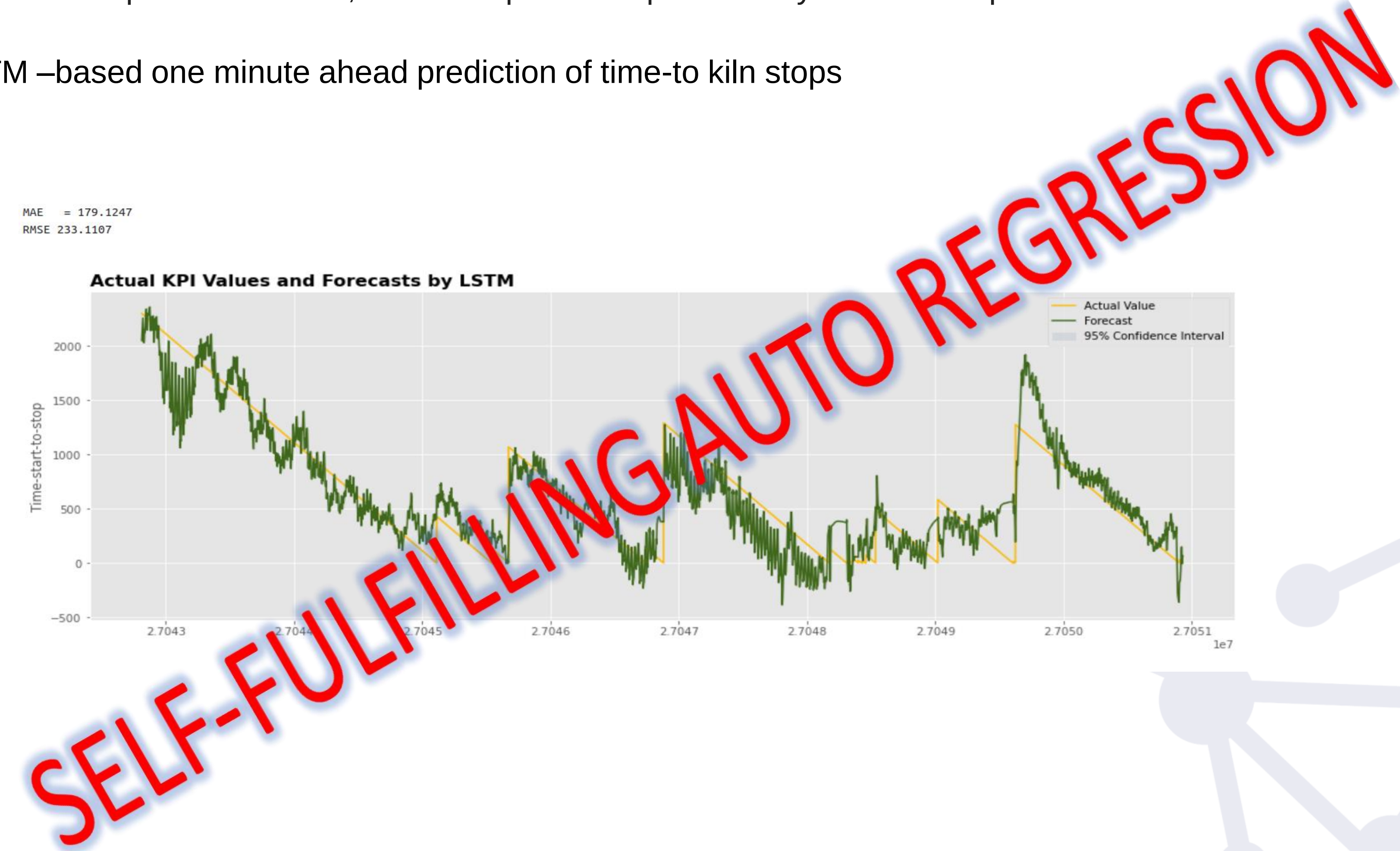
- **Predictive model sensitivity testing:** test how the model behaves to changes in input parameters (PVs and SPs), to verify if the model is robust and can handle different operating conditions.

- **Optimizer performance tests:** verify how the optimizer behaves under different conditions and how much the performance improves compared to other methods currently in use.

- **Verification of compliance with targets:** It is important to verify whether the optimizer is meeting the set targets, i.e. whether the temperature is being maintained in the desired ranges. Tests can also be performed to verify how the optimizer behaves when unforeseen or unexpected conditions occur.

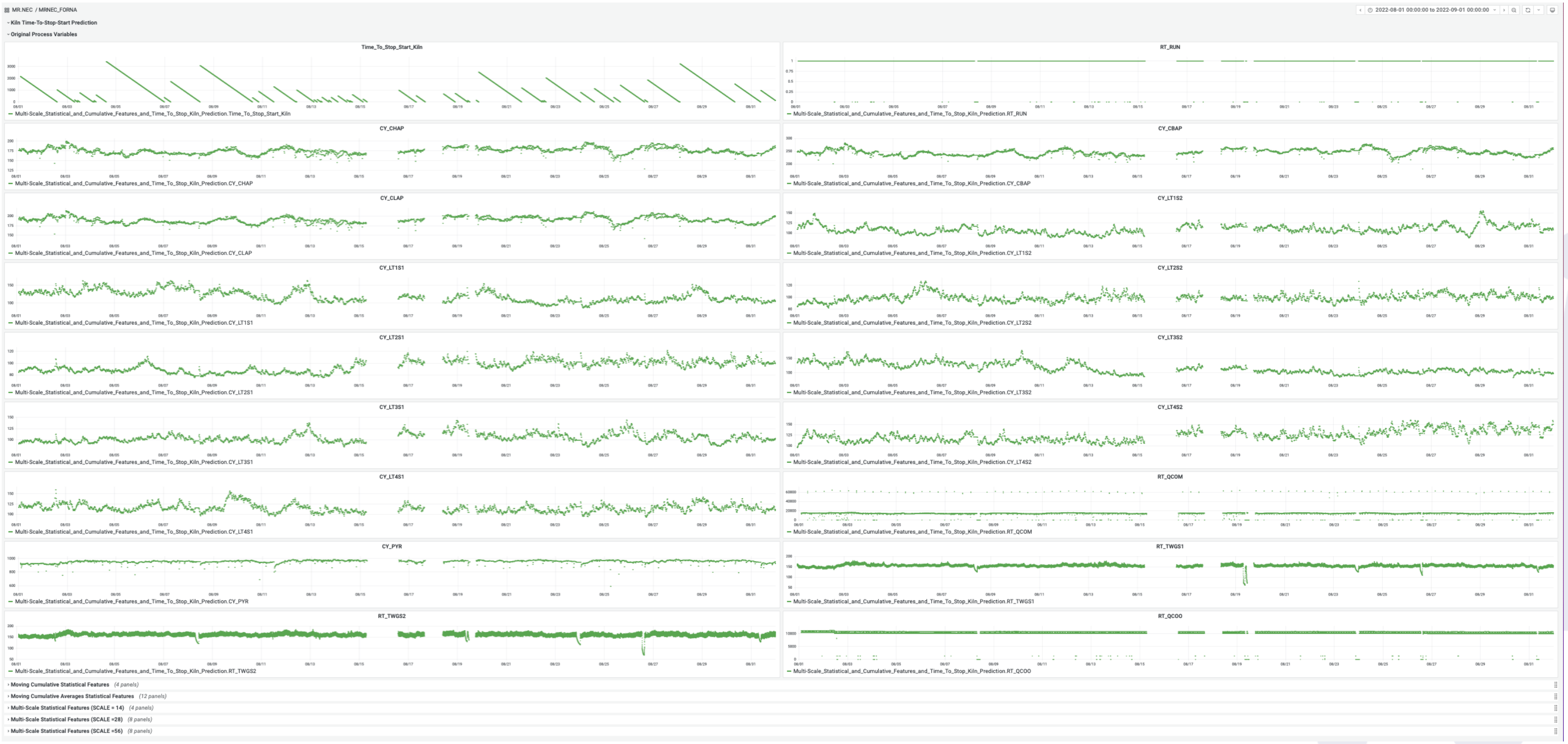
- Technologies developed for FORNA, but not expected to provide any benefits for production

Vanilla LSTM –based one minute ahead prediction of time-to kiln stops



Deep-learning methodology for prediction of set points reducing kiln stops

- Multi-scale cumulative statistical features as health index indicators (cumulative statistical moments)
  - Onset detection of process degradation
  - Time-to-stop prediction



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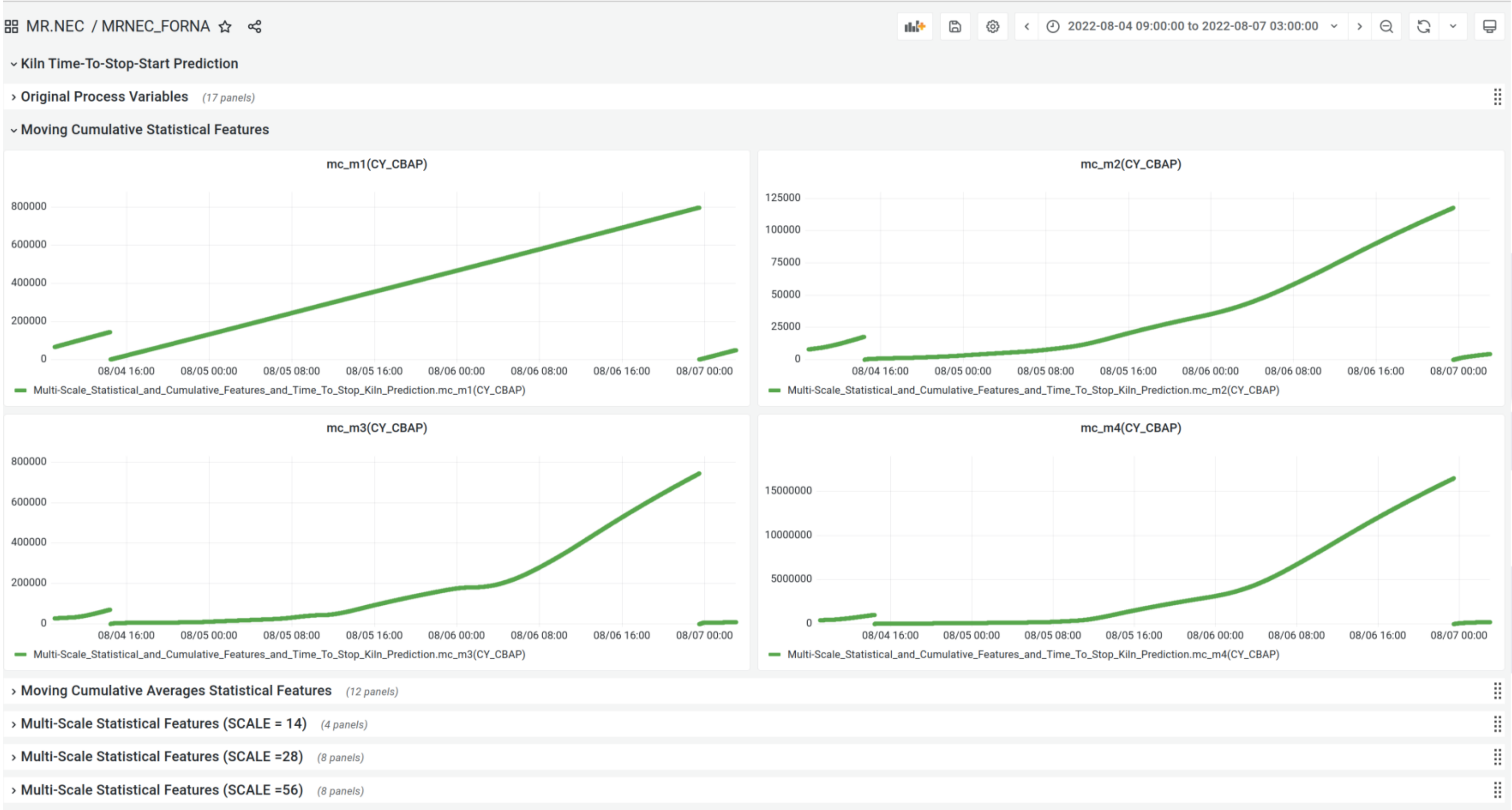

- Expectation demo phase (July – September 2023)
    - Which statistical features across process parameters relevant as process health indicators in terms of monotonicity , trend-ability, prognogsticity
    - Validity of statistical features in supporting operator
        - Detecting onsets of process faulty modes
        - Controlling process health and therewith down-time

Deep-learning methodology for prediction of set points reducing kiln stops

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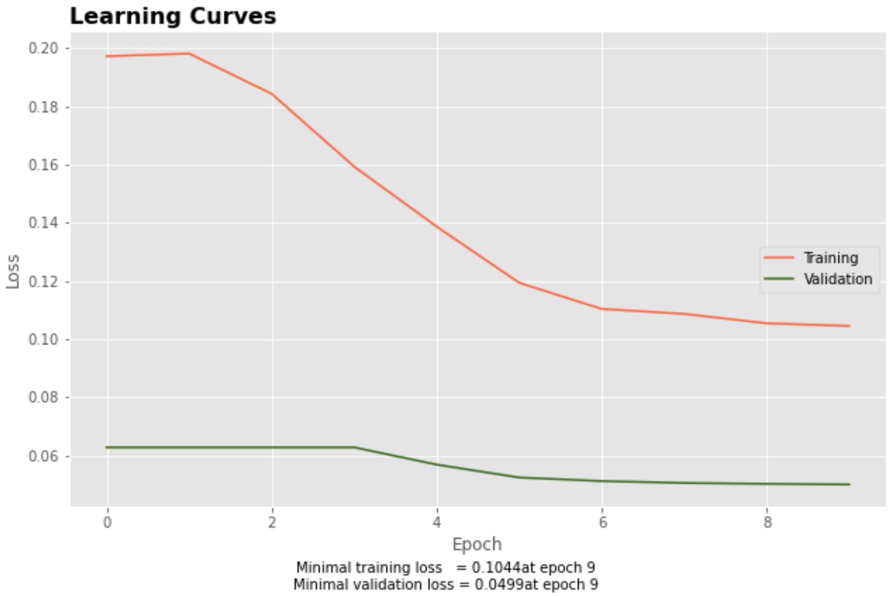
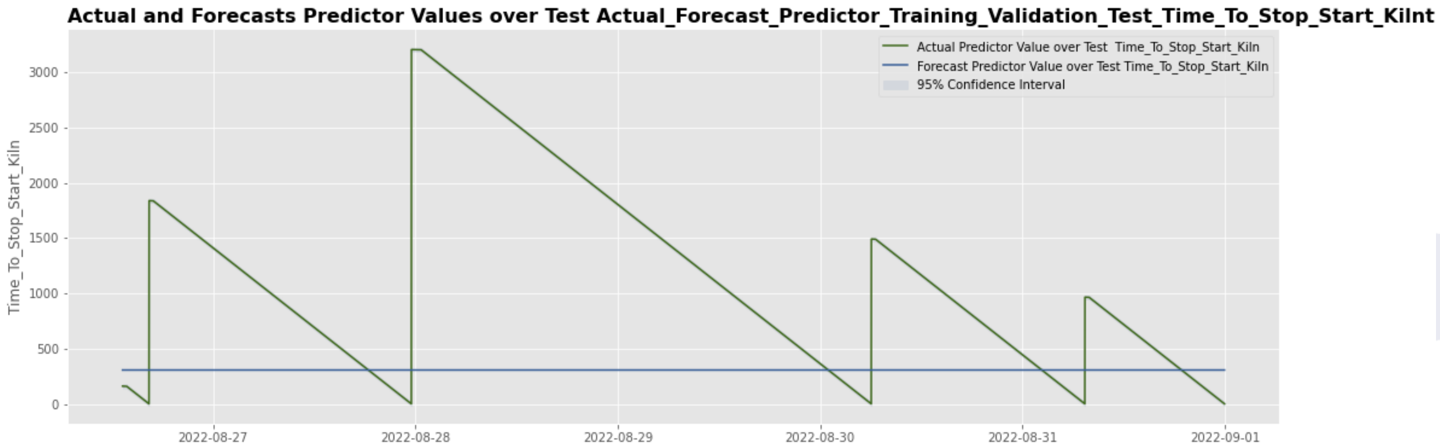
- Multi-scale deep learning models for prediction of (schedules of setpoints) improving process health / reducing down-time





- Expectation demo phase (July – September 2023)
    - What are relevant time-scales for prediction of time-to-stop due to particular type of faulty modes (clog formation)?
    - What are relevant time-scales for prediction of rescheduling processes in order to reduce down-time or improve process health?

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