VIVAVIS

DECODING THE FUTURE

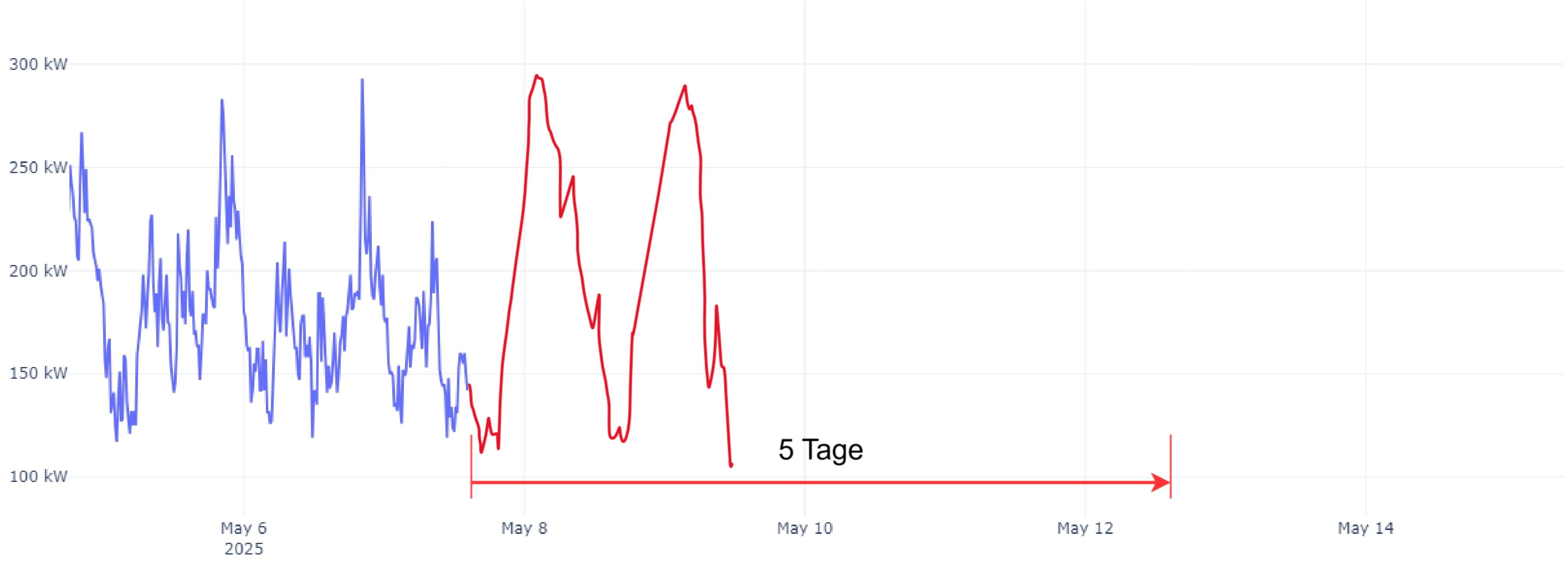
PROGNOSE MIT KI UND MACHINE-LEARNING


36
Achte auf uns!

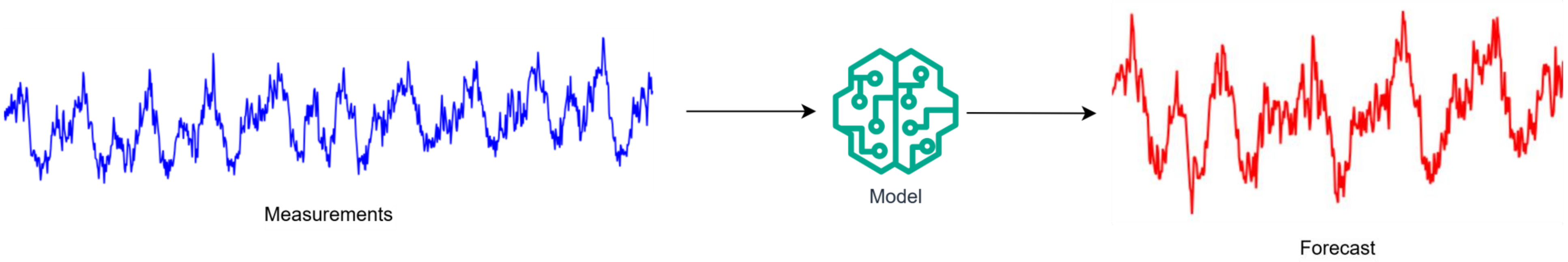
Warum Prognosen?

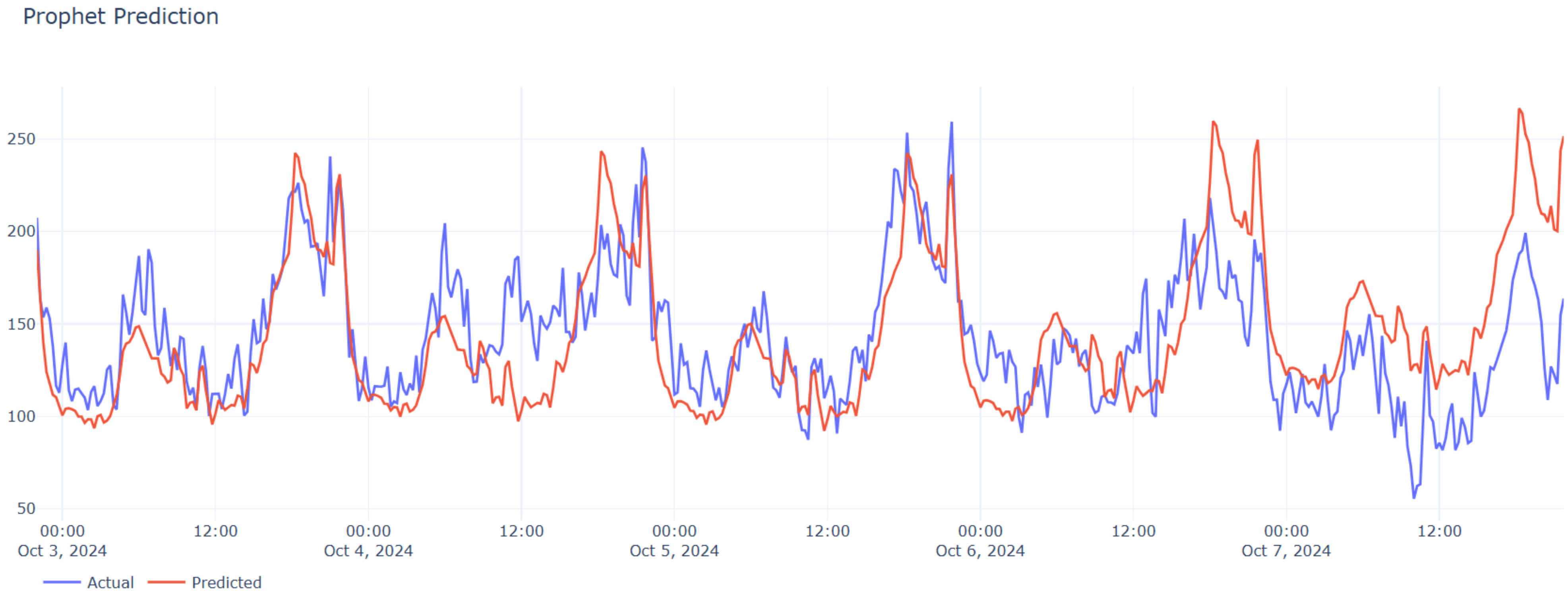
Datengrundlage

- Gemessene Wirkleistung an Trafos, 15 Minuten Durchschnitt

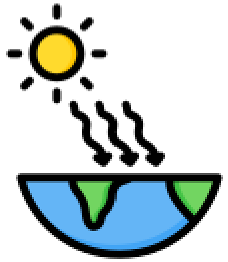


„Hello, Forecast!“ - Univariate Modelle (Prophet, ARIMA)



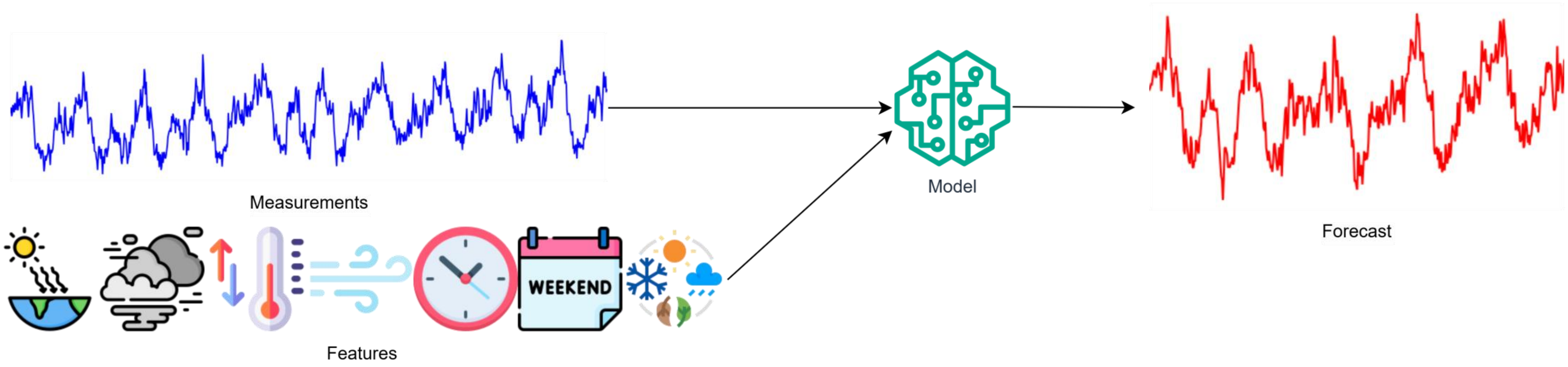


Wetterdaten – Ein Gamechanger?




- Vergleich von Anbietern
  - **Keiner ist wirklich gut**
  - **MeteoTest** erfüllt Anforderungen am besten

Multivariate Modelle



Features:

– Wetterparameter
– Zeitfeatures
– Saisonalitäten: `sin(hour), cos(day_of_year)`
– Feature Interaktionen

Modelle

– Neuronale Netze (LSTM, GRU)
– Gradient Boosting Modelle (XGBoost, LightGBM)

Modelle im Vergleich

	Genauigkeit	Trainingszeit	Aufwand
ARIMA	Mittel	Schnell	Gering
Prophet	Mittel	Schnell	Mittel
LSTM & GRU	Hoch	Langsam	Hoch
XGBoost	Hoch	Schnell	Gering
LightGBM	Hoch	Schnell	Mittel

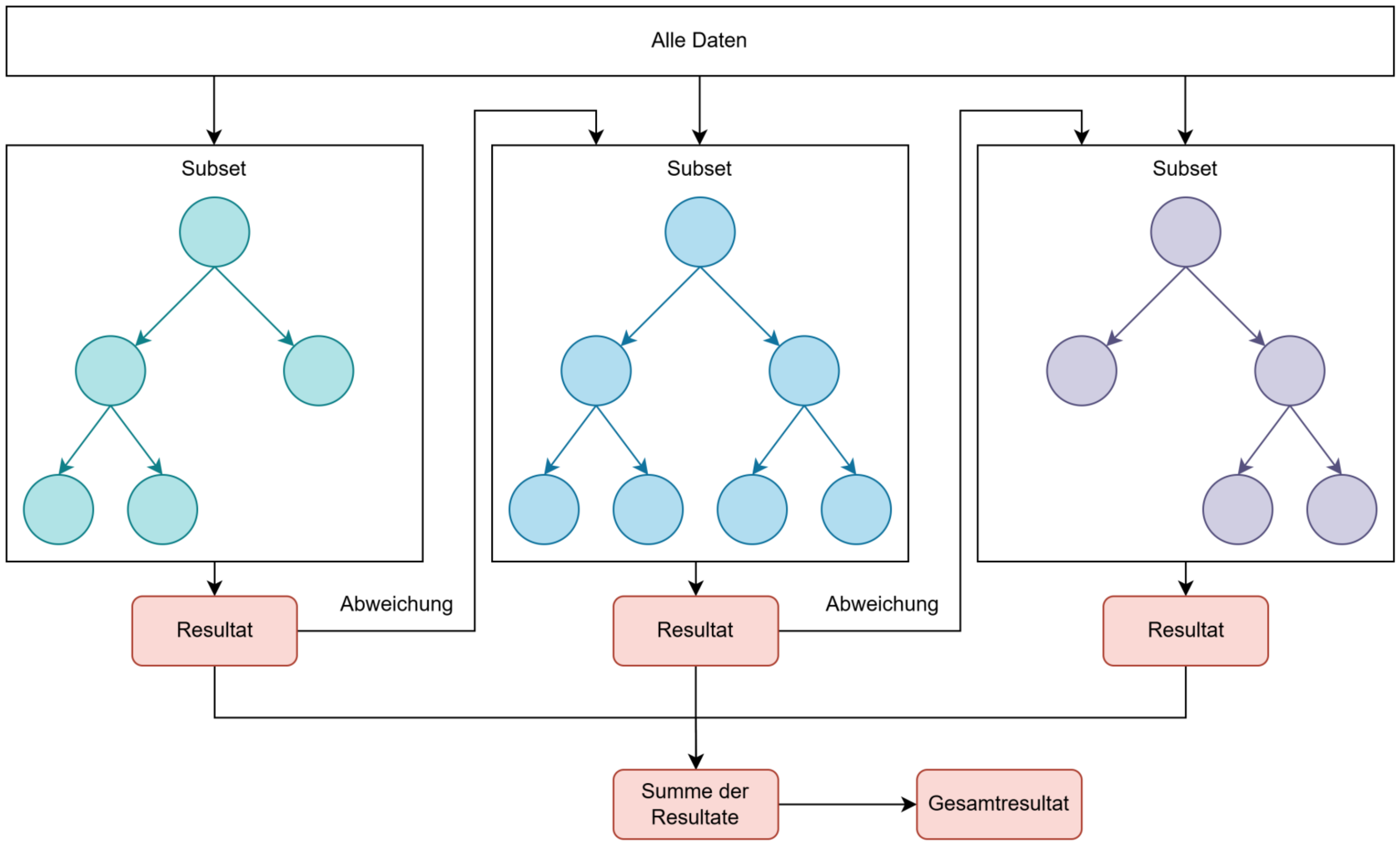
XGBoost 🚀 (Extreme Gradient Boosting)

- Effizient – Keine GPU erforderlich
- Robust gegen fehlende Daten
- „Transparent“ – Welche Features für die Vorhersage wie wichtig sind

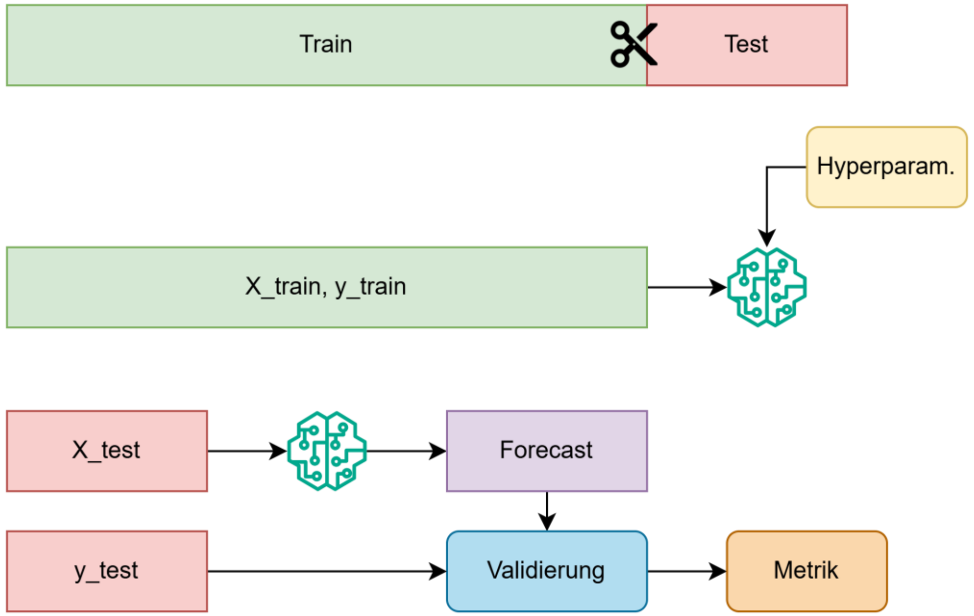
Timestamp	**TT**	**GHI**	**RH**	**DoW**	**Month**	**Hour**		**Target**
2025-05-01 09:00Z	17.1	743.4	60	Thursday	5	9	→	**137 kW**
2025-05-01 10:00Z	19.1	878	53	Thursday	5	10	→	**110 kW**
2025-05-01 11:00Z	21.0	958.3	47	Thursday	5	11	→	**88 kW**
…	…	…	…	…	…	…	…	…
2025-05-02 09:00Z	**18.7**	**763**	**57**	**Friday**	**5**	**9**	**→**	**? kW**

XGBoost 🚀 (Extreme Gradient Boosting)

- Eine Kombination aus vielen Entscheidungsbäumen, die Fehler iterativ korrigiert



XGBoost Training & Hyperparameter



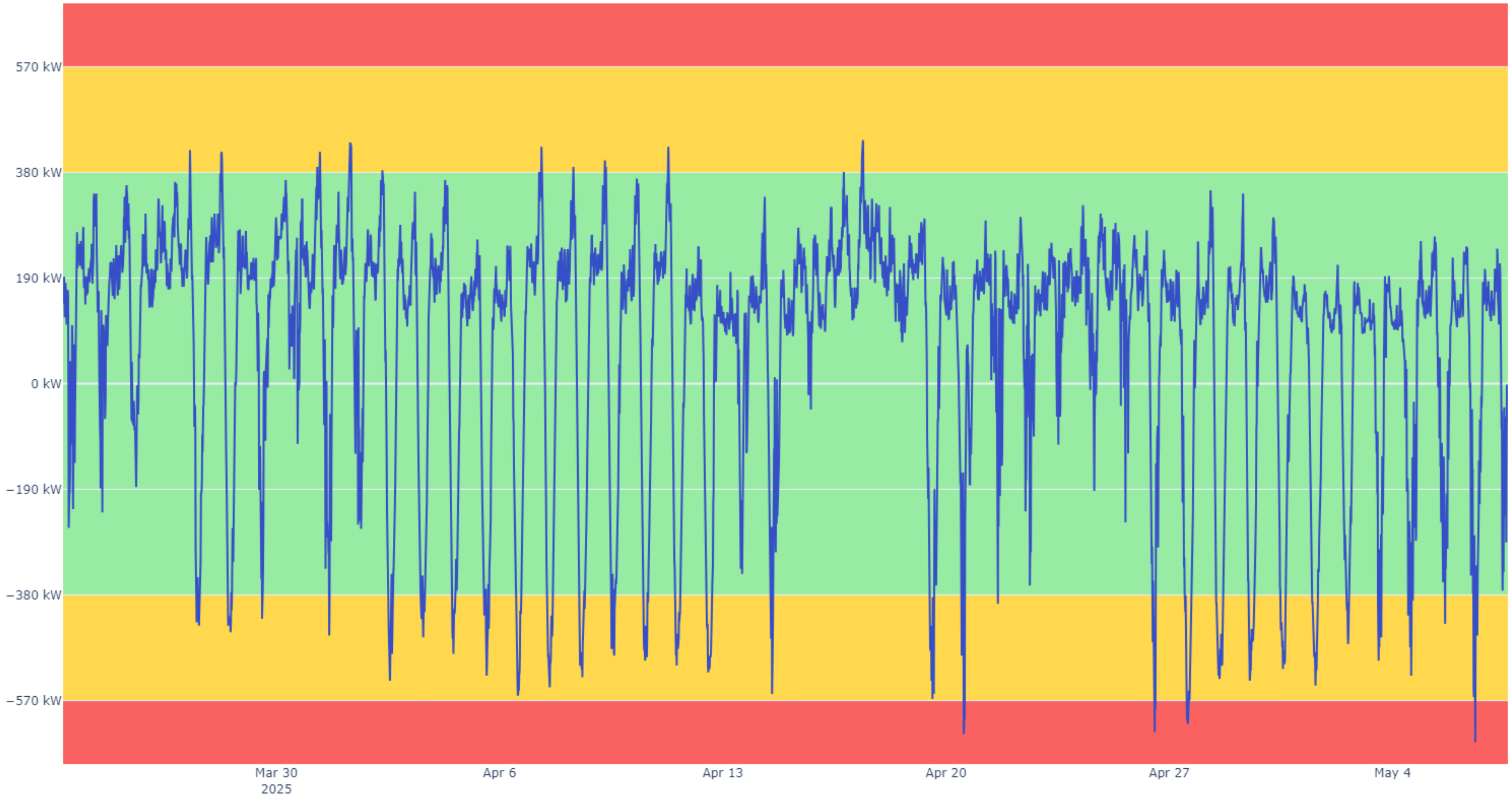
Hyperparameter:

- Anzahl Bäume
- Grösse der Bäume
- Mindestanzahl Daten pro Blatt
- Lernrate

Wann ist eine Vorhersage gut?

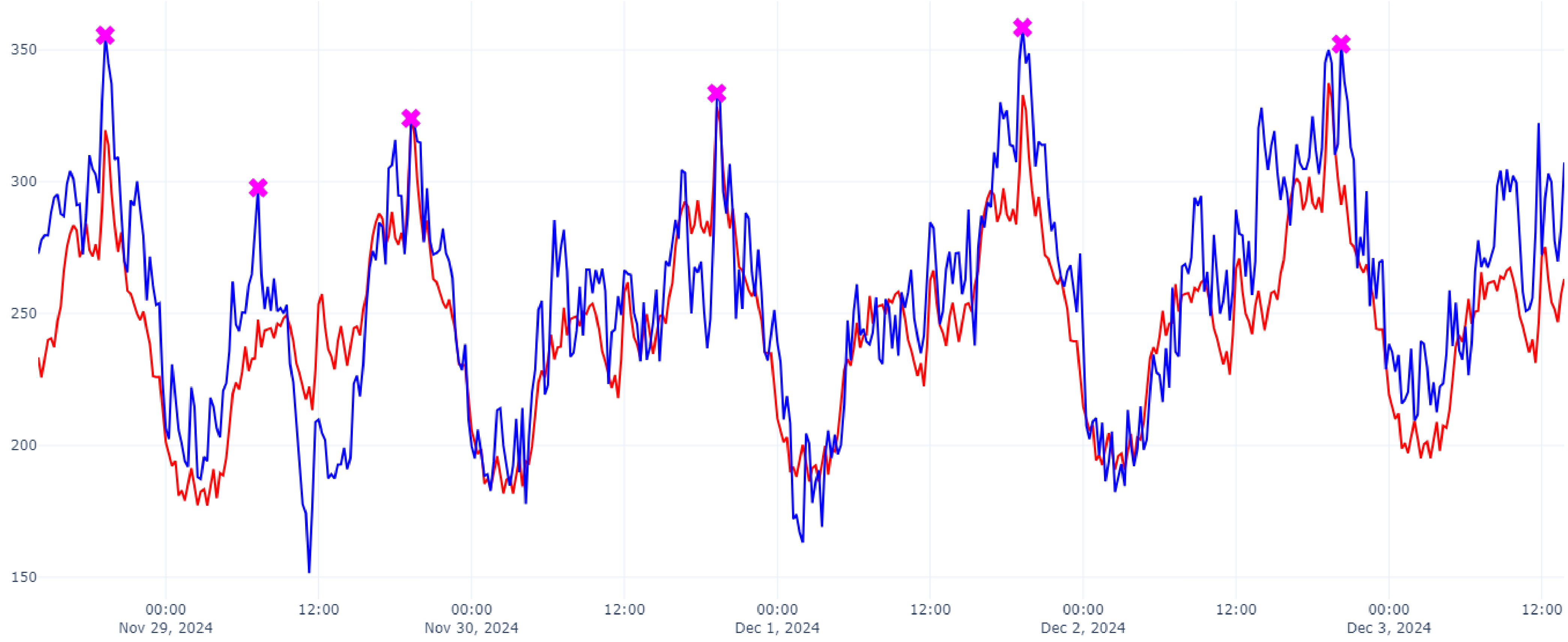
- $RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{true} - y\_pred)^2}{N}}$ → Grosse Fehler werden hart bestraft!

Wo muss das Model sehr gut sein?

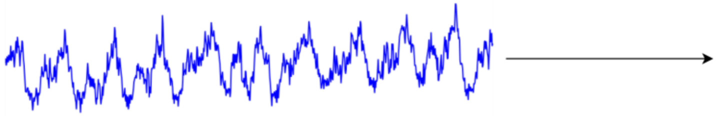


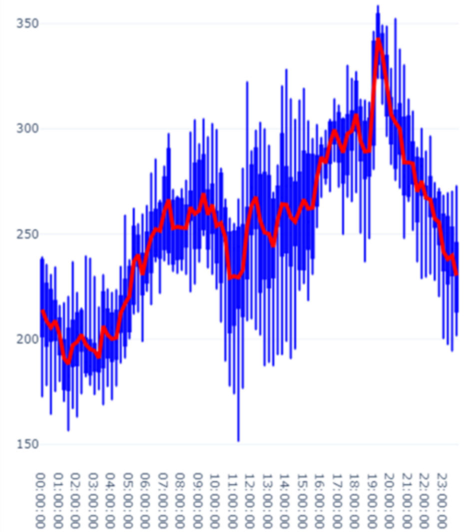
Wie gut werden Peaks erkannt?

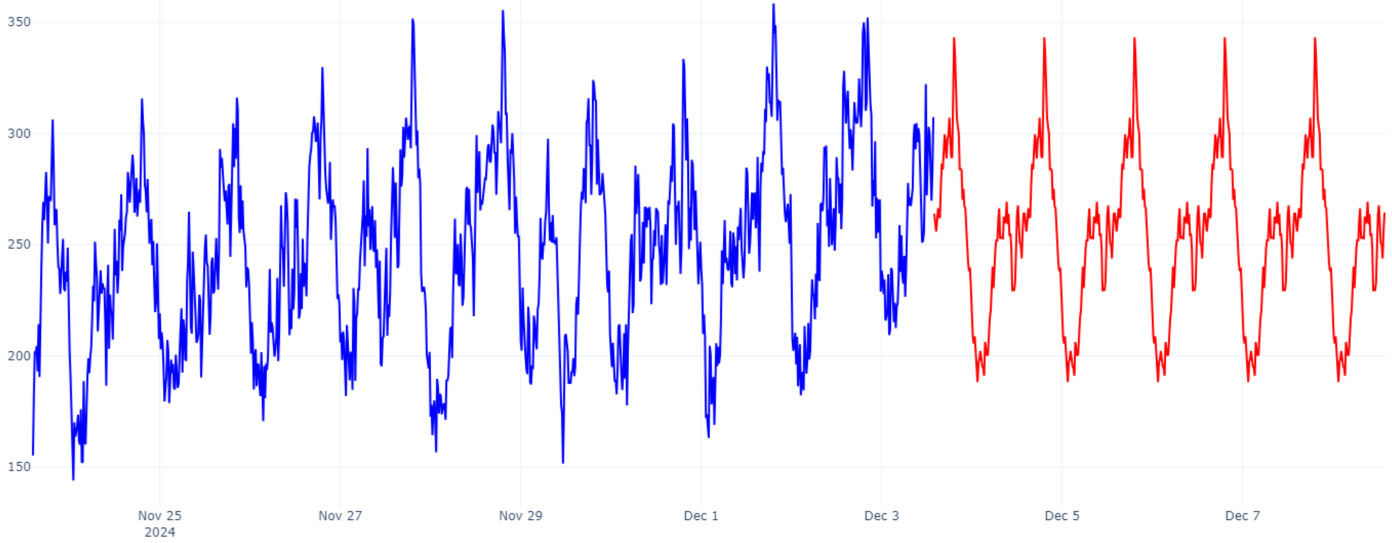
Peak Weighted Metric → Fehler bei Peaks (positiv / negativ) werden noch härter bestraft!



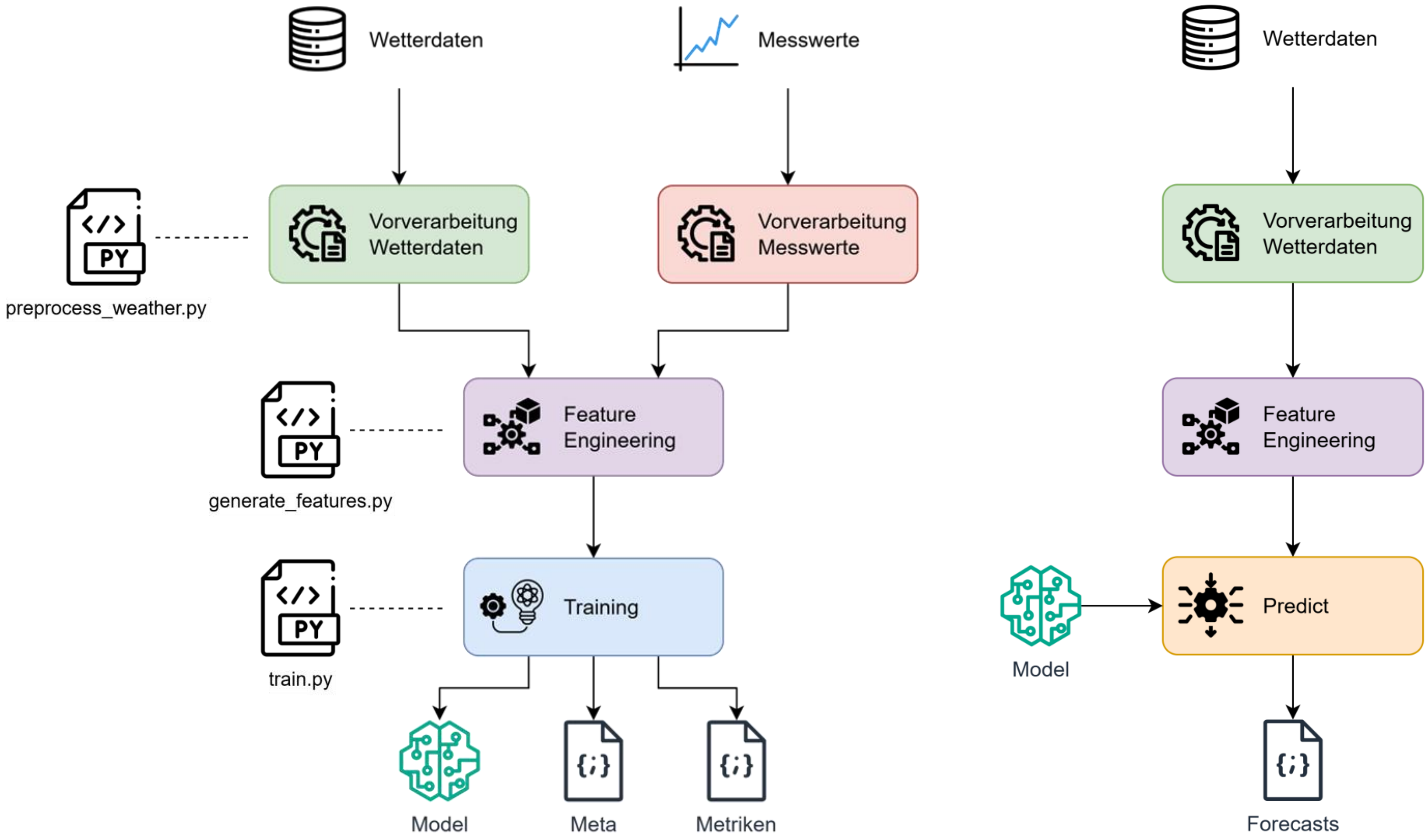
Fallback Model



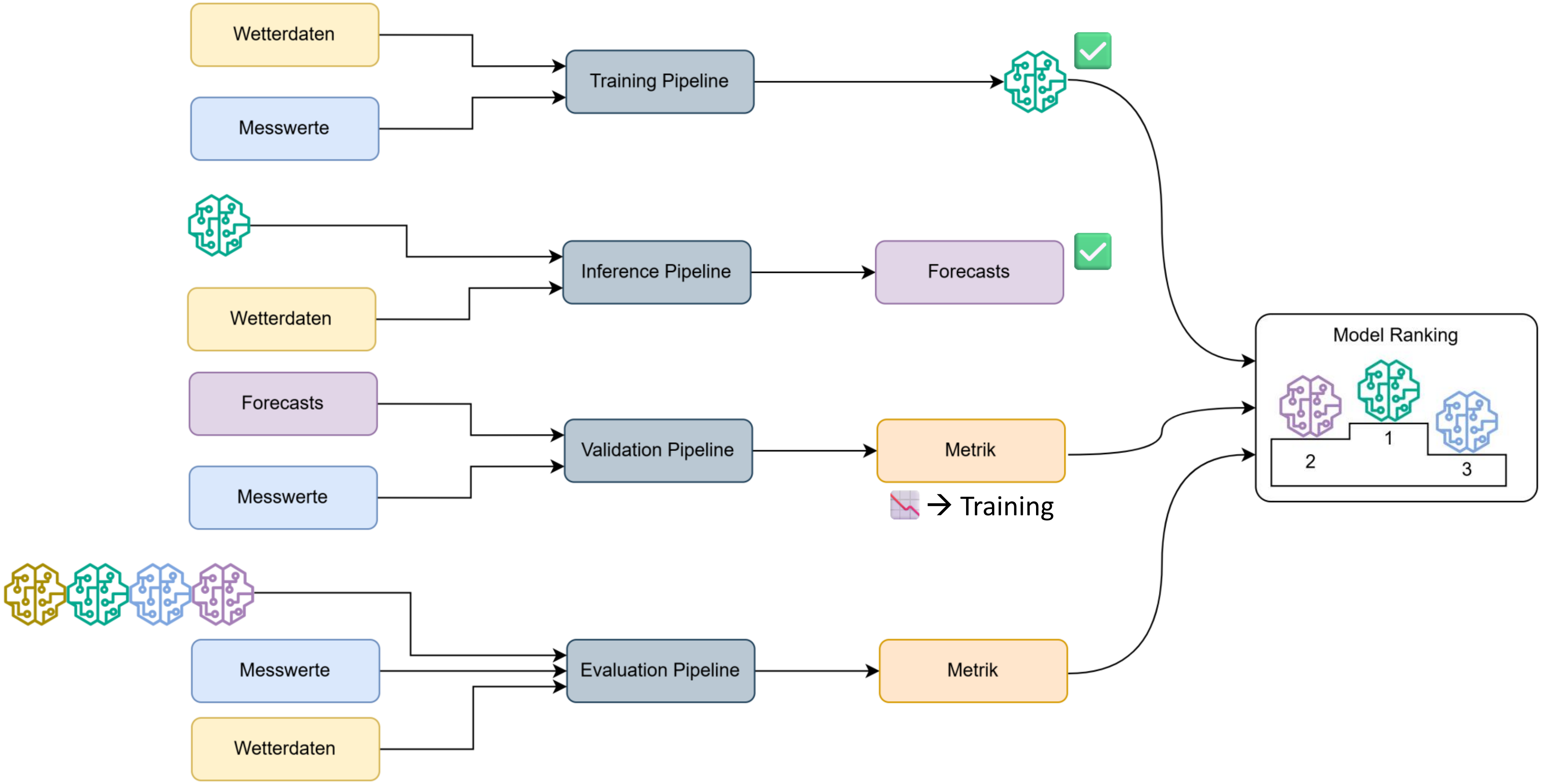




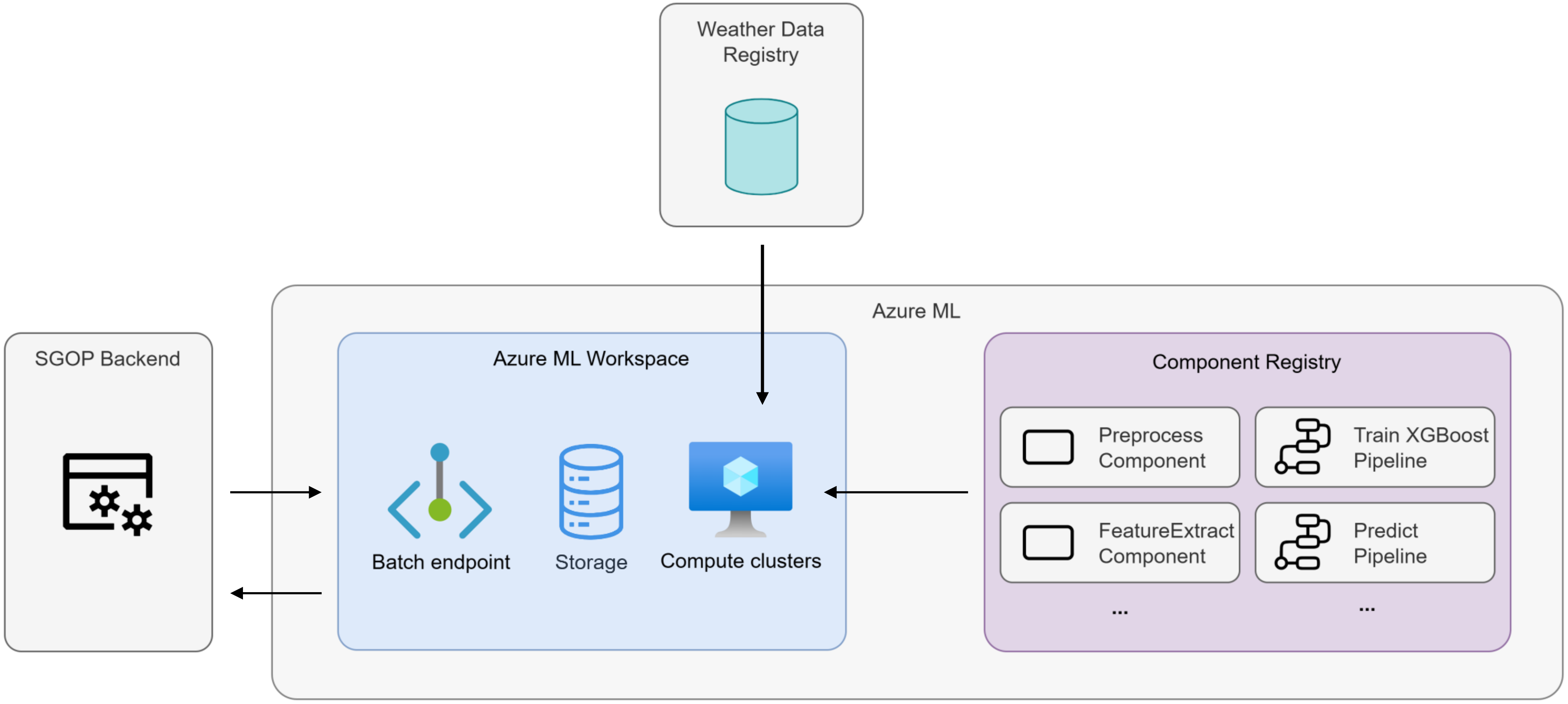
Vorbereitung für die Praxis - Modulare ML-Pipelines

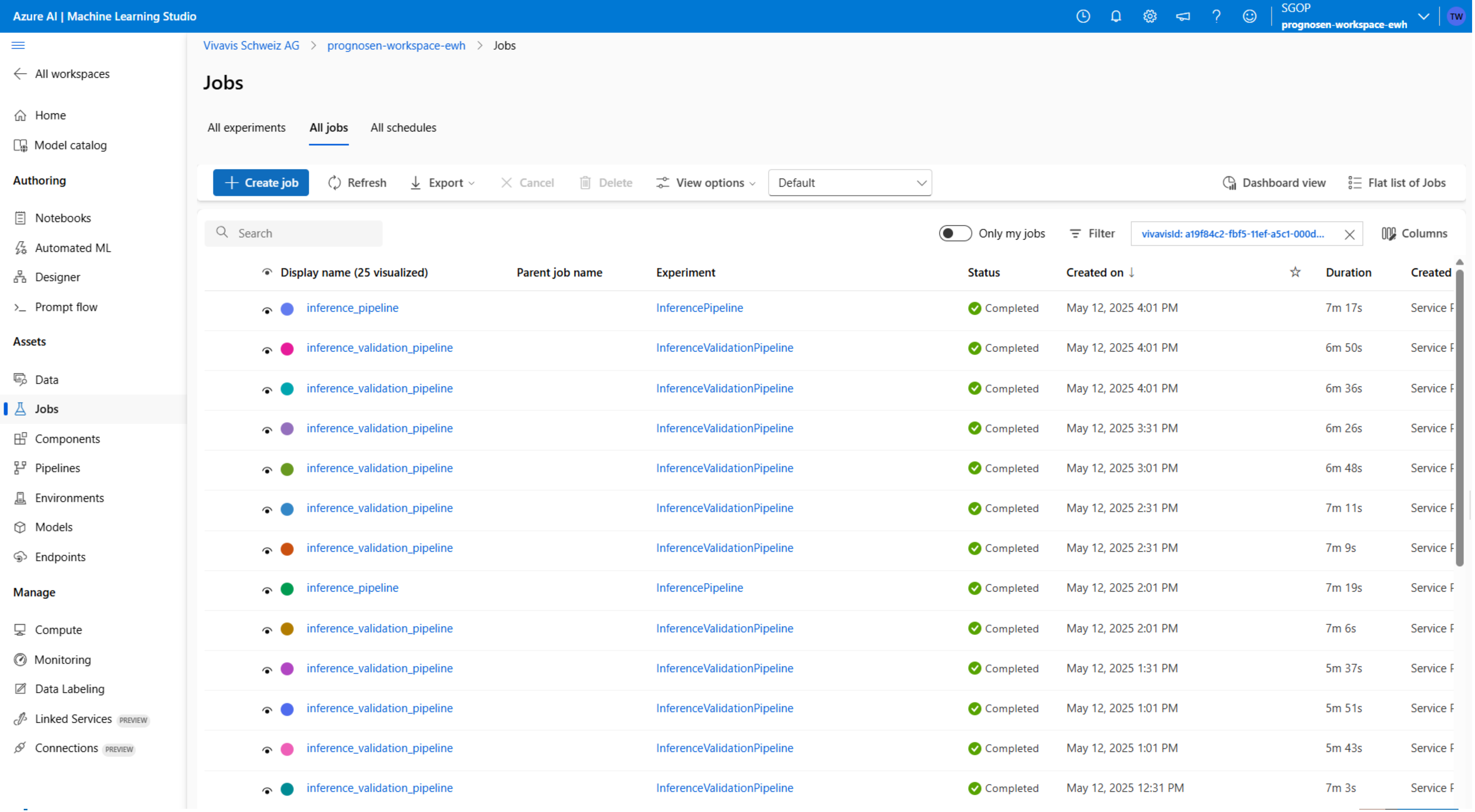


Umsetzung in die Praxis – ML-Pipelines



Infrastruktur – Azure ML




Azure AI | Machine Learning Studio
SGOP
prognosen-workspace-ewh
TW
All workspaces
Home
Model catalog
Authoring
Notebooks
Automated ML
Designer
Prompt flow
Assets
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Jobs
Components
Pipelines
Environments
Models
Endpoints
Manage
Compute
Monitoring
Data Labeling
Linked Services PREVIEW
Connections PREVIEW
Vivavis Schweiz AG > prognosen-workspace-ewh > Jobs
Jobs
All experiments
All jobs
All schedules
Create job
Refresh
Export
Cancel
Delete
View options
Default
Dashboard view
Flat list of Jobs
Search
Only my jobs
Filter
vivavisId: a19f84c2-fbf5-11ef-a5c1-000d...
Columns
Display name (25 visualized)
Parent job name
Experiment
Status
Created on
Duration
Created
inference_pipeline InferencePipeline Completed May 12, 2025 4:01 PM 7m 17s Service F
inference_validation_pipeline InferenceValidationPipeline Completed May 12, 2025 4:01 PM 6m 50s Service F
inference_validation_pipeline InferenceValidationPipeline Completed May 12, 2025 4:01 PM 6m 36s Service F
inference_validation_pipeline InferenceValidationPipeline Completed May 12, 2025 3:31 PM 6m 26s Service F
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inference_pipeline InferencePipeline Completed May 12, 2025 2:01 PM 7m 19s Service F
inference_validation_pipeline InferenceValidationPipeline Completed May 12, 2025 2:01 PM 7m 6s Service F
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inference_validation_pipeline InferenceValidationPipeline Completed May 12, 2025 1:01 PM 5m 51s Service F
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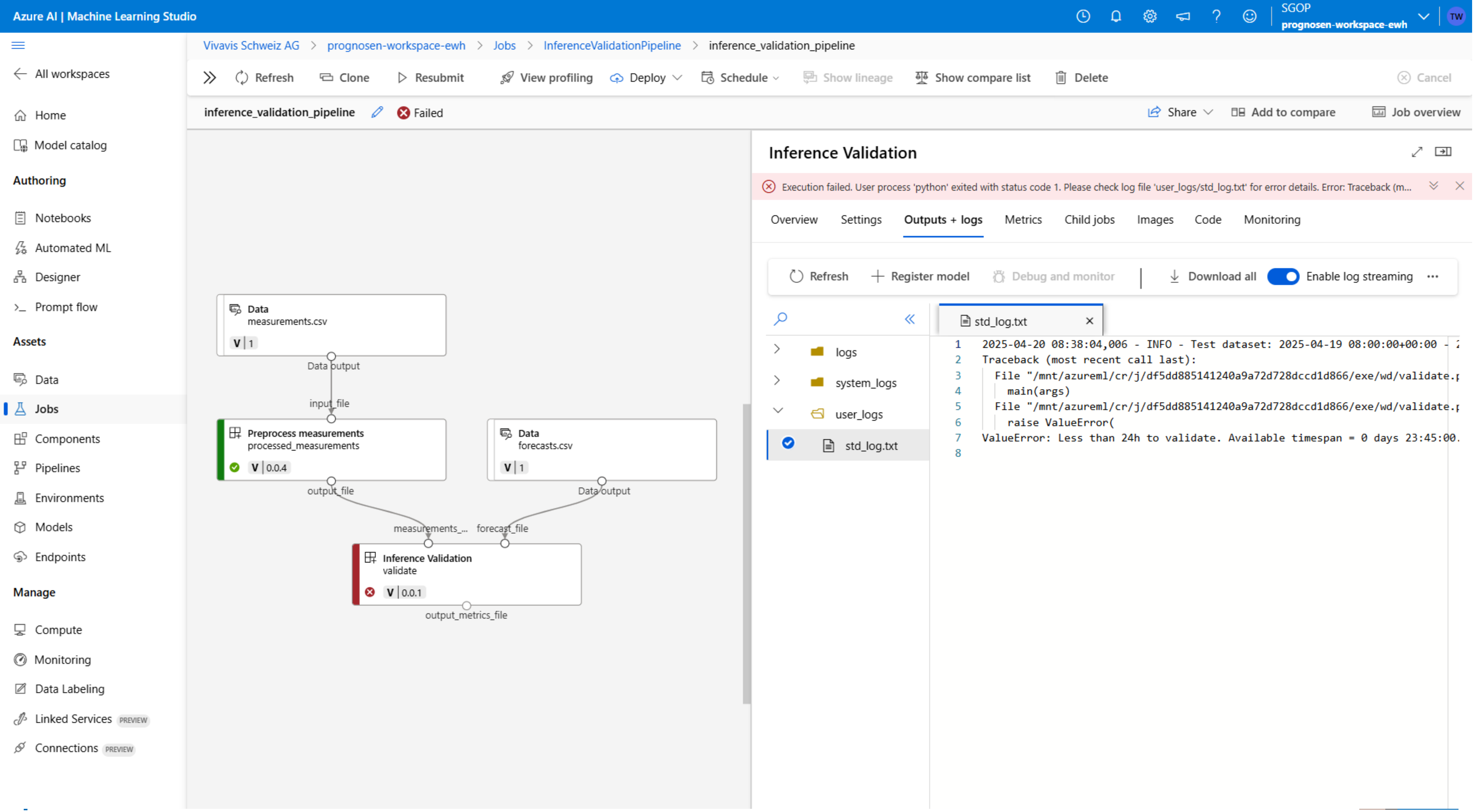

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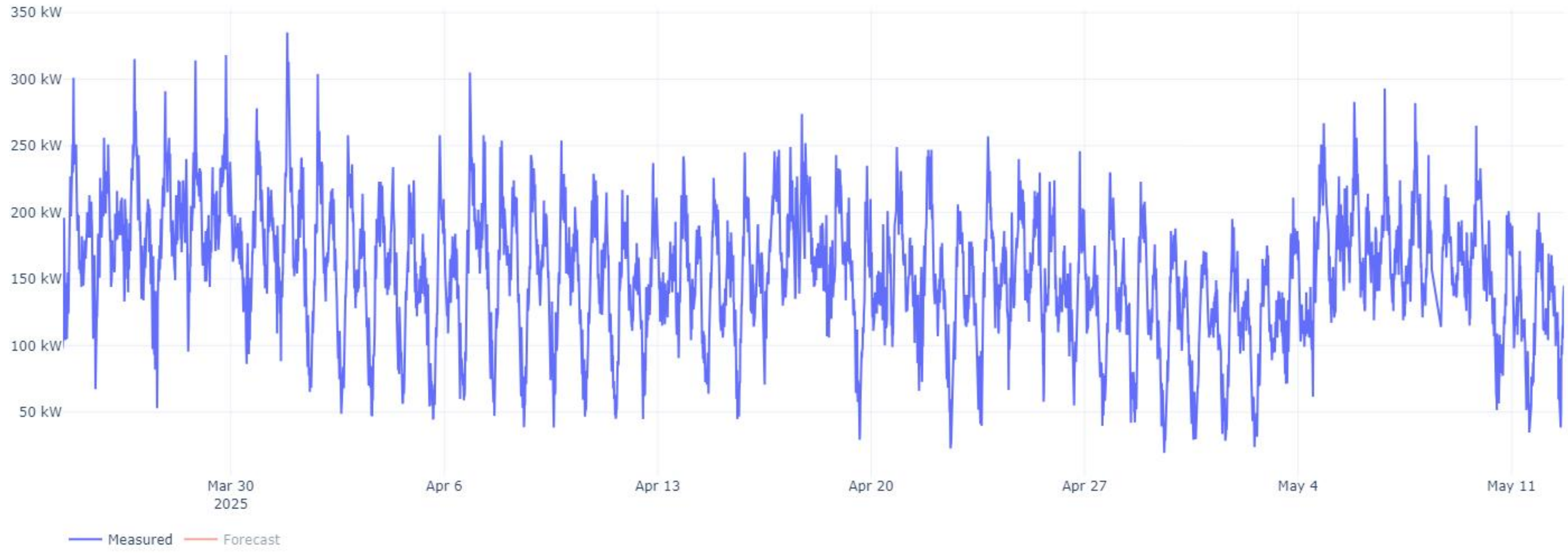
SGOP
prognosen-workspace-ewh
Vivavis Schweiz AG > prognosen-workspace-ewh > Jobs > InferenceValidationPipeline > inference_validation_pipeline
All workspaces
Home
Model catalog
Authoring
Notebooks
Automated ML
Designer
Prompt flow
Assets
Data
Jobs
Components
Pipelines
Environments
Models
Endpoints
Manage
Compute
Monitoring
Data Labeling
Linked Services PREVIEW
Connections PREVIEW
Refresh
Clone
Resubmit
View profiling
Deploy
Schedule
Show lineage
Show compare list
Delete
Cancel
inference_validation_pipeline
Failed
Share
Add to compare
Job overview
Data
measurements.csv
Data output
input_file
Preprocess measurements
processed_measurements
output_file
Data
forecasts.csv
Data output
measurements_...
forecast_file
Inference Validation
validate
output_metrics_file
Inference Validation
Execution failed. User process 'python' exited with status code 1. Please check log file 'user_logs/std_log.txt' for error details. Error: Traceback (m...
Overview
Settings
Outputs + logs
Metrics
Child jobs
Images
Code
Monitoring
Refresh
Register model
Debug and monitor
Download all
Enable log streaming
logs
system_logs
user_logs
std_log.txt
2025-04-20 08:38:04,006 - INFO - Test dataset: 2025-04-19 08:00:00+00:00 -
Traceback (most recent call last):
File "/mnt/azureml/cr/j/df5dd885141240a9a72d728dccd1d866/exe/wd/validate.
main(args)
File "/mnt/azureml/cr/j/df5dd885141240a9a72d728dccd1d866/exe/wd/validate.
raise ValueError(
ValueError: Less than 24h to validate. Available timespan = 0 days 23:45:00.

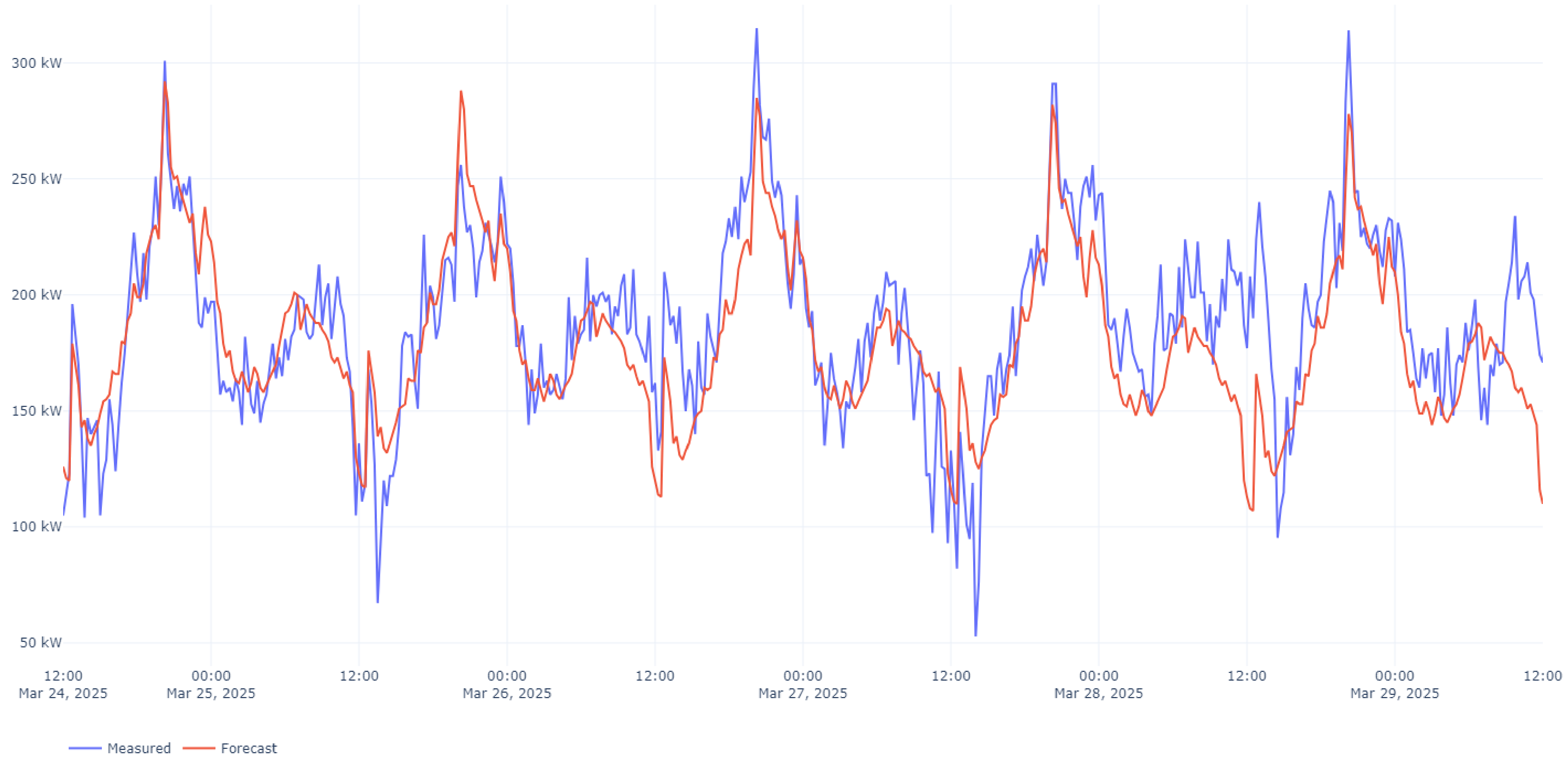
TS Rietli, Herrliberg

Kaltstart – Entwicklung ab dem ersten Datenpunkt

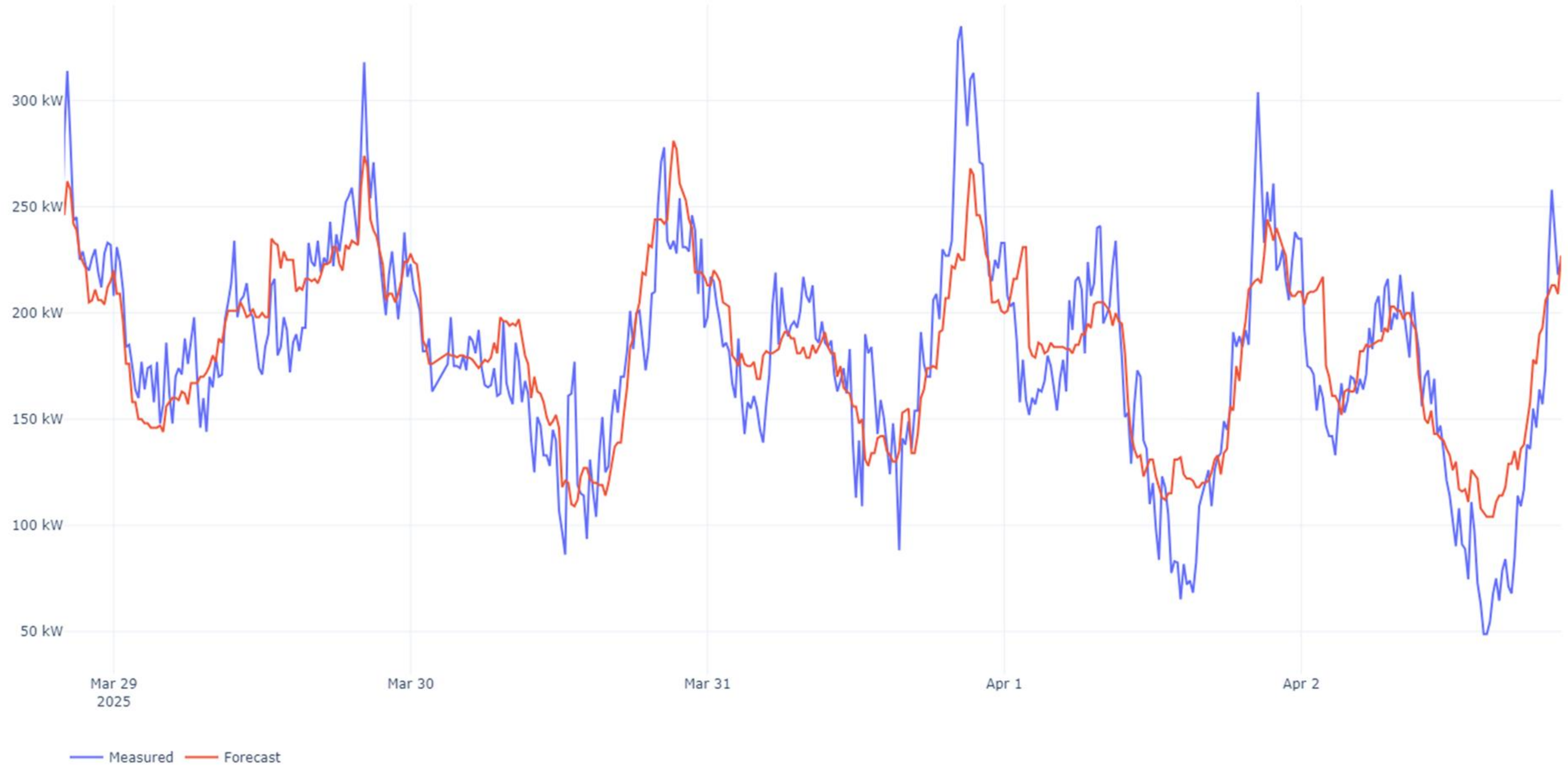
- Messwerte Trafo Rietli, Herrliberg



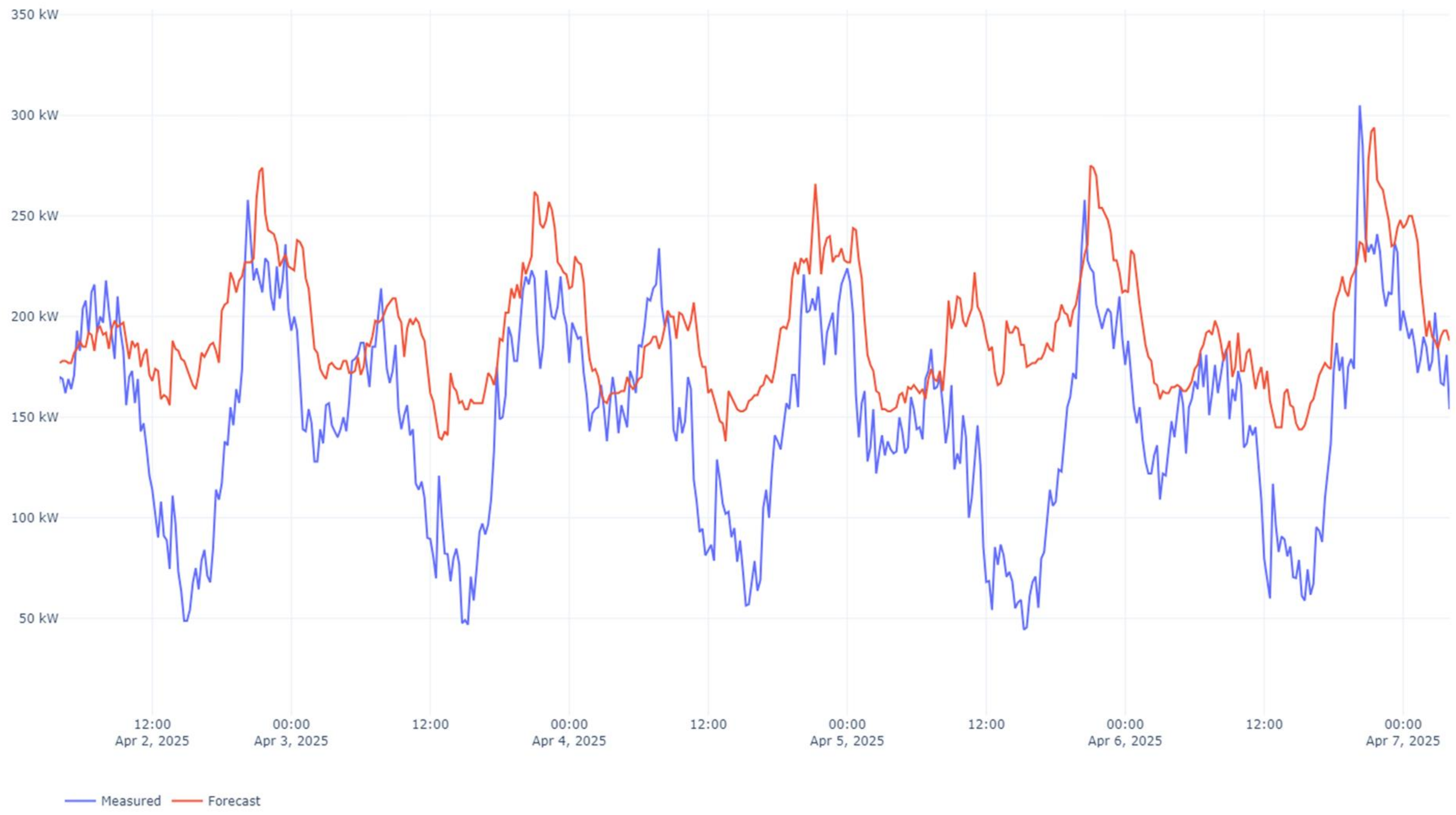
Tag 10: Fallback Model



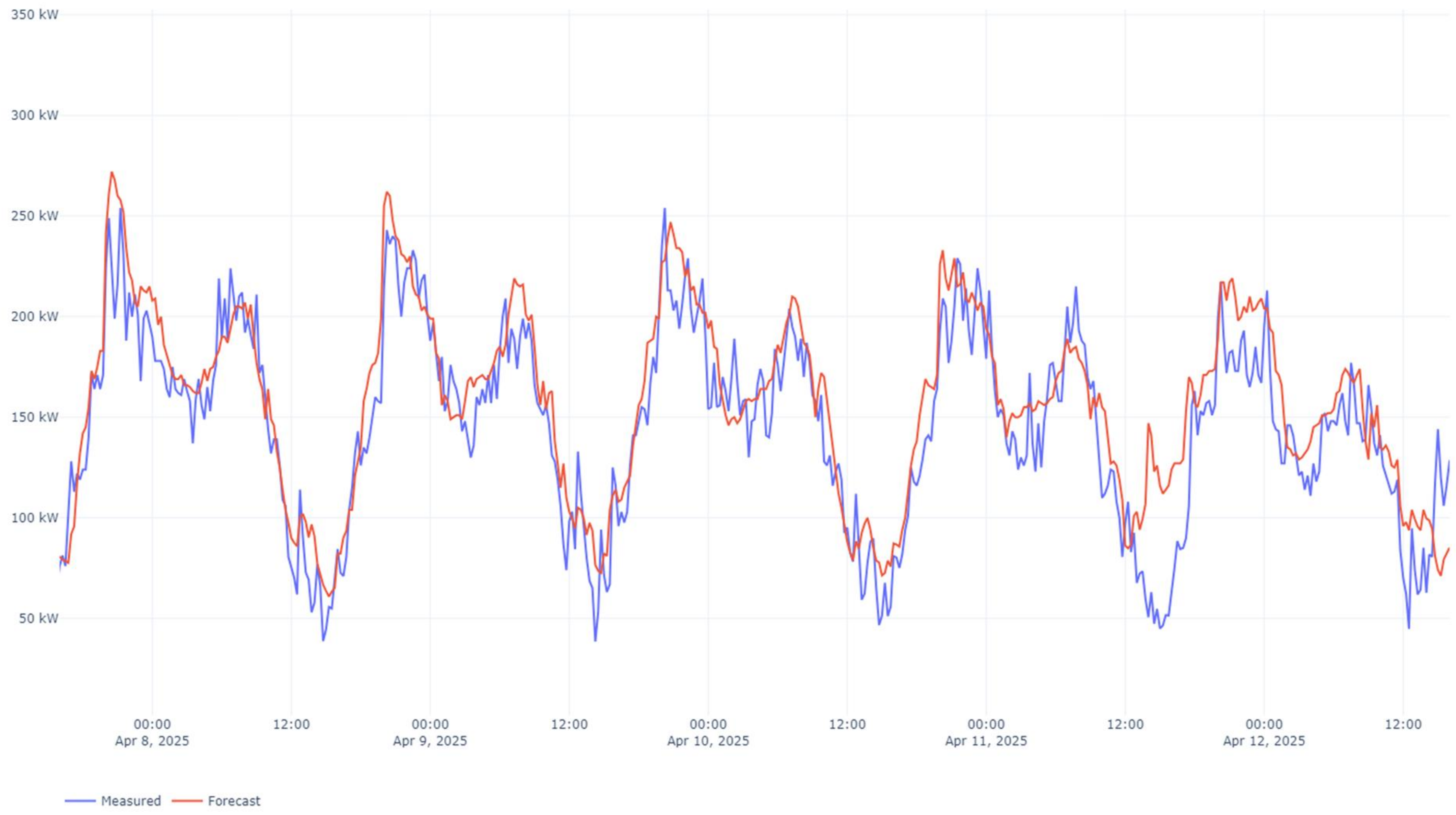
Tag 14: XGBoost



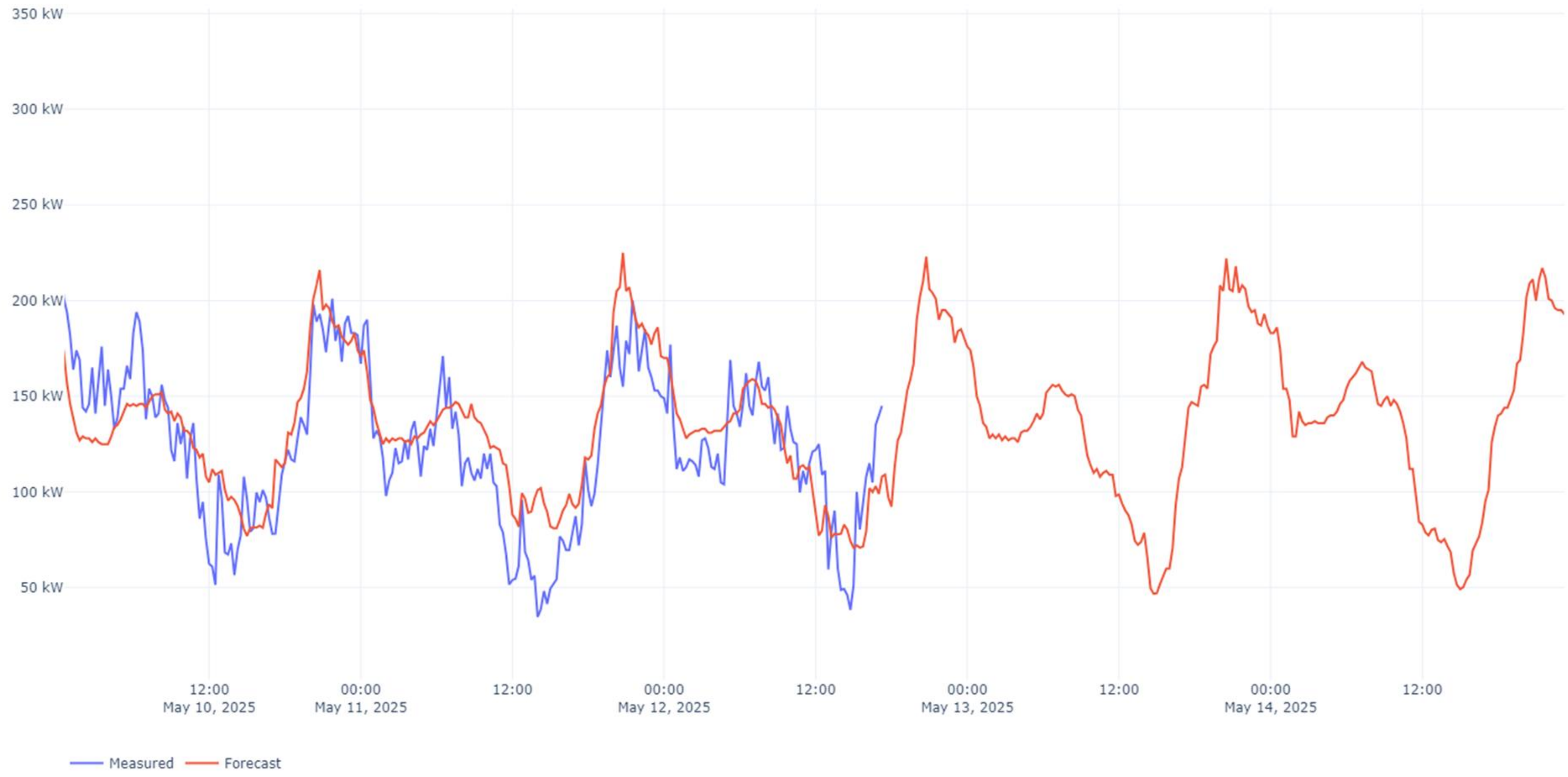
Tag 18: **Komplett daneben!**



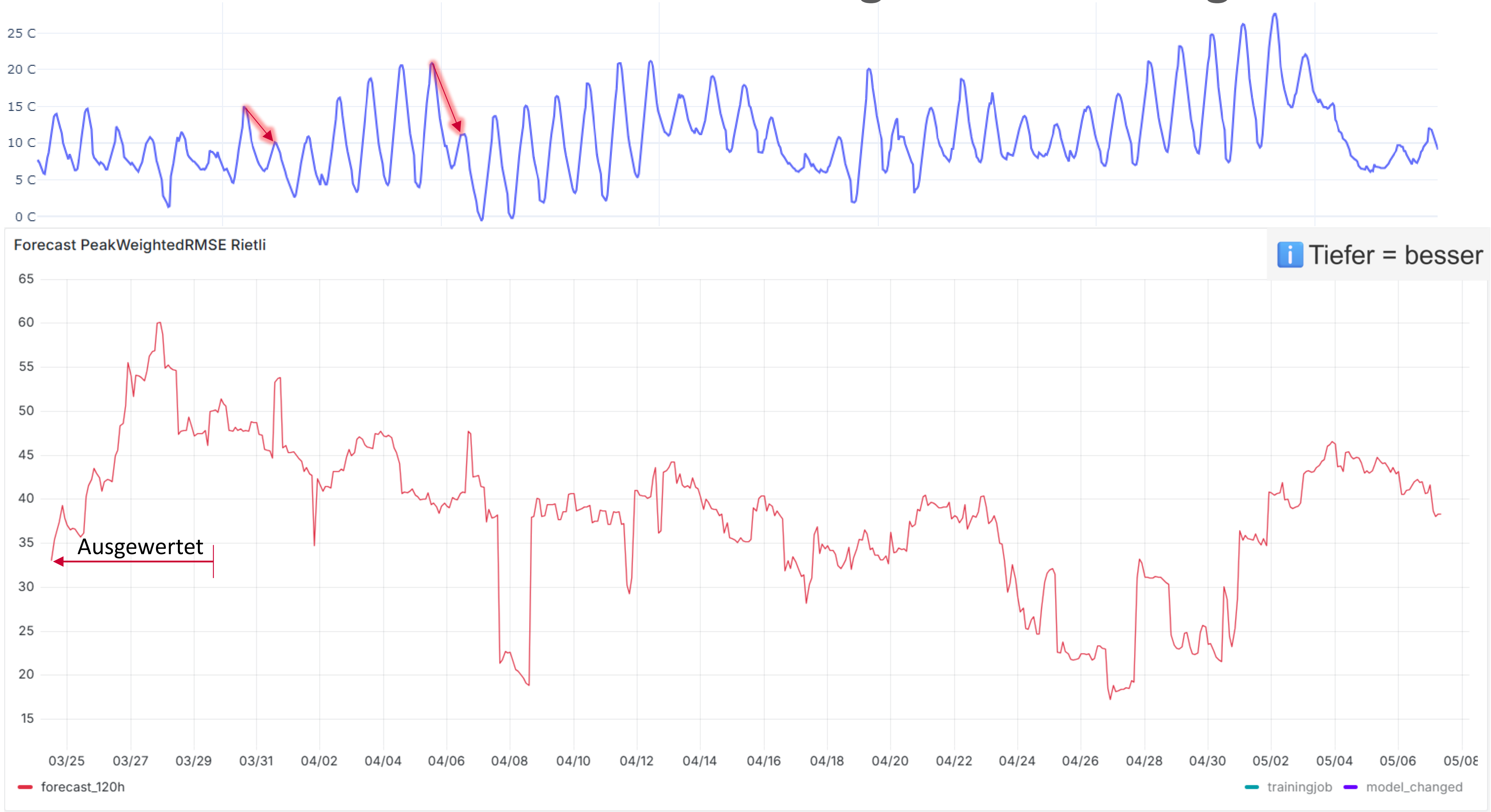
Tag 26: Neue Muster wurden gelernt



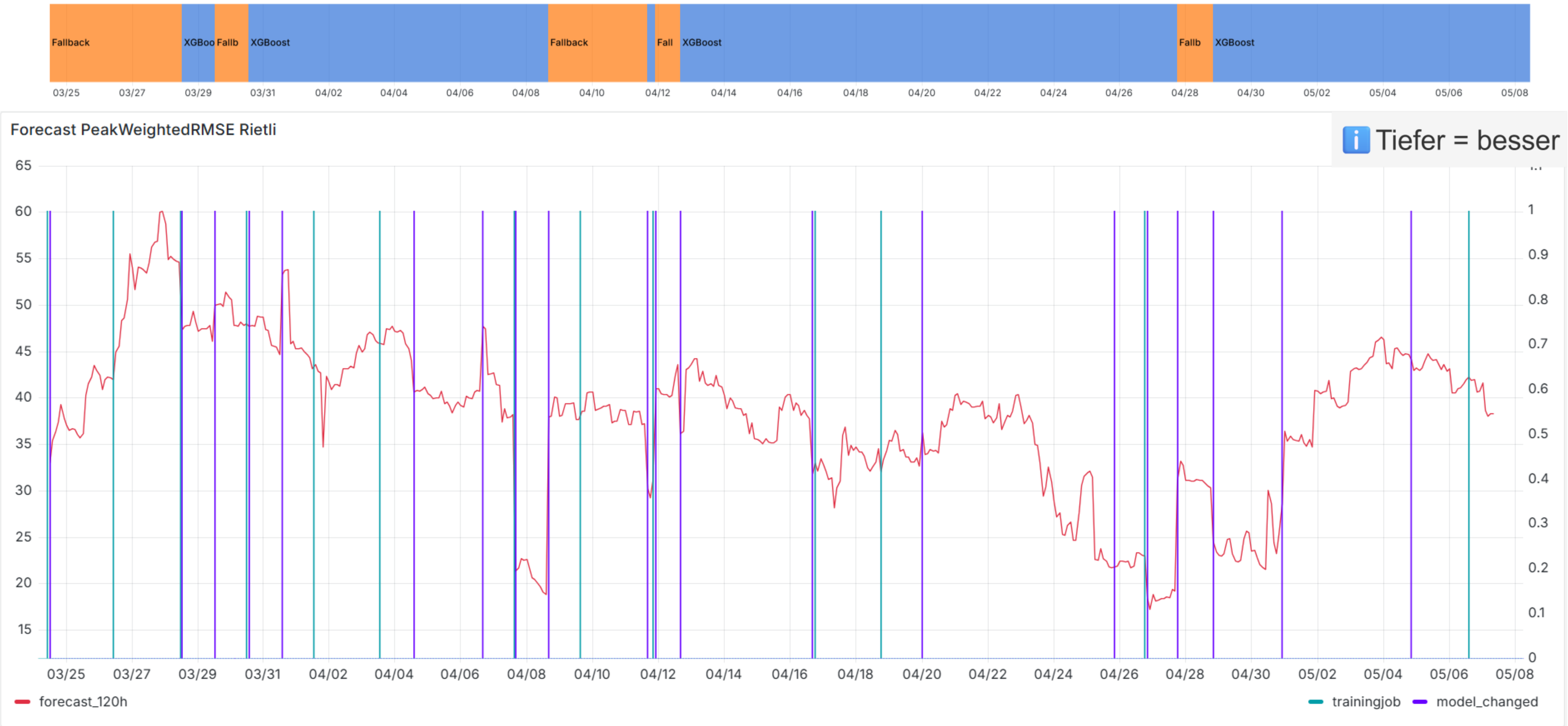
Aktuelle Forecasts



Kontinuierliche Qualitätsüberwachung und Retraining

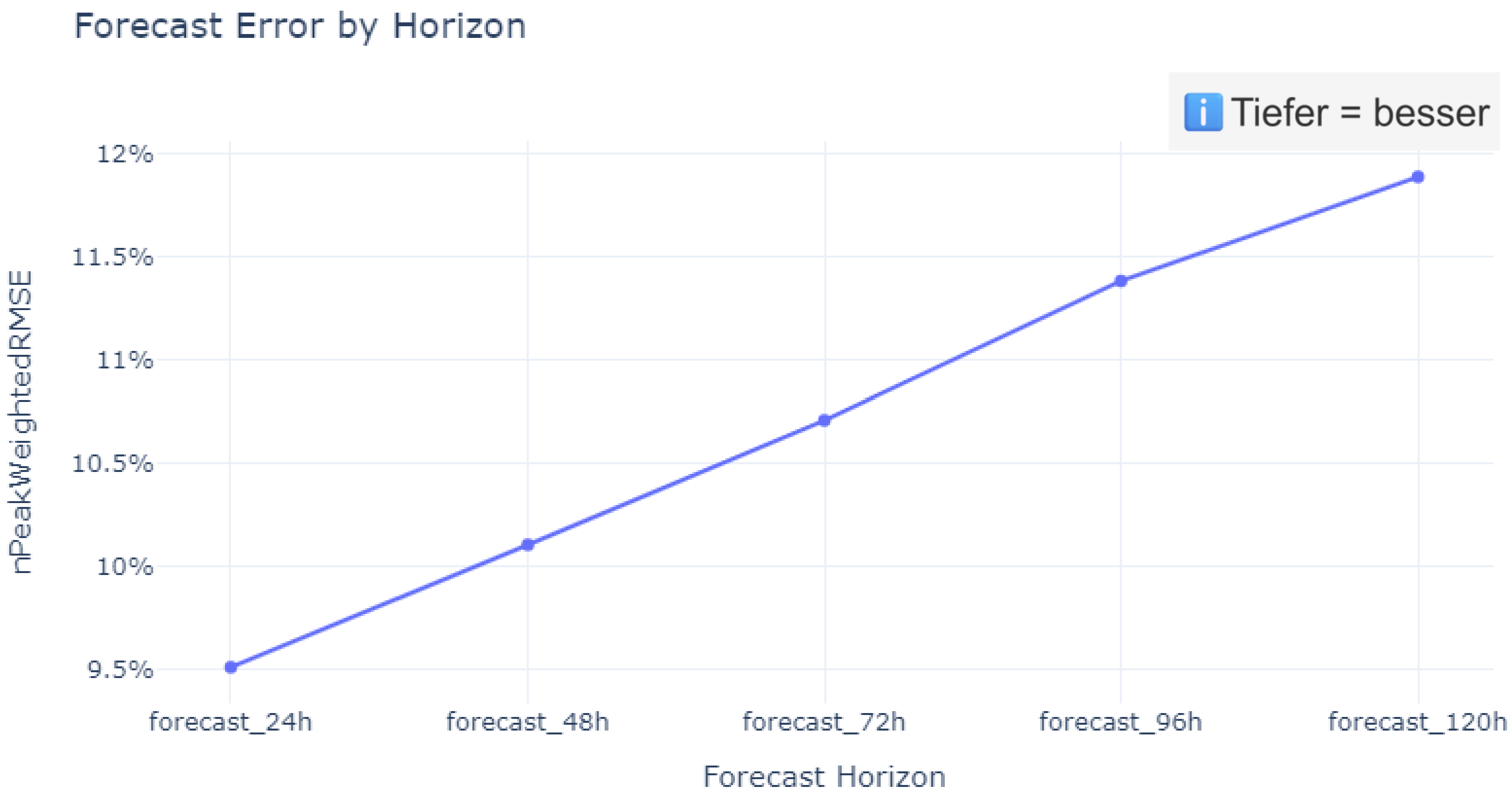


Kontinuierliche Qualitätsüberwachung und Retraining

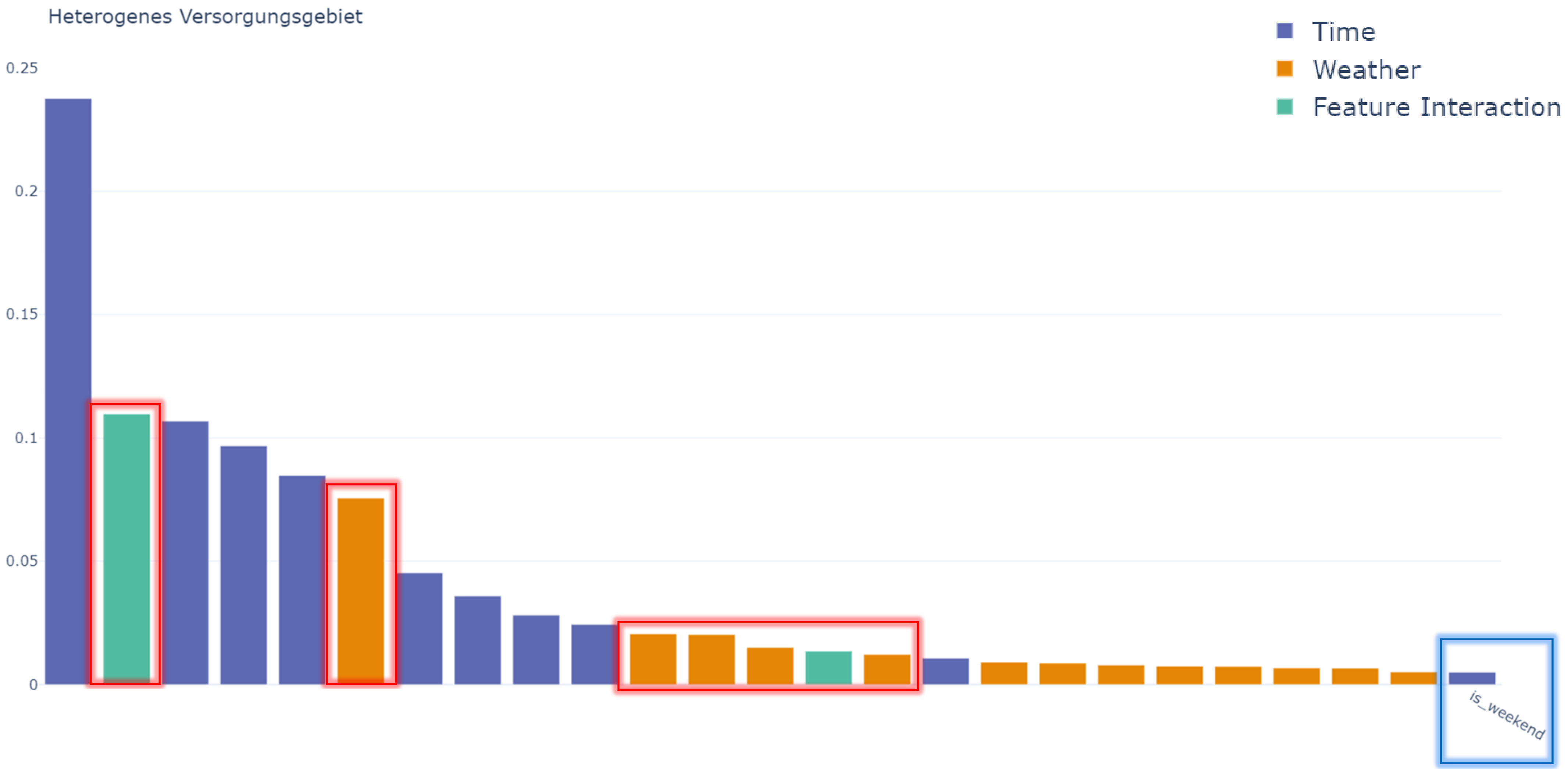


Vorhersagefehler TS Rietli erste 10 Wochen

- PeakWeightedRMSE, Normiert mit Messwertspanne

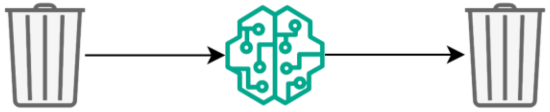


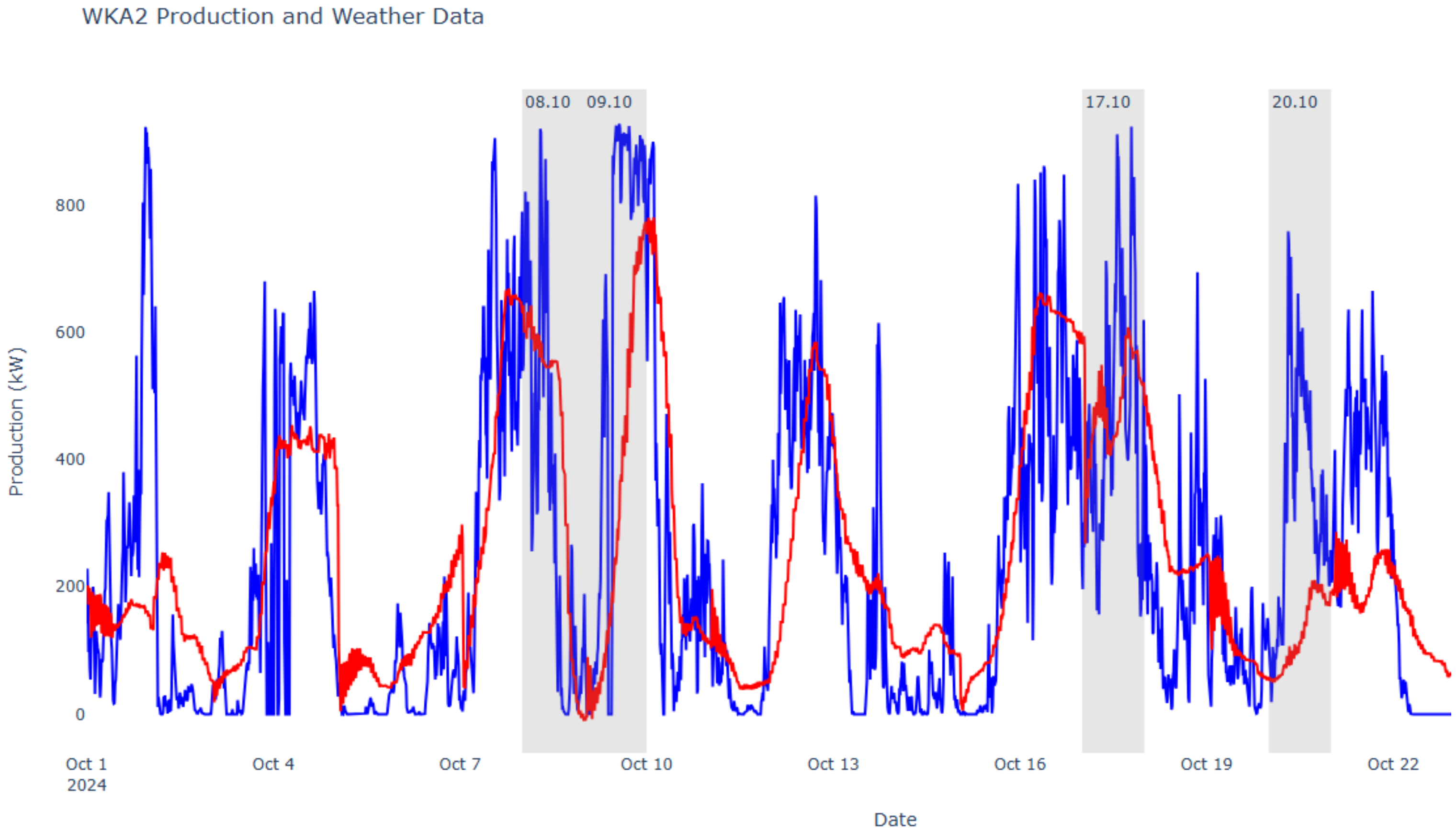
Feature Relevanz aller Models



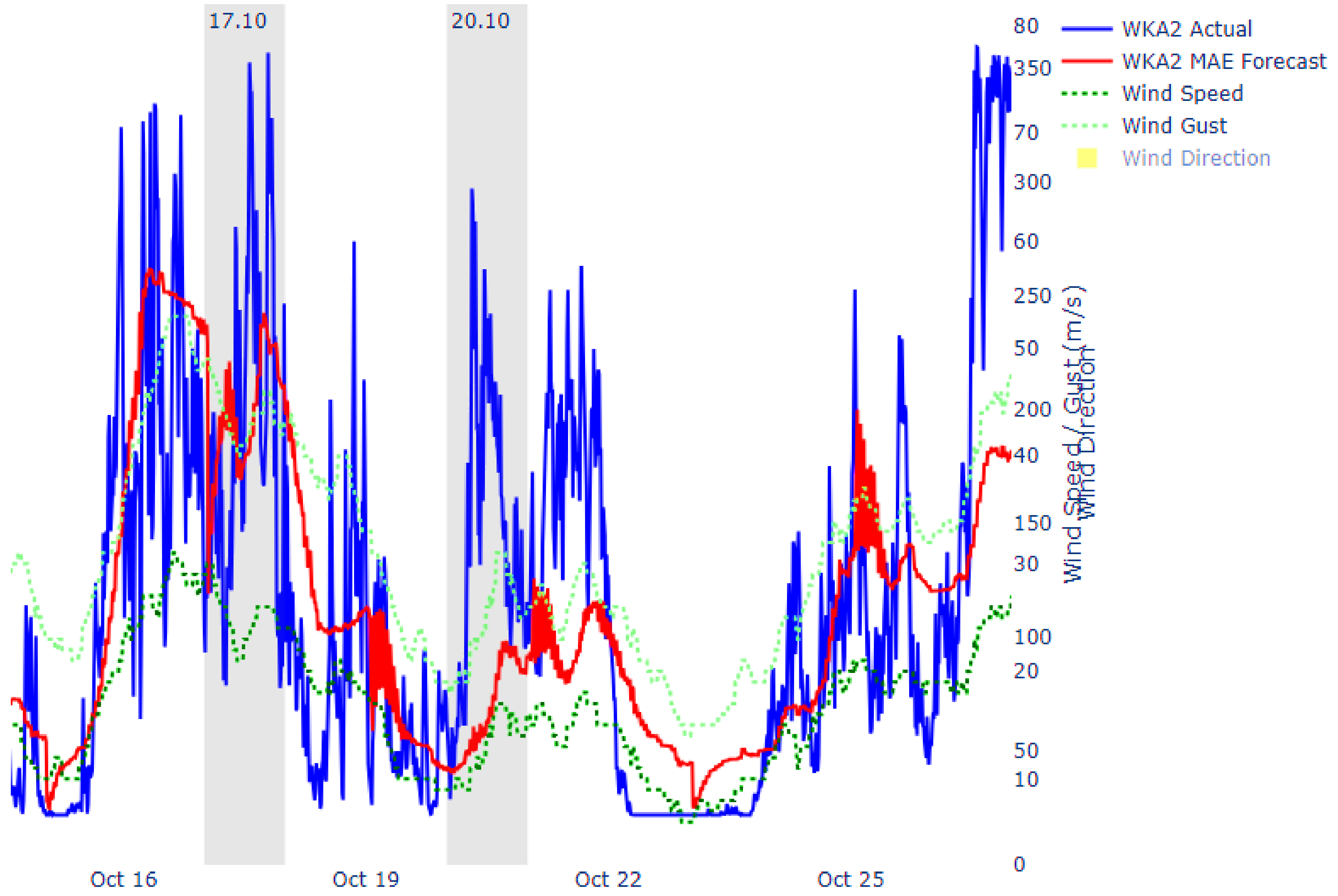
⚠️ Grenzen von KI

- Garbage In, Garbage Out



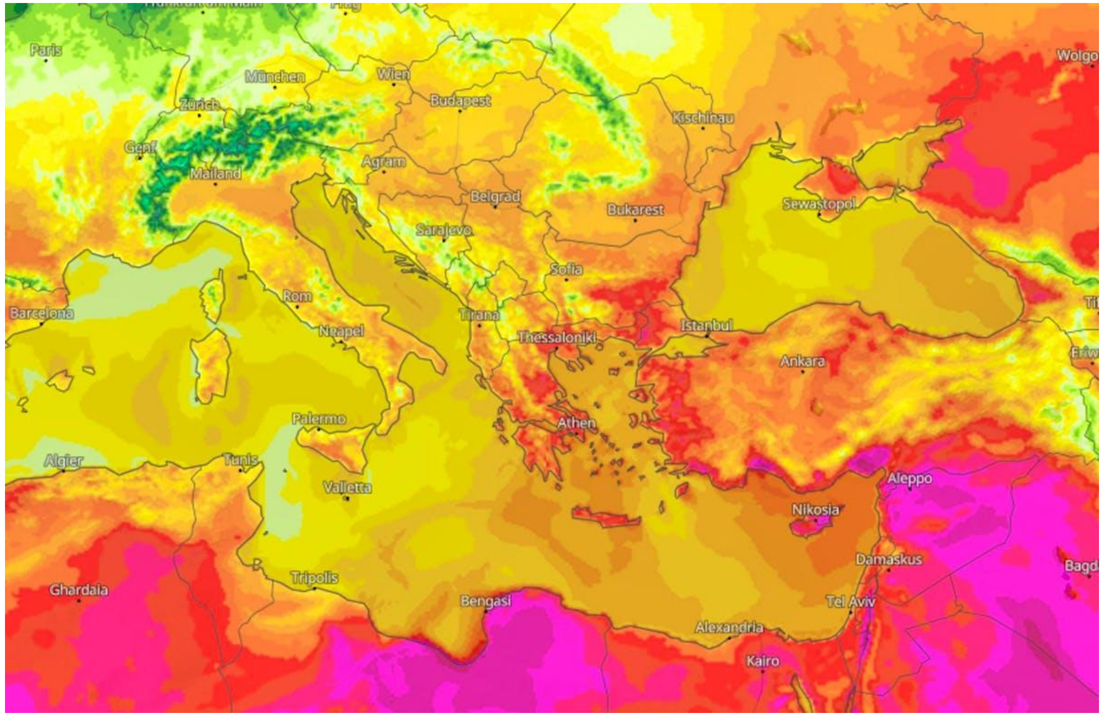


GIGO – Falsche Wetterprognosen



⚠️ Grenzen von KI

- Komplett neue Situationen



Ergebnisse und Lessions Learned

✅ Skalierbares Vorhersagesystem, das
- sich selbstständig optimiert
- bereits mit sehr wenigen Daten realistische Forecasts liefert
- vollständige Rückverfolgbarkeit der Prognosen ermöglicht

💡 Lessions Learned

- Vertraue niemals einer Wettervorhersage
- KI ist nur so gut die ihre Daten – *Garbage In, Garbage Out*
- Es ist entscheidend zu wissen, **was man nicht weiss**
- Verstehe, was das Model versteht

Azure ML

XGBoost

Rietli

MLOps

Let’s Talk!

GIGO

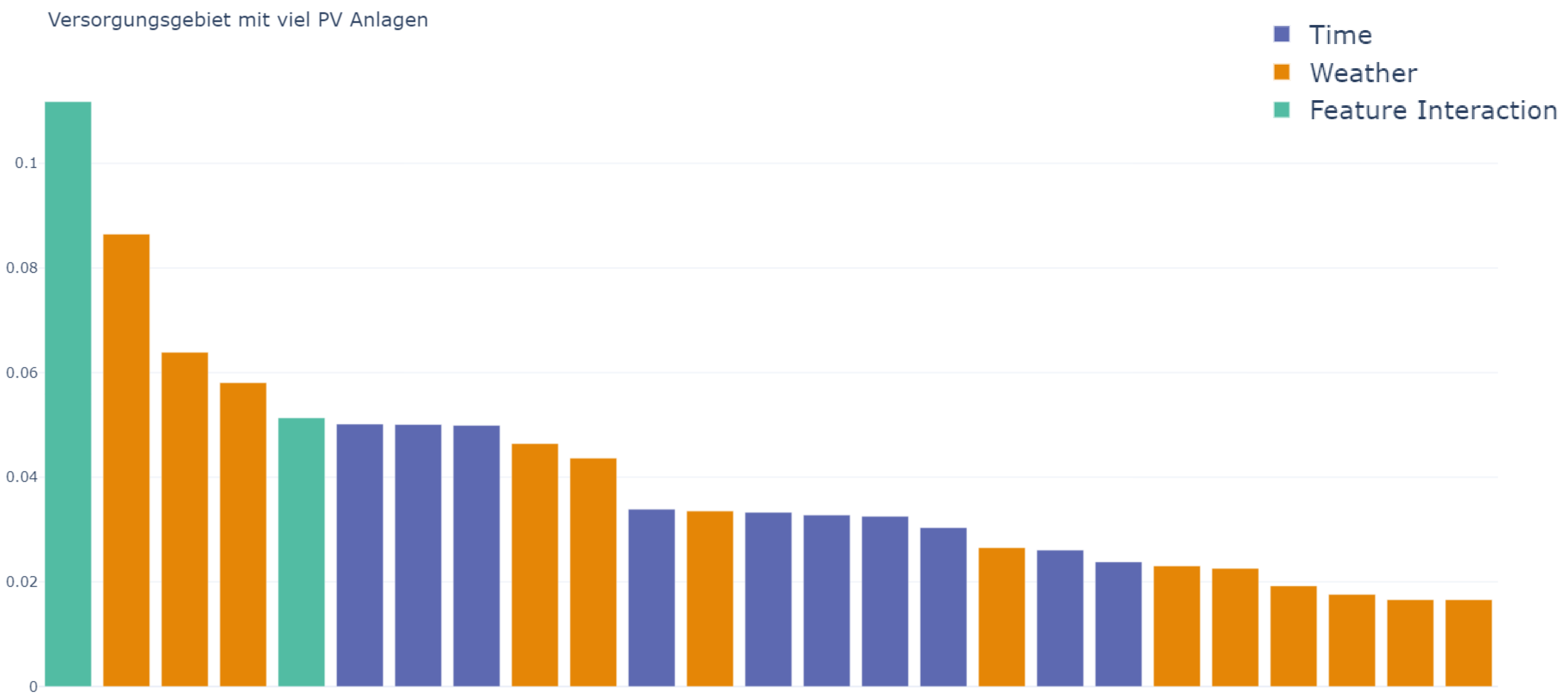
Wetterdaten

Genauigkeit

Features

Erweiterte Folien

Features in Trafokreis mit Solaranlagen



TK mit viel PV