UNIVERSITÀ DI TRENTO

A forecasting system for electricity production and customer demand

Department of Information Engineering and Computer Science

Master’s Degree in Artificial Intelligence Systems

Supervisors

Elisa Ricci

Daniele Miorandi

Student

Samuel Bortolin

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Problem Statement

- Global energy crisis caused an **increased volatility** in the electricity market
- Crucial for electricity suppliers to optimize the purchase of the necessary electricity
- Avoid to resort solely to the instantaneous electricity market
- **Plan energy procurement strategies avoiding cost fluctuations and imbalance fees**
- Offer customers the necessary electricity and supply it at a competitive price

Problem Statement

- Vital to forecast **customers' electricity demand**
- Crucial to forecast **production from own electricity generation facilities**
- Understand the consumption habits of individual customers by establishing a reference **consumption baseline**
- Personalized energy solutions (dynamic pricing scheme, energy storage systems, …)

MIWenergía Datasets

- Aggregated consumption data over all their customers, from **2 to 4 thousand** (19 months)
- Production data from **8 photovoltaic plants** (from 2 to 10 months)
- Individual consumption data from **3 customers** (from 9 to 15 months)
- Weather data from Murcia airport, including solar energy data, as additional features

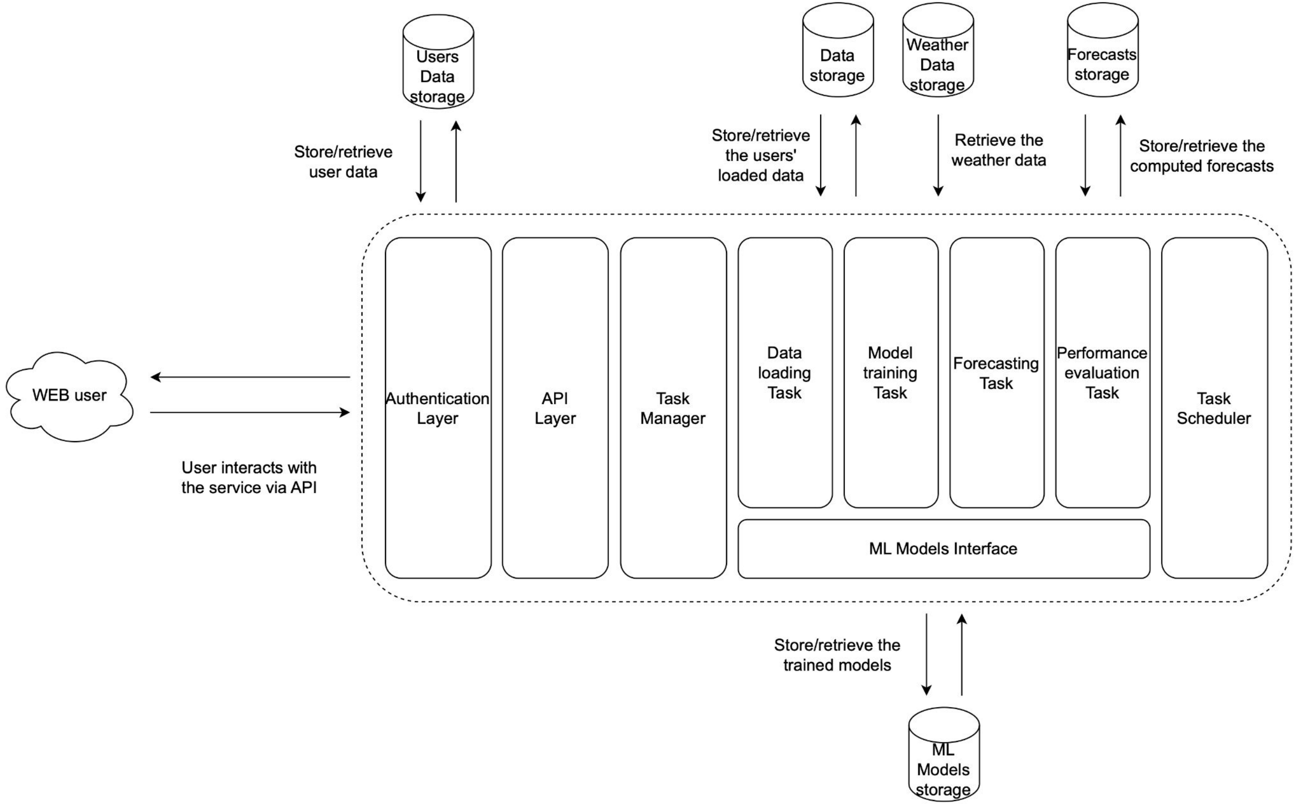
Research Questions

- Can the customers' electricity demand be forecasted based on past aggregated **consumption data over the customers** and historical weather data?
- Can the photovoltaic plants' production be forecasted based on past aggregated **production data over the photovoltaic plants** and historical weather data, including solar energy data?
- Can a consumption baseline of individual customers be established based on past **consumption data of individual customers** and historical weather data?

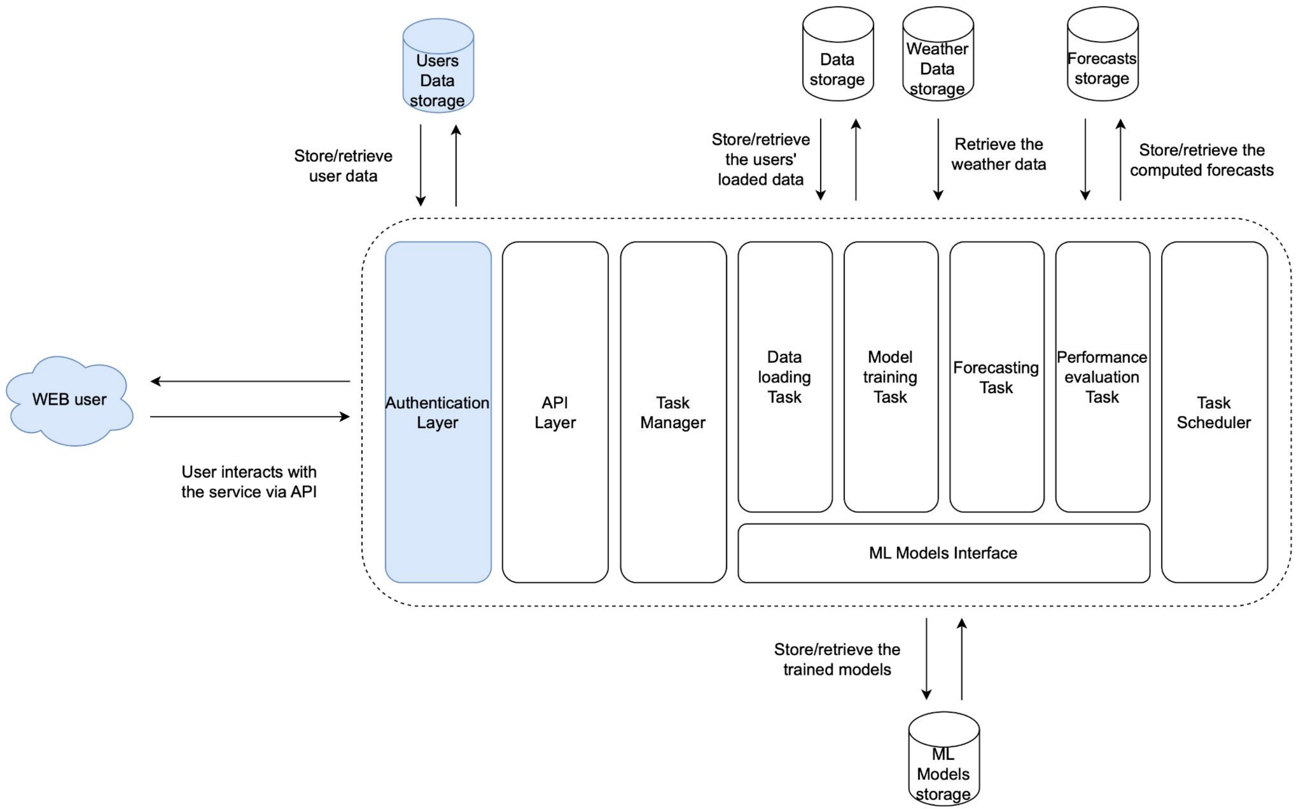
Achievements

- Designed a **novel forecasting system** for addressing the research questions
- Implemented a **prototype** of the system with a focus on key components
- Comprehensively evaluated the performance of a set of **developed models** for :
  - Electricity demand forecasting
  - Electricity production forecasting
  - Consumption baseline forecasting

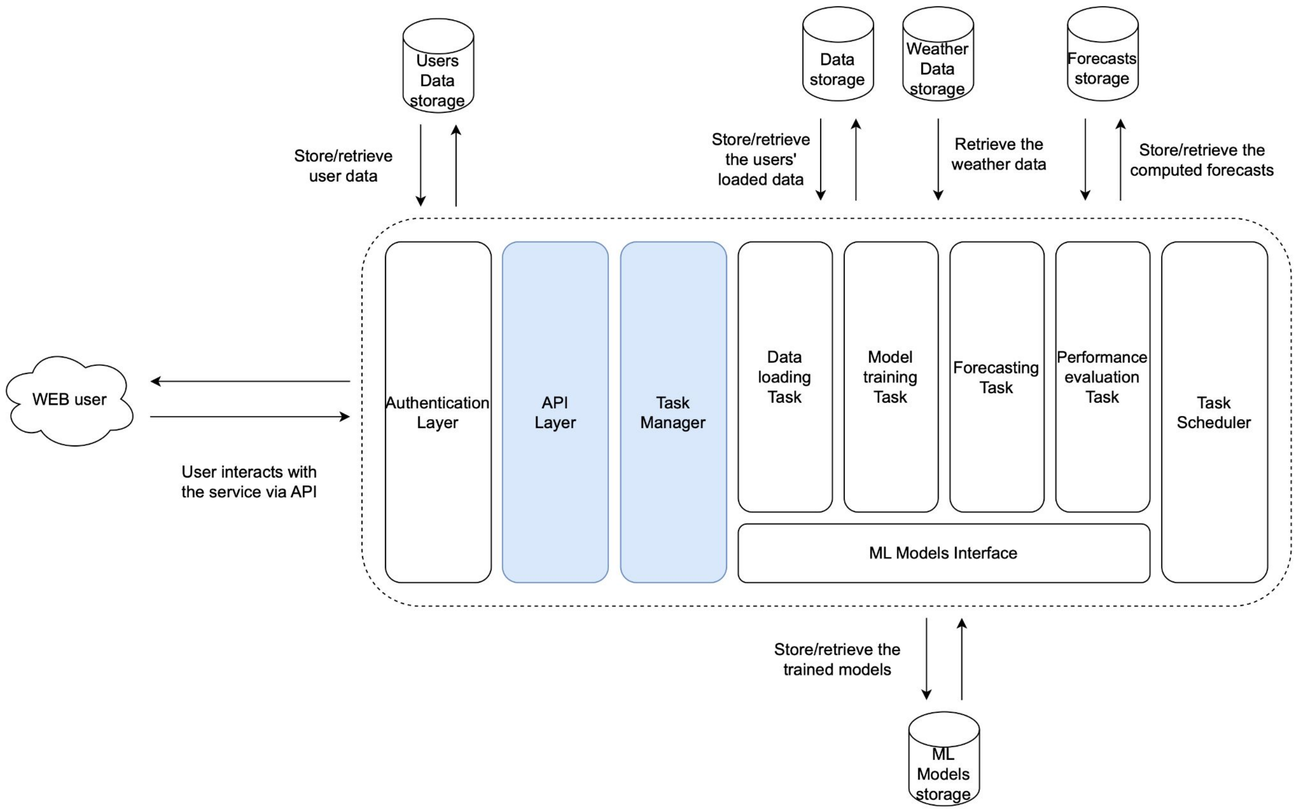
Forecasting System



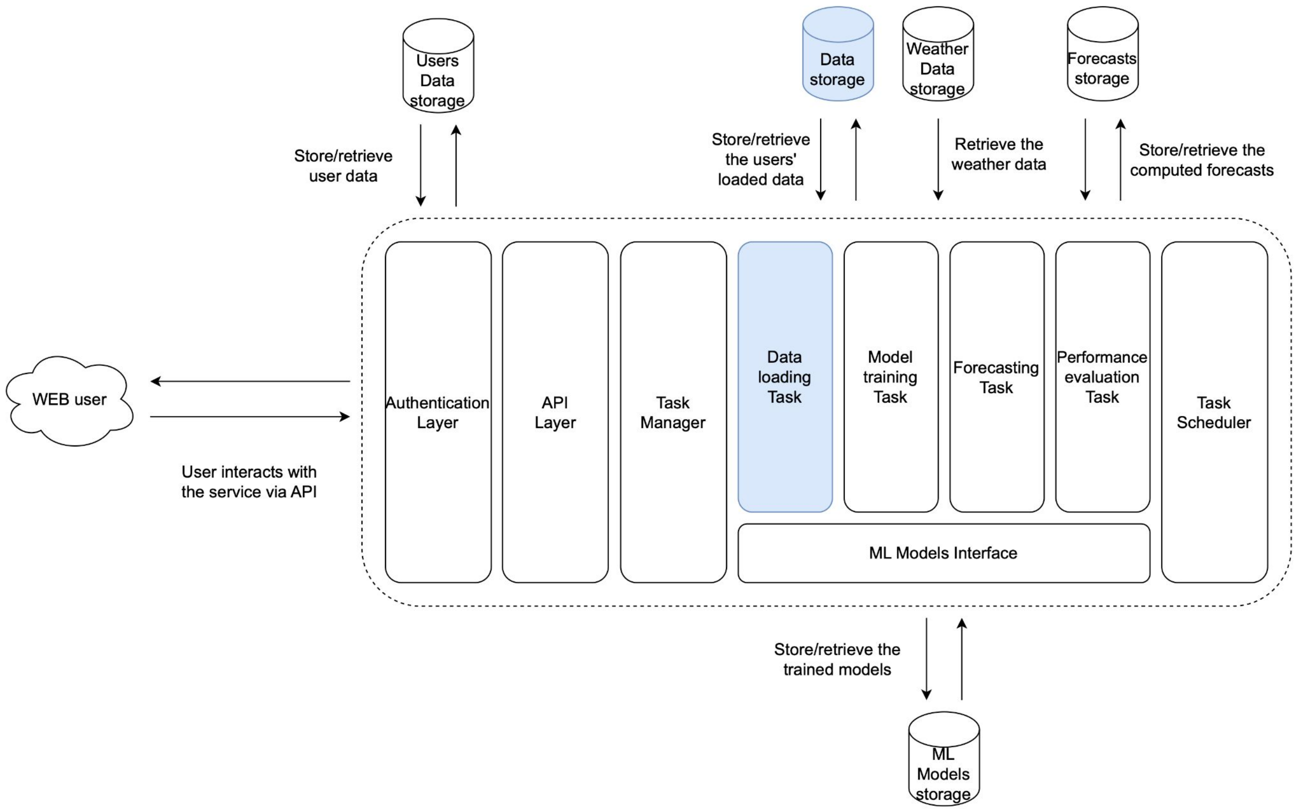
Forecasting System



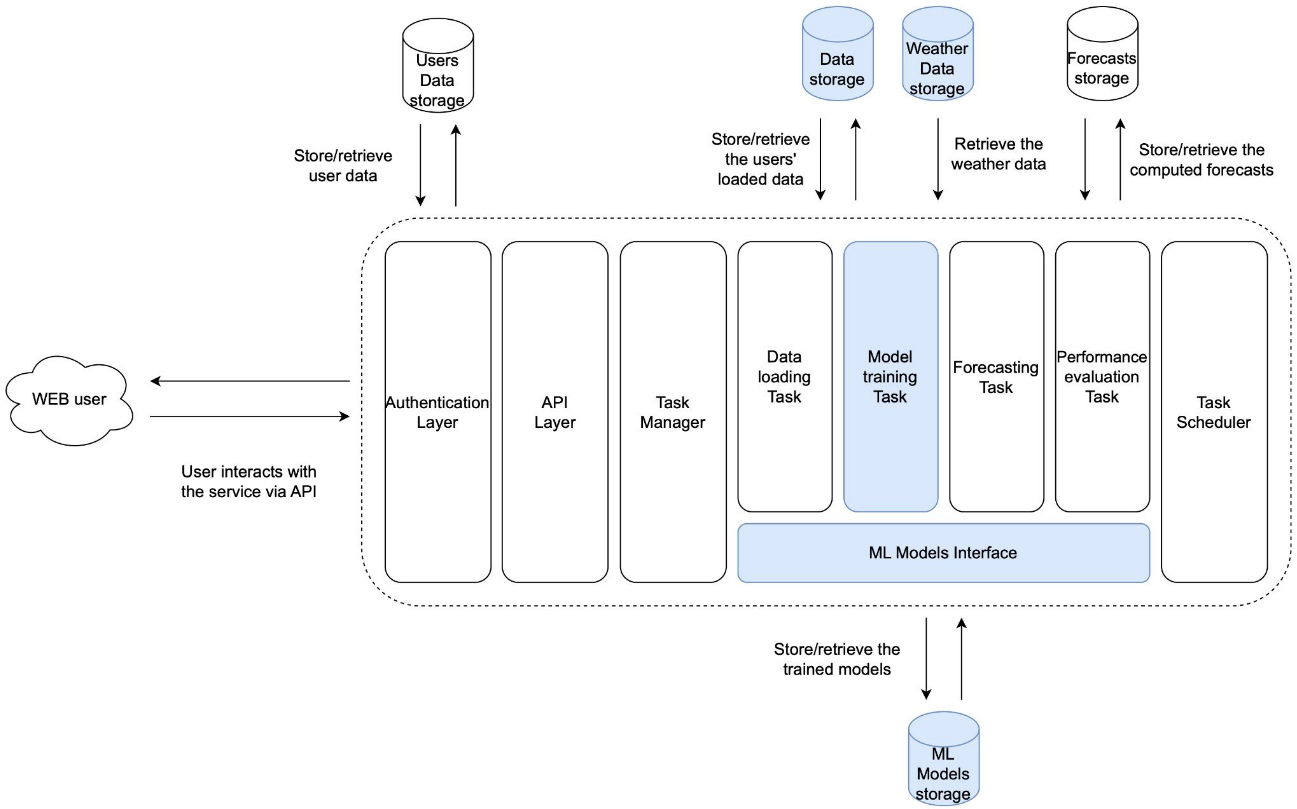
Forecasting System



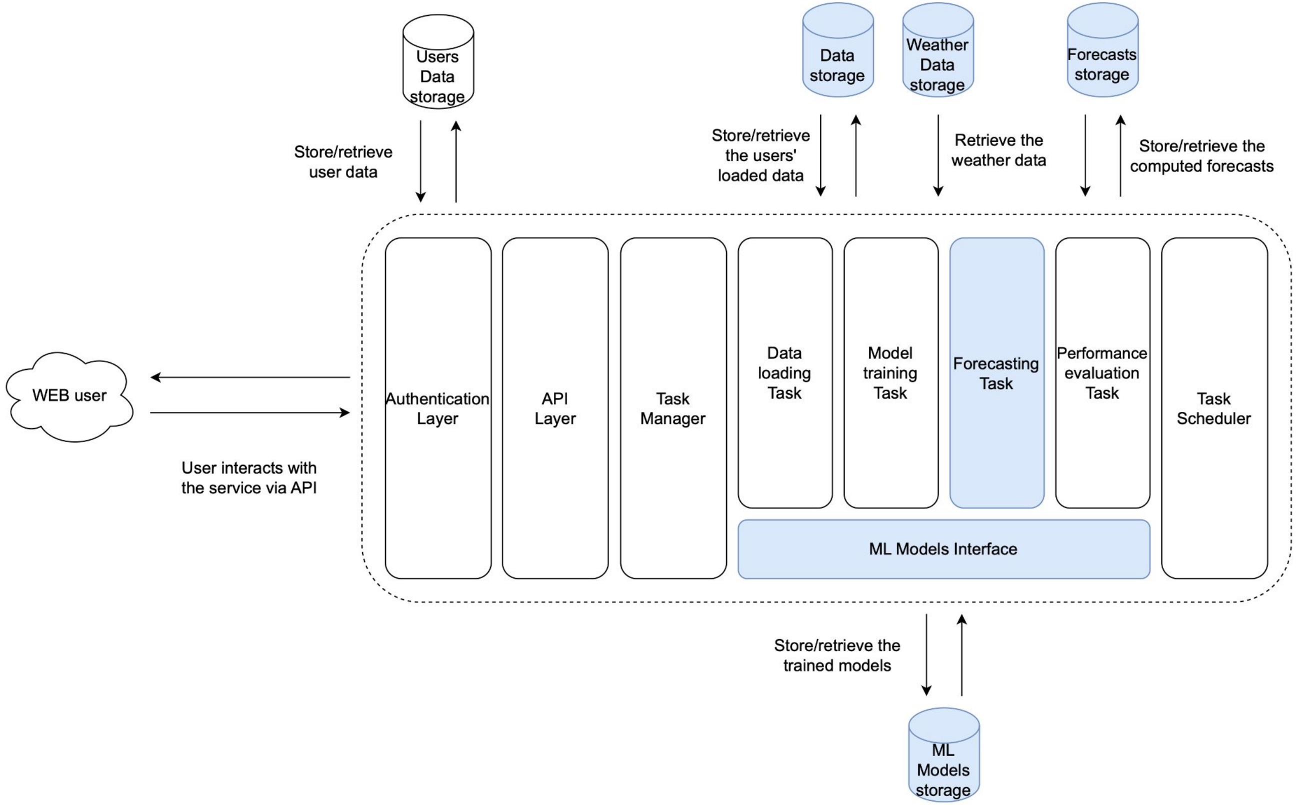
Forecasting System



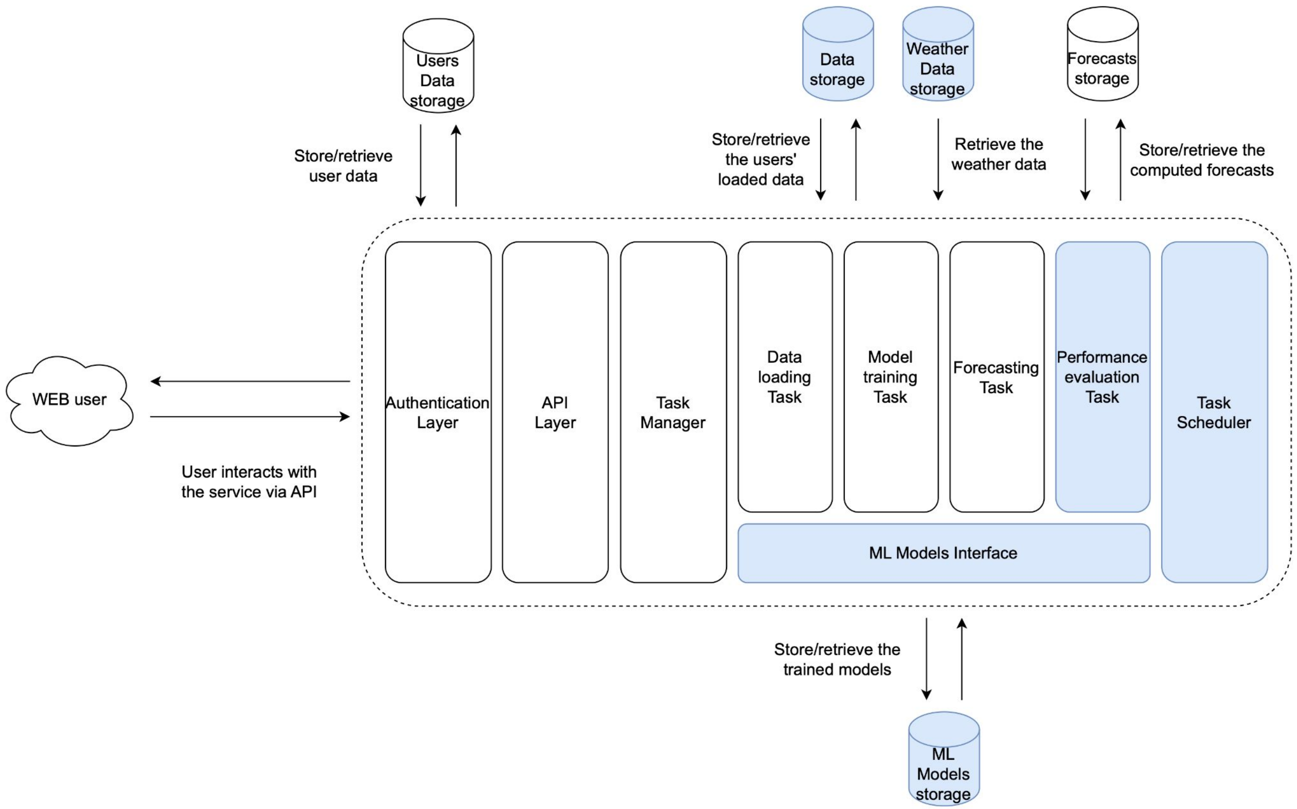
Forecasting System



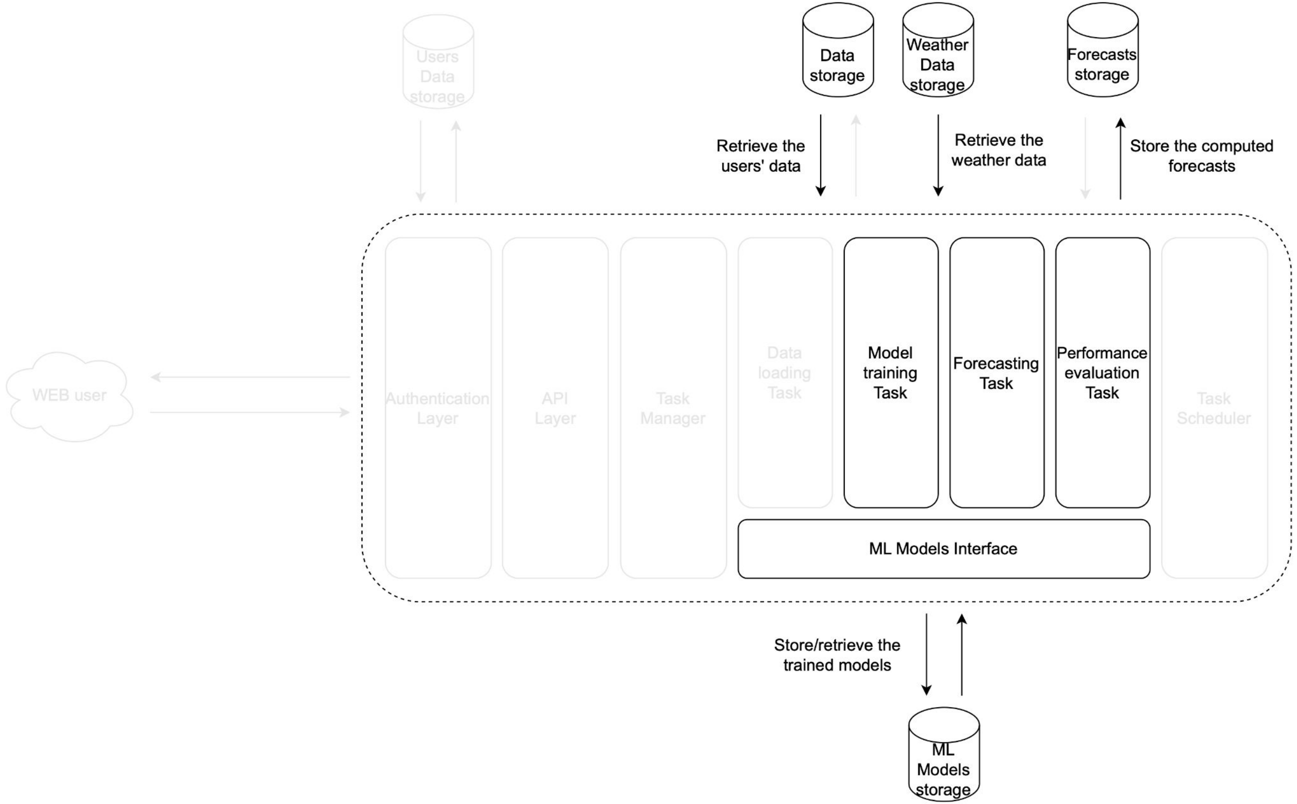
Forecasting System



Forecasting System



Implemented Prototype



Models

- Baselines: combination of previous days or weeks
- Statistical: ARIMA/SARIMA
- ML: SVR, Hist gradient boosting regressor, XGBoost regressor, and Prophet
- DL: LSTM, GRU, CNN, and TFT
- AutoML
- Combinations of Baselines, Prophet, and DL models

Performance Evaluation

MAPE and MAE as error metrics

Blocked k-fold cross-validation

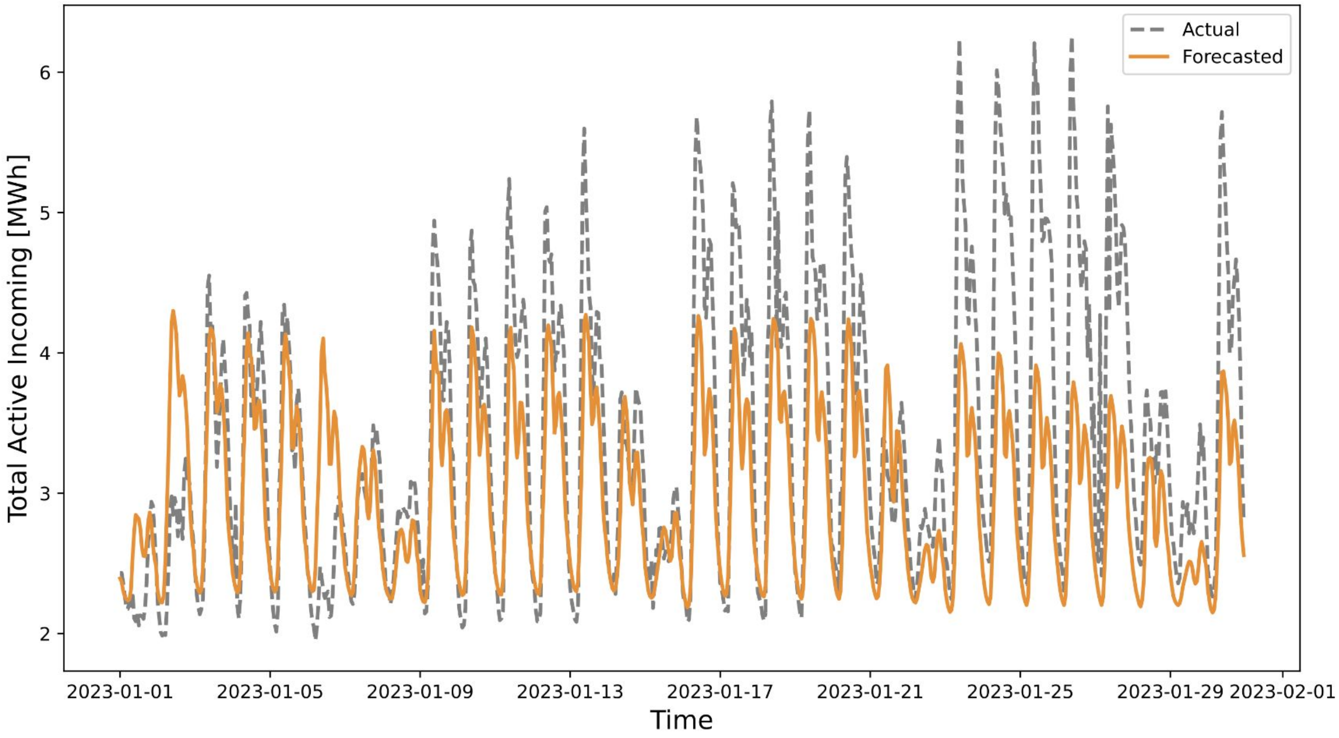
Test on the **last split**

Hourly Results

k = 12
Split size = 30 days

Model	Blocked k-fold cross-validation MAPE	Test on the last split MAPE
TFT	15.0 ± 4.3	14.8
Best combination: GRU + One Week Baseline	/	14.8
GRU	30.8 ± 14.5	16.8
AutoML	/	17.0
CNN	34.6 ± 15.8	17.5
One Week Baseline	12.9 ± 4.3	17.6
SARIMA	15.4 ± 4.6	18.5
One Day Baseline	22.9 ± 7.1	20.5
LSTM	34.1 ± 11.9	23.2
Hist gradient boosting regressor	14.5 ± 5.5	29.3
SVR	61.8 ± 22.6	29.5
Prophet	28.7 ± 7.1	31.6
XGBoost regressor	16.9 ± 8.9	37.8

TFT Forecasts

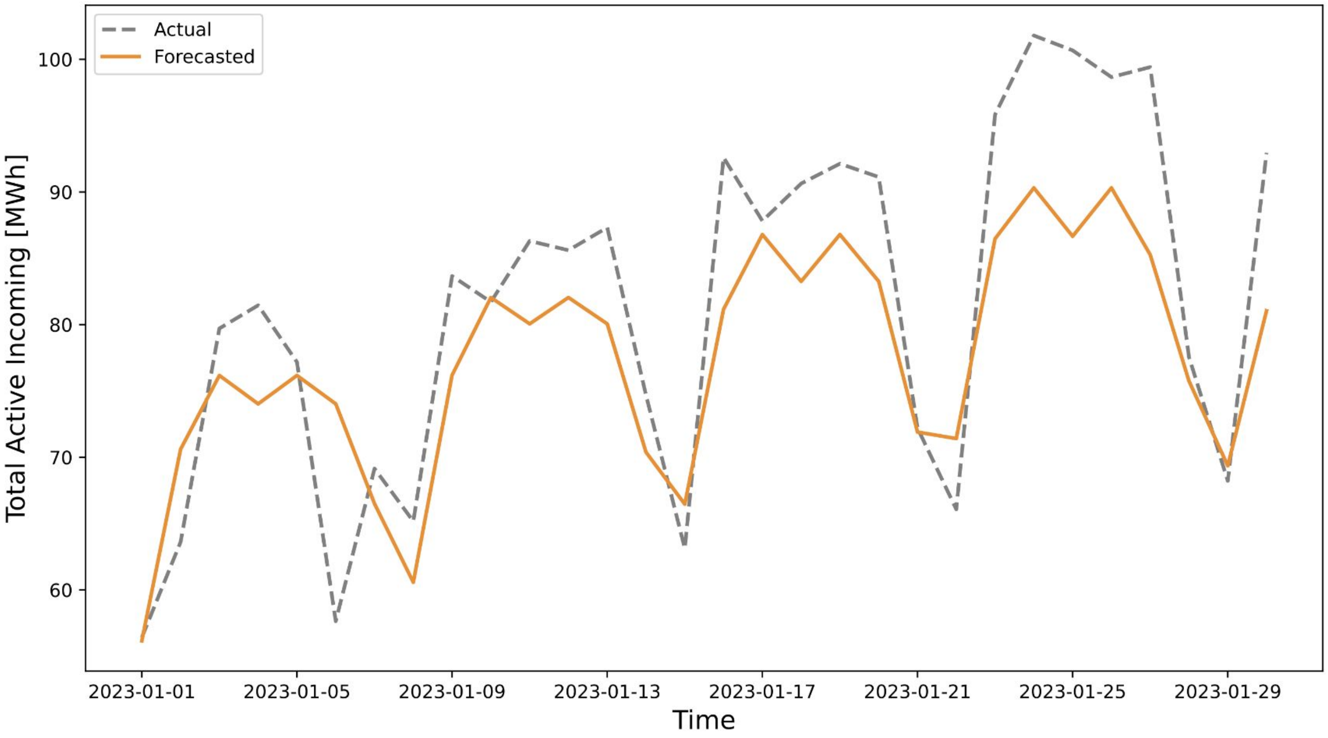


Daily Results

k = 12
Split size = 30 days

Model	Blocked k-fold cross-validation MAPE	Test on the last split MAPE
CNN	50.6 ± 36.8	7.5
XGBoost regressor	13.0 ± 4.4	7.7
Hist gradient boosting regressor	13.0 ± 5.5	9.8
Best combination: CNN + One Week Baseline	/	12.3
LSTM	29.6 ± 13.8	14.5
TFT	13.7 ± 5.1	14.9
One Week Baseline	11.5 ± 4.8	18.4
SARIMA	11.9 ± 7.0	19.6
GRU	28.8 ± 29.3	20.5
AutoML	/	21.0
One Day Baseline	22.8 ± 8.2	21.5
Prophet	19.1 ± 10.8	26.3
SVR	53.6 ± 22.4	39.8

CNN Forecasts

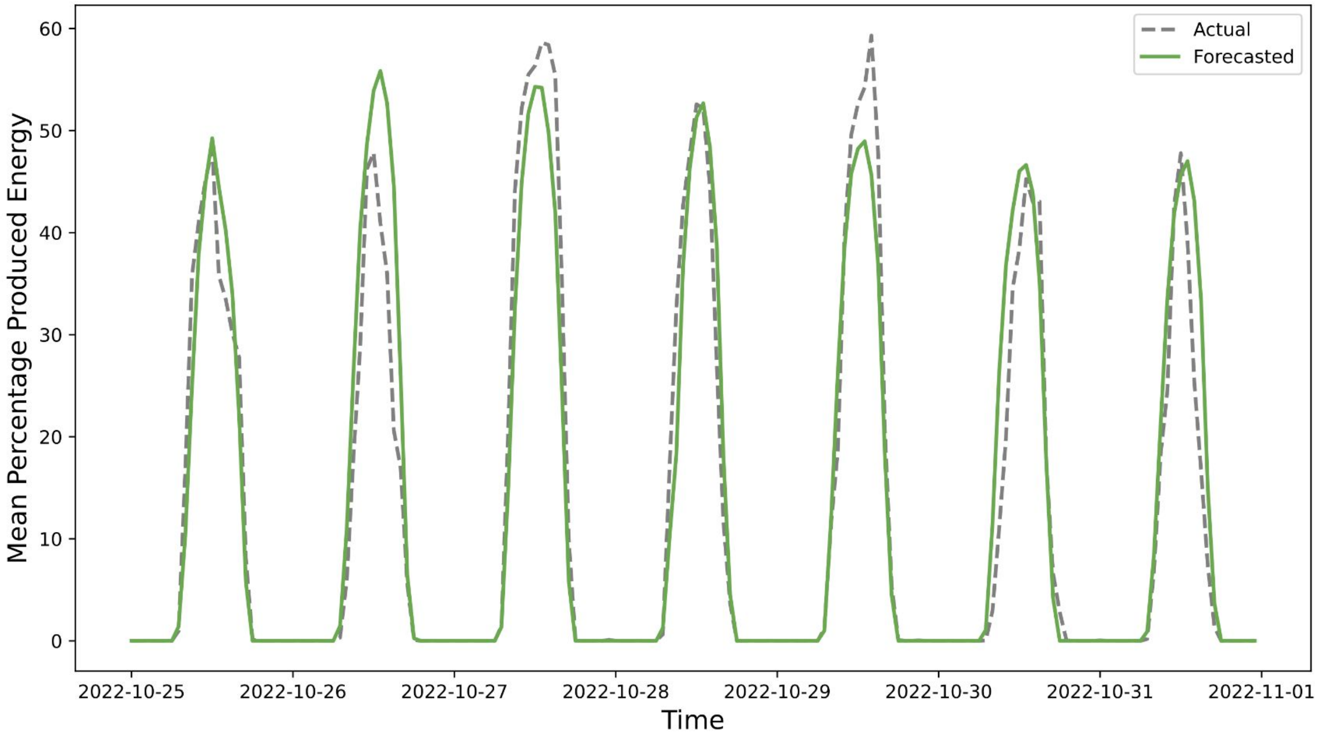


Hourly Results

k = 12
Split size = 7 days

Model	Blocked k-fold cross-validation MAE normalized on PV plants' nominal power	Test on the last split MAE normalized on PV plants' nominal power
GRU	5.7 ± 1.8	2.8
Hist gradient boosting regressor	4.2 ± 1.0	3.0
SVR	5.2 ± 1.1	3.1
CNN	6.0 ± 1.5	3.3
Best combination: LSTM + One Day Baseline	/	3.4
XGBoost regressor	4.6 ± 1.0	3.4
LSTM	5.2 ± 1.5	3.5
TFT	4.7 ± 1.4	3.6
ARIMA	5.1 ± 1.4	3.6
Prophet	7.9 ± 1.6	4.4
One Day Baseline	6.8 ± 3.1	4.6
AutoML	/	5.9

GRU Forecasts



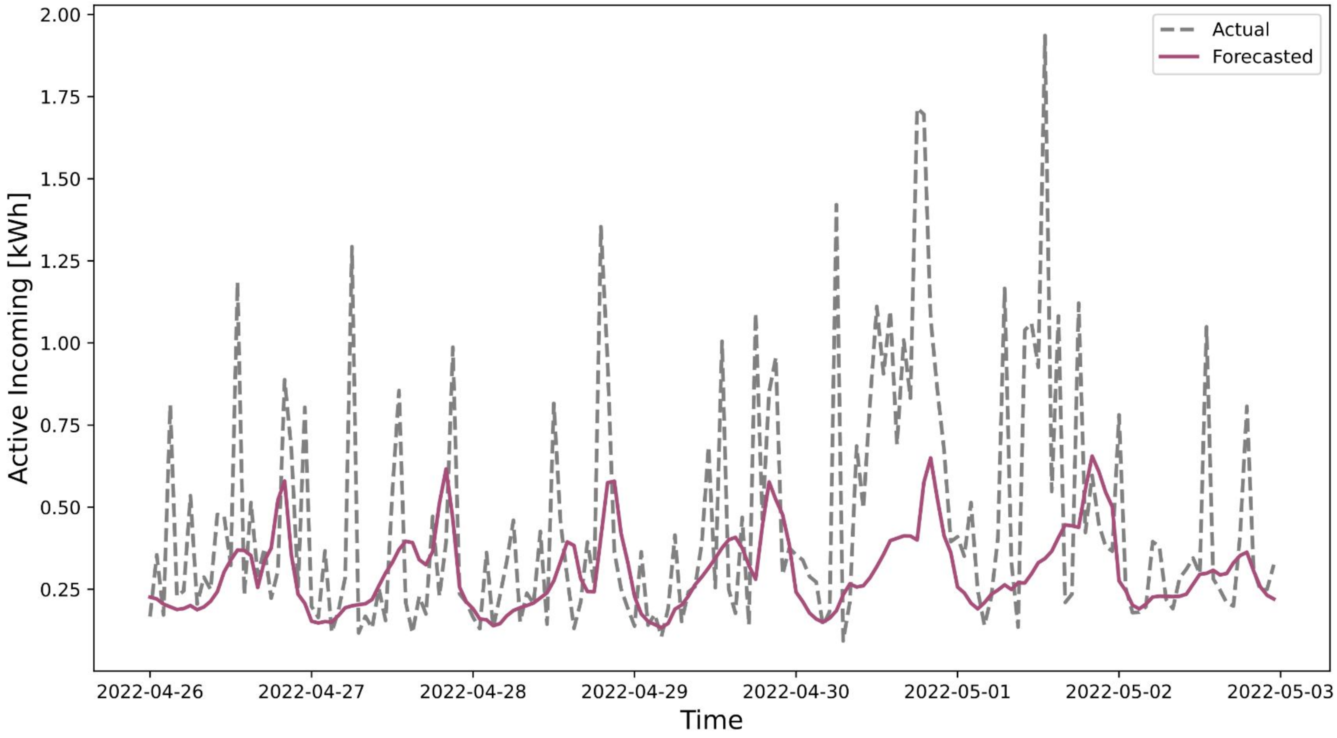
Hourly Results

k = 12
Split size = 7 days

Model	Blocked k-fold cross-validation MAPE — MAE [kWh]	Test on the last split MAPE — MAE [kWh]
TFT	47.3 ± 5.6 — 0.29 ± 0.03	44.2 — 0.23
Hist gradient boosting regressor	54.0 ± 7.0 — 0.26 ± 0.02	50.4 — 0.23
SVR	60.3 ± 6.8 — 0.28 ± 0.03	60.4 — 0.24
SARIMA	74.2 ± 10.0 — 0.27 ± 0.02	78.0 — 0.24
XGBoost regressor	73.7 ± 9.5 — 0.28 ± 0.02	68.1 — 0.25
Prophet	83.8 ± 10.2 — 0.28 ± 0.02	81.9 — 0.25
GRU	58.9 ± 19.6 — 0.31 ± 0.04	42.6 — 0.26
LSTM	111.9 ± 212.1 — 0.46 ± 0.52	44.2 — 0.27
4 Week Baseline	74.1 ± 12.5 — 0.28 ± 0.03	79.1 — 0.27
12 Week Baseline	74.3 ± 13.7 — 0.27 ± 0.02	89.2 — 0.28
One Week Baseline	82.7 ± 12.8 — 0.33 ± 0.03	70.5 — 0.28
One Day Baseline	75.8 ± 14.0 — 0.32 ± 0.04	71.3 — 0.29
CNN	148.2 ± 30.1 — 0.51 ± 0.11	70.2 — 0.32
AutoML	/	61.6 — 0.34

MAE

TFT Forecasts

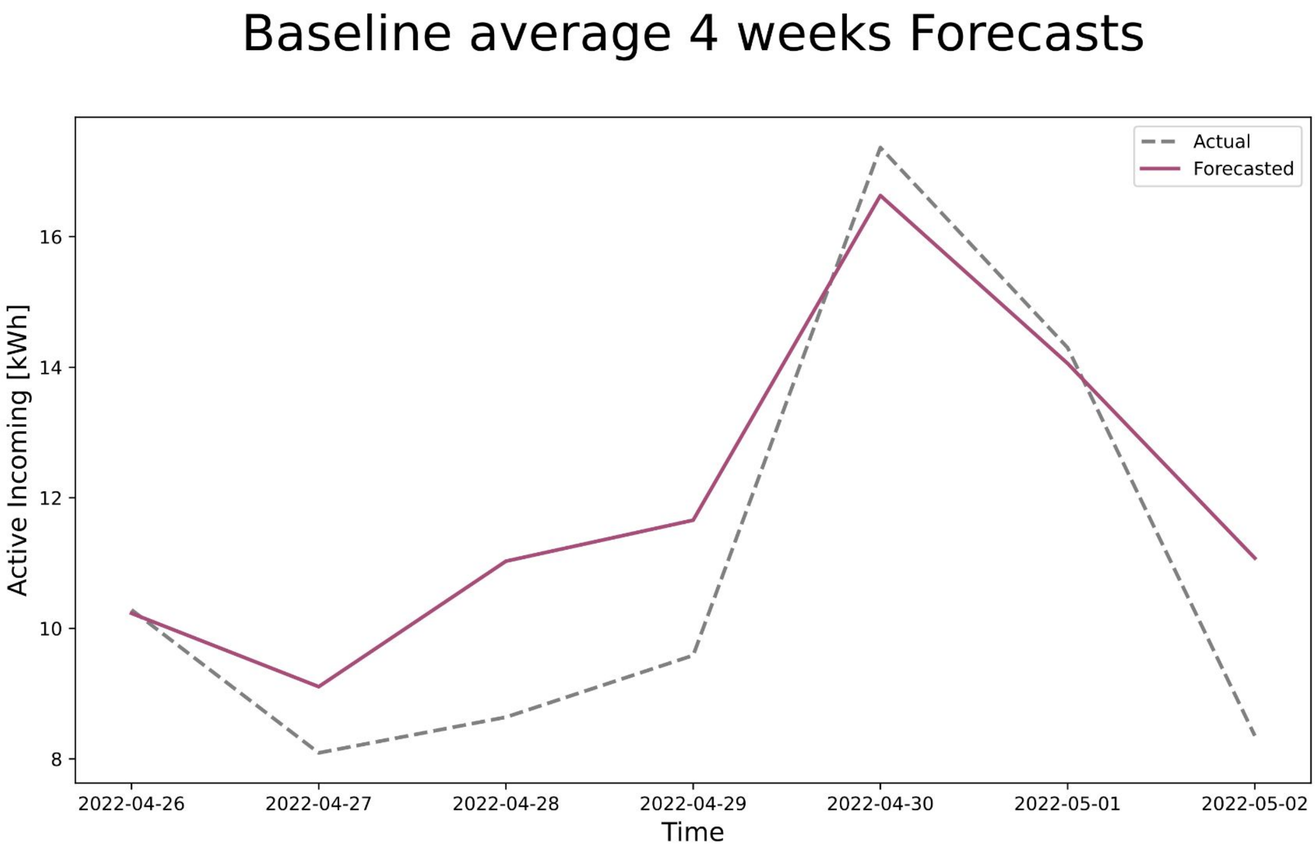


Daily Results

k = 12
Split size = 7 days

Model	Blocked k-fold cross-validation MAPE — MAE [kWh]	Test on the last split MAPE — MAE [kWh]
4 Week Baseline	16.2 ± 4.9 — 1.9 ± 0.6	14.4 — 1.3
One Week Baseline	19.6 ± 7.5 — 2.3 ± 0.9	14.5 — 1.6
CNN	28.5 ± 17.5 — 3.3 ± 1.9	13.5 — 1.8
SARIMA	16.4 ± 4.8 — 1.9 ± 0.5	17.1 — 1.8
TFT	16.7 ± 6.3 — 2.0 ± 0.6	14.6 — 1.8
Hist gradient boosting regressor	15.4 ± 3.7 — 1.9 ± 0.4	16.8 — 1.9
12 Week Baseline	15.6 ± 4.4 — 1.9 ± 0.5	20.0 — 2.0
XGBoost regressor	17.6 ± 4.9 — 2.1 ± 0.6	21.4 — 2.1
AutoML	/	19.9 — 2.2
GRU	18.7 ± 3.4 — 2.5 ± 0.5	17.9 — 2.4
LSTM	19.0 ± 3.5 — 2.5 ± 0.6	18.4 — 2.4
One Day Baseline	20.4 ± 3.9 — 2.7 ± 0.6	19.0 — 2.4
Prophet	17.4 ± 5.2 — 1.9 ± 0.4	25.5 — 2.5
SVR	18.1 ± 3.2 — 2.4 ± 0.6	23.4 — 2.7

MAE


Baseline average 4 weeks Forecasts
Actual
Forecasted
Active Incoming [kWh]
16
14
12
10
8
2022-04-26
2022-04-27
2022-04-28
2022-04-29
2022-04-30
2022-05-01
2022-05-02
Time

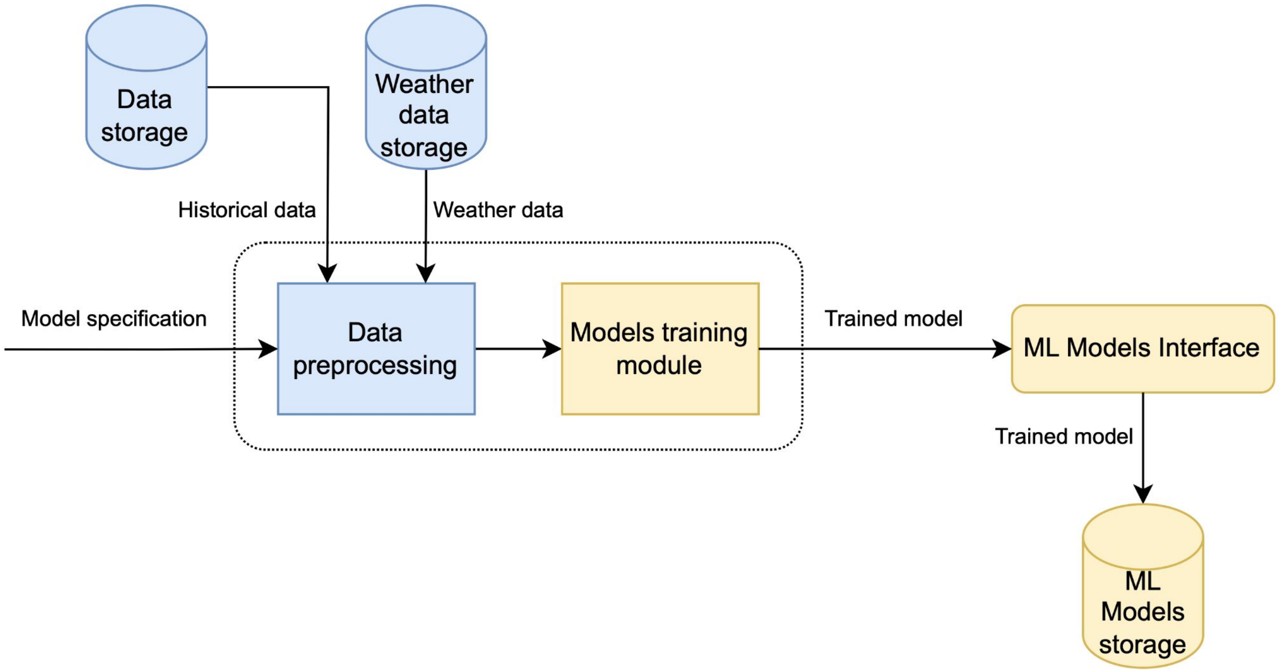
Conclusions

- Global energy crisis caused an **increased volatility** in the electricity market
- Designed a **novel forecasting system** and implemented a **prototype** of the system
- **Electricity production and customer demand can be accurately forecasted**
- **Consumption baseline** cannot be accurately forecasted considering the high variability of the data of the provided customers and the **limited amount of historical data**
- AutoML struggled to achieve competitive results and model combinations resulted in an improvement to DL models only in a limited number of cases

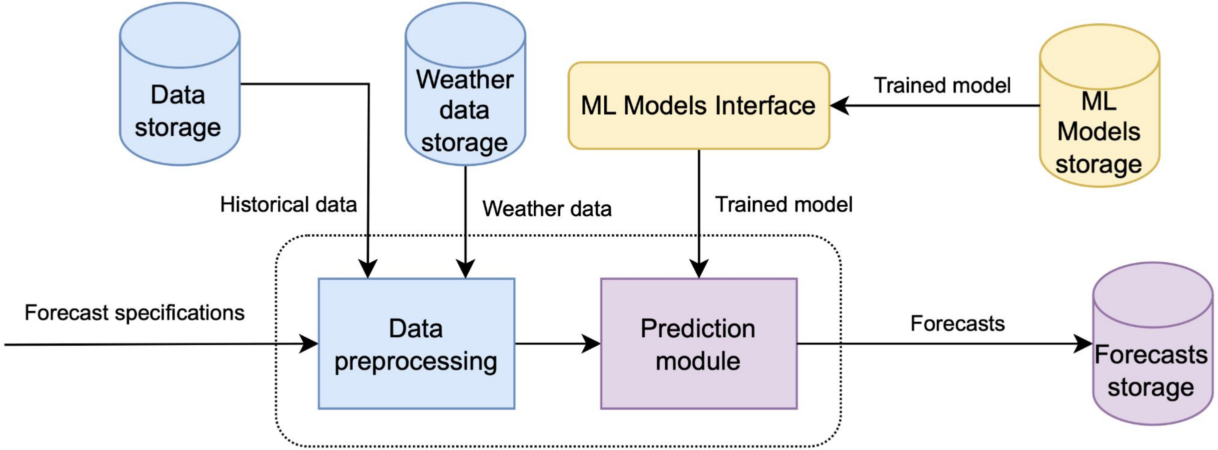
Future Directions

- **Ensemble learning** techniques
- Additional features (socio-demographic, household composition, …)
- Consumption disaggregation
- Full-fledged **SaaS solution implementation**

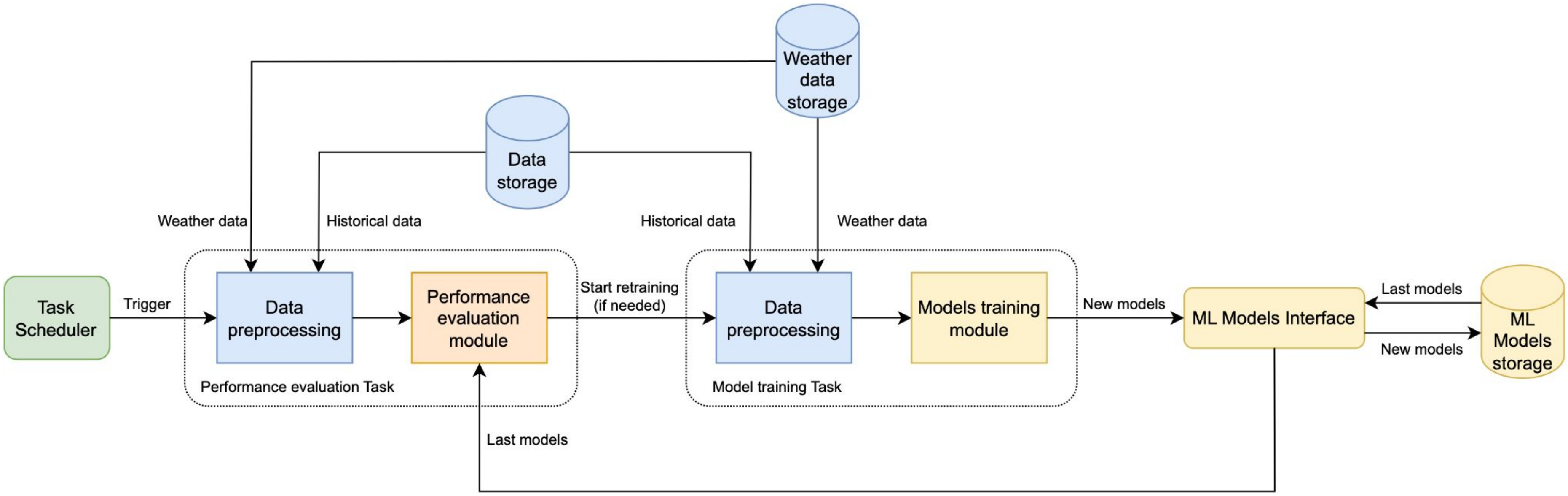
Model Training



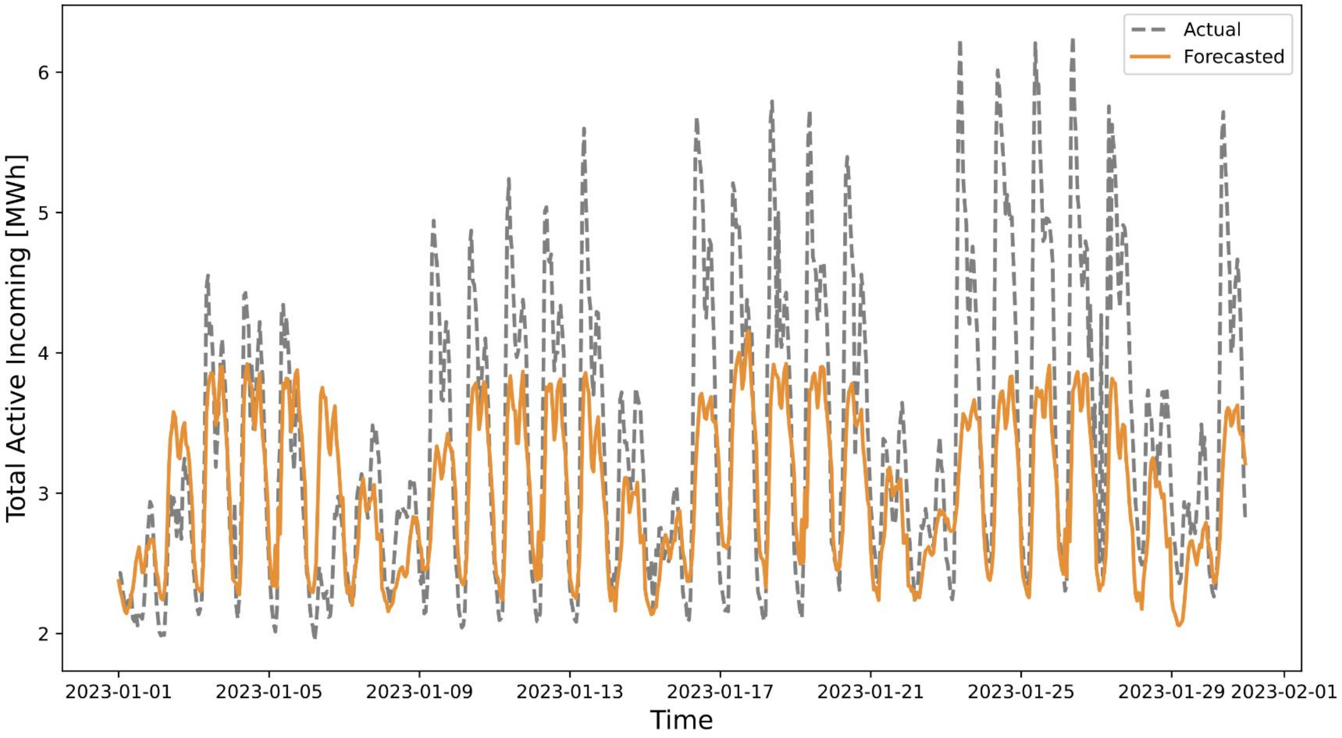
Forecasting



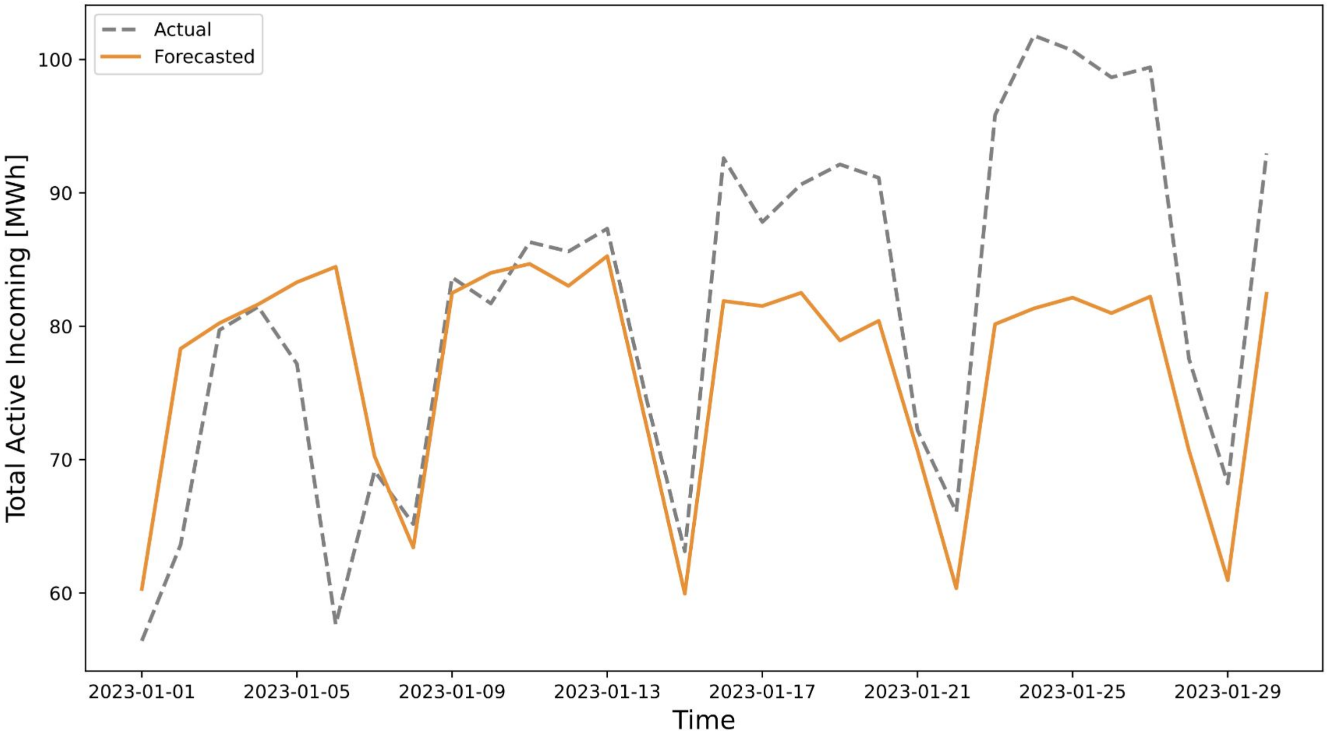
Task Scheduler



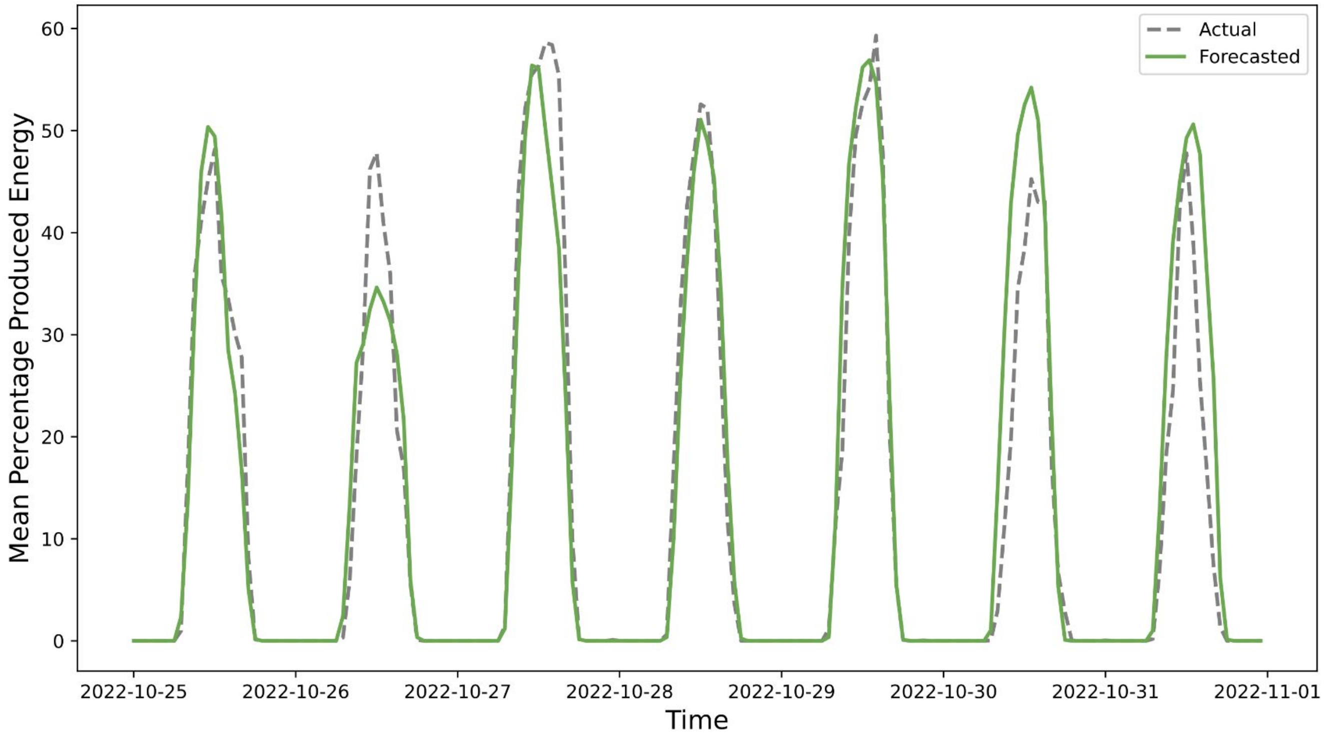
One week baseline combined with GRU Forecasts



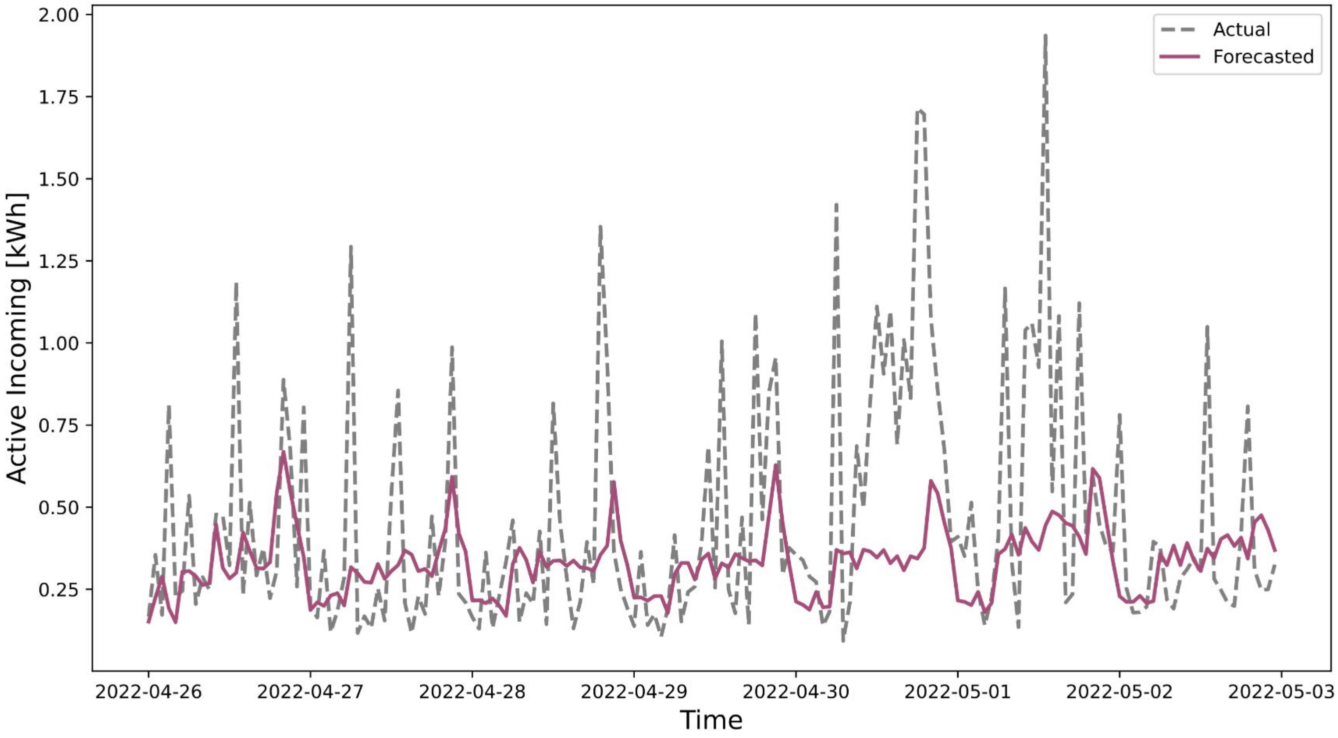
HistGradientBoostingRegressor Forecasts



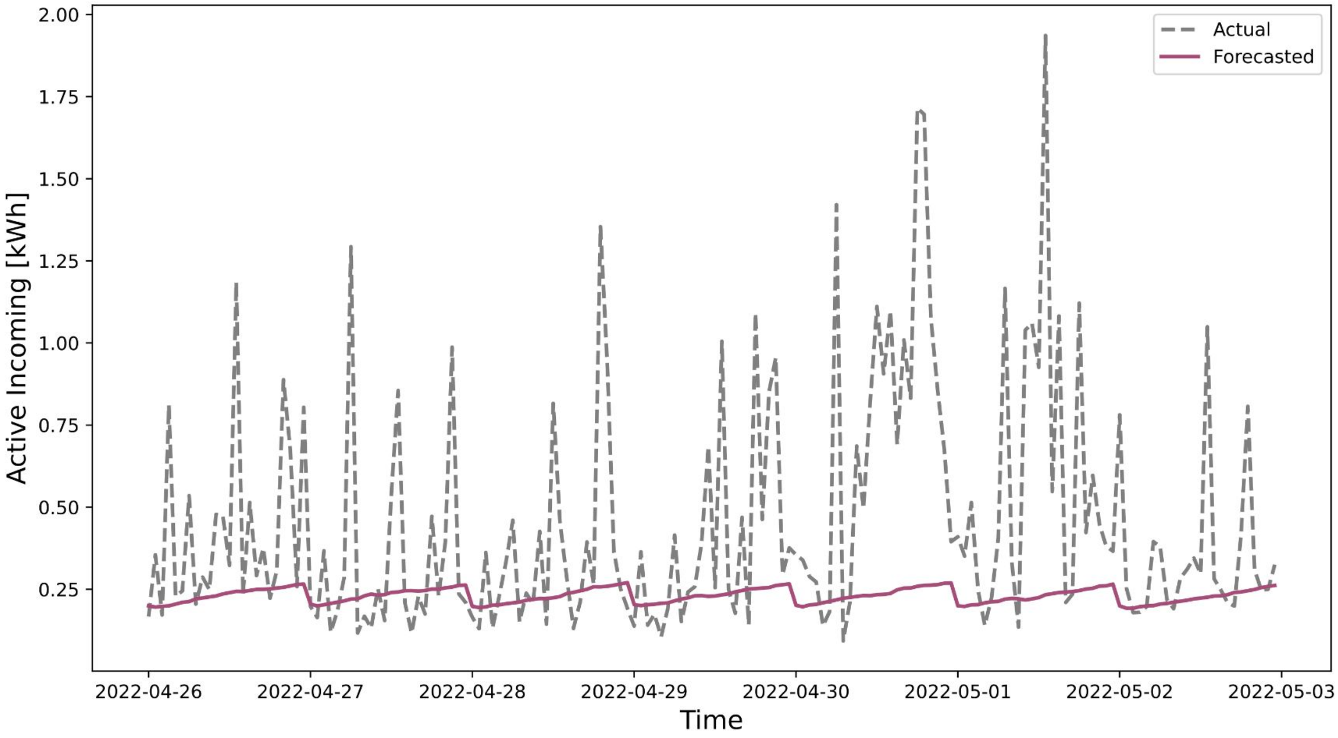
HistGradientBoostingRegressor Forecasts



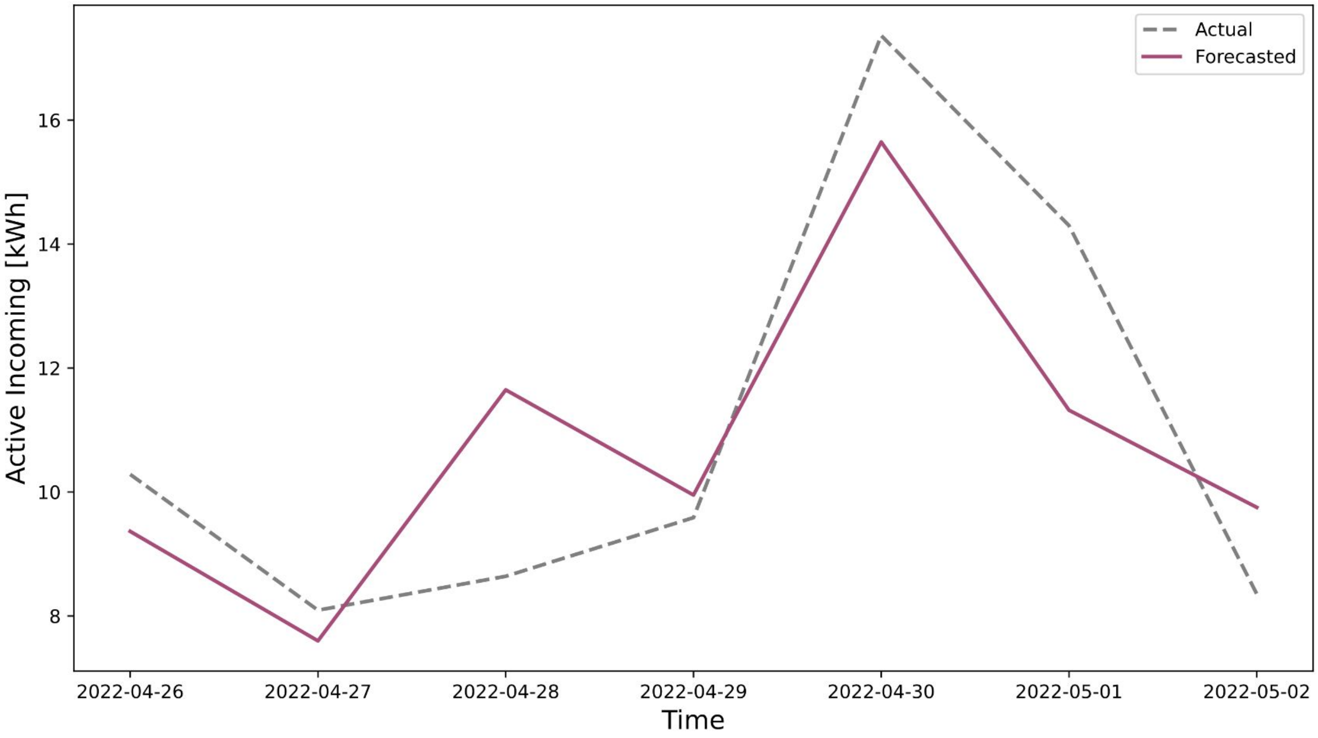
HistGradientBoostingRegressor Forecasts



GRU Forecasts



Baseline one week Forecasts



CNN Forecasts