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AI-assisted decision support for operational planning in distribution systems

AISOP

https://aisopproject.com

Masters Thesis presentation:

| Low voltage load forecasting using ensemble Methods

| Dimitrios Papadopoulos

September 17th 2024

Funding Partners

Smart Energy Systems ERA-Net

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FCT Fundação para a Ciência e a Tecnologia

FFG Promoting Innovation.

Federal Ministry for Economic Affairs and Energy

Federal Ministry Republic of Austria Transport, Innovation and Technology

Republic of Slovenia Ministry of Infrastructure

Academia Scientiarum Latviensis

ADEME Agence de l'Environnement et de la Maîtrise de l'Energie

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
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Swiss Federal Office of Energy SFOE

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Ministry of Energy www.energy.gov.il

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seai Sustainable Energy Authority of Ireland

Ministerio de Ciencia, Innovación y Universidades
CDTI Centro para el Desarrollo Tecnológico Industrial
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MIUR Ministero dell'Istruzione dell'Universita' e della Ricerca

Scottish Enterprise

PtJ Projektträger Jülich Forschungszentrum Jülich

Guvernul României Ministerul Educației Naționale

Business Finland

TÜBİTAK

NWO

EUDP Energiteknologisk udvikling og demonstration

Innovation Fund Denmark

The National Centre for Research and Development

Swedish Energy Agency

The Research Council of Norway

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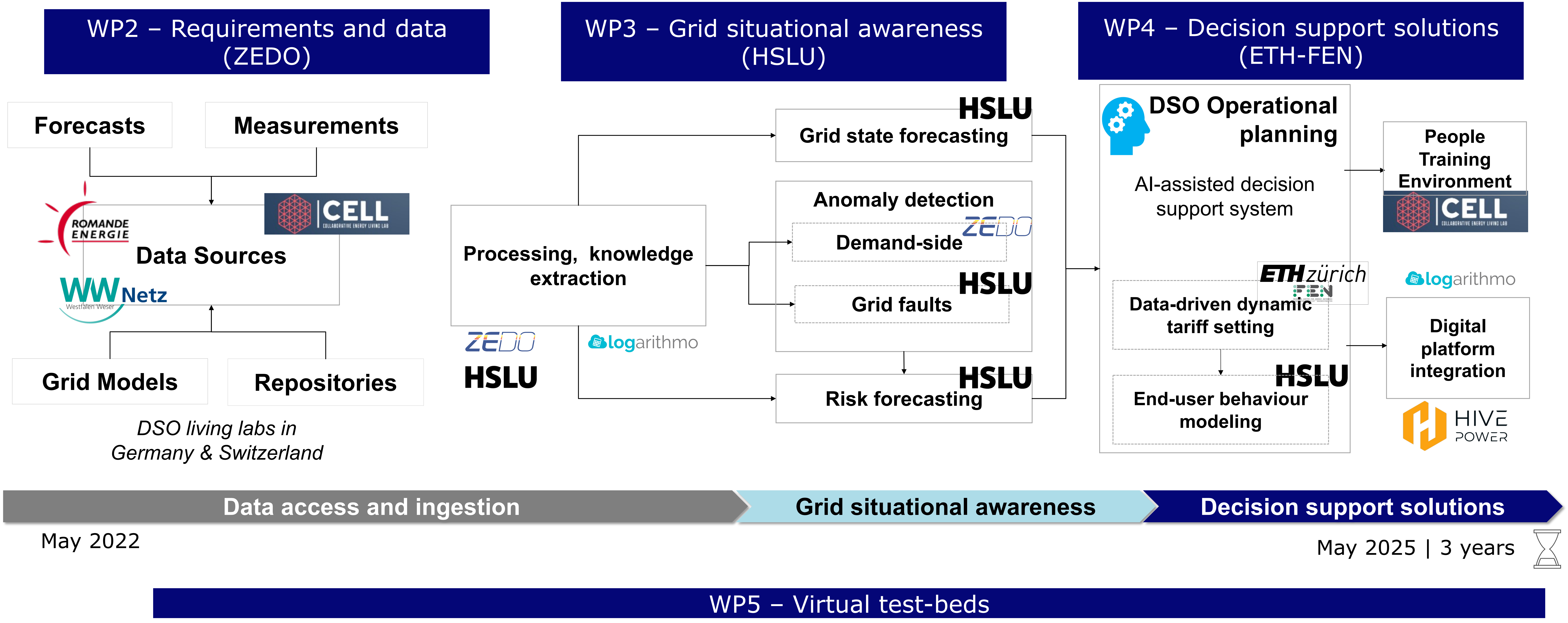
Guvernul României Ministerul Cercetării și Inovării

Flanders Innovation & Entrepreneurship

Flanders State of the Art

AISOP goal is an **AI-assisted decision support system** for distribution grids with high penetration of DERs (TRL 2 – Concept to TRL 6 – Prototype)



Advisors: ENDA PRIME, BKW, egi Elia Grid International, amprion connects

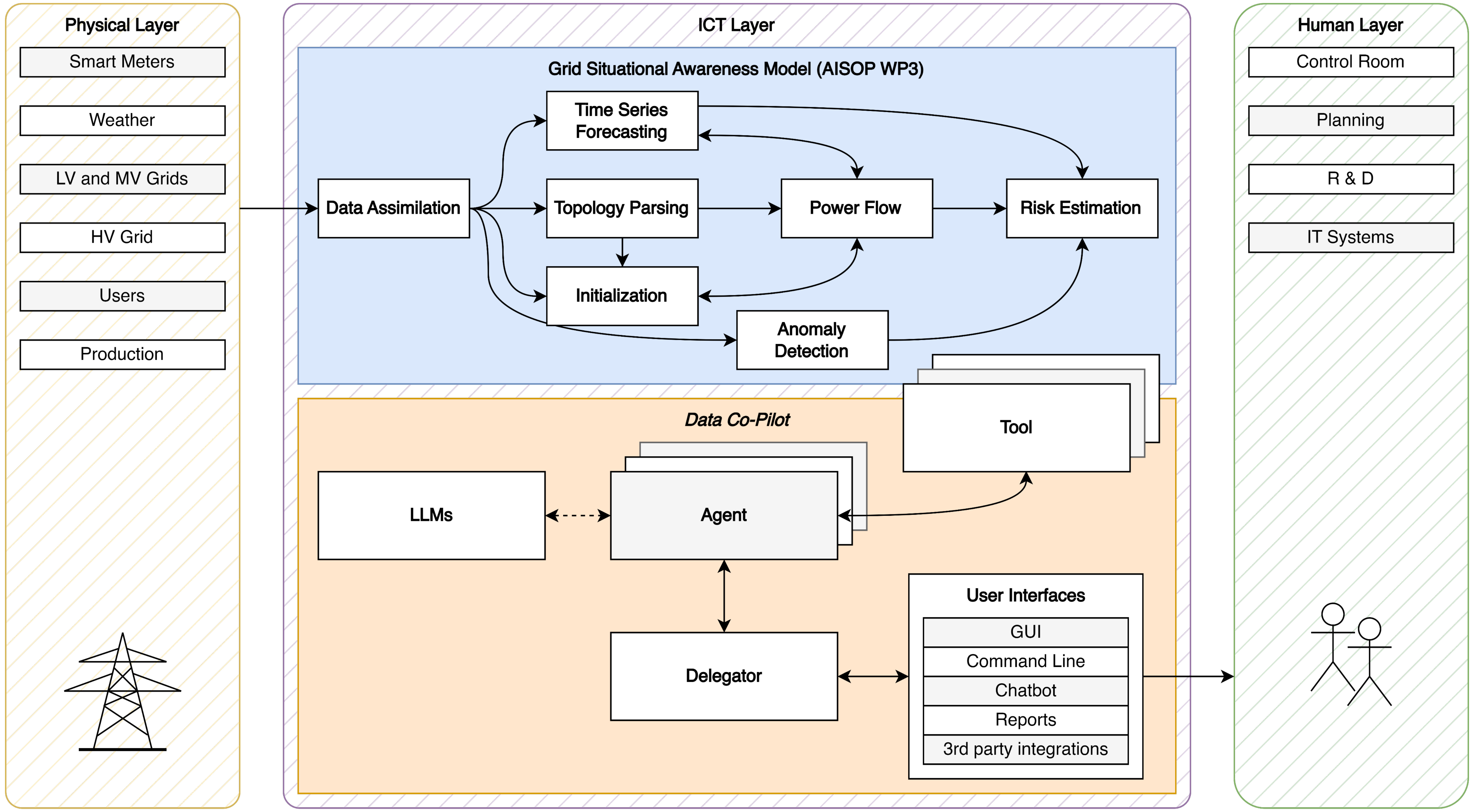
Tools for situational awareness – Data co-pilot concept

User interface to various data sources, enabling DSOs to perform analytics workflows.

- **Detection of anomalies and trends:** monitor the grid and identify potential issues that may not be immediately apparent from raw data alone.

- **Grid simulation**: forecasts and scenarios of grid conditions to plan against grid overloading.

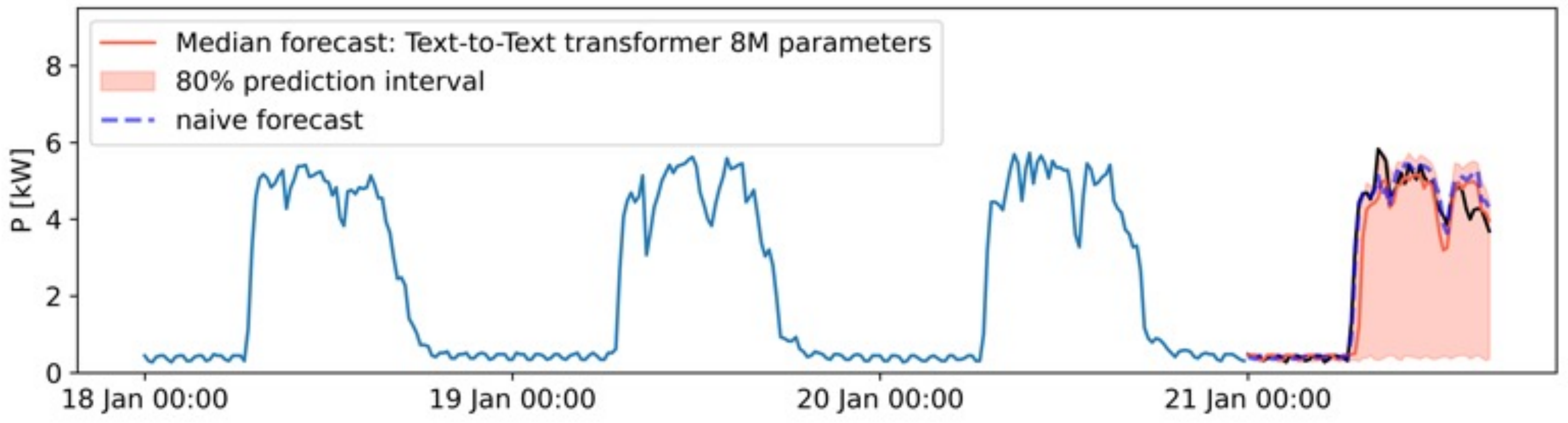
- **Risk estimation**: analysing historical data and future scenarios to quantify risk of operating in states with too high or too low voltage or load, summarises the state of operation and gives input to the design of dynamic tariffs.



A DATA CO-PILOT FOR ELECTRIC DISTRIBUTION UTILITIES TO SUPPORT GRID SITUATIONAL AWARENESS presented at AI for Energy Utilities track at AI and Machine Learning conference AMLD EPFL 2024 (https://zenodo.org/records/11639570)

Tools for situational awareness – Analytics workflows using only data and AI models

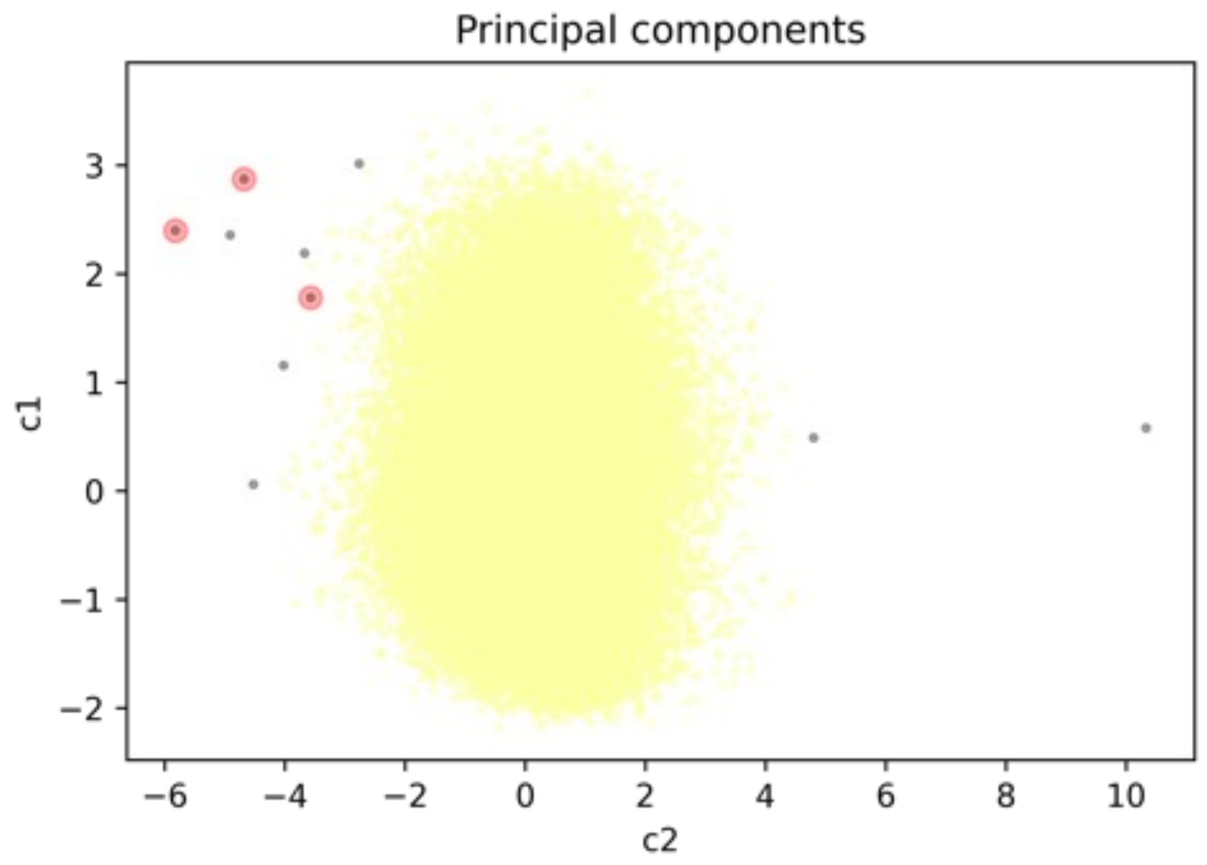
- **Load Forecasting** on generic smart meter data.

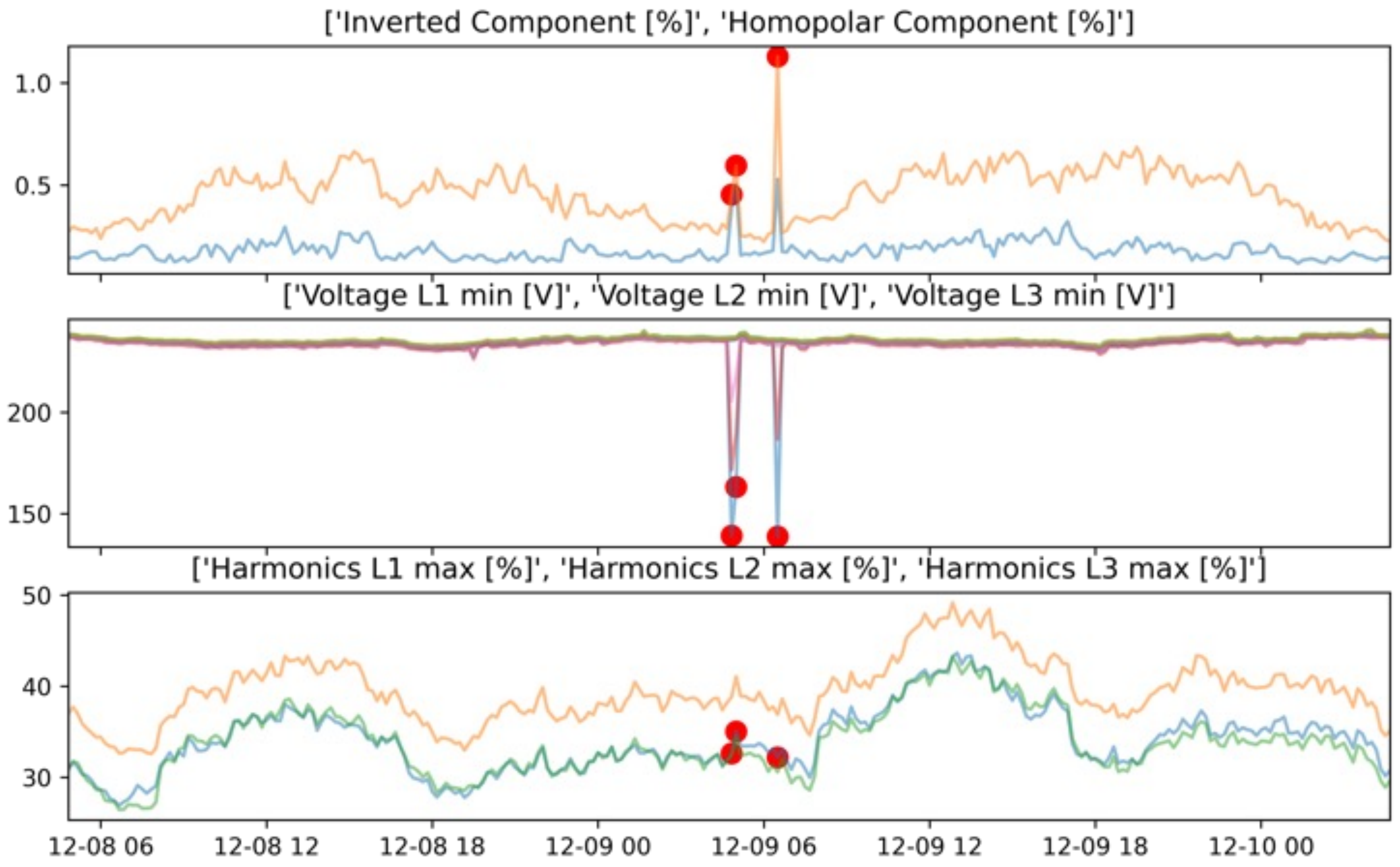


	Dummy	Naïve	T5 zero-shot
P [kW]	0.610 ± 0.386	1.504 ± 0.771	1.281 ± 1.153
Q [kVAr]	0.398 ± 0.323	0.737 ± 0.397	0.692 ± 0.544

Comparison of dummy, naïve (e.g., average of past data), and DL forecast for P and Q of load 4 over a period of one month. The DL model is a pretrained Text-to-Text transformer, T5 architecture with 8M parameters, used as a zero-shot inference tool, without fine tuning. For both models the input is data of the three previous days. The DL forecast has a mean RMSE lower that the naïve forecast, its standard deviation is significantly larger. Both the naïve and the DL forecast can be easily improved, and more extensive comparisons will be performed.

- **Anomaly detection** on data recorded by GridEye sensor.





A data set with 58 quantities that describe voltage, power, current, harmonics, and grid frequency; 10-min values from October 2018 to December 2019 recorded by a grid monitoring device installed at the LV side of a distribution transformer operated. Two clusters of points c1-c2 plane are detected, one corresponds to a normal behaviour, and the other to odd values that might represent an anomaly. Three points are highlighted and mapped to the original time series, where the distortion in the voltage is observed.

"A framework for data-driven decision support for operational planning in active distribution networks" presented at CIRED 2024 Vienna Workshop (https://virtual.oxfordabstracts.com/#/event/public/4945/submission/359)

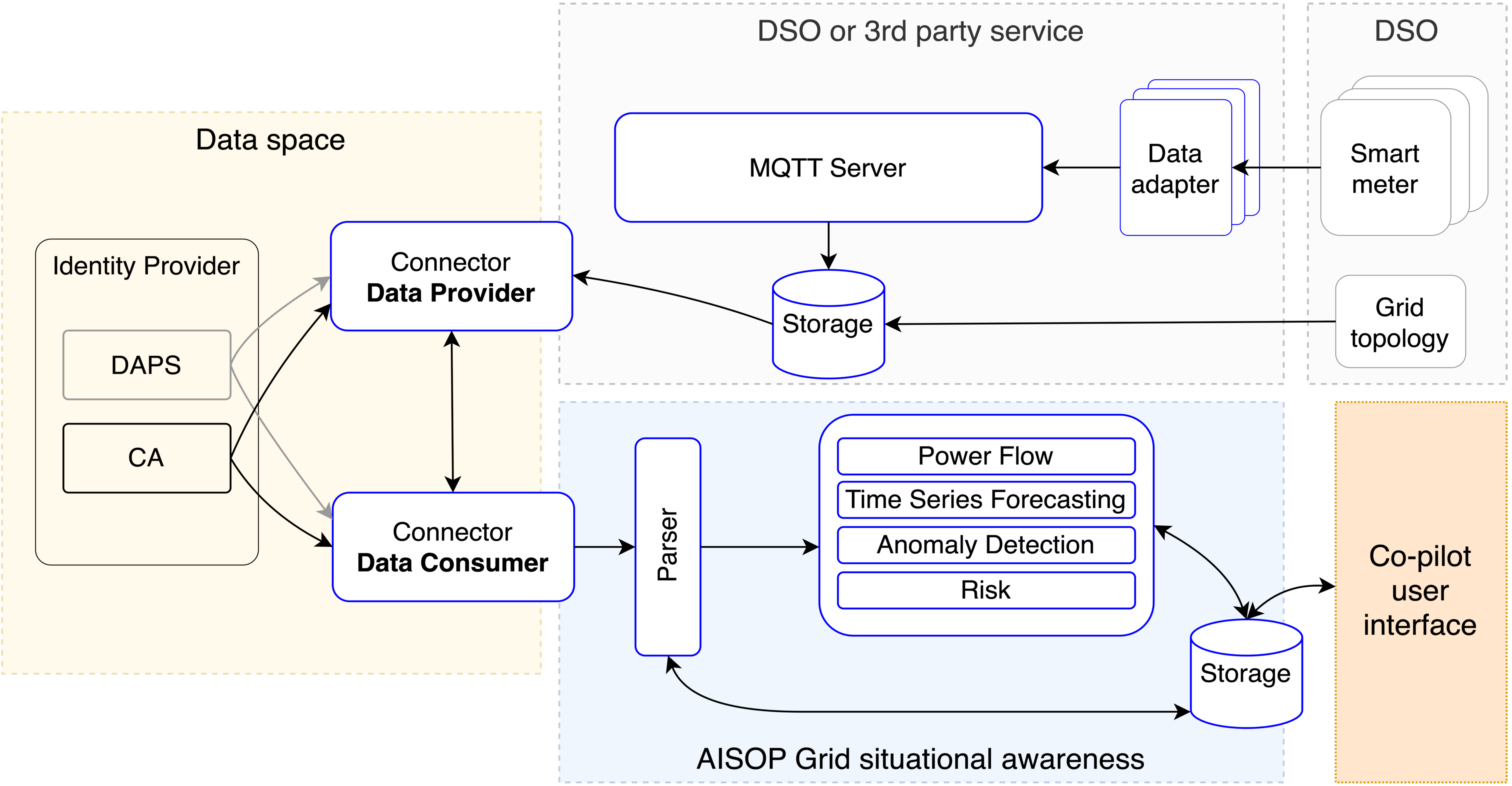
Architecture of virtual demonstrator: AISOP federated data assimilation for Situational Awareness

Parser

- Accesses data and converts it to AISOP data models.
- Establishes Single Source of Truth (SSoT) then feeds data to other modules.

Data space

- Federates the access to data.
- Identity provider manages dynamic attributes and certificates of data providers and data consumers.



Proposed architecture of AISOP WP5 Virtual Demonstrator: data space is implemented as a pre-configured Minimum Viable Data Space (International Data Spaces Association)

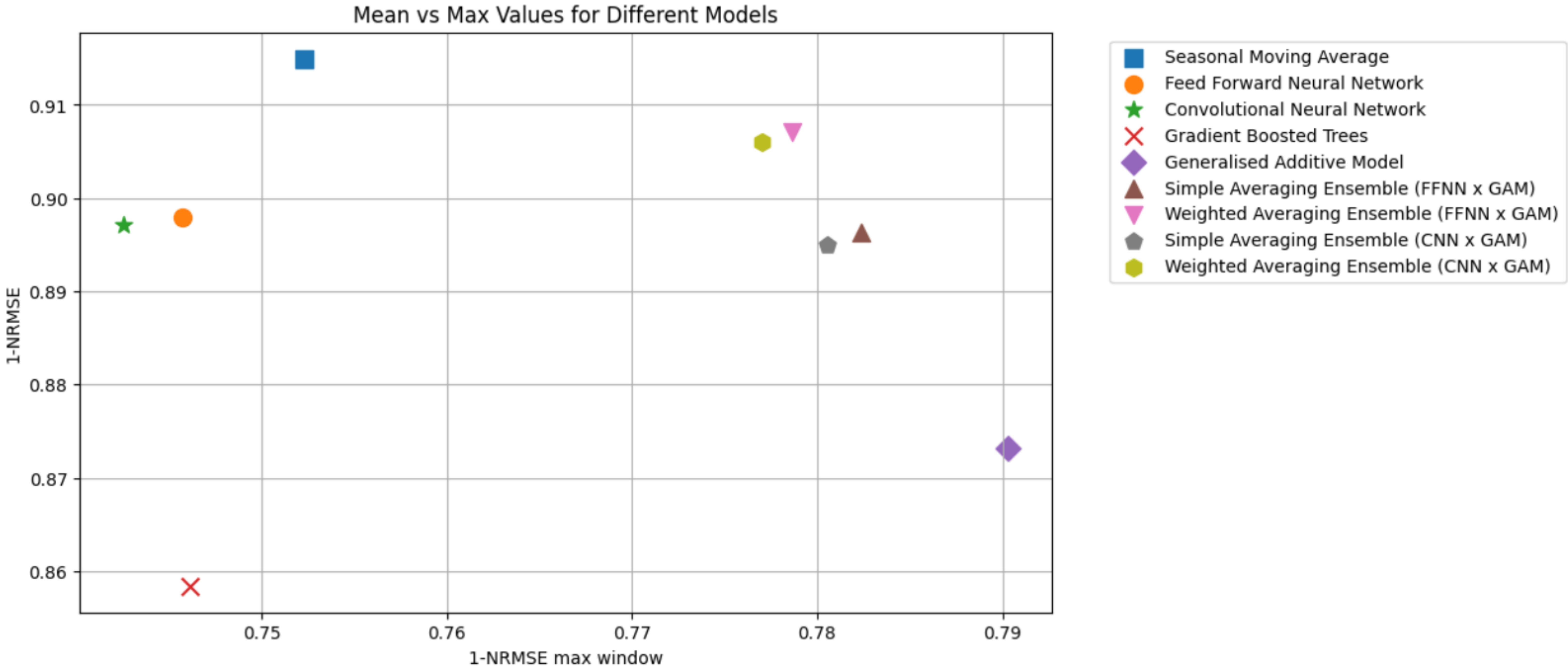
Forecasting plays an important role for grid situation awareness

1. Nowadays forecasts are readily available

- More and more data accessible.
- Open-source tools.
- Many forecast providers, lower costs.

2. How to select the best forecasts becomes more relevant

- In theory combinations of forecasts (ensembles) will yield better results.
- For some use cases better forecasts are not necessarily those with lower average error metrics.



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Open data from Centralschweizerischen Kraftwerke AG (CKW AG)

- id: The consumer’s anonymized smart meter ID.
- timestamp: 15 minutes timestamps in UTC format.
- value_kwh: the energy consumption per 15 minute timestamp.
- The data was preprocessed and saved in a compact format for every ID.

Column name	**Description**	**Data type**
id	the anonymized ID	text
timestamp	the UTC time at the start of a 15-minute time window to which the consumption refers	ISO-8601 timestamp
value_kwh	the consumption in kWh in the time window	float

CKW dataset description

https://aisopproject.com/resources/open-smart-meter-data-from-central-switzerland/

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Low voltage load forecasting using ensemble methods

Author: **Dimitrios Papadopoulos**

Project Dissertation submitted as part of the requirements for the MSc in Applied Information and Data Science at the School of Business, Lucerne University of Applied Sciences and Arts

Lucerne University of Applied Science and Arts

Master in Applied Information and Data Science (MSc IDS)

August 2024

HSLU Lucerne University of Applied Sciences and Arts

Low voltage load forecasting using ensemble methods

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Master in Applied Information and Data Science (MSc IDS)

Spring Semester 2024

Lucerne, 15 August 2024

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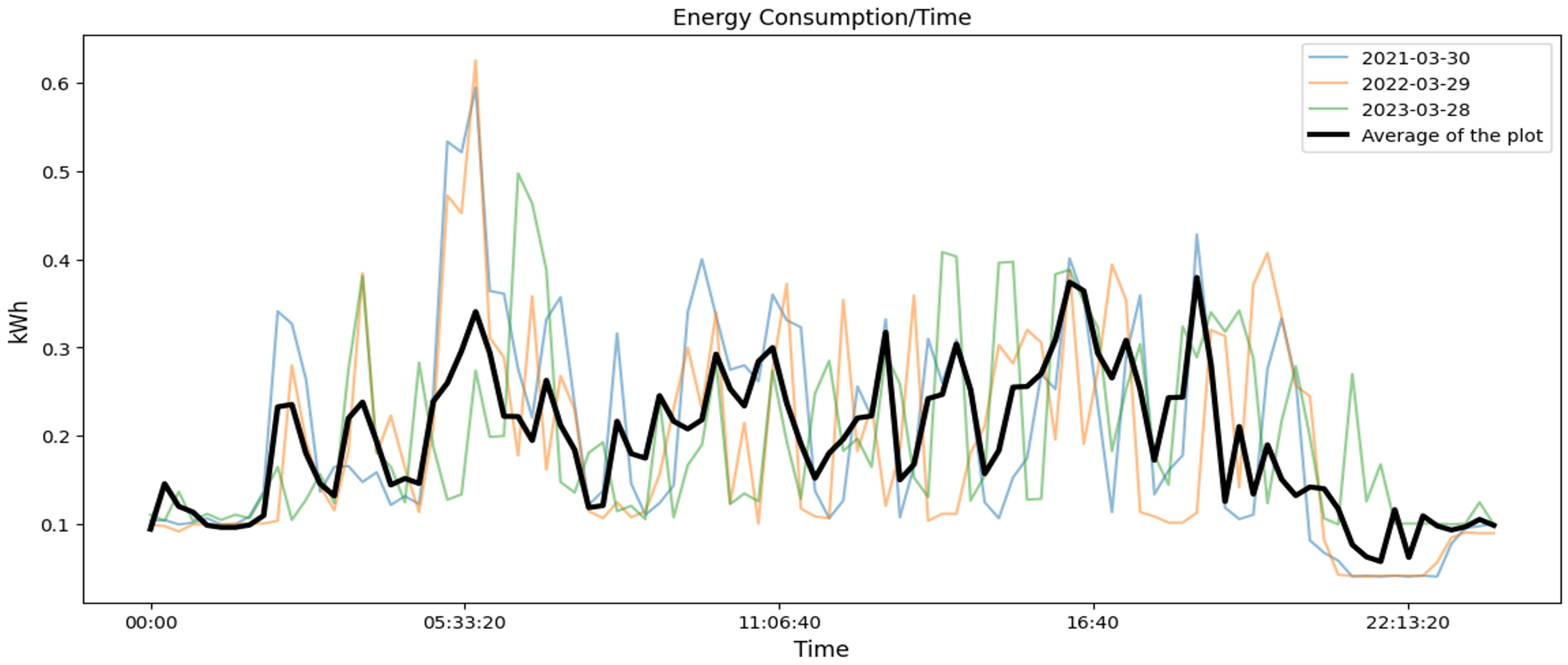
Exploratory analysis

- A CKW ID selected which could be a small business or a household.
- It has smaller values at night and higher values within the day.
- The time series plot shows an example date (Last Tuesday of March) and their average within years 2021, 2022, 2023 where the pattern is similar.



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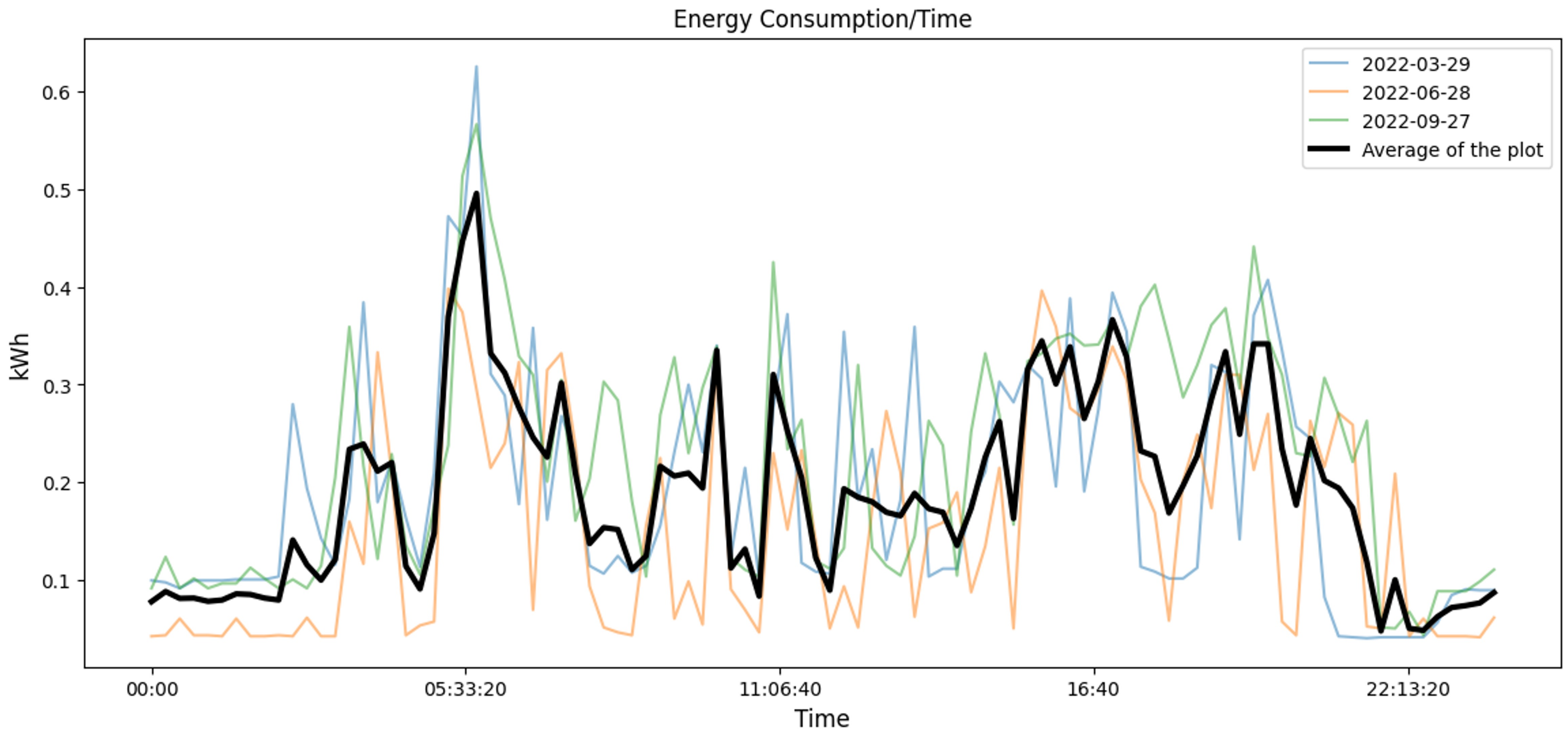
Exploratory analysis

- A CKW ID selected which could be a small business or a household.
- It has smaller values at night and higher values within the day.
- The time series plot shows an example date (30th March) and their average within years 2021, 2022, 2023 where the pattern is similar.
- Additionally, within the same year (2022) on a different seasons(March, June, September) the pattern is similar as well.



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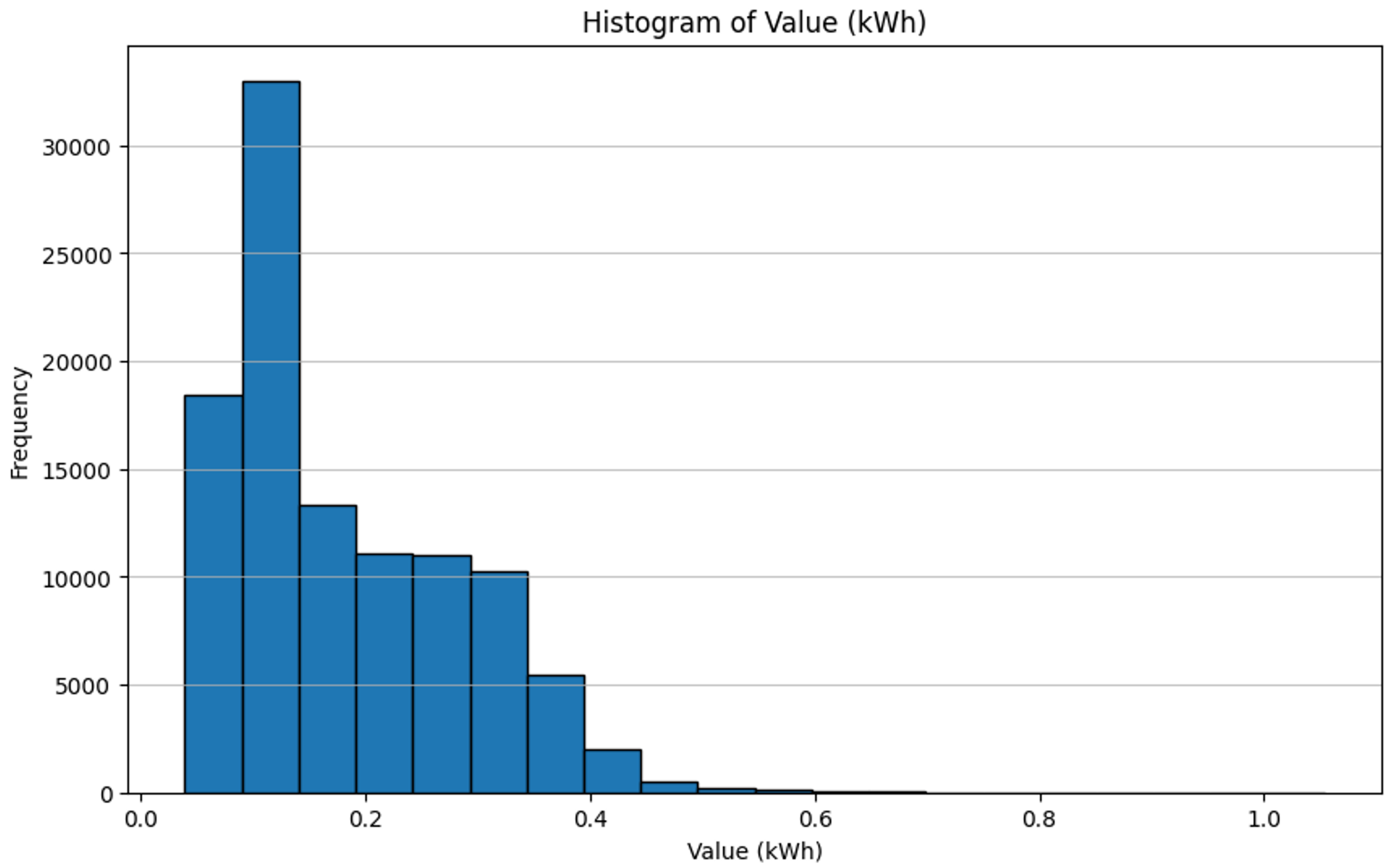
Exploratory analysis

- By creating the histogram of all the values included in the dataset for years 2021-2023, one can observe non negative values.
- The histogram of the data shows right skewness.
- The most of the observations are in the range of 0.05-0.2 kWh and fewer in the range of 0.4-0.7 kWh.
- The shape of the histogram is expected, as smart meter data, in some cases it follows a lognormal distribution (Haben et al., 2023).



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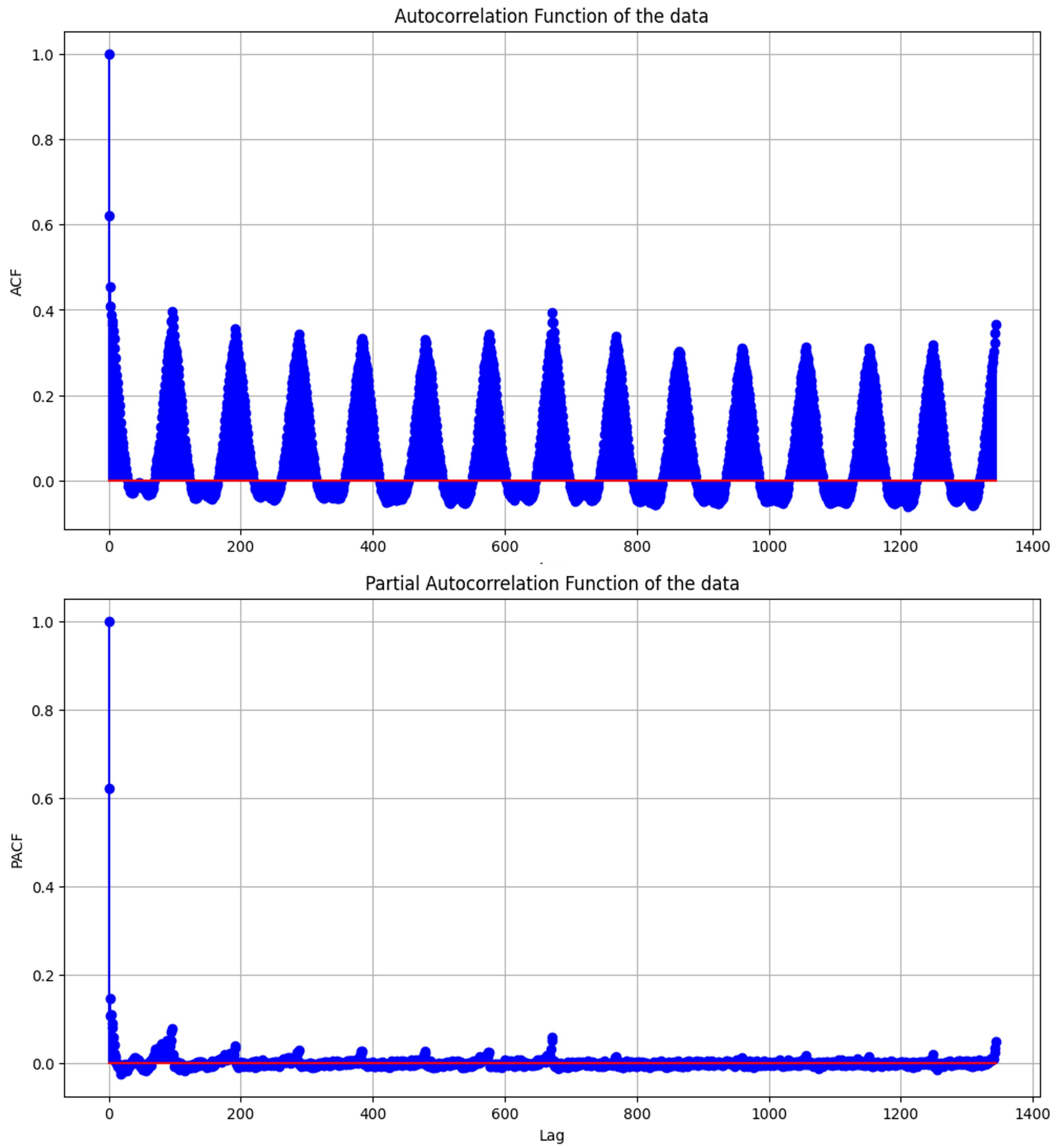
Exploratory analysis

- ACF of the data shows a strong seasonal effect for lag 96 which is the daily seasonality.
- PACF shows higher peaks on lags 672 and its multiples which is the weekly seasonality.



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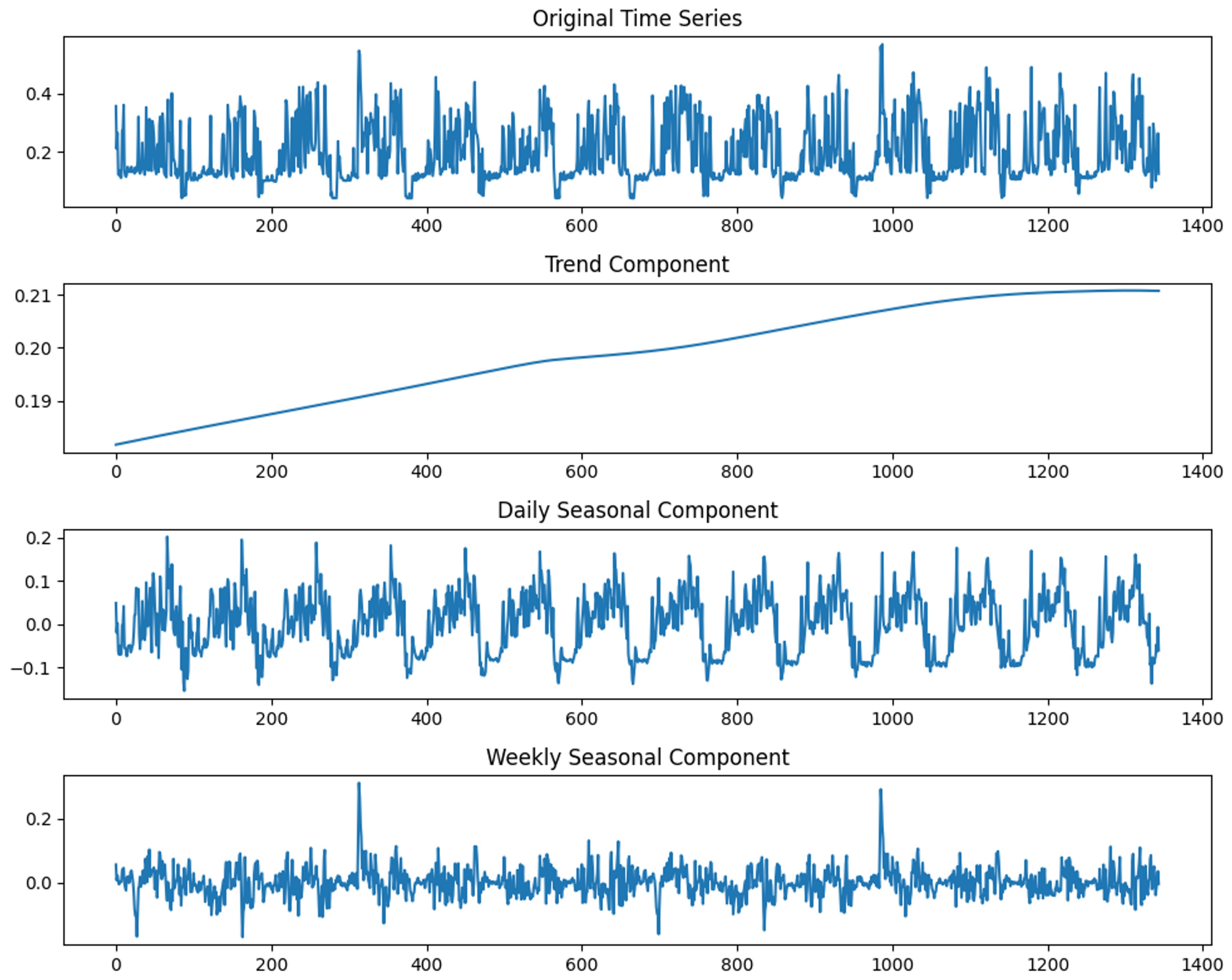
MSTL decomposition

- As the data has multiple seasonal components, MSTL decomposition (Dettling, 2020),can be applied to look at the patterns.
- By the decomposition one can observe the original data as well as the trend and different seasonal components.
- By plotting the decomposed data of two weeks, one can observe the daily seasonal pattern but also the weekly patterns in which the data has similar peaks.



MSLT applied and plotted on year 2022. Example of plotting the first 2 weeks of 2022.

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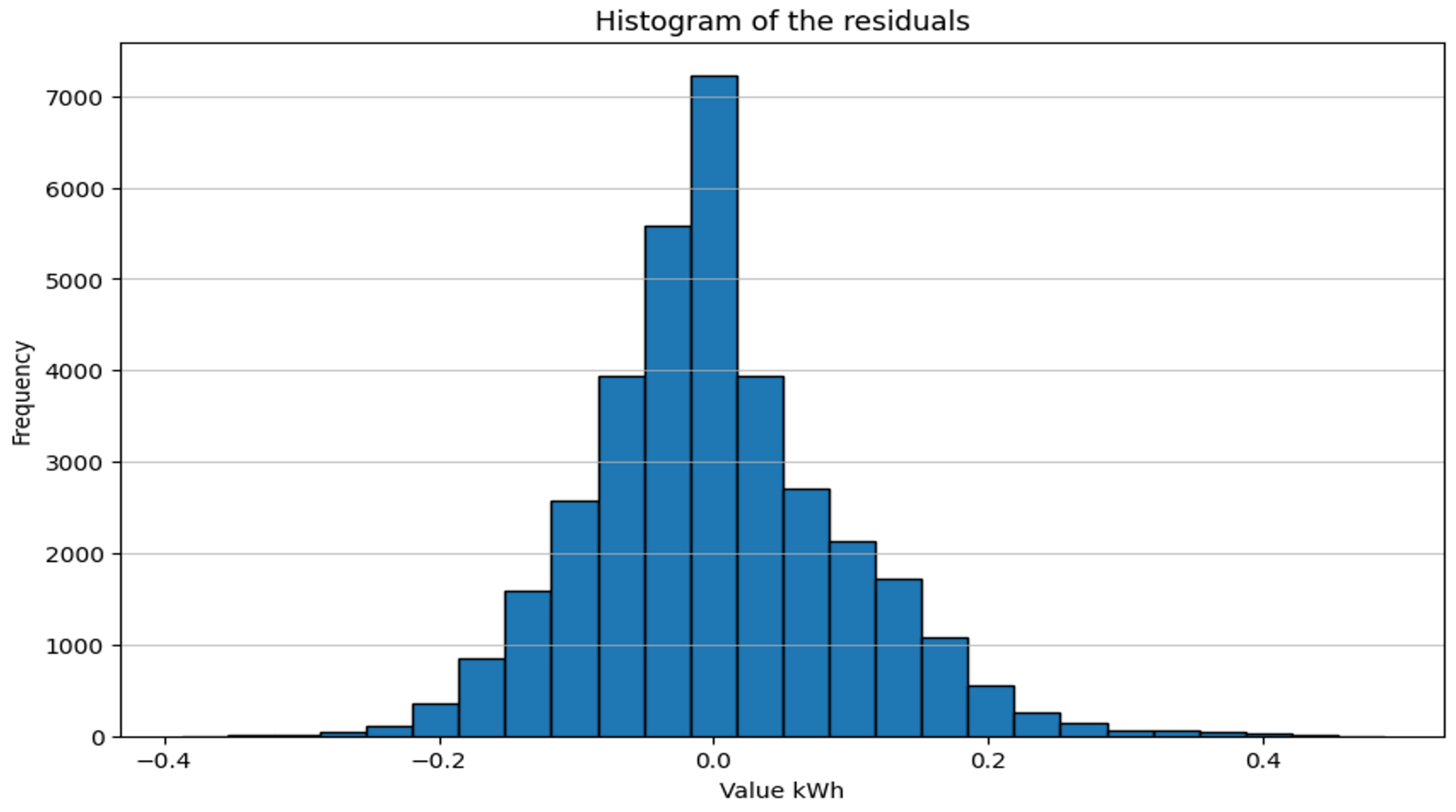
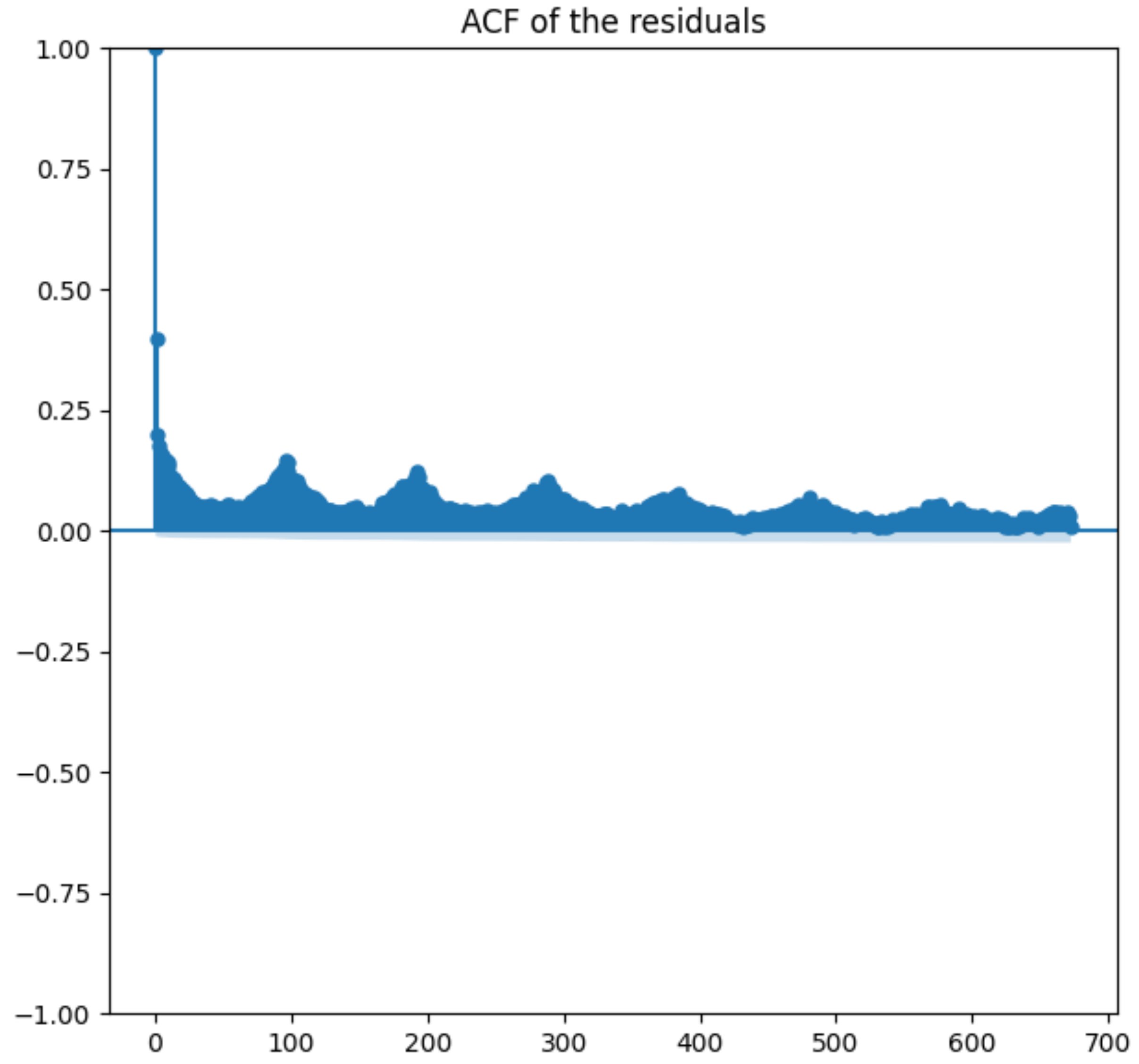
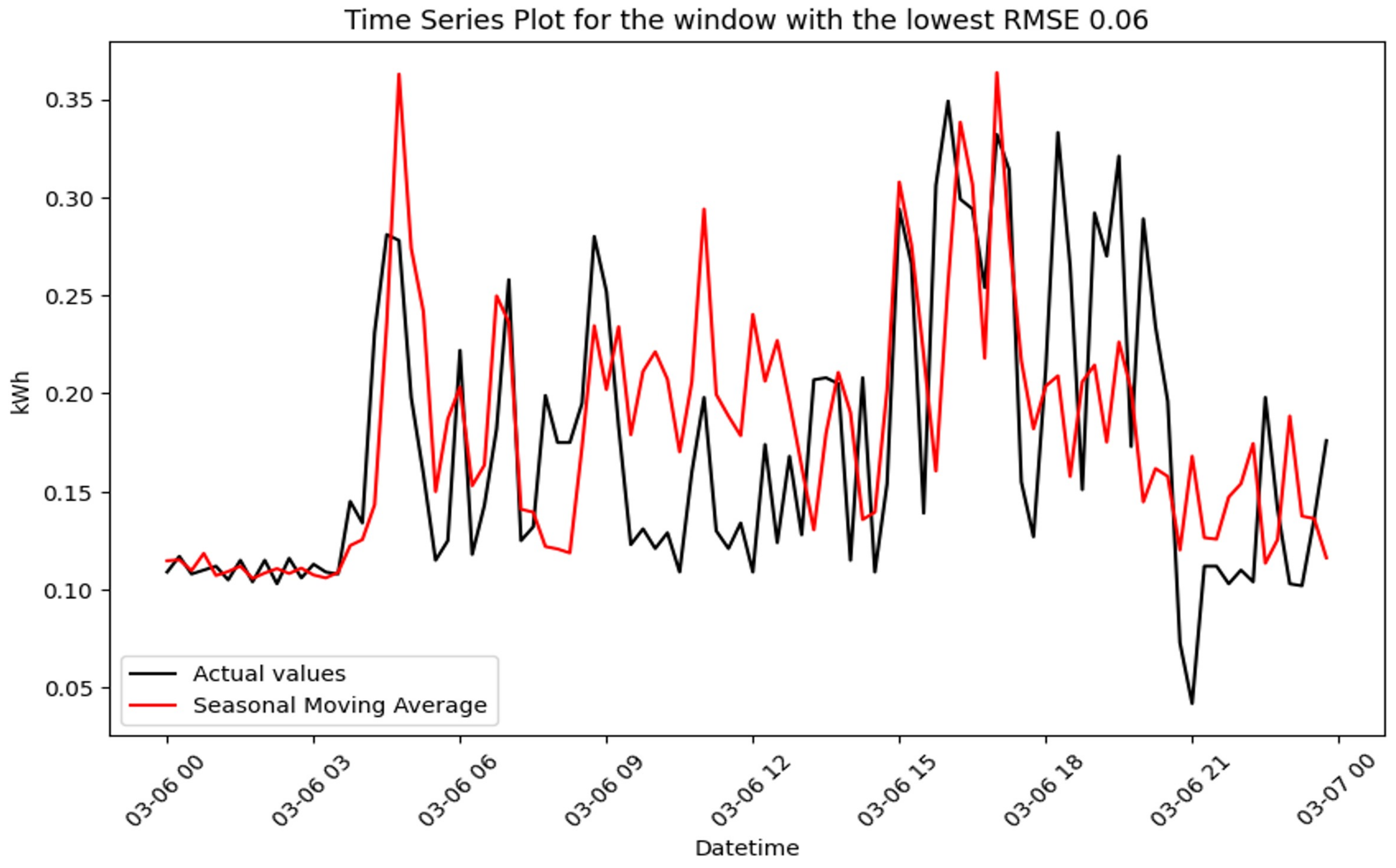
Model evaluation: Benchmark model- Seasonal Moving Average

- The result is that the total RMSE is 0.093 kwh.
- The model seems to be able to follow the pattern.
- The mean of the residuals is 0.0008 which is very close to zero.
- When the forecast captures most of the patterns and trends, the histogram of the residuals usually follows a normal distribution, which seems to be the case.







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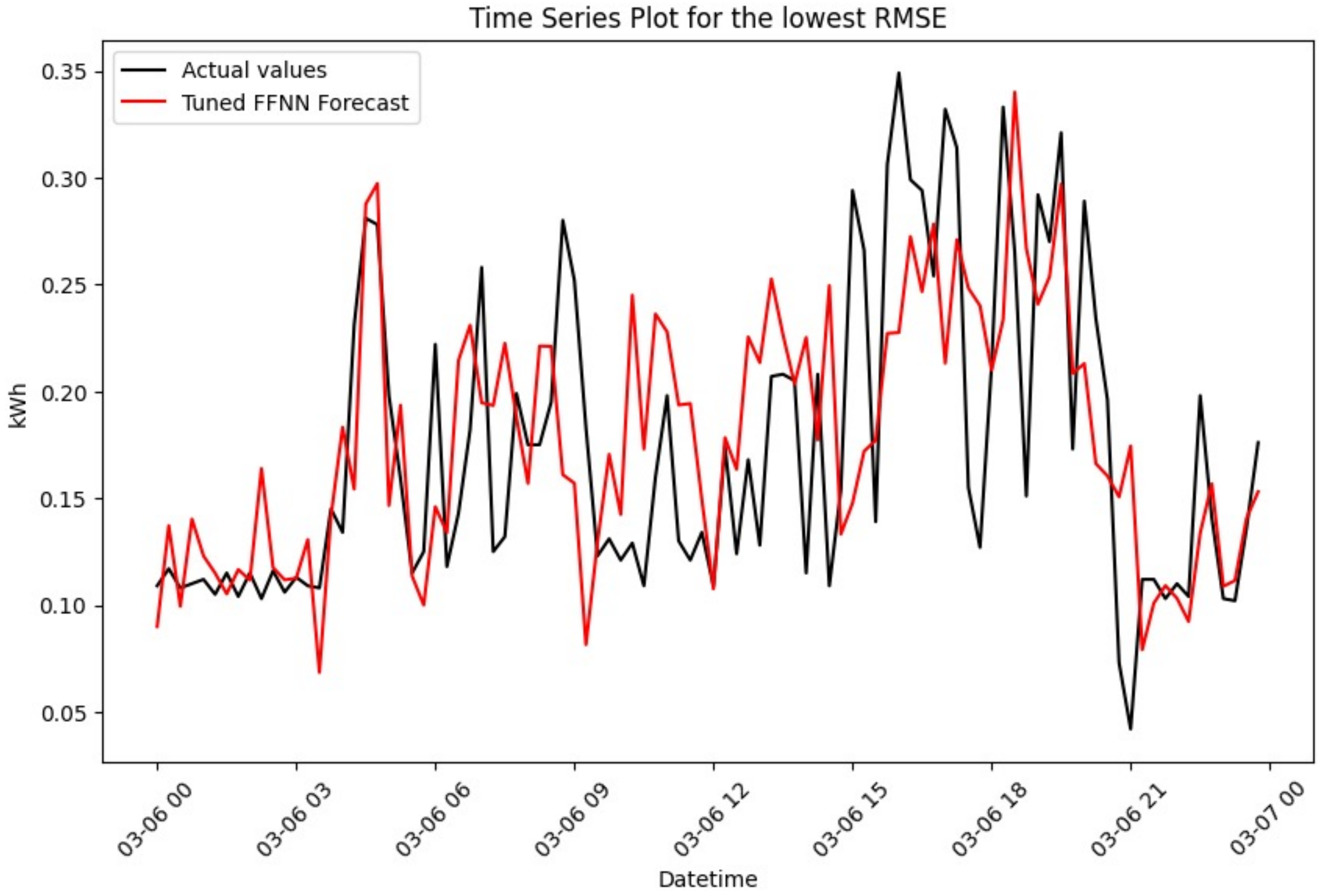
Model evaluation: Feed forward neural network with 2 week input and 4 hidden layers

- The time series plot behaviour seems quite good while the forecasted values peaks seem to be able to follow the actual values.
- The variation of the peaks is similar to the one of the actual values.
- The trend is behaving similarly as well.



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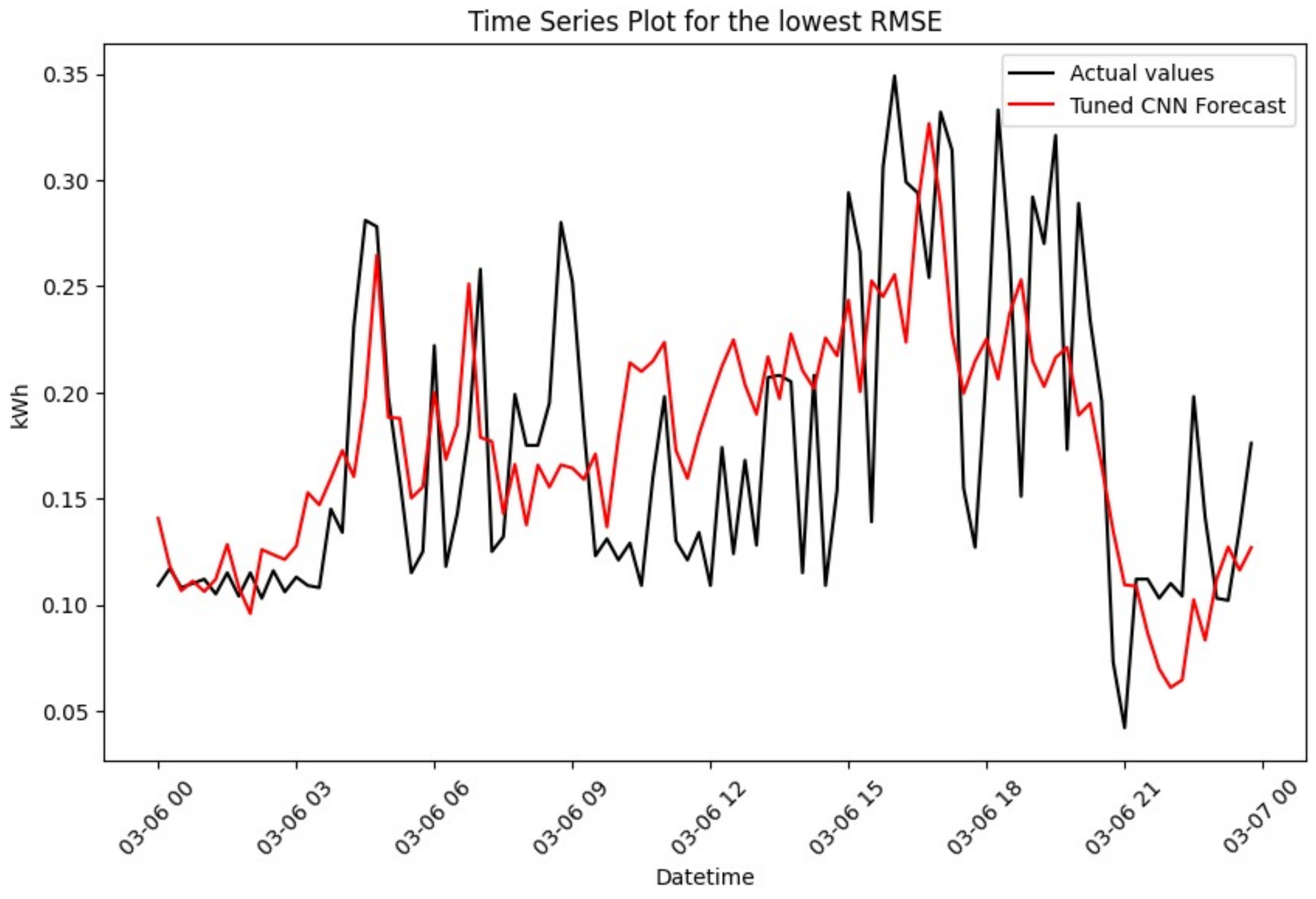
Model evaluation: Convolutional neural network with 2 week input and 3 hidden layers

- The behaviour of the plots is similar to those of the Feed Forward Neural Networks.



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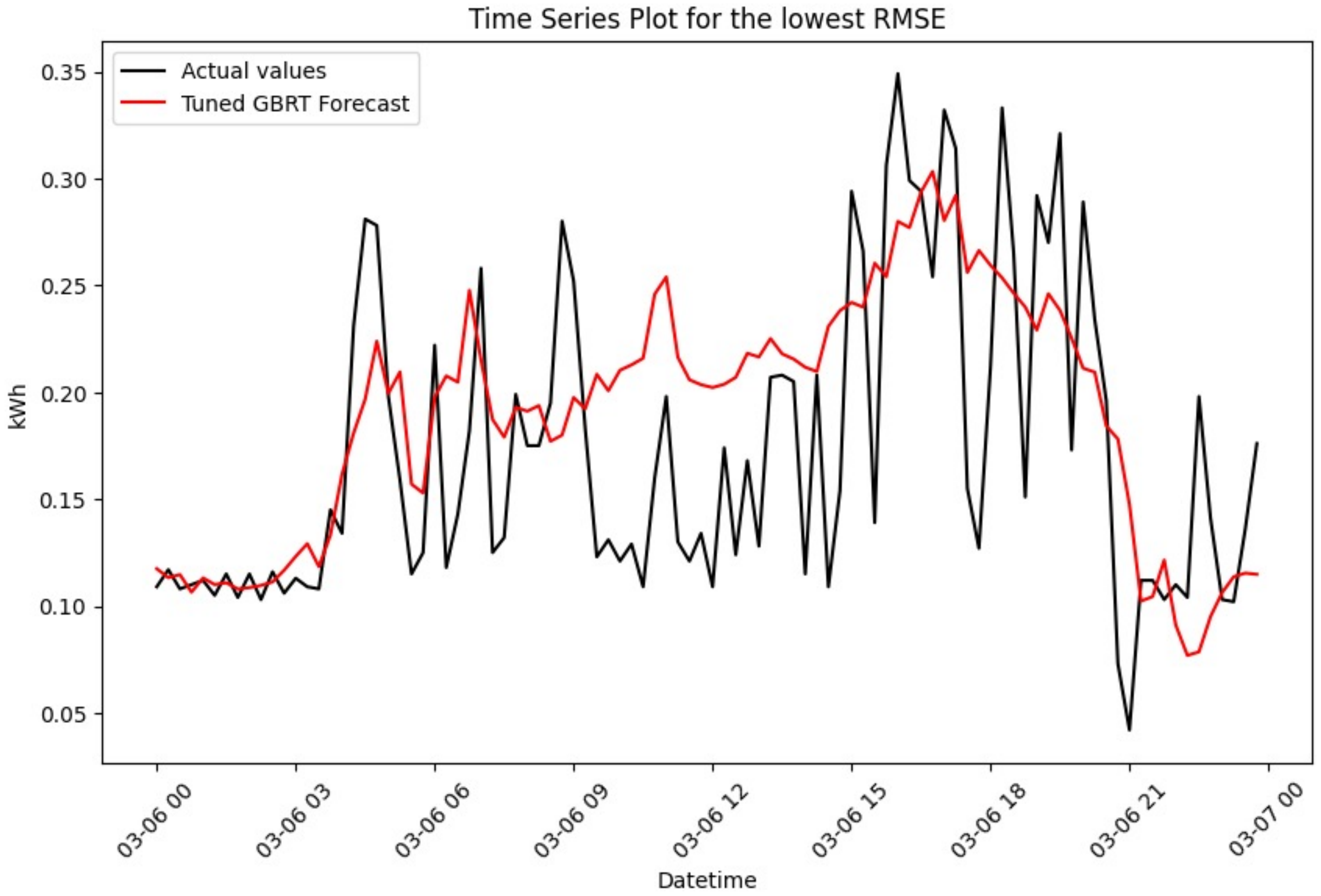
Model evaluation: Gradient Boosted trees of depth 1

- The forecasts follow the trend of the actual data well with a smaller variation of the peaks.



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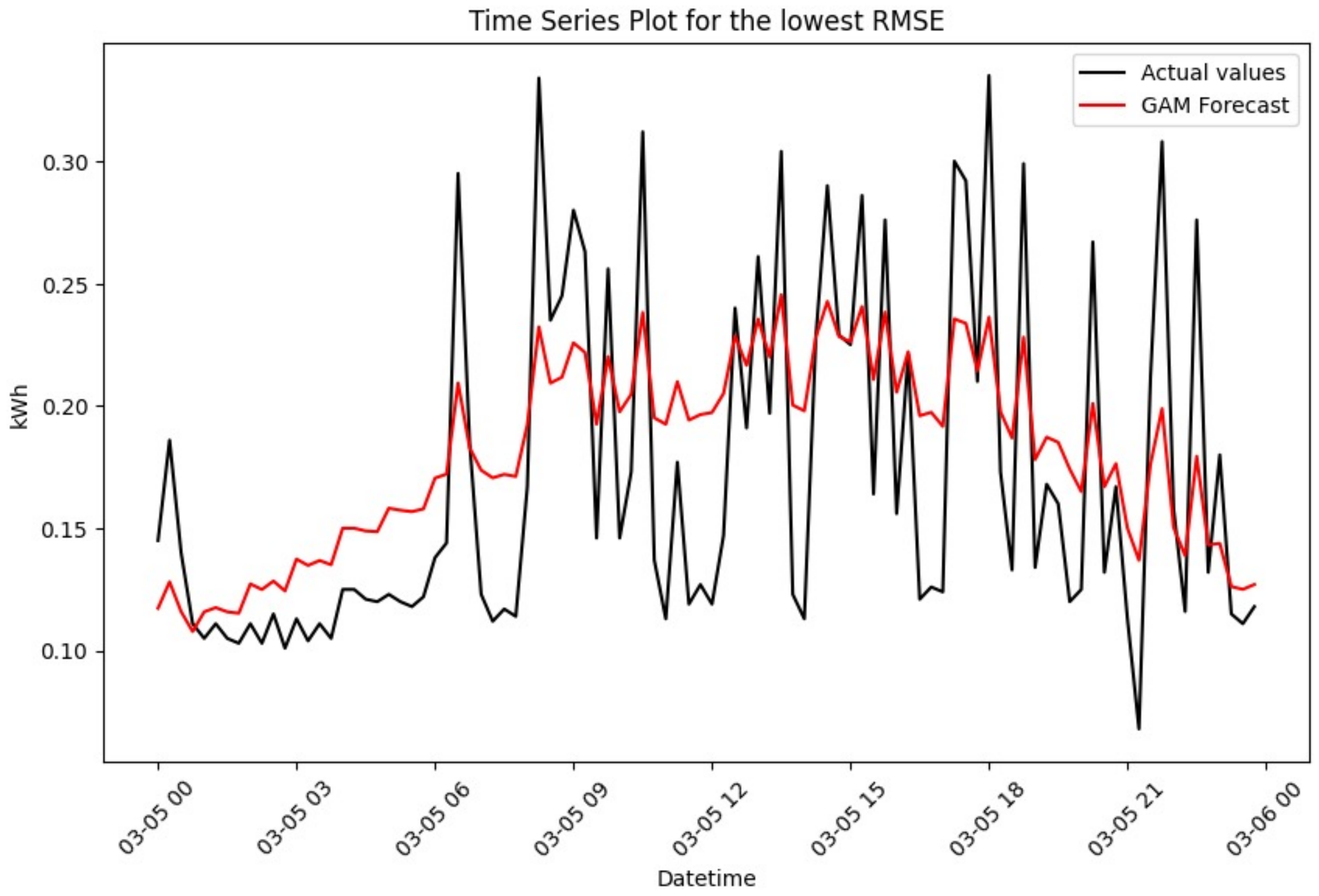
Model evaluation: Generalised Additive Model

- This behaviour can be explained by looking at the time series, in which the trend is captured by the model, but the variation is smaller compared to the actual time series.



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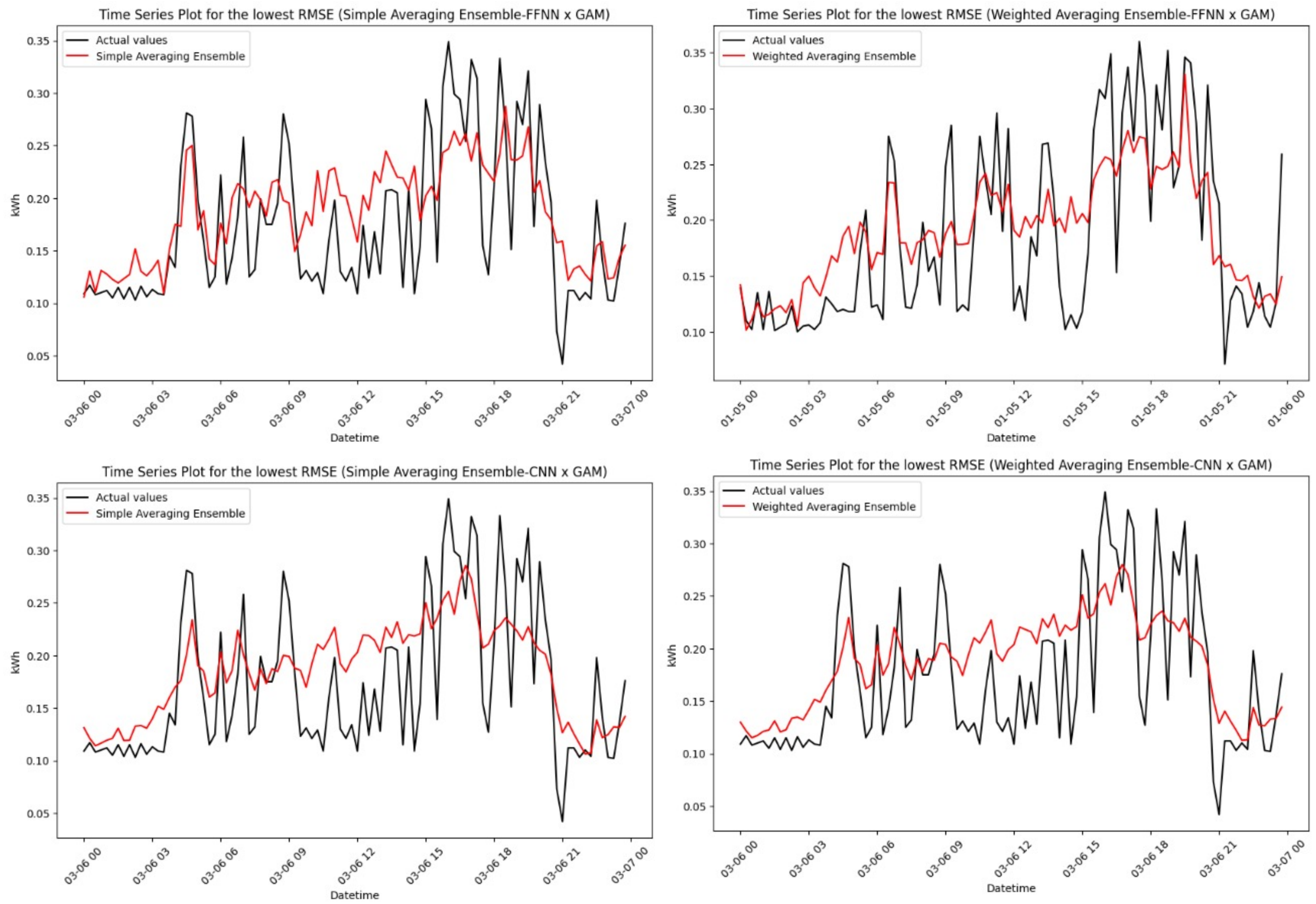
Model evaluation: Simple and weighted averaging ensembles

- All the ensembles have a similar behaviour by the graph assessment, those considered the best behaving is the weighted averaging ensembles while their metrics are better in comparison to the simple averaging ensembles.
- More specifically, the one behaving the best is the weighted averaging ensemble, with base fused models the CNN and the GAM.



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How well do ensemble models perform compared to a gradient boosted tree?

- As of all the RMSE values, the ensembles seem to behave better in comparison to the GBRT (~0.01 kWh)

	RMSE total	Mean RMSE per window	St. Dev RMSE per window	RMSE max per window	Mean of the residuals	St. Dev of the residuals	ACF value at lag 96
GBRT-tuned	0.085651	0.084091	0.016273	0.198767	0.001130	0.085600	0.135333
Averaging ensemble (FFNN x GAM)	0.076829	0.075464	0.014417	0.175076	0.00267	0.076800	0.157896
Weighted averaging ensemble (FFNN x GAM)	0.075083	0.073731	0.014183	0.171696	0.00251	0.075000	0.163759
Averaging ensemble (CNN x GAM)	0.076173	0.074753	0.014641	0.175761	0.00371	0.076100	0.154973
Weighted averaging ensemble (CNN x GAM)	0.074625	0.073229	0.014369	0.172422	0.00341	0.074500	0.159783

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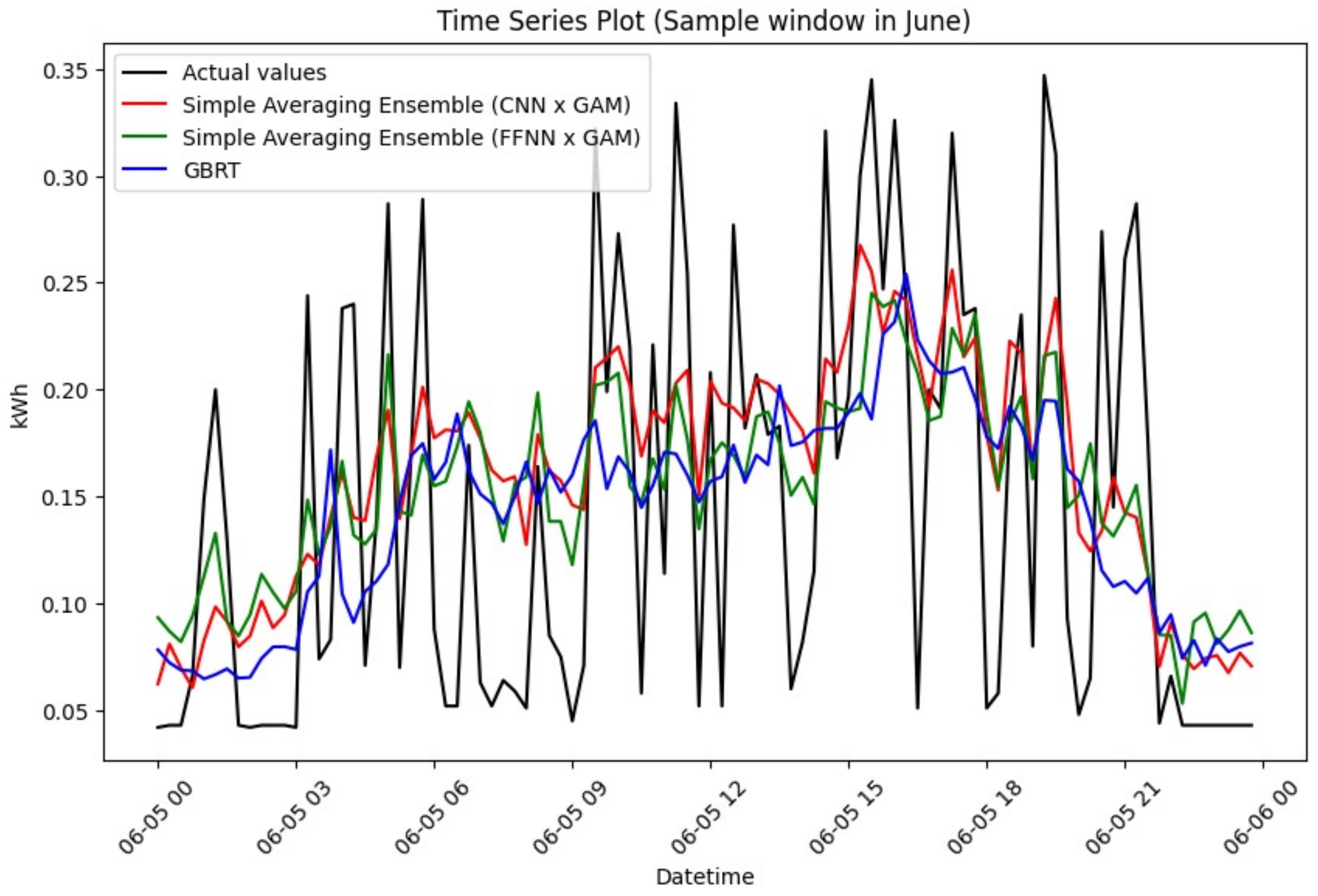
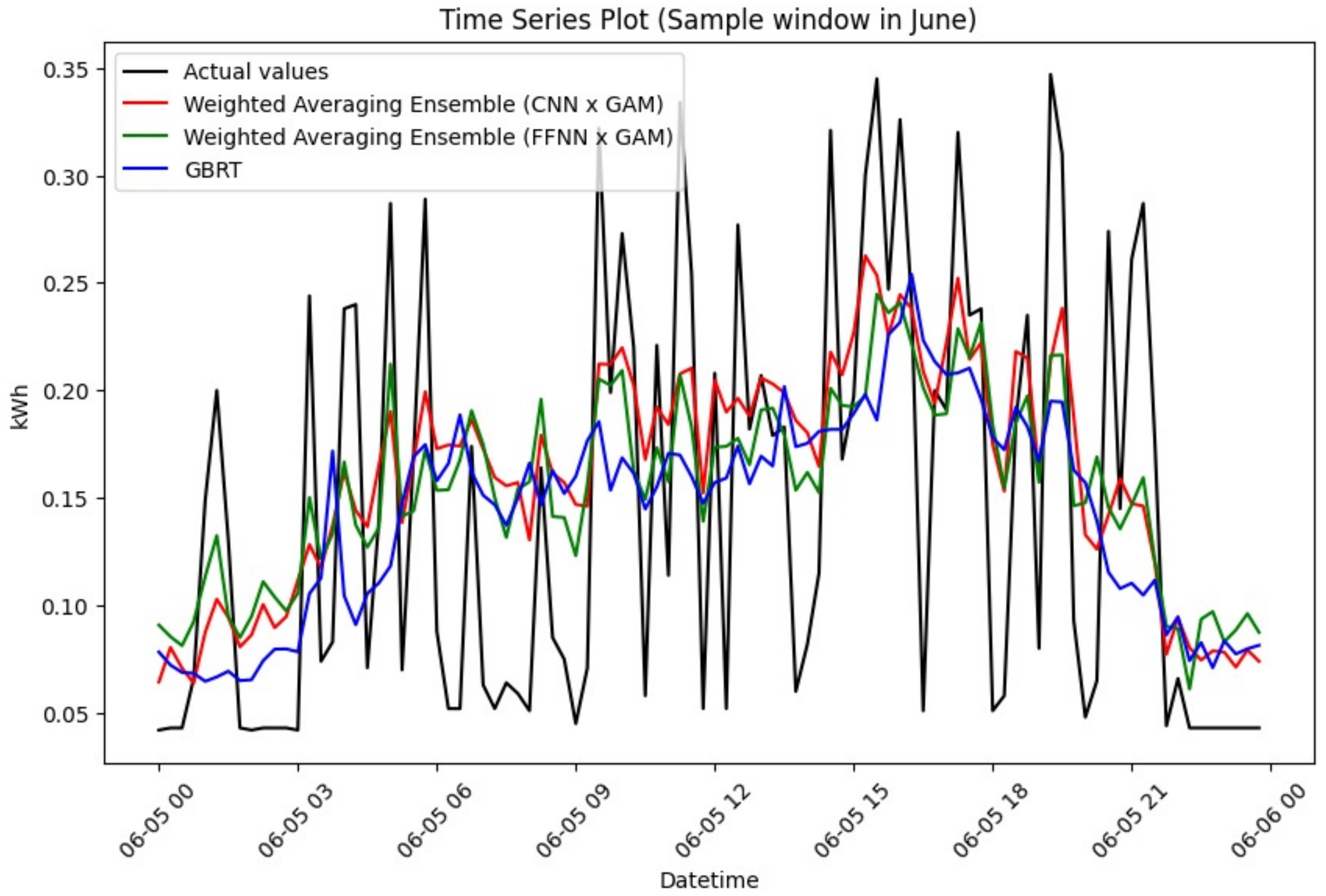
How well do ensemble models perform compared to a gradient boosted tree?

- The behaviour of both ensembles and GBT seems to be good when plotting time series plots.
- It seems that the variation of the peaks is higher in the ensembles compared to the GBT.
- As the trend is well followed by the GBT and the ensembles, it is difficult to compare which case behaves better.
- Therefore, by the metrics assessment, it seems that ensembles are overall slightly better compared to the GBT.





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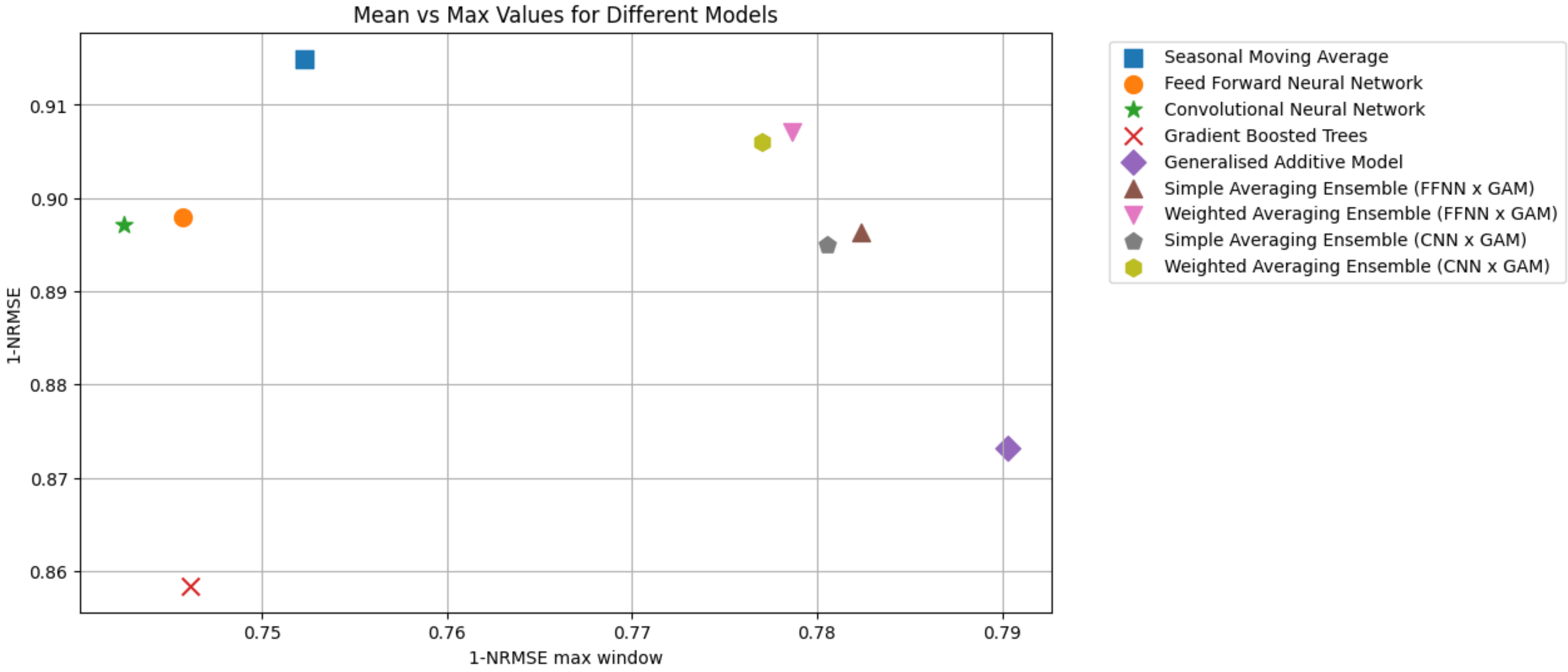
Do the models built on one smart meter data, perform well on data from another smart meter?



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Conclusion

- Forecasts are becoming easier and easier to produce, however, in order to maximize value of forecasts versus costs, data and model management and monitoring become relevant.
- In AISOP we have experimented with several univariate time series forecasting methods from basic baseline methods that rely on simple averaging of load profiles to advanced methodologies that rely on pre-trained deep neural networks.
- In this context, the Master thesis work presented explored the performance of ensembles of simple neural network models using open smart meter data.
- Results reported in the Master thesis work, such as
    1. quantification of errors from different methods, can be used as a baseline for further model development; and
    2. usage of multiple forecast performance metrics to compare different forecasts can be further developed for model management and monitoring.
- Moreover, the relevance of building forecast models aimed at different use cases, by taking care that the right performance metrics are applied to obtain forecasts with the desired characteristics, was highlighted in various discussions with stake holders of AISOP project: load forecasts for grid congestion need to deliver good predictions of larger values of load and their timing.