Outlier detection results validation and imputation model description (small data model)

D4

Authors:

Aleix Badia (Beedata Analytics)

Helena Boltà (Beedata Analytics)

Daniel Pérez (Beedata Analytics)

Verified by the appointed Reviewers	Dmitry Belichenko (ENTSO-E), 03.02 and 23.03. 2023
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About OneNet

The project OneNet (One Network for Europe) will provide a seamless integration of all the actors in the electricity network across Europe to create the conditions for a synergistic operation that optimizes the overall energy system while creating an open and fair market structure.

OneNet is funded through the EU's eighth Framework Programme Horizon 2020, "TSO – DSO Consumer: Large-scale demonstrations of innovative grid services through demand response, storage and small-scale (RES) generation" and responds to the call "Building a low-carbon, climate resilient future (LC)".

As the electrical grid moves from being a fully centralized to a highly decentralized system, grid operators have to adapt to this changing environment and adjust their current business model to accommodate faster reactions and adaptive flexibility. This is an unprecedented challenge requiring an unprecedented solution. The project brings together a consortium of over seventy partners, including key IT players, leading research institutions and the two most relevant associations for grid operators.

The key elements of the project are:

1. Definition of a common market design for Europe: this means standardized products and key parameters for grid services which aim at the coordination of all actors, from grid operators to customers;
2. Definition of a Common IT Architecture and Common IT Interfaces: this means not trying to create a single IT platform for all the products but enabling an open architecture of interactions among several platforms so that anybody can join any market across Europe; and
3. Large-scale demonstrators to implement and showcase the scalable solutions developed throughout the project. These demonstrators are organized in four clusters coming to include countries in every region of Europe and testing innovative use cases never validated before.

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List of Abbreviations and Acronyms

Acronym	Meaning
AI	Artificial Intelligence
DSO	Distribution System Operators
ENTSO-E	European Network of Transmission System Operators for Electricity
EDSO	European Distribution System Operators
E-REDES	Electricity distributor of the EDP Group
VITO	Flemish research organisation in the area of cleantech and sustainable development.
ES	Spain
FR	France
GPU	Graphics Processing Unit
LOF	Local Outlier Factor
MAD	Median Absolute Deviation
TPU	Tensor Processing Unit
TSO	Transmission System Operator
UCTE	Union for the Coordination of Transmission of Electricity
N-Beats	Neural Basis Expansion Analysis Method for interpretable Time Series

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Executive Summary

Data and analysis is increasingly becoming an integral part of the everyday electricity system and more specific in data exchanges among Transmission System Operators (TSO), Distribution System Operators (DSO) and consumers. With a growing emphasis on data-led decision making across different organizations, trust in the quality of data is vital. Low quality data is propagated along the organization via erroneous data-driven decisions. A common error-prone use case would be forecasting. Fitting forecasting models with erroneous data would lead to predicting erroneous scenarios. With the AI data quality toolbox developed in the project we expect to improve the quality of the data managed by the data provider.

In this deliverable we provide method description and evaluation results of the outlier detection and imputation methods (small data). The method is based on obtaining a baseline model which represents the common dynamics of a time series and comparing its backcasting results against measured time series. Differences between backcast and measured time series are analysed in order to score dissimilarity. High dissimilar points are considered outliers. The baseline method was previewed to be based on the LSTM autoencoders method, which is a self-supervised method based on neural networks that can build a model representing a compression representation of a sequence of data, in this case a time series. In our context, considering the time series supplied by ENSTO-e, we've analysed multiple deep learning methods (autoencoders, etc) to be used in baseline modelling and finally decided to use N-BEATS. The architecture of N-BEATS has a number of desirable properties that can be useful in ENTSO-E use cases: i) Being interpretable. It's easier to obtain, describe and understand patterns identified by the model, ii) Applicable without modification to a wide array of target topics. Time series in the ENTSO-E use case are from different topics (see 2.3.1.1) having different dynamics Fast to train. There're a lot of different time series in the ENTSO-E use case and each one has different dynamics. Because of that, we want to train a model of baseline time series of energy events which ultimately leads to a learnt model able to detect 'normality' as the distribution used to train the model is different from the outliers events distribution.

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1 Introduction

Data quality services are focused on analysing data in order to detect, identify, quantify and fix issues in the provided data. Type and source of issues are multiple and diverse. In this specific project, the use cases are focused on aggregated data from the European Network of Transmission System Operators for Electricity (ENTSO-E) [1], association of grid operators in Europe, and complementary on smart grids data from other use cases out of the OneNet Project. More specifically, we are using hourly electricity data consumption from our own database, which is formed by 100.000 residential consumers of Spain, to pre-evaluate the accuracy of the method.

In order to provide a full-stack quality pipeline the outlier detection and imputation methodology evaluation has been merged in the same deliverable. The evaluation of the outlier detection and imputation methodology is required in order to identify which, when and how to be used.

In this deliverable the information detailed is:

- Description of the detection and imputation methods.
- Description of the evaluation methods.
- Evaluation results for the outliers detection method.
- Evaluation results for the imputation method.

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2 Content

2.1 Description of the detection methods

Each of the time series have specific domain properties and outliers. Although all the time series are energy domain related, each of them has different dynamics depending on different factors. The dynamics of time series can depend on economics, weather, logistics, etc. A customizable method is proposed to properly support outlier detection in different time series dynamics.

Baseline based

The method is based on comparing the expected dynamics of the time series against the real ones. If the time series is free of outliers there should be no big difference between expected and real data. If the time series has outliers there should be a difference between expected and real data. The baseline model is used to describe and obtain expected dynamics of the time series considering history.

We've analysed multiple deep learning methods (autoencoders, etc) to be used in baseline modelling and finally decided to use N-BEATS. The architecture of N-BEATS has a number of desirable properties [1] that can be useful in ENTSO-E use case:

- Being interpretable. It's easier to obtain, describe and understand patterns identified by the model
- Applicable without modification to a wide array of target topics. Time series in the ENTSO-E use case are from different topics (see 2.3.1.1) having different dynamics
- Fast to train. There're a lot of different time series in the ENTSO-E use case and each one has different dynamics

In fact, such architecture thus departs from traditional usage of recurrent networks and has several advantages to traditional approaches [2]:

- Faster training: all operations are parallelized on Graphics Processing Unit (GPU) o Tensor Processing Unit (TPU), making training much faster than with recurrent networks.
- Lightweight networks: N-BEATS blocks are much more configurable and thus can yield lighter networks, very useful for small problems or when running on embedded devices.
- Fully configurable backcast and forecast: N-BEATS can use arbitrarily long sequences in the past, and forecast arbitrarily in the future. This is configured once for every model, depending on the problem

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N-BEATS is a deep neural architecture based on backward and forward residual links and a very deep stack of fully-connected layers. The architecture consists of a sequence of stacks, each of which combine multiple blocks. The blocks connect feedforward networks via forecast and backcast links. Each block sets its focus on the residual error, which the preceding blocks could not disentangle. Each block generates a partial forecast, with its focus set on the local characteristics of the time series. The stack aggregates the partial forecasts across the blocks it comprises and then hands the result over to the next stack. The stack purpose is to identify non-local patterns along the complete time axis by analyzing history patterns. Finally, the partial forecasts are pieced together to a global forecast at the model level. See N-BEATS architecture in Figure 2.1.1

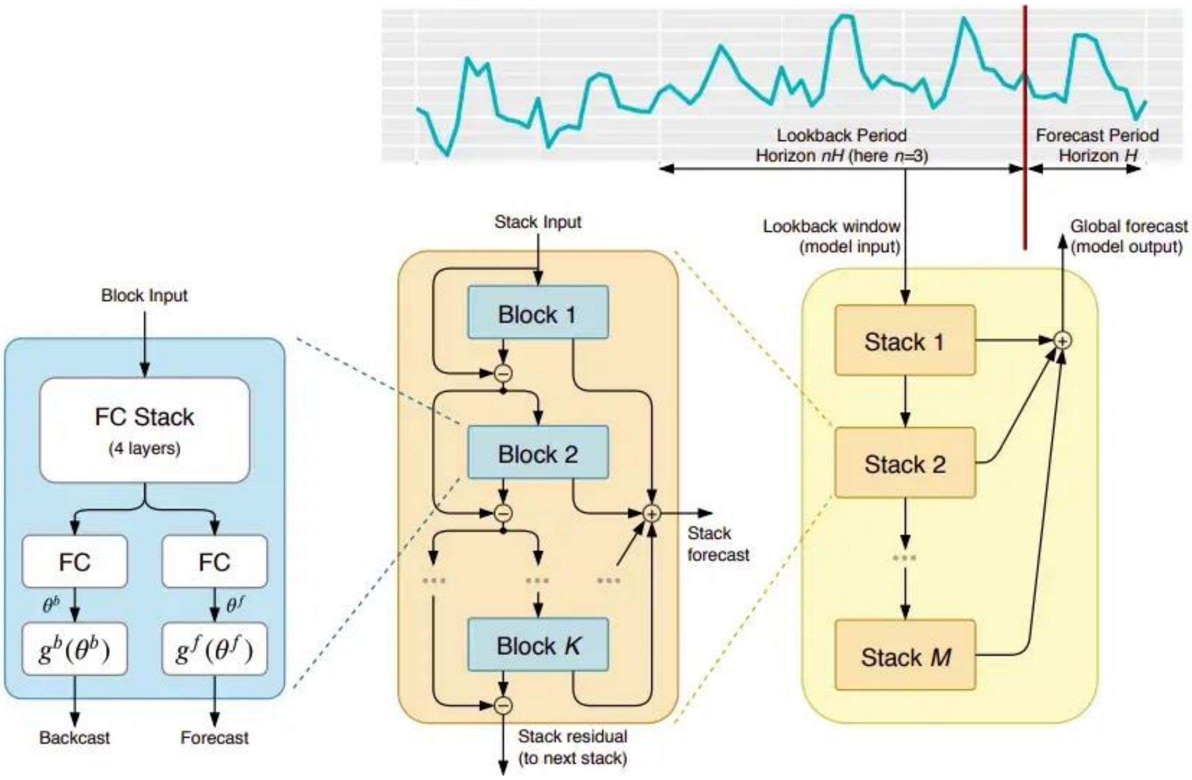

Figure 2.1.1. N-BEATS architecture (source: N-BEATS paper)

The N-BEATS customization settings, also known as hyperparameters, are:

Hyperparameter	**Description**
input_size	The size of the input layer
output_size	The size of the output layer

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n_blocks	Number of blocks
fc_width	The width of each fully connected layer in each block of a stack
batch_size	The batch size defines the number of observations the model will process before it updates its matrix weights
n_epochs	How many training cycles it is supposed to run

There are two ways to initialize hyperparameters:

- Use default hyperparameters provided by the project
- Manual curation. Use domain knowledge of each of the time series
- Automatic optimization. Use an optimization process to tune hyperparameters in order to maximize accuracy. This method is the suggested one in case of available labelled data or at least quite curated data.

Once the baseline is obtained backcasting is used in order to identify which was supposed to be the expected dynamics in history. The expected dynamics are compared against the real in order to identify big differences.

The comparison between expected and real data is done via the analysis of the residual between both:

1) Calculate residual between expected (backcast) and real data
2) Identify anomalous values in the residuals
3) Classify anomalous values in the residuals as outliers

Identification of the anomalous values in the residuals is done using Local Outlier Factor (LOF). The LOF algorithm is an unsupervised anomaly detection method which computes the local density deviation of a given data point with respect to its neighbours. It considers as outliers the samples that have a substantially lower density than their neighbours. The number of neighbours considered (parameter n_neighbours) is typically set greater than the minimum number of samples a cluster has to contain, so that other samples can be local outliers relative to this cluster, and smaller than the maximum number of close by samples that can potentially be local outliers.

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2.2 Description of the imputation method

Each of the time series have specific domain properties and outliers. Although all the time series are energy domain related, each of them has different dynamics depending on different factors. The dynamics of time series can depend on economics, weather, logistics, etc. The used imputation is based on obtaining the expected value using the baseline model previously described in the detection method. Using baseline is possible to backcast values and obtain values in the gaps.

The N-BEATS customization settings, also known as hyperparameters, are:

Hyperparameter	**Description**
input_size	The size of the input layer
output_size	The size of the output layer
n_blocks	Number of blocks
fc_width	The width of each fully connected layer in each block of a stack
batch_size	The batch size defines the number of observations the model will process before it updates its matrix weights
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There are two ways to initialize hyperparameters:

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2.3 Evaluation results

2.3.1 Data used in evaluation

2.3.1.1 Data providers

ENTSO-E transparency platform is used as the data provider to validate outlier detection algorithms. The ENTSOE-E transparency platform provides data grouped in seven main topics:

- Load. Data about power consumption
- Generation. Energy production and production forecasts
- Transmission. Data about power transfers over borders between areas
- Balancing. Data about Regulation energy used to keep the electrical transmission grid in balance
- Outages. Data about planned maintenances and failures inside the electrical transmission grid
- Congestion Management. Data about actions taken to relieve overloaded parts of the electrical transmission grid
- System Operations. Data about electricity transmission system operation

The specific data used for the evaluation of the detection methods is the one described in table 2.3.1.1.

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Table 2.3.1.1 - Data selected from ENTSO-E transparency platform

Name	Description	Document Type	Process Type	Business Type	Data unit	Time resolution	Country	Amount of series
Actual Total Load [6.1.A]	Actual total load per bidding zone per market time unit, the total load being defined as equal to the sum of power generated by plants on both TSO/DSO network	A65	A16		MW	15 minutes 60 minutes	ES DE FR	3
Aggregated Generation per Type [16.1.B&C]	Actual aggregated Net generation output (MW) per market time unit and per production type.	A75	A16		MW	60 minutes	ES DE FR	3 x 3 Nuclear Solar Wind
Total Capacity Nominated [12.1.B]	For every market time unit and per direction between bidding zones the total capacity nominated (MW) from capacity allocated via explicit allocations only.	A26		B08	MW	60 minutes	FR	2 x bidding zone
Forecasted Day-ahead Transfer Capacities [11.1]	The forecasted NTC (MW) per direction between bidding zones, including technical profiles. only in NTC allocation method	A61			MW	60 minutes	FR	2 x bidding zone

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2.3.1.2 Outlier detection scenarios

Synthetic outliers are used as the data provided by ENTSO-E is not already classified and has no kind of label to be used as outlier identification. Synthetic data is an industry workaround to evaluate scenarios which are in the domain knowledge but with no available data. Synthetic outliers are created to evaluate the model under outlier scenarios not present in data. Outliers are domain specific but typical outlier patterns are:

- Spikes
- Plateaus
- Null values
- Anomalous patterns

The most common outlier types identified in power industry time series are:

- **Global outliers**. A data point is considered a global outlier if its value is far outside the entirety of the data set in which it is found. See example in Figure 2.3.1.2.1, 2.3.1.2.2, 2.3.1.2.3

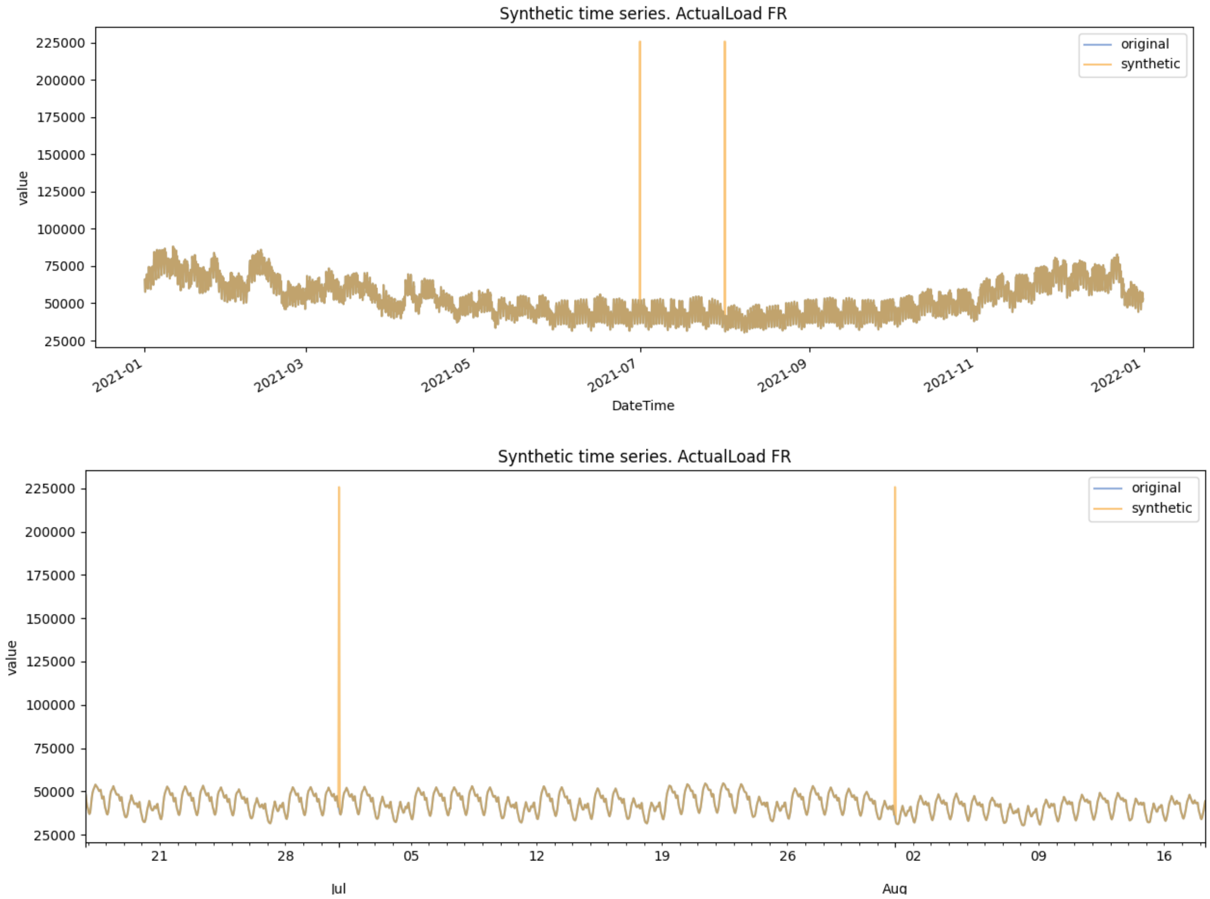

Figure 2.3.1.2.1 - Global outlier . Spike

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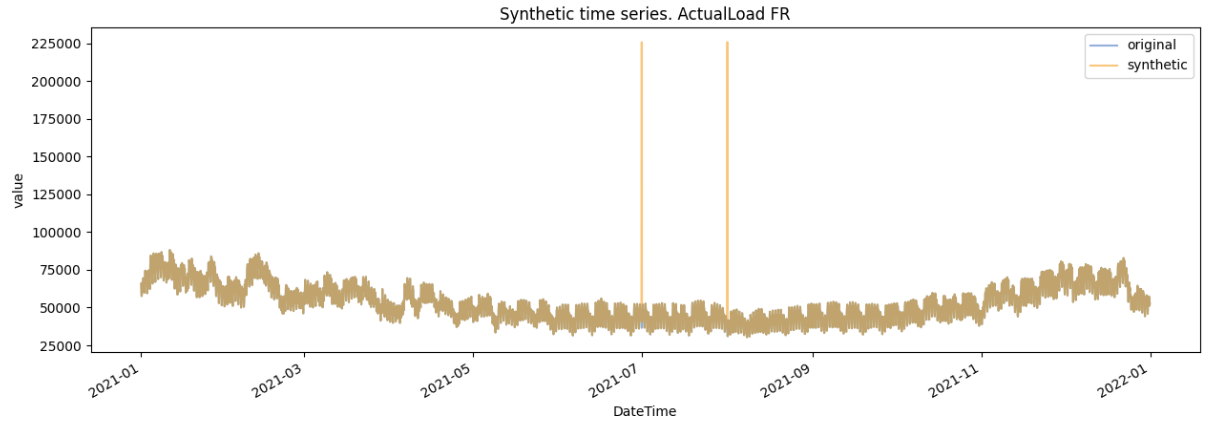

Figure 2.3.1.2.2 - Global outlier. Plateau

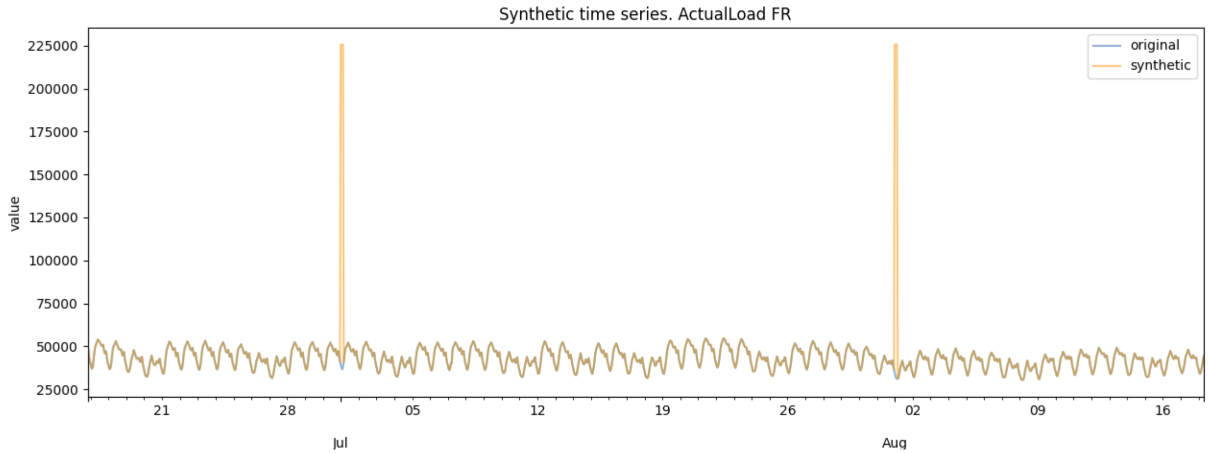

Figure 2.3.2.1.3 - Global outlier. Plateau

- **Contextual outliers.** Contextual outliers are data points whose value significantly deviates from other data within the same context. The “context” is almost always temporal in time-series data, such as records of a specific quantity over time. Values are not outside the normal global range, but are abnormal compared to the seasonal pattern. See examples in Figure 2.3.1.2.4, 2.3.1.2.5, 2.3.1.2.6 and 2.3.1.2.7

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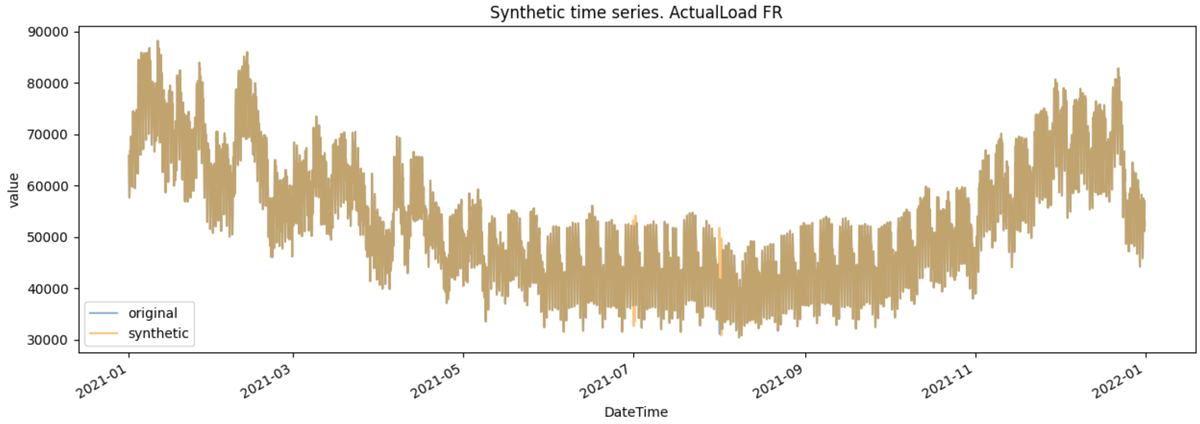

Figure 2.3.1.2.4 - Contextual outlier 2 day

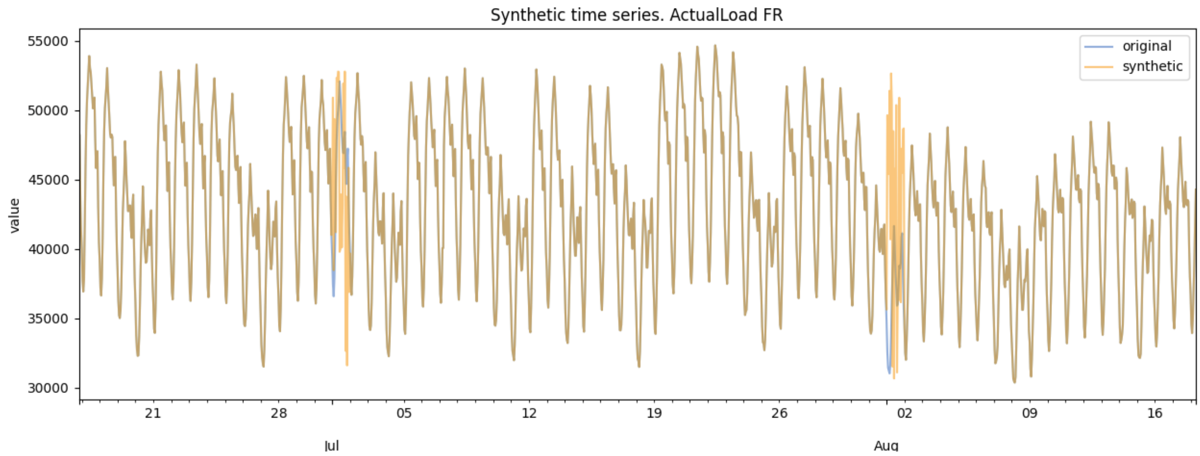

Figure 2.3.1.2.5 - Contextual outlier 2 day

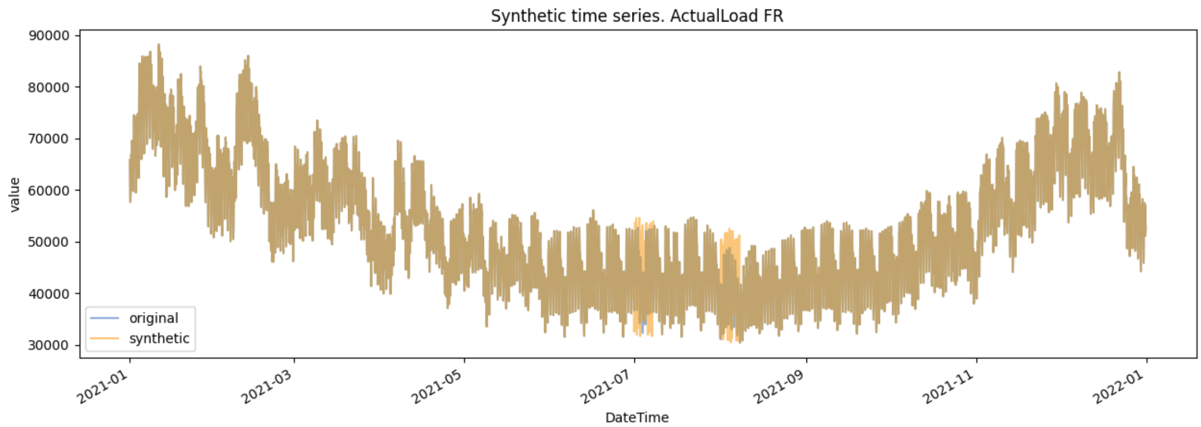

Figure 2.3.1.2.6- Contextual outlier 2 week

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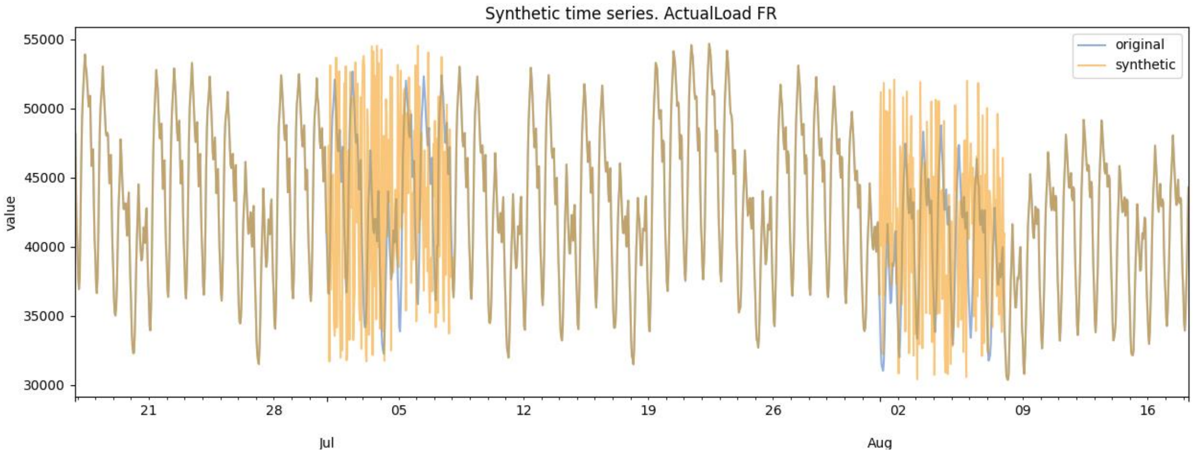

Figure 2.3.1.2.7 - Contextual outlier 2 week

- **Collective outliers**. A subset of data points within a data set is considered anomalous if those values are considered as a collection which deviates significantly from the entire data set, but the values of the individual data points are not themselves anomalous in either a contextual or global sense. In time series data, one way this can manifest is as normal peaks and valleys occurring outside of a time frame when that seasonal sequence is normal or as a combination of time series that is in an outlier state as a group. See some examples in Figure 2.3.1.2.8, 2.3.1.2.9, 2.3.1.2.10 and 2.3.1.2.11

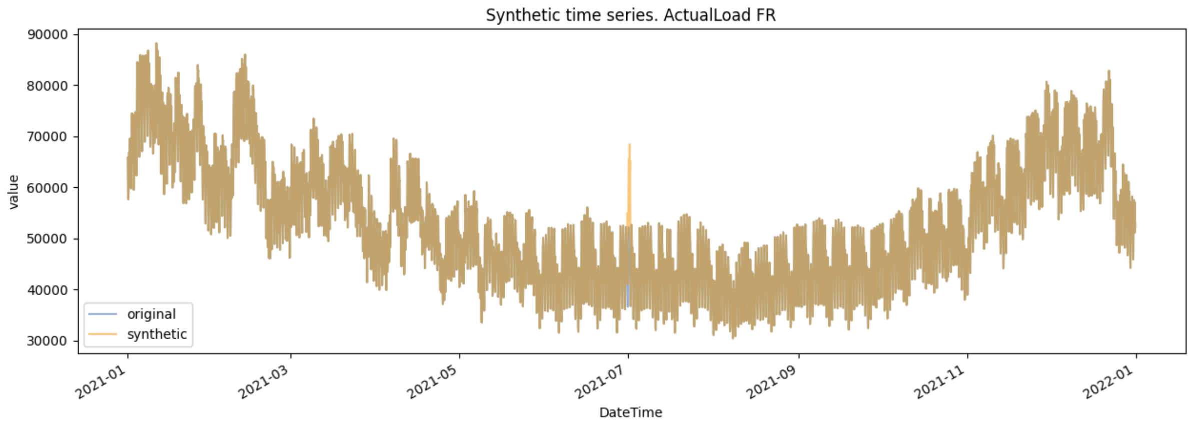

Figure 2.3.1.2.8- Collective outlier 1 day

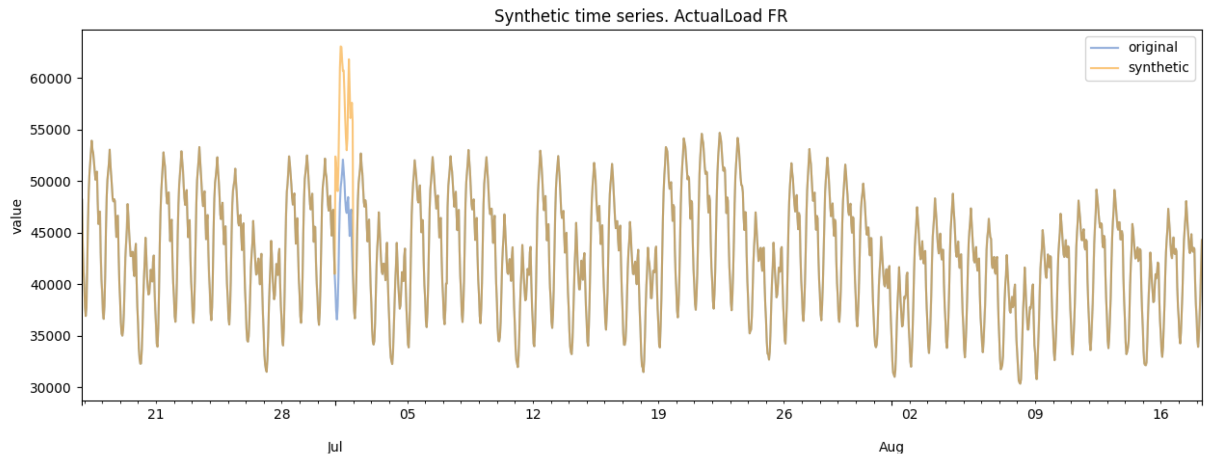

Figure 2.3.1.2.9- Collective outlier 1 day

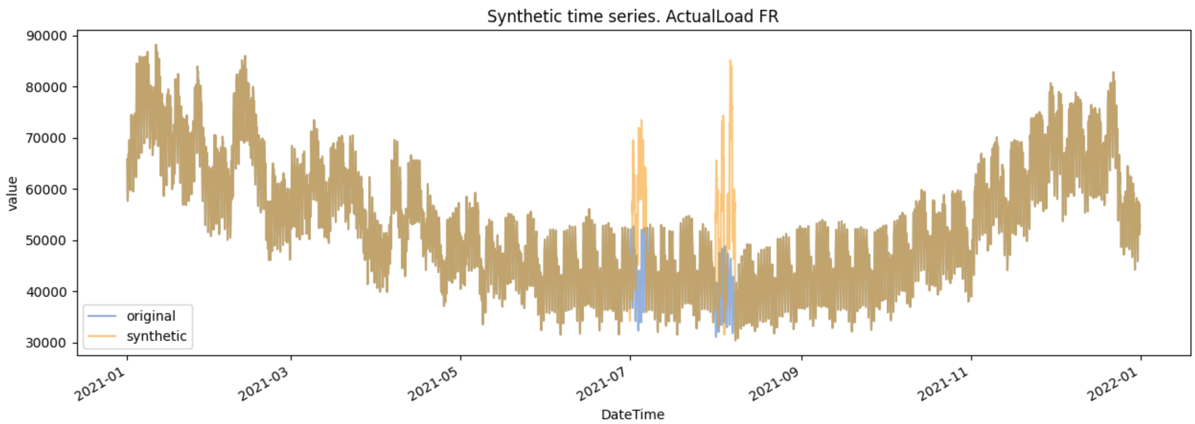

Figure 2.3.1.2.10- Collective outlier 2 week

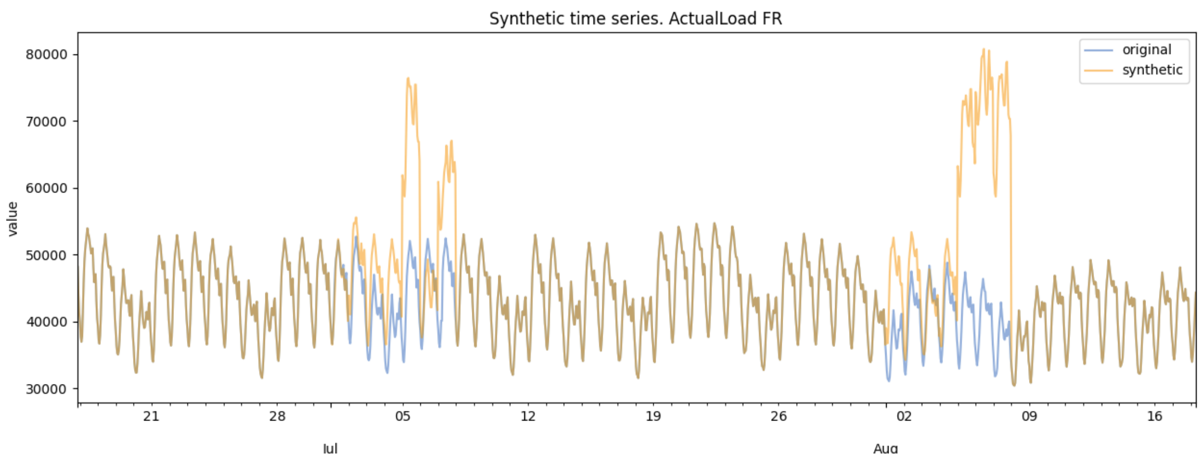

Figure 2.3.1.2.11- Collective outlier 2 week

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Different gains and time lengths are applied to these typical outlier patterns in order to evaluate in which cases the model is able to properly classify samples

Synthetic outliers used to evaluate the detection method are agreed with partners and introduced in deliverable D1. See Table 2.3.1.2.1

Table 2.3.1.2.1 - Specification of the outlier scenarios

Id	Time series	Type of outlier	Value (*)	Season	Duration	Frequency (*)	Pattern
1	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
2	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike
3	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
4	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike
5	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
6	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike
7	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
8	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike
9	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
10	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike
11	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
12	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike

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13	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
14	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
15	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
16	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
17	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
18	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
19	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
20	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
21	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
22	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
23	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
24	Forecasted Day-ahead Transfer Capacities [11.1]	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
25	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
26	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
27	Actual Total Load [6.1.A]	Global	x3 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau

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28	Actual Total Load [6.1.A]	Global	x1.5 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
29	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
30	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
31	Total Capacity Nominated [12.1.B]	Global	x3 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
32	Total Capacity Nominated [12.1.B]	Global	x1.5 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
33	Actual Total Load [6.1.A]	Contextual	Random values in min-max range (month)	Summer	1 day	1 time	Daily
34	Actual Total Load [6.1.A]	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily
35	Total Capacity Nominated [12.1.B]	Contextual	Random value in min-max range (month)	Summer	1 day	1 time	Daily
36	Total Capacity Nominated [12.1.B]	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily
37	Forecasted Day-ahead Transfer Capacities [11.1]	Contextual	Random value in min-max range (month)	Summer	1 day	1 time	Daily
38	Forecasted Day-ahead Transfer Capacities [11.1]	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily
39	Actual Total Load [6.1.A]	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
40	Actual Total Load [6.1.A]	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily

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41	Total Capacity Nominated [12.1.B]	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
42	Total Capacity Nominated [12.1.B]	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily
43	Forecasted Day-ahead Transfer Capacities [11.1]	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
44	Forecasted Day-ahead Transfer Capacities [11.1]	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily
45	Actual Total Load [6.1.A]	Collective	Random sort of daily values	Summer	1 day	1 time	Daily
46	Actual Total Load [6.1.A]	Collective	Random sort of daily values	Winter	1 day	1 time	Daily
47	Total Capacity Nominated [12.1.B]	Collective	Random sort of daily values	Summer	1 day	1 time	Daily
48	Total Capacity Nominated [12.1.B]	Collective	Random sort of daily values	Winter	1 day	1 time	Daily
49	Forecasted Day-ahead Transfer Capacities [11.1]	Collective	Random sort of weekly values	Summer	1 day	1 time	Daily
50	Forecasted Day-ahead Transfer Capacities [11.1]	Collective	Random sort of weekly values	Winter	1 day	1 time	Daily
51	Actual Total Load [6.1.A]	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
52	Actual Total Load [6.1.A]	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily
53	Total Capacity Nominated [12.1.B]	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
54	Total Capacity Nominated [12.1.B]	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily

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55	Forecasted Day-ahead Transfer Capacities [11.1]	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
56	Forecasted Day-ahead Transfer Capacities [11.1]	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily
57	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
58	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike
59	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
60	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike
61	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
62	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
63	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
64	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
65	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
66	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau

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67	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x3 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
68	Aggregated Generation per Type [16.1.B&C] Nuclear	Global	x1.5 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
69	Aggregated Generation per Type [16.1.B&C] Nuclear	Contextual	Random values in min-max range (month)	Summer	1 day	1 time	Daily
70	Aggregated Generation per Type [16.1.B&C] Nuclear	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily
71	Aggregated Generation per Type [16.1.B&C] Nuclear	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
72	Aggregated Generation per Type [16.1.B&C] Nuclear	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily
73	Aggregated Generation per Type [16.1.B&C] Nuclear	Collective	Random sort of daily values	Summer	1 day	1 time	Daily
74	Aggregated Generation per Type [16.1.B&C] Nuclear	Collective	Random sort of daily values	Winter	1 day	1 time	Daily
75	Aggregated Generation per Type [16.1.B&C] Nuclear	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
76	Aggregated Generation per Type [16.1.B&C] Nuclear	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily
77	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
78	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike

79	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
80	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike
81	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
82	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
83	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
84	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
85	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
86	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
87	Aggregated Generation per Type [16.1.B&C] Solar	Global	x3 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
88	Aggregated Generation per Type [16.1.B&C] Solar	Global	x1.5 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
89	Aggregated Generation per Type [16.1.B&C] Solar	Contextual	Random values in min-max range (month)	Summer	1 day	1 time	Daily
90	Aggregated Generation per Type [16.1.B&C] Solar	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily

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91	Aggregated Generation per Type [16.1.B&C] Solar	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
92	Aggregated Generation per Type [16.1.B&C] Solar	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily
93	Aggregated Generation per Type [16.1.B&C] Solar	Collective	Random sort of daily values	Summer	1 day	1 time	Daily
94	Aggregated Generation per Type [16.1.B&C] Solar	Collective	Random sort of daily values	Winter	1 day	1 time	Daily
95	Aggregated Generation per Type [16.1.B&C] Solar	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
96	Aggregated Generation per Type [16.1.B&C] Solar	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily
97	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Summer	1 time step	1 time	Spike
98	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Summer	1 time step	1 time	Spike
99	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Winter	1 time step	1 time	Spike
100	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Winter	1 time step	1 time	Spike
101	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike
102	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Summer	1 time step	4 times per month	Spike

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103	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
104	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Winter	1 time step	4 times per month	Spike
105	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
106	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Summer	10 time step	2 times per month	Plateau
107	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x3 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
108	Aggregated Generation per Type [16.1.B&C] WindOn	Global	x1.5 percentile %95 value in time series	Winter	10 time step	2 times per month	Plateau
109	Aggregated Generation per Type [16.1.B&C] WindOn	Contextual	Random values in min-max range (month)	Summer	1 day	1 time	Daily
110	Aggregated Generation per Type [16.1.B&C] WindOn	Contextual	Random value in min-max range (month)	Winter	1 day	1 time	Daily
111	Aggregated Generation per Type [16.1.B&C] WindOn	Contextual	Random value in min-max range (month)	Summer	1 day	2 times per month	Daily
112	Aggregated Generation per Type [16.1.B&C] WindOn	Contextual	Random value in min-max range (month)	Winter	1 day	2 times per month	Daily
113	Aggregated Generation per Type [16.1.B&C] WindOn	Collective	Random sort of daily values	Summer	1 day	1 time	Daily
114	Aggregated Generation per Type [16.1.B&C] WindOn	Collective	Random sort of daily values	Winter	1 day	1 time	Daily

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115	Aggregated Generation per Type [16.1.B&C] WindOn	Collective	Random sort of daily values	Summer	1 day	2 times per month	Daily
116	Aggregated Generation per Type [16.1.B&C] WindOn	Collective	Random sort of daily values	Winter	1 day	2 times per month	Daily

(*) Syntax of the value is x times the percentile of the time series (i.e. x2 percentile %95 value, means that the outlier value will be 2 times the percentile %95 calculated over the specific time interval of the time series.

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2.3.1.3 Imputation scenarios

Synthetic gaps are used as the data provided by ENTSO-E. Synthetic data is an industry workaround to evaluate scenarios which are in the domain knowledge but with no available data. Synthetic gaps are created to evaluate the model under gaps scenarios not present in data. Gaps are domain specific but typical gap patterns are:

- Multiple continuous days gaps. Five full day gaps used
- Multiple non-continuous days gaps. Three full day gaps used with a filled days between each
- Partial days. Three partial day gaps (12:00 to 23:00) used with a filled days between each
- Single hours gaps. Three single hour gaps (12:00 to 13:00) used with a filled days between each

See synthetic gaps summary in Table 2.3.1.3.1

Table 2.3.1.3.1 - *Specification of gap scenarios*

Id	Time series	Type of gap	Season	Duration	Pattern
1	Actual Total Load [6.1.A]	five_days	winter, spring, summer, autumn	5 days	24 hours gap
2	Actual Total Load [6.1.A]	single_days	winter, spring, summer, autumn	3 days	24 hours gap
3	Actual Total Load [6.1.A]	partial_day	winter, spring, summer, autumn	3 days	12 hours gap
4	Actual Total Load [6.1.A]	single_hours	winter, spring, summer, autumn	3 days	1 hour gap
5	Total Capacity Nominated [12.1.B]	five_days	winter, spring, summer, autumn	5 days	24 hours gap

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Id	Time series	Type of gap	Season	Duration	Pattern
6	Total Capacity Nominated [12.1.B]	single_days	winter, spring, summer, autumn	3 days	24 hours gap
7	Total Capacity Nominated [12.1.B]	partial_day	winter, spring, summer, autumn	3 days	12 hours gap
8	Total Capacity Nominated [12.1.B]	single_hours	winter, spring, summer, autumn	3 days	1 hour gap
9	Forecasted Day-ahead Transfer Capacities [11.1]	five_days	winter, spring, summer, autumn	5 days	24 hours gap
10	Forecasted Day-ahead Transfer Capacities [11.1]	single_days	winter, spring, summer, autumn	3 days	24 hours gap
11	Forecasted Day-ahead Transfer Capacities [11.1]	partial_day	winter, spring, summer, autumn	3 days	12 hours gap
12	Forecasted Day-ahead Transfer Capacities [11.1]	single_hours	winter, spring, summer, autumn	3 days	1 hour gap
13	Aggregated Generation per Type [16.1.B&C] Nuclear	five_days	winter, spring, summer, autumn	5 days	24 hours gap
14	Aggregated Generation per Type [16.1.B&C] Nuclear	single_days	winter, spring, summer, autumn	3 days	24 hours gap
15	Aggregated Generation per Type [16.1.B&C] Nuclear	partial_day	winter, spring, summer, autumn	3 days	12 hours gap
16	Aggregated Generation per Type [16.1.B&C] Nuclear	single_hours	winter, spring, summer, autumn	3 days	1 hour gap

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Id	Time series	Type of gap	Season	Duration	Pattern
17	Aggregated Generation per Type [16.1.B&C] Solar	five_days	winter, spring, summer, autumn	5 days	24 hours gap
18	Aggregated Generation per Type [16.1.B&C] Solar	single_days	winter, spring, summer, autumn	3 days	24 hours gap
19	Aggregated Generation per Type [16.1.B&C] Solar	partial_day	winter, spring, summer, autumn	3 days	12 hours gap
20	Aggregated Generation per Type [16.1.B&C] Solar	single_hours	winter, spring, summer, autumn	3 days	1 hour gap

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2.3.2 Quality evaluation indicators

2.3.2.1 Outlier detection

During the initial data exploration some organic potential outliers were identified. As the data provided is not labelled an unsupervised outlier method was proposed. The potential presence of non-labelled outliers in the training data can corrupt the results of the outlier detection methodology. The evaluation of the outlier detection algorithms using synthetic scenarios cannot be only based on the F1-score as the accuracy component would consider true positive outliers in the original as false positives. Recall (see Figure 2.3.2.1.1) is used In the evaluation of the outlier detection method using the synthetic scenarios recall. Recall will be the main indicator and accuracy will be analysed in each specific case.

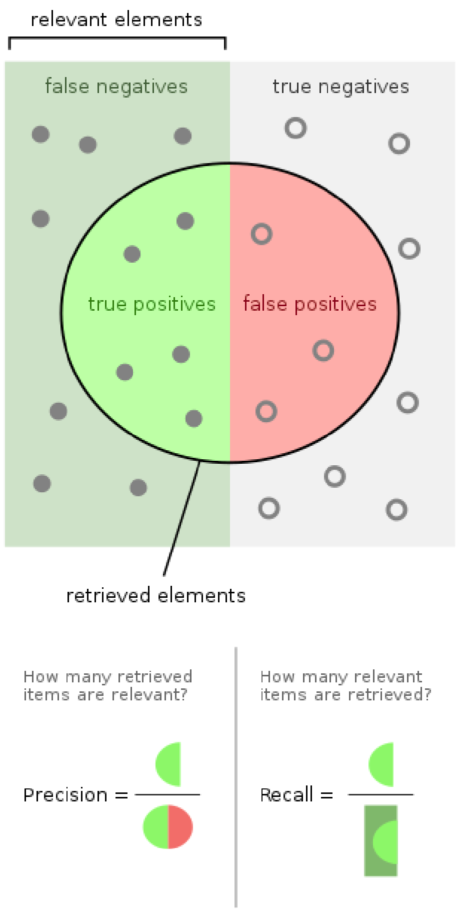

Figure 2.3.2.1.1. F1 description [3]

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2.3.2.2 Imputation

As no labelled data is available the evaluation is done using forecasting evaluation and synthetic gaps data evaluation. Synthetic gaps are created analysing the properties of domain specific outliers (duration, interval, etc). Synthetic gaps are removed from the time series so missing time points are present in data. Imputation is done over the missing points and results are compared against real measurements.

The evaluation criteria used for both forecasting and synthetic outliers is nRMSE (Normalized Root Mean Square Error):

$$NRMSE = \frac{RMSE}{\bar{y}}$$

2.4 Evaluation results

2.4.1 Outlier detection evaluation

The results of the evaluation method previously described is presented as benchmarking analysis. Benchmarking has been done to compare the results of the outlier detection algorithm against other methods used in the industry.

- Local Outlier Factor (LOF) [4]. Already introduced in baseline model residual analysis
- Median Absolute Deviation (MAD) [5]. The Median Absolute Deviation is a robust measure of the variability of a univariate sample of quantitative data. It can also refer to the population parameter that is estimated by the MAD calculated from a sample. For a univariate data set X1, X2, ..., Xn, the MAD is defined as the median of the absolute deviations from the data's

$$\tilde{X} = \text{median}(X)$$

$$\text{MAD} = \text{median}(|X_i - \tilde{X}|)$$

See recall benchmarking results below in Table 2.4.1.1

Some initial considerations are required:

- Manual curation of positives is required in order to calculate precision so F1-score. Recall is used instead
- **Baseline based models are not automatically tuned to obtain best recall. Hyperparameters are manually curated to make it easier to describe the kind of potential outliers detected by the model. See samples below to identify kind of anomalies detected**

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Table 2.4.1.1 - Specification of the outlier scenarios

Time Serie	**Type of Outlier**	**LOF**	**MAD**	**Baseline Based**
ActualTotalLoad	global_spike_plateau	1	1	1
ActualTotalLoad	contextual	0.04	0	0.52
ActualTotalLoad	collective	0	0	0.3
AggregatedGenerationPerType_NUCLEAR	global_spike_plateau	1	1	0.89
AggregatedGenerationPerType_NUCLEAR	contextual	0.12	0	0.42
AggregatedGenerationPerType_NUCLEAR	collective	0	0	0.17
AggregatedGenerationPerType_SOLAR	global_spike_plateau	0.4	1	0.9
AggregatedGenerationPerType_SOLAR	contextual	0.04	0.6	0.55
AggregatedGenerationPerType_SOLAR	collective	0	0.44	0.35
ForecastedDayAheadTransferCapacities	global_spike_plateau	1	1	1
ForecastedDayAheadTransferCapacities	contextual	0.82	0	0.0
ForecastedDayAheadTransferCapacities	collective	0	0	0.0
TotalCapacityNominated	global_spike_plateau	1	1	0.78
TotalCapacityNominated	contextual	0.03	0	0.2
TotalCapacityNominated	collective	0.01	0	0.4

Multiple examples of outlier detection method are available at Appendix A - Outlier detection evaluation results.

2.4.2 Imputation evaluation

See the imputations results in Table 2.4.2.1:

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Table 2.4.2.1 - Specification of the outlier scenarios

TimeSerie	**Type of gap**	**nRMSE**
ActualTotalLoad	five_days	0.004136
ActualTotalLoad	partial_days	0.005070
ActualTotalLoad	single_days	0.006744
ActualTotalLoad	single_hours	0.001724
AggregatedGenerationPerType_NUCLEAR	five_days	0.006488
AggregatedGenerationPerType_NUCLEAR	partial_days	0.006147
AggregatedGenerationPerType_NUCLEAR	single_days	0.009065
AggregatedGenerationPerType_NUCLEAR	single_hours	0.001860
AggregatedGenerationPerType_SOLAR	five_days	0.037005
AggregatedGenerationPerType_SOLAR	partial_days	0.034263
AggregatedGenerationPerType_SOLAR	single_days	0.045540
AggregatedGenerationPerType_SOLAR	single_hours	0.011162
ForecastedDayAheadTransferCapacities	five_days	0.003999
ForecastedDayAheadTransferCapacities	partial_days	0.006220
ForecastedDayAheadTransferCapacities	single_days	0.009054
ForecastedDayAheadTransferCapacities	single_hours	0.001893

Multiple examples of outlier detection method are available at Appendix A - Imputation evaluation results

3 Conclusions

Conclusions regarding outlier detection:

- Manual curation of positives is required in order to calculate precision so F1-score
- Accuracy is highly related to the properties of the time series. As it was expected, high stochastic time series have worse results.
- Accuracy in global spike and plateau outliers is quite good in all methods
- Detection in contextual and collective outliers is mainly working in time series with clear patterns and trends like ActualToalLoad or AggregatedGenerationPerType. LOF could work under some specific time series properties.
- Pattern based algorithms described in D3 provides better results in time series like ForecastedDayAheadTransferCapacities and TotalCapacityNominated
- Baseline based algorithms detects potential (false/true) positives which should be manually reviewed
- Automatic hyperparameter tuning must be used to improve the results once labelled data is available
- Hyperparameter tuning can be used to generate different kinds of outlier signals. Soft and strict hyperparameter tuning can be used to create warning and severe outliers

Conclusions regarding imputation:

- Deviation is highly related to the properties of the time series. Best results are obtained in low stochastic time series and worse results are obtained in high stochastic time series
- Partial day gaps and single hour gaps are best predicted as they provide daily pattern contextual information to the imputation method
- Automatic hyperparameter tuning must be used to improve the results once outlier labelled data or extra information on gaps is available
- Additional extra-information like holiday, specials days or specific domain specific data (weather, market info, time series correlation, …) could be added to improve prediction

References

[1] N-BEATS Introduction https://towardsdatascience.com/n-beats-unleashed-deep-forecasting-using-neural-basis-expansion-analysis-in-python-343dd6307010

[2] N-BEATS description https://www.deepdetect.com/blog/11-ts-forecast-nbeats/

[3] F1 score description https://en.wikipedia.org/wiki/F-score

[4] LOF introduction https://www.dbs.ifi.lmu.de/Publikationen/Papers/LOF.pdf

[5] MAD introduction https://en.wikipedia.org/wiki/Median_absolute_deviation

[6] Deep Learning introduction https://en.wikipedia.org/wiki/Deep_learning

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Glossary

Capacity. Capacity is the rated continuous load-carrying ability of generation, transmission, or other electrical equipment, expressed in megawatts (MW) for active power or megavolt-amperes (MVA) apparent power.

Demand - Consumption. Demand is the rate at which electric power is delivered to or by a system or part of a system, generally expressed in kilowatts (kW) or megawatts (MW), at a given instant or averaged over any designated interval of time.

Deep Learning: Deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input. For example, in image processing, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces [6]**.**

Precision. A metric for classification models. Precision identifies the frequency with which a model was correct when predicting the positive class.

Recall. A metric for classification models that described how many did the model correctly identify out of all the possible positive classes.

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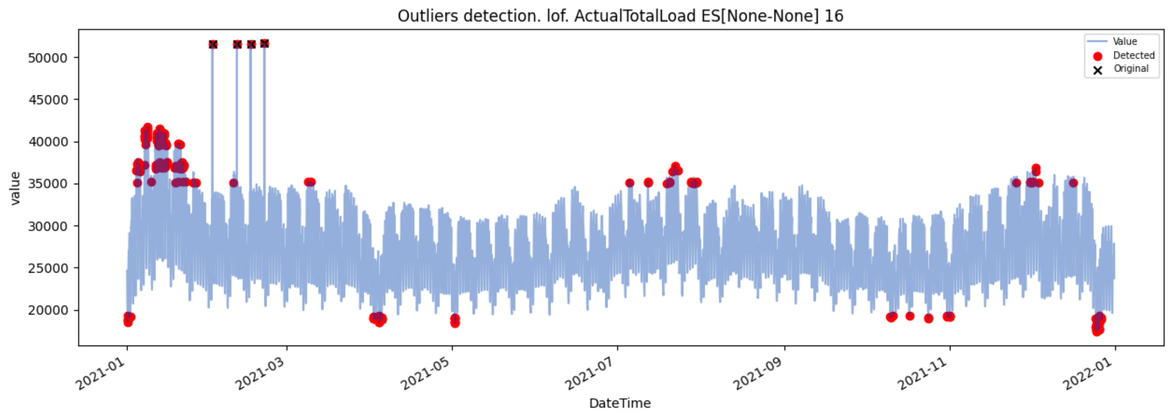
Appendix A

A.1 Outlier detection evaluation results

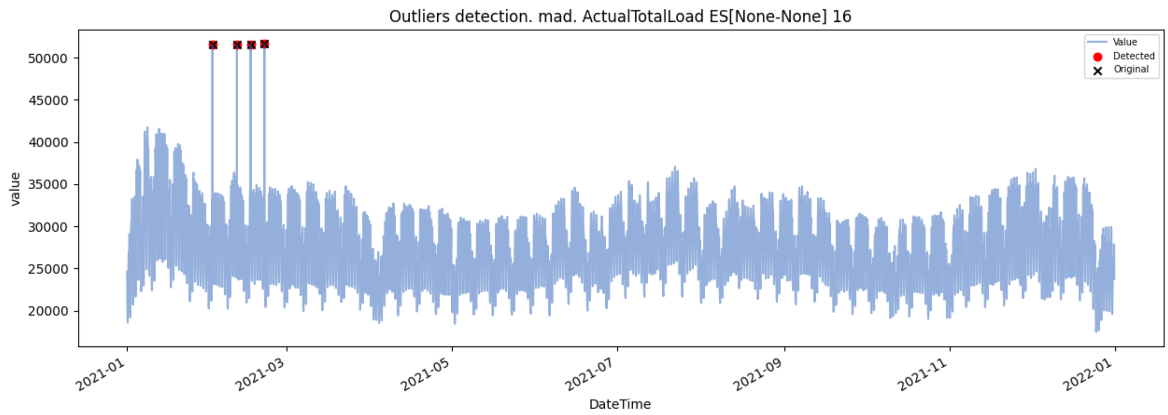
The results per each kind of time series introduced in the evaluation description are displayed below. The red dots are the predicted outliers detected in the time series by the outlier detection.

ActualTotalLoad.global_spike_plateau

LOF



MAD



Baseline based

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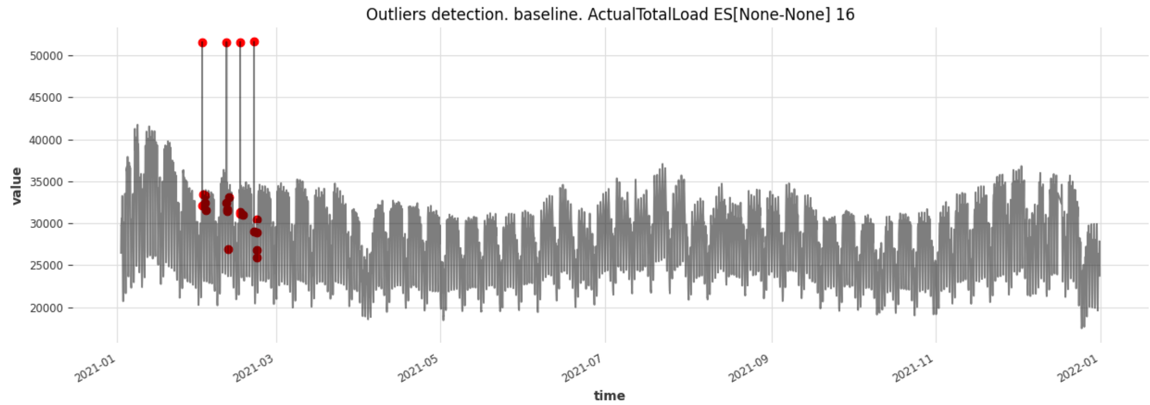
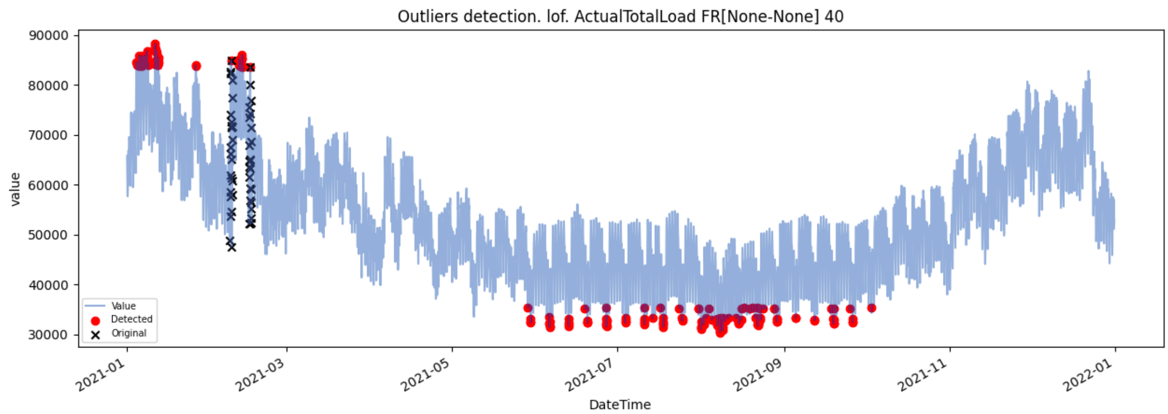
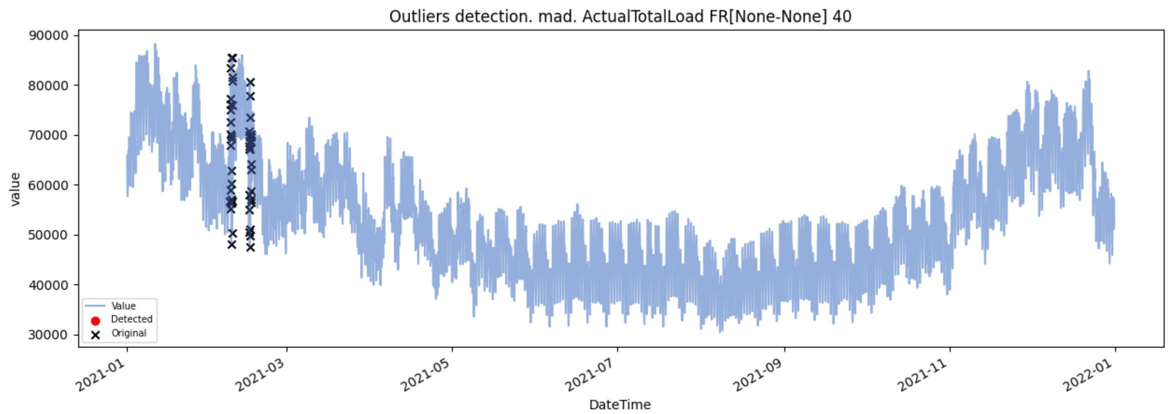


ActualTotalLoad.contextual

LOF



MAD



Baseline based

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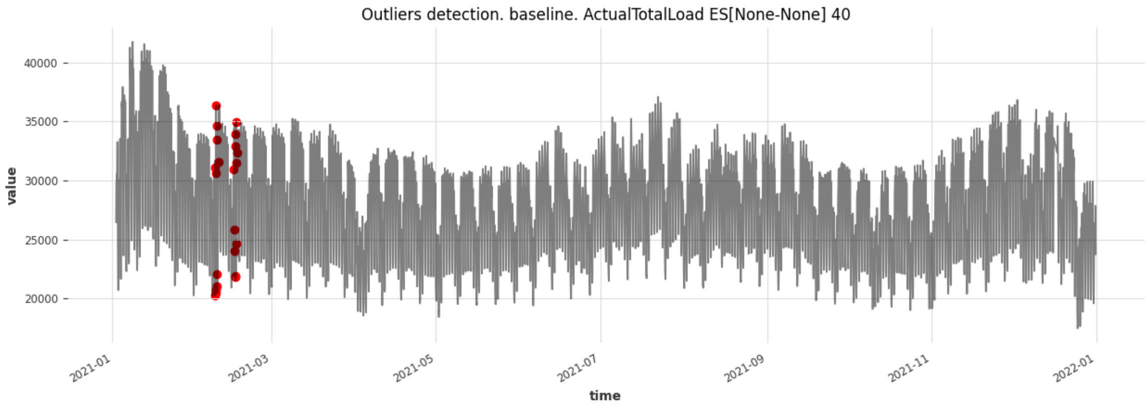
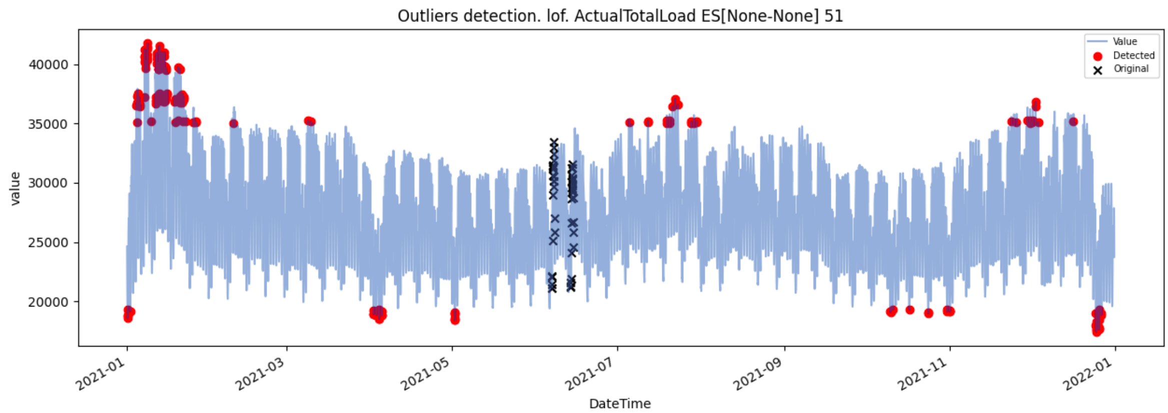
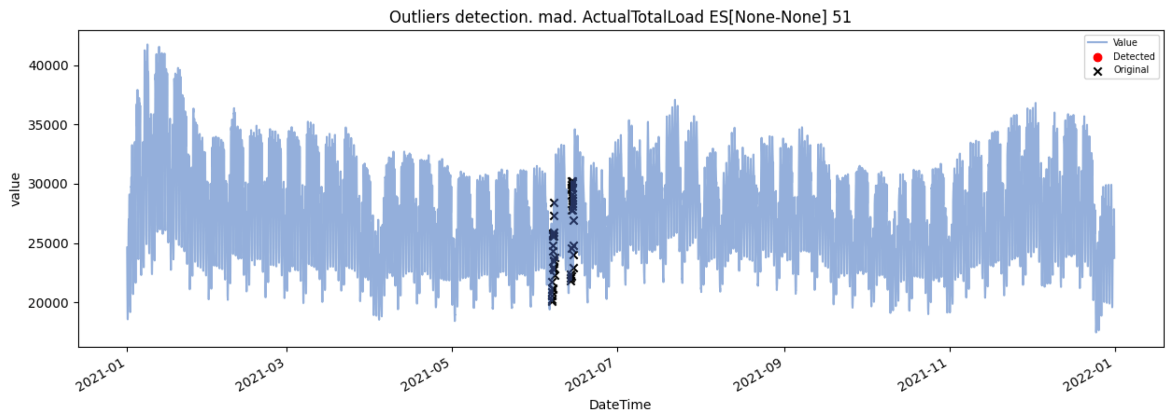


ActualTotalLoad.collective

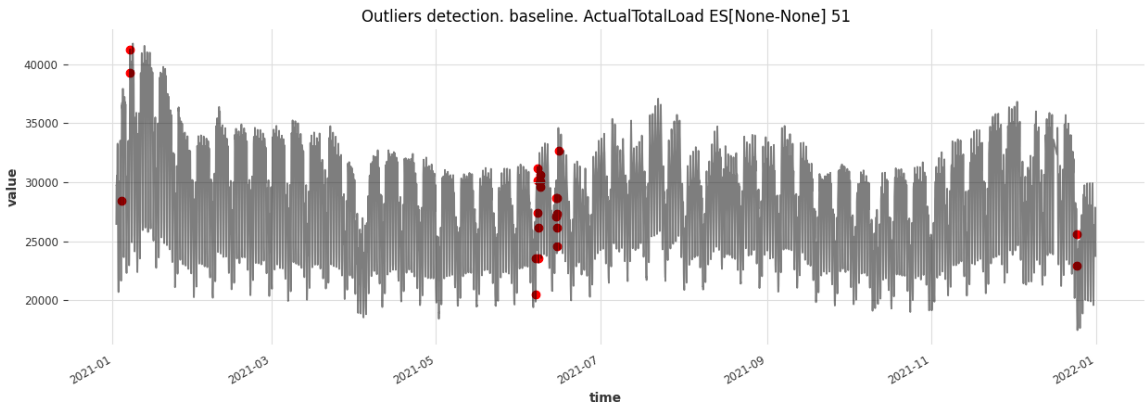
LOF



MAD

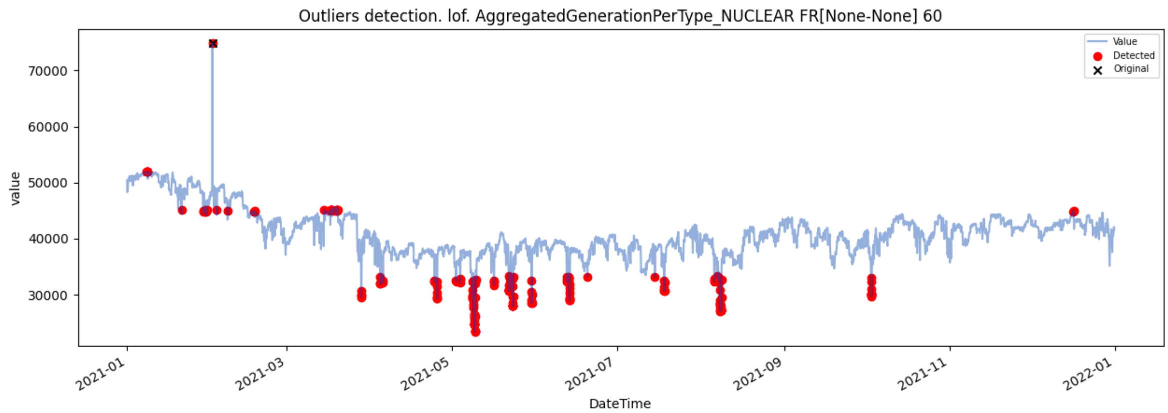


Baseline based

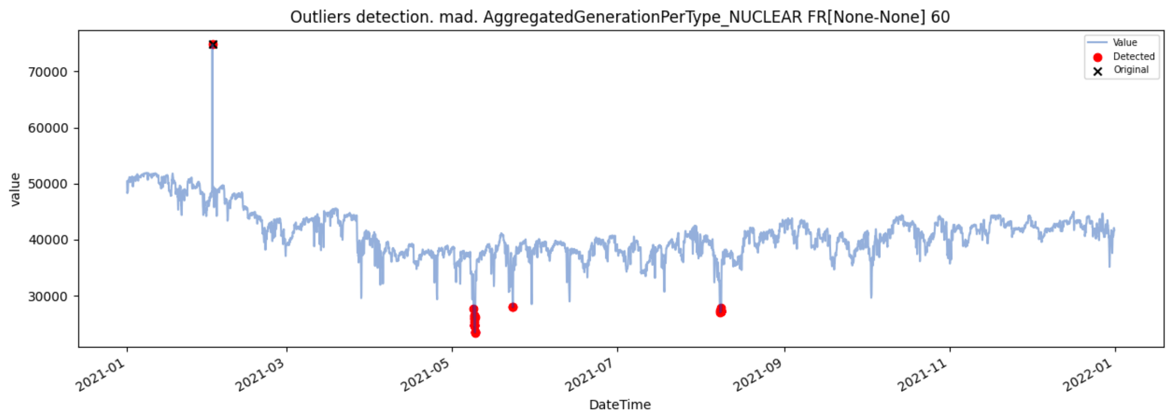


AggregatedGenerationPerType_NUCLEAR.global_spike_plateau

LOF



MAD



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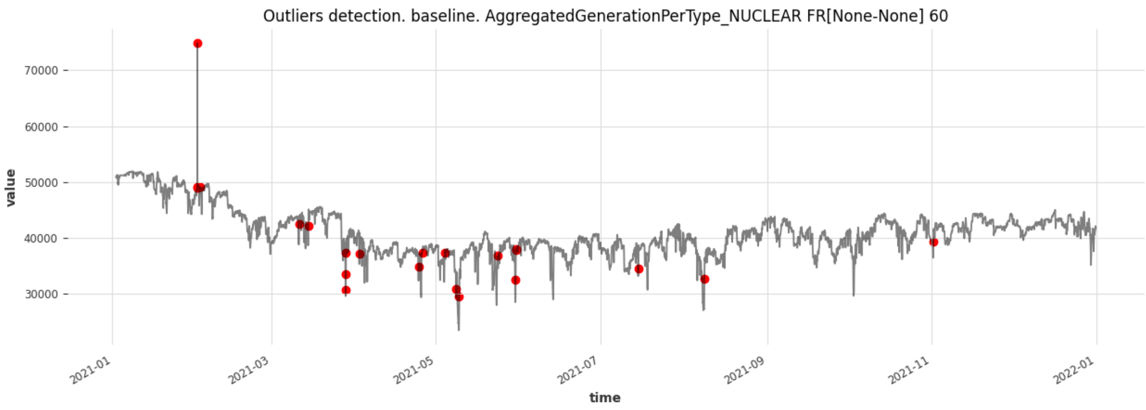
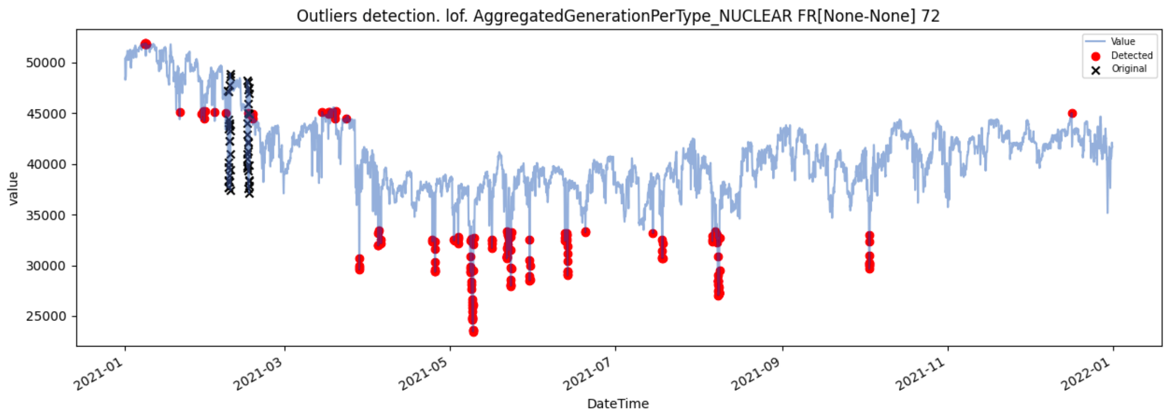
Baseline based

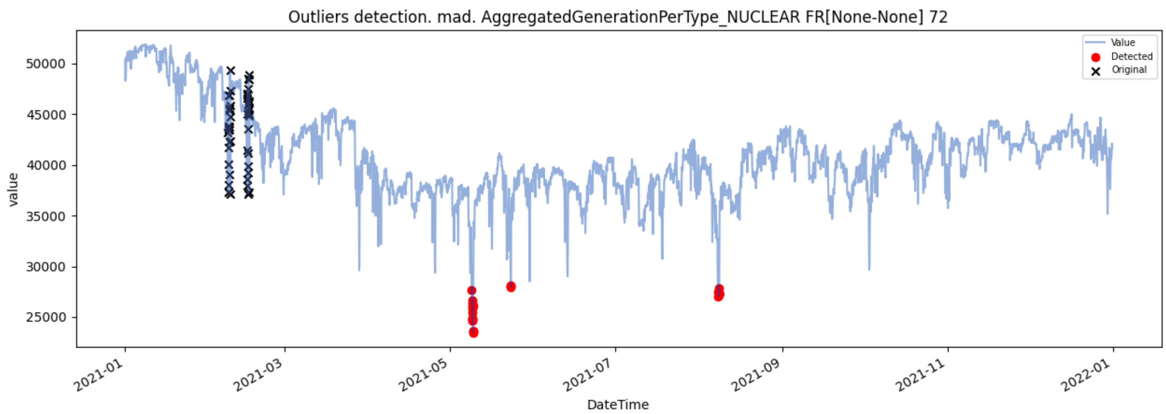


AggregatedGenerationPerType_NUCLEAR.contextual

LOF



MAD



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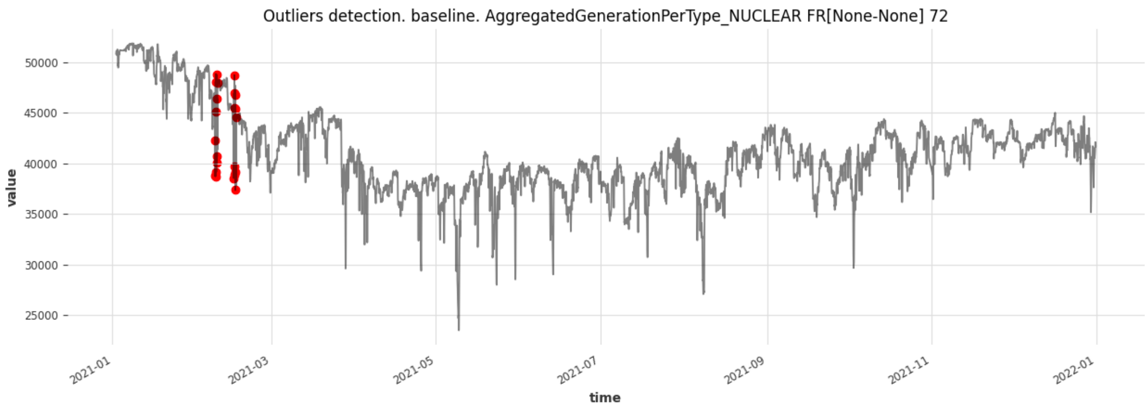
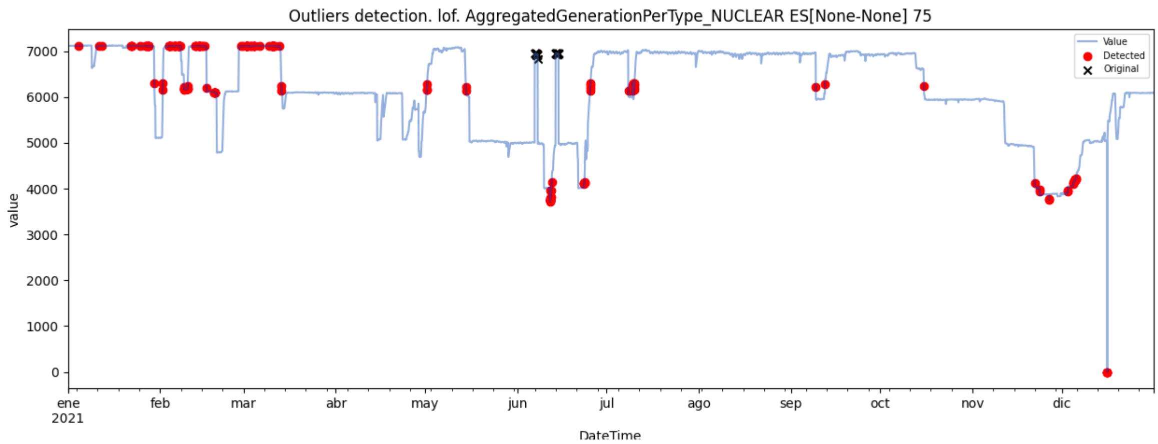
Baseline based



AggregatedGenerationPerType_NUCLEAR.collective

LOF



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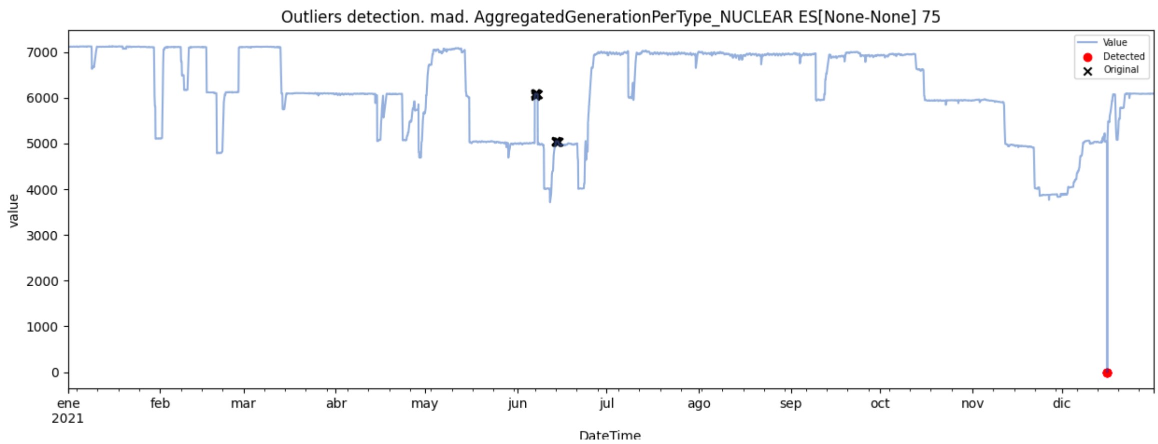

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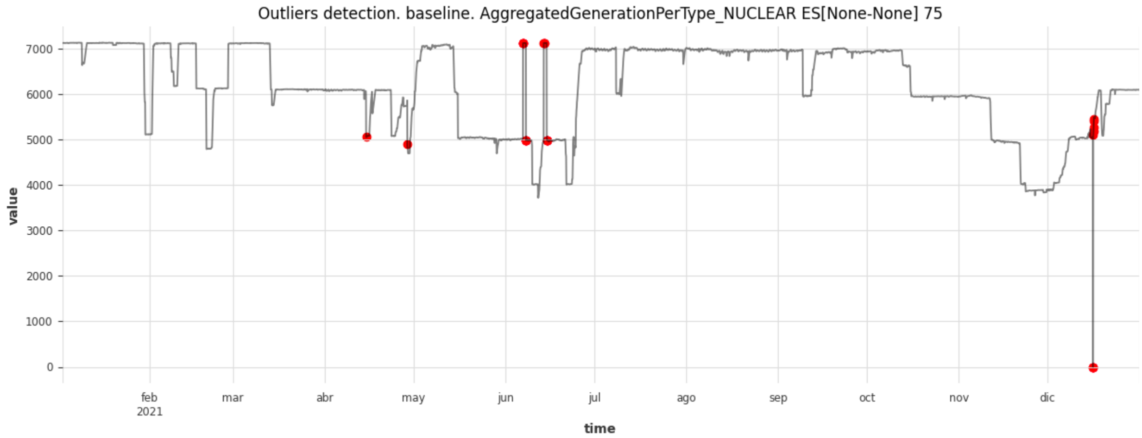
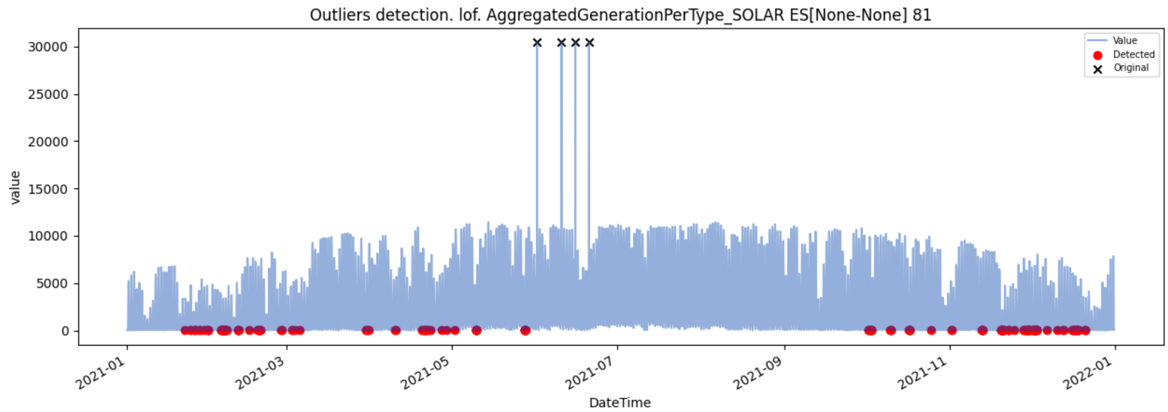


AggregatedGenerationPerType_SOLAR.global_spike_plateau

LOF



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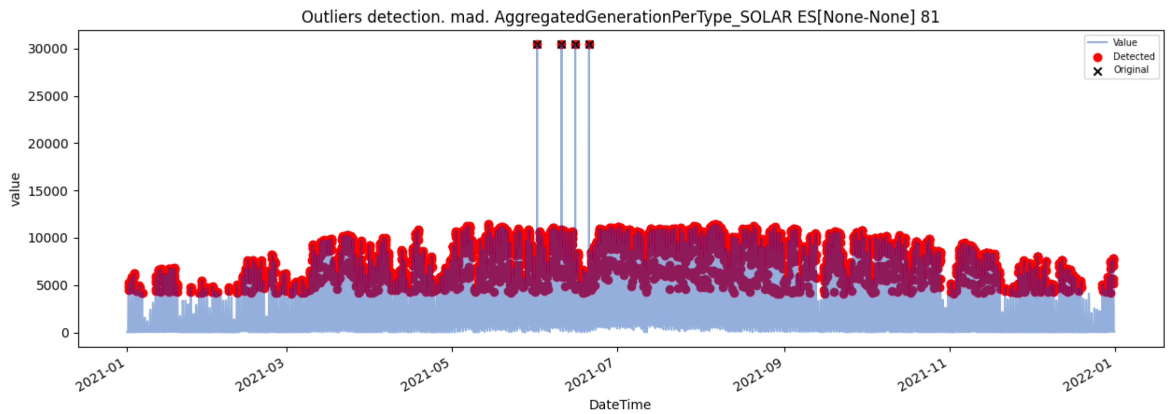

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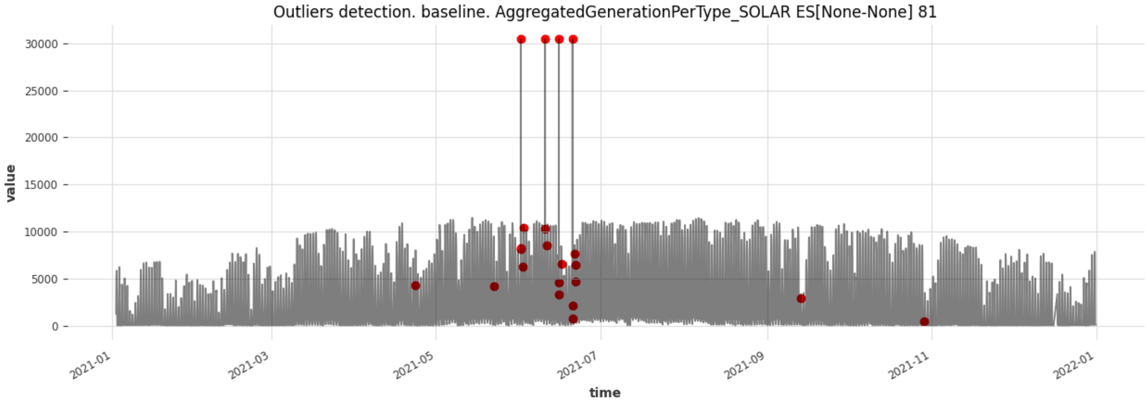
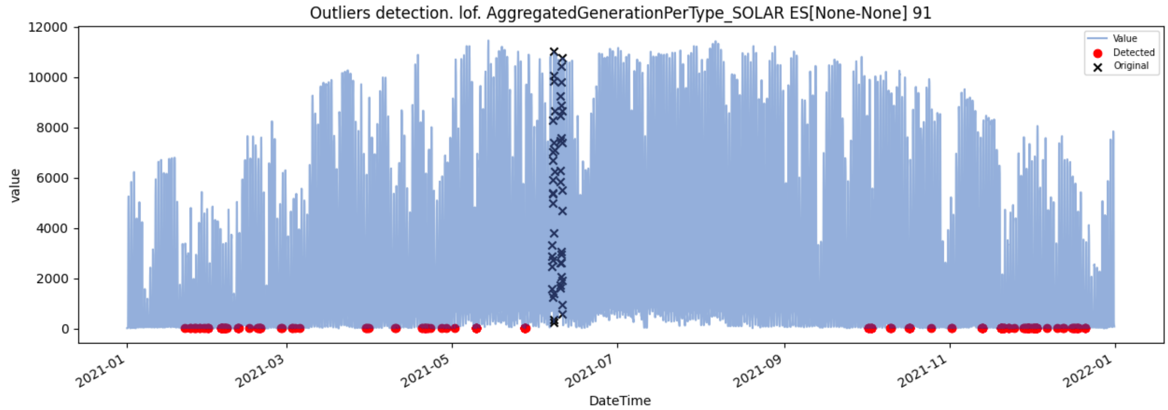
Baseline based



AggregatedGenerationPerType_SOLAR.contextual

LOF



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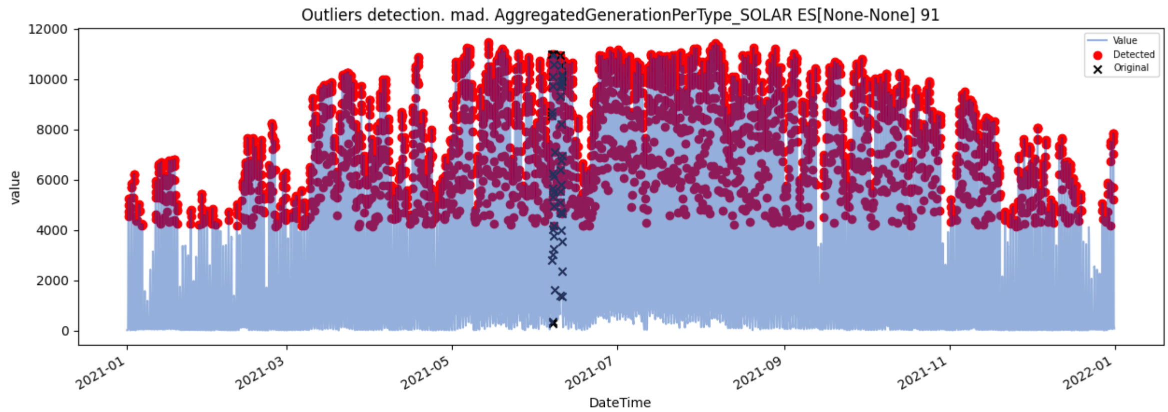

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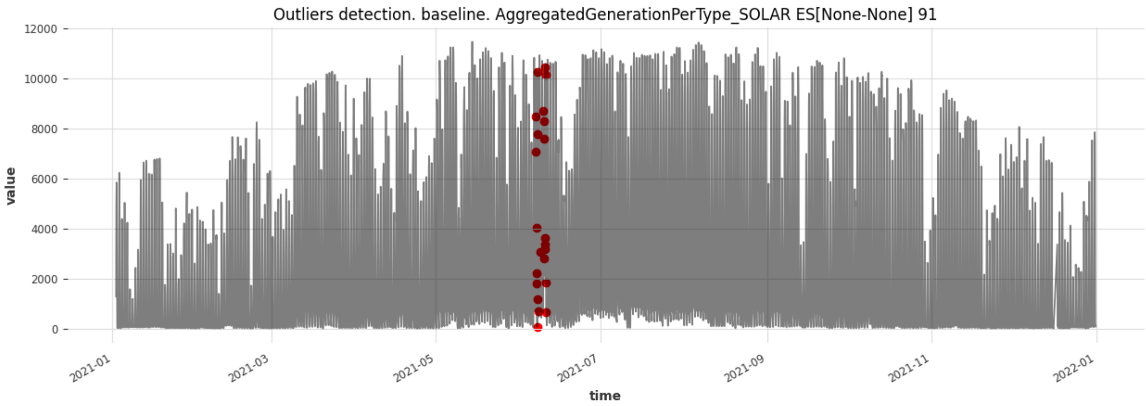
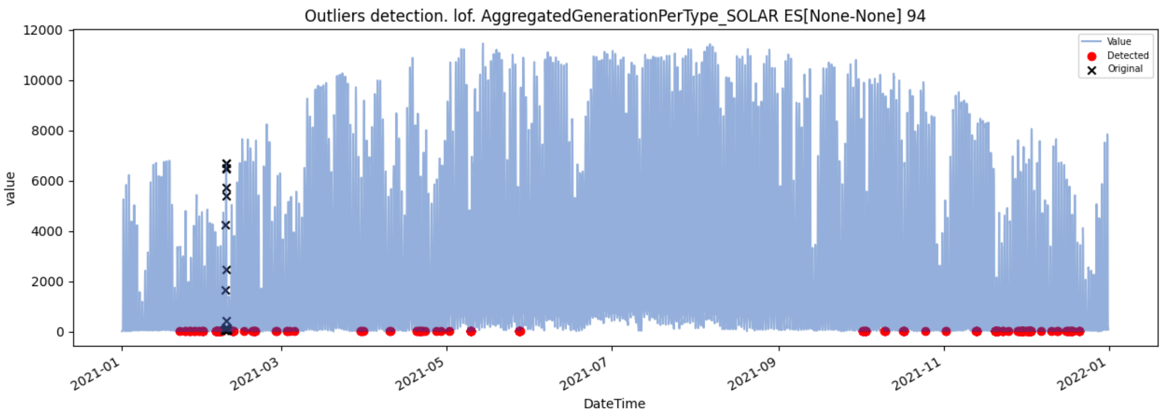
Baseline based



AggregatedGenerationPerType_SOLAR.collective

LOF



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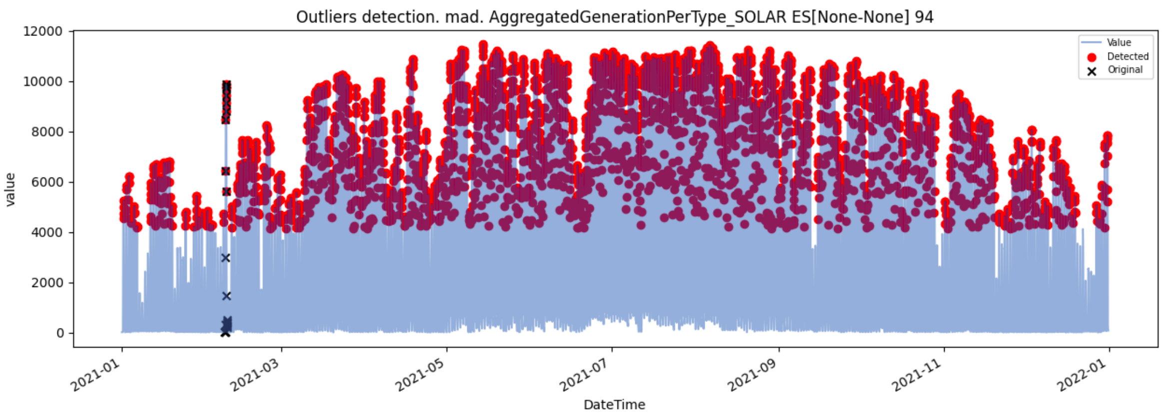

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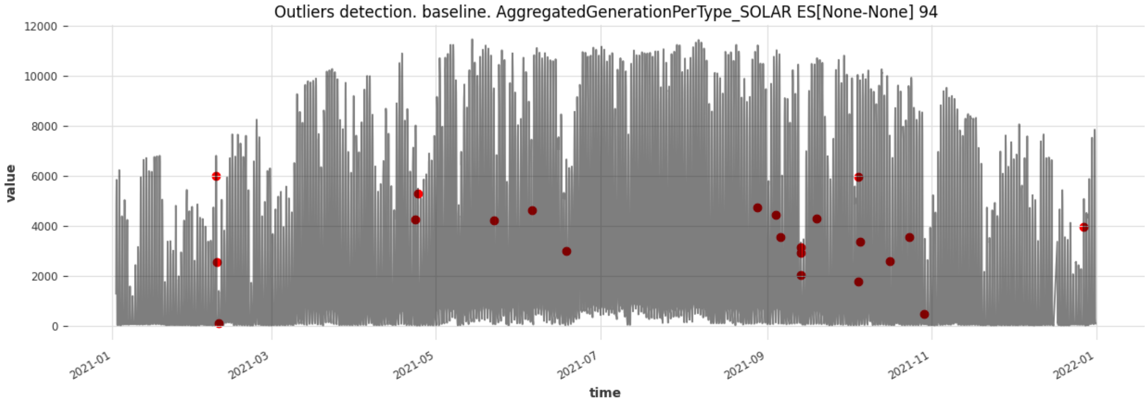
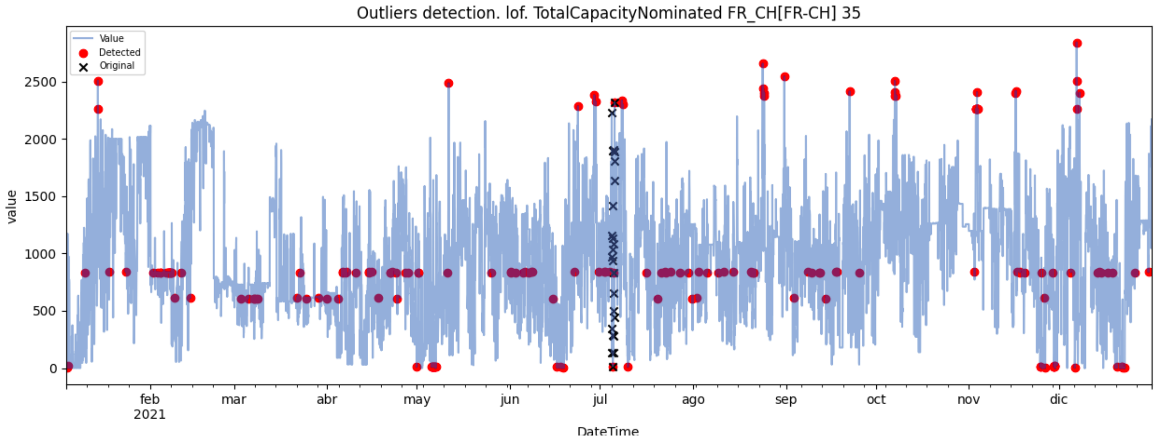
Baseline based



TotalCapacityNominated.contextual

LOF



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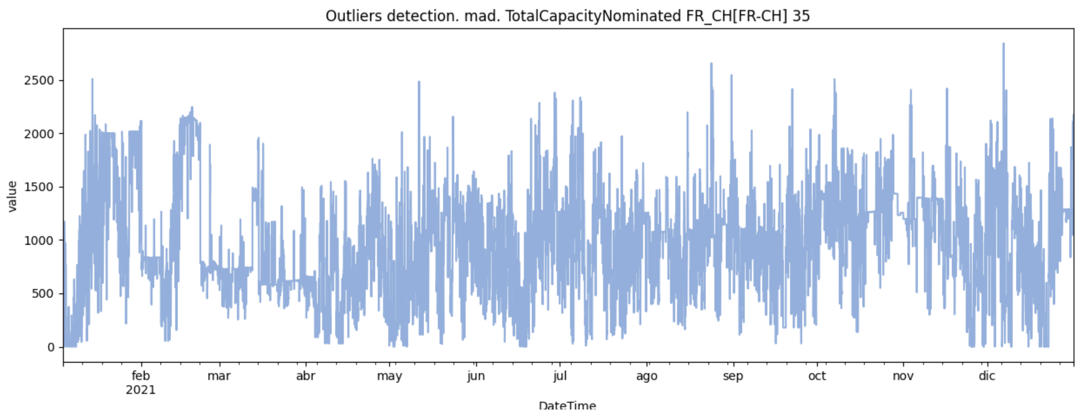

Baseline based

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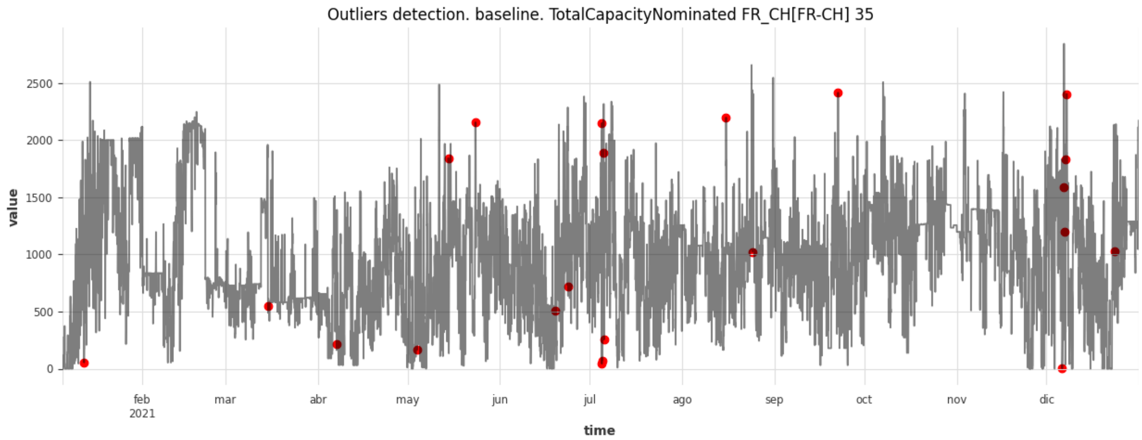
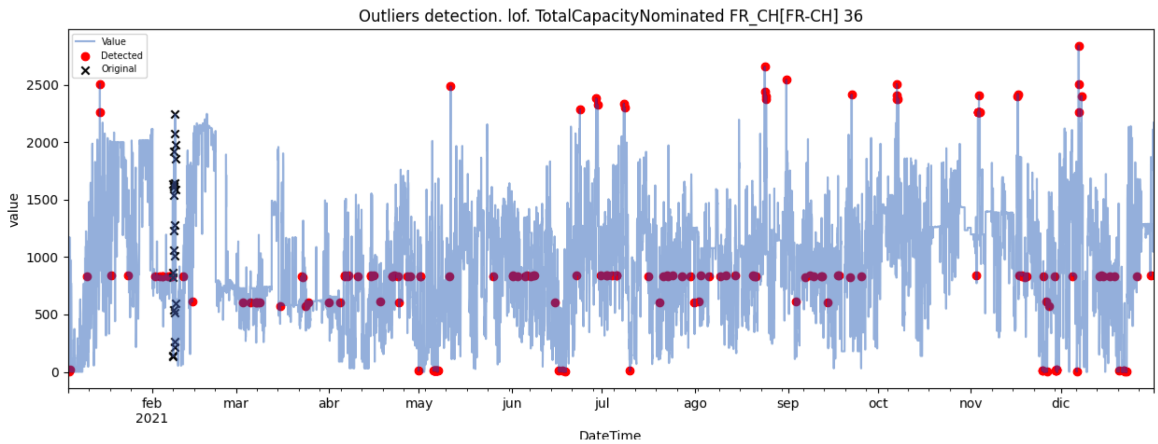


TotalCapacityNominated.collective

LOF



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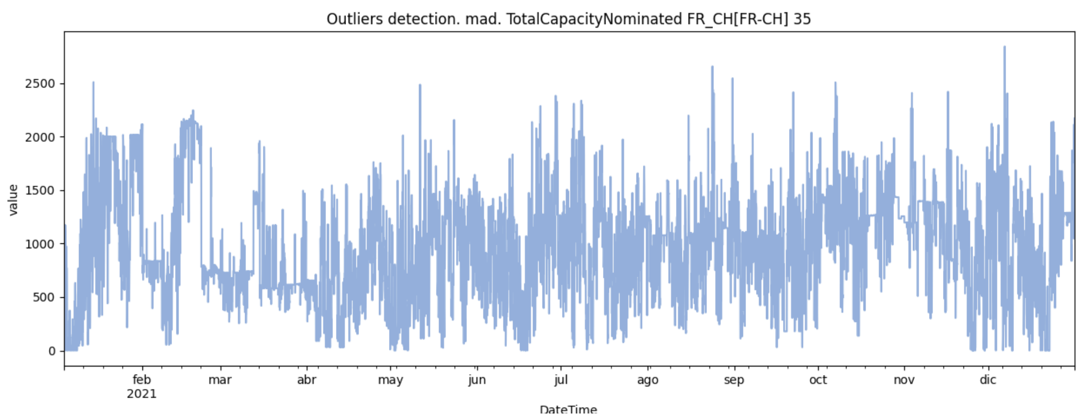
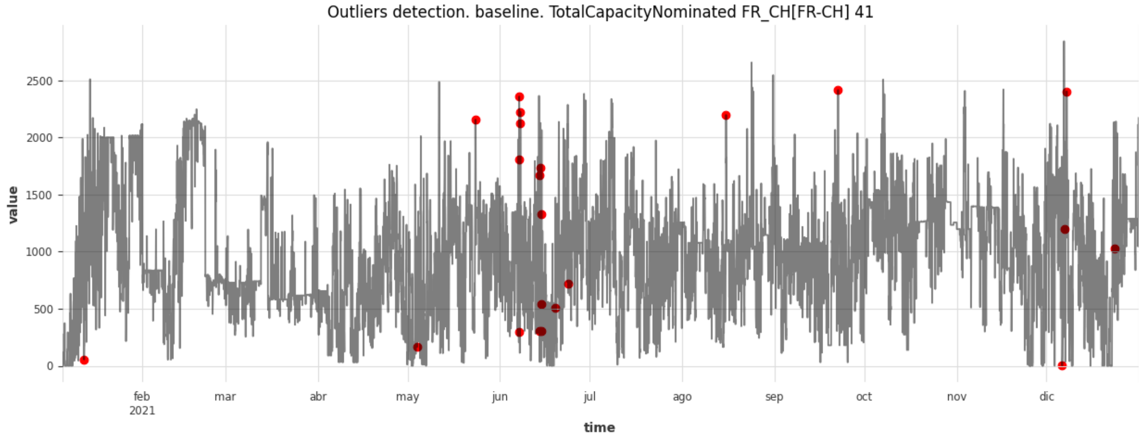


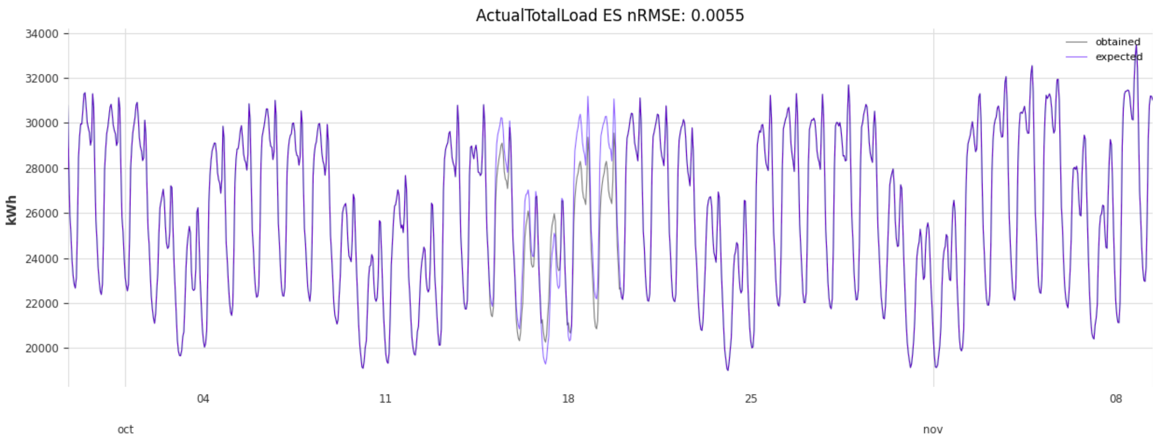
Baseline based

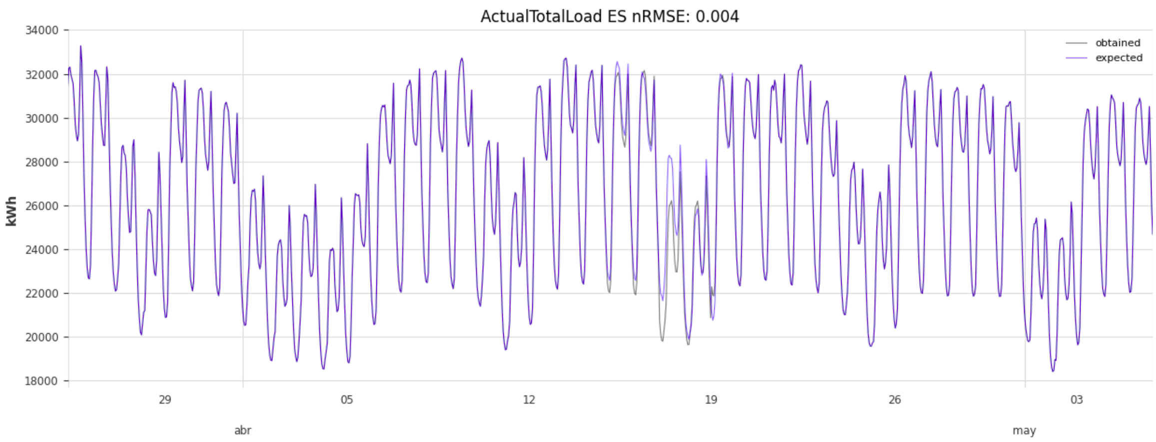

Outliers detection. baseline. TotalCapacityNominated FR_CH[FR-CH] 41
value
2500
2000
1500
1000
500
0
feb
2021
mar
abr
may
jun
jul
ago
sep
oct
nov
dic
time

A.2 Imputation evaluation results

The results per each kind of time series introduced in the evaluation description are displayed below. The blue time series corresponds to obtained imputation results and the orange time series corresponds to expected imputation results, so the original time series.

ActualTotalLoad.five_days





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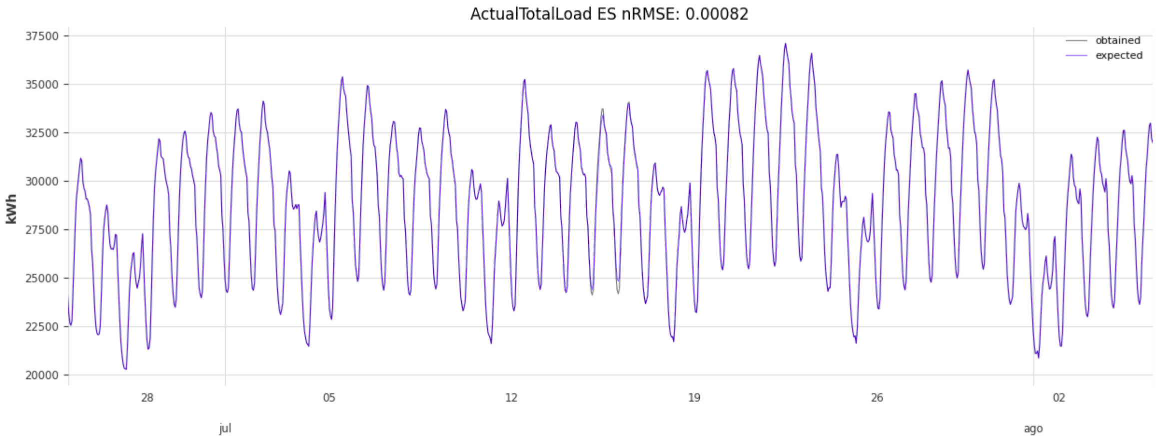
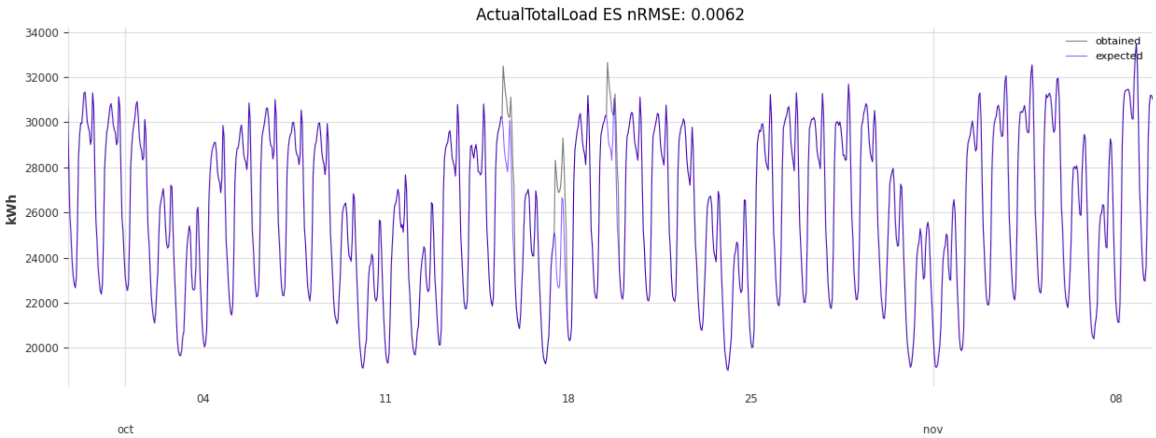
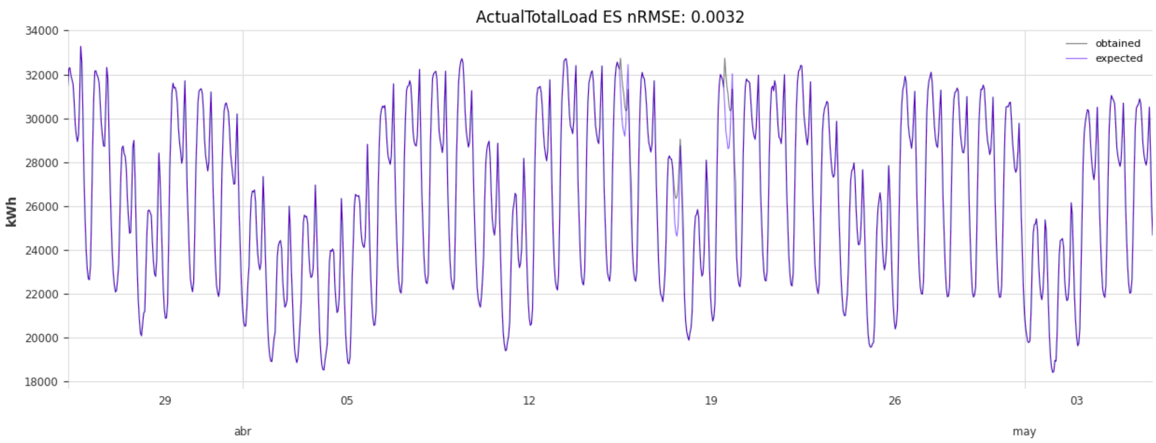


ActualTotalLoad.partial_days





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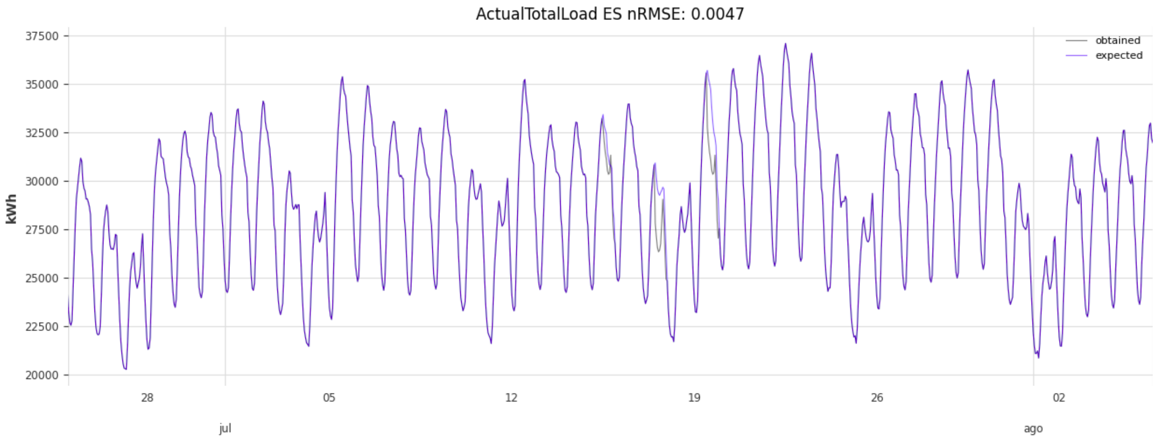
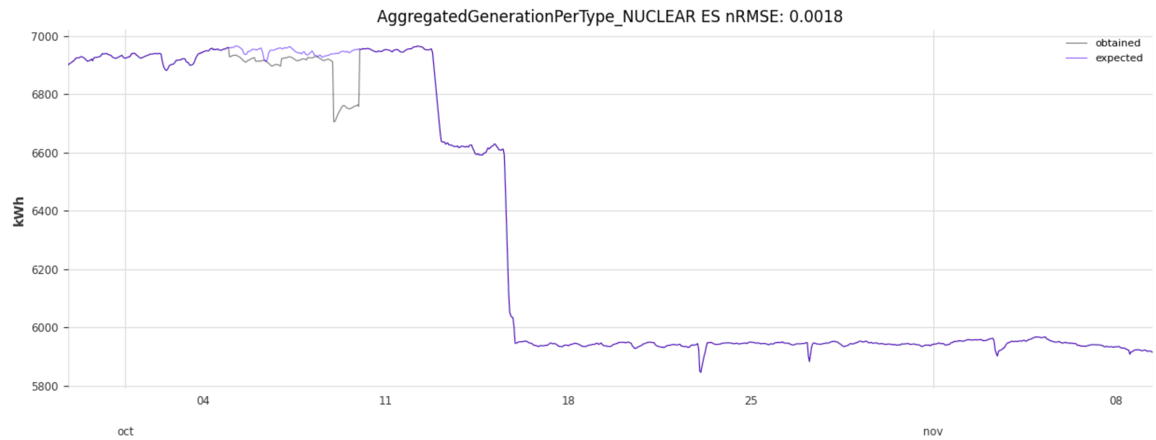
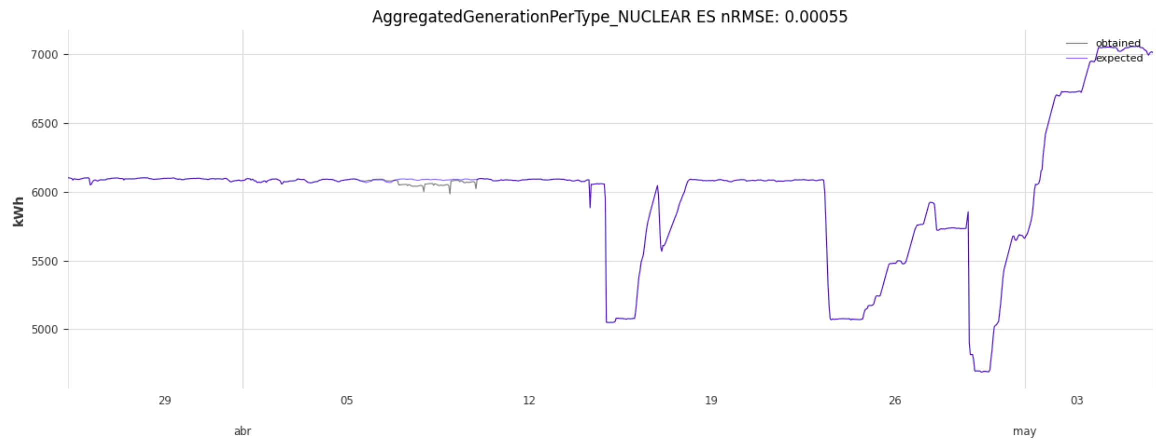
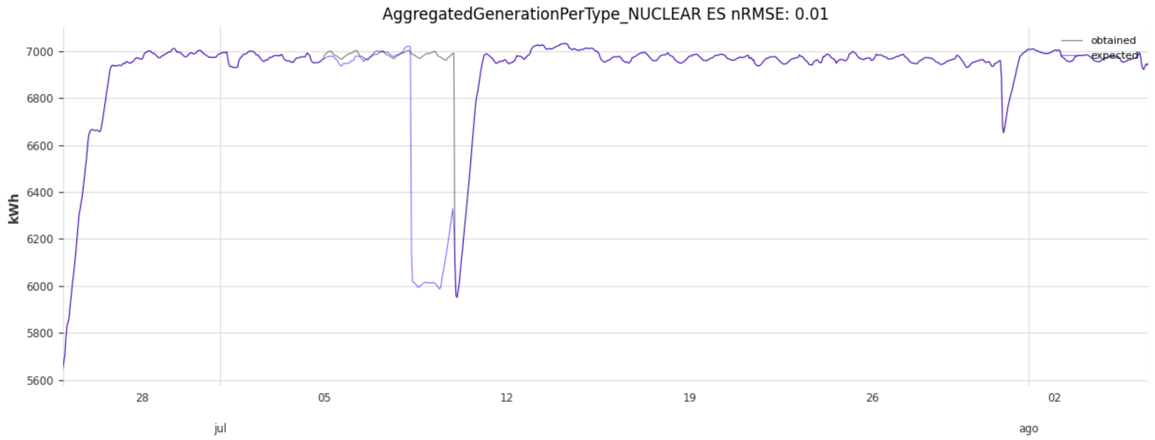


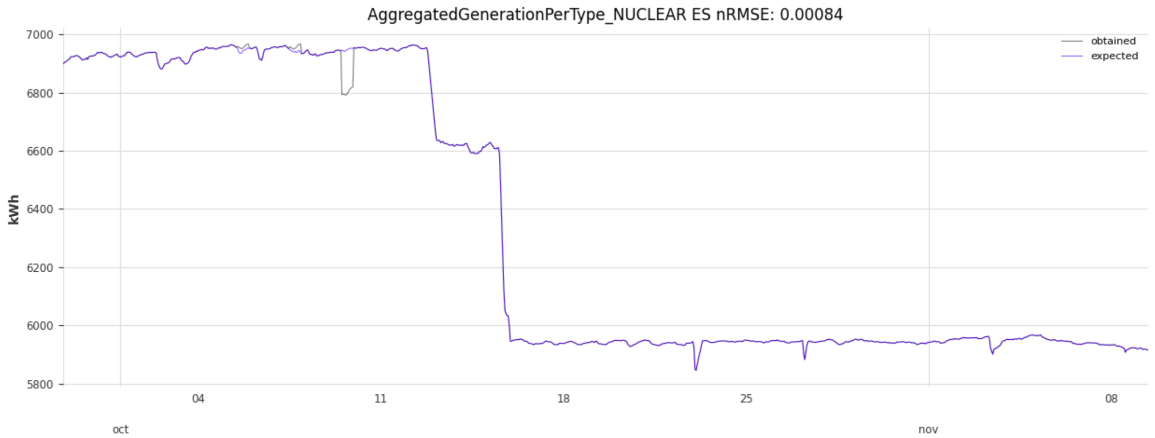
AggregatedGenerationPerType_NUCLEAR.five_days

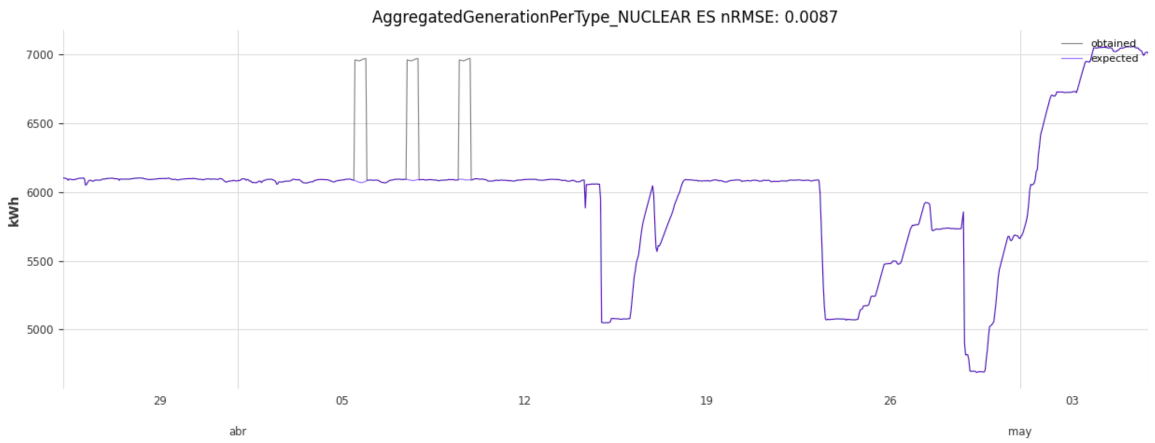


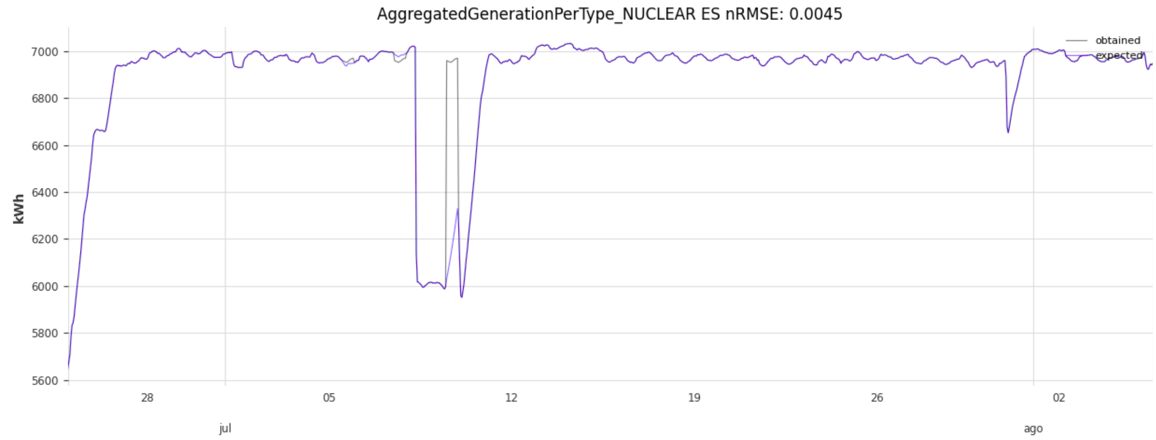




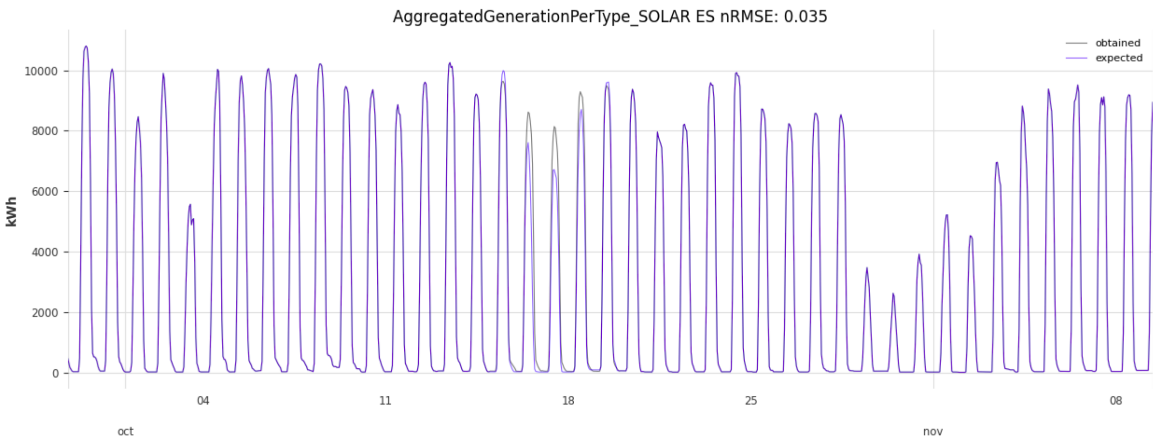
AggregatedGenerationPerType_NUCLEAR.partial_days

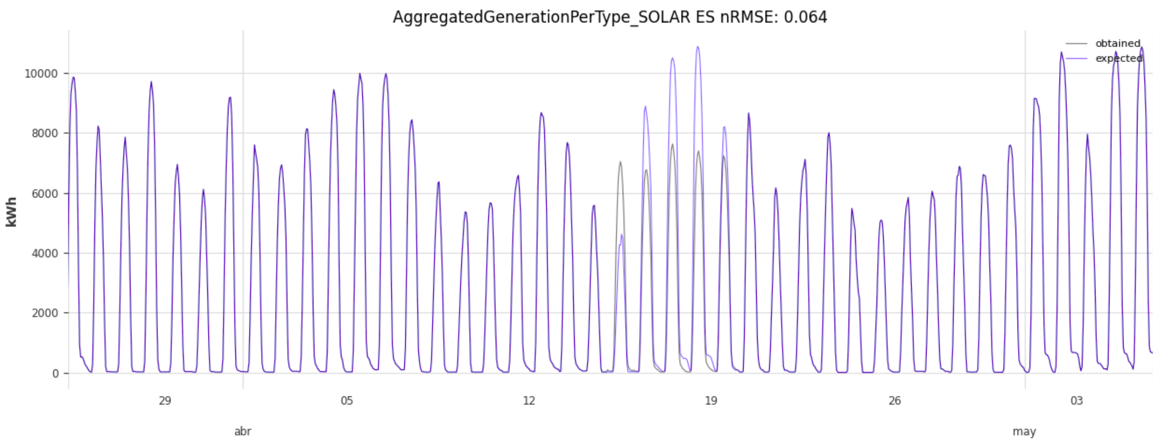


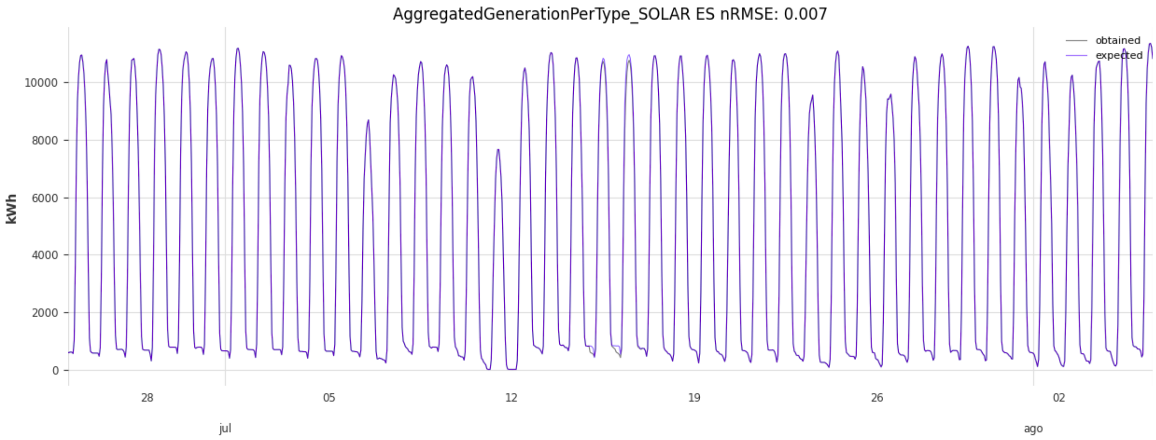




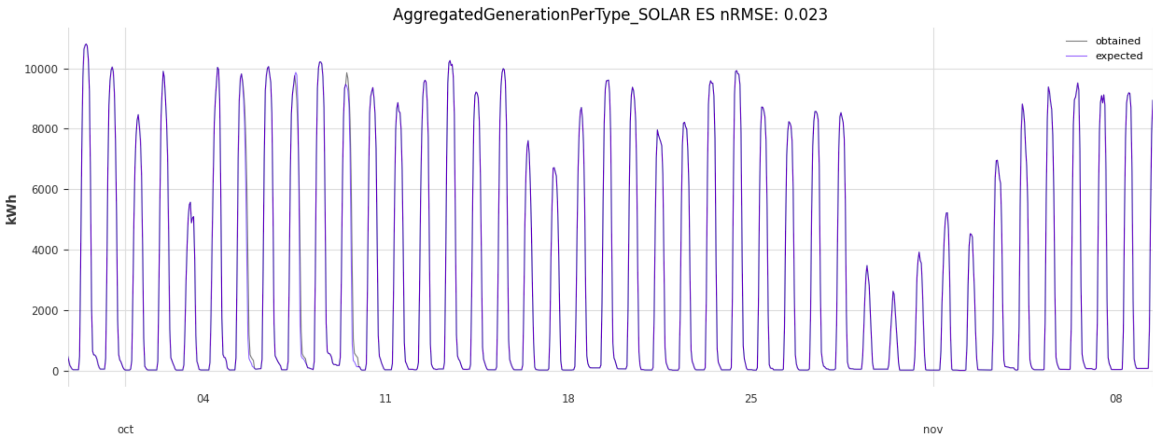
AggregatedGenerationPerType_SOLAR.five_days

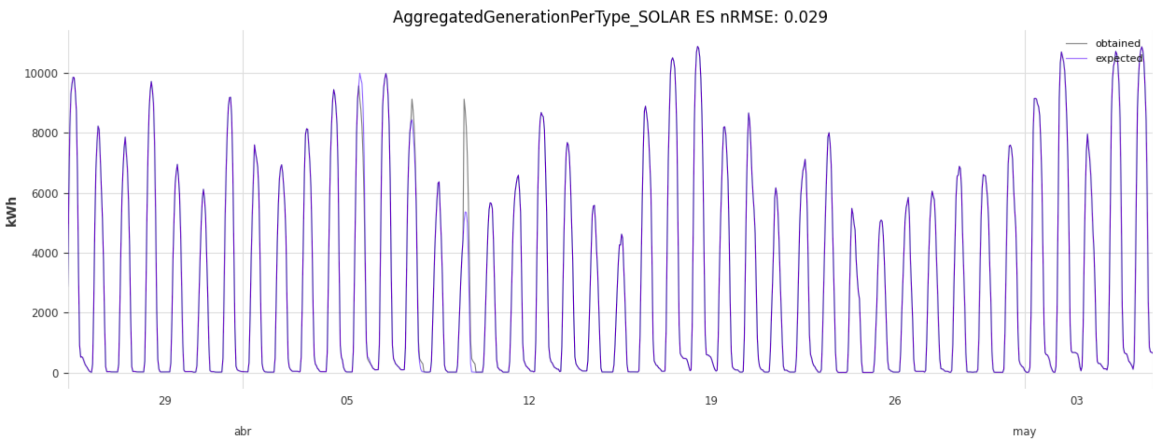


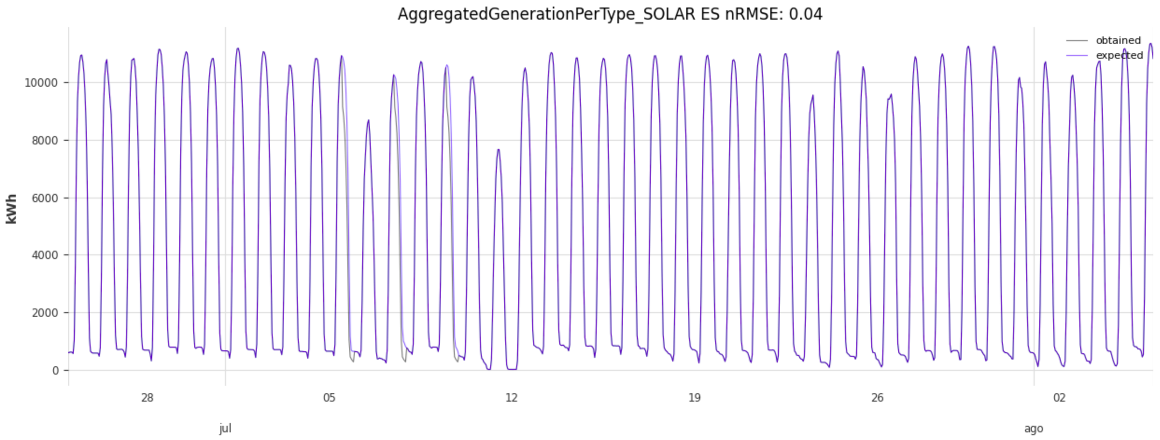




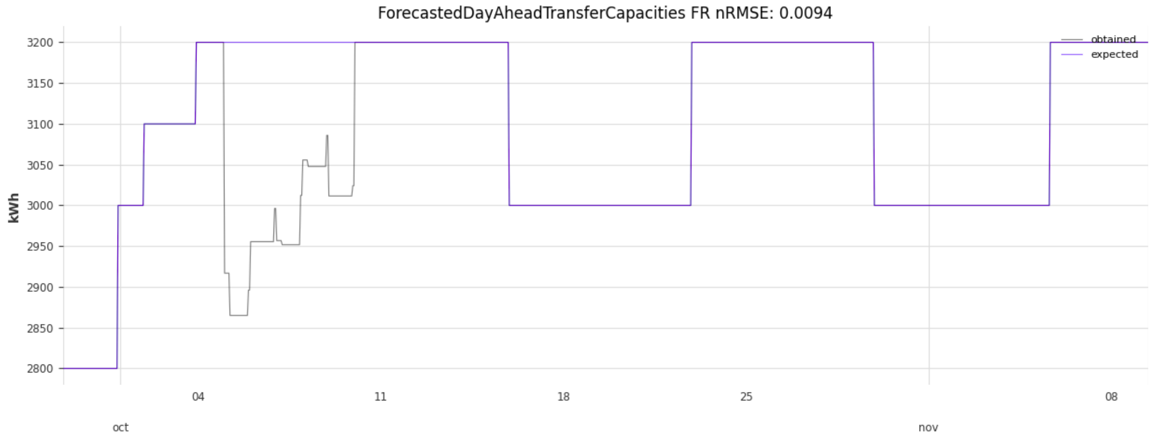
AggregatedGenerationPerType_SOLAR.partial_days

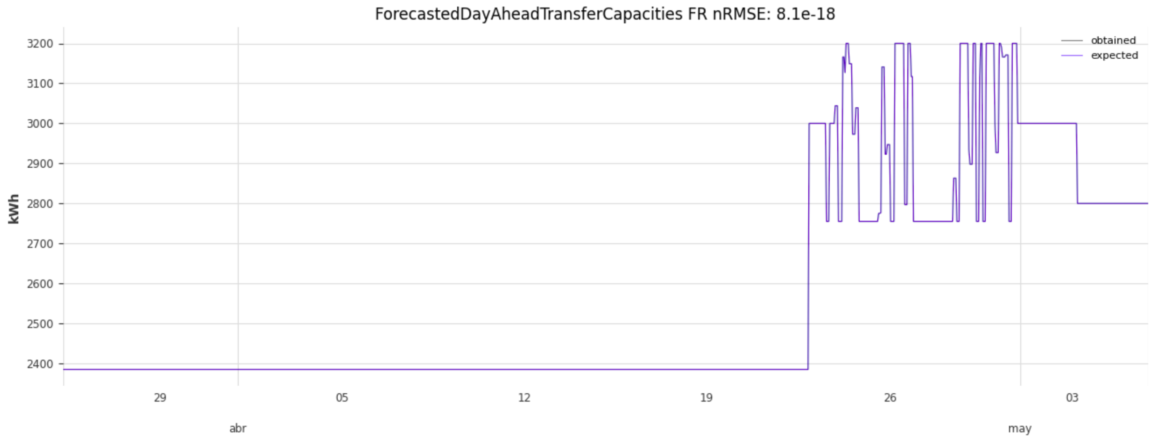






ForecastedDayAheadTransferCapacities.five_days





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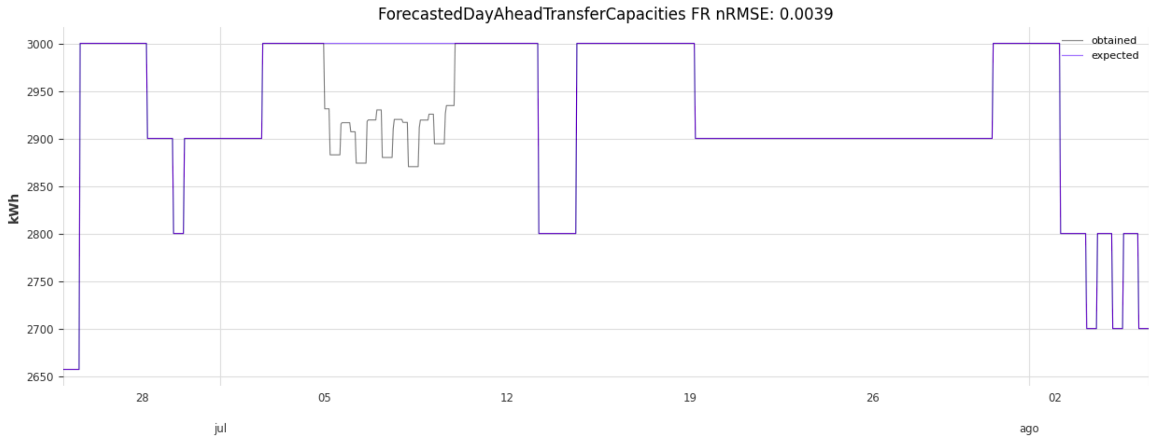
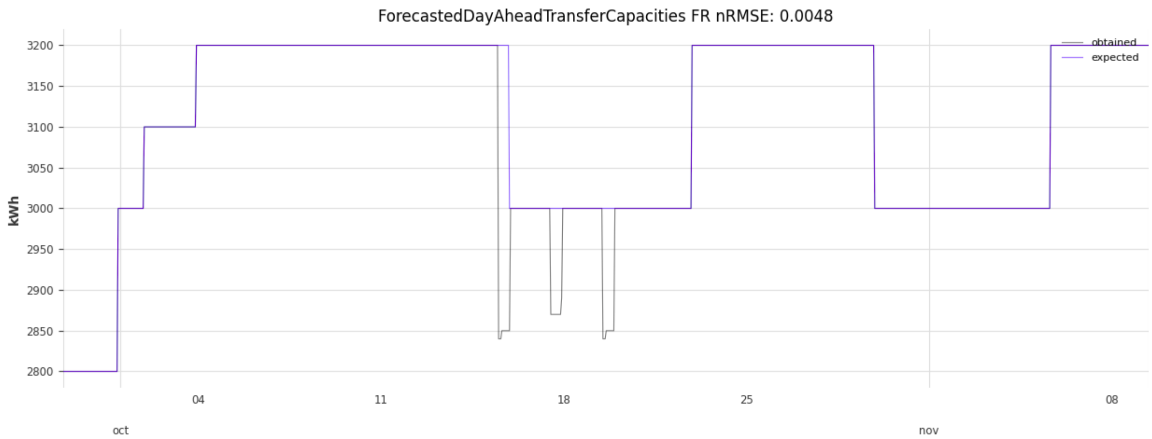
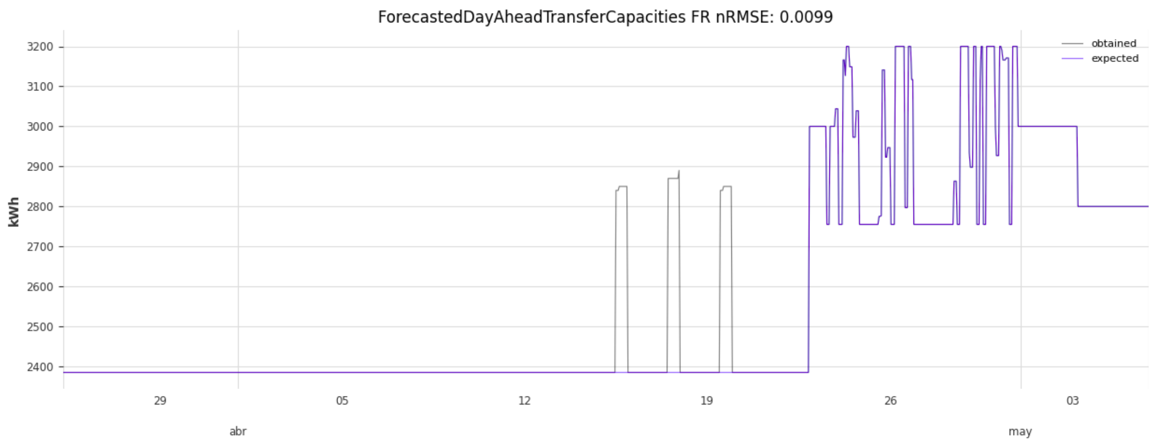
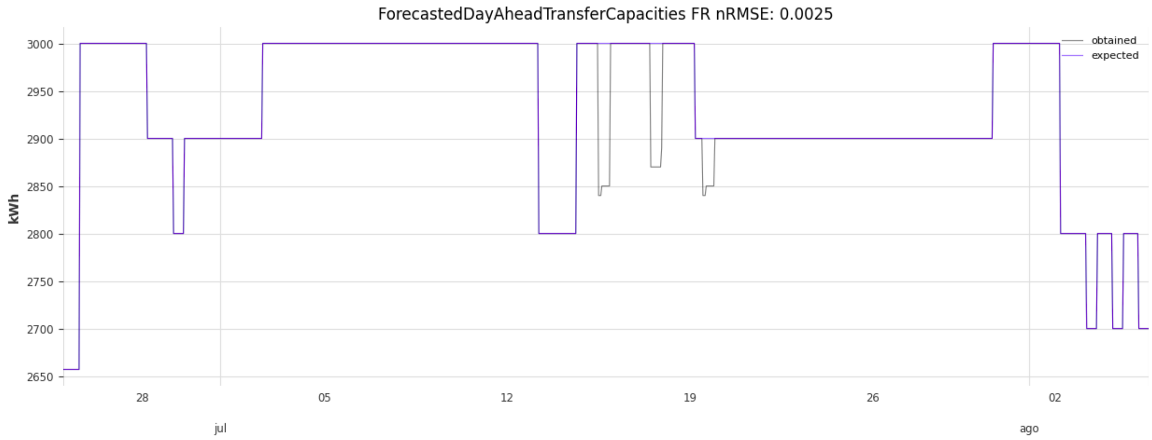


ForecastedDayAheadTransferCapacities.partial_days







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