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témavezető aláírása

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pályázó aláírása



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2 helység, ország

3 Amennyiben a poszter megjelent, a Magyar Pedagógia publikációs stílusa, illetve az abban nem tárgyalt esetekben az Amerikai Pszichológiai Társaság (APA) hivatkozási szabványa szerint.

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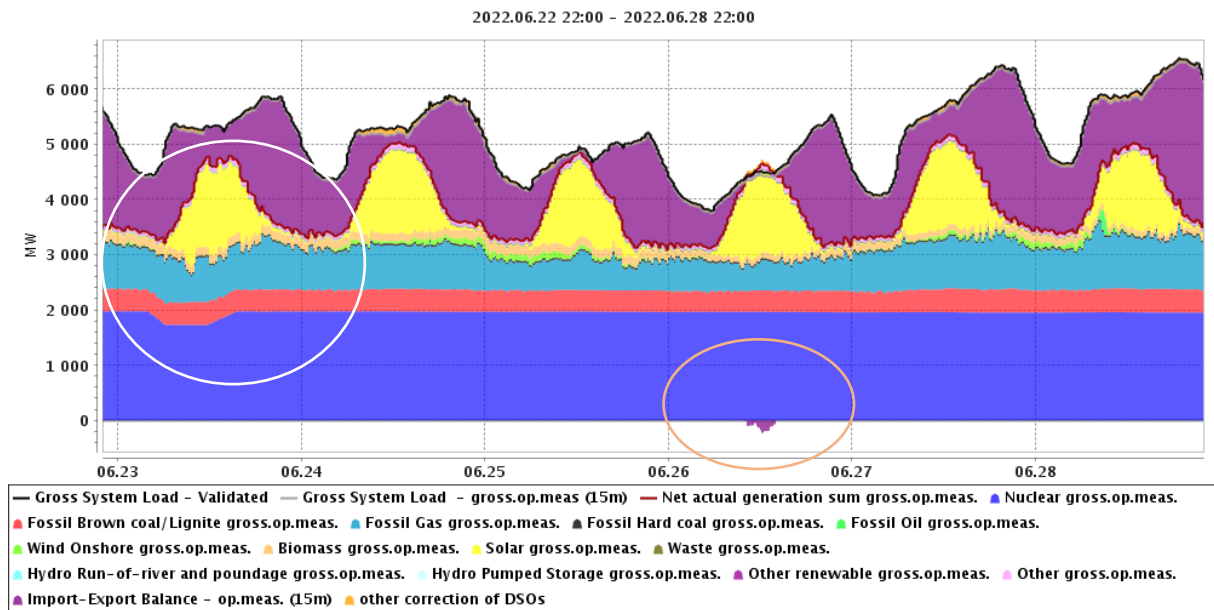
SUPPORTING THE NETWORK INTEGRATION OF RENEWABLE ENERGY SOURCES WITH MACHINE LEARNING FORECASTING

Abstract

The proposed presentation is a review of my latest research works in the field of renewable integration, including two different topics that are connected by the machine learning based methodology. First, some results and practical findings are shown about photovoltaic power forecasting, which is followed by introducing the key concepts and simulation results regarding an analysis over short-term imbalance forecasting for proactive mFRR controlling. These topics are highly related and are parts of a proposed long-term research framework to investigate further possibilities of reducing the system stress caused by the intermittent renewables by offering better designability and management with improved forecasts.

Introduction

The project framework started in 2020 with the topic of photovoltaic power forecasting with machine learning techniques. As for the motivation behind, the ever-growing ratio of the photovoltaic generation in the power grid [1] can be highlighted. In fact, in Hungary, the situation is even more acute, as it is a plain Central-European country surrounded by mountains, so the highest potential is in solar power as stated by the National Energy and Climate Plan [2], which supposed 6 and 12 GW installed capacity for 2030 and 2040. The current 2 GW industrial and 1.3 GW domestic capacity already causes serious import-export volatility as shown by the energy mix visualization of Figure 1. The first highlighted case represents a day



1. Figure: The Hungarian energy mix between June 22-28, 2022

with most likely a bad forecast resulting the load reduction of the Paks Nuclear Power plant, while four days later one could witness the rare situation of Hungary being a net exporter.

The motivation is clear, the power system must evolve to fulfill the modern requirements provided by the distributed intermittent generation by renewables and the volatility of consumption. On one hand, it is obvious that more flexibility is needed from the hardware side, however on the management side there might be some low hanging fruits to take. The main idea is that a better forecast means better scheduling, which allows more favorable operation on a lower cost-level. In the followings, some parts of the proposed framework are presented in chronological order.

Solar power forecasting

The models for photovoltaic power forecasting can be generally categorized as physical, statistical or hybrid methods. In the past years' research activity, the ratio of statistical models is growing rapidly, already reaching the level of traditional physical ones [3]. Some key differences of the approaches are listed on Table 1.

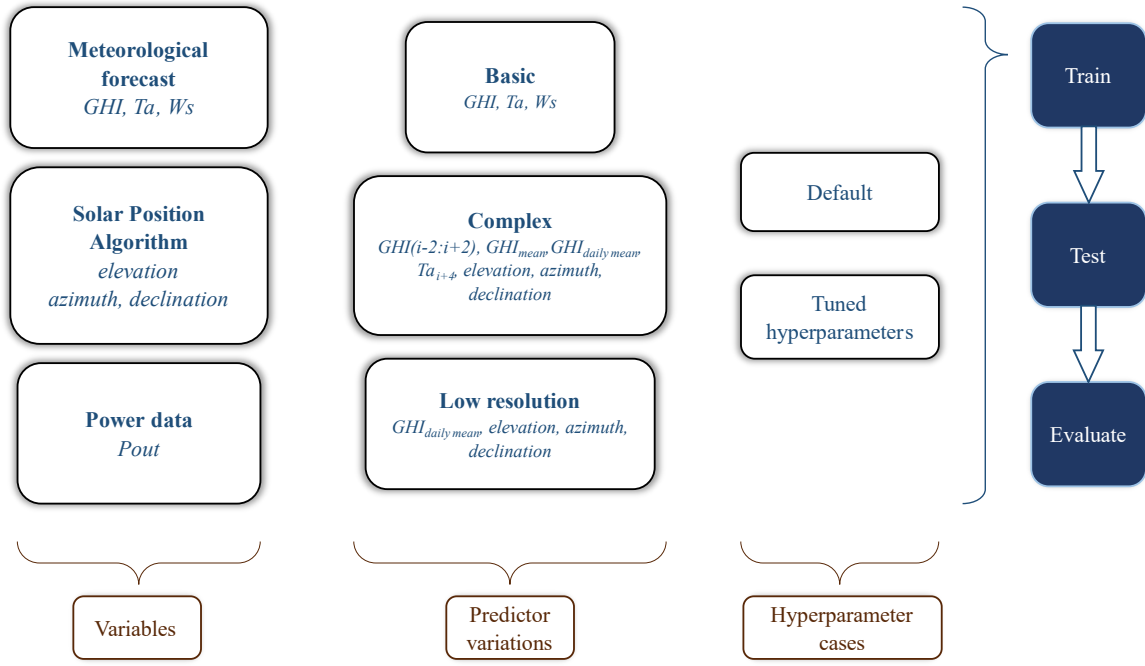
1. Table: comparison of the main features of physical and statistical concepts.

Physical modelling		Data-driven methods ANN, SVM, RF, XGBoost etc.
Pros:	• Well-published model chain concepts • No previous data needed • Same accuracy level from the first day (except from post-tuning)	• No need for design data • Able to cope with local features (unique weather, shadowing) • Capable of decreasing weather forecast inaccuracy
Cons:	• Sensitive for design data and it's quality • Not able to decrease weather forecast errors • Feedback on local features (weather, shadowing) is harder	• Previous data needed ○ same weather model! ○ undisturbed production is necessary ▪ <u>self-regulating can be an issue!</u> • Post-processing needed

For physical or hybrid models the following papers are suggested: [4], [5], however this framework focuses on statistical methods so far.

In a recent publication 24 machine learning models were tested with different predictor combinations for day-ahead photovoltaic power forecasting with the following highlights [6]:

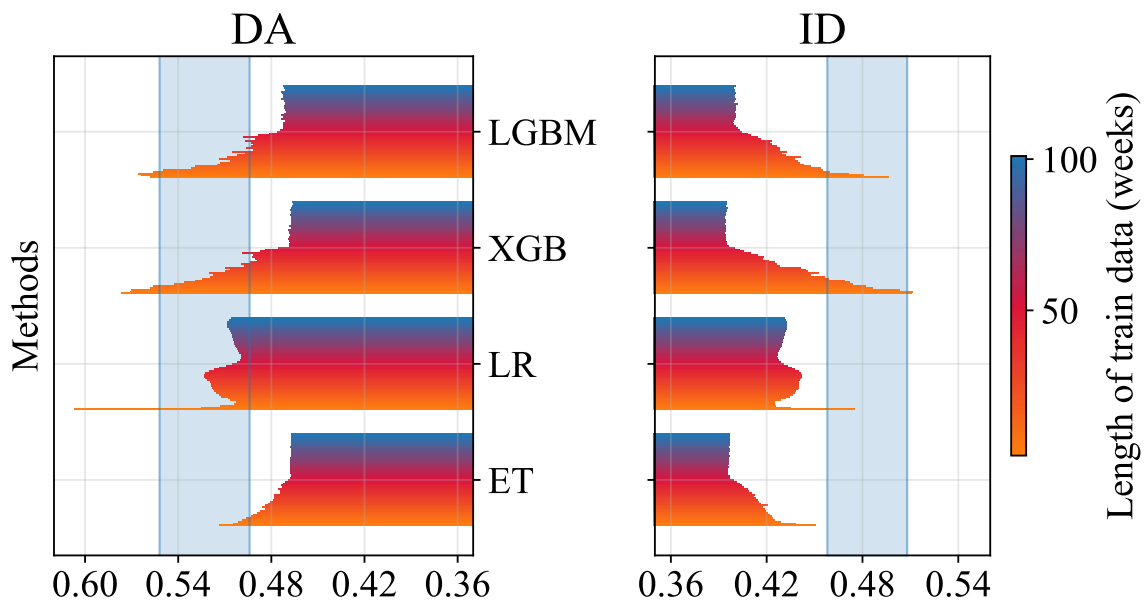
- Kernel ridge and multilayer perceptron are the overall most accurate models.
- Predictor selection is even more important than model selection.
- Hyperparameter optimization is essential for the highest accuracy.
- Up to 13.9% RMSE improvement over a baseline linear regression model.



2. Figure: Predictor combinations and the base concept of the study[6]

This research has been lately extended by an exhaustive investigation on the effect of training-time using some powerful but fast-learning models [7]. The test compared for every 2-week test period, 51 different train length settings from 2 to 102 weeks. The learning curves of the tested models can be seen on Figure 3.

Average nRMSE results with increasing the training time



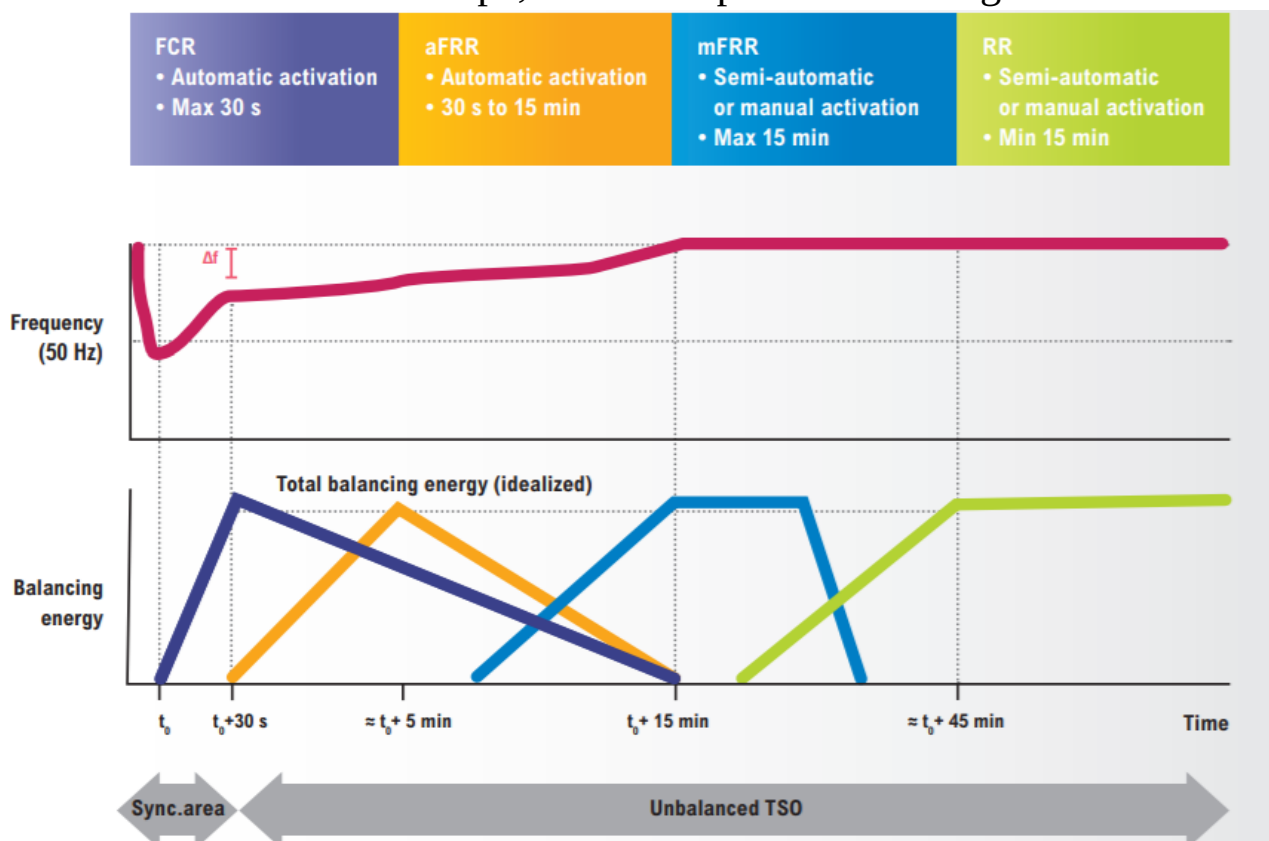
3. Figure: Learning curves compared to the range of physical models from [4].

The results of the study showed the followings:

- The measured power data from the recent past (more than 1.5h) has significant effect on the intraday scheduling with more than 15% for nRMSE improvement, almost twice higher than without.
- ExtraTrees Regression is an accurate method, reaching physical models (same weather forecast) in 12/2 weeks in DA/ID horizon.
- XGBoost and LGBM needs more attention to proper regularization and hyperparameter tuning.
- It is not recommended to use more than 52-54 weeks for training since the added value is negligible.
- Comparing the results of studies using different data length can be based on the presented learning curves.

Short-term imbalance forecasting for proactive mFRR controlling

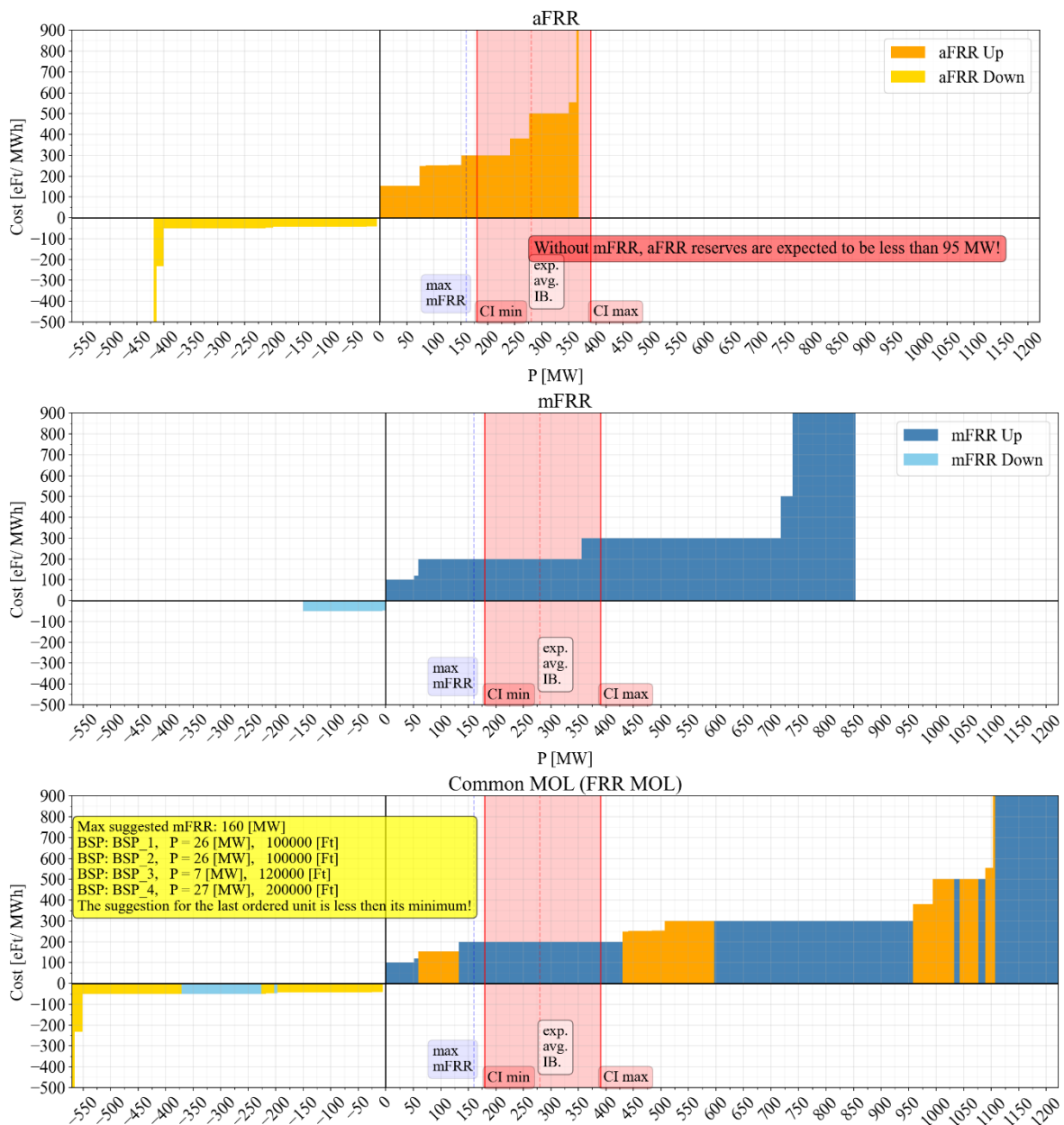
To understand this topic a general knowledge about the frequency restoration reserves is needed where the ENTSO-E's definitions are the standards in most of Europe, which are presented on Figure 4.



4. Figure: Standard design for the activating balancing reserves [9]

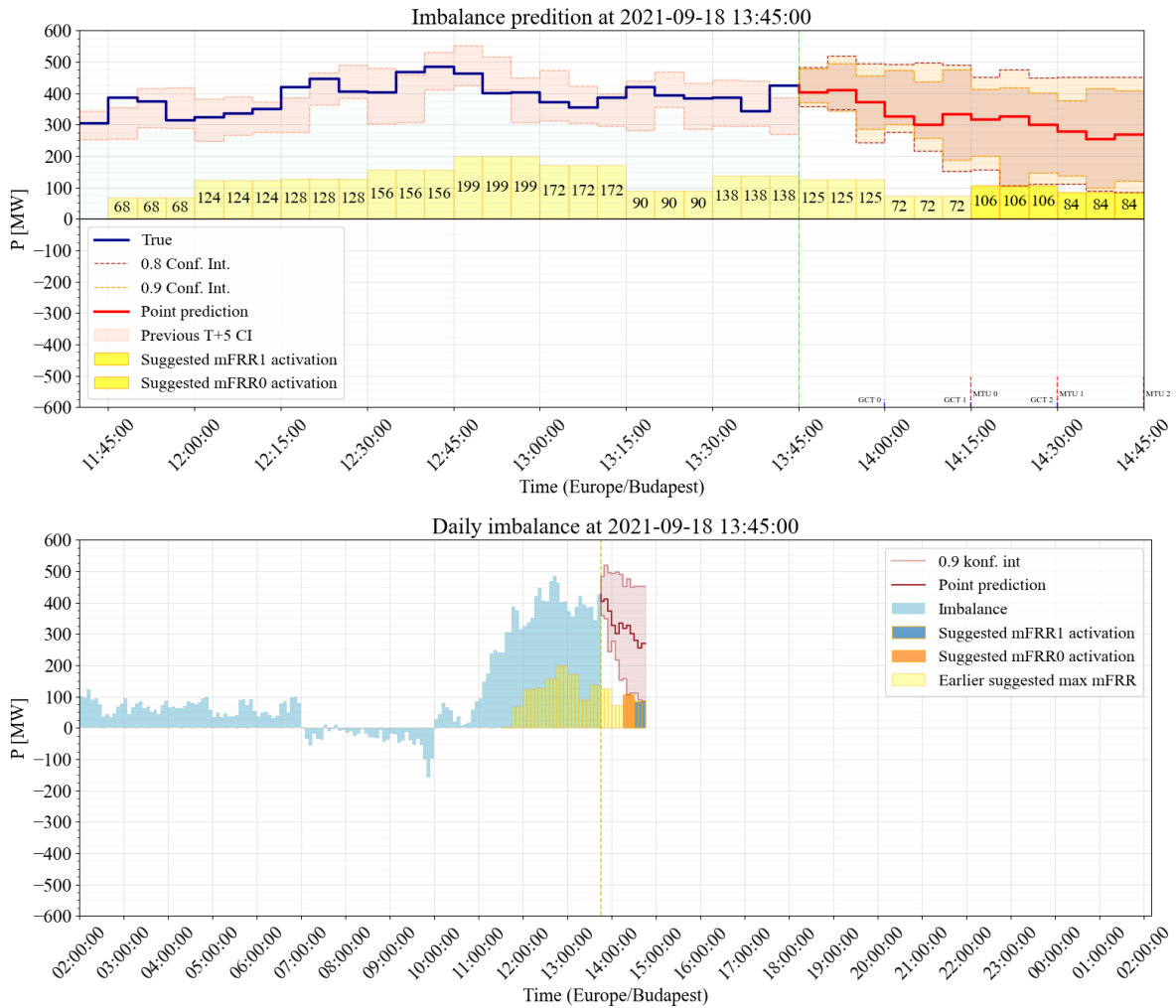
The base idea of this topic is to use mFRR reserves as equivalents of aFRR. Since they differ in activation time and method, a proper forecast and proactive planning is required. By these, the existing capacities can be utilized in a better way, on a lower cost-level, presented on Figure 5. by the benefits of the common merit order of the two services.

Regarding the methodology, Gradient Boosting from scikit-learn [8] is used for the quantile regression, while several other algorithms were



5. Figure: presentation of the economic benefits of handling aFRR and mFRR as equivalent products.

tested for the deterministic forecast. At each timestamp, the algorithms forecast for the next one hour's 5-min intervals (as shown on figure 6), based on relevance-sorted predictors containing data like solar prognosis, gross system load plan, past imbalance and its components' values, import-export plans and so on so forth.



6. Figure: Actual and daily presentation of imbalance forecasting and possible proactive mFRR activation.

The results were promising, therefore the Hungarian TSO has already been working on the implementation of this system, and the methodology is planned to be published in the next year.

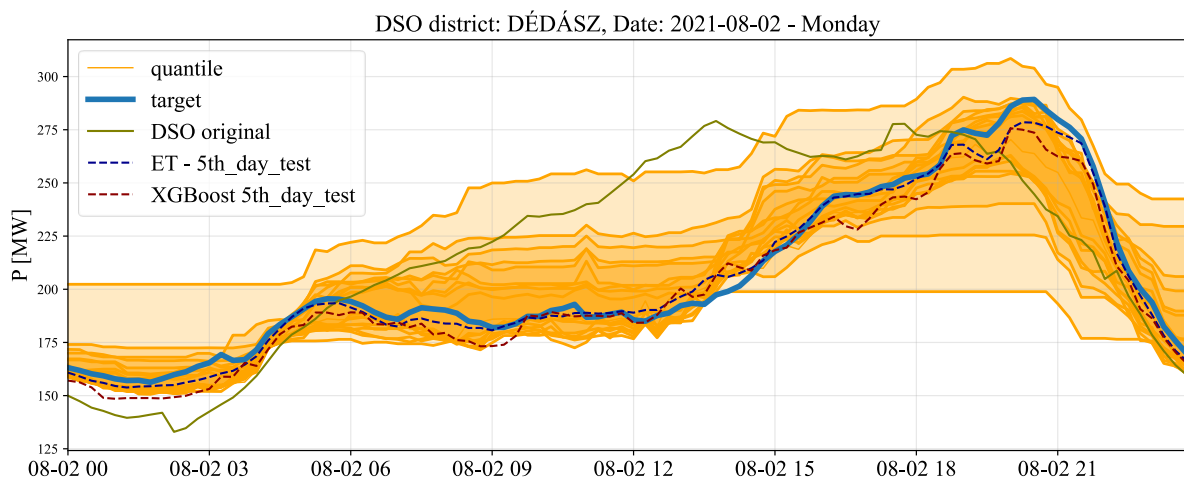
Plans for the future

The future holds extremely strong challenges as the balancing capacities do not follow the growing demand for flexibility resulting

deficiency more often. In the next years, joining to the MARI and PICASSO platforms will open a new market for balancing services, however the new definition of the aFRR product is going to decrease the current capacity even more. So proactive mFRR controlling is supposed to be a hot topic in the next years too.

To develop the process, the following works are planned:

- developing the solar prognosis by implementing the previous work;
- creating a hybrid forecasting module for domestic scale PV production;
- improving the DSO profile prediction for domestic consumption based on the previous module and include it in the imbalance forecasting framework (Figure 7.).



7. Figure: Detail from the next step of the framework - domestic consumption profile forecasting

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