Public consultation

Study on the daily prediction of non-contracted balancing energy bids

October 1, 2021

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EXECUTIVE SUMMARY

In line with European legislation, Elia determines the FRR / aFRR / mFRR reserve capacity needs for its LFC block. While FRR / mFRR needs are already dimensioned dynamically, i.e. on a daily basis based on the expected system risks, an implementation plan for a dynamic dimensioning of the aFRR needs was presented in 2020. These dynamic dimensioning methods are developed by Elia to minimize the reserve capacity needs due to increasing shares of variable renewable generation. As a next step, Elia is now investigating the possibility to optimize the allocation of the required reserve capacity needs to contracted and non-contracted balancing means trough a dynamic calculation of the available balancing means, i.e. the available non-contracted balancing energy bids, the available reserve sharing and the required balancing capacity to be procured. This is in contrast to the current approach in which this allocation is still calculated periodically based on the availability of non-contracted capacity balancing means and subtracting the potential 'firm' capacity from the required mFRR / aFRR balancing capacity to be procured.

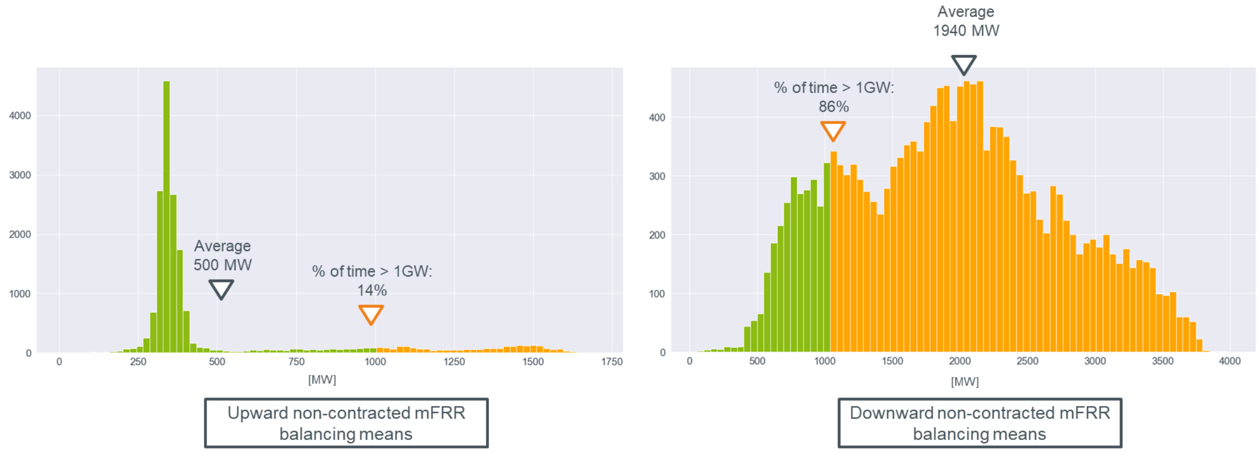
The objective of this study is to analyze if Elia's available non-contracted balancing energy bids for the next day can be predicted in order to facilitate a dynamic calculation of the balancing means. For this, a machine learning approach is put forward in which an algorithm is trained, based on historic observations, to predict the available non-contracted balancing means for each quarter-hour of the next day. These non-contracted balancing means include the non-contracted balancing energy bids and the available reserve sharing with other TSOs. When considering to account these volumes in the calculation of the balancing capacity to be procured, the volumes are to be predicted, similar to the dynamic FRR dimensioning process, before the capacity auctions, i.e. at the latest 7 AM of the day for which the balancing capacity is to be procured.

In a **first step**, the target variables (to be predicted) and features (input data) to make the predictions are identified. Five target variables are determined: (1) the mFRR non-contracted balancing energy bids, based on available regulation capacity published by Elia, (2) the available non-contracted bids provided by the pumped-hydro storage units, (3) the available mFRR reserve sharing, (4) the total non-contracted mFRR balancing means and (5) the total non-contracted aFRR balancing means. In order to predict these target variables, a list of up to 168 features has been composed for which a correlation matrix helps to select the most relevant features to be incorporated in the machine learning algorithms.

In a **second step**, Elia composed a list of relevant machine learning algorithms. Based on the expected accuracy, complexity and suitability, three models were selected for a quantitative analysis: a linear regression, a random forests and a neural networks model. A textbook approach is followed to train the algorithms in order to find the best performing algorithm of the three selected methods. Based on a historic data set for a period of two years (from April 16, 2019 until April 15, 2021), the best performing algorithm is found to be the random forests, being able to predict, on average, the highest available volume of non-contracted balancing energy bids while maintaining a confidence level of 99%.

In a **third step**, simulations are conducted to create time series of predicted non-contracted balancing means. The time series of predicted non-contracted upward mFRR balancing means show that for upward, a potential volume of 500 MW can be predicted, on average, while a volume of 1000 MW can be ensured for 14% of the time. It has to be understood that a large contribution is provided by the available mFRR reserve sharing, and this up to a current maximum limit of 312 MW following the system operation guidelines. **It is confirmed that there is a potential value for this prediction tool and this potential is expected to further increase with additional volumes brought by a consumer-centric market design and the upcoming EU balancing energy platforms.** However, one of the main conditions to harness this value is to find appropriate procurement mechanisms to deduct this capacity from the balancing capacity to be procured.

Histogram of available non-contracted mFRR balancing means



In contrast, the time series of predicted non-contracted downward mFRR balancing means demonstrate a potential volume of nearly 1940 MW, on average, while a volume of 1000 MW can be ensured for up to 86% of the time. It is important to understand that these volumes are always lower than the observed availability. This is explained as the forecast tool aims to forecast guaranteed volumes, expected to be available with a 99% confidence level. For instance, when looking at the available volumes on the downward side over the same period, a volume of 1000 MW can be ensured for up to 97% of the time. **The results confirm the current approach to not procure downward mFRR balancing capacity and it can therefore be concluded that there is no potential value for this prediction tool as long as observed non-contracted balancing means continue to cover the downward mFRR reserve capacity needs.**

The analysis for the non-contracted aFRR balancing means demonstrates that no substantial volumes of aFRR non-contracted balancing energy bids can be predicted at this point in time. This is explained by the fact that the available data was limited to only 9 months (as from the implementation of the new product design at the end of September 2020) while during this period largest part of the time, no or very limited volumes are available, particularly for upward aFRR. **Conclusion is that at this point, no potential for predicting the available non-contracted aFRR balancing means can be confirmed.**

In a **fourth and final step**, Elia proposes a roadmap to pursue a dynamic calculation of the balancing means. In first instance, a follow-up study is needed taking into account new system evolutions in the calculations of the potential being the explicit bidding of mFRR, the 12.5 minute full activation time for mFRR and the connection to the European balancing platforms for mFRR and aFRR. These modifications are expected to have an effect on the results, although it is currently very uncertain to which extend. As the last of these modifications will only be implemented in the final quarter of 2022, and more than a year of data is needed to conduct meaningful analyses, this update can only be conducted the soonest in 2023 or 2024. However, while awaiting the results of this analysis, expecting to confirm the potential, Elia proposes to already analyze procurement aspects of a dynamic allocation in 2022. This study will focus on the possibilities and impact of partially / intermittently reduce balancing capacity procurement on mFRR.

1. Introduction

1.1. Context

Market players are responsible for balancing injections and offtake in the system. As represented in (Figure 1), they currently nominate an energy portfolio one day in advance (day-ahead) that guarantees an equilibrium and, by moving closer to real-time, resolve any imbalance in their portfolio. It is therefore necessary for the market to have sufficient flexibility, both intra-day and real-time, to compensate for forecast errors in generation, in particular with regard to renewable energy sources and offtake. In addition, the flexibility available in the system must always allow for the loss of power plants (unavailabilities known a day advance, as well as an unforeseen unavailability after day-ahead)[1].

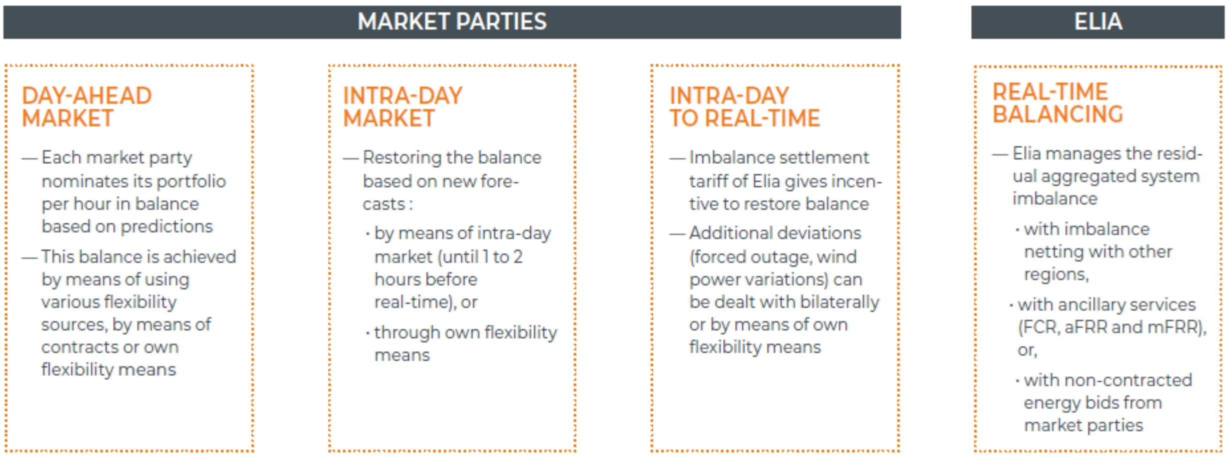


Figure 1 : Time horizons of flexibility (Elia's adequacy and flexibility study 2021)

The role of the transmission system operator in managing flexibility is complementary to the market's role, because it neutralises the residual imbalance between injection and offtake that is not covered by market players. By means of the imbalance settlement tariff, Elia incentivises the market to adhere to their balancing responsibility as much as possible. This imbalance tariff is driven by the cost of activating balancing energy to resolve the residual system imbalance, both in an upward (to deal with energy shortage) and downward (to deal with energy surplus) direction. Due to this 'reactive' balancing mechanism, a large part of the required flexibility is delivered by intra-day markets and real-time actions and not by Elia.

TSOs use reserve capacity to cover the residual system imbalance as represented in Figure 2. If an imbalance in the system occurs, this results in an increase or decrease in system frequency. Because the control zones of the ENTSO-E network - also called the Load Frequency Control (LFC) blocks of which the Elia LFC block represents the Belgian

[1] Note that discussions are ongoing relating to the removal of the requirement that requires market parties to communicate a portfolio in balance in the day-ahead time frame. This is expected to enhance flexibility management, moving further towards the real-time (cf. Elia's Public consultation on the proposal of amendment of the T&C BRP on elia.be)

geographical area - are connected, a frequency disturbance impacts the entire synchronous zone. For this reason, the Frequency Containment Reserve (FCR) must restore the balance between the power provided and the power supplied. It is used to stabilize the frequency at a level greater or smaller than the initial frequency, rather than balancing the Elia LFC block.

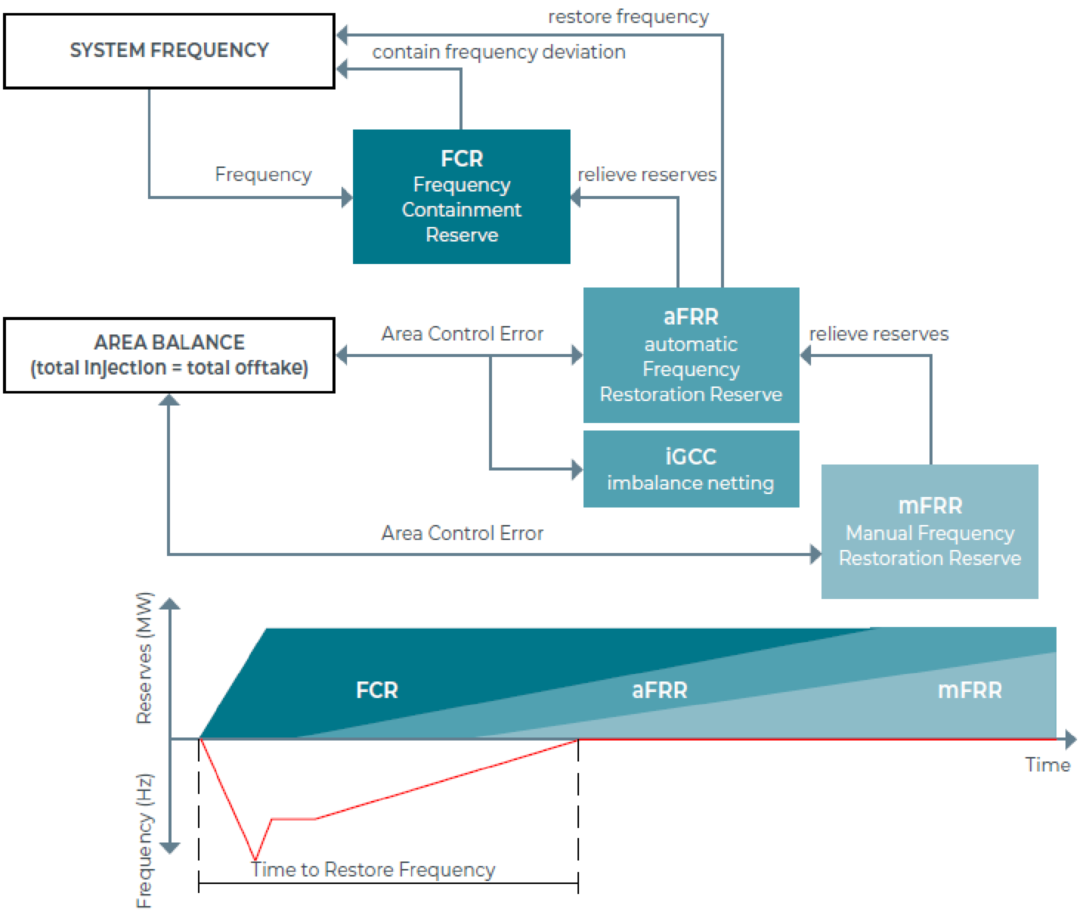


Figure 2: Schematic overview of the activation of operating reserves

The Frequency Restoration Reserve (FRR) must free up the FCR of the synchronous zone to prevent network instability, or even a failure of the entire electricity system, in the event of additional system imbalances. Each control area is therefore obliged to maintain its balance which is monitored by means of quality criteria assessing the Area Control Error (ACE), i.e. the real-time deviation between measured and scheduled cross-border exchanges on a quarter-hourly (and even on a minute-by-minute) basis.

Unlike the FCR, the FRR ensures that the frequency in the synchronous zone is restored, and that the control zone is re-balanced. The automatic FRR (aFRR) is mainly used to compensate for short and random imbalances. The manual FRR (mFRR) serves as compensation for long, persistent and/or very extensive imbalances.

- aFRR must be activated automatically within 30 seconds and must be fully available within 7.5 minutes. Note that Elia is investigating the possibility of reducing this down to 5 minutes;

- mFRR is manually activated and must be fully available within 15 minutes; this is due to be reduced to 12.5 minutes in 2022.

1.2. Reserve capacity requirements in Elia's LFC block

The required FCR volume is dimensioned by ENTSO-E for the synchronous area of continental Europe. It is calculated on the largest contingency, currently the loss of 3000 MW, complemented by a probabilistic analysis. This volume is allocated to the corresponding LFC blocks according to their weight (in terms of consumption and generation) in the synchronous zone. The methodology is specified in the synchronous area operational agreement and is approved by all relevant regulators. The FCR capacity in Belgium is 87 MW in 2021.

The required FRR reserve capacity is dimensioned by Elia for its LFC block. First the needs are determined with a methodology presented in Elia's LFC block operational agreement[2]. As from February 3, 2020, Elia implemented a daily dynamic dimensioning for up- and downward FRR needs. The volumes are thereafter allocated towards the different products for balancing capacity with a methodology presented in the LFC Means[2].

- *Dynamic dimensioning methodology for the FRR needs*

As required by Article 157(2)b of the Commission Regulation (EU) 2017/1485 of 2 August 2017 establishing a guideline on electricity transmission system operation (hereafter referred to as "SOGL"), ELIA determines the positive and negative FRR needs based on a combination of a probabilistic and deterministic methodology (Figure 3). The **probabilistic methodology** is based on estimating the imbalance risks for each quarter-hour of the next day and determining the required reserve capacity on FRR to cover 99.0% of the imbalance risks, i.e. the 99.0% percentile of the probability distribution curve of the positive and negative LFC block imbalances. The probabilistic method is based on machine learning algorithms relating the imbalance risk to day-ahead predicted system features such as renewable generation, demand, weather conditions, as well taking into account the imbalance risks due to forced outages of available power plants and the Nemo Link interconnector.

[2] Published on https://www.elia.be/en/electricity-market-and-system/system-services/keeping-the-balance

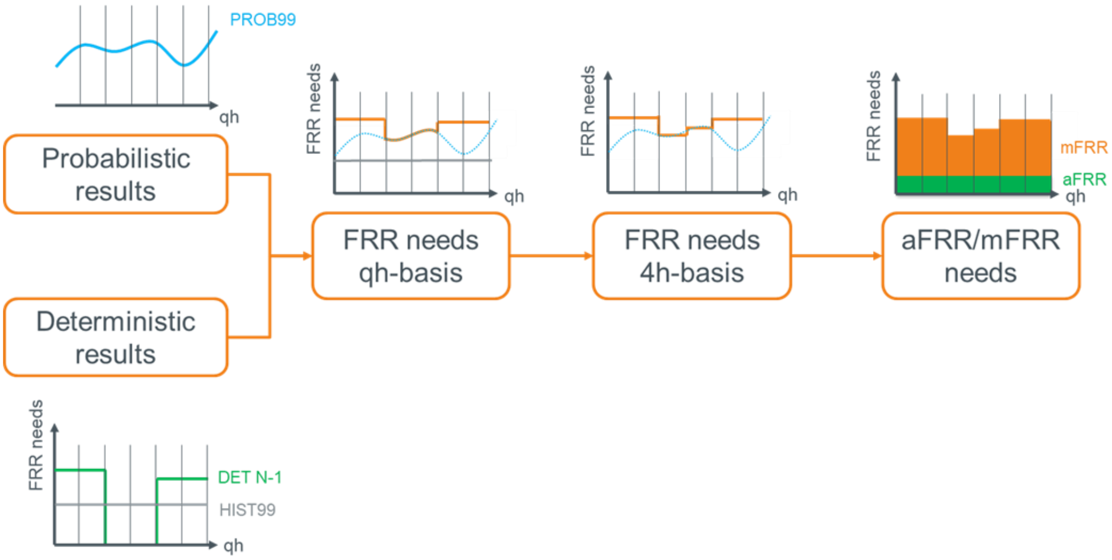


Figure 3: Calculation process of the FRR/aFRR/mFRR needs

In parallel, Elia considers the dimensioning incident by means of a **deterministic methodology**. This method has to ensure that the positive and negative FRR needs shall not be less than the positive and negative dimensioning incident of the LFC block, as required by Articles 157(2)e and 157(2)f of the SOGL. The dimensioning incident is defined by Article 3 of the SOGL as the highest expected instantaneously occurring active power imbalance within a LFC block in both positive and negative direction. Finally, Elia applies an additional **minimum threshold** to ensure that the required positive and negative reserve capacity is sufficient to cover at least the positive and negative historic LFC block imbalances for 99.0% of the time in order to be in line with Articles 157(2)h and 157(2)i of the SOGL.

Both methodologies are used in parallel to calculate the positive and negative FRR reserve capacity required for every quarter-hour of the next day. The required reserve capacity for each quarter-hour is determined based on the maximum value of the deterministic and probabilistic methodologies. The result is expressed in periods of 4 hours by means of the maximum over all quarter-hours in this period. The calculation is conducted before 7 AM.

Note that the mFRR needs are determined by subtracting the FRR needs with the results of a 'static' aFRR dimensioning methodology for which the methodology and results are determined as well in the LFC block operational agreement. Note that Elia presented at the end of 2020 its proposal for a 'dynamic' aFRR dimensioning, based on the risk for aFRR activations for the next day. Similar to the FRR needs, this risk is determined by means of machine learning algorithms trained on historic system conditions. The main advantage of these dynamic methodologies is that they allow to minimize reserve capacity needs by adapting the reserve needs to the risk of the system.

<u>*Methodology to determine the FRR means to be contracted*</u>

In compliance with Article 32 of Commission Regulation (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing, hereafter referred to as "EBGL", Elia conducts an analysis on optimal provision of reserve capacity. This analysis shall take into account the following options for the provision of reserve capacity:

- procurement of balancing capacity within control area and exchange of balancing capacity with neighboring TSOs, when applicable;
- sharing of reserves, when applicable;

- the volume of non-contracted balancing energy bids which are expected to be available both within their control area and within the European platforms taking into account the available cross-zonal capacity.

On an ‘ad hoc’ basis, Elia determined the share of non-contracted balancing energy bids and sharing of reserves which can be accounted as ‘firm’ in the determination of the balancing capacity to be procured.

Following this ‘static’ analysis, the aFRR balancing capacity is always equal to the aFRR needs (taking into account the absence of aFRR sharing and the limited potential of non-contracted energy balancing bids). The aFRR capacity is determined symmetrically meaning that the downward reserve capacity is equal to the upward reserve capacity. In contrast, the upward mFRR needs are assumed to be partially covered with the sharing of mFRR but not by non-contracted balancing energy bids after showing limited potential, at least when analyzed on a ‘static’ basis. In contrast, the downward mFRR needs are assumed to be fully covered with sharing of mFRR and non-contracted balancing energy bids. More information can be found in Elia’s LFC Means[2].

1.3. Trends and evolutions

Increasing shares of variable **renewable generation** sources such as wind and solar power, characterized with a variable generation and limited predictability, were expected to impact the LFC block imbalances and TSO reserve capacity requirements. These trends incentivized Elia to re-inforce its ‘reactive’ balancing market design, providing incentives to market players to balance their portfolio or help restoring the system balance. This balancing market approach seemed rather succesful maintaining stable LFC block imbalance and Area Control Errors levels, despite increasing renewable generation (Figure 4).

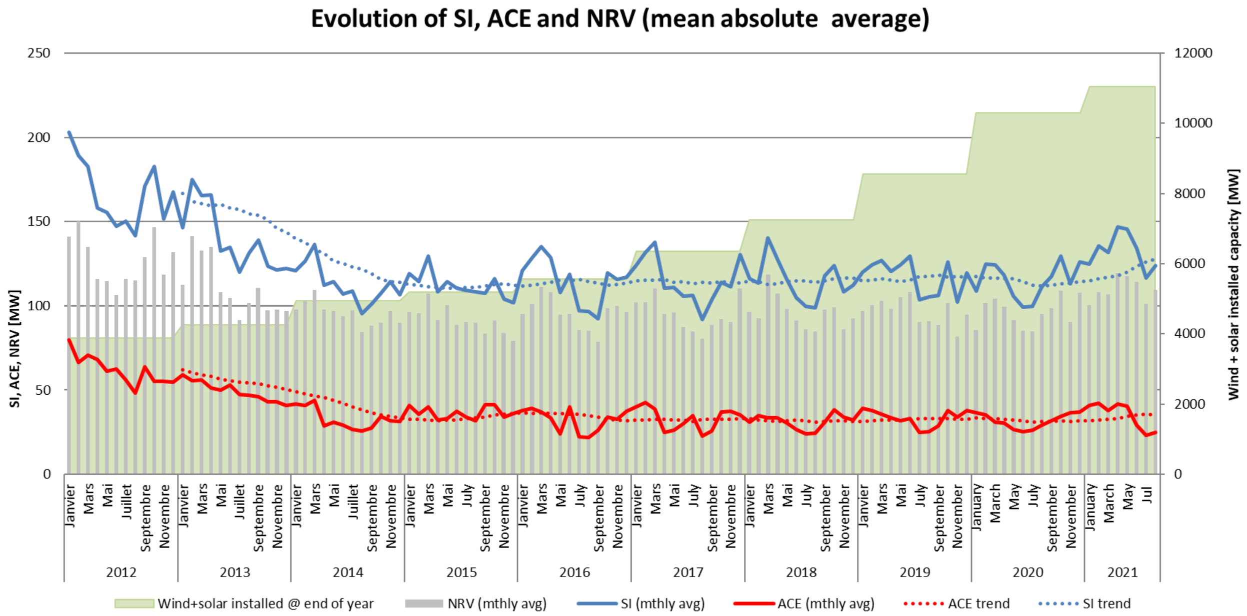


Figure 4: Evolution of the LFC block imbalance (SI), Net Regulation Volume (NRV) and Area Control Error (ACE) in view of increasing renewable generation (wind and solar)

These stable LFC block imbalance levels allowed, with help of its dynamic dimensioning approach to maintain stable reserve capacity needs and limit the impact of renewable generation on ancillary service costs. In contrast, contracted balancing capacity requirements were even reduced and downward mFRR procurement is avoided by means of taking into account cross-border flexibility (by means of mFRR reserve sharing) and non-contracted balancing energy bids to the extend possible.

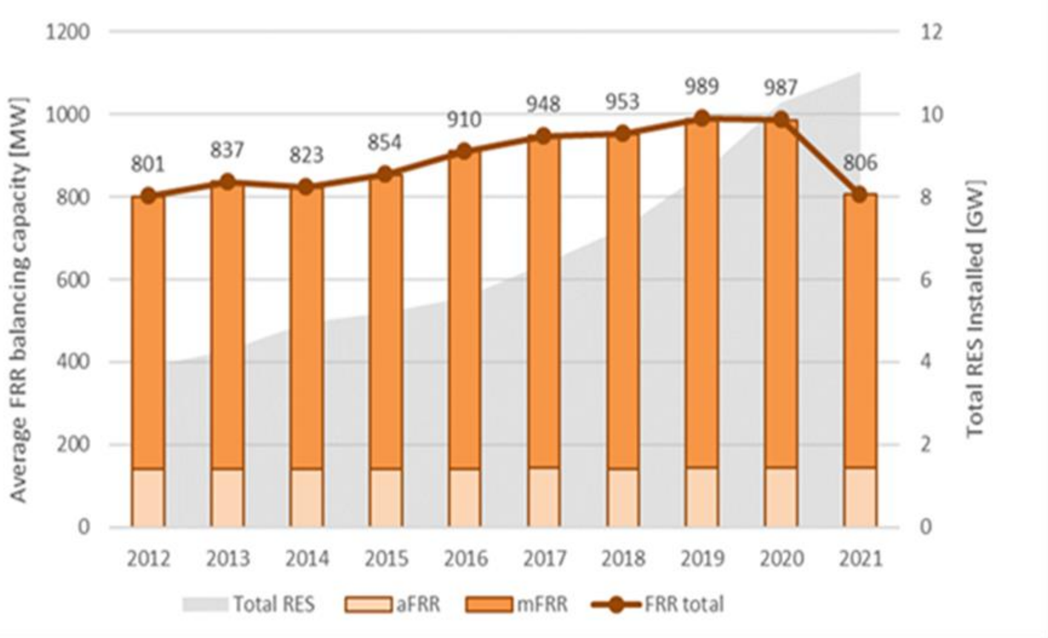


Figure 5: Evolution of contracted balancing capacity requirements between 2012 and 2021

Nevertheless, recent studies of Elia (MOG 2 system integration study, aFRR dimensioning study and Adequacy and flexibiltiy study) put forward increasing reserve capacity needs towards the future. Under a referene scenario with improving performance of market players to balance their portfolio, FRR needs are expected to increase towards 1246 MW towards 2028. This is explained by increasing renewable generation, in particular due to increasing shares of offshore generation. Obviously, further enabling the ability of market players to balance their portofolio and the system is required to keep this inrease under control.

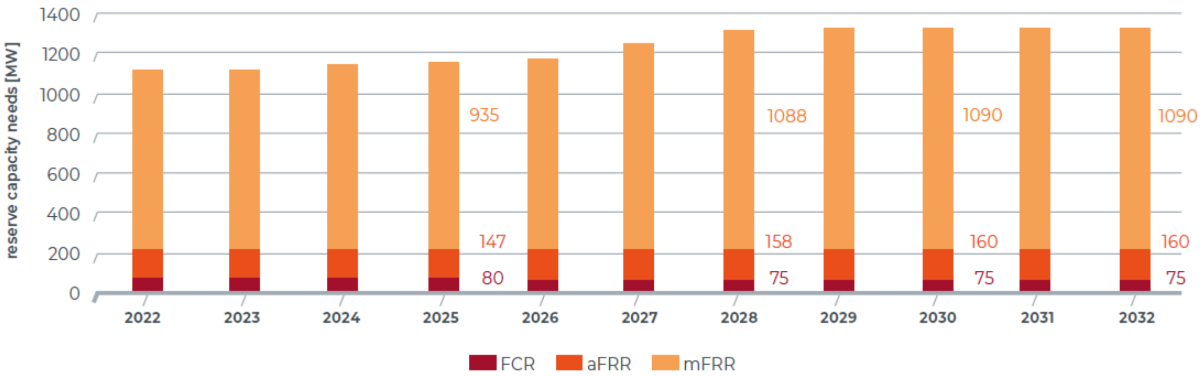


Figure 6: Reserve capacity projections between 2022 and 2032 (Elia's MOG 2 System Integration study, 2021)

Besides stabilising the FRR needs, the procurement cost of balancing capacity can be managed by increasing the share of non-contracted balancing means, i.e. through reserve sharing or non-contracted balancing energy bids. These shares are already increased by means of a reduction of 250 MW of upward mFRR (following the expected availability of sharing) and downward mFRR procurement (following availability of FRR sharing and non–contracted balancing energy bids, including renewable flexibility). Nevertheless, this still follows a 'static' calculations analyzing available capacities observed over the last two years. To further enable the contribution of this non-contracted capacity whenever sufficiently firm, and reduce balancing capacity to be procured where possible, Elia investigates in this study the potential of dynamic calculation where the availability of non-contracted balancing means are predicted for the next day, in order to be taken into account accordingly.

1.4. Scope and Objective

The objective of this study is the development, testing and validation of a method for forecasting the volume of non-contracted balancing energy offers available within Elia's LFC Block. The timeframe for this prediction should allow this capacity to be reliably taken into account in a daily calculation of balancing capacity to be purchased (in the context of daily dynamic sizing of reserve requirements).

The scope of the study is therefore limited to confirming the possible to develop a successful method to predict this capacity with an acceptable accuracy. Only when the potential is confirmed, several follow-up analyses will be required on :

- the **balancing energy exchange platforms for aFRR and mFRR** which are planned to be implemented in 2022. It will therefore not be possible to quantitatively determine the impact of cross-border balancing energy bids in this study. Note that the volumes which will be available on the European platforms are subject to a lot of uncertainty and relevant volumes can only be determined by means of a return on experience.
- the effect of **recent and foreseen product developments for aFRR and mFRR** which are not (fully) represented yet in the available observations. For mFRR, explicit bidding and a reduction of the full activation time foreseen in 2022 will likely have an impact on the available volumes. For aFRR, the new product design was only launched in October 2022 and suffered of teething problems. Although Elia will conduct is best efforts to make the methods as robust as possible, the algorithms are likely to be updated after a return on experience on these evolutions
- on the **procurement aspects of a dynamic calculation of the available FRR means**. While this study focuses only on the 'predictability' of non-contracted balancing means this analysis will be an important milestone towards implementation.

For the above-mentioned reasons, focus of the study is also not on optimizing the machine learning methodologies. Aim is to find and develop the algorithm which can provide an acceptable prediction while the final calibrating the algorithms will need to be conducted just before or during the final implementation phase, taking into account the above-mentioned evolutions.

1.5. Approach

The investigated methodology is based on two general principles:

1. **the calculation has to be conducted as close as possible to real-time:** the closer the prediction available energy bids can be done to real-time, the higher the accuracy of the prediction. This due to the fact demand and renewable generation forecasts become more accurate closer to real time while market players can adapt their positions accordingly by means of intra-day markets or portfolio management. Obviously, the re-scheduling of generation, storage and demand impacts the remaining flexibility which can be submitted to the TSO as available non-contracted balancing energy bids.

2. **the calculation has to be conducted before the balancing capacity procurement** : in the FRR dimensioning, it was already explained that the dimensioning and procurement has to be conducted before the day-ahead market closure to ensure the availability of balancing capacity to be procured. Which resulted in a time process with a procurement of the FRR balancing capacity at 9 AM D-1 (aFRR) and 10 AM D-1 (mFRR), and the publication of the dimensioning of the FRR needs before 7 AM D-1[3].

In view of these constraints, it is proposed to align the dynamic calculation of the available FRR means (Figure 7). Implications of the above-mentioned approach is that the prediction can only be based on data which is available at 4 AM at D-1 for every period of the next day, e.g. by means of system condition forecasts. Note that at the moment of prediction, 96 separate forecasts are made for every period of 15 minutes for the next day, which is the highest resolution possible with current system data resolution. In a final step, this resolution will need to be transformed to the product length of 4 hours for aFRR and mFRR.

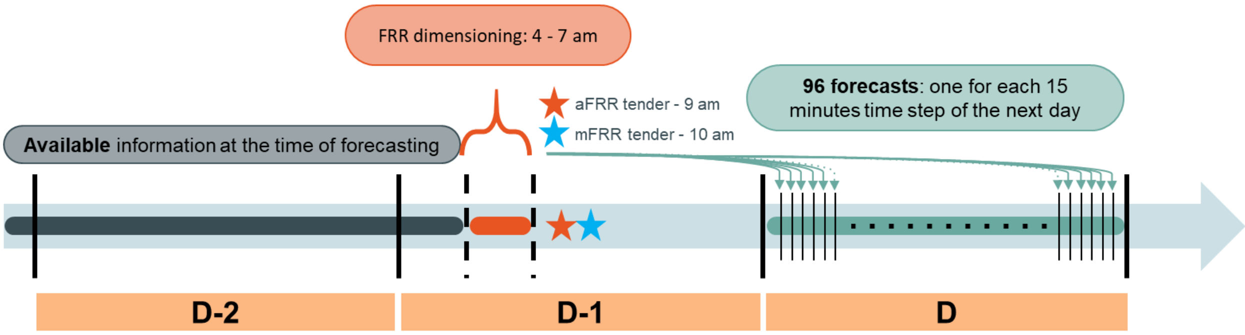


Figure 7: Overview of the timing of a dynamic FRR means calculation

In order to forecast the available FRR means for the next day, a machine learning methodology is pursued. Such methodology is based on training algorithms on historical observations representing data sets of system conditions and available FRR means. Elia implements best practices on implementing machine learning methodologies as depicted in the checklist in Figure 8. While point 1 and 2 are dealt with in Section 2 on data collection, point 3-5 are dealt with in Section 3 on the selection and implementation of the right methodology.

[3] It is assumed for this study that the future aFRR balancing capacity procurements is at 9 AM D-1. Note that currently, the aFRR balancing capacity procurement organized through two auctions: one organized in D-2 at 4 PM and a second one D-1 at 9 AM.

1. Data collection, cleaning, transformation

- Collect largest possible set of relevant features in view of the outcome
- Transformations of the features and treat adequately the missing data

2. Correlation study

- Matrix of correlations between features and the outcome
- Matrix of correlations between the features mutually

3. Model selection

- Pre-selection of relevant categories in view of the problem type
- 1 simple methods is selected for quantitative analyses to find a minimum performance level (linear regression)
- 2 more complex models are selected for quantitative analyses to increase performance level (neural networks / random forests)

4. Set up learning environment

- Based on a random split in training data (75%) and test data (25%)
- Based on k-fold cross validation (up to 20)

5. Determine Performance indicators

- Justify performance indicators in view of the problem type : quantile loss function, reliability and average FRR means volume

Figure 8: Checklist of best practices on machine learning

In view of the above-mentioned methodology, the structure in this report is built upon four steps (Figure 9). The first two steps are focusing on getting the data and methodologic aspects right: step 1 (Section 2) identifies the relevant system conditions (features) to successfully predict the non-contracted balancing energy bids (target). Step 2 identifies the statistical methodologies which might be successful in predicting the non-contracted balancing energy bids (Section 3).

The last two steps focus on the results and recommendations: step 3 presents the result of the different methodologies put forward providing an analysis of the best algorithm, but also giving insight in the potential volumes of non-contracted balancing energy bids (Section 4) while step 4 puts forward the planning for implementation (Section 5).

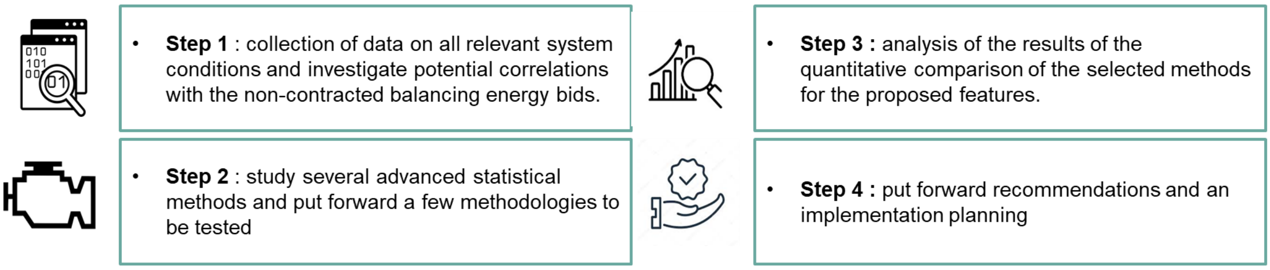


Figure 9: overview of the different steps followed during the study

2. Data

When implementing the machine learning methodologies, historic observations are used upon which the algorithms are trained to make predictions. These historic observations are categorized in **target variables,** i.e. the variables to be predicted, and **features**, i.e. input variables on the basis of which the target variables are to be predicted.

In a first step of this study, the relevant target variables and features are identified. In a second step, correlations between the target variables and features, but also the features mutually are quantitatively investigated and represented in a correlation matrix. The objective is to identify the most promising features for calibrating the algorithms as a too large amount of feature can negatively impacts the performance of the algorithm in terms of accuracy, interpretability or computational time.

The pre-selection and the selection based on the correlation matrix is discussed in this section based on historical time series available between January 1, 2018 and February 28, 2021[4]. The resolution of the data is, where possible, set at 15 minutes which aligns with the highest available resolution of the target parameters[5]. When calibrating the algorithms, the time period of the selected features is updated towards July 1, 2019 until June 30, 2021 in order to conduct the simulations with the latest data available.

2.1. Target variables

Figure 10 categorizes the target variables, i.e. the variables which need to be predicted, into five categories. For **aFRR non-contracted balancing energy bids** (category 5), the target variable is based on the explicit bids received from market parties. This is implemented for aFRR as from October 2020, which allows to collect the relevant time series of up- and downward aFRR non-contracted balancing energy bids. As already explained before, the period which can be analyzed (October 2020 until February 2021) considers a relatively short period to analyze correlations. Even more problematic is that the product design still suffered from teething problems, and that most periods are characterized by low or negligible non-contracted balancing energy bids.

In addition, largest part of the observed non-contracted balancing energy bids is provided with CCGT units, which is related to the fact that these units are scheduled for the provision of contracted aFRR balancing energy bids. Correcting the non-contracted volumes for these cases where these would not be available without the reservation of these units would even further increase periods with low or negligible non-contracted balancing energy bids.

[4] Note that data related to aFRR balancing capacity procurement only starts as from 1st October and mFRR balancing capacity procurement as from 2nd February 2020 related to the 'go live' of the daily procurement.

[5] When the original time series have a resolution lower as 15 minutes, a re-sampling is conducted by means of an interpolation method, e.g. an hourly time series is transformed into quarter-hourly time series.

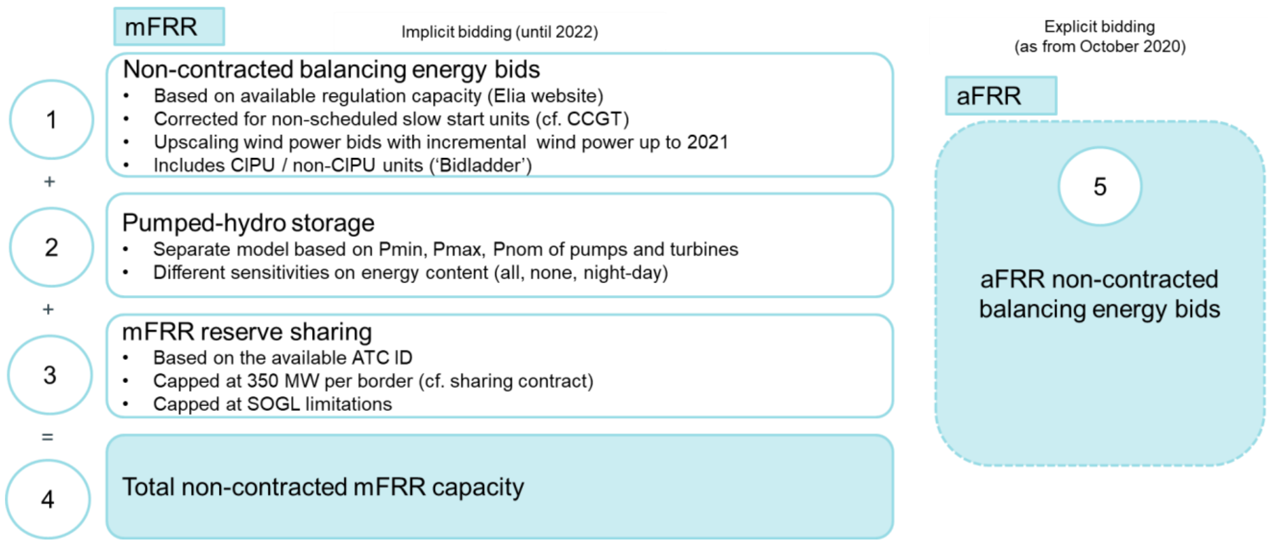


Figure 10: Categories of target variables

In contrast, for **mFRR non-contracted balancing energy bids**, implementation of explicit bidding for mFRR is only planned in 2022, which leaves no other choice than to resort to current implicit calculations where available bids are calculated by Elia, based on day-ahead and intra-day schedules of large generation units and pumped-hydro storage[6], taking into account the unit's scheduled availability, and minimum and maximum power levels.

An analysis of the available volumes in 2020 is shown in Figure 11, presenting that upward volumes are pre-dominantly delivered with pumped-hydro storage (PHS) and CCGT units. It is however to be noted that the available volumes of pumped-hydro storage are uncertain due to implicit bidding, while the upward volumes provided by CCGT are overestimated following accounting capacity during unscheduled periods. The contribution of other technologies is relatively small. In contrast, the downward volumes are pre-dominantly delivered with pumped-hydro storage, CCGT units and wind power.

The total non-contracted mFRR capacity (category 4) is composed out of different categories:

- the **available regulation capacity** (category 1), as published on the website of Elia. This includes all units larger than 25 MW, formerly referred to as CIPU units, except from the pumped-hydro storage units. The available capacity is calculated by Elia by comparing the last generation schedules with the minimum / maximum power levels. Note that other technical constraints such as power ramp rates and start-up times are not taken into account and may therefore give a too optimistic view on the available mFRR. For this reason, and because CCGT units provide a large contribution to the available capacity, the capacity of the CCGTs is corrected by excluding capacity from units for which the last schedule indicates that the unit is not foreseen to be dispatched at that moment. The above-mentioned capacity also includes energy bids delivered by 'limited controllable' technologies representing units with some additional technical constraints (e.g. combined-

[6] DPSU formerly referred to as CIPU units falling under the bidding obligations following Article 248 of the Federal Grid Code.

heat and power, wind power and nuclear power). The time series also includes explicit bids from smaller units (including energy constrained units), formerly referred to as non-CIPU units ('Bidladder'), but this adds no significant volumes.

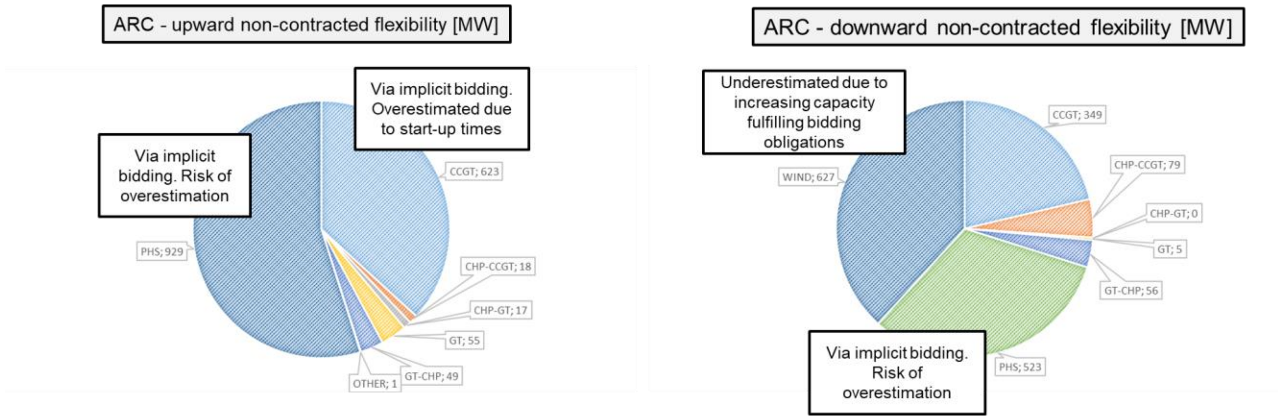


Figure 11: Available regulation capacity (including pumped-hydro storage) per technology in 2020

- the **available pumped-hydro storage capacity** (category 2), as these are not included in the available regulation capacity published by Elia. This flexibility is calculated by comparing the scheduled injection or off-take with the scheduled availability and maximum and minimum power levels of the pumps and turbines. Similar to the LFC Means calculations, energy limits are taken into account, though in simplified way assuming remaining upward capacity only contributes at night (between 4 AM and 8 AM) and downward capacity only at day (between 8 AM and 4 AM). Developing a specific model for storage is complex and out of scope of this study, mainly since such model would become irrelevant after the implementation of explicit bidding in 2022. For this reason, a sensitivity analysis will be conducted on this target variable with a case where no energy constraints are accounted (assuming there is always some remaining energy for pumping or generation after day-ahead, and a case where no remaining energy is assumed. Both extreme cases are probably not representative for reality but allow to understand the impact of pumped-hydro storage on the final result.

- thirdly, the non-contracted balancing energy bids are complemented with the available capacity on **reserve sharing** (category 3)**.** This is represented by the available transmission capacity after intra-day, and thus available for the activation of reserve sharing, and capped at 350 MW per border, being the commercial value of each of Elia's four reserve sharing agreements with RTE, Tennet, NGESO and Amprion (as From November 2020). Finally, legal limits following the system operation guidelines are taken into account, determined around 312 MW (30% of the dimensioning incident) for upward reserves and around 550 MW / 0 MW for downward reserve (determined as the difference between the dimensioning incident and the probabilistic dimensioning). The value varies between 550 MW if Nemo Link is scheduled in export or undecided, and 0 MW if it is scheduled in import or maintenance, as currently specified in the LFC block operational agreement.

Note that due to the above-mentioned characteristics of the data, the non-contracted mFRR capacity equals the FRR capacity, i.e. including capacity which can also be used for providing non-contracted aFRR balancing energy bids.

As explained earlier, predicting the mFRR sharing capacity in day-ahead is not the focus of the study but included to provide a complete view on the total potential. Moreover, as explained in Section 1.4, optimizing this algorithms is not useful before the implementation of the EU balancing energy platforms. The machine learning algorithms and selected features will therefore not be optimized for reserve sharing potential. Note that for each category on mFRR, capacity is predicted by means of separate models for up- and downward direction.

2.2. Features

An analysis is conducted towards the potential value of all known time series which could potentially be used as input variables or features for predicting the target variables. These will be presented by means of different categories as shown in Figure 12. It is stressed again that only the data available at the moment of prediction can be used as input for the model. For this reason, focus is put on **forecasted system conditions**, i.e. predicted values available in day-ahead, before the day-ahead market closure. Typical examples are wind power and demand predictions.

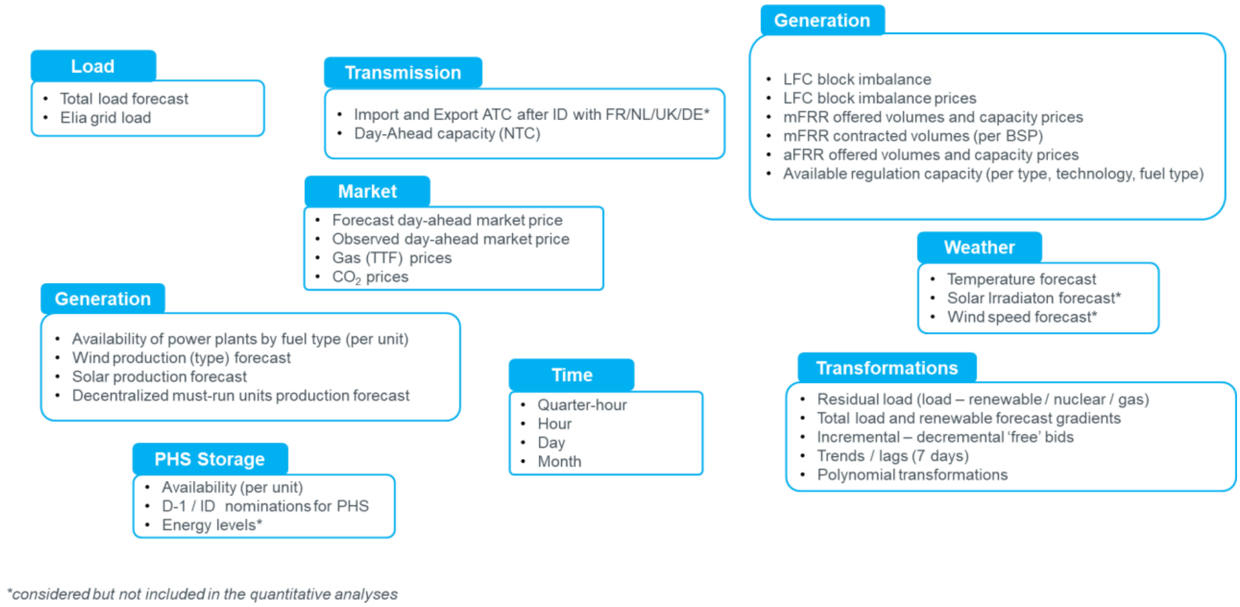


Figure 12: Overview of investigated features

In contrast, time series of **observed system conditions**, or information available after the prediction can only be taken into account by means of 'lagged' values of the previous day. Such can be considered as a very simplistic forecast and the predictive value is therefore rather low in general. Nevertheless, such approach can make sense when there is an autocorrelation between the values and those of the previous days. In general, when a dedicated forecast is available, this feature is used above the lagged actual measured as it expected that the forecast will give a better performance.

2.2.1. Demand features

The demand in the LFC block can impact the schedules of generation, demand, storage and interconnectors which impacts the available flexibility in the system. For this reason, the day-ahead "**Total load forecast",** available on Elia's data download page, is analyzed. This time series includes all electrical loads on the Elia grid and in underlying distribution networks, including electrical losses, and is estimated based on a combination of measurements, computations and extrapolations of injections of power plants, including generation in the distribution networks. Imports on borders are added. Exports on borders and energy used for energy storage are deducted.

This data is complemented with the estimated **"Elia grid load"** available on Elia's data download page. The Elia-grid load is based on real injections into the Elia grid. It includes the measured net generation of the local power stations that inject power into the Elia grid, the net inflows from the distribution network to the Elia Grid and the net import on borders. Exports on borders and energy used for energy storage are deducted.

2.2.2. Generation features

Flexibility in the system can be impacted by the generation schedules of conventional generation units. For this reason, in first instance, the "**Available Capacity Forecast by Unit",** available on Elia's data download page is analyzed. For DP_{SU} facilities, formerly referred to as CIPU (Contract for the Injection of Production Units) and with an installed power > 100 MW, this gives an overview of the forecasted capacity, by production unit, for a period extending from one day ahead to the end of the current year. Note that the generation schedules themselves are not included in the analysis due to the lack of forecasts, and that the correlations with the 'lagged' values will be outperformed by taking into account a price forecast (cf. Section 2.2.4).

Solar, wind power generation and decentralized generation (run-of-river hydro, combined heat-and power,…) profiles can impact the available flexibility in the system directly, by means of downward regulation capabilities, but also indirectly by impacting the generation schedules of generation and storage units. For this reason, the **day-ahead forecasted generation profiles for wind power and solar** as published on Elia's website are used. For wind, an additional categorization is made between connection level (transmission or distribution level) and location (offshore or onshore) For the **day-ahead decentralized generation**, available data at Elia is used.

2.2.3. Storage features

Pumped-hydro storage is known to be a large contributor to the Belgian system's flexibility. In first instance, **Day-Ahead and intra-day nominations** for PHS, disaggregated by plant and unit are used from Elia's available data. Nominations include the dispatched power, and the maximum and minimum power levels. However, as no forecasts are available, the values of the previous day are used. In addition, the **unit's availability level**, similar to the conventional generation features, is taken into account.

2.2.4. Electricity market features

Available flexibility is expected to be related to the day-ahead electricity price as it drives the generation, storage and demand schedules and therefore the available flexibility after-day-ahead. For this reason, the **"forecasted day-ahead market price"** is taken into account based on a forecast tool available at N-SIDE. The tool is based on a specific machine learning algorithm taking into account various local and regional features. In addition, as a benchmark, the **"actual observed day-ahead market price"** is included as well by means of the lagged value of the previous day. Finally, these features are complemented by means of the relation with the intra-day market by taking into account a transformation on **the difference of the 'lagged' actual day-ahead and intra-day (weighted average) market price.**

As **gas prices** and **CO_2 prices** are relevant for the dispatch of gas-fired thermal units, both gas and CO_2 prices are taken into account. As no forecasts were available, the last values known before the day-ahead market closures based on the settlement prices (DA or Weekend products) published by the ICE[7].

2.2.5. Balancing market features

To represent balancing market features, **real-time imbalance volumes** and **imbalance prices** are taken into account, as published on Elia's data download page. In theory, these could play a role if they could be predicted by market players and used to re-schedule their portfolio. Also **aFRR / mFRR contracted / offered volumes and capacity prices** per CCTU (and per gate) are analyzed to capture potential correlations between target variables and the reservation prices of aFRR and mFRR of the previous day. Due to the lack of forecasts, the values of the previous day have been used.

Also the autocorrelation with the target feature is taken into account by including the 'lagged' value of the **available regulation capacity**, i.e. per type, technology and fuel type.

2.2.6. Weather condition features

Weather features can have an indirect impact on the available flexibility in the system through their influence on demand and renewable generation. For wind speed and solar irradiation predictions, these weather conditions are already well captured by solar power and wind power forecasts. For this reason, only the **day-ahead forecasted temperature** is taken into account. Furthermore, real-time measurements are not considered as useful because the 'lagged' values of the previous day are expected to provide less accuracy compared with specialized forecast tools.

2.2.7. Cross-border transmission capacity features

In first instance, the relation between the target variables and the "**day-ahead net transfer capacity"** available as published on Elia's data download page has been considered. For the border between Belgium and the United Kingdom, Day Ahead net transfer capacity (NTC) is the Day Ahead forecast transfer capacity agreed on the specific border, calculated using a CNTC method (Coordinated NTC). These NTC Day Ahead values are reported at the boundary of the Elia control area, on the Belgian side of the Nemo Link HVDC cable. Note for the other borders, available transmission capacity is determined as part of the flow-based market and no specific features are available to take into account. As an alternative, the week-ahead net transfer capacity could be considered but this is fount to capture no new correlations.

Note that the day-ahead import / export schedules are not considered as they are expected to only have an indirect value as due to the intuitiveness of Euphemia's results: the schedules are related to day-ahead prices which is already

[7] https://www.theice.com/solutions/data

included in the analysis by means of a forecasted price. Furthermore, as a lag would have to be applied because these are not available at the time of the forecast.

In addition, as the available non-contracted capacity through sharing is taken into account, the observed "**available transmission capacity after the last intra-day gate"** for each electric border (France, The Netherlands, and United Kingdom). Import and export are treated as separate features. This information is not known at the time of prediction which is the reason to work with the values of the previous day (D-2). Note that for the feature selection phase, the border with Germany is ignored at this point[8] as data was only available as from November 2020.

2.2.8. Time features

Time features such as **time within the hour, hour of the day, day of the week and month of the year** are investigated as these might show a relation to the target features (e.g. day versus night). These are transformed into continuous variables in order to align with the other time series used in this study. The transformation is conducted by means of sinusoidal - sin(x) - and cosinusoidal - cos(x) - functions.

2.2.9. Transformations on features

Sometimes, the performance of machine learning algorithms can be improved by pre-processing features by means of mathematical operations, also known as feature engineering This can reveal correlations which remain undiscovered when only looking at the correlation between the target and the original feature. However, as this is relevant for the feature selection process, it is to be noted that the more advanced machine learning methodologies such as artificial neural networks or random forests are generally able to capture more complex non-linear relations.

In first instance, such transformations are conducted based on market knowledge. The **day-ahead predicted residual demand** is taken as a first transformation by subtracting the day-ahead predicted solar and total wind power from the total load as it is known that this indicator plays a large role on the scheduling of generation, storage and demand units. Gradients transformations are also conducted on all RES generation and load forecast as well as on residual demand; this is performed by subtracting the value of the feature from the value in the previous period. It is also tested if **aggregating the up- and downward non-contracted balancing energy** bids of the previous day gives a better relation to the target parameters compared to analyzing the up- and downward non-contracted balancing energy bids individually.

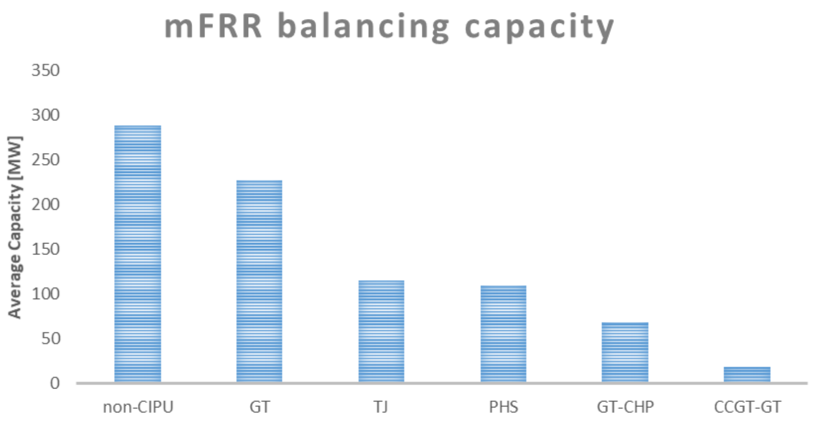
Secondly, as part of good machine learning practices, **polynomial transformations** are conducted on every feature, as well as using '**lagged' values** of each feature over the past 7 days.

[8] The available ATC after intra-day on the border with Germany is later included in the simulations

In depth: capturing correlations between contracted and non-contracted mFRR balancing energy bids

An additional analysis is conducted to understand if the potential relation between the available non-contracted balancing energy bids and the contracted capacity and if this relation can be taken into account by machine learning algorithms. The figure below shows how mFRR balancing capacity (February 4, 2019 to January 31, 2021) is currently mainly provided with smaller units (formerly known as non-CIPU), gas turbines (GT) and turbojets (TJ) and pumped-hydro storage (PHS). Note that :

- ⇨ The non-CIPU is currently not providing any non-contracted reserves
- ⇨ PHS, GT and TJ are assumed to provide mFRR from stand still
- ⇨ GT-CHP is bound to specific technical constraints
- ⇨ CCGT is negligible in providing reserved mFRR



It is previously shown that largest part of relevant capacity for non-contracted upward balancing energy bids is provided with GT + TJ + PHS + CCGT. While the last does not play a substantial role in balancing capacity, the first three are able to provide mFRR from ‘standstill’ : analysis shows periods where GT and TJ provide both non-contracted and contracted mFRR in Elia’s available regulation capacity while all mFRR providing gas turbines and turbojets are found to be provide non-contracted mFRR while not bidding any contracted mFRR. However, it has to be noted that non-contracted balancing capacity is currently calculated by Elia under ‘implicit bidding’ and impact of explicit bidding and evolution of full activation time towards 12.5 minutes can the non-contracted volumes but difficult to quantify this impact. For these reasons, **it is expected that, at least in theory, replacing contracted with non-contracted capacity should not have a negative effect on the operational availability of non-contracted capacity delivered**. However, which does not mean that former mFRR providing units may leave the market (‘peakers’) which relates to adequacy discussions. Without experience with explicit bidding, such conclusions are very preliminary as other unknown elements can play a role of which Elia is not aware of.

Furthermore, the machine learning are assumed to be able to capture relations between the offered, contracted capacity per BSP and the available non-contracted balancing energy bids per unit. Further feature engineering can improve the strength of the relation. In practice, in the current market, the relation remains too weak to capture any relations today. **Further investigation is possible in a later stage when system evolutions would demonstrate a potential relation between contracted and non-contracted capacity.**

2.3. Correlation matrix

A correlation matrix is developed depicting all linear correlation between the above mentioned features and the target variables, as well as the different features and target variables mutually. Based on this correlation matrix, a selection of features is made to calibrate the algorithms. Full correlation matrices are available but cannot be depicted as a whole in this report due to the high number of features investigated (164 in total, including feature transformation). For this reason, this report discusses the summary for the correlation between target variables and features for each of the five categories.

It should be noted that in the correlation matrices presented, the name of the time series ending with "d-1" or "d-2" denote that this realized value has been lagged. For instance, the feature prices_da_market_d-1 correspond to the day-ahead market price for Belgium from the previous day. Furthermore, it is clarified that the residual load is computed using the difference between forecasted values (e.g. load, wind production, solar production) such as this information is available at the time of forecast. Note that a clarifying list of acronyms of variables is included in Annex.

2.3.1. Category 1 : available regulation capacity

Figure 13 presents the largest correlation coefficients for the up- and downward available regulation capacity (category 1) as explained in Section 2.1. The total available regulation capacity is the sum of 'controllable' capacity (IC / DC) and 'limited controllable' capacity (ILC / DLC). While the downward 'limited controllable' capacity is mainly originating from wind power bids, there are almost no upward 'limited controllable' bids observed.

For the upward capacity, it is found that the available regulation capacity of the previous day: total (0.68), gas-fired (0.68) and CCGT (0.67) show the highest correlation coefficients, as well as the forecasted residual load minus the available nuclear and gas-fired capacity (0.59). Other relatively high correlations are found with the day-ahead price forecast (0.50), the residual load minus the nuclear generation (0.53), the forecasted day-ahead price (0.50), residual load of the previous day (0.47), the day-ahead prices of the previous day (0.43) and the available regulation capacity of the previous day **:** total (0.40), gas-fired units (0.40), CCGT (0.40) and wind power (0.34). Finally, and to minor extend, there is also a correlation with the limited controllable capacity of the previous day (0.24) and the forecasted wind power (0.33). Note that these results are the same for the subcategory of 'controllable' capacity as there are almost no 'limited controllable' volumes for upward.

For the downward capacity, it is found that the available regulation capacity of the previous day: total (0.58), gas-fired units (0.58) and CCGT (0.58) show the largest correlations. Also the 'limited controllable' available downward regulation capacity from wind power of the previous day (0.54) and the wind power forecast (0.47) show a large correlation. This is due to the substantial contribution of the 'limited controllable" capacity through wind as show by the correlation coefficients from this sub-category. Other significant correlations are found with the available limited controllable capacity of the previous day, the forecasted day-ahead prices and the day-ahead price of the previous day, the residual load minus nuclear generation, the available regulation capacity of the previous day **:** total (0.40), gas-fired (0.40), CCGT (0.40) and wind power (0.34) play a less significant role.

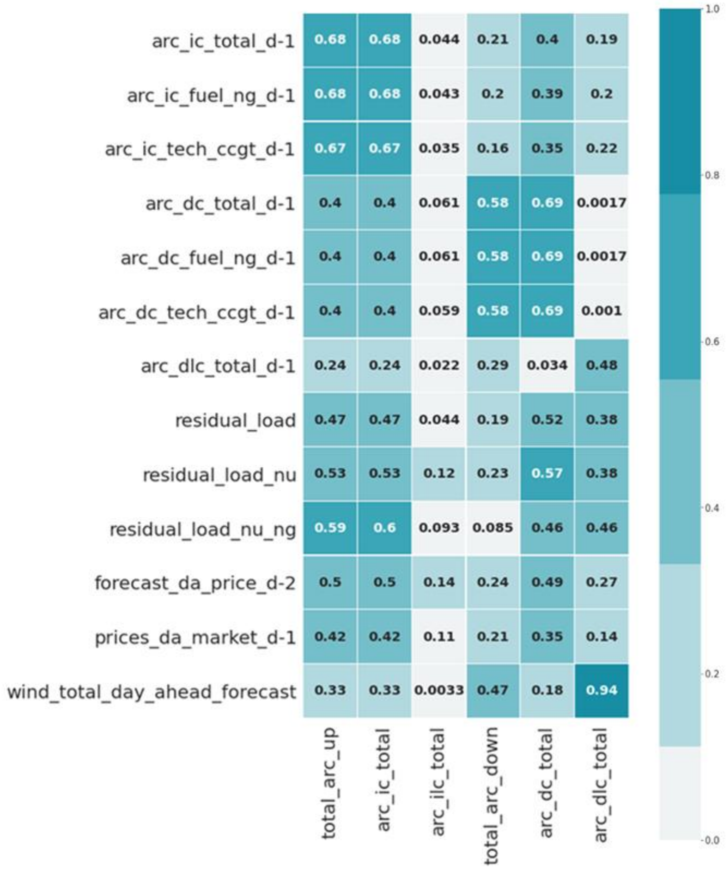


Figure 13: correlation matrix for the available regulation capacity (category 1)

2.3.2. Category 2: available pumped-hydro storage non-contracted balancing energy

Figure 14 shows that the available upward pumped-hydro storage non-contracted balancing energy shows a high correlation with the available upward non-contracted capacity of the previous day (0.64). Also the residual load of the previous day (0.46), the total load forecast 0.46), the time of day (0.36) and the forecasted day-ahead market price (0.34) show relatively high correlations. Low correlations are observed with the downward non-contracted capacity of the previous day (0.21) and the time of day F1 (0.25), which refers to the transformation to a continuous function by means of the co-sinus function.

For the downward side, the downward non-contracted capacity of the previous day (0.46) shows the highest correlations. In contrast, the upward non-contracted capacity of the previous day (0.22), the total load forecast (0.13), the time of day (0.23) and the time of day F1 (0.20) show relatively low correlations.

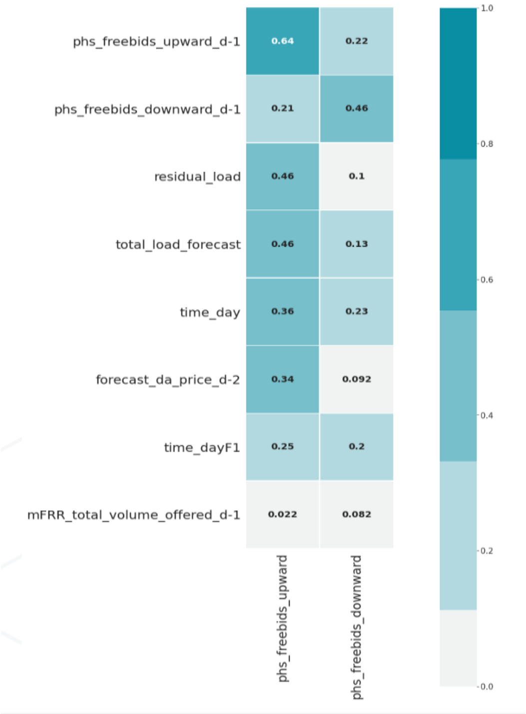


Figure 14: correlation matrix for the available pumped hydro storage capacity (category 2)

2.3.3. Category 3 : available mFRR reserve sharing

Figure 15 show the correlations for the available mFRR reserve sharing, represented by the available transmission capacity after intra-day with France, The Netherlands and United Kingdom. Correlations are found to be relatively weak compared to previous categories. For the export side, using the available sharing on export with France gives the highest correlations (0.29). The main reason for the low correlations is that the available transmission capacity on which the available sharing depends on regional features are not included in the scope of this study.

Note that for individual borders, relevant correlations are found for the United Kingdom, where a correlation is found to exist between the available sharing on export and the lagged values (0.68), as well as gas prices (0.39), together with the forecasted day-ahead electricity market price for Belgium (0.29).

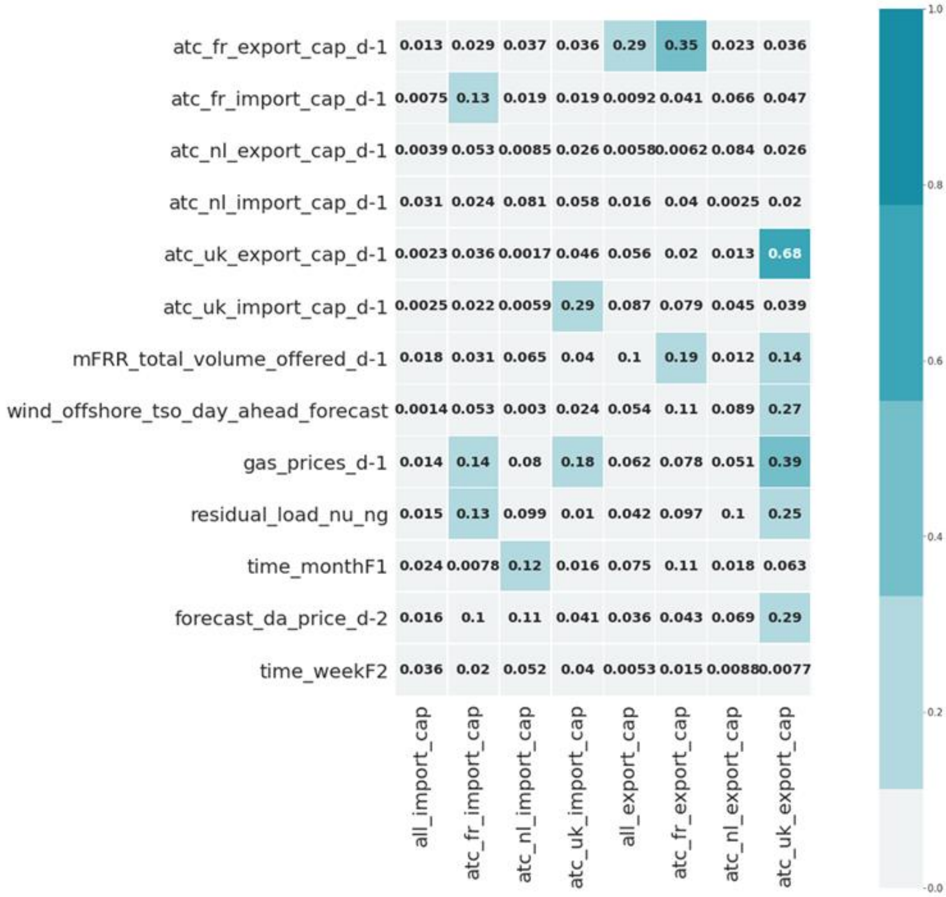


Figure 15: correlation matrix for the non-contracted total mFRR balancing means (category 4)

2.3.4. Category 4: non-contracted mFRR balancing means

Figure 16 shows that for the upward non-contracted mFRR balancing means, the largest correlations are found with the downward non-contracted mFRR balancing means of the previous day (0.50) and the time of the day (0.45). Other smaller correlations are shown with the total load forecast (0.17), the upward non-contracted balancing energy bids of pumped hydro of the previous day (0.18) and the available reserve sharing on Nemo Link for the previous day (0.14).

For the downward non-contracted mFRR balancing means, a very large correlation is found with the downward non-contracted mFRR balancing means of the previous day (0.78). Additionally, large correlations are found with the total load forecast (0.48), the non-contracted downward volumes provided by pumped-hydro storage during the previous day (0.47) and the time of day (0.46). Smaller correlations are found with the wind power forecasts (0.29) and the gas prices of the previous day (0.21).

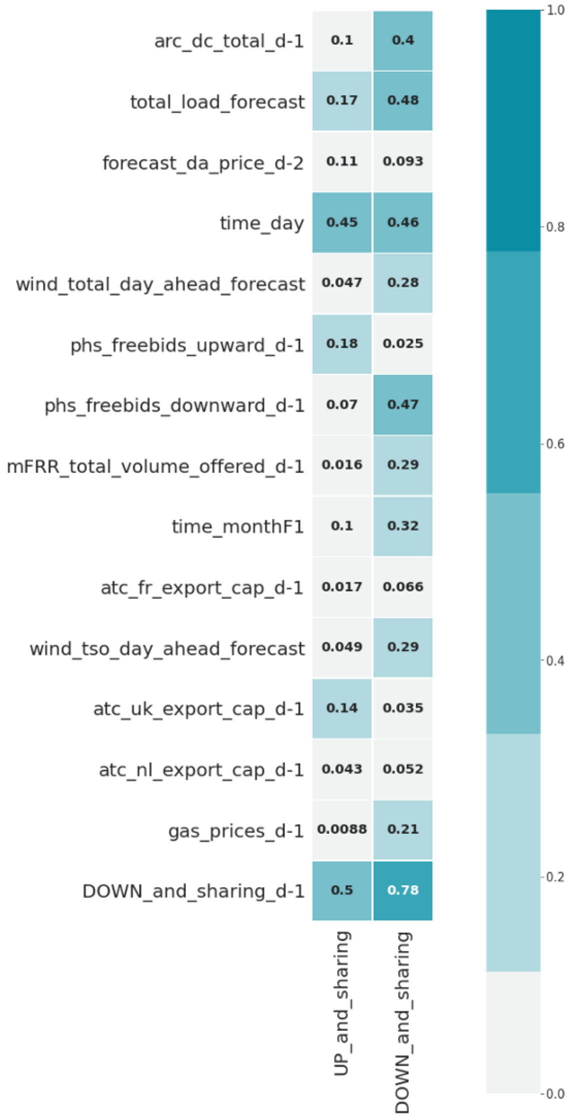


Figure 16: correlation matrix for the non-contracted total mFRR balancing means (category 4)

2.3.5. Category 5 : non-contracted aFRR balancing energy bids

For the analysis on non-contracted aFRR balancing energy bids, the correlation matrix show that in general, the correlation coefficients remain relatively low for the upward direction. The upward volumes seem to be impacted by the non-contracted upward balancing bids of the previous day (0.28), the incremental bids from pumped-hydro storage (0.23), the forecasted day-ahead price (0.18) and the total load forecast (0.11).

In contrast, the correlations for the downward volumes are substantially higher and volumes are impacted by the downward available regulation capacity of the previous day (0.47), the total load forecast (0.44), the non-contracted downward balancing bids of the previous day (0.42) and to lower extend the forecasted day-ahead price (0.29), the decremental bids from pumped-hydro storage (0.24) and the total wind power forecast (0.22).

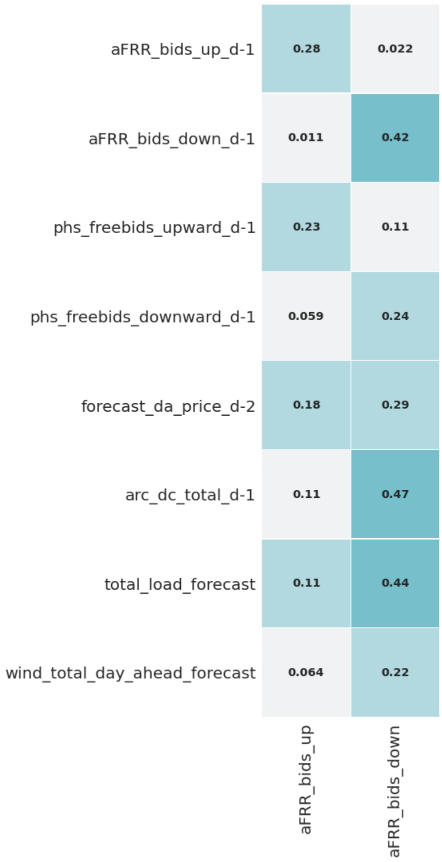


Figure 17: correlation matrix for the non-contracted aFRR balancing energy bids (category 5)

2.3.6. Selection of features

The best features for each component of the targets have a correlation coefficient (abs. val.) around:

- IC/DC: 0.68
- PHS: 0.46
- DLC: 0.94
- ATC: 0.45

Given the high linear correlations obtained, even linear models (such as a linear regression) should be able to generate relevant forecasts, and may compete against complex models. This analysis gives us a top candidate list of best features for each target component. Those best candidates are used as a basis into the model to produce a simple and interpretable forecast. More features are added gradually.

It should be noted that state-of-the-art machine learning models are able to assign themselves coefficients (or weights) to the different input features that the user provides for the training process, such as they automatically assign a relevance on the provided information. This advocates for incorporating many features but note that this burdens computational time. For this reason, correlation analysis is used as a preliminary process where it is tired to create the most suitable feature framework for the model. In other words, the end goal is to train the different models using the, a-priori, highest correlated features which are available at the time of forecast.

On the other hand, not all relevant features show linear correlations with the targets and can be captured with a correlation analysis. For this reason, it might, based on expertise and market knowledge, be justified to include additional features. The following table summarizes which final features have been used to predict each of the target values.

CATEGORY 4. Up	CATEGORY 4. Down	CATEGORY 5. Up	CAT EGORY 5. Down
arc_dc_total_d-1	arc_ic_total_d-1	phs_freebids_upward_d-1	forecast_da_price_d-2
total_load_forecast	total_load_forecast	phs_freebids_downward_d-1	arc_dc_total_d-1
forecast_da_price_d-2	time_day	aFRR_bids_up_d-1	total_load_forecast
time_day	phs_freebids_upward_d-1	total_load_forecast	aFRR_bids_down_d-1
wind_total_day_ahead_forecast	mFRR_total_volume_offered_d-1	time_day	arc_ic_total_d-1
phs_freebids_upward_d-1	time_monthF1		wind_total_day_ahead_forecast
phs_freebids_downward_d-1	gas_prices_d-1		
mFRR_total_volume_offered_d-1	atc_fr_import_cap_d-1		
time_monthF1	atc_nl_import_cap_d-1		
atc_fr_export_cap_d-1	atc_uk_import_cap_d-1		
wind_tso_day_ahead_forecast	UP_and_sharing_d-1		
atc_uk_export_cap_d-1			
atc_nl_export_cap_d-1			
gas_prices_d-1			
DOWN_and_sharing_d-1			

CATEGORY 2. Up	CATEGORY 2. Down	CATEGORY 3. up	CAT EGORY 3. down
arc_ic_total_d-1	arc_dc_total_d-1	total_load_forecast	total_load_forecast
total_load_forecast	total_load_forecast	time_day	forecast_da_price_d-2
time_day	forecast_da_price_d-2	mFRR_total_volume_offered_d-1	time_day
phs_freebids_upward_d-1	time_day	time_monthF1	wind_total_day_ahead_forecast
time_monthF1	wind_total_day_ahead_forecast	gas_prices_d-1	mFRR_total_volume_offered_d-1
	phs_freebids_upward_d-1	atc_fr_import_cap_d-1	time_monthF1
	phs_freebids_downward_d-1	atc_nl_import_cap_d-1	atc_fr_export_cap_d-1
		atc_uk_import_cap_d-1	wind_tso_day_ahead_forecast
			atc_uk_export_cap_d-1
			atc_nl_export_cap_d-1
			gas_prices_d-1

CATEGORY 1. Up	CATEGORY 1. Down
arc_ic_total_d-1	arc_dc_total_d-1
total_load_forecast	total_load_forecast
time_day	forecast_da_price_d-2
forecast_da_price_d-2	time_day
time_monthF1	wind_total_day_ahead_forecast

3. Methodology

3.1. Machine learning method selection

Figure 19 provides an overview of the different categories of machine learning methods. Focus in this study is on **supervised learning methods** which are typically used when dataset variables are labelled as features or outcome and which is the case in this application. **Unsupervised learning methods** are generally used when this information is not provided. However, this does not mean they cannot be used for a supervised learning problem as well. For instance, the k-means clustering is successfully implemented (in combination with a Nearest Neighbor algorithm) in Elia's FRR dimensioning, where the outcome and features are also well defined. **Reinforcement learning methods** are used when an algorithm is trained based on dynamic interactions with an environment (typically used in robotics and gaming) and is out of scope of this study.

In supervised learning, a distinction is made between regression and classification. Focus in this study is on **regression,** where the objective is to predict a numerical or continuous variables, in this case the available non-contracted balancing means (up- and downward aFRR / mFRR). **Classification** is generally used when predicting discrete variables although several algorithms can also be used for continuous variables.

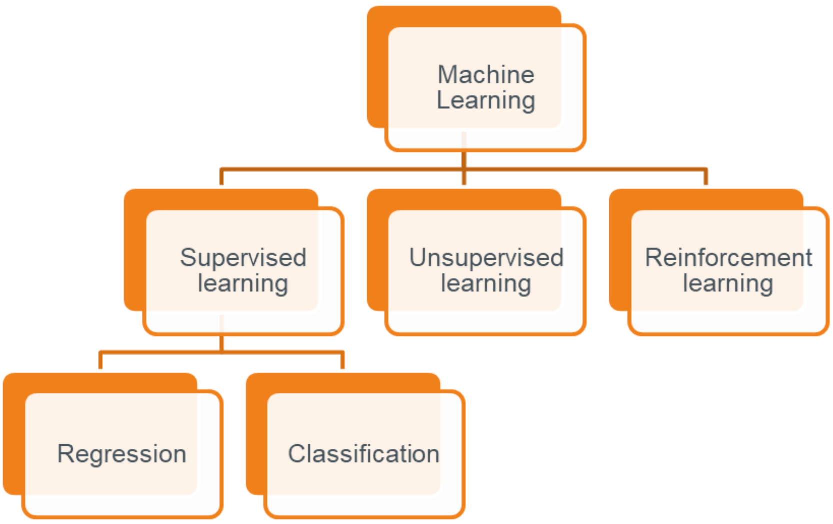


Figure 18: Overview of machine learning categories

Figure 19 provides an overview of the most well-known algorithms used in industry. Most are supervised learning methods, but also a non-supervised learning method is listed (k-means). Although some of the methods are typically used for classification (cf. Decision Trees), all these methods can be used to solve regression problems. Note that an educative explanation of each algorithm type is beyond the scope of this study. The necessary information can be found in specialized literature.

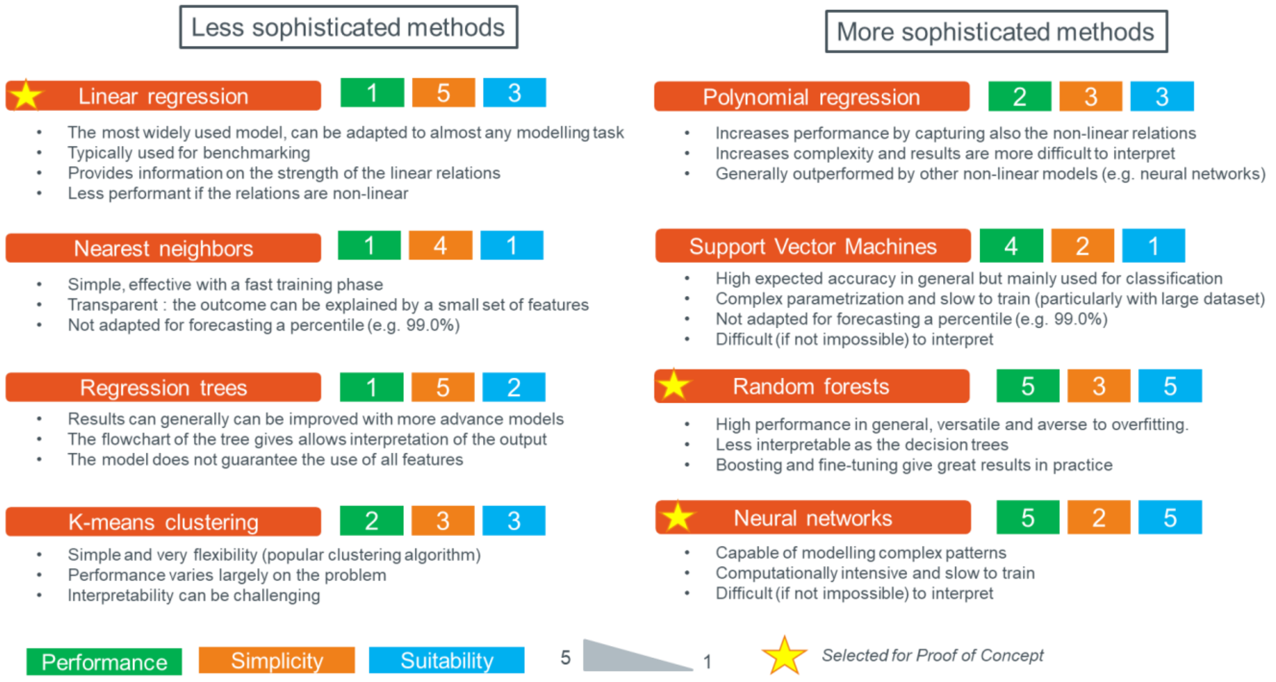


Figure 19: Overview of the qualitative pre-selection of methods for the Proof of Concept

Analyzing the performance of all different methods in a quantitative way is time consuming. Indeed, it requires building the model, and finding the right parameters, which is particularly demanding for the sophisticated methods such as support vector machines and artificial neural networks. Therefore, a pre-selection is made based on a qualitative selection of these algorithms based on **accuracy, simplicity and suitability**. While the accuracy is preferably kept as high as possible, it generally goes at the cost of lower simplicity. The latter is related to interpretability which is important in the context of FRR dimensioning, a certain level of interpretability is required to justify ex post the dimensioning and procurement of FRR balancing capacity, since the reservation costs impacts the TSO's costs for ancillary services, and so the transmission tariffs. For this reason, when two methods would score equally on accuracy, it would be advised to select the method with the highest simplicity. Finally, a third criteria used here is suitability for the selected problem which generally relates in this case to the ability to predict a certain percentile (e.g. 99% confidence) rather than a point forecast.

The pre-selection puts forward a **linear regression** as less sophisticated methods. This methodology, very simple and intuitive, is generally used as a benchmark, demonstrating the minimum potential for the use of machine learning, This benchmark is complemented with a **random forests** and **artificial neural networks,** method which are more sophisticated to further increase accuracy.

Note that these two methods are selected above other advanced methods such as support vector machines and polynomial regressions. Despite the fact that **support vector machines** are typically known for achieving high accuracy, they are also characterized by a complex parametrization and require a lot of computational time for training when working with large data sets, as it is currently the case in this study. On the other hand, the artificial neural networks are expected to also provide high accuracy as well, but with less complexity in the parametrization. In contrast, **polynomial regressions** are found to be outperformed by random forests on accuracy and suitability, for the same level of simplicity.

3.2. Set up learning environment

Figure 20 illustrates the allocation of available data over the training and test set. As recommended by good machine learning practices, the data is split randomly into a training set (75% of the data) and a test set (25% of the data). This test set will only be used for the final evaluation of the method, i.e. when computing the different KPIs.

With training set, a 10-fold cross validation is conducted to test and find the parameter settings. The data set is divided in 10 folds or bins, of which one fold is used to assess the performance of the model. This exercise is then repeated 10 times, with different folds, allowing to obtain each time a slightly different performance. Such approach allows to ensure the results are sufficiently robust helping to select the best parameter for the method.

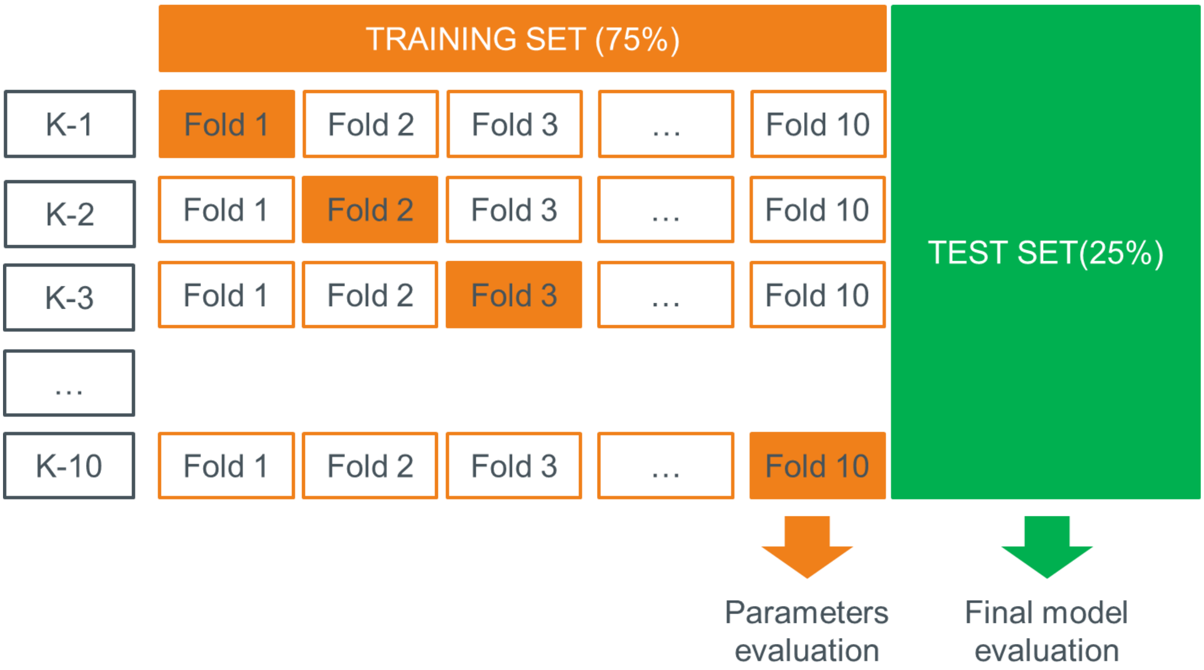


Figure 20: Illustration of a 10 fold cross-validation

3.3. Determining the performance criteria

The performance of the algorithms are assessed over the separate test set, i.e. data which is only used to assess the performance of the model, and not to train the algorithms, or calibrate the parameters. The first criteria is the **reliability** level which investigates the ability of the algorithm to determine the FRR means with a confidence level of 99.0%. In other words, 99.0% of the observed balancing means should be above the forecast level in order to avoid overestimating the available means. Note that theoretically, this reliability level should approach 100% in order to make sure that FRR needs are adequately covered but setting the reliability level this high would mitigate the potential of a dynamic methodology. If the test set shows that the reliability is below 98.9%, i.e. that the FRR means cover less than 98.9% of the sizing variable, the algorithm (or its parametrization) is discarded.

For all algorithms matching the above mentioned criteria, the **mean absolute error** over the test set is used for further assessment. Due to the nature of the problem (assessing a risk rather than predicting a value), this mean absolute value is calculated based on a quantile loss function. This quantile loss function[9] compares the real-time observed value with the predicted 99.0% percentile values. If the value falls outside this [0%; 99%] confidence bandwidth, it will have a larger impact on the mean absolute error than if it falls within the interval. If it is found that another model on the same family (i.e. with a different parametrization) has already achieved a better result, the model is discarded. This process is conducted iteratively until the results converge to a certain mean absolute error which becomes difficult to further improve.

Finally, the dynamic potential with a certain algorithm, if any exists, and a parametrization which achieve reasonable results, is assessed by means of the **average forecast value**, i.e. the average volume of available FRR means. The higher the available FRR means, the larger the dynamic potential, at least when above the static value. Note that further investigation, particularly for the sophisticated methods can still result in incremental improvements

3.4. Calibration of the algorithms

3.4.1. Linear regression

A linear regression in one of the simplest machine learning methods (Figure 21, left), yet also one of the most used ones thanks to its simplicity and interpretability. The idea behind a simple linear regression is to find the line that fit the best on a cloud of points. From an algebraic point of view, a linear function (so two parameters a and b in the equation Y = a.X+b) is searched such that it minimizes the sum of the distances for every observation from this linear function, typically by means of an ordinary least squares method.

To apply this method on FRR means forecasts, a multiple instead of a simple linear regression is used, which extends the simple linear regression with several explanatory variables ($X_1,\ldots X_t$) instead of just one, as in the previous example. In addition, a quantile loss function, instead of the ordinary least square method is used, in order to forecast a quantile, i.e. percentile value. By doing so, if the forecast aims at predicting a value that has to be below the observation 99% of the times, the quantile in the quantile loss function is set at 99%. In the case of the simple linear regression, instead of being "in the middle" of the cloud of points, the produced line will now be more or less above 99% of the points. This is referred to in the literature as quantile regression[10].

Along with its simplicity, the advantages of the linear regression is that there is no parameter configuration (i.e. besides finding the coefficients in the linear function). For these reasons, this type of method is frequently used as a benchmarking method. One of the main advantages is that it also depicts the strength of the correlations which is useful to interpret the results. In general, these type of methods are less suitable when the features and outcomes show non-linear relations, which are indeed also the case in this study. It is therefore expected that this benchmark method will be outperformed by the other methods.

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[9] $L_q(pred, obs) = max[q(obs - pred), (q - 1)(obs - pred)]$ comparing the delta between the predicted value (pred) and observed value (obs)

[10] Koenker, R. (2005). Quantile Regression. Cambridge University Press. pp. 146–7.

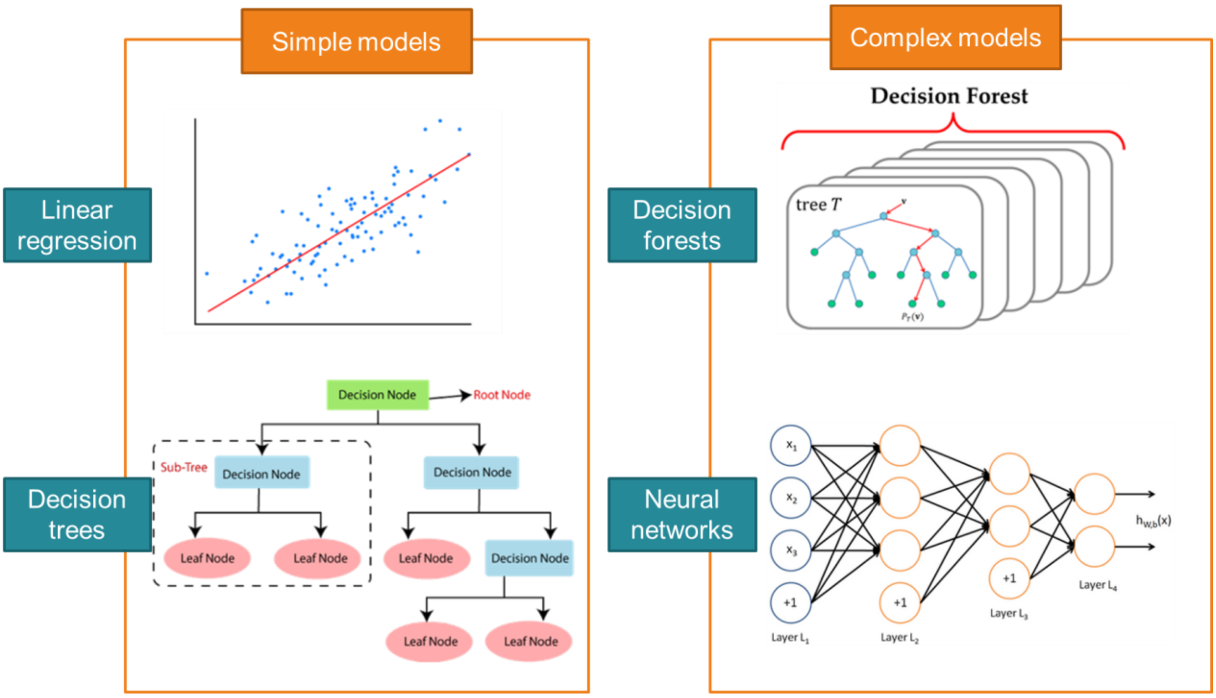


Figure 21: Graphical illustration of a linear regression (upper left), a decision tree (lower left), a random forest (upper right) and neural networks (down right).

3.4.2. Random forests

Random forest (Figure 21, upper right) are based on building a large number of individual decision trees that operate as an ensemble. Ensemble methods are techniques that create multiple models and then combine them to produce improved results. In the present case: a random forest is an “ensemble method” since it creates multiple models (decision trees) and combines them (into a forest). Decision tree algorithms (Figure 21, lower left) are built on “if-else statements” that can be used to predict a result based on data. Although these types of methods are typically used for classification problems (the models are then called classification trees), these are also widely used for regression problems, and hence referred to as regression trees. Here, because the available non-contracted balancing means deal with continuous variables, it concerns a regression tree.

Each individual tree in the random forest produces a prediction, then a global prediction is reached (for instance by taking the average of all the prediction in the case of a continuous variable). These types of models generally provide a high performance while being versatile, and robust against different problems. Of course, complexity is larger as with the individual decision trees and this method also coming at a cost of less interpretability compared to the decision trees. A forest of quantile regression trees is used.

The nodes are split based on a entropy-based method. After sensitivity analyses up to an amount of trees of 500 and the height up to 8, the number of trees in is specified at 220 (mFRR upward/mFRR downward) and 200 (aFRR up- and downward) while the height of each tree is specified at 7 for mFRR targets and 5 to aFRR targets. A large number of small trees is a good way to avoid overfitting problems. A gradient boosting algorithm[11] is used which builds the trees iteratively, and take into account the weaknesses of trees already built in each new tree. After sensitivity analyses between 0.05 and 0.80 is included on the learning rate and fixed at 0.1 (mFRR up/mFRR down) and 0.15 (aFRR up- and downward). This parameter is linked to the weight attributed to each tree for computed the final forest prediction.

Note that due to relatively low amount of data and the low volume considered for aFRR means, the fine-tuning process was irrelevant (almost always the same result independently of the parameter selection). More data are needed for a relevant fine-tuning. The parameters below seems to be perform best on the available sample

3.4.3. Artificial neural networks

Artificial neural networks model the relationship between a set of input and output signals (Figure 21, lower right). The concept is that each neuron has inputs and produce a single output which can be sent to multiple other neurons. The neurons are stacked into different layers to produce the global network. After a training phase, a new input (a set of values for the different features) can be feed to the neurons on the first layer, those will produce an output that will be sent to the second layer of neurons, which can be send to the third layer, and so on. This process continues until it reaches the final layer that will output the final result, i.e. the prediction of the available non-contracted balancing means.

To produce an output, a single neuron first takes as inputs some values computed on the previous layers, those inputs are combined into a weighted sum (the weight depends on the links that connect different neurons). Then the neuron adds a bias term to this weighted sum and passed the result through a (usually non-linear) activation function to produce its output[12]. The goal of the learning process is to determine the neuron's weight and bias in order to minimize the observed errors when using the network. After the learning process, a specific value can be given to in first layer of the network (i.e. values for each feature) and the output of the last neuron is the forecasted outcome.

Artificial neural networks are versatile learning algorithms which can be applied in nearly any learning task. They are often applied to problems where the input data and output data are well defined, yet the process that relates the input to the output is complex and hard to interpret due to the non-linear nature. These types of models are therefore computationally intensive, slow to train and due to their difficult interpretability, sometimes referred to as a 'black box' methods.

The neural network for this study is built on six sequential complete layers so every node of the layer number N is linked to every node of the next layer number N+1. Sensitivities up to 10 are assessed with a number of features per layer up to the amount of features investigated. A "relu" activation function (also known as "rectified linear unit") is used for the layers except for the first and the last one for which a linear activation function is used. The 'relu' function is

[11] Hastie, T.; Tibshirani, R.; Friedman, J. H. (2009). "10. Boosting and Additive Trees". The Elements of Statistical Learning (2nd ed.). New York: Springer. pp. 337–384.

[12] Artificial intelligence (3rd ed.). Addison-Wesley Pub. Co. 1992.

wildly used and allows to not activate all neurons at the same time which is computationally efficient[13]. Several sensitivities are conducted to determine the amount of layers (between 5 and 10) and the amount of neurons per layer (between 5 and the number of features considered). The learning rate is a hyper-parameter that controls how quickly the weights are adapted to the problem.

	Upward mFRR	Downward mFRR
Amount of layers	8	8
Notes per layer	11, 11, 11, 11, 11, 11, 5, 1	11, 11, 11, 11, 11, 11, 5, 1
Learning rate	0.10	0.10

Before the training of the network, a Gaussian kernel initializer is used which allows to set up the initial weight randomly in the network, otherwise the learning process can suffer from unwanted and avoidable bias (for instance if we set up manually the weight of the network to zero). When training a neural network (i.e. adjust the weights in the network), an iterative method is used called the stochastic gradient descent[14]. Here, a stochastic gradient descent is applied which is based on adaptive learning rate per dimension (Adadelta)[15] that have shown good results in practice[16]. Again, as the interest lays in quantile prediction rather than average point forecasts, a quantile loss function is used in the learning process.

From a practical point of view, Keras is used to design the network which is a user-friendly framework for neural networks built on top of TensorFlow 2.0, an open source software library for Python.

[13] LeCun Y., Bottou L., Genevieve B. O. and Müller K.-R. (1998). "Efficient BackProp". In G. Orr; K. Müller (eds.). Neural Networks: Tricks of the Trade. Springer.

[14] Bottou, L. (1998). "Online Algorithms and Stochastic Approximations". Online Learning and Neural Networks. Cambridge University Press.

[15] Rumelhart, David E.; Hinton, Geoffrey E.; Williams, Ronald J. (8 October 1986). "Learning representations by back-propagating errors". Nature. 323 (6088): 533–536.

[16] Zeiler, Matthew D. (2012). "ADADELTA: An adaptive learning rate method".

4. Results

4.1. Setting up the reference scenario

4.1.1. Assumptions

In order to compare the performance of several algorithms, and facilitate the interpretation of the results, a reference scenario is built for which simulations are conducted. The reference scenario targets to obtain representative results if predictions would have been made for 2021.

Figure 22: Visual representation of the historic time period for training the algorithms

A dataset has been constructed for the selected targets and features for the period from April 16, 2021 until April 15, 2021 (Figure 22). This data was selected to represent the latest, and therefore most representative, data when conducting the simulations during the summer of 2021, while avoiding the maintenance period of the pumped-hydro storage units of Coo-Trois-Ponts between 15/4/2021 and 15/7/2021. During this exceptional planned maintenance, all pumps and turbines were set as unavailable[17]. As these units are expected to have significant impact on the results, and such events are rare, excluding these periods results in a better representativeness of the results. Nevertheless, one sensitivity is conducted for the period between July 1, 2019 and June 30, 2021 to assess the impact of this maintenance event on the results. In contrast to the mFRR balancing means, the period between July 1, 2019 and June 30, 2021 is used as reference period for the aFRR balancing means. This time period remains representative for the simulations on which is assumed to be hardly impacted by the maintenance of Belgium's largest pumped-hydro plant.

As explained in the previous sections, in order to further improve the representativeness of the results, a few corrections have been made to the mFRR target variables which are currently still calculated by Elia in an implicit way:

- in the incremental bids, the available time series on Elia's website (available regulation capacity) have been corrected by removing time periods where CCGTS are not scheduled (based on the latest nominations) since these plants are not able to provide mFRR in such situations.

[17] One turbine of the six is foreseen remain in maintenance until 31/8/2021 (cf. ENTSOE-E **Transparency Platform**)

- In the decremental bids, the available time series on Elia's website (available regulation capacity) have been corrected by taking into account the last nominations of wind power parks subject to bidding obligations (cf. subject to the Terms and Conditions Scheduling Agent) and upscaled towards 2021 by means of the expected incremental installed capacity between the observed time series and 2021. Note that a sensitivity is conducted without this upscaling in order to depict the effect of this extrapolation.

As explained earlier, the reference scenario is based on a day versus night pumped-hydro schedule, completed with a sensitivity having full or no availability of non-contracted mFRR balancing energy bids after day-ahead. Available mFRR reserve sharing is now based on day-ahead predictions of the available transmission capacity after intra-day while taking into account relevant limits set by the system operation guidelines : 312 MW for upward and 550 MW for downward (if predicted in export or undefined). Finally, all algorithms are based to predict the available FRR means with a confidence level of 99%. This means that the predicted volume is expected to be available with a certainty of 99%.

4.1.2. Available non-contracted mFRR balancing means

Figure 23 (left) represents a distribution of the realized total non-contracted upward mFRR balancing means under the above-mentioned assumptions. Note that, as these have been implicitly calculated by Elia based on the last known schedules, these may also contain capacity which would have been eligible for providing non-contracted aFRR balancing means. The distribution of available volumes demonstrates an average volume of 789 MW. Nevertheless, this would only result in a volume of 319 MW for 99% of the time or a volume larger than 1000 MW for 21 % of the time (the current upward FRR needs remain around 1000 MW). Although this may seem substantial, it should be noted that this already takes into account the mFRR sharing contribution.

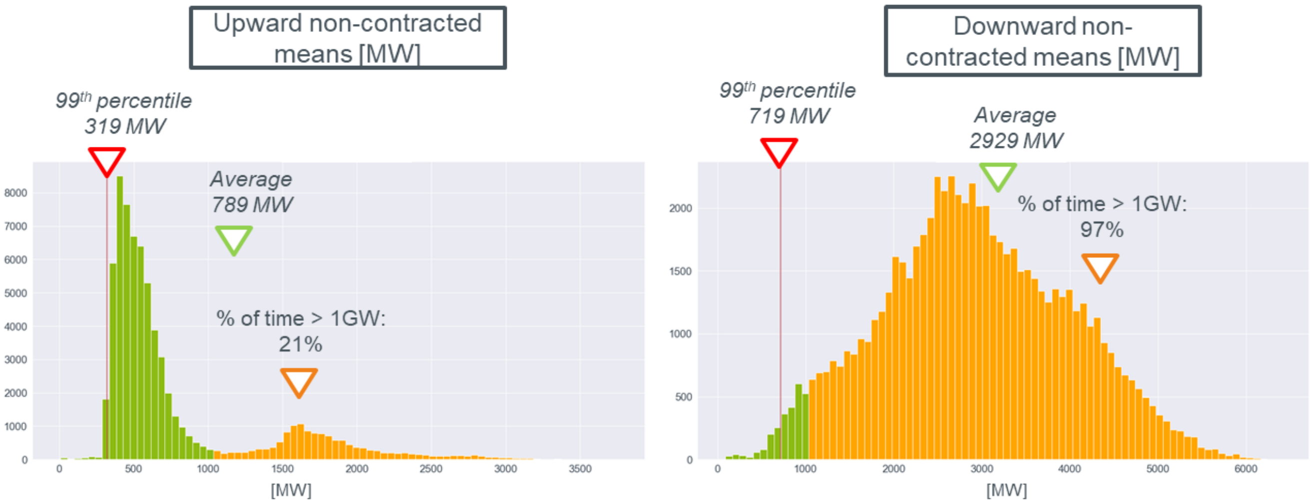


Figure 23: available non-contracted mFRR balancing means for upward (left) and downward (right) balancing

Figure 24 (up) shows the breakdown of this volume per category: the non-contracted available regulation capacity (incremental bids), the available non-contracted pumped-hydro storage bids and the available mFRR reserve sharing. It is concluded that the above-mentioned 'static' potential is mainly following the mFRR reserve sharing contribution for which at least around 250 MW is available for most of the time. This confirms the current value considered in the LFC Means currently determining the allocation of the balancing means. This volume is complemented with pumped-hydro storage flexibility which can be very large in capacity (exceeding 1 GW) but remains relatively low in frequency as it assumed to be only available during night. The incremental bids vary between 0 MW and 1000 MW and are currently coming only from thermal capacity.

Although the distributions may show substantial volumes, it should be reminded that as long as remaining in a static approach, one should only look at volumes which are almost guaranteed to be available (represented by 99^{th} percentile) and that large part of this potential, i.e. 250 MW is already captured by means of mFRR reserve sharing. Capturing the additional volume of the 319 MW would require a partial procurement strategy which is demonstrated to be difficult to realize in practice[18].

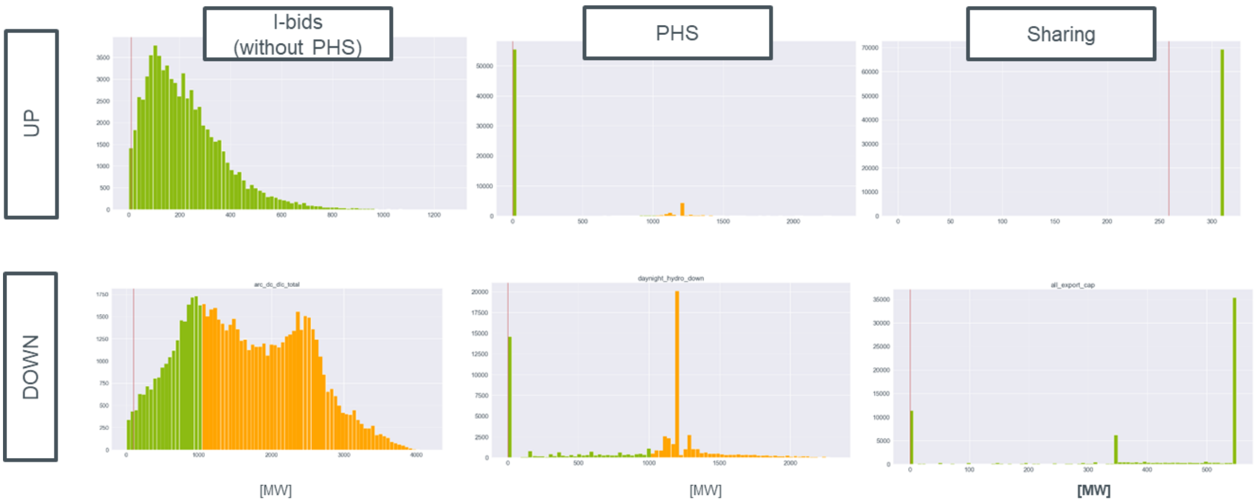


Figure 24: Histogram of available non-contracted mFRR balancing means for upward (up) and downward (down) balancing per category

In contrast, Figure 23 (right) represents a distribution of the realized total downward non-contracted mFRR balancing means. The distribution of available volumes demonstrates an average volume up to 2929 MW. Nevertheless, this only results in a volume of 719 MW for 99% of the time or a volume larger than 1000 MW for 97 % of the time (the maximum downward FRR needs are around 1000 MW). Note that these availabilities are currently considered sufficient in the previous LFC Means analyses to cover the downward mFRR needs without procurement.

Figure 24 (down) showing the breakdown per category show that these volumes mainly come from the available downward regulation capacity (decremental bids), including wind power, complemented with available pumped-hydro storage (during the day time) up to volumes exceeding 1 GW and mFRR reserve sharing (up to 550 MW). The discrete profile with high frequency of values around 0 MW, 350 MW and 550 MW is explained by the total limit (550 MW) and the limits per border (350 MW).

[18] Elia's study on study on the evolution towards a daily procurement of mFRR (2017).

4.1.3. Available non-contracted aFRR balancing means

Figure 25(left) represents the distribution of non-contracted upward aFRR balancing energy bids obtained via explicit bids received since October 2020. It is to be noted that frequency and volumes of positive bids is very low. It is observed that 71 % of time, the available volume remains at 0 MW, while the average lays hardly exceeds 7.4 MW. At no point in time, the available volume exceed 140 MW, the expected average aFRR needs in a dynamic dimensioning context[19].

On the other hand, Figure 25(right) shows larger frequency and volumes for non-contracted downward aFRR balancing energy bids. It is observed that 32 % of time, the available volume remains at 0 MW, while the average lays around 56 MW. On 15 % of the time, the available volume exceeds 140 MW.

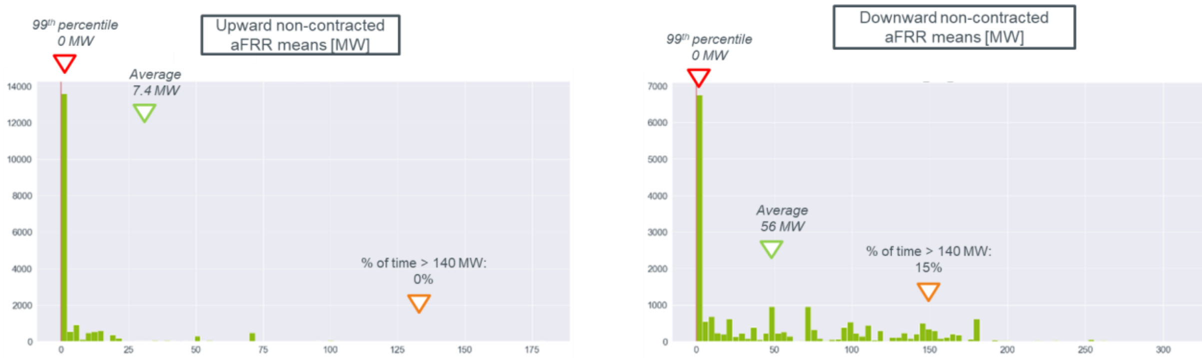


Figure 25: Histogram of available non-contracted aFRR balancing means for upward (left) and downward (right) balancing

It is to be noted that a large part of the non-contracted aFRR means are provided with remaining capacity on units which deliver the contracted aFRR. In the case of CCGT, playing the major role, it may mean that without balancing capacity procurement, the non-contracted balancing energy bids would neither be available, at least in in moments where the clean spark spread is negative. When implementing the right features, this effect should be captured by the machine learning methods.

4.2. Comparison of forecast algorithms

The performance of the three pre-selected algorithms in Section 3.1 are assessed over the separate test set, i.e. data which is only used to assess the performance of the model, and not to train the algorithms, or calibrate the parameters. The first criteria which is investigated is the ability of the algorithm to predict the available FRR means with a **reliability** level of 99.0%. For all algorithms matching the above mentioned criteria, the **mean absolute error** (MAE) over the test set is used for further assessment. Due to the nature of the problem (assessing a risk rather than predicting a value), this mean absolute value us calculated based on a quantile loss function. This quantile loss function[20] compares the real-time observed value with the predicted 99% percentile values. If the value falls outside this [0%; 99%] confidence bandwidth, it will have a lager impact on the mean absolute error, contrary to the case when it falls within the interval.

[19] Elia's study on a dynamic methodology for aFRR dimensioning (2020)
[20] $L_q(pred, obs) = max[q(obs - pred), (q - 1)(obs - pred)]$ comparing the delta between the predicted value (pred) and observed value (obs)

While the reliability and the mean absolute error are used to calibrate the algorithm towards acceptable performance, the **volume** indicates the average non-contracted balancing energy bids for the next day which can be predicted as 'firm'.

Table 1 represents the final results for the three algorithm categories which are quantitatively analyzed towards their ability to forecast the non-contracted balancing means, compared to the 'static' methodology. The latter is based on a fixed value based on the 99th percentile of the probability distribution. It is also shown that even the simple linear regression model achieves a prediction resulting in higher volumes as under the fixed 'static' volume.

Under the best calibration found, the sophisticated models can deliver better predictions as the linear regression, and in particular the random forests in which the predicted available FRR means deliver the highest volumes. This result is observed for as well up- as downward mFRR non-contracted balancing means. It can be seen that the difference between a neural network and random forests is not very large, but as the random forests are less complex and more interpretable, these are put forward as the best solution for this problem. For this reason, all further analysis will be conducted with random forest models. However, algorithms will be calibrated separately for up- and downward mFRR and when assessing individual subcategories: pumped-hydro storage, mFRR reserve sharing and available regulation capacity using the selected features following Section 2.

Table 1: Performance of the several algorithm for forecasting the non-contracted mFRR means compared to a static approach

		Static	Linear regression	Random Forests	Neural Networks
UPWARD	Volume [MW]	319	388	500	463
	Reliability	99.0%	99.0%	98.9%	99.0%
	MAE	5.4	4.53	3.24	3.95
DOWNWARD	Volume [MW]	719	1704	1940	1756
	Reliability	99.0%	99.0%	98.9%	98.9%
	MAE	23.0	13.5	10.84	13.76

Note that the random forests is for this reason also assumed to provide the best accuracy for aFRR. However, Table 2 shows that, under the best settings, no significant potential is yet witnessed due to the limited availability of positive and significant volumes, as well as the limited data set of nine months, no further analyses seemed useful at this point. It might probably make sense to pursue further analysis when obtaining a sufficiently large data set approaching a length of two years, while facing a more liquid market.

Table 2: Performance of the random forest algorithm for forecasting the non-contracted aFRR means compared to a static approach

	Upward				Downward		
Metric	Static	Metric	Dynamic	Metric	Static	Metric	Dynamic
Volume [MW]	0	Volume [MW]	0	Volume [MW]	0	Volume [MW]	2.2
Reliability	100%	Reliability	100%	Reliability	100%	Reliability	98.9%
MAE	0.4	MAE	0.3	MAE	2.8	MAE	1.9

4.3. Simulation results

4.3.1. Upward non-contracted mFRR balancing means

Figure 26 (up) represents the distribution of the total predicted non-contracted upward mFRR balancing means. When comparing to the 'static' distributions in the previous sections, the results show a different distribution, with lower volumes in general. This is explained as by the forecast approach, predicting the available means to be available with a 99% certitude. This is ensured by the algorithm by penalizing overestimations harder in comparison to underestimations. It can be seen that the average predicted volume is found to be 500 MW while the amount of time the volume higher than 1 GW is found to be 14%.

Figure 26: Histogram of predicted available upward non-contracted mFRR balancing energy bids (upper) and breakdown per category (lower)

When breaking down the contribution of forecasted reserve sharing, pumped-hydro storage and other incremental bids contribution (Figure 26, down), it is found that the prediction of the available mFRR sharing provides a large contribution as this capacity seems to be (cf. also the static distribution in Section 4.1.2) available for most of the time. When looking at the other distributions it is found that pumped-hydro storage provides very limited contribution and other, mainly thermal, incremental capacity only provides contribution up to 150 MW.

However, as the ‘static’ distribution shows that the required mFRR needs are not always covered, and procurement of upward balancing capacity is expected to remain required, implementing a forecast tool on the available means provides a potential to support a dynamic calculation to avoid or partially reduced balancing capacity procurement during certain periods. The implementation of the market implications is of course subject to further investigation and conclusion of this result limits itself here to confirming that a ‘firm’ volume of non-contracted capacity can be predicted.

4.3.2. Downward non-contracted mFRR balancing means

Figure 27 (up) represents the distribution of the total predicted non-contracted balancing means. Similar to upward, the results show a different distribution, with lower volumes in general, as with the static distribution. It can be seen that the average predicted volume is found to be 1940 MW while the amount of time the volume higher than 1 GW is found to be 86%.

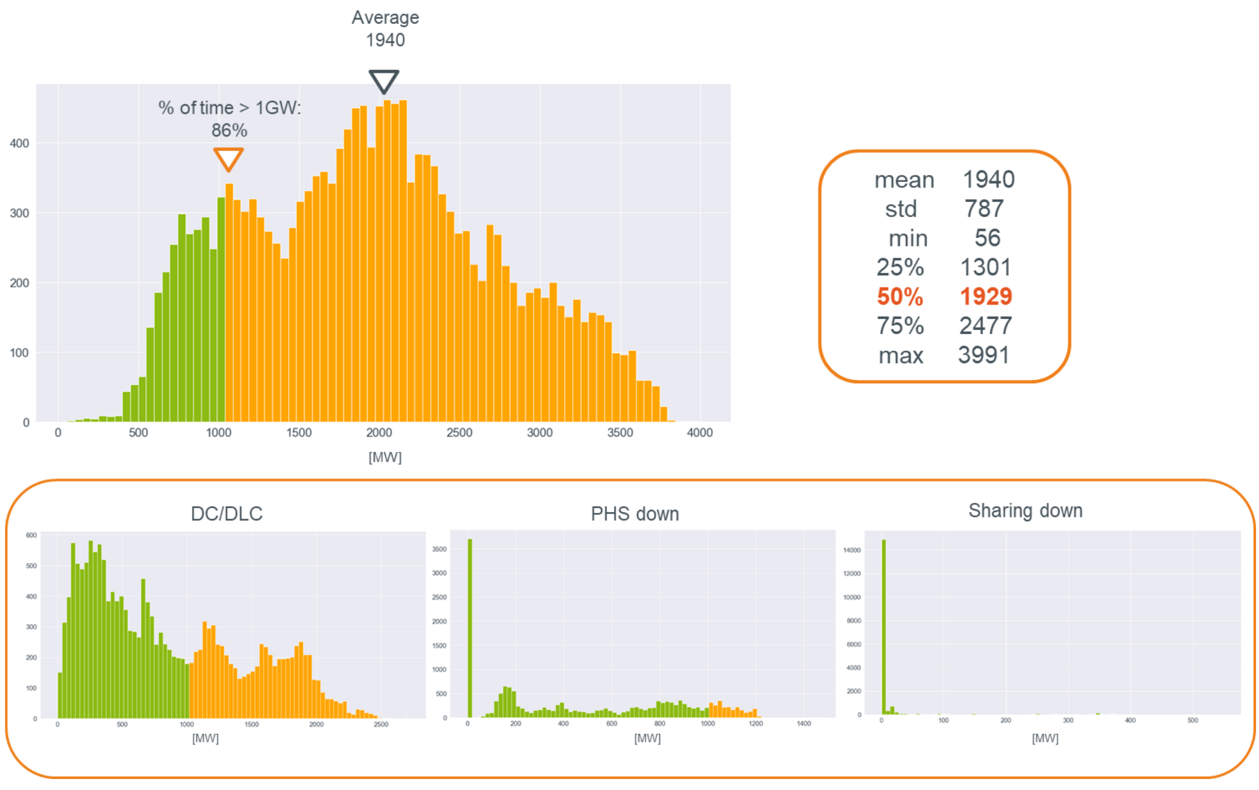


Figure 27: Histogram of predicted available downward non-contracted mFRR balancing energy bids (upper) and breakdown per category (lower)

When breaking down the contribution of forecasted sharing, pumped-hydro storage and other decremental bids contribution Figure 27 (down), it is found that the prediction of the available mFRR sharing does not perform very well and results in a distribution which is much lower as the real distribution. This is partially explained by the discrete aspect trough the introduction of several caps, i.e. 350 MW per cable and 0 MW or 550 MW total following SOGL. An algorithm based on regression is maybe not the best choice to predict the mFRR sharing contribution and a suitable alternative might be classification method. However, optimizing the algorithms for predicting the available mFRR sharing volumes today is not deemed very useful in view of the upcoming evolutions on the European balancing platforms in 2022. When looking at the other distributions it is found that the main contribution comes from decremental capacity, including wind power and pumped-hydro storage.

However, as the ‘static’ distribution shows that the required mFRR needs are almost always covered, and no procurement of downward balancing capacity is expected to be required, implementing a forecast tool on the available means is of little value for the dimensioning. In contrast, relying on such tool would, with a coverage of only 86% of the time, not comply with reliability standards and require procurement with corresponding costs. However, it is not excluded that such predictions may be useful for operational reasons, i.e. predicting periods with higher / lower available flexibility.

4.3.3. Non-contracted aFRR balancing means

A separate analysis is conducted for aFRR. The random forest algorithm has been calibrated to predict the explicit aFRR non-contracted balancing energy bids. Figure 28 (left) shows that the algorithm is not able to provide any predictions. This is explained by the limited availability of explicit bids (as demonstrated in section 4.1.3) in combination with a limited training set (only 9 months) while imposing a high reliability requirement (99%). Therefore, at this point, no other meaningful analysis on predictability can be made. Indeed, changing algorithms is not expected to substantially improve the outcome of the predictions, at least not before facing liquidity and additional data.

Figure 28 (right) shows that the downward faces similar issues, although to lesser extend due to the availability of higher liquidity on the downward side. Nevertheless, 40% of the 15-minute intervals between 1st October 2020 and 30th of June 2021, the downward volume of non-contracted aFRR means is below 5 MW. In combination with the high reliability level, this explains the low volumes that are predicted. While other algorithms might be able to overcome this issue, it is not considered very useful as long as no more data becomes available (at least two years).

For the above-mentioned reasons, no strong conclusions on a dynamic procurement method for aFRR can be made at this point in time. There is no reason to assume that volumes, after facing sufficient liquidity, cannot be predicted, but the current availability of data does not allow to confirm this hypothesis.

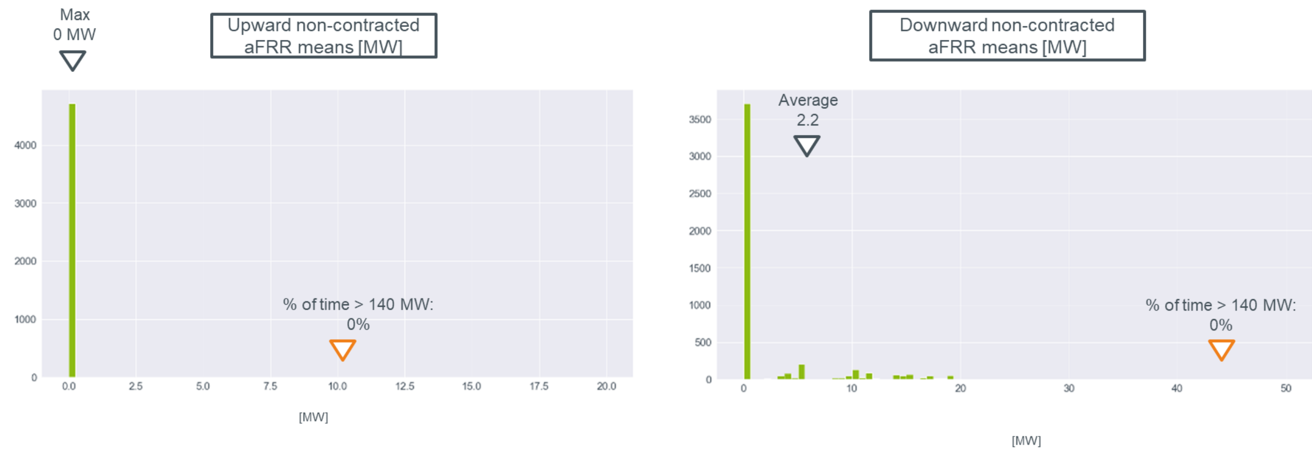


Figure 28 : Histogram of predicted available upward (left) and downward (right) non contracted aFRR balancing energy bids

4.4. Sensitivities

4.4.1. Pumped hydro storage schedules

Pumped-hydro storage is found to provide a substantial contribution to the non-contracted balancing energy volumes. Nevertheless, it is expected that this contribution depends largely on the assumptions taken on available energy levels which remain subject to large uncertainty until the implementation of the explicit bidding for mFRR. Indeed, a day versus night modelling is probably too simplistic, certainly when facing further increase in variable renewable generation.

To obtain some insight on the impact of this assumption, a sensitivity to the reference scenario is conducted when assuming no pumped-hydro storage availability (e.g. pumped-hydro is fully optimized and all energy is assumed to be needed to meet current and future planned schedules) versus full availability (e.g. pumped-hydro storage is assumed to always be able re-optimize trough short-term market and deviate from the planned schedules). Both scenarios are extreme cases which are unlikely to be true in reality.

Figure 29 shows how excluding pumped-hydro storage from the analysis reduces upward non-contracted mFRR balancing means to the original 'static' levels, limiting the potential value of the prediction. Also on the downward side, it would impact the ability to cover the downward mFRR needs. On the other hand, taking the case without energy limits would seriously increase the upward volumes up to a coverage of the mFRR needs from 13% to 70%, while the downward coverage is, despite the increase in average volumes, only increasing from 86% to 98%.The asymmetric effect is due to the assumption that night time period (between 4 AM and 8 MW) is much shorter than the day-time period (between 8 AM and 4 AM).

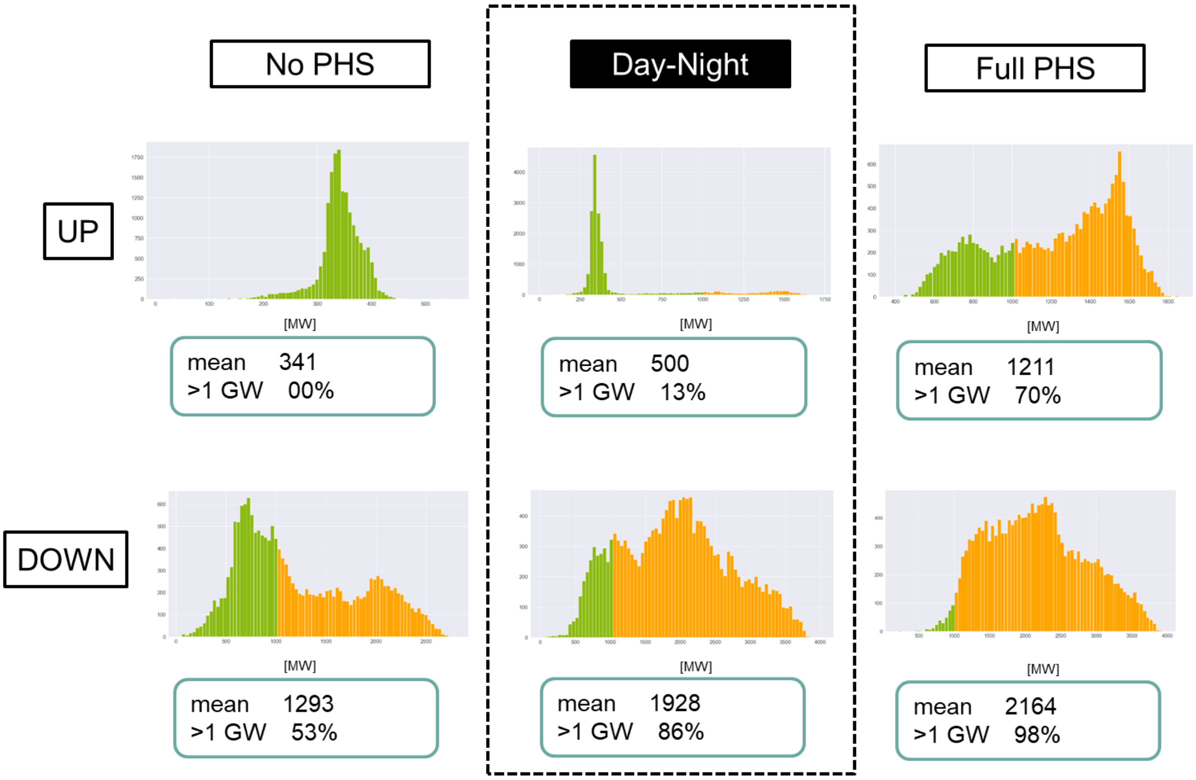


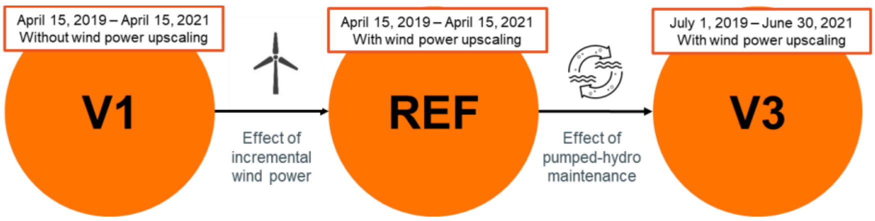
Figure 29: Histograms of available non contracted balancing energy bids for mFRR.for sensitivities on pumped-hydro storage operation

Both sensitivities are obviously extreme and the day-night profile is considered to remain an acceptable starting point for analysis until explicit bids can be taken into account. Furthermore, the results give general insight in the potential contribution of electricity storage technologies such as batteries which can react in the full activation time requirements of mFRR.

4.4.2. Additional sensitivities on the reference scenario

Figure 30 presents the results of a few additional variations on the reference scenario which have been conducted to give some insight in the effect of incremental wind power combined with the implementation of the new interconnection with Germany, as well as the effect of the pumped-hydro plant of Coo-Trois-Ponts maintenance.

In first instance, a scenario without wind power upscaling and without the new interconnector to Germany slightly increases the predicted available non-contracted mFRR balancing means. This effect is mainly due to the additional sharing capabilities which make the mFRR reserve sharing more predictable explaining why there is no effect on the 'static' results. In contrast, the effect of incremental wind power is, as expected, substantial but only in the downward direction. In second instance, the effect of the period with the maintenance of Coo-Trois-Ponts results decreases the predicted up- and downward mFRR means. The effect is larger for the downward side due to the assumptions taken on pumped-hydro storage (only available between 4 AM and 8 AM).



Upward

static	V1	REF	V3
P99[MW]	319	319	320
% of time above 1 GW	21%	21%	19%
dynamic	**V1**	**REF**	**V3**
Average [MW]	489	500	473
% of time above 1 GW	10%	13%	10%

Downward

static	V1	REF	V3
P99 [MW]	547	719	661
% of time above 1 GW	93%	97%	95%
dynamic	**V1**	**REF**	**V3**
Average [MW]	1426	1939	1843
% of time above 1 GW	69%	86%	78%

Figure 30: available non contracted balancing energy bids for mFRR.for sensistivities on the reference scenario

5. Implementation planning

Section 4 confirms the possibility to predict the mFRR non-contracted balancing means with sufficient accuracy for an application in a dynamic calculation of the balancing means. However, the study focused only on the 'predictability' of non-contracted balancing means which is only the first condition for pursuing an implementation of a dynamic allocation of FRR balancing means to cover the respective needs.

Simulations confirm this predictability for upward mFRR balancing capacity, where the forecast can potentially be used to reduce balancing capacity requirements. In contrast, for the downward mFRR reserves, there is no real potential for a reduction of balancing capacity volumes as long that there is no need for procurement. Finally, for the aFRR balancing capacity, it is currently not possible yet to confirm the potential to predict available non-contracted balancing energy bids.

Elia therefore proposes to further investigate the implementation of a daily prediction of non-contracted balancing energy bids in function of a dynamic calculation of the balancing means. This could allow to further minimize the balancing capacity procurement volumes and costs. A multi-year roadmap is proposed in Figure 31 with in first instance a study in 2022 that investigates the procurement aspects when replacing (part of) the upward mFRR balancing capacity with non-contracted balancing energy bids. Objectives are to present potential procurement solutions for accounting non-contracted in the allocation of balancing means, identify risks and potential risk mitigation for market stability and update to the extent possible the results and conclusions based on additional data.

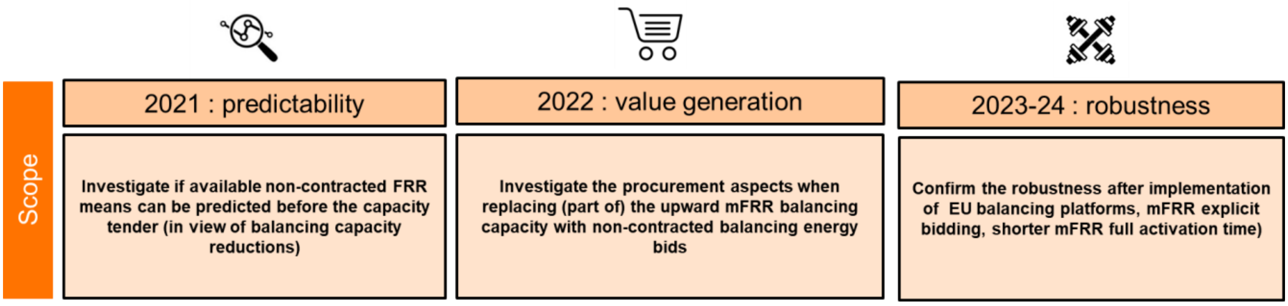


Figure 31: Proposed roadmap before starting implementation

However, it is for a fact that the impact of upcoming market evolutions in 2022 being the implementation of the EU balancing platforms and the implementation of explicit bidding and 12.5 minute FAT for mFRR cannot be investigated to full extend in 2022. Indeed, the proposed forecast tool is trained on historic data and sufficient data will only become available in the course of 2023 and 2024. This means an additional study focusing on the robustness of the prediction tool and the dynamic procurement mechanism will be required after 2022. This study will target to confirm the results and value of implementing a dynamic calculation of the means together with the planning for the implementation, i.e. revision of regulatory documents, calibration of the algorithms, development of operational process and modification of the required software tools).

The proposed multi-year implementation roadmap will allow to first fully understand the potential and the implications for the market before starting the implementation of a dynamic calculation of the balancing means.

6. Conclusions

The objective of this study was to analyze if Elia's available non-contracted balancing energy bids for the next day can be predicted. For this, a machine learning approach is used in which algorithms are trained, based on historic observations, to predict the available non-contracted balancing means for each period of the next day. These non-contracted balancing means include the non-contracted balancing energy bids and the available reserve sharing with other TSOs. This prediction is assumed to be conducted before the balancing capacity auctions, in parallel with the daily dimensioning of the reserve capacity needs, i.e. at the latest 7 AM of the day for which the balancing capacity is to be procured.

Main conclusions is that the non-contracted upward mFRR balancing means can be predicted to an acceptable extend, demonstrating a potential volume of 500 MW, on average, while a volume of 1000 MW can be ensured for 14% of the time (Figure 32, left). It has to be remarked that a large contribution is provided by the available mFRR reserve sharing, of which a large part (250 MW) is currently captured in the 'static approach. Nevertheless, i**t can therefore be concluded that there is a potential value for such prediction tool and this potential is expected to further increase with additional volumes brought by a consumer-centric market design and the upcoming EU balancing energy platforms.** However, one of the main conditions to harness this value is to find appropriate procurement mechanisms to deduct this capacity from the balancing capacity to be procured.

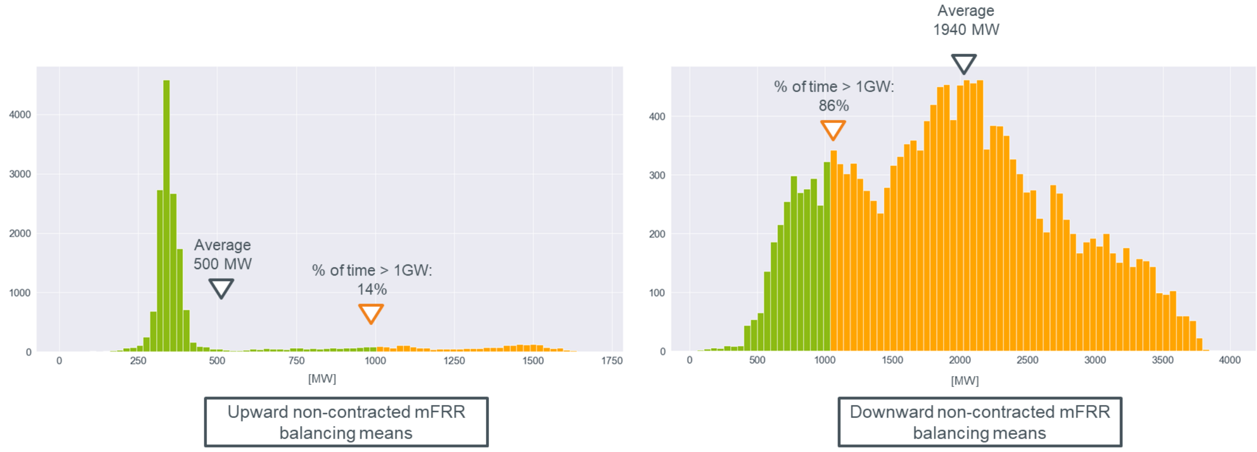


Figure 32: Histogram of available non-contracted mFRR balancing means for upward (left) and downward (right)

In contrast, the non-contracted downward mFRR balancing means demonstrate a potential volume of nearly 1940 MW, on average, while a volume of 1000 MW can be ensured for up to 86% of the time (Figure 32, right). It is important to keep in mind that these volumes are always lower compared to the observed availability. This is explained as the forecast tool aims to forecast guaranteed volumes, expected to be available with a 99.0% confidence level. For instance, when looking at the available volumes on the downward side over the same period, a volume of 1000 MW can be ensured for up to 97% of the time. **The results confirm the current approach to not procure downward mFRR balancing capacity and it can therefore be concluded that there is no potential value for this prediction tool as long as observed non-contracted balancing means continue to cover the downward reserve capacity needs.**
Firstly, results for the non-contracted aFRR balancing means demonstrate that no substantial volumes can be predicted at this point in time. This is explained by the fact that the available data was limited to only 9 months (as from the

implementation of the new product design in October) while during this period largest part of the time, no or very limited volumes are available, and this in particular for upward aFRR. **Conclusion is that at this point, no potential for predicting the available non-contracted aFRR balancing means can be confirmed at this time due to lack of a robust context and data set.**

Based on a historic data set for a period of two years (from April 16, 2019 until April 15, 2021), the best performing algorithm is found to be the random forests algorithm, being able to predict, on average, the largest volumes of non-contracted balancing energy bids while maintaining a confidence level of 99%. This algorithm is used to predict the non-contracted balancing means based on a set of 168 features. The algorithms are trained and calibrated according to machine learning best practices. However, due to current data limitations (cf. aFRR) and upcoming market evolutions (cf. EU balancing platforms, mFRR explicit bidding and 12.5 minute mFRR FAT) it is required to update this analysis at a later point in time.

Based on these results, Elia proposes to follow an implementation roadmap to pursue a dynamic calculation of the allocation of the balancing means. In first instance, a follow-up study is needed taking into account the new system evolutions. These modifications are expected to have an effect on the available volumes of non-contracted balancing means which can be predicted, although it is currently very uncertain to which extend. As these modifications will only be implemented in the final quarter of 2022, and more than a year of data is needed to conduct meaningful analyses, this update can only be conducted the soonest in 2023 or 2024. However, while awaiting the results of this analysis, expecting to confirm the potential, Elia proposes to already analyze procurement aspects of a dynamic allocation in 2022. This study needs to focus on the possibilities and impact of partially / intermittently reduce balancing capacity procurement on mFRR.

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ANNEX

acronym	variable
aFRR_bids_down	**available non-contracted upward aFRR balancing energy bids**
aFRR_bids_down_d-1	available non-contracted upward aFRR balancing energy bids of the previous day
aFRR_bids_up	**available non-contracted downward aFRR balancing energy bids**
aFRR_bids_up_d-1	available non-contracted downward aFRR balancing energy bids of the previous day
arc_dc_down	**available downward regulation capacity from controllable units**
arc_dc_fuel_ng_d-1	available downward regulation capacity from controllable gas units of the previous day
arc_dc_tech_ccgt_d-1	available downward regulation capacity from controllable ccgt units of the previous day
arc_dc_total_d-1	available downward regulation capacity from controllable units of the previous day
arc_dlc_total	**available downward regulation capacity from limited controllable units**
arc_dlc_total_d-1	available downward regulation capacity from limited controllable units of the previous day
arc_ic_fuel_ng_d-1	available upward regulation capacity from controllable units of the previous day
arc_ic_tech_ccgt_d-1	available upward regulation capacity from controllable ccgt units of the previous day
arc_ic_total	**available upward regulation capacity from controllable units**
arc_ic_total_d-1	available upward regulation capacity from controllable units of the previous day
arc_ilc_total	**available upward regulation capacity from limited controllable units**
atc_export_cap	capped available export transmission capacity after intra-day
atc_fr_export_cap	capped available export transmission capacity after intra-day with France
atc_fr_export_cap_d-1	capped available export transmission capacity after intra-day with France of the previous day
atc_fr_import_cap	capped available import transmission capacity after intra-day with France
atc_fr_import_cap_d-1	capped available import transmission capacity after intra-day with France of the previous day
atc_import_cap	capped available import transmission capacity after intra-day
atc_nl_export_cap	capped available export transmission capacity after intra-day with the Netherlands
atc_nl_export_cap_d-1	capped available export transmission capacity after intra-day with the Netherlands of the previous day
atc_nl_import_cap	capped available import transmission capacity after intra-day with the Netherlands
atc_nl_import_cap_d-1	capped available import transmission capacity after intra-day with the Netherlands of the previous day
atc_uk_export_cap	capped available export transmission capacity after intra-day with the United Kingdom
atc_uk_export_cap_d-1	capped available export transmission capacity after intra-day with the United Kingdom of the previous day
atc_uk_import_cap	capped available import transmission capacity after intra-day with the United Kingdom
atc_uk_import_cap_d-1	capped available export transmission capacity after intra-day with the United Kingdom of the previous day
DOWN_and_sharing	**total downward mFRR balancing capacity means**
DOWN_and_sharing_d-1	total downward mFRR balancing capacity means of the previous day
forecast_da_price_d-2	day-ahead market electricity prices of the previous day
gas_prices_d-1	gas prices of the previous day
mFRR_total_volume_offered_d-1	offered mFRR balancing capacity volume of the previous day
phs_freebids_downward	**available downward regulation capacity on pumped-hydro storage**
phs_freebids_downward_d-1	available downward regulation capacity on pumped-hydro storage of the previous day
phs_freebids_upward	**available upward regulation capacity on pumped-hydro storage**
phs_freebids_upward_d-1	available upward regulation capacity on pumped-hydro storage of the previous day
prices_da_market_d-1	day-ahead market electricity prices of the previous day
residual_load	forecasted total load minus forecast of renewable generation(PV, Wind)
residual_load_nu	forecasted total load minus forecast of renewable generation and available nuclear capacity
residual_load_nu_ng	forecasted total load minus forecast of renewable generation and available nuclear and gas capacity

time_day	time (discrete function)
time_dayF1	day by means of continuous sin(x) function
time_monthF1	months by means of sin(x) continuous function
total_arc_down	**available downward regulation capacity**
total_arc_up	**available upward regulation capacity**
total_load_forecast	total load forecast
UP_and_sharing	**total upward mFRR balancing capacity means**
UP_and_sharing_d-1	total upward mFRR balancing capacity means of the previous day
wind_off-shore_tso_day_ahead_forecast	offshore wind power forecast
wind_total_day_ahead_forecast	wind power forecast
wind_tso_day_ahead_forecast	tso connected wind power forecast

In bold : target variables