

FINAL REPORT

System Imbalance forecast and its publication to stakeholders



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CREG incentive on System Imbalance forecast and evaluation of its publication

1. Introduction

The System Imbalance is a key indicator for the state of the system as it shows the difference between the Area Control Error (ACE) and the activated ancillary services (NRV). This makes that the SI is a key decision making factor – along with others - for the activation of (additional) balancing reserves. Hence, having the ability to accurately predict the SI of the future quarter-hours may improve the overall decision-making process for the activation of balancing reserves. This is especially relevant for the accession to the future balancing platform (MARI and PICASSO) where the activation lead-time will increase. Furthermore, this project allows a greater understanding of the different drivers of the System Imbalance.

The project consists in selecting, training and implementing a data mining type model (such as ARIMA, neural network, Support Vector Machine...) to predict the system imbalance and then testing it in parallel run in different system conditions. The project also includes an analysis of the relevance of making this representation of system imbalance (SI) available relevant stakeholders. The work presented in this report builds further on an earlier proof of concept (PoC), more information on this PoC is available in annex 3 of decision B658E¹.

This report describes the different data mining techniques and the process applied for the variable selection. In addition, it explains the selection of the linear regression model as the basis for the testing phase. Chapter X presents feedback from this testing phase and finally we present an implementation plan.

The selection of the linear model and the initial proposal for publication format was consulted from 31st of August 2021 until 30th of September 2021. The consultation report did not include a proposal for an implementation plan, rather it sought feedback on the publication format, time-horizons and dependencies with other projects. Following the public consultation, a proposal for implementation plan was presented during the WG Balancing on the 28th of October 2021. The consultation report can be found in Annex of this document.

1.1 Deliverables and timeline

The incentive as defined in decision B658E of the CREG sets out three deliverables. First, by January 31st 2021, the data set and model should be selected. The selection of the linear regression model was agreed by the CREG and presented in the WG balancing in March 2021.

¹ <https://www.creg.be/sites/default/files/assets/Publications/Decisions/B658E68Annex3.pdf>

Second, the consultation of draft report containing a description of the used method to select the data mining model on the basis of statistical indicators complemented by an analysis on the relevance of the publication of the system imbalance and a proposal for an implementation plan. In agreement with the CREG, this report will not include a proposal for an implementation plan. Rather it shall focus on identifying potential interdependencies with other evolutions on the balancing market and requesting feedback on the publication format. Following this consultation, Elia presented an implementation plan proposal in the WG Balancing of October.

2. Forecasting models

This chapter describes the process that was followed to derive the relevant variables for the System Imbalance forecasting model. In addition, it assesses the impact of increasing the so-called look back horizon and extending the number of variables considered.

Next, this chapter contains a high-level description of the different data mining models that were considered in the scope of this project.

2.1 Introduction

The forecast of the System Imbalance (SI) proof-of-concept of 2019 was developed using a multivariate linear autoregressive model. The SI estimate for quarter-hour (qh+k) is determined by the SI of the previous quarter-hours as well as other variables of the previous quarter-hours. In addition to these lagged variables, the model uses one-minute measurements happening during the current quarter-hour (qh), up to minute 8 in that quarter-hour.

A generic equation for such a model is given in Figure 1.

$$\begin{aligned}
 SI_{\text{Forecast}}(qh + k) &= \text{Intercept} + \sum_{n=1}^{\text{lookback}} SI(qh - n) * \text{Weight}_{SI(n,k)} \\
 &+ \sum_{n=1}^{\text{lookback}} NRV(qh - n) * \text{Weight}_{NRV(n,k)} + \sum_{n=1}^{\text{lookback}} GDV(qh - n) * \text{Weight}_{GDV(n,k)} \\
 &+ \sum_{n=1}^{\text{lookback}} GUV(qh - n) * \text{Weight}_{GUV(n,k)} + \sum_{n=1}^{\text{lookback}} PPOS(qh - n) * \text{Weight}_{PPOS(n,k)} \\
 &+ \sum_{n=1}^{\text{lookback}} PNEG(qh - n) * \text{Weight}_{PNEG(n,k)} + \dots \\
 &+ \sum_{n=1}^8 SI_{\text{minute}}(qh, n) * \text{Weight}_{SI_{\text{minute}}(n,k)} \\
 &+ \sum_{n=1}^8 NRV_{\text{minute}}(qh, n) * \text{Weight}_{NRV_{\text{minute}}(n,k)} + \dots
 \end{aligned}$$

Figure 1 – Multivariate Autoregressive model for SI forecasting.

In Figure 1, parameter k is called the forecasting horizon. Conventionally speaking, the estimate for current quarter-hour (qh+0) is named S0 (with k=0), the estimate for qh+1 is named S1 (with k=1) and the estimate for qh+2 is named S2 (with k=2).

Training such a model requires finding weights for each of the term in the equation. Thus even though the model is a relatively simple linear model, the number of terms in the model can grow quickly with the quarter-hours used in the past and the different variable types used (NRV, GUV...), as illustrated in Table 1.

Quarter-hours in the past					Minutes in qh				
96	...	3	2	1	Variable	1	2	...	8
Weight SI qh-96	..	Weight SI qh-3	Weight SI qh-2	Weight SI qh-1	SI	Weight SI min 1	Weight SI min 2	...	Weight SI min 8
Weight NRV qh-96	...	Weight NRV qh-3	Weight NRV qh-2	Weight NRV qh-1	NRV	Weight NRV min 1	Weight NRV min 2	...	Weight NRV min 8
Weight GUP qh-96	...	Weight GUP qh-3	Weight GUP qh-2	Weight GUP qh-1	GUP	Weight GUP min 1	Weight GUP min 2	...	Weight GUP min 8
Weight GDV qh-96	...	Weight GDV qh-3	Weight GDV qh-2	Weight GDV qh-1	GDV	Weight GDV min 1	Weight GDV min 2	...	Weight GDV min 8
Weight PPOS qh-96	...	Weight PPOS qh-3	Weight PPOS qh-2	Weight PPOS qh-1	PPOS	-	-	...	-
Weight PNEG qh-96	...	Weight PNEG qh-3	Weight PNEG qh-2	Weight PNEG qh-1	PNEG	-	-	...	-
Weight LOAD qh-96	...	Weight LOAD qh-3	Weight LOAD qh-2	Weight LOAD qh-1	LOAD	-	-	...	-
Weight WIND qh-96	...	Weight WIND qh-3	Weight WIND qh-2	Weight WIND qh-1	WIND	-	-	...	-

Table 1 Weights in the multivariate autoregressive model, note that Load and Wind include both intra-day forecast and actual production terms

Note that the model developed in 2019 considered a look-back horizon of 96 qh and variables families. Further research has been conducted in 2021 and is presented in this document section.

2.2 Variable selection

The model used in the 2019 proof-of-concept was an autoregressive model. This model included variables at quarter-hour granularity (SI, NRV, GDV....) and variables at minute granularity (SI, R2...). If we consider the values of each variable at different timeframes as individual model features, then we can consider that the model was using more than a thousand variables.

In order to use more sophisticated model, such as Support Vector Machines (SVM), or Artificial Neural Networks (ANN) it is necessary to select wisely the features to include in the model. Indeed, SVM and ANN are computationally intensive, and cannot be use practically with the thousands of variables used in the baseline autoregressive model. Of course, this feature selection can also benefit the baseline autoregressive model.

In this study, the variables at quarter-hour granularity have been included up to 96 quarter-hours back in the past (one day) with respect to the quarter-hour to forecast. The variables at minute granularity have been taken up to minute 8 in the quarter-hour, given this would be the most recent information available at the time an activation decision is made. When the activation lead-time would increase, less minute data would be available for the forecasting model.

2.2.1 Variable selection – correlation

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In order to identify the feature importance, the correlation between each feature and the system imbalance has been calculated. The results are shown in Figure 2, it appears that the features at minute granularity present the highest correlation, in the vicinity or above 90%. They are followed by the System Imbalance at quarter-hour granularity.

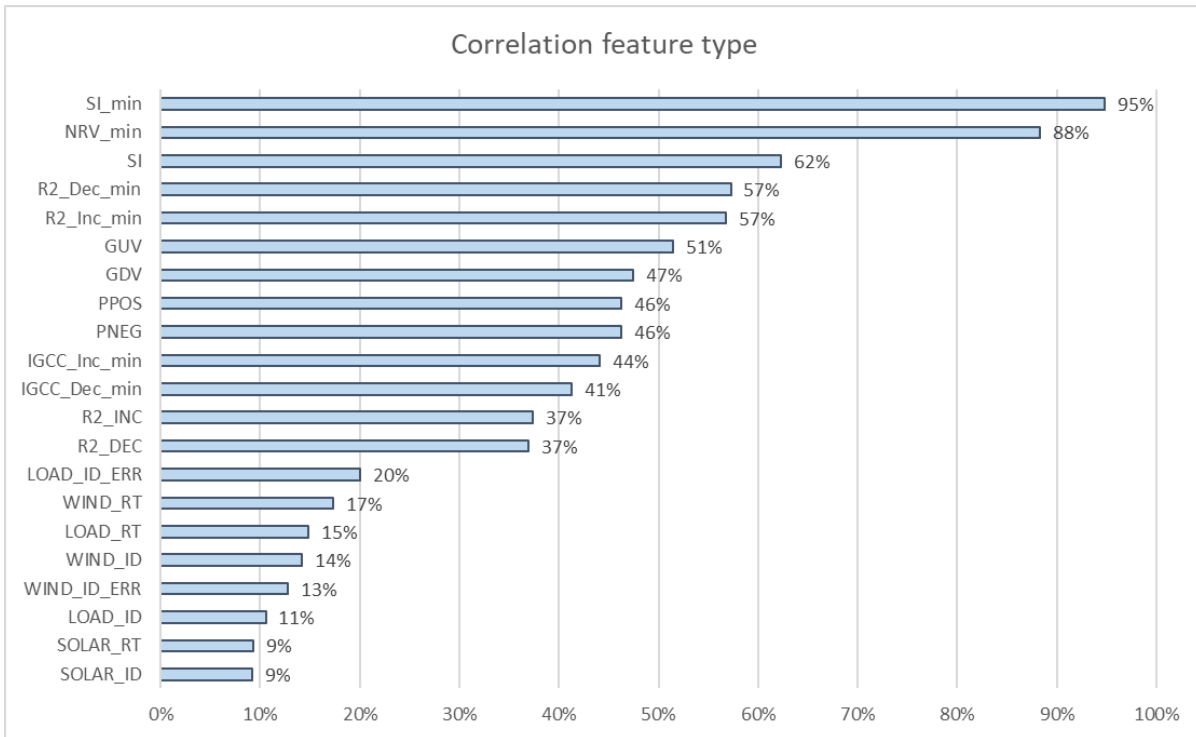


Figure 2 Correlation of S0, in absolute value, per feature

However, the correlation decreases significantly when looking further in the future (S1, S2 and further forecasts) as shown in Figure 3. This implies that it is possible to come with an accurate model for S0, but that for S1, S2 and further it will be more challenging.

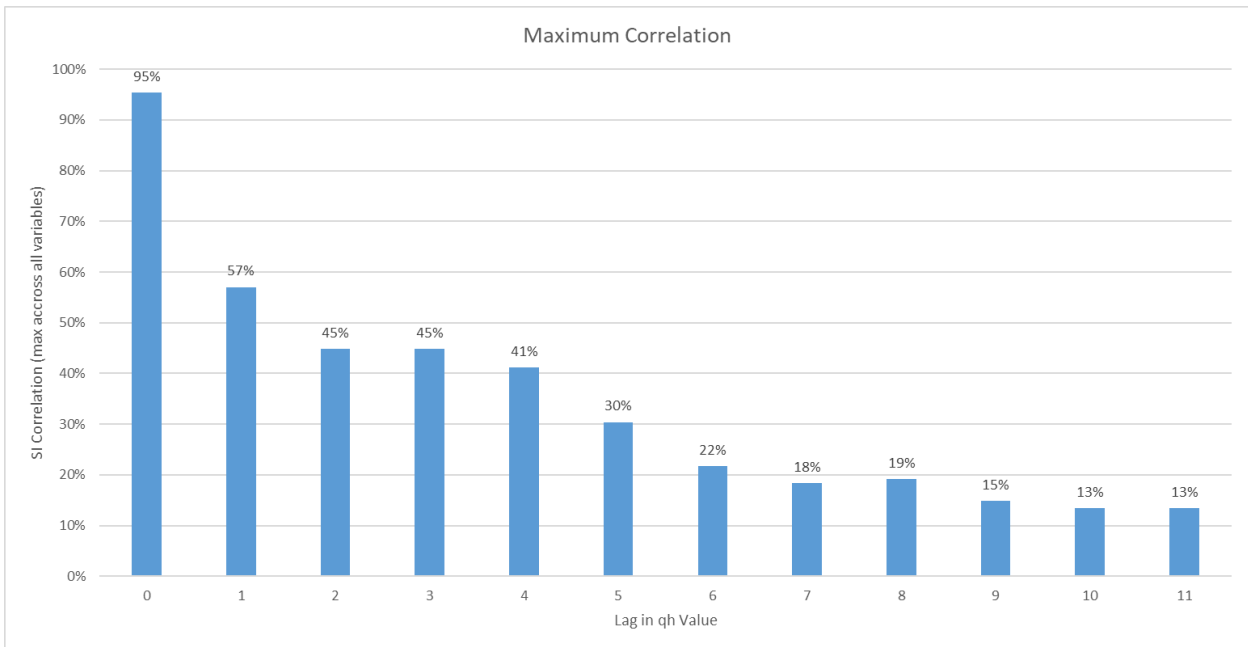


Figure 3 Correlation of SI at quarter-hour $qh+k$ (with k from 0 to 11) with variables at quarter-hour qh

A description of the different variables used is provided in Table 2.

Variable Type	Description
SI	System Imbalance
GUV	Gross Upward Volume of activated reserves
GDV	Gross Downward Volume of activated reserves
PPOS	Price of Positive Imbalance (same as PNEG)
PNEG	Price of Negative Imbalance (same as PPOS)
LOAD_RT	Real-Time Total Load Estimation
LOAD_ID	Intraday Forecast of Total Load
LOAD_ERR	Error of intraday forecast of total load
WIND_RT	Real-Time total wind production estimation
WIND_ID	Intraday forecast of total wind production
WIND_ERR	Error of intraday forecast of total wind production
SOLAR_RT	Real-Time total Solar production estimation
SOLAR_ID	Intraday forecast of total solar production
SOLAR_ERR	Error of intraday forecast of total solar production
R2_Dec	Decremental R2 activation
R2_Inc	Incremental R2 activation
IGCC_Inc	International Grid Control Cooperation imports
IGCC_Dec	International Grid Control Cooperation exports
_min	Variable taken at minute granularity
NRV	Net Regulation Volume

Table 2 Variable Types and description

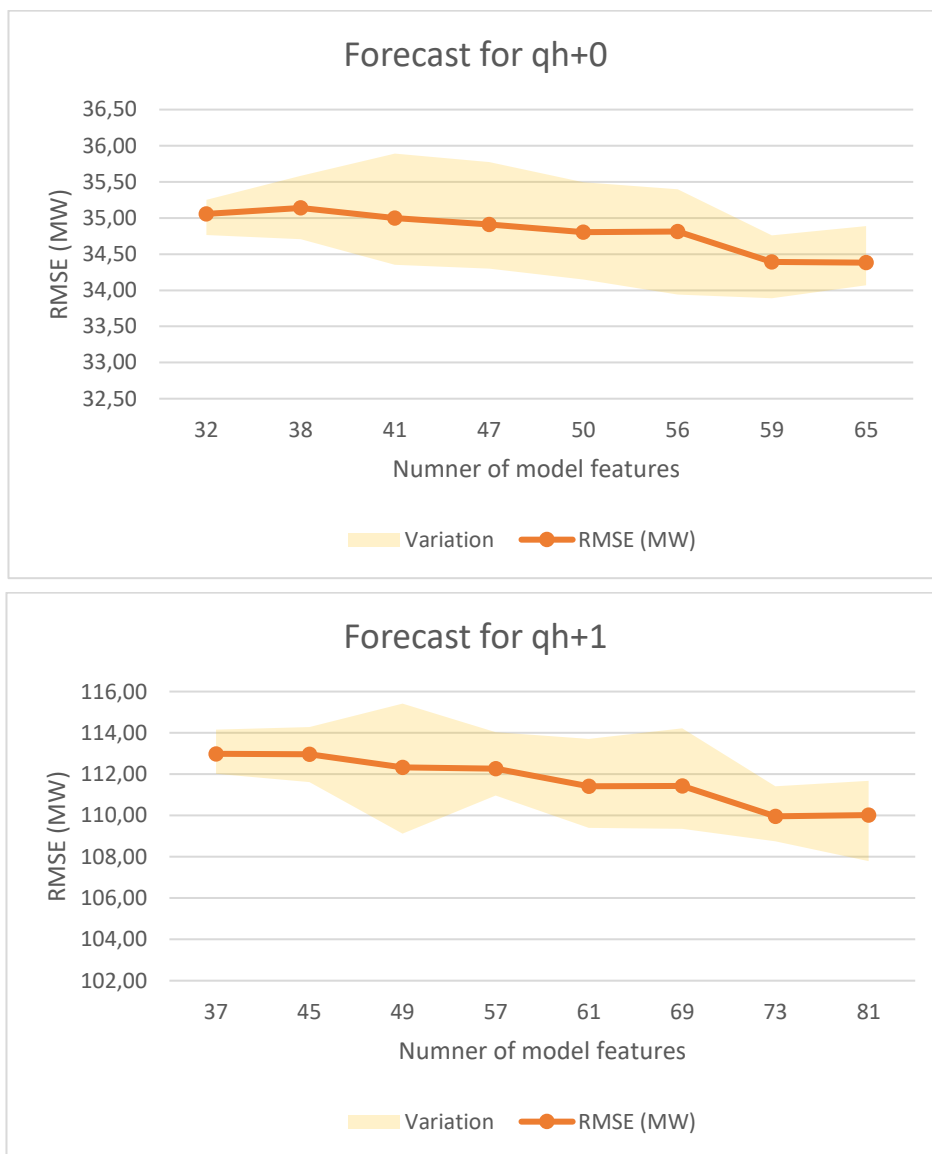
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2.2.2 Variable selection – combination of variables

In order to measure the influence of each variable type in the accuracy, and the impact of the look-back horizon, several simulations have been conducted.

In each of these simulations, a different combination of variable types (as described in Table 2) has been tested. For the case of a look-back of 4 quarter-hours, the results are provided in Figure 4. These results show that adding extra features to the model improves the accuracy marginally.



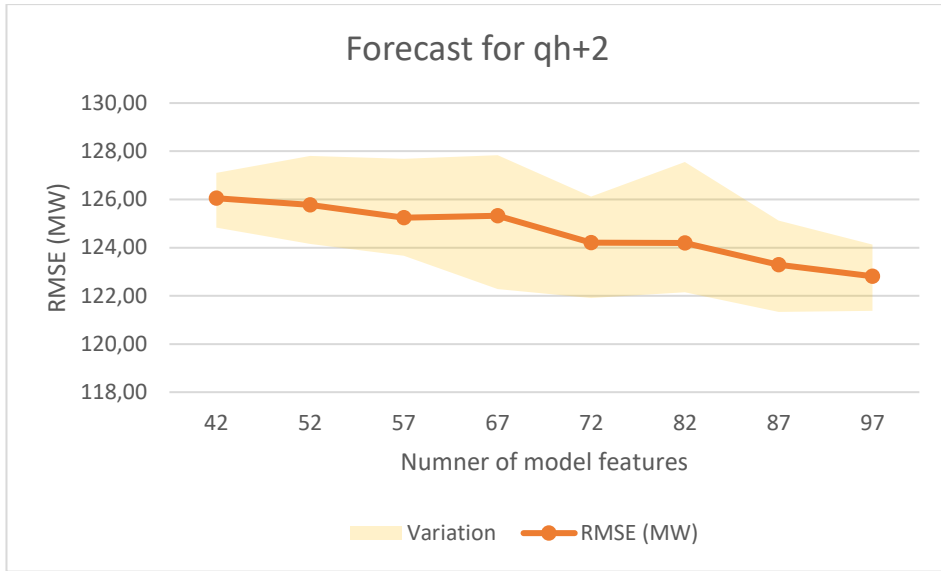


Figure 4 Model accuracy obtained for a look-back of 4qh and different combinations of variables

2.2.3 Variable selection – Look-back horizon

Too much historic data for training the model might decrease performance because trends of the past do not always persist. Too few historic data for training might also have a negative impact because the model might fail to pick up current trends. There is an optimum in the lookback horizon that we determined experimentally.

In the plot below the mean absolute percentage error of the linear model is plotted vs. the amount of training weeks it was given:

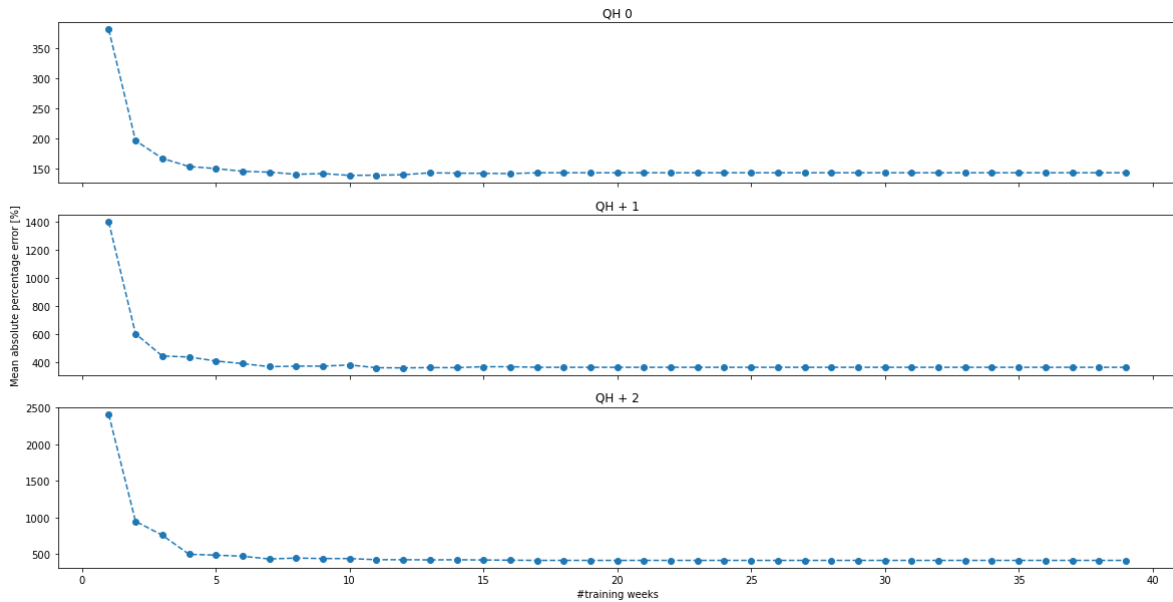


Figure 5 model error in function of training weeks

So the values on the x-axis are the size of the train set for the linear model, from 1 week of train data to 39 weeks of train data. The values on the y-axis are the performance of the model on the test set, which was 12 weeks of unknown data. We can see that after roughly 8 weeks of train data there is a plateau where the accuracy doesn't get better anymore if we add more weeks of training data. This is interesting, we can use only 8 weeks of train data and keep our accuracy while being computationally much less expensive than 39 weeks of train data. Therefore, the lookback horizon we will use for the historic data is 8 weeks.

There is a second horizon that is quite important for the models, which is the lookback horizon used during live predictions i.e. how many quarter hours do we look in the past while doing a live prediction?

In the graphs below you can see the results for some experiments with a linear model. On the x-axis the amount of quarter hours in the past is plotted, on the y-axis the RMSE:

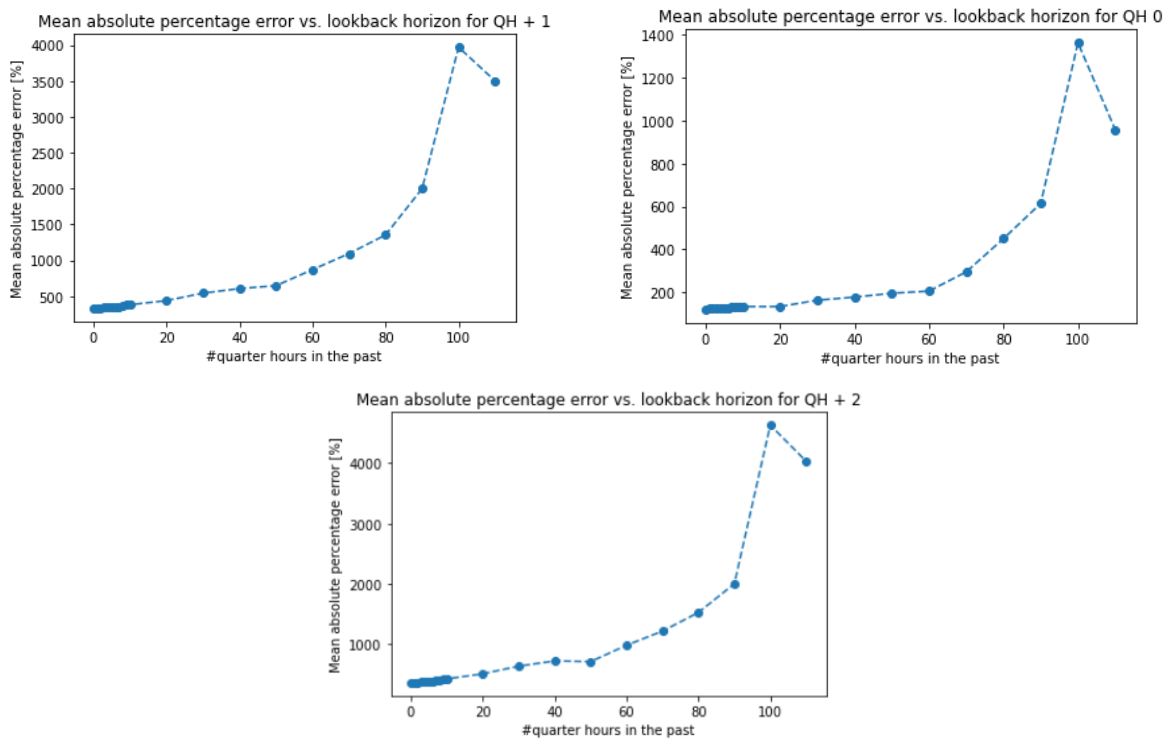


Figure 6 error in function of lookback horizon

The graphs show some interesting things. Firstly, the accuracy goes up until around 3 quarter hours of lookback horizon. Then the accuracy gets worse if we add more quarter hours in the past. The accuracy keeps going down until we add 96 quarter hours of data, then we see a dip in all three graphs. So adding data of exactly 1 day ago in the live predictions might increase accuracy. Otherwise looking only 3 quarter-hours in the past is the optimum for the accuracy of the model during live predictions.

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2.2.4 Recursive Feature Extraction (RFE)

In previous subsection, an optimal variable selection has been provided by testing different combinations of variable types and different look-back time horizons.

In order to further optimize the variable selection, a statistical technique has been tested. This technique is called Recursive Feature Extraction (RFE). With this technique, different models are tested, starting with a model with all variables and then recursively extracting variables in order to find an optimum.

RFE was tested to check if further model improvement could be obtained, but did not provide any significant improvement to the variable selection procedure.

2.3 Machine Learning

2.3.1 Model Families

Different models have been used in this study to compare the performance obtained with each of them.

The first model type used is a **linear regression model**, this model basically implements the equation depicted in Figure 1 and is quite straightforward to use.

The second model tested are **Artificial Neural Network (ANN) model**. This model represents a significant complexity leap from linear models. ANN require several choices (such as the number of layers, neuron per layer, activation functions...). For this specific example, an Artificial Neural Network model, a single hidden layer architecture was chosen. The input layer has a neuron for each input variable) with an Exponential Linear Unit (ELU)² activation function. The hidden layer has half of the neurons of the input layer, using also an ELU activation function and the output layer has a linear activation function. This architecture is depicted in Figure 7

² Fast and accurate deep network learning by Exponential Linear Units (ELUS), Djork-Arne Clevert, Thomas Unterthiner & Sepp Hochreiter, 2016, [1511.07289.pdf \(arxiv.org\)](https://arxiv.org/abs/1511.07289)

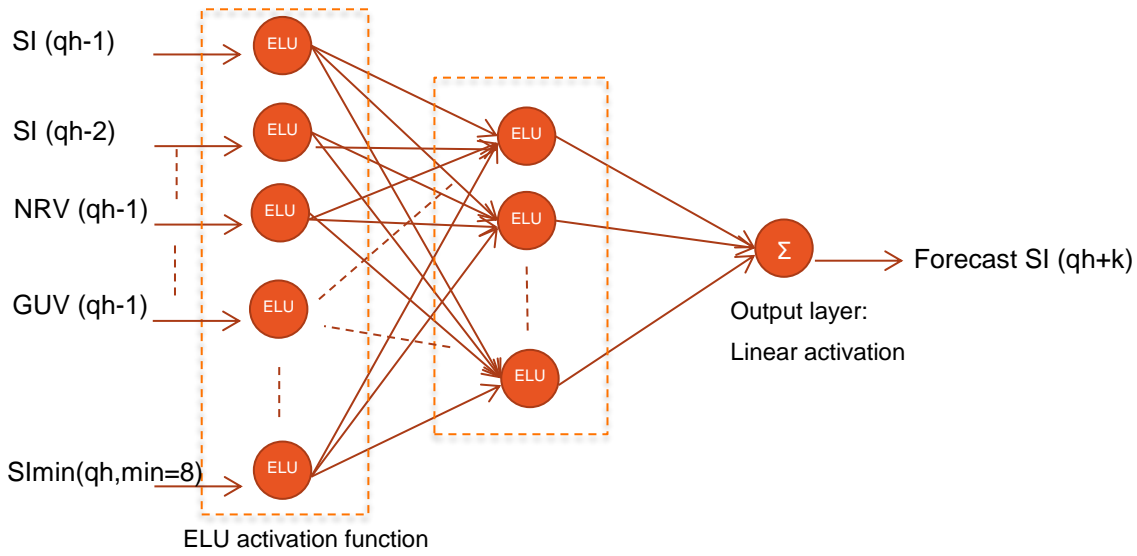


Figure 7 Artificial Neural Network Architecture

The third model type tested consist of a regression based on **Support Vector Machines (SVM)**. These models are also very demanding in terms of computational power and require different choices to be made (radial function for instance). For this exercise, a kernel function was used as radial function.

A last model type was tested, consisting of **regression trees**, these models are rather simple in nature, comparable to linear regression.

2.3.2 Training techniques

In machine learning, a dataset is provided for training the model and estimating its accuracy. It is recommended, to avoid overfitting, to split the dataset into two distinct sets, a train set and a test set. The train set is used to train the model and the test set is used to evaluate the model performance on a set that was not used for the training.

In the machine learning literature, it is often recommended to follow a k-fold cross validation approach for producing statistically meaningful results on model performance. In a k-fold cross-validation, several train-test exercises are performed on random splits of the dataset into train and test. This is illustrated in Figure 8.

In this manner, k-fold cross-validation can highlight if the model performance varies according to the train/test split.

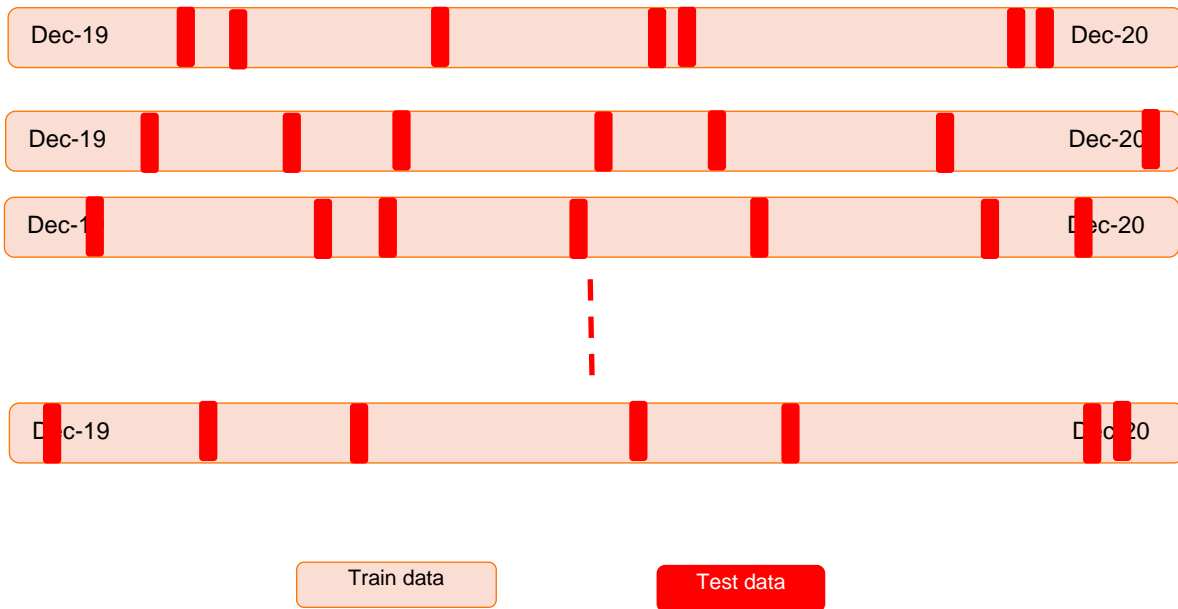


Figure 8 K-fold cross-validation on a yearly dataset

However, when it comes to time-series estimation, it is necessary to evaluate the model performance in circumstances close to operations. During operations, the model will obviously use data that is known at the moment the forecast is made. Therefore, a time-series estimation model has to be trained in such a way that only known data is used. Thus, using a k-fold cross-validation as-is, would train the model with data in the future and test it with data in the past. For instance, using 12 months of consecutive data as train data and a month of test data, just after the train data. This is shown in Figure 9:

12/19	01/20	02/20	03/20	04/20	05/20	06/20	07/20	08/20	09/20	10/20	11/20	12/20
Train Set											Test Set	

Figure 9 Train/Test split using consecutive data for train and following data for test

It must also be noted that k-fold cross-validation is computationally intensive, as the train/test operation is repeated several times.

In order to assess on one hand the achievable model performance into operations and the statistical meaningfulness of the results, the two approaches have been followed in this study:

- Model evaluation with consecutive train and test periods
- Model evaluation with k-fold cross-validation, with 10 repetitions.

3. Selection of the data mining model

3.1 Introduction

The model performance evaluation is done using different statistical indicators, such as the RMSE, Max. Error or R-squared, these are described in Figure 10:

$$\begin{aligned}
 \text{Absolute Error}_i (MW) &= \left| SI(qh + k)_i - SI_{Forecast}(qh + k)_i \right| \\
 \text{Mean Absolute Error (MAE)} &= \text{Average (Absolute Error)} \\
 \text{Root Mean Squared Error (RMSE)} &= \sqrt{\sum_i \text{Absolute Error}_i (MW)} \\
 P99 &= 99\text{th quantile of Absolute Error} \\
 \text{Max Error} &= \text{Max}_i(\text{Absolute Error}_i) \\
 R \text{ squared, } R2 &= \frac{\text{covariance}(SI(qh + k), SI_{Forecast}(qh+k))}{\sigma(SI(qh + k)) \sigma(SI_{Forecast}(qh+k))} \\
 \text{Mean absolute percentage error (MAPE)} &= \frac{100}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \text{ where } A_t \text{ is the actual value and } F_t \text{ the forecast}
 \end{aligned}$$

Figure 10 – Statistical indicators used to assess model performance

3.2 KPI evaluation

3.2.1 S0 Forecast: Model comparison with 3 quarter-hour lookback

The forecast of S0 (SI at the end of current quarter hour) is done in this case by feeding variables up to 3 quarter-hours in the past. The models are trained using consecutive train and test set.

In this case, it appears that the linear model is providing the best performance for most indicators, followed closely by the ANN model. The SVM and Tree model have significantly worse performance.

Model Type	MAE (MW)	RMSE (MW)	P99 (MW)	Max Error (MW)	R2
Linear	26,45	34,44	99,46	178,28	0,962
ANN	26,66	35,09	100,66	168,49	0,959
Regression Tree	30,86	42,45	129,57	457,15	0,941
SVM	32,71	69,70	172,42	1283,25	0,840

Figure 11 qh+0 Forecast with consecutive train/test and 4qh lookback

3.2.2 S0 Forecast: Model comparison at different lookback horizons

The forecast of S0 (SI at the end of current quarter hour) is done in this case with different lookback horizons, 3 and 12 quarter-hours. The models are trained using consecutive train and test set.

Two conclusions can be drawn from the results, first is that increasing the lookback horizon does not improve the results (for most indicators), and that in both cases (3 or 12 quarter-hour lookback) the linear model performance is better than the one from the other models.

Model Type	Look-back (qh)	MAE (MW)	RMSE (MW)	P99 (MW)	Max Error (MW)	R2
Linear	3	26,45	34,44	99,46	178,28	0,962
Linear	12	26,83	34,80	99,46	163,77	0,962
ANN	3	26,66	35,09	100,66	168,49	0,959
ANN	12	30,69	40,26	116,95	215,10	0,948

Figure 12 qh+0 Forecast with consecutive train/test for 4qh and 12qh lookback

3.2.3 S0, S1 and S2 Forecast: Model comparison at different forecast horizon

In this case, a model with 3 quarter-hour lookback is trained for different forecasting horizons:

- S0: SI at end of current quarter-hour
- S1: SI at next quarter-hour
- S2: SI two quarter-hours in the future.

The results in Figure 13 show different outcomes. First, the linear model remains the model with the best performance at the different forecasting horizons, with the ANN model presenting marginally worse performance. In this case, the SVM and Tree model performance is omitted for clarity. Second, the forecast performance worsens when looking further into the future. For instance, the RMSE goes from 34,44MW to 122,91MW in the case of the linear model when changing the forecast horizon from S0 to S1.

Forecast Horizon qh in the future	Model	MAE (MW)	RMSE (MW)	P99 (MW)	Max Error (MW)	R2
0	Linear	26,45	34,44	99,46	178,28	0,962
0	ANN	26,66	35,09	100,66	168,49	0,959
1	Linear	88,82	122,91	382,34	1209,87	0,518
1	ANN	90,26	124,90	385,47	1256,21	0,502
2	Linear	102,34	141,14	411,62	1322,37	0,365

2	ANN	103,26	142,44	426,87	1363,32	0,353
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Figure 13 Forecast with consecutive train/test and 4qh lookback for different forecasting horizons

3.2.4 S0, S1 and S2 Forecast: Model comparison at different forecast horizon and different variables. K-fold cross validation

In this case, a model with 3 quarter-hour lookback is trained for different forecasting horizons:

- S0: SI at end of current quarter-hour
- S1: SI at next quarter-hour
- S2: SI two quarter-hours in the future.

Furthermore, different variables combinations (Figure 2) are tested and each combination is trained using a k-fold cross-validation. As explained previously, a k-fold cross-validation has to be interpreted carefully, as technically speaking, the models are being trained with data in the future from the test set.

The results in Figure 13 show different outcomes. First, the linear model remains the model with the best performance at the different forecasting horizons, with the ANN model presenting marginally worse performance. In this case, the SVM and Tree model performance is omitted for clarity. Second, the forecast performance worsens when looking further into the future. For instance, the RMSE goes from around 35MW to around 105MW in the case of the linear model when changing the forecast horizon from S0 to S1. Note that these results are different from the ones in Figure 13. This difference can be explained by the fact that the train and test set are different from the one used to produce the results in Figure 13

In Figure 14, Figure 15 and Figure 16 the results for S0, S1 and S2 are given respectively. The conclusions from previous sections remain valid: the linear model is providing the best forecasting performance, and the forecasting performance decreases significantly with the forecasting horizon. However, these plots show that the performance can vary depending on the variable set used and the fold performed, in particular the max error. This difference with the max error might be due to particular situations in the test set.

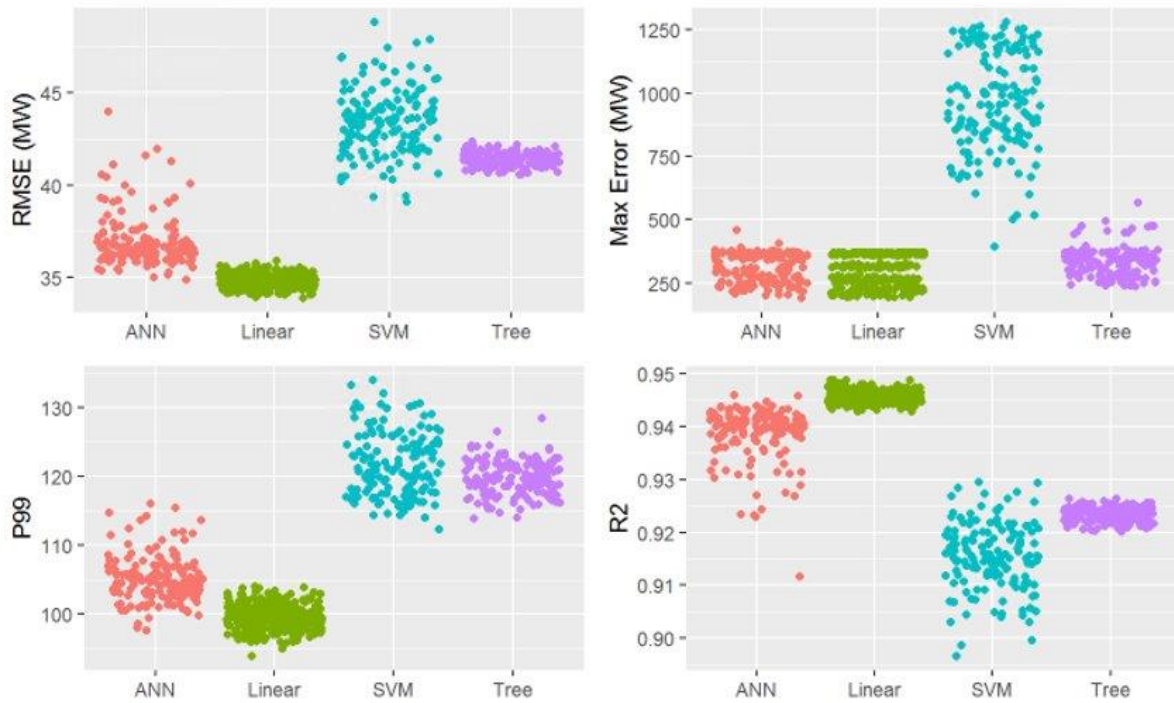


Figure 14 qh+0 Forecast with k-fold cross-validation and different variable combination

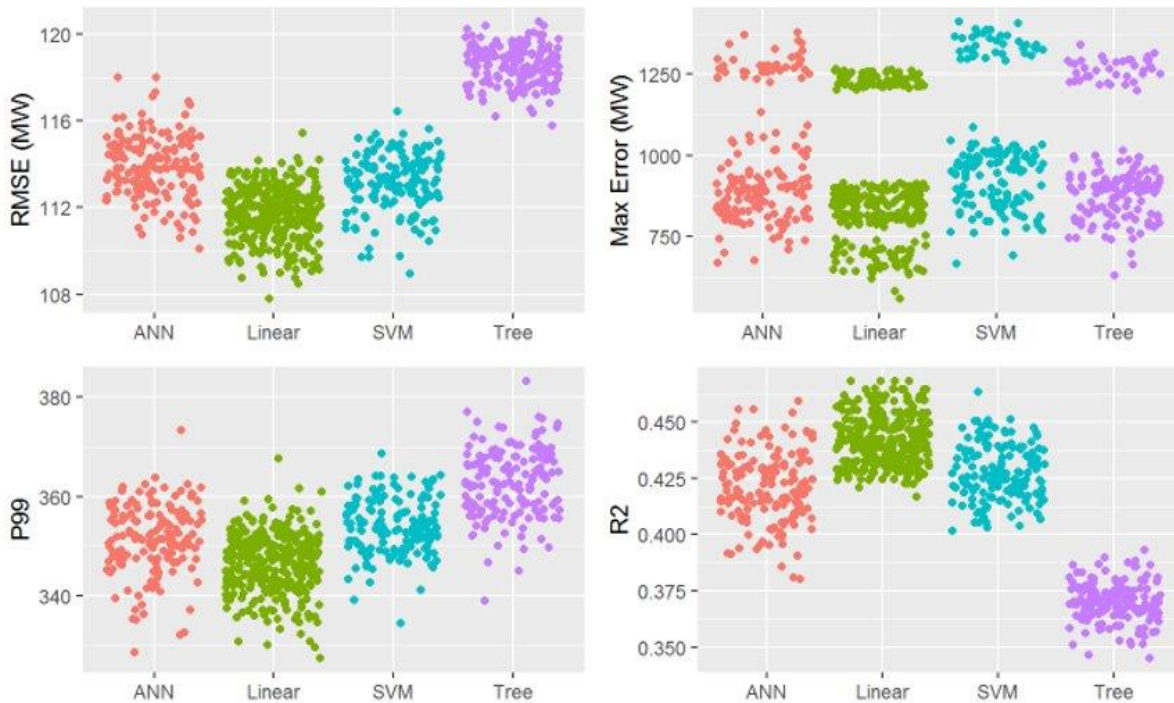


Figure 15 qh+1 Forecast with k-fold cross-validation and different variable combination

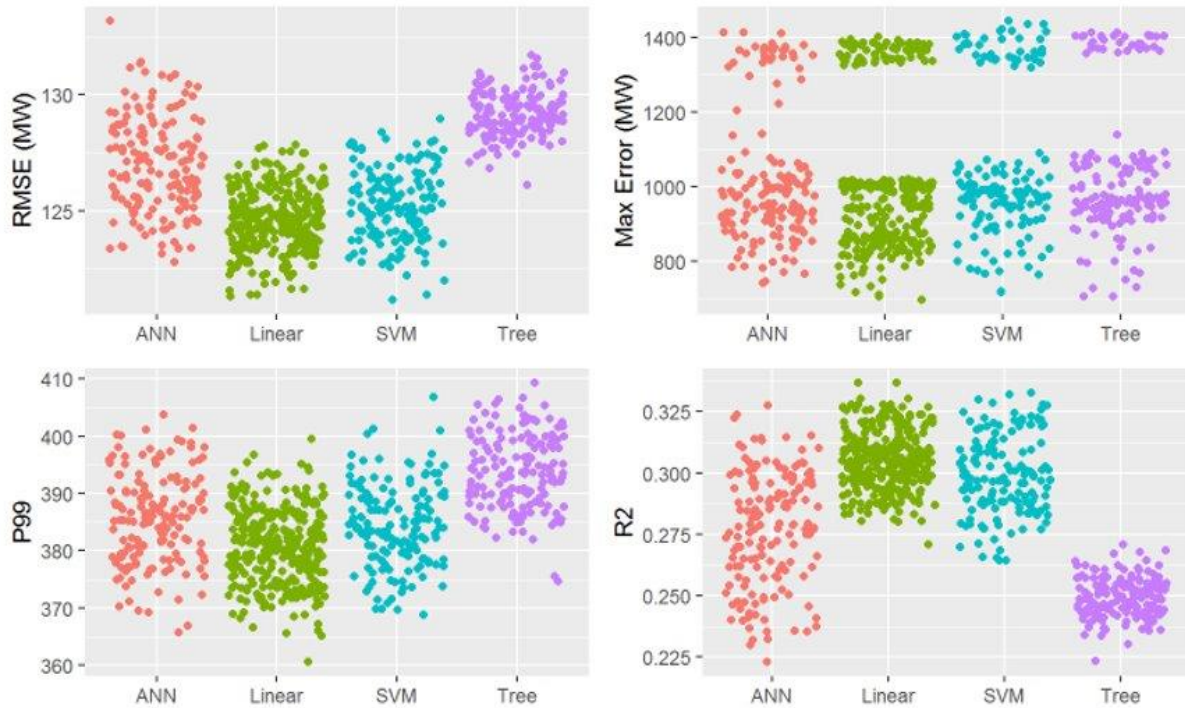


Figure 16 qh+2 Forecast with k-fold cross-validation and different variable combination

3.3 Model performance conclusions

Significant research has been done in the area of System Imbalance forecasting. The following topics have been addressed:

- Variable selection
- Look-back horizon analysis
- Machine learning model type comparison
- Train/Test split using consecutive data
- Train/Test split with k-fold cross-validation

The results show that the linear model has the best performance, despite its simplicity, and this at all forecasting horizons (S0, S1 and S2). It also appears that extending the look back horizon does not improve the model performance. The k-fold cross-validation has shown that the model performance is contained in a limited range, with the exception of the max error that can present significant variations (probably due to particular quarter-hours present in the test set).

3.4 Evaluation of the selected model under different conditions

To ensure the validity of the model under all circumstance, the performance is evaluated under specific conditions, which might occur in real time (such as storm situation, outages, large SI). In order to capture a sufficient amount of events the evaluated period was extended to cover the period of August 2020 until May 2021.

3.4.1 Storm events

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A notification is generated when the forecasting tool detects a Storm event in the North Sea in the next 36 hours. The total storm impact in terms of wind power generation drop and the timing of the storm are published. Over the course of the evaluation period 14 days with storm events were observed. The analysis focusses on the day of the storm event as published by Elia and not only the forecasted time interval to cover potential forecasting error (change in timing).

Figure 17 shows the difference between the forecasted and actual wind production on September 25 and 26 2020. Two elements might impact the quality of the SI forecast, first the significant forecasting error and second the large swings in wind generation. Especially the second effect translated into large swings of the system imbalance as illustrated in Figure 18.

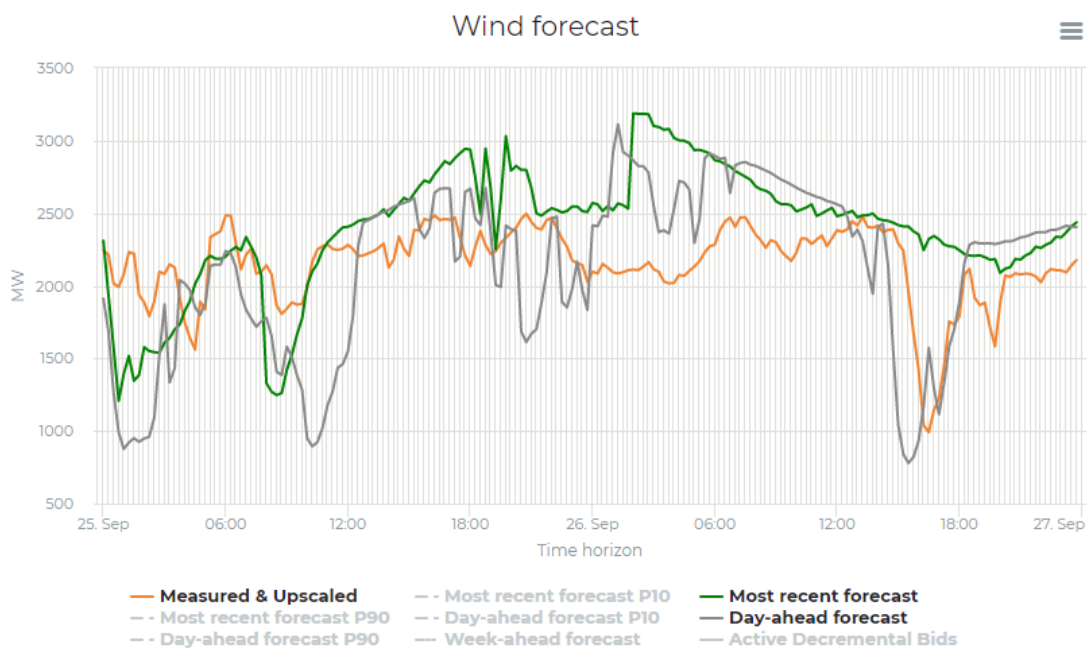


Figure 17 wind forecast during storm event on 25 and 26/09/2020

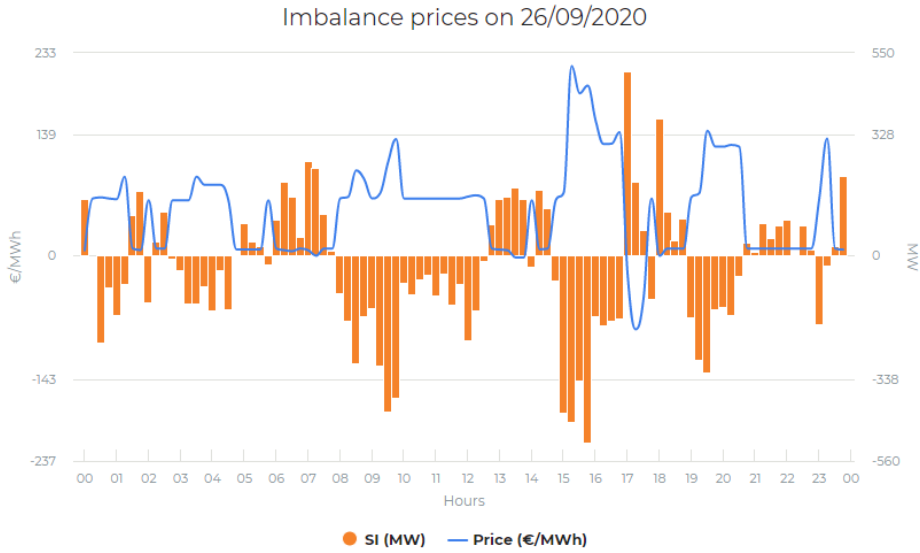


Figure 18 System imbalance and prices for September 26th 2020

By calculating the KPIs on the days where a storm event was detected we see that for the ongoing Qh (Qh0) the performance indicators are very similar. For the future quarter hours, we see a slight deterioration of the performance indicators, especially for the R² and RMSE. Given the limited amount of timestamps, comparing the Max error and the P99 is less relevant. Overall, the linear model is able to handle storm events comparatively well. We see no strong deterioration of the relevant performance indicators.

	All timestamps			During storm events		
	QH0	QH1	QH2	QH0	QH1	QH2
MAE (MW)	23	91	104	26	104	121
RMSE	30	124	140	34	140	159
P99 (MW)	86	389	431	95	423	503
Max Error (MW)	252	1274	1456	252	605	725
R2	0,97	0,47	0,32	0,97	0,42	0,26
Count	28603	28604	28603	768	768	768

Table 3 Comparison of KPI during storm events

3.4.2 High system imbalance and system imbalance ramps

A second situation where the model might fail to predict the system imbalance accurately is during high system imbalances or during strong change of system imbalance. To evaluate these situations the dataset is reduced to events where the absolute system imbalance exceeds 300 MW or where the difference between two subsequent quarter-hours exceeds 300 MW. The threshold of 300 MW was selected to ensure sufficient data points were available for the analysis.

Comparing the KPIs of Table 3 and Table 4 it is clear that indeed the relative error increases in high SI and high SI ramp situation (as seen by an augmentation of the MAE and RMSE). However, the R² value improve significantly for all quarter-hours.

	SI > 300 MW			High SI ramp (>300 MW between Qhs)		
	QH0	QH1	QH2	QH0	QH1	QH2
MAE (MW)	30	219	280	31	298	239
RMSE	39	256	312	40	327	285
P99 (MW)	115	608	685	113	656	663
Max Error (MW)	252	1274	1456	167	1274	1456
R2	0,99	0,72	0,59	0,98	0,70	0,38
Count	2328	2329	2329	536	536	536

Table 4 Performance KPIs during high SI and high SI ramp situations

Further exploring the distribution of forecasting error vs the observed SI in Figure 19 shows a relatively stable minimum, average and maximum error over all observed SI values (keeping in mind the few observations at the tails) for Qh0. Looking at the same distribution for Qh2, the spread of error remains similar. However, a bias of the SI forecasting error in the direction of the SI can be observed. This would indicate that the linear model is not able to well forecast large SI for future quarter-hours. This observation is confirmed in Figure 20 where the SI forecasts are plotted against a load duration curve of the SI.

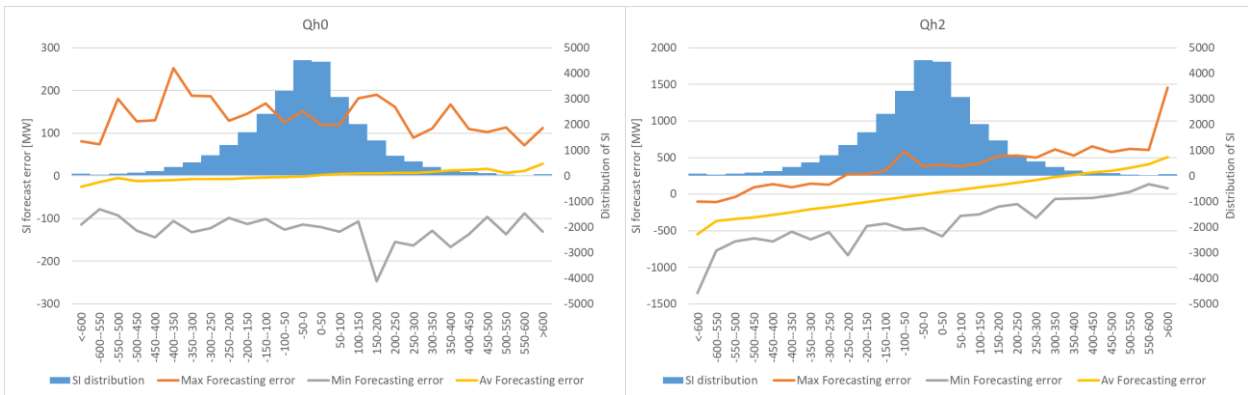


Figure 19 Forecasting error vs distribution of SI

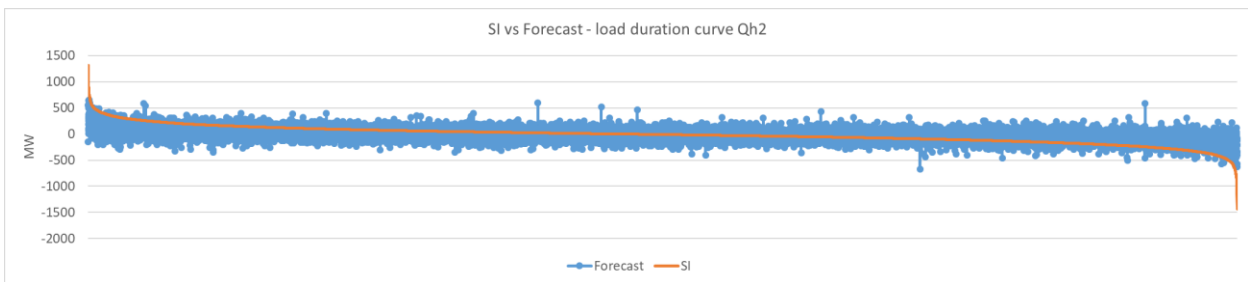


Figure 20 SI load duration curve and SI forecast

3.4.3 Impact of outages on SI forecast quality

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A final element in the evaluation of the model was the performance during an outage of a production unit. This assessment was done using the data published (for the considered time period) on the Elia website³ and only considering forced outages of generation units.

Figure 21 shows the distribution of the SI for Qh0 (current quarter-hour) and indicates whether a Forced Outage (FO) has taken place during that quarter hour. From the graph, one could not derive the volume of generation that was lost during the outage. Although the share of quarter hours with forced outages is relatively higher at the tails of the SI distribution curve, the absolute number is low. Hence, high SI events may happen together with a FO, but this situation is rather rare. Furthermore, outages are observed in almost the entire distribution of the SI.

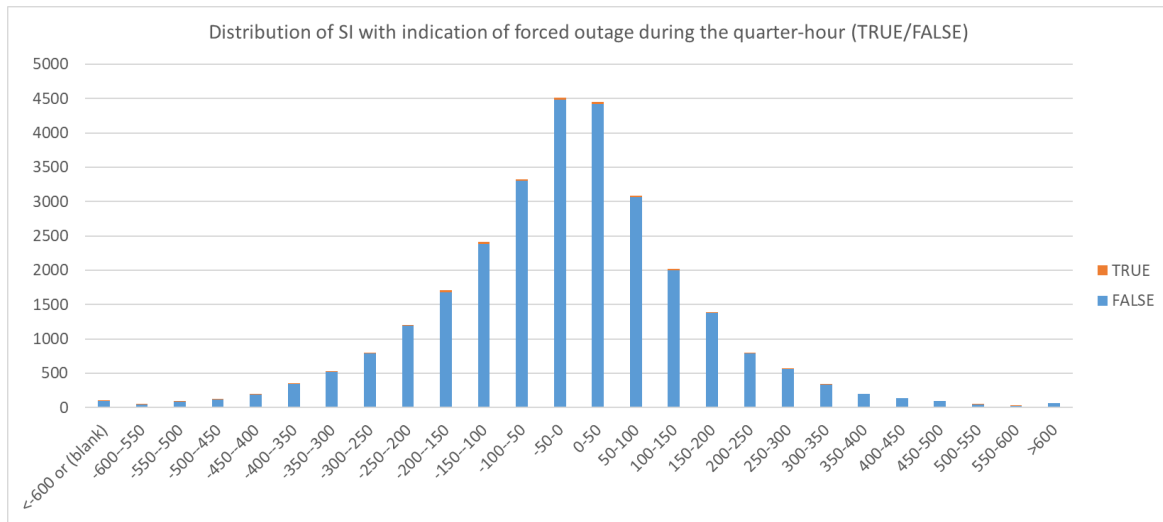


Figure 21 Distribution of SI for QH0 indicating a Forced Outage during the Qh

The number of outages is quite limited (only 257 quarter-hours were observed in the dataset), hence the KPIs shown in Figure 22 are of questionable statistical relevance. When evaluating the model using the KPI, no strong change in performance is observed from splitting the outage situation from the no-outage situation when it comes to the forecasting of the SI. Even considering whether or not an outage has taken place in the previous 4 quarter-hours (to capture the effects of an outage at the end of the quarter hour or long lasting effects), no strong changes in KPIs can be observed.

³ <https://www.elia.be/en/grid-data/power-generation/planned-and-unplanned-outages>

All timestamps			
	QH0	QH1	QH2
MAE (MW)	23	91	104
RMSE	30	124	140
P99 (MW)	86	389	431
Max Error (MW)	252	1274	1456
R2	0,97	0,47	0,32
Count	28603	28604	28601

Outage during current Qh				Outage during past h			
	QH0	QH1	QH2		QH0	QH1	QH2
MAE (MW)	22	110	131	MAE (MW)	24	104	123
RMSE	29	149	176	RMSE	31	140	162
P99 (MW)	82	488	544	P99 (MW)	86	472	518
Max Error (MW)	121	552	814	Max Error (MW)	161	763	814
R2	0,98	0,43	0,21	R2	0,98	0,49	0,33
Count	257	257	257	Count	1002	1002	1002

no outage during current Qh				no outage during past h			
	QH0	QH1	QH2		QH0	QH1	QH2
MAE (MW)	23	91	104	MAE (MW)	23	91	103
RMSE	30	124	140	RMSE	30	123	140
P99 (MW)	86	388	429	P99 (MW)	86	387	426
Max Error (MW)	252	1274	1456	Max Error (MW)	252	1274	1456
R2	0,97	0,47	0,32	R2	0,97	0,47	0,32
Count	28346	28347	28344	Count	27601	27602	27599

Figure 22 KPIs considering Forced Outages

3.5 Conclusion

Elia proposes to use the linear model for the forecasting of the System Imbalance. The model has proven to be the most accurate of the different models. It relies on simple concepts avoiding any potential black box effect. The linear model was evaluated in different situations such as storm events and was proven robust.

4. Testing phase in operations

The linear model was implemented in a Proof of Concept so that the SI forecast could be tested in operations. This chapter describes the set-up and feedback (both qualitative and quantitative) received during the one month testing phase which ran from November 1st to November 30th 2021.

4.1 Set-up for testing phase

During a one month period the forecast of the system imbalance was tested in an operational environment. Operators were presented with the forecast of the SI in real-time. In order to ensure a coherent feedback, the proof of concept (PoC) showed both the linear forecast and the categorical forecast (using a random forest). At each quarter-hour, and when the operational situations permitted it, operators were asked to indicate whether they found the information useful with a simple yes / no vote. An illustration of the interface presented to operators can be seen in the figure below. At the end of the testing phase further feedback was gathered from operators.

Summary of predictions:

time	Linear predictions [%]	(-inf, -500.0]	(-500.0, -250.0]	(-250.0, -150.0]	(-150.0, -100.0]	(-100.0, 100.0]	(100.0, 150.0]	(150.0, 250.0]	(250.0, 500.0]	(500.0, inf]
14:15	19	0	4	5	7	78	8	5	1	0
14:30	5	0	4	11	8	57	8	7	4	0
14:45										

Latest time in data used for linear prediction: 2021-12-06 14:14

Latest time in data used for random forest prediction: 2021-12-06 14:14

Data quality for these predictions was 100 %

Was this prediction useful for you?

Please enter an explanation if necessary

YES NO

Thanks for the feedback. Your last feedback was registered at 14:15:25.

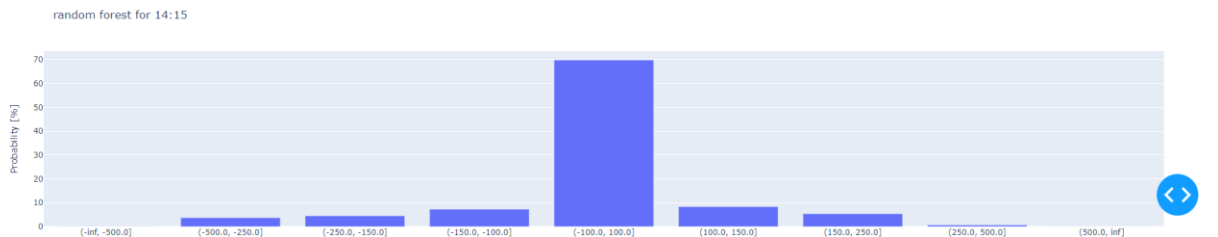


Figure 23 interface for the PoC

Ahead of the operational test, Elia made several changes to the linear model as presented in the previous chapter. The first notable change was the introduction of a forecast for each minute of the quarter hour. Hence, instead of training a single model on minute 8, 15 different models were trained. This change allowed an overall greater quality and robustness of the operational tool.

Secondly, the number of indicators used in the forecast was reduced. This was driven both by robust data availability as model complexity (given 15 different models were running both for a linear prediction and with a random forest). The set of indicators listed in Table 2 was reduced to SI, NRV, GUV, and GDV.

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During the initial stages of the testing phase data issues were observed, leading to erroneous forecasts or no forecast at all. After some additional tweaks, the tool ran relatively stable for the duration of the testing phase. This, however emphasizes the need for a robust tool if it is to be used in an operational environment. Hence, during the implementation phase, special attention will be given to ensure robustness of the underlying data exchanges.

4.2 Qualitative feedback from the testing phase

The goal of the testing phase was to assess whether the forecast of the SI would support the operators in their decision making process for the activation of balancing reserves. Hence having an operational feedback during and after the testing phase is key to assess the value of such an SI forecasting tool.

Overall, the added value of the PoC was limited according to the feedback received, three main concerns were raised. First, the forecasting accuracy is not sufficient to take operational decision in real time. Second, the interface used during the PoC needs further refinement to support the decision making process. Finally, the tool should be sufficiently robust to support 24/7 operations and should deliver the data close to real time. A replacement strategy for missing data should be envisaged. These elements will be considered in the implementation of the tool which will support the publication of the forecast. Furthermore, there is a need to better integrate the categorical predication in the decision making process.

4.3 Quantitative evaluation

Although 15 different models were implemented during the PoC, the quantitative evaluation is performed on the model for minute 8, as such the performance during the PoC can be compared against earlier analysis.

4.3.1 Assessment of KPIs

The forecasting accuracy was monitored during the PoC. In line with the previous analysis, a focus was put the previously selected KPIs. Looking at the results of the different forecasting horizons, a slight deterioration of the indicators can be observed for the linear model. The probable cause is the reduction of indicators used in the SI forecast. The categorical prediction was overall inaccurate due to a lack of training depth.

Table 5, Table 6 and Table 7 show the calculated KPIs. For Qh0, the observed KPIs are worse than expected, but the RMSE stays below 100 MW. For Qh+1 and Qh+2 there is only a slight change in KPIs compared to previous analyses. When removing outliers from the observations, the KPIs for all forecasting horizons approach the expected values.

KPI QH0	Expected	Observed	No outliers
RMSE [MW]	35	50	37
P99 [MW]	100	168	93
Max error [MW]	313	372	103

MAE [MW]	27	34	30
----------	----	----	----

Table 5 KPI for QH0 forecast during PoC

KPI QH+1	Expected	Observed	No outliers
RMSE [MW]	122	134	120
P99 [MW]	382	411	299
Max error [MW]	1209	592	327
MAE [MW]	88,8	102	94

Table 6 KPI for Qh+1 forecast during PoC

KPI QH+2	Expected	Observed	No outliers
RMSE [MW]	141	147	127
P99 [MW]	411	435	307
Max error [MW]	1322	660	355
MAE [MW]	102	111	100

Table 7 KPI for Qh+2 forecast during PoC

4.3.2 Performance assessment during specific events

In line with the model evaluation performed in section 3.4, the same assessment is performed for the forecasting performed during the PoC.

4.3.2.1 Storm events

During the period of the PoC, no storm events were detected.

4.3.2.2 High System Imbalance or high System Imbalance ramps

Using the same evaluation criteria as before (i.e. the absolute value of the SI or difference in SI between two quarter hours exceeds 300 MW), the following KPIs can be calculated for Qh0. It is clear that the performance of the model during the PoC is significantly worse than during the analysis phase. Although the number of observations is relatively low, there is a clear deterioration of the KPIs compared to the ones presented in section 3.4.2.

KPI Qh0	High SI (abs(SI) > 300 MW)	High SI ramp
---------	----------------------------------	--------------

RMSE [MW]	96	326
P99 [MW]	358	659
Max error [MW]	372	662
MAE [MW]	61	300
Count	137	67

Table 8 KPI for high SI and high SI ramps during PoC

4.3.2.3 Impact of outages on SI forecast quality

In a similar way as in the previous paragraph, we can assess the performance of the model during the outage of a generation unit. Previously, it was concluded that generation outages only had a limited impact on the KPI, we can derive a similar conclusion for Qh0 and Qh+1 forecasts during the PoC while for Qh+2 we see a much strong deterioration. No strong conclusions can be drawn from this assessment given the limited amount of occurrences (26) and limited volume (max 413 MW) of outages.

Quarter Hour	Category	RMSE (MW)	MAE(MW)	P99 (MW)	Max Error (MW)
Qh0	Forced Outage	65	48	133	133
Qh0	No Outage	48	34	161	373
Qh+1	Forced Outage	149	128	243	243
Qh+1	No Outage	134	102	410	653
Qh+2	Forced Outage	204	164	430	445
Qh+2	No Outage	144	109	432	660

Table 9 KPI for outage situations during the PoC

4.3.3 KPI performance in function of forecasting model

During the PoC a model was trained for each minute of the quarter hour and not just a single model trained for a forecast at minute 8. This allows us to compare the evolution of the model performance during the quarter hour. The forecast of Qh0 and Qh+1 clearly improves with more data becoming available, while the forecast quality for Qh+2 remains somewhat stable. The time dependency of the forecasting quality is especially relevant for the near future where decision on the activation of balancing reserves for Qh+1 will have to be made at an earlier time during the quarter hour.

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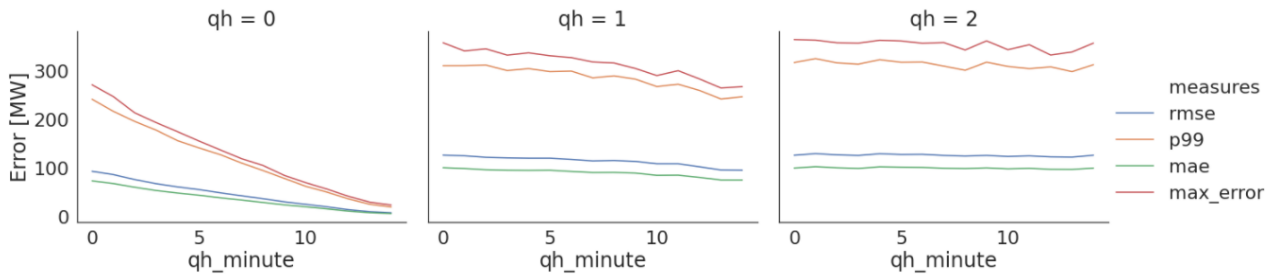


Figure 24 Evolution of KPIs throughout the quarter hour

4.4 Conclusions

The testing phase showed that the quality of the forecasts was slightly worse than the initial analyses which supported the selection of the linear model. This can be observed both for the overall KPIs as for special situations. The probable cause lies with the reduction of model depth and set of indicators. It should be noted that some filtering of outliers was needed to obtain KPIs in line with the ones presented in section 3.2. Analysis showed that, as expected, forecasting quality improves along the quarter hour.

5. Publication of the SI forecast

5.1 Publication format and time horizon

5.1.1 Publication format

Elia proposes to publish the forecast of the SI for Qh0, Qh+1 and Qh+2 after the industrialisation of the tool developed for the testing phase (PoC) and after additional work to improve the forecasting quality. Furthermore, the final decision to start the publication will be subject to an evaluation of model quality. Elia proposes to use an RMSE of 100 MW as threshold.

Following the feedback from the public consultation, where market parties expressed their preference for the categorical predication, Elia proposes to publish the information summarized in the table below. This publication remains subject to attaining a sufficient level of accuracy for each forecasting time horizon. Elia will publish the prediction of the SI forecast as well as the interval probability with the interval ranges as defined in table below. Elia does keep the right to redefine these ranges subject to further work.

Quarter Hour	Linear model prediction[MW]	Interval probability									
		[-inf; -500 MW]	[-500 MW; -250 MW]	[-250 MW; -150 MW]	[-150 MW; -100 MW]	[-100 MW; 100 MW]	[100MW; 150 MW]	[150 MW; 250 MW]	[250 MW; 500 MW]	[500 MW; inf]	
13:15 - 13:30	61	...%	...%	...%	...%	...%	...%	...%	...%	...%	...%
13:30 - 13:45	90	...%	...%	...%	...%	...%	...%	...%	...%	...%	...%
13:45 - 14:00	105	...%	...%	...%	...%	...%	...%	...%	...%	...%	...%

Figure 25 data to published

The data will not be included in the balancing dashboard but made available via the Elia open data platform in the form of an API. Data used in the model, but available via other API's would not be included in the publication. The publication would be accompanied with the necessary quality indicators and legal disclaimers on the quality and liability of the publication. It will be made clear that Elia puts this information at the disposal of the market parties in an effort to increase market's ability to better balance the energy system, but that under no circumstances this information implies a shift in responsibility or liability towards Elia.

5.1.2 Forecast quality as prerequisite for publication

Initially, Elia proposed to only start the publication of the SI forecast if the quality was sufficient, i.e. an RMSE below 100 MW for the forecast at minute 8. During the publication, several market parties expressed agreement with this approach. Stating that such a publication would only have an added value for market parties if the publication was sufficiently accurate and reliable, and that a publication with a low accuracy could result in additional risk for market parties. There were no specific proposals on what the right accuracy would be (as an alternative to the earlier proposed threshold).

To address the concerns of market parties, Elia proposes a two-step approach which is detailed in the section on the implementation plan. In short, Elia will take time to investigate the addition of forward looking data such as cross border nominations or other indicators proposed during the publication consultation ahead of the start of the publication.

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If this would prove to be insufficient, then Elia may decide to not go ahead with the publication of certain forecasting horizons (e.g. Qh+2).

Instead of evaluating the performance of the respective models at minute 8 during the quarter hours, Elia will perform the assessment for the model at minute 5. Although the intention is to train a separate model for each minute of the quarter hour – see section 5.1.3, the accession to the MARI platform will increase the lead time for the activation of mFRR, hence the model for minute 5 will be most representative for the operational decision making process.

5.1.3 Frequency of publication and model update

During the public consultation, market parties requested two additional features:

- A frequent update of the model so that changes in the balancing market can be captured swiftly
- A publication of the forecast on minute bases instead of a single forecast each quarter hour.

In order to accommodate these request, Elia proposes to extend the scope of the initial project so that not one, but 15 models are trained one for each minute of the quarter hour. Every minute the forecasting results from the respective model would be published. This approach allows greater accuracy compared to only using one model for all 15 minutes of the quarter hour. In addition, Elia commits to a monthly update of the model using a look back horizon of 8 weeks.

5.2 Qualitative assessment of the publication

Elia sees a number of advantages for the publication of the SI forecast when the model is considered to be sufficiently accurate. First, the publication of an accurate system imbalance forecast might enable a higher implicit reaction from market parties in the balancing markets. Secondly, we see that the forecasting quality of the current quarter hour and the use of a simple linear model will allow a higher transparency on the main drivers of the SI, this would in turn allow market parties to better balance their portfolio. Finally, after an evaluation period the publication would allow an ex-post analysis on the implicit reaction of market parties on this publication.

At this time, Elia does not see strong concerns against the publication of the SI forecast, but a number of smaller points were identified. First, we can observe that the reactive balancing model in Belgium seems to work well given that the NRV and SI has remained relatively stable even with the high increase in RES. This is somewhat confirmed by the lack of strong correlation of RES forecasts and the SI observed in this study. Hence, it is yet to be seen whether market parties will react to the proposed publication. Second, assuming an accurate forecast for the future quarter-hours – in combination with the available ATCs, a market party could derive whether or not they will have a domination market position in the balancing timeframe.

In terms of REMIT impact, Elia does not see the publication of the forecasted SI as an insider information. We only see the obligation to inform the market when the publication fails (outage of the tool).

During the public consultation, stakeholders expressed a mixed view on the publication of SI forecast. Their concerns were mainly related to potential adverse effects in case all market parties start using potentially erroneous data as input for their models. Moreover, they find that the current levels of accuracy do not merit an implicit reaction by

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BRPs. On the other hand, market parties do put forward that added value of such publication, they recognize that it might activate additional flexibility at the right time and the increased transparency could be beneficial for smaller players.

Overall, Elia believes that with an increase in accuracy most of the concerns for the publication can be addressed.

5.3 Implementation plan

Elia proposes to go ahead with the implementation and publication of the SI forecast, subject to obtaining a sufficient quality. Hence, Elia would propose a phased approach.

5.3.1 Phase 1: model improvement

Feedback from the consultation and from the testing phase shows that the quality of the Qh+1 and Qh+2 forecast is not sufficient for operational use or publication. Hence, Elia proposes to look at different ways to improve the accuracy. As noted in the consultation report, Elia proposes to include forward looking data (such as cross border nominations). Moreover, Elia will assess the indicators proposed by stakeholders during the public consultation. In line with the results from the PoC, the model depth and number of indicators will be re-evaluated. Finally, Elia might reassess the use of the linear model if the improvements are not sufficient.

At the end of phase 1, Elia will evaluate the performance against the threshold of 'RMSE < 100 MW'. If this threshold cannot be reached for a certain forecasting horizon (Qh0, Qh+1 or Qh+2), the data will not be included in the publication. The current quality of the Qh+0 forecast is considered sufficient for publication, but will be included in the analyses of phase 1.

The work on phase 1 will kick-off in Q2 2022. The results will be presented in the WG Balancing.

5.3.2 Phase 2: Implementation

After phase 1, and for the forecasting horizons which meet the quality criteria, Elia will proceed with the implementation of the publication in phase 2. Following operational feedback, this implementation phase will also improve the interface for operators and ensure robustness of the publication.

If target for RMSE below 100 MW for a specific forecasting horizon is achieved, Elia would make available the forecast via the Open Data platform. The publication would be accompanied with the necessary quality indicators and legal disclaimers on the quality and liability of the publication. It will be made clear that Elia puts this information at the disposal of the market parties in an effort to increase market's ability to better balance the energy system, but that under no circumstances this information implies a shift in responsibility or liability towards Elia.

In terms of REMIT impact, Elia does not see the publication of the forecasted SI as an inside information.

The implementation would kick-off after phase 1 and is expected to take place in Q3 2022.

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Once the implementation has finished, Elia will start the publication of the relevant time horizons. During the consultation period, market parties expressed their concern of starting the publication during significant changes in the balancing market introduced by, for example, MARI or a change in the DA balancing obligation. Elia believes that a regular retraining of the model will be necessary to capture these changes and to ensure sufficient quality of the publication. The planning for the retraining will be assessed to guarantee the quality of the results.

5.3.3 Phase 3: evaluation period

After a minimum of six months of publication, Elia proposes to introduce a new evaluation moment. During this assessment, Elia would focus both on the performance of the models and the operational feedback. Furthermore, this moment allows to assess the market parties' reaction to the publication of the SI forecast (i.e. do we see a significant change in SI KPIs after the introduction of the publication or can we derive a reaction from the market on this publication). To account for significant changes in the balancing market, the period used for the evaluation might not start directly after the publication. In other words, in case we observe an impact to the SI forecast due to e.g. the go-live of iCaros phase 1, we might only start the 6 month evaluation period at that time.

After this assessment, Elia will report its findings in the balancing WG.

Annex 1: Description of the model used during the testing phase

During the testing phase scheduled for later this year, the following indicators will be used for the prediction of the System Imbalance using the linear model described in this report. In preparation of this testing phase, additional indicators might be added. The model used during the testing phase will be included in the final report.

	Wind power	Wind powerIntraDay	Solar IntraDayForecast	Solar Measurement	SI_Cumulative	SI_Instantaneous	NRV_Cumulative	NRV_Instantaneous	IGCC_I	IGCC_D	SI	GUV	GDV	PPOS / PNEG	R2_I	R2_D
Wind power	100%	99%	-19%	-18%	5%	6%	-5%	-5%	2%	-1%	12%	-3%	14%	-11%	-3%	17%
Wind powerIntraDay	99%	100%	-19%	-18%	5%	5%	-4%	-5%	2%	-1%	11%	-3%	14%	-11%	-2%	16%
Solar IntraDayForecast	-19%	-19%	100%	99%	5%	5%	-5%	-6%	0%	1%	6%	3%	13%	-3%	0%	10%
Solar Measurement	-18%	-18%	99%	100%	7%	8%	-7%	-8%	-1%	2%	9%	1%	16%	-6%	0%	11%
SI_Cumulative	5%	5%	5%	7%	100%	92%	-92%	-84%	-48%	42%	43%	-32%	34%	-31%	-14%	22%
SI_Instantaneous	6%	5%	5%	8%	92%	100%	-90%	-90%	-52%	46%	40%	-30%	33%	-30%	-13%	21%
NRV_Cumulative	-5%	-4%	-5%	-7%	-92%	-90%	100%	95%	54%	-48%	-39%	32%	-34%	31%	11%	-18%
NRV_Instantaneous	-5%	-5%	-6%	-8%	-84%	-90%	95%	100%	57%	-51%	-36%	29%	-33%	30%	10%	-17%
IGCC_I	2%	2%	0%	-1%	-48%	-52%	54%	57%	100%	-25%	-24%	27%	-11%	13%	4%	-8%
IGCC_D	-1%	-1%	1%	2%	42%	46%	-48%	-51%	-25%	100%	19%	-7%	26%	-8%	-2%	4%
SI	12%	11%	6%	9%	43%	40%	-39%	-36%	-24%	19%	100%	-74%	68%	-73%	-51%	51%
GUV	-3%	-3%	3%	1%	-32%	-30%	32%	29%	27%	-7%	-74%	100%	-18%	71%	65%	-17%
GDV	14%	14%	13%	16%	34%	33%	-34%	-33%	-11%	26%	68%	-18%	100%	-42%	-12%	64%
PPOS / PNEG	-11%	-11%	-3%	-6%	-31%	-30%	31%	30%	13%	-8%	-73%	71%	-42%	100%	52%	-29%
R2_I	-3%	-2%	0%	0%	-14%	-13%	11%	10%	4%	-2%	-51%	65%	-12%	52%	100%	-14%
R2_D	17%	16%	10%	11%	22%	21%	-18%	-17%	-8%	4%	51%	-17%	64%	-29%	-14%	100%

Annex 2: consultation report