UNIVERSIDAD PONTIFICIA COMILLAS

ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA (ICAI)

OFFICIAL MASTER'S DEGREE IN THE ELECTRIC POWER INDUSTRY

Master's Thesis

ANALYSIS AND PREDICTION OF THE NEGATIVE PRICES ON THE GERMAN SPOT POWER MARKET

Author:	**Guillermo Huerta Iranzo**
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Madrid, July 2019

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SUMMARY

The high growth of the RES generation share in Germany, together with the still significant inflexibility of the conventional thermal generator groups, has increased the number of hours in which the German spot power market is trading at a negative price, reaching 2% the annual hours. This fact has led to the establishment in the last German Renewable Energy Sources Act (EEG 2017) of a rule whereby if the spot market price is negative for 6 or more consecutive hours, the RES generation loses its source of subsidy. However, in the absence of accurate prediction models of the occurrence of negative hours in the literature, and high levels of subsidies, curtailing and losing subsidies is still riskier for most operators than having to accept negative prices in case of 6-hour- rule applies

In order to remedy this situation, a binary classification model of the market price has been developed (positive and negative), considering the main explanatory factors of these prices, resulting from the theoretical analysis of the market. Due to the complex interaction of the high set of explanatory variables, the classification models based on machine learning, such as those studied and used ensemble methods of classification trees, demonstrate to obtain a greater precision with respect to their similar simple methods for the problematic faced .

The finally developed model, based on the technique of Adaptative Boosting, exceeds an accuracy ratio of 92% and accuracy of negatives (Sensitivity) of 98%, values well above those obtained with ordinal classification trees.

The economic performance of a 500 MW wind farm during 2018 has also been studied, comparing the most common bidding approaches of the RES generators with the result of applying the price prediction of the model. Thus, resulting in a reduction of more than 50% of the economic opportunity cost with respect to these, derived from a better adaptation to the occurrence of negative prices.

Additionally, as a result of the set of previous developments, the level of significance of each predictor is verified in the occurrence of negative prices, confirming most of the premises of the theoretical analysis, and concluding further that the net burden of the countries interconnected with Germany has a greater importance than the variation of the minimum thermal generation level of the country.

Finally, the relationship between the effectiveness of the 6-hour rule and the liquidity of the intraday markets is demonstrated, and it is currently concluded as effective.

ACKNOWLEDGEMENT

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1. INTRODUCTION

1.1. Electricity Spot Markets and Negative Prices

During the last decade, the global electricity sector has been characterized by a significant penetration of renewable energy sources (RES). This development has been justified by the need to address global warming, through the reduction of greenhouse gas emissions, and also the will to reach energy independence in fossil and nuclear fuel-dependent countries.

Concretely in Europe, EU Member States (MS) have adopted several and different National support schemes for RES along the previous decade and this one, attempting to comply with the targets of RES share in consumption determined by the Directives of the European Parliament[1].

One of the main outcomes of these new scenarios is the spot price decrease on yearly average. On power exchanges, market clearing prices are driven by supply and demand curves, which helps to maintain the electricity system balanced. Thus, prices fall when a high and inflexible power generation (e.g. sum of Nuclear, Carbon or RES generation) appears simultaneously with low electricity demand, reaching prices even below zero (see right figure, as representation of this phenomenon).

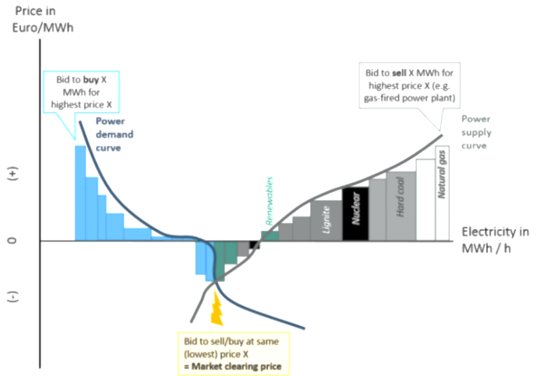

Figure 1 - Supply and Demand curves, Neg. Prices

In some EU MS, such as Germany, the occurrence of negative prices is increasingly frequent due to the high growth of the Variable RES generation share, together with the still significant inflexibility of conventional thermal generation. As a matter of fact, the German bidding zone (which also includes Luxembourg, henceforth, named as DE-LU) fixed more than 400 hours of negative prices during the period 01/2017 - 05/2019, equivalent to 2% of the period.

According to EPEXSPOT [1], these prices are not considered a market failure, but an indicator for the participants of this one, since these prices encourage them to be more flexible and respond to fluctuations in energy supply. However, in the latest publication of the German regulation "*Renewable Energy Sources Act (EEG 2017)"* [2], it is enacted the *EEG 2017 § 51 "6 hour rule"*, which has been designed to incentivize curtailment of subsidized RES built after 01/01/2016: subsidy payments cease if day ahead prices are negative for at least 6 consecutive hours.

As indicative data, losses through forgone subsidies of an average offshore park lie between 5 and 8 million EUR/year and are significantly impacting current valuations [3]. On the other hand, in the face of inaccurate day-ahead spot price predictions and high subsidy levels, curtailing and losing subsidies is until now riskier for operators than having to accept negative prices in case the 6-hour-rule applies. Therefore, this apropos legislation could not be ever effective if RES generators are not able to predict more accurately the occurrence of negative prices.

1.2. Motivation of this Master's Thesis

The need to create a precise prediction model of the occurrence of negative prices in the German DAM arises for two reasons. The first one is to reduce the uncertainty of the RES generation in terms of predicting the periods of consecutive negative prices in the market, in order to encourage its offer to reflect the real variable costs of its generation, through support in the "6h-rule ".

[1] The most recent one [Directive (EU) 2018/2001 on the promotion of the use of energy from renewable sources, Art. 3] establishes the objective of at least 32% of RES share in the Union's gross final consumption in 2030, to be collectively ensure by the EU MS.

On the other hand, the absence of prediction models of energy market prices oriented to the accurate prediction of negative price events, since those found in the literature, having a greater scope (focused on the Price forecast of the entire range of values), tend to be less accurate with respect to the concrete prediction of negative prices, since these ones are often even considered as outliers.

As Germany is the EU MS with the greatest installed capacity of variable renewable generation, it is also one of the countries with the highest price volatility and the one with the highest number of hours cleared with negative prices, on average, in recent years. Therefore, given that a precise prediction model of negative prices could contribute to the attenuation of the same event, it would be of significant relevance for a country that pretends to be a reference in terms of its ambitious reform policy of the current energy mix, towards one led by renewable energy.

1.3. Master's Thesis Objectives

The main objectives of this Master Thesis are the analysis and prediction of the negative-price events on the German spot power market. To that end, two different but linked sub-goals have been considered:

On the hand, this study aims to determine which parameters have a large influence on the occurrence of negative spot prices, by means of a theoretical approach based on the properties, data and literature about the German electric power industry, its applicable regulation and the observed behaviours of the wholesale market participants.

On the other hand, once the explanatory variables of the electricity price depression have been identified, this study aims to develop an adequate model able to predict with enough accuracy the occurrence of negative market prices in the German spot power market, setting a methodology for this purpose.

Finally, as a result of both sub-goals, it is intended to check both results. Thus, verifying the veracity of the assumptions resulting from the theoretical analysis, by means of the values of significance of the resulting predictors of the model. In addition, any discrepancy or unexpected result will be subjected to a more in-depth analysis, in order to find out if it is a mistake relative to the model, or on the contrary, a finding about the causes of the negative market prices.

1.4. Structure of the Report

Firstly, a survey of the literature about the different trends in electricity price forecasting will be carried out, with focus on the concerning classification methods.

Thereupon, it is developed a theoretical analysis regarding the key factors on the occurrence of negative prices on the German spot power market. Additionally, it is also included an assessment of the available and required data to perform the predictive model, developing several estimators for the explanatory variables whose forecasts are not available.

Once the predictors of the negative prices have been identified, the proposed methodology for the development of an adequate classification model will be detailed, both specifying the data treatment, and the parametrization of the considered model.

Afterward, the multiple results of the execution of the model will be presented, dividing these according to the evaluation of the methodology and model used, or to the assessment of the market framework.

Finally, the conclusions and findings resulting from the group of previous developments are presented. Both the verification of the relationship between the results of the theoretical analysis and the model is made, as well as an evaluation of the effectiveness of the "6h rule".

2. STATE OF THE ART

2.1. Electricity Price Forecasting

Electricity price forecasting has become an area of active research during the last decades, due to the increase of competition levels and restructuring. A diversity of models can be found regarding the analysis and prediction of the impacts of different dynamic disturbances (such as fuel prices or RES integration), physical constraints (e.g. network congestions) and gaming behaviours (e.g. bidding strategies) on market efficiency and prices. These models, taking the classification of Weron [1], ranges from:

- **Fundamental methods**: which try to capture and model the impacts and relation of important physical and economic factors present in the production and trading of electricity, in order to describe the price dynamics.
- **Multi-agent or equilibrium models:** these simulate the operation of the power market, conceived as a system of heterogeneous agents, which interact with each other, in order to build the price process by matching demand and supply in the spot market.
- **Statistical or econometric approaches**: based both on the direct application of statistical load forecasting techniques, and on implementations of econometric models of the electricity market. However, its common approach is not useful to forecast negative price events, since its simplicity would trip with the temporary randomness of these events.
- **Reduced-form models**: grouping quantitative and stochastic models, which characterize the statistical properties of the market price over time, excelling at risk analytics and derivatives valuation.
- **Computational intelligence techniques**: which combine elements of learning, evolution and fuzziness to create approximations capable of adapting to complex dynamic systems. The main classes considered of CI techniques are Support Vector Machines, Artificial neural networks and fuzzy systems. Nonetheless, the approach introduced later as Ensemble learning, is also included within this set of techniques.

It must be also commented, that multiple electricity price forecasting methods result from a hybrid solution of the previous categories.

However, the different models found in the literature and collected in the set of the aforementioned methodologies, are focused on the forecasting of the entire range of electricity price values, so that this greater scope tends to result in a lower precision with respect to the accurate prediction of negative prices, since they are often even considered as outliers.

Therefore, given this problem, the objective result of the model has been reoriented to the binary classification of market prices in positives and negatives. Thus, focusing the precision of the model on the proposed objective. The models indicated for solving this type of problem are the so-called statistical classification methods, specifically, the most widespread in classification problems with categorical variables, such as the one concerned, is the classification tree.

2.2. Statistical Classification

There is a broad set of models belonging to the branch of statistical classification, nonetheless, most of them can be grouped in those based on Frequentist procedures (e.g., Fisher's linear discriminant analysis) and Bayesian procedures (e.g., Bayesian hierarchical modeling).

Regarding the model to be developed, models based on the first group should be discarded directly, since the frequentist procedures, although of proven effectiveness, are models that require independent metric variables to develop the classification. In fact, these are closely related to the analysis of variance (ANOVA) and regression, which also try to express a dependent variable by linear combination of other measurements or features. In the same fashion, these models can also be related to the Principal Components Analysis (PCA), since both examine the linear combinations of a set of variables that best explain the data.

However, for the problem in question seeking response, the prediction of negative price events in the market, there are some non-metric (categorical) variables considered of relative predictive importance, such as the day of the week, or the classes that arise of the clustering of the price curve (valley, intermediate and peak). In addition, the existence of certain dependencies among some variables considered for prediction, would greatly affect the quality of the models based on the previous methodology.

Therefore, the review of the literature in this subsection will be focused on the second group of statistical classifiers, those based on Bayesian procedures, which can be used with categorical variables, and some of these are not affected by the interrelation of explanatory variables. Moreover, these ones, unlike the previous ones, provide a natural way of considering any available information about the relative sizes of the different classes within the overall observations. Therefore, they are especially useful considering the abnormal distribution of negative prices in the total set of market prices.

As was advanced in the previous subsection, the most widespread model in classification problems with categorical variables, such as the one concerned, is the classification tree. This is a Quantitative Model able to classify a given output (price sign) in classes by splitting the input space of predictors, resulting in a white-box model which is hierarchical.

To build this kind of classification models, in addition to the training set of data to generate the algorithm, a test set is used to estimate the future prediction error, consisting on unseen observations not used to train the statistical learning method. The test set allows fixing the trade-off between model complexity (nº of nodes) and training error (oversmoothing and overfitting).

However, the use of this model for the prediction of negative prices does not result in high precision. This is due to the complex interaction of the numerous sets of explanatory variables in the occurrence of these events. Thus, the ordering of the hierarchical predictor scheme that characterizes simple classification trees excludes multiple possibilities of negative prices occurring due to a simultaneity of factors not collectively collected by a branch of the classification tree.

This problem is solved with the ensemble methods of classification trees, which belong to the set of machine learning methods or CI techniques. Since its prediction is the result of the weighted average of all the predictions of its set of trees (also called "weak learners"), its structure is much more flexible or adaptive to any complex simultaneity of factors not collected jointly by the branch of a tree of classification.

2.2.1. Ensemble of Classification Trees

In general, ensemble methods are algorithms that combine multiple algorithms into a single predictive model in order to decrease variance, decrease bias, or improve predictions.

These ones are usually divided into two main categories, parallel methods (where the models that make up the ensemble are generated independent of each other) and sequential methods (where the learners are generated sequentially, depending on each other).

With respect to the use of classification trees as "weak learners" or "weak classifiers", the main approaches regarding ensemble methods founded in the literature are:

Bootstrap aggregation techniques (Bagging): belonging to the group of parallel ensemble methods, these algorithms are designed to reduce the variance of the classification trees, thus improving the stability and accuracy of the model. They works creating several subsamples of the training data, by choosing sets randomly with replacement, and then, each subsample is used to train their classification trees. After all the models have been built, the algorithm chooses as predicted category (output class) the one that has been more predicted by the set of learners. Additionally to the original Bagging method, there is another popular extension over bagging:

- *Random Forest*: based on bagging techniques, this method in addition to taking randomly the subsamples, it also takes random subset of features at each candidate split, instead of using all features to grow the classifiers, thus constructing a collection of decision trees with controlled variance. It is very suitable to handle higher dimensionality data, and also corrects the overfitting problem of other ensemble methods.

Boosting techniques: belonging to the group of sequentially ensemble methods, since their internal classification trees are learned sequentially with early trees fitting simple models to the data, and then analyzing data for errors. In other words, consecutive trees (random sample) are fitted under the goal of solving for net error from the precedent tree. Thus, when an observation is misclassified by a learner, its weight is increased so that next hypothesis is more likely to classify it correctly. The main boosting methods used are:

- *Adaptive Boosting (AdaBoost):* is adaptive in the sense that subsequent learners are tweaked in favor of those instances misclassified by previous trees, being sensitive to noisy data and outliers, and usually less susceptible to overfitting than other learning algorithms.

- *Gradient Boosting*: uses gradient descent algorithm which is able to optimize any differentiable loss function. Thus, the ensemble of learners is built one by one and individual trees are summed sequentially. Next learner tries to recover the loss (as difference between actual and predicted values). Therefore, this method works well with interactions, although is prone to overfitting.

3. THEORETICAL ANALYSIS OF THE OCCURRENCE OF NEGATIVE PRICES ON THE GERMAN SPOT POWER MARKET

3.1. Introduction

This section aims to assess and determine which parameters have a large influence on the occurrence of negative spot prices in the Day-Ahead Market of EPEXSPOT DE-LU, by means of a theoretical approach based on the properties, data and literature about the German electric power industry, its applicable regulation and the observed behaviours of the wholesale market participants.

To begin with, and as previously identified in the subsection *1.1. Electricity Spot Markets and Negative Prices*, the first factors which will be analyzed in this section, due to its significant impact on the occurrence of negative market prices, will be the RES generation and the inflexible conventional generation (mainly carbon and nuclear plants), whose important shares in the German power sector along the last years can be checked in the following figure.

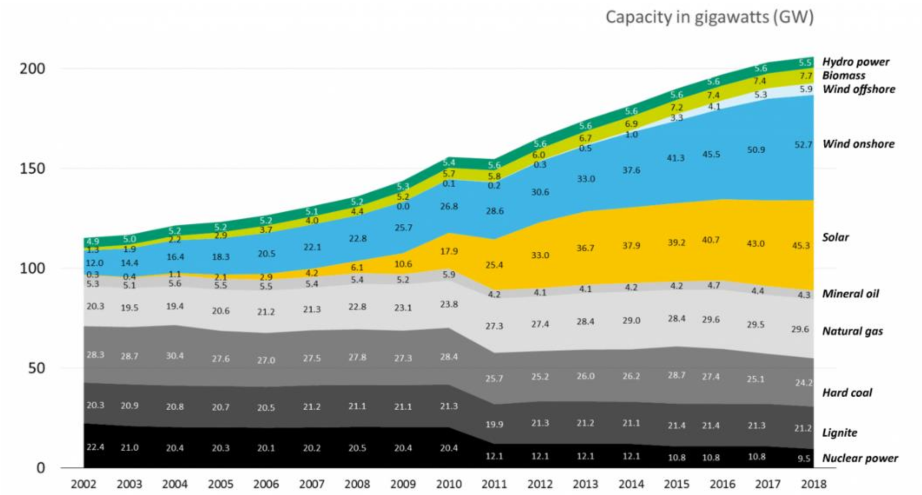

Figure 2 - Installed net power generation capacity in Germany. Source: [1]

3.2. Impact of RES on Market Prices

Renewable generation has significantly increased its share of annual generation and installed capacity in Germany in recent years, as can be seen in figure 2. At the same time, Germany's EEG 2017 regulation establishes multiple mechanisms to support renewable energies, as detailed in table 1. This means that, in general, renewable generation offers a price equivalent to its variable production costs (O&M) minus the subsidy quota, which usually results in generation offers at a negative price.

Type of support	Process determining the level of support	PV	On-shore wind	Off-shore wind	Bio-energy	Hydro-power	Duration of support (years)
Feed-in Premium	Tendering procedure	●	●	●	●		
Feed-in Tariff	Administrative procedure	●	●		●	●	20
Feed-in Premium	Administrative procedure	●	●		●	●	

Table 1 - Support schemes by technology in Germany. Source: [2]

In the particular case of renewable generation with Feed-in Tariff support mechanisms, for which it is remunerated at a fixed price per generation unit, that is, independently of the market price, its hourly generation is reflected at the minimum market price (-500 €/MWh).

However, as can be seen in the 4, 3, 2 figures, the level of renewable generation, both in an aggregate manner, and separating by technologies (mainly wind and photovoltaic), does not directly determine the positive/negative price of the market, as occasionally is thought, although it shows a high relation to medium and high positive prices.

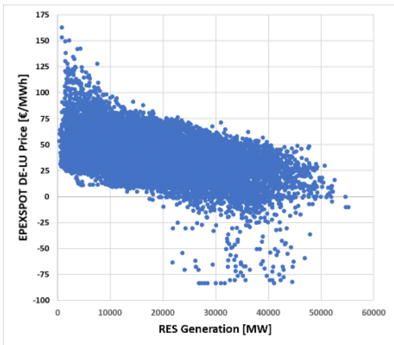

Figure 5 - RES [MW] vs Price [€/MWh]

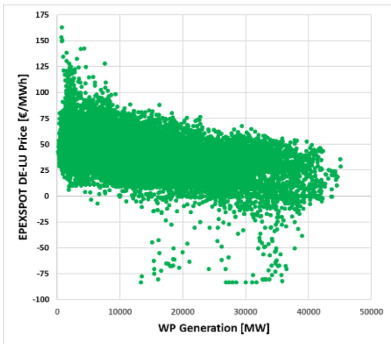

Figure 4 - WP [MW] vs Price [€/MWh]

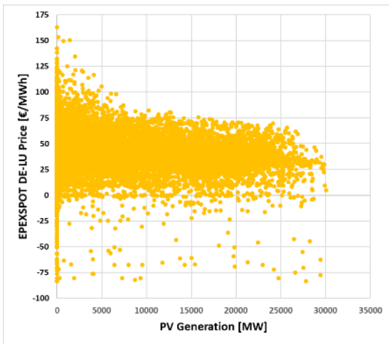

Figure 3 - PV [MW] vs Price [€/MWh]

This is mainly due to the variation in the level of demand, that is, for the same level of renewable generation, the probability of giving a period of negative price is greater the lower the level of demand, since the amount of load to cover for non-renewable technologies is lower (having a certain percentage of these that also offer a negative price, as detailed in the subsection *3.3. Minimum Conventional Generation Level)*.

This last concept, commonly called net load or residual demand, does show a greater significance in the occurrence of negative prices, as discussed in the next subsection.

3.2.1. Net load or Residual demand

The net load is defined as the difference between the level of demand and the level of renewable generation for a given moment. Thus, it represents in essence the amount of energy that must be covered by conventional generation. However, this term can be defined in different ways, depending on the purpose of its use, since it often refers only as renewable energies to wind and photovoltaic generation, due to its greater presence in the electricity markets.

However, a more precise definition of the net charge should also include as renewable energy, all those present in the market whose merit order is precedent to conventional technologies, such as, for example, the run-of-the-river hydro-plants, or other subsidized and non-dispatchable renewables.

In this study, the definition that only considers wind and photovoltaic generation is maintained, since as will be detailed below, they are the only renewable technologies for which prediction data are generally available, as well as being the ones with the highest percentage of generation in the market.

The following graph shows the high relation between the net charge and the daily market price, even though, to a lesser extent, in the negative price range.

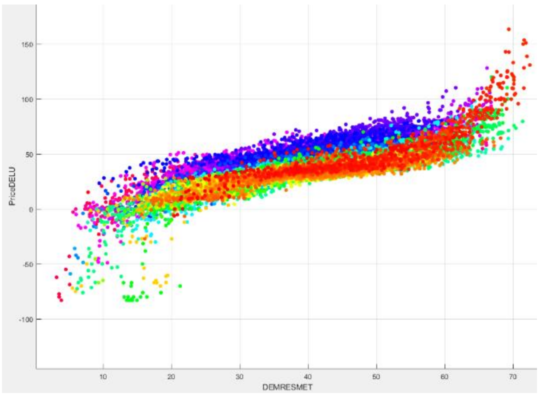

Figure 6 - Dispersion chart of German Net Load and DAM prices

The logic of this relationship is direct, because the greater the residual demand, the more conventional generation can be dispatched, and therefore, technologies with higher marginal cost will determine the market matching price.

However, this ratio is attenuated for the range of net load in which negative prices are given, since in this range, there is another determining factor of these ones, the minimum conventional generation level, whose concept and characteristics for the German power market are detailed in the following subsection.

Approximately, the negative prices begin to occur when the residual demand is less than 25 GW, since this level of demand can be covered by the aforementioned thermal minimum generation, which, as will be explained, also offers its power generation. market at a negative price.

However, as can be inferred from the previous figure, this level of thermal minimum generation is not constant, since otherwise the resulting price of the electricity market would approximate to be negative determinately from a certain level of net load.

It must be mentioned too, about the existence of two variables that also directly affect the establishment of the market matching price. These are the German electric import and export levels, since they are respectively added to the supply curve (at a minimum price, -500 €/MWh) and demand curve (at a maximum price, +3000 €/MWh). This procedure, as well as import/export levels, are determined by the algorithm of single price coupling of the Day-Ahead Market (DAM) for the PCR region, EUPHEMIA.

The import/export capacities of each country interconnected with Germany, as well as their relative influence on the prices of the German Day-Ahead Power Market, will be analyzed in the 3.4. subsection.

3.3. Minimum Conventional Generation Level

As previously introduced, not only the subsidized RES generation offers at negative price in the power market, but also inflexible thermal generators.

The inflexibility of these generators is not only characterized by the ramping constraints during the operation, which have been decreasing since their commissioning thanks to the introduction of new technologies in these generators. The main cause of its operational inflexibility is the high cost of shut-down and stat-up these thermal plants, which causes that they submit negative bids (known as opportunity cost bidding) to avoid that expensive costs. In a similar fashion, the CHP plants with heat-management or power plants that are contracted as balancing reserves also submit negative bids on the power exchange.

In recent years, up to 28 GW of conventional thermal generation (including nuclear power plants) were always in operation in Germany, irrespective of the wholesale price level. This minimum generation level consisted of 8 GW "must run" capacities, which were required for system and grid services and around 20 GW relative to inflexible thermal capacities, both detailed further below.

As commented before, "must-run" capacity refers to generation which is required steadily to provide system services, such as balancing and contribution to secure grid operations. Namely, part of this generation is required for redispatch, around 0.5 to 2.5 GW (to handle congestions in the domestic grid). A higher proportion, 3.5 to 5.5 GW, is required for providing balancing energy, and for backing up these balancing capacities, another 1.5 to 2.5 GW are also demanded.

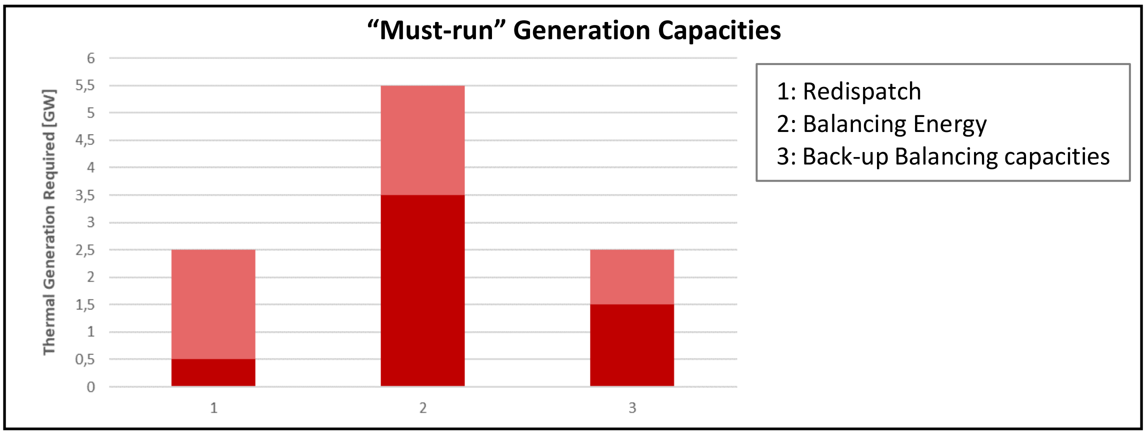

Figure 7 - Components of the "Must run" generation of Germany

On the other hand, as previously mentioned, the largest share of thermal minimum generation, up to 20 GW, stems from inflexible power plants. Mainly, this comprises plants which high start-up and shut-down costs, ramping constraints and those whose energy is used for on-site power demands or have heat delivery obligations (CHP plants, 6-7 GW running undisturbedly). An important factor is the so-called minimum load of power plants, the minimum output level of a thermal plant once it is switched on, which can amount to 15% to 40% of its installed capacity.

Finally, as it will be addressed in following sub-sections, it must be pointed that 75% of this inflexible generation stems from nuclear and lignite plants.

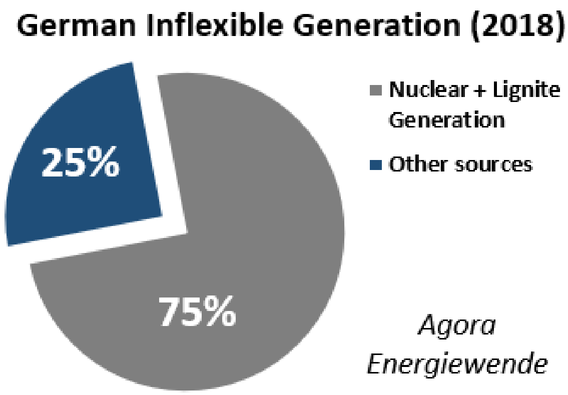

Figure 8 - Share of German Inflexible Generation (2018). Source: [4]

3.4. Scheduled Commercial Exports and Imports

As mentioned in subsection 3.2.1., The level of German import and export of electricity is an influential factor in determining the price of the German Power Exchange. This is due to the single European matching mechanism performed by the EUPHEMIA algorithm, which, based on the available interconnection capacities between the countries, makes an implicit matching of the energy exchanges between them, in order to optimize the net social welfare of the entire interconnected region (PCR).

Thus, bidding zones whose local matching price would be lower, export additional energy to areas whose local matching price would be higher, decreasing the most expensive generation thereof. In this way, and as far as the interconnection capacity allows, it is intended to balance the clearing prices of all the regions, emulating a single market in which only the lowest cost generation is dispatched, for the global demand of the PCR.

Therefore, it is important to detect the values and fluctuation of the export and import levels of Germany with its neighboring countries, since these exchanges modify the supply curve (imports) and demand curve (exports) of the German wholesale market. In particular, imports are added as an offer at the minimum price (-500 € / MWh), and exports as demand at the maximum price (+3000 € / MWh).

Because of this, when Germany imports electricity, the supply curve shifts to the right, decreasing the final price of the market, in the same way it happens with exports and the demand curve, moving to the right and increasing the market price.

The following figure shows for each interconnection with Germany, the values calculated for the German net commercial exports (negative values of the average imports), the 25th and 75th percentiles (line and box edges, respectively), and the extreme values not considered outliers (inside the whiskers) and outliers (plotted individually using the '+' symbol).

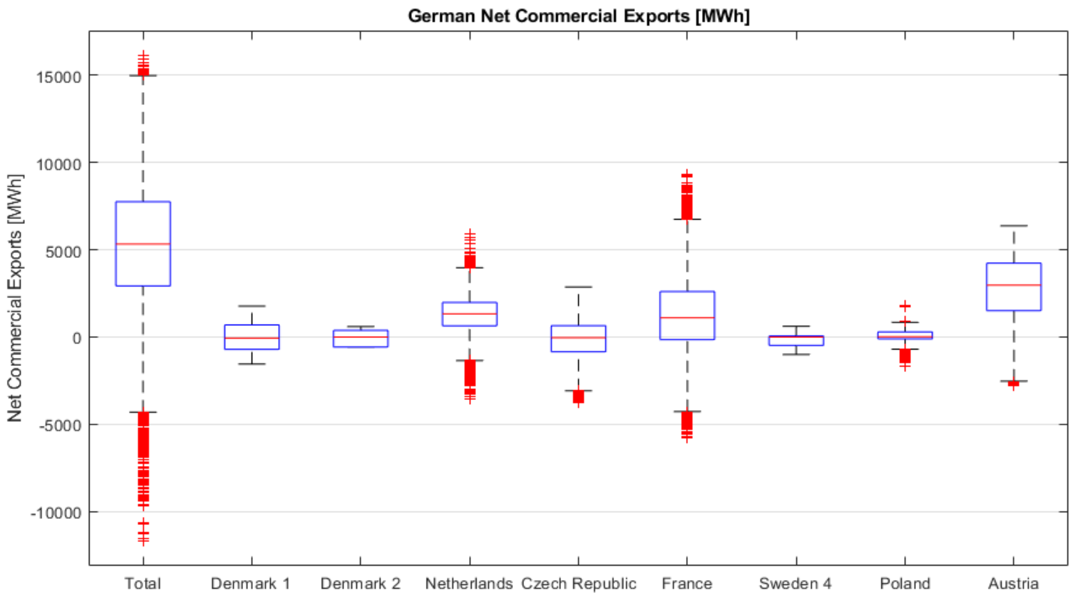

Figure 9 - German Scheduled Net Commercial Exports (2017-2019)

It can be observed in the figure above (first left box), that Germany is a country mainly exporter, which means that most of the time its prices are lower than the rest of neighboring countries, which is logical considering its high percentage of generation renewable (which, as explained above, lowers market prices).

On the other hand, the significant number of times in which Germany imports a high amount of energy (> 5000 MWh), reflects the occasions in which its generation is more expensive than the one of the compendium of its neighboring countries, mainly, as it can be intuited of the graph, due to imports from France, a country with an energy mix based mainly on nuclear (74.1%) and renewable (15%) technologies, both with low variable costs.

However, the other countries also sometimes export to Germany, which considering the average value of the exchanges (Germany as exporter), could mean situations in which either the price of Germany is higher than normal (high net load), or else the market price of other countries is lower than usual (low net load).

This last situation is especially relevant in the prediction of negative prices in the German market, since those countries whose market price reaches negative values (mainly those with a high share of RES generation), could end up inducing negative prices also in the German market (displacement of the supply curve). This issue will be addressed in greater detail in the subsection *3.5.1. Net load of interconnected countries*.

3.5. Information and Data Availability

The set of factors previously analyzed, together with certain market behaviors and time-based parameters, which will be detailed in this section, explain almost unequivocally (except for exceptional events) the occurrence of negative prices in the German electricity market.

However, although the historic value of these factors is available data, not all of them have forecasts available for the next day. So, of wanting to use them as explanatory variables or predictors of the model to develop, it is necessary to estimate them at least for the next day.

It should be clarified in advance, that the data used for the development of the model, also known as the training data set, will always be the set of real measurements/historical data of the factors considered. On the other hand, once the model is developed, its use to predict the occurrence of negative prices will be based on the predicted values of the variable inputs used in the model.

Therefore, it is important to have accurate forecasts of these variables for the periods to be predicted by the model. Luckily, for most European countries, the forecast of the variables considered most significant[2] in the occurrence of negative prices - which are the level of demand and wind and photovoltaic generation (in order to obtain the net load) - is available online, both on the ENTSOe transparency website, and through private providers.

However, the other variables considered significant after the previous analysis, that is, the minimum conventional generation level and the value of exports / imports of the interconnected countries, are not available in the future, or at least publicly. This is because both are actually the result of the trading in the market, so obtaining its prediction, apart from being a highly complex challenge (due to the number of variables that determine its value), is not considered relevant as factors of transparency of the European market, since they are not included as such in *Regulation (EU) No 5 43/2013 of 14 June 2013 on submission and publication of data in electricity markets.*

However, due to the categorical nature of the variable that is intended to predict (positive / negative market price), and the properties of the chosen model, which does not use regression methods or time series, but the ensembled classificatory relationship of the predictors with the response variable, no explanatory variables are truly required whose relationship with the result could be directly modelled in a continuous manner. Therefore, variables significantly related to the previous ones are likewise considered relevant for the model, being their predictive capacity assessed and determined intrinsically and finally by the model.

Thus, the hourly minimum conventional generation level, with a view to predicting negative prices, can be replaced by two estimated variables, as justified and detailed in section 3.6., Which are the hourly nuclear generation level, and the average daily level of minimum lignite generation, since both reflect 75% of the behavior of the inflexible conventional generation.

On the other hand, and as will be detailed in the following subsection, the export / import level of the countries interconnected with Germany is strongly linked to the net load of these, with respect

[2] As it can be checked in the subsection *5.2.1. Significance of the Predictors*

to Germany's one, a relationship that intrinsically generates the model developed, in case of being significant for the prediction of the negative price of Germany.

In addition, and as previously mentioned, there are additional variables related to the behavior of market participants, mainly based on temporary factors and price evolution, which can be considered relevant as explanatory variables of the model.

On this regard, temporary variables such as time of day, day of the week, season and holidays are included, which directly influence the thermal plants short-term and medium-term generation planning (e.g., O & M periods or weekly unit-commitment), so they can be of significance for the model.

Likewise, the clustering[3] of the German hourly demand profile has been developed, based on the historical average profile (01/2017-05/2019), in order to classify each observation as belonging to one of the 3 daily periods considered: valley, intermediate and peak.

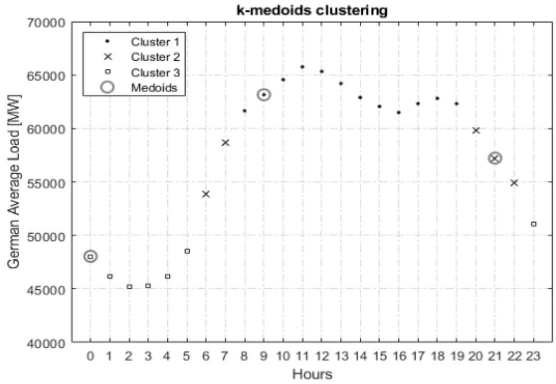

Figure 10 - Clustering of Demand Profile (Peak, Intermediate, Valley

On the other hand, from the analysis of the German power exchange during the occurrence of prolonged negative prices, and as can be seen in Figure 11, it is usual for the initial and final hours of these negative periods to have net load values (main predictor) significantly higher than the average resulting from the set of hours with negative prices.

Therefore, the following variables are included in the model: the net load value of the hour before and after the target time, as well as the average value of the preceding 2 and 4 hours. In parallel, in order to classify this target time as initial or final of a continuous period of negative hours, the number of subsequent / previous hours of prices in descent or rise, respectively, is entered as a variable, given the V shape of the profile of net load during prolonged periods of negative price.

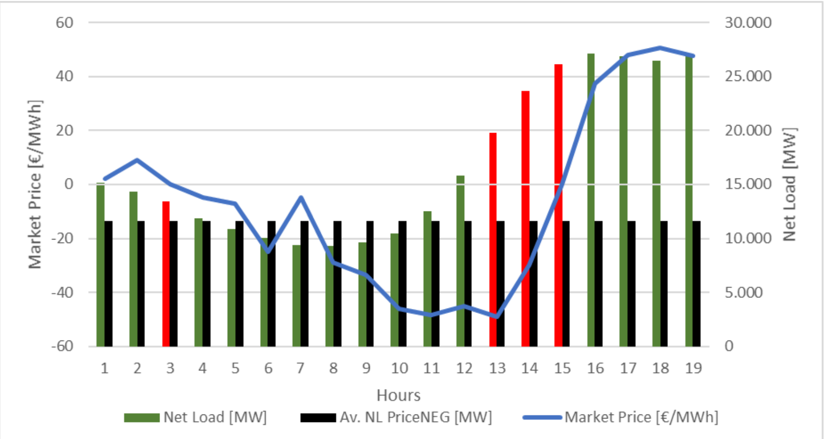

Figure 11 - Ramping effect on Negative Prices

[3] The clustering technique used is: k-medoids clustering

3.5.1. Net load of interconnected countries

As mentioned above, the level of export / import of the countries interconnected with Germany is strongly linked to the net load of these, with respect to Germany, due to the intrinsic relationship of these variables with the respective local prices. Likewise, the significance of the relationship between this German net load and the rest of the countries is directly evaluated by the developed model, discarding any relation with a low level of predictive importance.

However, due to the fact that the greater the number of explanatory variables, the efficiency of the model decreases, a preliminary theoretical analysis is then carried out, in order to select or discard those countries whose level of export / import is not significant at the time of predicting the occurrence of negative prices in Germany.

For this, starting from the principle or approximation that the conventional energy mix of each country is adapted to its maximum level of demand, and given that the variable that is intended to be used is the net load, whose variation is product of the level of demand and renewable generation , then the shares of installed RES capacity in each country are studied, along with their level of electrical export to Germany.

Thus, it is understood that the higher the RES share, not only the net load will reach lower levels, but it will also increase its hourly fluctuation, thus increasing the volatility of its prices with respect to those of Germany (key factor in imports during periods of negative price in Germany).

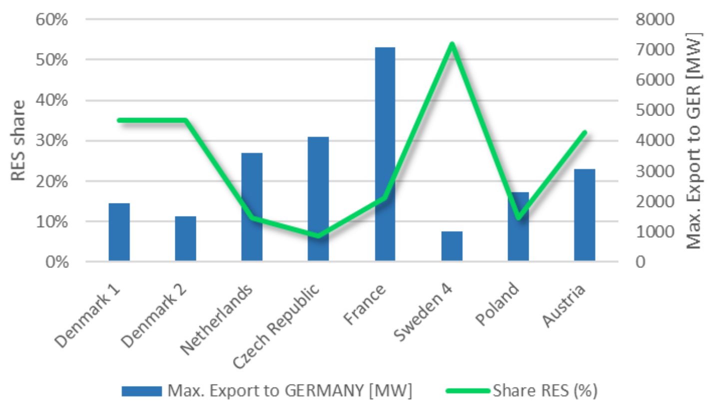

Figure 12 - EU interconnections and RES shares

From the analysis of the upper graph, at least two countries can be discarded for the classification model. In the first place, Sweden, due to its low registered maximum level of export to Germany, which implies an insignificant impact in the determination of the market price during periods of low net charge.

Secondly, Czech Republic can also be ruled out, because due to its low renewable share, the chances of low net load in this country do not reach levels where the typical marginal thermal generation does not clear in the market, so the times it exports energy to Germany, it is due to situations in which Germany has a market price above normal (high net load). Therefore, Czech Republic can be excluded, or rather its net load, from being an influential factor in the occurrence of negative prices.

3.6. Estimation of Nuclear and Lignite Generation

As previously mentioned, by far the largest share of inflexible thermal generation, around 75% of this one, stems from nuclear and lignite plants. On the other hand, the previously detailed "must-run" capacities, as its name implies, can be considered steady "around the clock", so they cannot be treated as predictor variables of the market price. Therefore, the estimation of both nuclear and lignite generations (focused on scenarios of low net load value), can be consider as a reasonable proxy variable of the minimum conventional generation level for every predicted period.

3.6.1. Estimation of Nuclear generation

Although the enacted planning for the phase-out of the German nuclear generation is close to completion, the still 7 active plants, aggregating more than 9 GW of inflexible generation, still show some impact in the occurrence of negative market prices.

As shown in the following figure, the German nuclear generation has some flexibility when the net load level falls below 22.4 GW. As it is also represented, this generation can be clustered according to its scheduled availability capacity [EEX] for periods of net load greater than said response margin. For the remaining set of hours, their inclusion in each cluster has been determined in addition to their scheduled availability capacity, by a criterion of ramp constraints between consecutive hours, by which, if a load variation exceeding 450 MW/h of descent or rise, that observation is considered belonging to the lower or upper cluster, respectively.

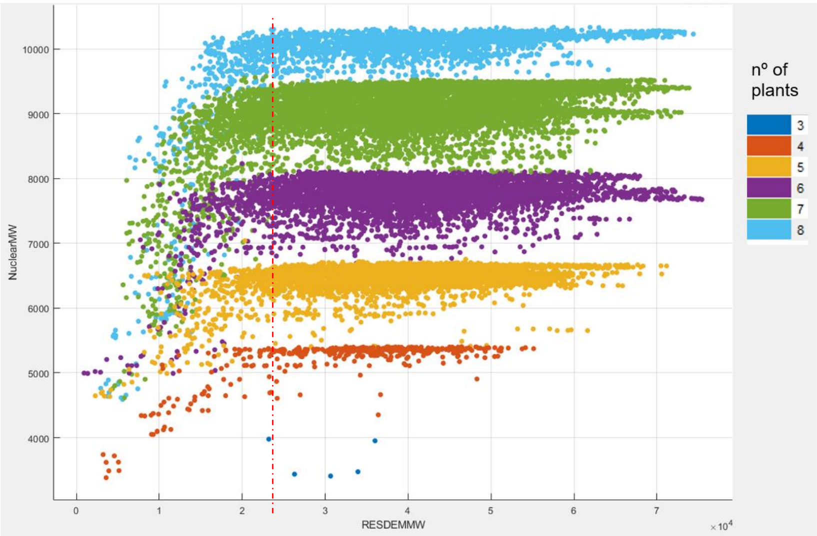

Figure 13 - Clustering of Nuclear Generation (Dispersion Chart Nuclear- NL)

As can be seen, the previous clustering is equivalent to the number of nuclear plants that were operational for each period. Therefore, if the hourly generation level registered for the nuclear generation set [ENTSOE] is divided among the number of active plants for that period (cluster), the following distribution of observations results (Net load, Av. Nuclear generation per plant):

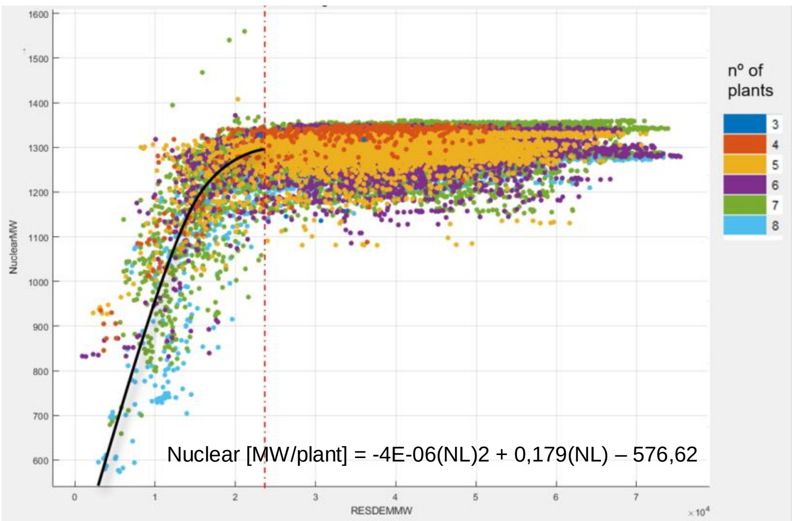

Figure 14 - Quadratic regression of Nuclear Gen and Net Load

As shown directly on the graph, a quadratic regression was performed for the net load range in which the flexible behavior of nuclear generation is observed, in order to obtain the relationship between both variables. Specifically, the resulting quadratic formula approximates the nuclear generation value per plant, based on the forecasted net load (threshold 0-22.4 GW). Thus, multiplying the resulting value by the cluster (nº of running plants) corresponding to the nuclear schedule availability capacity for that period, the level of nuclear generation can be estimated for any range of forecasted net load (for NL > 22.4GW → Nuclear production = sched. availability capacity).

3.6.2. Estimation of minimum Lignite generation level

The minimum generation of lignite plants is influenced, not only by the available capacity (significant variations due to the decommissioning of these plants), but also by the continued duration of low prices (<15 €/MWh) or negative prices in the wholesale market. Thus, when the prediction of the cost associated with these prices exceeds the Short-term total costs[4] of each of these plants, or in other words, their cost of startup and running, the minimum thermal generation is reduced.

On the other hand, the main cause of an abnormally continuous duration of low or negative prices is a low average value of the net load, as can be seen later.

Thus, for the estimation of the minimum generation level of lignite plants during periods of low net load (<25 GW), the relationship between this net load and the minimum lignite generation level has been studied. Specifically, the purpose is to estimate the generation of lignite that will be offered at a negative price, based on the expected net load levels for the Day-Ahead wholesale market.

Therefore, historical data (01/2017 to 05/2019) of the level of lignite generation during periods of negative price have been analyzed, and contrasted with the net load levels for those periods.

The most accurate estimate is to consider the average of both levels during each continuous historical negative price period, and to multiply weightedly the variation of the average net load between last period and the next estimate, to the level of lignite generation of the period prior to the period to estimate.

In other words, the last historical period in which negative prices occurred, together with the respective average levels of net charge and lignite generation, would be maintained as a reference period, for a period of low average value of the net load, estimate the minimum thermal generation during that period.

The formulation of the method is as follows:

$$Lign.Gen\ (MW)|_{\sum_j^H NL<20GW} = \frac{1}{P}\sum_i^P Lign.Gen\ (i) \cdot \frac{\frac{1}{P}\sum_i^P Net\ Load\ (i) - \frac{1}{H}\sum_j^H Net\ Load\ (j)}{K}$$

Being:

$Lign.Gen\ (MW)|_{\sum_j^H NL<20GW}$: *Estimation min. lignite generation for periods of average net load value lower than 20 GW.*

H: nº of hours of the estimated period.
P: nº of hours of the last period of negative prices.
j and i: hour index of the hours of each period.
K: constant of proportionality between variations of Net Load and Lignite Generation.

[4] Short-term fixed + variable costs.

The value of K has been obtained through the minimization function of the historic error of estimation, as follows:

$$Min \sum \left(\frac{1}{P} \sum_{i}^{P} Lign.Gen\ (i) - \frac{1}{P^*} \sum_{i^*}^{P^*} Lign.Gen\ (i^*) \cdot \frac{\frac{1}{P^*} \sum_{i^*}^{P^*} Lign.Gen\ (i^*) - \frac{1}{P} \sum_{i}^{P} Net\ Load\ (i)}{K} \right)$$

Being:

P^* and i^*: nº of hours and hour indexes of the previous period of negative prices.

As can be seen in the following figure, the described method estimates most of the time an average value of minimum level of lignite generation, during negative prices, with little deviation from the real average value. This, as mentioned above, is based on the ratio of the average net load value with respect to the costs and duration of this period of continued negative prices.

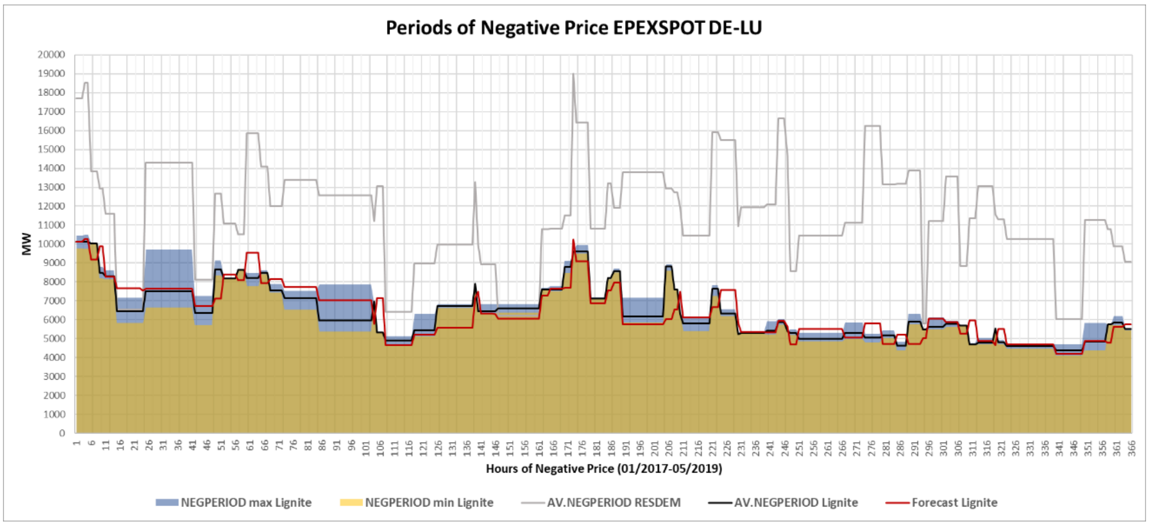

Figure 15 - Estimation of Minimum Lignite Generation Level

Since the way to estimate this value is based on the last period of negative price recorded, and the respective values of net charge and lignite generation, in light of the decommissioning of a lignite plant, its effect will be recorded after the next negative price occurrence.

4. PROPOSED METHODOLOGY

4.1. Introduction

As introduced in the subsection *2.2. Statistical Classification*, although the model whose use has been most widespread in problems of classification with categorical variables is the classification tree, its use for the prediction of negative prices does not result in high precision.

This is due to the complex interaction of the numerous set of explanatory variables in the occurrence of these events. Thus, the ordering of the hierarchical predictor diagram that characterizes the simple classification trees, excludes multiple possibilities of negative prices occurring due to a simultaneity of factors not collectively collected by a branch of the classification tree.

This problem is solved with the ensemble methods of classification trees, which belong to the set of machine learning methods or CI techniques. Since its prediction is the result of the weighted average of all the predictions of its set of trees (also called "weak learners"), its structure is much more flexible or adaptive to any complex simultaneity of factors not collected jointly by the branch of a tree of classification.

Therefore, once the adequacy of the ensemble methods to the problem has been determined, the following steps are to analyze the characteristics of the data set, to tune relevant model parameters and features in order to adapt this one to the target quality measurements, and to perform an optimization of the remaining set of hyperparameters of the ensemble method.

4.2. Data Pre-processing

An important preliminary step to the development of any prediction model is to analyze the data in order to know the distribution of the sample, the existence of missing values, the number of observations available, etc.

In this case, the main factor to take into account will be the distribution of the sample. Since the occurrence of negative market prices is an unusual event, the data set will present a strong imbalance of classes (regarding positive vs. negative prices). In these cases, binary classification problems often lead to unsatisfactory results regarding the prediction of new observations, especially for the small class. In order to lay more weight on the cases of this class, it exists several correction methods which tackle the imbalanced classification problem.

Generally, these methods can be broken into cost-based and sampling-based approaches. The first ones will be assessed in detail in the following subsection (since they are related with the hyperparameters tuning), while the latest ones are related to this process of data pre-processing.

The sampling-based approaches are divided further into undersampling methods (elimination of randomly chosen cases of the majority class) and oversampling methods (generation of additional cases of the minority class by copying or artificial observations), or even a mixture of both.

In this case, thanks to the initial theoretical analysis of the data set, it has been ascertained from the premise of significance of the net load, that there is an absence of negative prices data for values higher than 22.4 GW of this net load, in turn checking an annual trend of decrease of this threshold value.

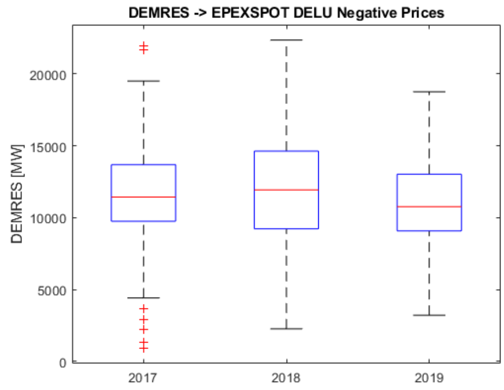

Figure 16 - Net load level trend over the last years

Therefore, previous sampling-based approaches have not been required. Simply restricting the data set to those observations whose net load is less than this threshold (22.4 GW), results in a distribution of 20-80% of the classes, without losing any observation of negative price, nor versatility of the sample.

Despite not being a balanced proportion, distribution values better than 10-90% are considered to be treated by the model through cost-based approaches.

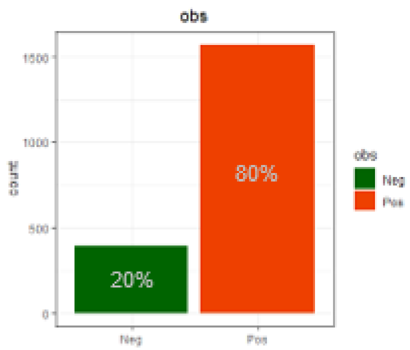

Figure 17 - Distribution of classes in the Data set

Regarding the size of the sample, one of the basic principles enunciated in the literature of machine learning models is "it depends". This answer, although it may seem imprecise, defines a basic precept: the amount of data required depends on many factors, mainly based on the complexity of the problem (nominally the unknown underlying function that best relates the input variables to the output one) and the complexity of the learning algorithm (nominally the algorithm used to inductively learn the unknown underlying mapping function from specific examples). Being the first factor unknown, for the second one can be used the reason by analogy. For example, for "average" modeling problems, ideally are needed tens or hundreds of thousands of observations, however, for classification problems around just one hundred, and conversely, for deep-learning approaches, such as neuronal networks, or non-linear problems, millions or tens-of-millions. In general, it is usually considered that for machine learning methods are required thousands of observations, no fewer than hundreds, and as much as possible.

With respect to the selection of the training data set and the testing data set, the scope of the model must be taken into account. For this case, it is about predicting prices for the next day, and therefore, in practice the model is intended to be reprocessed on a daily basis, thus adding the observations recorded the day before in the training data set. Therefore, a distribution greater than 80-20% of the data set in training and testing, respectively, would subtract actual quality from a model whose final use will have more than 99% of the data in the training set.

The final selection of these percentages has been made based on the partition factor of the cross-validation process used internally by the model, which in advance, will be of 10 partitions. Then, equivalently, 10% of the data set will be reserved for use as testing data, separated randomly from the sample, and verifying that the original distribution of the output categories is respected.

4.3. Tuning of Model Hyperparameters and Classification Options

In this section, the multiple parameterization possibilities of the model will be analyzed and determined. First, those related to the mentioned cost-based methods to tackle the imbalanced classification problem. Afterward, what classification options to use for the correct adaptation of the model to the case study. Finally, the definition of those hyperparameters to be used for the optimization of the model, and their considered optimal ranges.

4.3.1. Imbalanced classification problem

Returning to the problem of the imbalance of categories in the data set, as mentioned above, there are some cost-based methods to correct the imbalance classification problem, which can be used independently or jointly:

- To set empirical prior probabilities, thus the class probabilities are determined from class frequencies in Y (vector of observed classes).
- To assign observation weights: additional factor to increase the prior probability of each observation belonging to the minority class, or decrease it to the majority one. It also enable the assignment of different weights to each observation, but it is usefulness will be introduced later.
- To specify the cost matrix of misclassification classes, causing the same effect than previous options. In fact, if the values for both either weights or costs and prior are setting, the first ones are renormalized to add up to the value of the prior probability in the respective class.

In conclusion, all these techniques are ways to penalize classification, imposing an additional cost on the model for making classification mistakes on the minority class during training.

Nonetheless, these penalization methods are only really useful when there is not chance to change the model performance metric. Otherwise, it is proved better for optimization and less complex (though less tunable) to select as performance metric one of the following: Kappa, Sensitivity, Precision, ROC or F-score, being Sensitivity and the last one, the most suited metrics for the given classification problem (considering negative prices as the "positive class").

4.3.2. Classification, Ensemble and Cross-validation options

Depending on the characteristics of the predictor variables, the level of complexity desired for the model, its precision in the classification of future observations or the requirements of subsequent analysis of the model output, there are multiple parameters that can be adjusted for the correct modeling of the classifier, in function of the above concerns. The most important for the classification of negative prices are:

- **Algorithm used to select the best split predictor**: since standard CART tends to select split predictors containing many distinct values (e.g., continuous variables), over those containing few distinct values (e.g., categorical variables), it is advisable to use the interaction test algorithm instead, which is more sensible to heterogeneous data sets, and also detecting irrelevant predictors. In addition, this algorithm allows the later analysis of predictor importance, information considered relevant for the understanding of the factors that cause the negative market prices.

- **Surrogate decision splits**: although the main use of finding surrogate splits at the branch nodes is related to data sets with missing values, this setting also allows the measurement of predictive association between predictors, which is also considered useful for the posterior analysis of the predictors.

- **Pruning the trees**: which decreases the complexity level of the algorithm, in order to avoid the overfitting problem in the training data. There are two main techniques of pruning, based on the minimization of the classification error rate, or based in the impurity of the terminal node. However, by optimizing the hyperparameters and the use of cross-validation techniques, both explained later, the model automatically determines the optimal level of complexity of the classification trees.

The rest of the parameters related to the complexity of the model, such as max. tree depth, merging of leaves and min. number of branch node observations, are not relevant in the methodology developed, since they will be indirectly optimized based on the hyperparameters considered in the following subsection.

- **Number of folds to use in the cross-validation**: firstly, it should be mentioned that for the correct optimization of the model, which will be explained in the following subsection, it is necessary to use cross-validation in order that the model can maximize the estimated accuracy for the testing data.

  This technique divides the training data into the selected number of partitions, separating one of them from the training data and testing against it the level of precision of the classifier generated in each iteration. This process is repeated for all the partitions, selecting the splitting criterion that minimizes the average error for the isolated partitions of the set of iterations. At a higher level, it is also used in the optimization of model hyperparameters.

  The level of overfitting of the model resulting from the optimization will depend to a large extent on the selected number of partitions. Values between 5 and 10 partitions are recommended, with greater overfitting to a greater number of them.

4.3.3. Hyperparameters used in optimization

There are two categories of hyperparameters used in the optimization of the model, those corresponding to the ensemble method, and those corresponding to the "weak learners" (classification trees). All of them have a delimitable range of values, by means of which the optimizing algorithm will iterate by selecting values within those ranges. However, a fixed value can be blocked for any of these hyperparameters, forcing the optimizer to always use that value.

The group of hyperparameters corresponding to the ensemble method consists of:

- **Ensemble-aggregation method**: The main ensemble methods based on classification trees as "weak learners" have been explained in subsection *2.2.1. Ensemble of Classification Trees*. However, within the boosting techniques could be included other interesting methods such as Gentle adaptive boosting or Robust boosting, to be considered by the optimizer if they are more accurate than the methods already described. In general, bagging methods are used to reduce variance, and boosting methods to reduce bias (what, as previously explained, results required for the studied classification problem of negative prices).

- **Number of ensemble learning cycles**: it must be taken into account, that the overfitting of ensemble methods increases with the number of learning cycles. It is not recommended to establish a maximum threshold greater than 500 cycles.

- **Learning rate for shrinkage**: weights the contribution of the last bach of observations vs all previous batches. Parameter intrinsically related to the previous one, because a small value of this one, requires a greater number of learning cycles, being able to increase the overfitting of the model. It is recommended not to delimit its range if used in optimization.

Secondly, the group of hyperparameters corresponding to classification trees consists of:

- **Maximal number of decision splits**: the higher number of decision splits, the greater complexity of the model, fostering the overfitting. Therefore, values lower than 30 are recommended, although the optimizer will choose that value that improves the estimated accuracy of testing data. Very small values, around 5, also result in strong learners if the nº of learning cycles is high.
- **Minimum number of leaf node observations**: the lower number of min. leaf node observations, the higher overfitting of the model. This value depends on the size of the data set, however, in any case is recommended a value lower than 5.
- **Number of predictors to select at random for each split**: unless the size of the training data is too high to acceptable computing times, it is recommended to use all the available predictors.
- **Split criterion**: It is recommended to allow the optimizer to choose between Gini's diversity index and the deviance criterion (also known as cross entropy). The latest is often used for maximum deviance reduction.

4.4. Optimization of the Model

For this aim, as previously introduced, it is used the Bayesian optimization of the aforementioned tunable hyperparameters of the ensemble method and the weak learners (in their bounded domain), to control its training by using as objective function the estimated misclassification error of the model (obtained through cross-validation).

The acquisition function (to choose next evaluation point) is the so-called Expected Improvement, which evaluates the expected amount of improvement in the objective function, ignoring values that cause an increase in the objective. In other words, define:

- x_{best} as the location of the lowest posterior mean.
- $\mu_Q(x_{\text{best}})$ as the lowest value of the posterior mean.

Then resulting the expected improvement as $EI(x,Q)=E_Q[\max(0,\mu_Q(x_{\text{best}})-f(x))]$.

Internally, the Bayesian optimization maximizes this acquisition function by estimating the smallest feasible mean of the posterior distribution $[\mu_Q(x_{\text{best}})]$, sampling several thousand points within the variable bounds, and taking several of the best (low mean value) feasible points, finally improving them using local search, to find the perceived best feasible point.

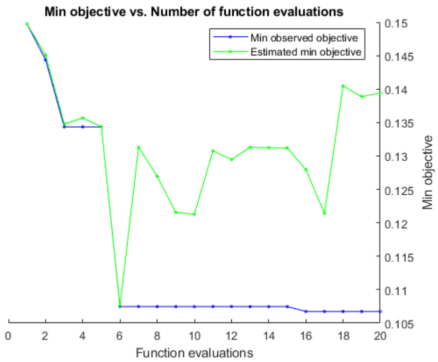

Figure 18 - Bayesian Optimization Process (Minimization of Misclassification error rate)

5. RESULTS AND DISCUSSION

5.1. Methodology and Output Results

In this section, an evaluation of the developed methodology will be carried out, through the analysis of the results coming from the model finally designed. The quality of the model output will be analyzed, as well as the parameters resulting from the optimization process of this one.

5.1.1. Forecast of Negative Prices

The main objective of this thesis was to develop a model capable of predicting the occurrence of negative prices in the German Spot Power Market, therefore, in order to analyze the level of precision or error of that model, and prior to the presentation of results, are detailed in the following subsection the main error measurements in classification problems.

5.1.1.1. Error measurement in classification problems

There are a variety of ways to measure how a model is performing, most of them based on the information presented in the so-called Confusion Matrix. These matrixes show the four type of results in classification problems, which are described below.

True Positive	False Negative Type II	Actual Positive
False Positive Type I	True Negative	Actual Negative
Predicted Positive	Predicted Negative	

Table 2 - Type of results in Confusion Matrix

- True Positive (TP): the number of observations correctly assigned to the positive class.
- False Positive (FP), also known as a Type I error: the number of observations assigned by the model to the positive class, which in reality belong to the negative class.
- False Negative (FN), also known as a Type II error: the number of observations assigned by the model to the negative class, which in reality belong to the positive class.
- True Negative (TN): the number of observations correctly assigned to the negative class.

Based on these four states, there are multiple derived quality indicators. The main relevant ones for classification methods are these:

Precision or Positive Predictive Value: ratio of true positives over all predicted positives. A value near to 1 means that the model returned substantially more relevant results than irrelevant ones, but it does not mean it may get all the right results that really exists.

$$PPV = TP/(TP+FP)$$

Sensitivity or True Positive Rate: reflects the classifier's ability to detect members of the positive class (pathological state). High sensitivity means that the model returned most of the relevant results. A good measurement when cost of missing a positive value is high.

$$TPR = TP / (TP+FN)$$

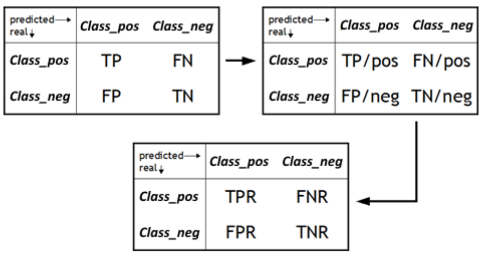

Figure 19 - Main derived quality rates

Specificity or True Negative Rate: measures the proportion of negatives that are correctly identified as such. A good measurement when costs of missing a negative value is high.

TNR = TN/(TN+FP)

Accuracy: ratio of correctly prediction observation to the total observations. It is usually used as the evaluation metric by the models, although it implies the adjustment of the model parameters to adapt the cost minimization of the positive or negative misclassificated values.

ACC = (TP+TN)/(TP+FP+FN+TN)

PR-AUC: measure of the area under the curve produced by graphing the ratio between Precision and the Recall (Sensitivity) at various threshold settings. Values ranging from 1–0.8 are considered great to good, 0.8-0.6 fair to poor, and below that is not better than random chance.

Although the following confusion matrices directly present the proportion of each type of result with respect to the set of positive and negative values, predicted and real, the most important metrics for our model can be considered: Sensitivity and Accuracy.

Since the error of predicting a negative period as positive can be considered to have a higher misclassification cost, since it could fragment a period of 6 or more negative hours, canceling the performance prediction of the "6h rule" concerned, the negative results will be considered, for the model, like the positive category (despite the risk of lexical confusion).

Thus, the sensitivity metric means the ratio of true predicted negatives prices over all the actual negative prices. And its complement, the proportion of true negative prices wrongly predicted.

Therefore, the expected model should accomplish a high sensitivity rate. On the other hand, a high accuracy measure is desired too, since otherwise, it would be easy to achieve a high sensitivity by considering many of the actual positive prices as negatives (although that misclassification cost was considered lower, also exists and it is significant).

5.1.1.2. Confusion matrixes of results

The Confusion Matrixes for the training data set (left) and test data set (right) of the developed model are presented below, in order to assess the performance of this one, by analyzing both, and comparing them with the confusion matrixes of the simplest optimized classification tree model (only one splitting) and the most optimized classification tree developed.

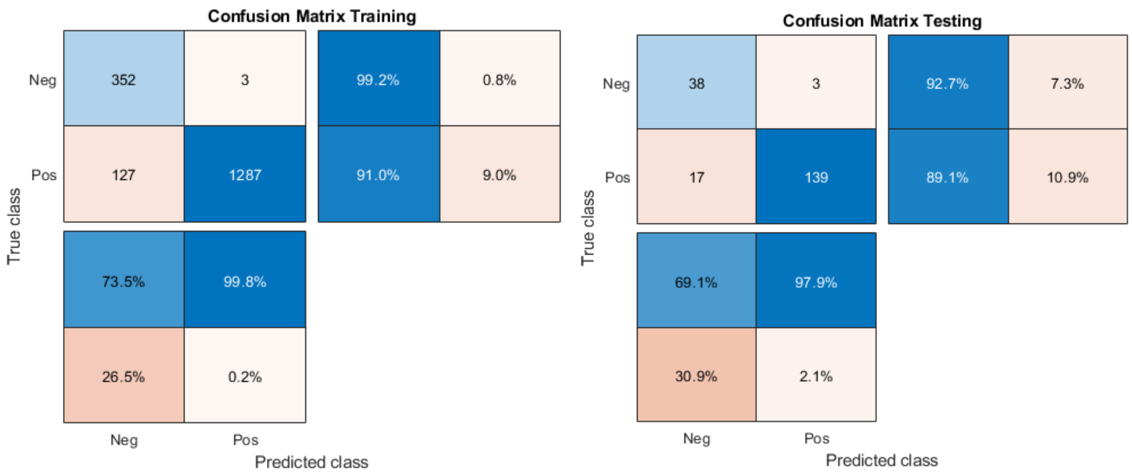

Figure 20 - Confusion Matrix of AdaBoost Model

Observing the Sensitivity rate (0.992) obtained for the training data, it seems clear that a high overfitting has been produced by the model, nonetheless, the resulted rate for the testing data set (0.927) is the best one achieved from all the model configurations studied. On the other hand, the achieved Specificity is lower than the previous ratio for both data sets (TR: 0.91 and TS: 0.89), although very similar among them. This fact is directly derived from the intended parametrization of the model, in order to artificially incentivize the maximization of the Sensitivity metric.

Since the evaluation metric of the developed boosting model was the accuracy, not only has the prior probabilities been adjusted for each class (according to the distribution of the observed classes), but also the observations have been weighted depending on the class they belong to, as well as on the belonging to periods of 6 consecutive hours of negative prices, increasing the prediction quality of these events.

In addition, the accuracy of both training and test data sets is respectively:

A good praxis in imbalanced classification problems whose majority class is the negative one, is to compare the Miss rate [or False Negative Rate = FN/(TP+FN)] of the model, with the assumption of considering all observations as negative class (in this case, positive prices). Thus, evaluating if this ratio has been improved against the simple case of considering all observations belonging to the majority class.

Miss rate of the model: FNR = 6/(1426+6) = 0,004
Miss rate of considering all majority class: FNR = 396/(1570+396) = 0,201

Therefore, in this respect, the quality of the model is greater than that of the base case, which is logical considering that the maximization of the TP has been incentivized, and therefore minimization of the FN.

Additionally, the performance or quality of the selected model (Adaptive Boosting) is analyzed against simple classification trees, less complex models and with greater interpretability. For this comparison, two classification trees have been developed in parallel, both determining their hyperparameters under the same Bayesian optimization methodology as in the previous case, limiting one of them to a single splitting (classification based on the most important predictor). .

Thus, the resulting confusion matrixes for both classification trees are:

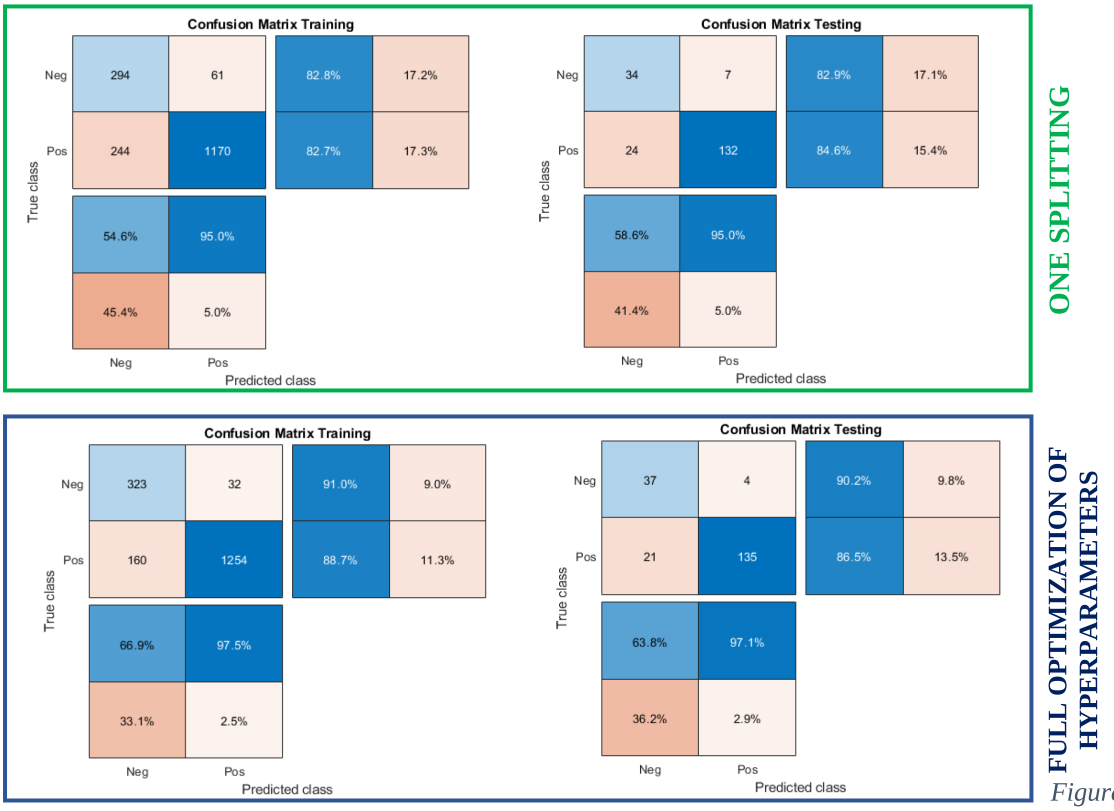

Figure 21 - Confusion Matrixes of Classification Trees

Therefore, comparing for the testing dataset the Sensitivity and Accuracy metrics of these models with those of the finally developed model of Adaptative Boosting:

	Sensitivity	**Accuracy**
One Splitting (CT)	82,9 %	84,3 %
Full Optimization (CT)	90,2 %	87,3 %
AdaBoostM1 (Ensemble of CTs)	92,7 %	89,8 %

Table 3 - Quality measurements of the prediction models

It can be verified that, the result of both classification trees, also shows a quite high level of Sentivity and Accuracy. However, although the full optimized classification tree achieves better predictive quality indicators than the simplest case, it is the ensemble method which shows the best prediction ratios, both for the occurrence of negative prices and for the success of both classes (positive and negative prices) together.

However, the aforementioned factor of overfitting in the training data that demonstrates this model of adaptative boosting, could mean the existence of a room for improvement regarding the methodology of hyperparameters optimization used, which will be detailed in the next subsection.

In this regard, the main parameter considered for which an additional optimization should be developed, linked to the one carried out using the proposed methodology, would be the factor or number of partitions of the cross-validation method used, thus increasing the balance of the indexes of precision and sensitivity of the model for training and test data sets.

Finally, it must be mentioned that the predicted class (price positive/negative) by the model for every observation, corresponds to the minimum expected misclassification cost among all classes. This is the product of multiplying the posterior probability of a determined class for the observation, times the true misclassification cost of classifying the observation as other class when its true class is the determined one.

Nonetheless, the model also provides the posterior probability (likelihood that a result comes from a particular class) of each observation for both possible classes. Thus, a market participant could always supervise the likelihood of each prediction, to check the quality or risk of this one.

5.1.2. Model and Hyperparameters

In accordance with the model optimization methodology and its hyperparameters, described in sections *4.3.3. Hyperparameters used in optimization* and *4.4. Optimization of the Model*, the values resulting from the optimization carried out to obtain the ensemble model are:

- **Ensemble-aggregation method:** AdaBoostM1 (Adaptative Boosting) [locked]
- **Number of ensemble learning cycles**: 17 [10, 40]
- **Learning rate for shrinkage:** 0.19057 [0.001, 1]
- **Maximal number of decision splits:** 25 [1, 30]
- **Minimum number of leaf node observations**: 6 [locked]
- **Number of predictors to select at random for each split**: all
- **Split criterion**: Deviance [Gini's diversity index, Deviance]

The decision to limit the ensemble method to an Adaptative Boosting model is previously justified in sections *2.2.1* and *4.3.3*, given its sensitivity to outliers, bias reduction and high correction capacity of misclassification errors without causing significant overfitting.

Following the rest of indications detailed in subsection *4.3. Tuning of Model Hyperparameters and Classification Options*, the following additional settings should be highlighted:

- It has been setting empirical prior probabilities to tackle the imbalance data set problem.

- In addition, weights has been assigned to observations according to their class and belonging to periods of "6h rule" application.
- The number of folds used in the cross-validation process is 10.
- Cost matrix has been defined considering double misclassification cost for negative prices, thus improving the Sensitivity metric over the Accuracy.
- Interaction test algorithm has been used to select the best split predictor (as advised).

5.2. Assessment of the Market Framework

Once the classification model has been developed and run, this section focuses on the analysis of the German power market. First, on the resulting explanation of the negative prices, and second, on the analysis of the bidding approaches of the RES generators, and the effect of introducing the prediction model developed.

Thus, the first thing to be addressed is the evaluation of the results related to the significance of the predictors (in terms of the occurrence of negative market prices), comparing these with the conclusions obtained from the initial theoretical analysis of the German electricity system.

Finally, as mentioned above, the economic efficiency of the model will be compared with the two main bidding approaches of the renewable generators, in order to verify its true performance.

5.2.1. Significance of the Predictors

From the realization of the assembled model of classification trees, as for the independent classification tree, the significance of each predictor can be obtained. These values are estimated by summing changes in the risk due to splits on every predictor and dividing the sum by the number of branch nodes.

In the case of the ensemble of classification trees, since the model is grown with surrogate splits, this sum is taken over all splits at each branch node including surrogate splits. Nonetheless, in the case of the independent classification tree, as it has been grown without surrogate splits, the sum is taken over best splits found at each branch node. Moreover, estimates of predictor importance do not depend on the order of predictors if you use surrogate splits, but do depend on the order if you do not use surrogate splits.

The predictor importance associated with every split is always computed as the difference between the risk for the parent node and the total risk for the two children.

Thus, the output values of predictor importance estimates for both models are presented below, (left for the AdaBoost model, and right for the Classification Tree Model).

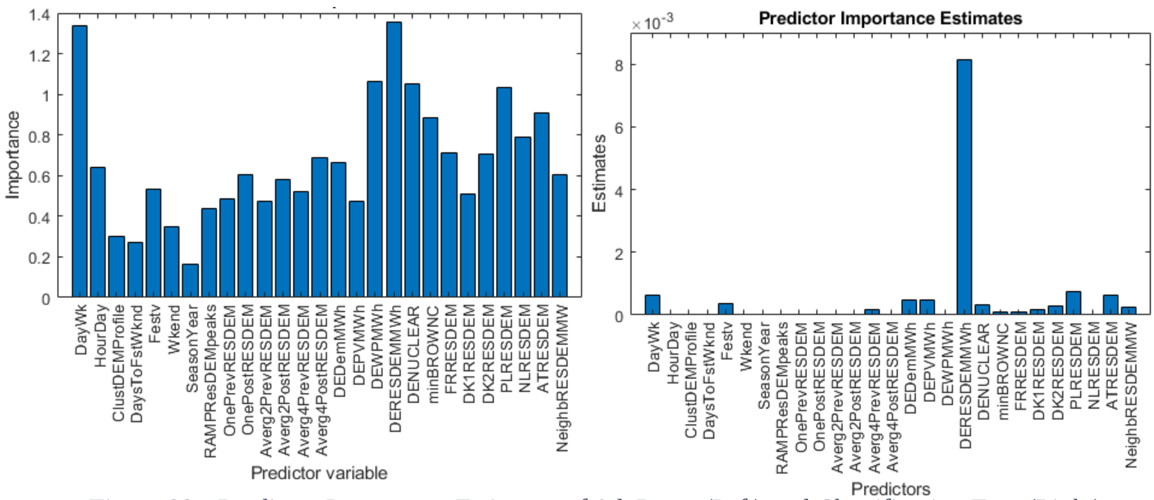

Figure 22 - Predictor Importance Estimates of AdaBoost (Left) and Classification Tree (Right)

As can clearly be seen from comparing both models, the growth of the AdaBoost model with surrogate splits, as explained above, by generating splits for all the predictors in each node, in addition to being a methodology that creates multiple trees using different predictors, the value of importance predictor results for all predictors, and in a more representative way, because this value does not depend on the order of predictors, just in the risk decreasing of splitting each one in every node.

On the other hand, the chart of predictor importance estimates of the Classification Tree, shows for the limited number of predictors used in that tree, the relative importance of each one, based on the risk reduction of splitting it, but considering also its order of node. That is why the predictor of net load (or residual demand) shows an order of importance much greater than the rest, which also throws an important conclusion: if only that predictor is used for a classification tree model, the accuracy of this one would not decrease significantly with respect to the previous case.

Now paying attention to the graph of the Adaptative Boosting model, which shows a more accurate approximation of the importance of each predictor, as discussed above, multiple conclusions can be highlighted.:

- The estimate made in section 3 is verified, about the major importance of the net load factor as predictor of negative prices, due to its high relation with the market clearing Price determination.
- Likewise, the value of the minimum thermal generation (nuclear + lignite generation), as well as that of the net loads of the interconnected countries, also show high importance in the prediction of negative prices, although it is verified with the results for the classification tree, that these variables always act as important predictors at subsequent levels (children nodes) of the net load level (parent node).
- Specifically, among the interconnected countries, for both models, the net load of Poland and Austria show greater significance, which would mean that their impact on the determination of negative prices in Germany is greater. In other words, the resulting level of import / export with these countries (by difference in their net loads) is decisive in the prediction of negative prices, depending on the German net load level.
- The greater importance of nuclear over lignite would be explained by the value represented by this nuclear, since it is the hourly generation, while lignite represents the minimum thermal generation level during periods of negative price. Therefore, nuclear has a value directly related to the hourly market price.
- Unexpectedly, both models consider the day of the week as a variable of vital importance for the prediction (first column on the left). This categorical variable, although its importance is logical, was part of a set of temporary variables (see Weekend, Time, Days to Weekend/ Holiday, Demand Curve Blocks, Seasons, etc.), so it is found that for models of classification, the day of the week is more important than any other time variable.
- From the set of input variables of the model relative to the average net load value of the hours before and after the target time, it is verified that the hours after the target time have greater importance in the determination of negative prices. Going back to the logic of these variables (explained in section *3.5. Information and Data Availability*), in occasions of price uncertainty, given the level of net load of that hour (lower levels of the tree), the average value of the net load for the next hours is always more significant than that of the previous hours.

Finally, it should also be mentioned that the analysis of the parallel classification tree (whose diagram is attached in Annex 8.2), given its lower algorithmic complexity, allows to easily interpret and detect which are the main predictors of positive and negative prices, and their values of classification. Although these factors are suitable for most of the cases, they do not include the explanation of the set of unusual circumstances.

Since, as previously mentioned, the ordering of the hierarchical predictor diagram, common to independent classification trees, excludes multiple possibilities of negative prices occurring due to a simultaneity of factors not jointly collected by a branch of the classification tree.

However, this problem is solved with the models of ensemble of classification trees, as in the case of AdaBoost, whose prediction is the result of the weighted average of predictions of multiple trees, adjusting the creation of each one, to the cases of error occurred in the previous tree.

5.2.2. Economic Performance

5.2.2.1. Introduction

In this subsection, it will be compared the economic return of the model with the two main bidding approaches of the RES generators, in addition to the resulting approaches to use the classification tree developed (attached in Annex 8.2.), and the more simplistic one of a single decision factor, whose development is described in section 5.1.

5.2.2.2. Bidding approaches

For the evaluation of the model economic efficiency, it must be determined before which bidding approaches are the most common among the RES generators so far. While it is true that each RES generator follows its own considerations to bid on the market, in general, and in the absence of an accurate prediction of the market price, they resemble the following two bidding approaches:

- Approach 1: Invariable price offer [€/MWh] = - (Price subsidy per MWh – VC)
- Approach 2: Invariable price offer [€/MWh] = VC

For this study, Variable Costs (VC) will be considered equals to 0. This consideration is usually taken also by many RES generators, which given the near zero VC of their generation, prefer to generate during hours with a price lower than this one, rather than controlling and decreasing the generation load of its units.

Thus, Approach 1 would result from those generators that face with the uncertainty of an event of six or more consecutive hours of negative prices, assuming the costs of their offer if that happened, and considering more beneficial with respect to Approach 2, the fact of being able to match short periods of negative prices in the DAM.

Conversely, Approach 2 would result from those generators that, faced with the uncertainty of happening six or more consecutive hours of negative prices, consider more beneficial to bid at their VC or at a price of 0€/MWh, thus avoiding the possibility of having to pay for its generation offered, when the "6h rule" applies.

Nonetheless, the above considerations are purely speculative, and these or other bidding approaches can be given for various reasons of different nature.

On the other hand, and based on the same economic precepts explained above, the following bidding approaches are introduced as a result of having an accurate forecast of the positive / negative market price. Thus, the price of the offer would coincide with that of Approach 1 for all those periods in which the "6h rule" did not apply, and otherwise with Approach 2, thus maximizing the possibility of matching their generation offered in the Day-Ahead Market.

In order to compare the economic performance of the developed model (based on adaptive boosting), we also introduce the results of using the developed classification tree, and the simplistic one of a single decision factor, thus remaining:

- Approach 3: based on predictions of Classification Tree (1 Splitting)
- **Approach 4: based on predictions of Adaptative Boosting (Developed model)**
- Approach 5: based on predictions of Classification Tree (Full optimized)

In addition, the different possibilities of subsequent adjustment of the study plant generation in intraday markets (IDMs) have also been considered, according to whether or not it has been matching in the DAM, and according to whether or not it applies the "6h rule". These possibilities are analyzed in detail in subsection *6.3. Efficacy of the "6h Rule" on the German Electricity Market*, which approximates the feasible matching percentages of the offered generation in the IDMs, according to the set of previously detailed possible situations.

5.2.2.3. Context

In this economic performance study, the economic opportunity cost of a German wind farm of 500 MW will be simulated, with respect to the different bidding approaches described, against the most efficient operation according to the purposes of the German regulation EEG 2017 (taking special consideration of Rule 51, described in the initial section 1.1.).

The year 2018 has been chosen as the study period. The DAM prices correspond to those of EPEXSPOT DE-AT-LU until September 30 (closing of this one) and those of EPEXSPOT DE-LU onwards. The hourly generation volume, as well as the prices of the IDM considered, have been provided in a confidential manner by a German wind generator, for the same period of study.

5.2.2.4. Results

The following table shows the results of the economic opportunity costs of the wind farm, for each of the bidding approaches described, with respect to the most economically efficient bidding approach possible (higher incomes for matching energy in the DAM and IDMs). It is also included the highest possible economic opportunity cost in the last row, whose bidding approach would be systematically opposite to the optimal for each period.

Bidding Approaches	**OPORTUNITY COST [€/year]**
AP.1 [*Invariable price offer [€/MWh] = - (Price subsidy per MWh – VC)*]	**-465.721,25**
AP.2 [*Invariable price offer [€/MWh] = VC*]	**-385.201,80**
AP.3 [*Based on predictions of Classification Tree (1 Splitting)*]	**-301.999,60**
AP.4 [*Based on predictions of Adaptative Boosting (Developed model)*]	**-197.713,82**
AP.5 [*Based on predictions of Classification Tree (Full optimized)*]	**-243.659,88**
Higher Opportunity Cost [*Opposite bidding approach to optimal*]	**-850.923,05**

Table 4 - Opportunity Cost according Bidding Approaches

As it can be checked, the bidding approach based on the predictions resulting from the developed model shows the lowest economic opportunity costs of all, being less than half that resulting from Approach 1, and more than a third less than that resulting from Approach 2. On the other hand, bidding approaches based on classification trees, although they improve the result with respect to Approach 1 and 2, do not reach the economic performance of using the developed model (Adaptative Boosting).

The following graphs show for each bidding approach, the hours in which economic opportunity costs were generated, marked with an orange line over the 2018 price history of the Day-Ahead market of EPEXSPOT DE-(AT)-LU.

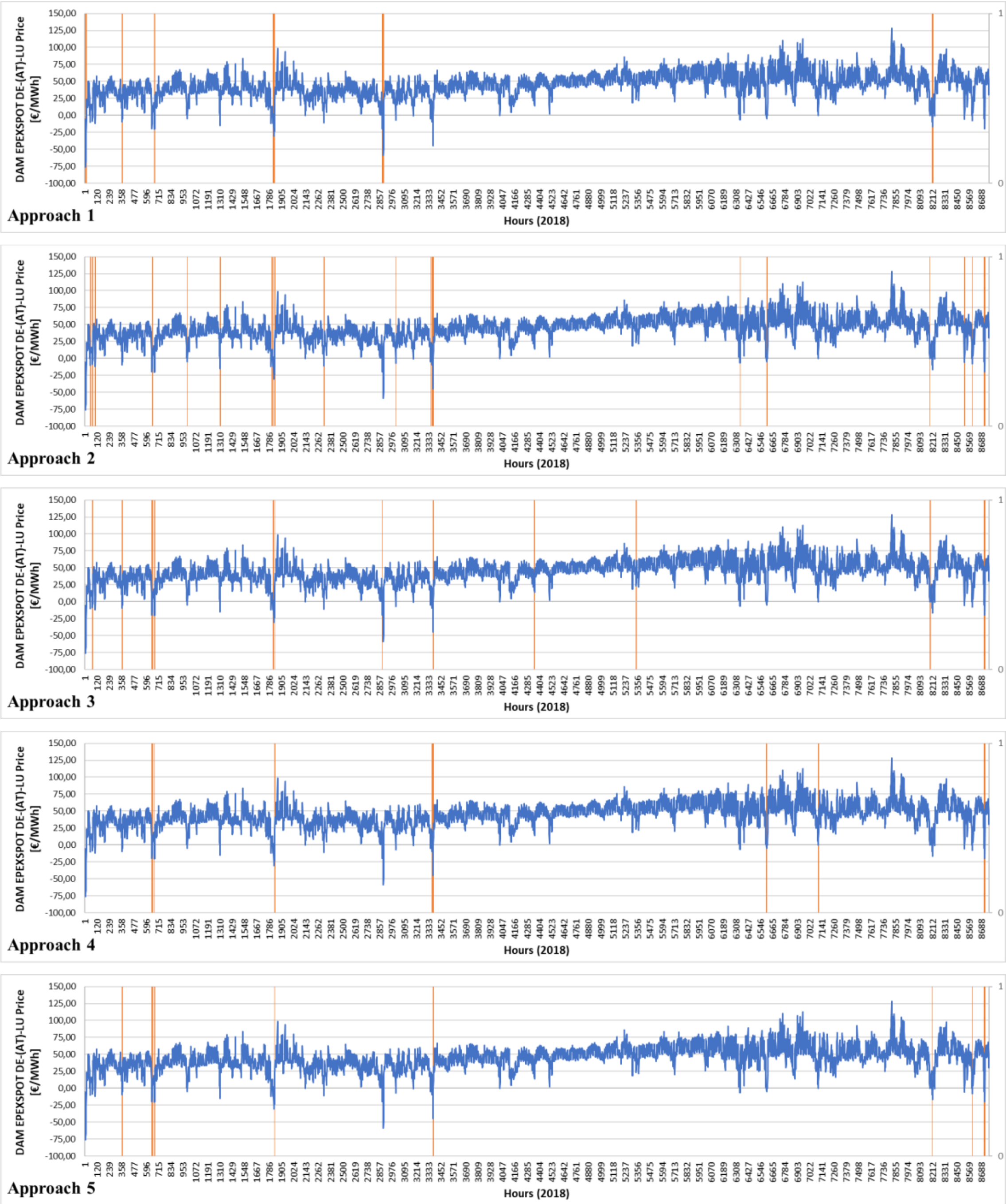

Figure 23 - Generation of Economic Opportunity Costs according to Bidding Approaches

It must be taken into account that the economic opportunity costs of each hour, represented in the previous graphs, vary according to their correspondence to periods in which the "6h rule" applies or not, as well as to the generation volume and prices of the markets. For example, for Approach 2, all the hours in which opportunity costs are generated correspond to periods of negative price in which the "6h rule" does not apply.

6. CONCLUSIONS AND FINDINGS

6.1. Summary of the Problem and Solution

The need to create a precise prediction model of the occurrence of negative prices in the German Spot Power Market arises for two reasons. The first one, to reduce the uncertainty of the RES generation in terms of the occurrence of consecutive periods of negative prices in the market, in order to encourage its offer to reflect the real variable costs of its generation, through the support in the "6h rule". On the other hand, the absence of electricity price forecasting models oriented to the accurate prediction of negative price events, since those found in the literature, having a greater scope (focused on the price forecast of the entire range of values), tend to be less accurate with respect to the accurate prediction of negative prices, since they are often even considered as outliers.

As Germany is the European country with the greatest installed capacity of variable renewable generation, it is also one of the countries with the highest price volatility and the one with the highest number of hours cleared with negative prices, on average, in recent years. Therefore, given that a precise prediction model of negative prices could contribute to the attenuation of the same event, it would be of significant relevance for a country that pretends to be a reference in terms of its ambitious reform policy of the current energy mix, towards one led by renewable energy.

Therefore, first, the binary classification of the spot market prices in positive and negative is determined as the objective result of the model. The models indicated for the resolution of this type of problem are the so-called classification methods, in particular, the most widespread in problems of categorical classification is the classification tree.

However, as mentioned above, the ordering of the hierarchical predictor diagram, typical of classification trees, excludes multiple possibilities of negative prices occurring due to a simultaneity of factors not jointly collected by a branch of the classification tree. This problem is solved with the ensemble methods of classification trees, as in the case of the AdaBoost used, whose prediction is the result of the weighted average of predictions of multiple trees, adjusting the creation of each one, to the error cases occurred in the previous tree.

Thus, by means of a Bayesian optimization of the set of hyperparameters of the model relative to the accuracy of this, and the manual selection of criteria such as the value of misclassification, cross-validation and splitting rule of the creation of the weak learners (set of internal classification trees of the model), an optimized model is obtained and adapted to the accurate prediction of negative market prices. The quality of the model is checked through the validation of the outputs generated for a testing data set, and the evaluation of the error obtained. If the desired prediction quality is not met, the criteria of the model will be readjusted according to the type of resulting failure.

6.2. Main Causes of Negative Price Periods on EPEXSPOT DE-LU

Once the significance of the predictors of the model is obtained, which is presented in subsection *5.2.1. Significance of the Predictors*, a detailed analysis of these results has been carried out, as well as an evaluation of the previously explained fundamentals that govern the occurrence of negative prices, originating the following conclusions and findings:

The consolidation of the net load factor as main predictor of negative prices, due to the previously studied high relation between this one and the market price determination (when net load falls below the usual inflexible generation level). In addition, having considered this value as the difference between the level of demand and photovoltaic and wind generation (Offshore & Offshore), the significant impact that both renewable technologies can produce on the decrease of the German power market price is concluded, reaching negative values not only at low levels of demand, but also in peak hours of consumption.

Likewise, the value of the minimum thermal generation (nuclear + lignite generation), as well as the net loads levels of the interconnected countries, also show high importance in the prediction of negative prices. However, and as can be check from the results of the classification tree, its significance in determining negative values of the market price is subject to a certain level of net load, below which they take on significance.

This significance results both from the proven flexibility of nuclear power plants in Germany, up to 40% reduction in load in the face of a stable price decrease, and in the same way, the load variation of up to 5 GW of inflexible fossil generation, produced by those plants that eventually decide to shut-down due to a forecast of prolonged low prices.

Nonetheless, as it can be observed from the analysis of significance of predictors of the model, as well as from the classification tree attached in Annex 8.2, together, the level of net load of the interconnected countries proves to have greater significance than the variations of the minimum conventional generation level. At least, with respect to 75% of the inflexible capacity of this generation, which is considered as the part that has some response to the prolonged price depressions, since the so-called "must-run" capacity is considered indifferent to it.

In particular, the effect of Denmark's wind generation is significant, which is capable of leading to negative residual demands in that country (higher RES generation than demand), being in many cases an electricity exporter to Germany (around 1.5 GW). This fact, is usually rather important when German net loads are between 12.3 and 14.7 GW, since it greatly influences the sign of the German market price.

Likewise, another interesting effect is related to Poland's net load, since for German net load values of 14.7 to 22.4 GW, the significance of this factor increases severely, raising the probability of positive prices on the German power market when Polish net load values are above 14.5 GW. Given the high Polish coal generation share (81%), net load values above the previous one would result in high Polish electricity market prices, resulting in a regular German export of around 1 to 1.5 GW. This fact would mean the increase of the German net load, decreasing its probability of occurrence of negative prices for the aforementioned net load band (14.7 to 22.4 GW).

With less significance but also remarkable, the inclusion of the RES generators as Balancing Responsible Parties (BRP), making them responsible for the payment of the imbalance costs that can generate, has determined a marked decrease in the balancing requirements of the system, due to the better prediction and adjustment of renewable plants over their forecasted generation. Therefore, this has meant a progressive reduction during the last years of the required "must-run" generation supplied by certain gas plants, what has decreased the average value of residual demand that determines the occurrence of negative market prices.

Similarly, but in the opposite direction, the increase in the number of hours of negative prices (2010-2016: 0.7% // 2017-2019: 2.1% of time) has been an incentive for conventional thermal generators (mainly lignite and hard coal plants), to reduce their minimum load capacity, as well as their ramp constraints, in order to respond more flexibly to market variations. Thus, also decreasing the margin of occurrence of negative prices. A very notable case is that of lignite power plants, whose level of generation during negative price periods has been significantly reduced over the last three years.

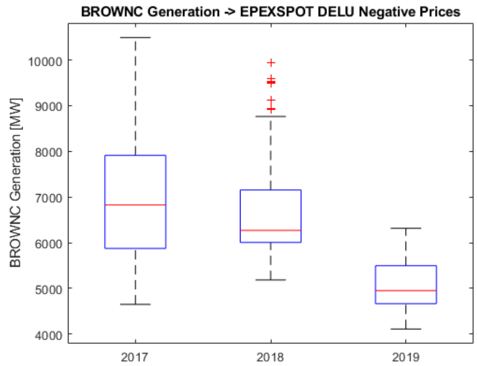

Figure 24 - German Lignite Generation during Negative Price Periods (Box Plot)

With forward-looking, the enacted German planning of total phase-out of its nuclear and carbon plants for 2022 and 2038, respectively, will signify a key point for the reduction of negative prices, as there will be much less inflexible generation in the market. In fact, who will play a key role in the determination of the market prices will be the greater exports/imports driven by the planned increase on cross border capacities, according to the TYNDP 2016, with Netherlands, Belgium, France and Switzerland. This fact will be also crucial to avoid high price peaks originated from the required flexibility otherwise provided by German gas plants.

6.3. Efficacy of the "6h Rule" on the German Electricity Market

From the analysis carried out in subsection *5.2.2. Economic Performance* , which compared the economic returns of the two main bidding approaches of the RES generators, different according to the internalization of the "6h rule", it was possible to conclude the following:

The economic performance of both bidding approaches, either bidding at price equal to the variable costs of the generation offer, or excluding the expected subsidization from those costs, depends mainly on the liquidity of the intraday markets.

First, it must be taken into account that all German support mechanisms for RES generators determined by the EEG 2017, apply to the feed-in generation, what means, regardless of the market in which it is sold, or even if it is imbalanced generation.

Therefore, the RES generators that offer according to their variable costs, in case of negative price so not matching their offers in the DAM, could instead try to match that generation in the IDMs, and in case of not applying the "6h rule ", also obtaining the subsidy for the generated energy.

On the other hand, the previous bidding approach has the risk of not being able to match in the IDMs all the expected generation volume, in addition to the fact that the final prices are on average around 25% lower than those of the DAM, when the price of this one is negative without applying the "6h rule".

The previous risk is avoided by those RES generators who offer at a negative price (that is, subtracting the expected subsidization from their variable costs). However, when applying the "6h rule", these in principle could only compensate the cost of the matched energy at a negative price, by buying in the IDMs also at a negative price. Nonetheless, this compensation turns out to be almost negligible, both because of the increase in the price of these markets compared to the DAM, and because of the level of liquidity of these ones, which has proven to be very low (<20% of the average hourly energy volume traded). In addition, the earlier generators, who offer at their variable cost, since they did not match their generation in the Day-Ahead for that hours, have the opportunity to match it (selling it) in the intraday markets.

To sum up, the level of economic compensation against negative prices of the generators that bid at 0 €/MWh will depend mainly on the liquidity existing in the IDMs to sell their expected generation. On the other hand, the level of economic compensation against negative prices and application of the "6h rule" of the generators that offer at a price < 0 €/MWh will depend on the existing liquidity in the IDMs to buy their forecasted generation.

Based on the previous precepts, it is considered as a key factor in the differentiation of the optimal bidding approach, the liquidity to sell the forecasted generation in the IDMs when the "6h rule" does not apply, since it additionally implies the income for the subsidy linked to that generation.

Thus, and as a result of the economic evaluation of both bidding approaches, it is estimated according to the simulations carried out, that is required a matching of the offered generation in the IDMs above 92% in order to result the "positive price" bidding approach from higher income, and therefore, the "6h rule" incentivized the RES generation to bid its variable costs in the DAM.

Currently, the German IDMs have a sufficient level of liquidity so that the volume of RES[5] generation matched in them is higher than the aforementioned one, even during periods of negative prices. However, this level could fall before an excess of RES generation offered in the IDMs for negative price periods of the DAM.

Therefore, the current efficiency of the "6h rule" can be confirmed, thus expecting an increase in the RES generation offers at a price ≥ 0 € / MWh, although it is uncertain if this trend could change, from the decrease of the IDMs liquidity to the matching of the RES generation offers.

The only premise that can be affirmed, is that the application of accurate models in the prediction of negative market prices, would guarantee in any situation the effectiveness of the "6h rule", since the bidding approach would be unequivocally suited to the expected periods of negative market prices.

6.4. Proposal for Future Researches

Because for future scenarios, it is expected to increase the percentage of RES generation that offers its variable cost in the market, in order to predict the behavior of this market, it is recommended to develop a regression analysis that approximates the relationship between the level of RES generation matched in the DAM and the actual forecast of RES generation for the Day-Ahead. The temporal evolution of this relationship is considered of equal interest, in the face of long-term estimates of the behavior of the German electricity system and possible regulatory requirements.

On the other hand, as mentioned previously, the level of nuclear generation is another predictor of a certain significance of the model, therefore, the more accurate its future estimate, the lower the error rates of the model predictions. That is why, once this fact is checked, the development of a better estimate of this variable is proposed, which is currently based on its scheduled available capacity and its response to variations in residual demand (regression calculated in section *3.6.1. Estimation of Nuclear generation*).

With regard to the current prediction model, it has been proven that its over-parameterization in order to improve its Sensitivity with respect to Accuracy (model performance metric), limits its optimization capacity. Therefore, the development of a model whose evaluation metric was directly the F1-score (harmonic mean of Precision and Recall), would simplify the treatment of the data and the set of restrictions over the hyperparameters. Thus, suppressing the current margin of error given by the inevitable overfitting of the model, consequence of the previous reasons, and thus obtaining a significant improvement of the precision over the testing data set; additionally, increasing the adaptability of the methodology to future and different market frameworks.

[5] Affirmation proved with a 500 MW Renewable generation plant.

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8. ANNEXES

8.1. Glossary of Terms

TERM	DESCRIPTION
CHP	Combined heat-and-power plants
CT	Classification Tree
DAM	Day-Ahead Market
EEG	Erneuerbare-Energien-Gesetz (Renewable Energy Sources Act)
IDM	Intra-Day Market
NL	Net Load (or Residual demand, as Demand level minus RES generation)
O&M	Operation & Maintenance
RES	Renewable Energy Sources
RF	Random Forest

8.2. Classification Tree