Assessing the Effects of Extreme Events on Machine Learning Models for Electricity Price Forecasting

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Abstract: Forecasting electricity prices in the face of extreme events, including natural disasters or abrupt shifts in demand, is a difficult challenge given the volatility and unpredictability of the energy market. Traditional methods of price forecasting may not be able to accurately predict prices under such conditions. In these situations, machine learning algorithms can be used to forecast electricity prices more precisely. By training a machine learning model on historical data, including data from extreme events, it is possible to make more accurate predictions about future prices. This can assist in ensuring the stability and dependability of the electricity market by assisting electricity producers and customers in making educated decisions regarding their energy usage and generation. Accurate price forecasting can also lessen the likelihood of financial losses for both producers and consumers during extreme events. In this paper, we propose to study the effects of machine learning algorithms in electricity price forecasting, as well as develop a forecasting model that excels in accurately predicting said variable under the volatile conditions of extreme events.

1 INTRODUCTION

Electricity price forecasting (EPF) is a broad subject, with numerous contemporary studies that set out to provide valuable insight to understand what mechanisms drive this highly volatile system (Weron, 2000). In this work, we set out to contextualize the respective research, to focus on studying extreme phenomena that shock the energy system and the corresponding impact it has on energy price and load forecasting. Consequently, we will follow up with introducing the relevancy of this topic, as well as outline clear objectives to accomplish with this paper.

In the context of EPF, an extreme event is an instance of abnormally low or high energy prices that can be caused, according to Liu et al. (Liu et al., 2022), by an oversupply of renewable energy and the exercise of market power. However, some of these instances are a reflection of the psychological expectations of bidding companies within the electricity market that is influenced in mid-term scope (Wen et al., 2021). On this note, and in light of the contemporary events such as the COVID-19 pandemic and Russian invasion of Ukraine, this position paper will focus on studying such occurrences.

The graph in Fig. 1 solidifies the idea that specific (extreme) events induce sharp variation in electricity prices, and studying its effects on price forecasting is a valuable asset. In the graph, we showcase two extreme events of recent history that are in the basis of the current energetic crisis, namely, COVID-19 pandemic and Russian war on Ukraine, represented by the gray and teal lines, respectively.

Since the occurrence of the COVID-19 outbreak, we note a steady, minimal, increase in electricity price, until we reach the beginning months of 2021, displaying a growing trend of electricity price by the time of international economy wake following the end of global pandemic. This is further intensified by the Russian war on Ukraine, which diminished overall electricity and natural gas supply for Europe.

What differentiates the electricity market, making it unique, is mainly the grid-based nature of electricity as a good. The lack of economically viable electricity storage options (Weron, 2014) pressures supply and demand to be constantly balanced in accordance to each other. In turn, at the wholesale level, the electricity price manifests great volatility throughout each day, to accommodate for the difference in demand at the respective peak and off-peak hours.

This variation is also present within the medium-term and long-term progression of the wholesale mar-

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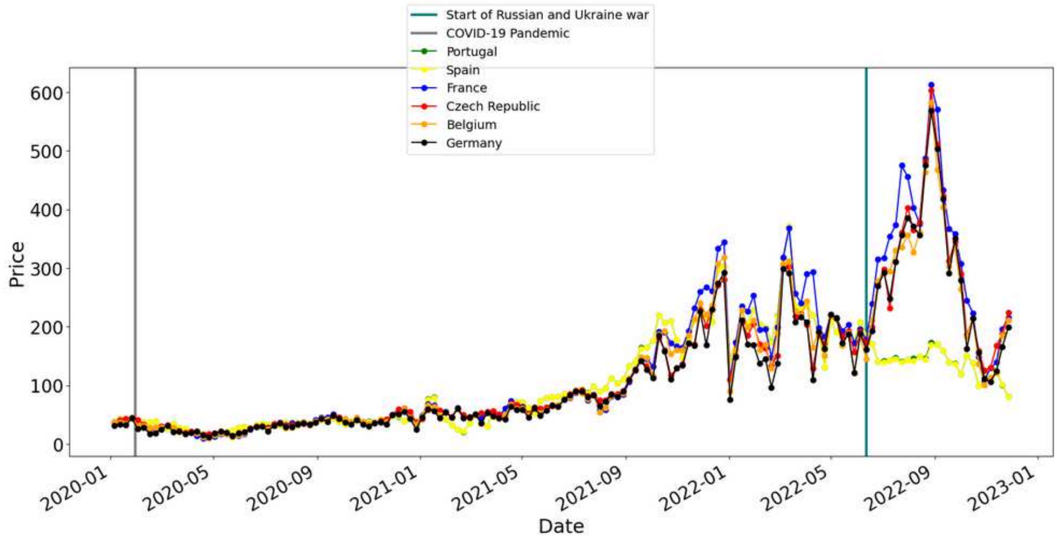

Figure 1: European day-ahead electricity price (Adapted from: (ENTSO-E, 2021)).

ket. Shifts in electricity price due to behavioral changes of consumers get diluted within larger degrees of data granularity, but other variables pose interesting correlations for being the foundation of acute increases in electricity price. Following the COVID-19 pandemic, the wake of international economy and rise of global energy demand both coincide with sharp increases in electricity price, aggravated by the ongoing war between Russia and Ukraine and cessation of gas supply (Council, 2022) that also coincide with increased energy prices. This bases the significance of this position paper.

For the following section, we will be laying out the significance of this problem, followed by section 3, where we dive into researching similar projects of related literature, then section 4 where we propose a solution framework for the existing problem, backed up by the theoretical foundation, and finally section 5 for the conclusion of this position paper.

2 RESEARCH OBJECTIVE

Due to the nature of the electricity spot market, which requires parties to submit bid prices the day before buying and selling energy, the value of accurately predicting electricity price is great. Furthermore, the existence of extreme events that greatly influence the market from a short-term perspective opens up the research possibility of achieving greater forecasting accuracy by investigating the most suitable models for this subject, and what variables have greater influence within these sporadic situations, thus defining our research objective.

Our proposition for the development of this paper is to have three different deliverable stages that reflect the respective states of our projects development. Data descriptive analysis is the first one, in which we gather our data from different sources and transform/clean it to fit our models. Additionally, we sustain an exploratory analysis on the data to extract the most suitable features as well as some data visualization to support our analysis and speculations. The second stage (model development) is for devising our forecasting models to be applied for our data, and the final stage (result evaluation) is where we analyze the results of our models and develop an hypothesis for explaining their results.

3 RELATED WORK

The following section will focus on structuring relevant background work to support our proposition of a solution for this position paper, starting with theoretical contextualization, followed by state-of-the-art modelling research.

3.1 Theoretical Contextualization

The liberalization of the Internal European energy market (IEM) aims, first and foremost, towards lowering electricity prices. This liberalization introduces a competitive force that stimulates firms to develop innovative technologies and achieve a more cost efficient operation (Pepermans, 2019), and be able to ensure business continuity.

Pepermans (Pepermans, 2019) represents the energy market liberalization clearly, where electricity generation companies used to encapsulate transmission and distribution roles, promoting market monopolisation and overseeing the definition electricity prices. After the IEM liberalization, companies were split (functionality wise), differentiating generation and distribution companies. Companies with the latter roles would bid in the electricity spot market (day-ahead) to balance supply and demand with generation companies and compete for lowest operational cost, culminating in an overall reduction in electricity cost. That being said, electricity price has shown a decreasing trend since 2011 while cross-border trade flows steadily increase, pointing to the idea that this trend is not only a consequence of the liberalization of the market, but instead the combination of several external variables and events.

The author highlights that we can't attribute the successful electricity price decline to the existing integration. A combination of other factors also influence this decreasing trend, namely the economic crisis of 2008 that drove electricity demand 6.8% lower and climate change and renewable policies pushing out thermal plants with higher marginal costs, further contributing to the existence of extreme events that have high short-term impact on electricity price

As we stated previously, according to Liu et al. (Liu et al., 2022), extreme events - such as natural catastrophes, epidemics, financial crises, and so on - reflect on the energy market as meaningful spikes on electricity prices (low or high) and can cause substantial damage to the economy. They can have long-lasting repercussions and are highly difficult to predict, making it necessary to study the impact of these events in different fields of research. The increased frequency of such events, added to the higher degree of magnitude they manifest incentives market bidders to take these events' effects into account in their forecasting models, as it will prove ever more useful for the future where conditions for extreme events are ever more likely to occur.

The unpredictable nature of these events causes sudden electricity price crashes in the market, usually with an intense degree of magnitude (as stated previously), which makes typical point forecasting models showcase low accuracy scores when accounting for occurrences of extreme events (Liu et al., 2022).

3.2 Prediction Modelling

Achieving accurate forecasting of time series has a plethora of characteristics that need to be taken into account, which we will be exploring before tackling specific models to develop. To begin, an ordered set of values that are measured at regular intervals of time is referred to as a time series. It is very useful in several fields, including finance, economics, and meteorology, and it is used to forecast short-term to long-term changes based on its data (Che and Wang, 2010).

On this topic, we define the scope of our forecasting objective. Within the context of EPF, the definition of time intervals for making predictions is not well established. Weron (Weron, 2014) states that short-term forecasting accounts for predicting values a few minutes to a few days ahead, medium-term for a few days to a few months and long-term for anything else.

External factors that influence the electricity market in short-term to medium-term are related to unexpected events that provoke fluctuations in the energy price due to psychological market expectations, while factors that affect the market long-term are more closely related to the basic supply and demand relationship of electricity as a good (Wen et al., 2021). This work focuses on assessing the effects of extreme events on EPF, as such, the time period for making predictions for EPF suits a medium-term scope, according to Weron's definition.

Exogenous features require careful consideration before developing a forecasting model. Several studies point to the existence of variables that heavily correlate with electricity price, specifically calendar variables, such as seasonality, and electricity demand (Weron, 2014) that constantly show a strong relations with electricity price. Other variables, depending on the context, can also be relevant. Bento et al. (Bento et al., 2022) discriminate another select group of variables that prove useful in this context: weather conditions, fuel costs and long-term trends, as well as broadening the seasonality variable into different ones of independent granularity (weekly, monthly, yearly).

The importance of variable correlation is high for EPF, and constructing a robust dataset that incorporates important variables promises positive results for our predictions. The variables mentioned previously showcase positive results within the overall field of EPF, but under our different circumstances of extreme events, results can differ.

Liu et al. (Liu et al., 2022) detail two different types of variables that are included in their MLgR model, being: historical prices and market characteristics. The purpose of this model is EPF in extremely low and high price situations. In both cases, market characteristic variables have the most weight for their predictions. For the lowest prices, reserve capacity has the most weight (33.94%), followed by interconnector flow (28.27%), VRE proportion (25.25%) and load demand (12.54%). For the highest prices, reserve capacity has, too, the most weight (37.00%), followed by reserve capacity (30.56%), VRE proportion (19,49%) and interconnector flow (12.95%).

According to their structure, Lu et al. (Lu et al., 2021) divide EPF models into four categories: a combination of a data cleaning method, optimizer, and basic model; a combination of data cleaning method and basic model; a combination of optimizer and basic model; and just the basic model. Typically, the most popular structure is the basic model alone, followed by the model with prior data cleaning. The hybridization of models and prediction architectures using multiple techniques is becoming a research focus and may be a future development direction.

EPF research is gathering noteworthy research popularity since the early 2000s (Weron, 2014), providing us with a vast amount of insights for the most suitable forecasting models within this context. Models that employ variable segmentation (separating models for each period), neural networks, which simulate nonlinear behavior, and forecast combinations are greatly endorsed by researchers in the field (Bunn, 2000).

3.3 Statistical Modelling

Statistical models are used to forecast future values, in this case of electricity price, by using a mathematical of historical data of electricity price and other exogenous variables that might be suitable (Weron, 2014). Additionally, according to Weron R., the attractiveness of these models stems from the requirement of physical interpretation that may aggregate to their respective components, facilitating the understanding of this type of model's behavior. Nevertheless, they are still criticized for their limited ability to model nonlinear behavior of electricity price and respective related variables. Still, their independent performance competes to the models that excel in nonlinear modelling.

Lu et al. (Lu et al., 2021), in their decade review of data-driven models for price forecasting, divide these models for EPF into 5 different categories, namely: TS models, regression models, ANN-based models, SVM-based models and decision tree-based models, where the first two categories belong in statistical forecasting models. According to these authors, TS forecasting is the prediction of future market development based on past market trends, whose primary models are the AR (Autoregressive) mode, the MA (Moving average) model, the ARMA model and the ARIMA model. ARMA is the combination of the AR and MA models and can be used to achieve simpler models the more the data is similar to a goodness of fit. The ARIMA model, which is based on the ARMA model, solves non-stationary sequence problems, allowing the original sequence to be distinguished. They state that the EPF works developed in the decade prior to this review (2021), the most popular statistical models are the ARMA, ARIMA and GARCH models, the latter being a regression model tailored for financial data. TS models are widely used for the short-term prediction of oil prices and electricity price, often as the dominant model, as well as auxiliary, illustrating the potential of their inclusion in hybrid models of machine learning and statistical algorithms.

According to these authors, regression forecasting is referred as the construction of a regression equation between variables and using it as a forecasting model based on market analysis. When employing these prediction methods it is vital to identify and collect data on the main market factors that influence the prediction objects. In this context of EPF, popular regression models are linear regression (LR), ridge regression (RR) and LASSO regression. Some common uses for these techniques include hourly prediction of electricity price, prediction of natural gas and crude oil daily prices and hybrid models.

Some authors defend that, in the context of EPF, hybrid models outperform the component models independently (Bissing et al., 2019). The hybridization of ARIMA and the multiple regression model combines the benefits of the two, by maintaining the magnitude of the values and the proper shape of the price per hour plot, respectively. Moreover, the combination of ARIMA and Holt-Winters was the best performing model in most situations, even when comparing to other hybrid models present in the literature.

3.4 Machine Learning Modelling

Multiple machine learning algorithms are well suited for EPF. Weron R. (2014) (Weron, 2014) studies the most common ones to execute this task, and in terms of machine learning models, defined by the author as 'computational intelligence models', two types are described: Deep learning models and Support Vector Machines (SVM).

According to Weron (Weron, 2014), an SVM is a classification and regression (SVR) tool that performs a nonlinear mapping of the data into a high dimensional space before utilizing simple linear functions to build linear decision boundaries between the data points in the new space, providing a less complex solution that is based on a global minimum of the optimized function and has a more flexible structure, less based on heuristics (i.e. an arbitrary choice of the model).

However, the usage of an SVM in EPF is usually a component of an hybrid model for predicting electricity price (Weron, 2014). Che et al. (Che and Wang, 2010) combine both ARIMA and SVR, that have shown to be effective in linear and nonlinear modelling, respectively, into a new model called SVRARIMA. The authors state that, due to the nature of electricity price time series, which include both linear and nonlinear components, forecasting electricity price using an hybrid model such as this is the best path to achieve accurate results. They conclude that, individually, their neural network model has the best average value for the evaluation metrics (RMSE and MAPE) when compared to ARIMA and SVR independently. However, the SVRARIMA model has the best results overall, even when compared to the hybridized model of NN and ARIMA. The authors explain that this can be expected due to the nature of SVR to maintain linear patterns undamaged, contrary to NN models, making week-ahead forecasting of electricity price more accurate for the hybrid model SVRARIMA. Nevertheless, Che et al. propose that simply combining the best individual models doesn't necessarily produce the best results, promoting, instead, a structured selection of the hybrid model.

Common variables that are included in EPF models, such as electricity load, showcase non-linear behavior (Busseti et al., 2012) which might lower the effectiveness of statistical models which excel at forecasting linear behaviour. The authors demonstrate that a deep learning architecture ensures more accurate predictions for large datasets with nonlinear patters when compared to linear and kernelized regression models. This supports the potential of using machine learning techniques for EPF under extreme event circumstances, which causes high degrees of volatility to the data. The deep recurrent neural network model was the authors' model with the best performance, outperforming both linear and kernalized regression as well as a feedforward neural network (FFNN). Busseti et al. state that the accuracy level achieved by their deep learning model approaches the same accuracy level of private sector demand forecasting services, which demonstrate a MAPE value of 0.84%-1.56%, further more supporting the usage of machine learning models under nonlinear conditions, which are aggravated by extreme events.

The potential of deep learning models is not exclusive to its inclusion into hybrid models. To predict the day-ahead price of electricity in the Turkish market, Ugurlu et al. (Ugurlu et al., 2018) developed several neural network architectures (CNN, ANN, LSTM and GRU) and tested their results independently, while using state-of-the-art statistical methods (Naive method, Markov regime-switching auto regressive model, self-exciting threshold autoregressive model and SARIMA) as benchmark models to assess the accuracy of their own. The results show a success of the neural network based models in comparison to the statistical one, with special attention to LSTM and GRU. In both seasonal and monthly comparison of results, GRU finds success in both analysis, and LSTM only in the latter. Both of these variables are important for time series forecasting, which can prove useful for developing a successful framework to predict electricity prices in short and medium-term.

Following the work of Zhang et al. (Zhang et al., 2020), we can identify a successful implementation of a hybrid framework for EPF, based on deep learning models. This framework is divided in four main modules: Feature preprocessing, deep learning-based point prediction, error compensation and probabilistic prediction. Feature preprocessing consists of detecting outliers and find the best correlating features. The second module is for extracting nonlinear features by means of deep belief networks, LSTM and CNN models. The following model, error compensation, is aimed towards reducing the residual error between forecasting and actual prices, and the final module is for calculating uncertainty at different levels of confidence. This proposed hybrid framework aims to overcome the underlying limitations that physical, statistical and machine learning methods have, combining multiple machine learning techniques that results in a competitive advantage of the model for point forecasting in terms of high-speed performance, simplicity and convenience as well as uncertainty risk control, both important features for a model in circumstances of high volatility and risk of the consequences of extreme events.

Other authors have developed hybrid models to for EPF. SEPNet (Huang et al., 2021) is the hybridization of a Variational Mode Decomposition (VMD), Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU). Due to the seasonal variation in the electricity price time series, the authors use electricity pricing data from New York City from 2015 to 2018 and divide it into four seasons (spring, summer, autumn, and winter). A CNN architecture is used to extract time-domain features from these intrinsic mode functions (IMFs) with varying center frequencies. The GRU is then used to process and learn the features collected by the CNN, producing the final prediction. Once again, the hybridization of these models outperform their accuracy independently, whereas the VMD-CNN algorithm, on the same data, has an improved MAPE and RMSE of 84% and 81%, respectively.

Regarding hybrid models, one interesting approach for EPF utilizes a fully neural network-based architecture developed by Kuo et al. (Kuo and Huang, 2018). Their model (EPNet) takes the price of electricity in the prior 24 hours and generates, as the output, the prediction of electricity price for the next hour. In this approach, they utilize a CNN for feature extraction and an LSTM for forecasting prices by analyzing the features extracted by the CNN. This CNN includes two 1D convolutional layers to improve training efficiency and batch normalization is used after the second convolutional layer, while using ReLU as the overall activation function.

The data preprocessing phase of this model's system flow begins with the original dataset being normalized, with values restricted to the range of 0 and 1, and then being divided into a training set and a test set. The optimizer then adjusts the EPNet parameters using backpropagation based on the resulting loss value. Following training, EPNet enters the testing phase, where the testing set is used as an input and the output is compared to real-world electricity prices to assess performance. EPNet's results are compared to those of SVM, RF, DT, MLP, CNN, and LSTM architectures separately, and EPNet obtains the lowest MAE and RMSE scores, confirming the potential of neural network architectures in EPF.

A fully neural-network based framework for EPF has also been proposed by Yang et al. (Yang and Schell, 2022), in the context of modelling extreme events, with highly volatile behavior. They state that the most popular statistical models for this purpose (ARIMA and GARCH) are falling out of use, given their inadequacy for high frequency time series, which is even more important under extreme events' conditions. Therefore, they propose a tri-branch CNN-GRU model (GHTnet) for forecasting electricity price, in real-time, under extreme conditions. The three distinct branches that make up the general model architecture—two GRU modules and one fully connected dense layer—share the same sub-architecture. To transform the output of the branches into the required prediction, all branches output to two successive dense layers.

The three branches that comprise the previous framework are: the sliding window branch, the day interval branch and the time series branch. The first one is based on GoogLeNet, which is a mature deep learning model based on CNNs. The interest of GoogLeNet for this framework is that the parallel layers of CNN provide the ability of extracting features on a different scale of the input, as well as alleviating overfitting, gradient explosion and gradient vanishing. The second branch takes historical price data as input and its purpose is to model long-term changes in the time series data, which can be ignored by gradient vanishing. The last branch takes time series statistics as inputs, since the inclusion of these features has been proven, in the author's work, that it can increase the ability of the model to capture extreme events. This is done by stacking CNN modules in order o extract date information and reduce the feature size.

Results showed that GHTNet outperformed state-of-the-art deep learning algorithms according to the MAE and MAPE criterion. It also outperformed popular statistical methods for EPF. The performance of each branch was evaluated, arriving at the conclusion that the GoogLeNet branch was the most important in achieving good prediction accuracy, and increasing the number of parallel CNNs further improved the performance of the model

To conclude, the definition of a model that can fit our needs in EPF under extreme events can be done through a plethora of ways. From fully statistical frameworks, machine learning models or the hybridization of the two, we can expect accurate predictions. However, understanding the context of our paper, regarding the volatility of extreme events, narrows down the definition of a suitable model for our paper regarding the consequences of extreme events in EPF.

4 PROPOSED SOLUTION

The proposed solution is to develop an hybrid forecasting framework with predictions based on neural network architectures. This framework has been proven to be effective in EPF, as stated previously, so it will be the base for the development of this position paper. This solution will incorporate a combination of data cleaning, preprocessing, and optimization, given that the main model for predictions will be based on neural network architectures.

In figure 2, we indicate said functional architecture of this proposed solution, to be explained further.

The data cleaning and transformation will be done by a thorough descriptive analysis of our original data and respective transformation into a single set. Afterwards, preprocessing methods will be incorporated (feature extraction and normalization) to allow for accurate predictions and standardization of the input data, with additional archetypal scaling techniques of the same input data. Afterwards, for all phases of model development, we propose two methods. One

Figure 2: Proposed solution functional architecture.

that is fully based on neural network architectures and another that incorporates the benefits of linear modelling of statistical methods with the nonlinear capabilities of a neural network model, as both architectures have been achieved great results in related projects in EPF.

For the fully neural network-based architecture, we propose a similar approach to Kuo et al. (Kuo and Huang, 2018). In the context of extreme events, electricity prices have additional volatility, which may indicate that algorithms for modelling nonlinear behavior, based on machine learning, may be better suited for this specific scenario. A CNN architecture has been proven successful for feature extraction purposes of the models, being potential candidates for it. For making the predictions, LSTM and GRU are popular for this purpose and have also been proven successful, therefore being the foremost candidate to incorporate in this model.

Given that the main purpose of this project is to investigate the effects of extreme events in EPF, we propose another framework, one that has the additional hybridization of a statistical method with the LSTM/GRU module for forecasting. As a statistical method, ARIMA seems the most popular choice, that has been extensively used in the field to great effectiveness. As a machine learning model, we will incorporate the previous architecture, of neural network-based preprocessing and prediction with CNN and LSTM/GRU respectively.

The development of these two models, and the comparison between the two, will allow us to better grasp if a fully machine learning-based framework is better suited for predictions in such an environment of extremely high and low electricity price spikes, or if the incorporation of statistical models, that are historically well suited to model linear behavior, is still beneficial. Furthermore, machine learning models, with special attention to neural networks in more recent years, have been showcasing great potential for modelling in EPF, and are stated by various author in the referenced works as an unexplored subject in this field, being greatly encouraged for future projects.

Prior to the development of said frameworks, and just as important, is the establishment of a robust and fitting set of data. To gather said data, we intend to on using, mainly, public electrical grid data, from ENTSO-E, and meteorological data from specific weather institutes that can provide fitting data to our problem. We have established, in previous sections, that extreme events have an underlying effect on the price of electricity, in turn effecting the electrical grid and its components. By including such variables in our framework, we speculate to successfully model the behavior of these events, as a creative variable.

For the subject of EPF, the amount of research that has been done in recent years is great. Multiple models have been developed that excel in this task, even during extremely volatile events. Developing a neural network based architecture for this solution was chosen because of the, relative, novelty of this types of models in the area, but also because of the great potential it seems to have. We want to research deeper into the capabilities of neural networks in this subject, and the great value they can contribute to electricity market bidding strategies. Furthermore, including a statistical model, like ARIMA, as it is popular in the field, will allow us to better assess the neural network potential, since we can gauge the performance of each framework independently.

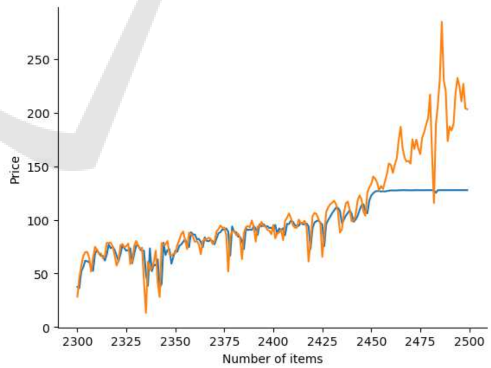

Figure 3: Training results of time series forecasting of electricity price (Adapted from: ENTSO-E).

The line graph that is showcased in figure 3 references the very incomplete and initial stages of the model development. The orange line represents the real training values for energy price, and the blue line represents the predicted training values, of the day-ahead market electricity price data, gathered from ENTSO-E (ENTSO-E, 2021). These predictions where made by developing a simple LSTM model for forecasting electricity price time series from July 2021 to November 2022. It is clear that the model lacks the capacity of correctly modelling the most volatile behavior, stating the express need for correctly modelling it.

5 CONCLUSIONS

This position paper provided the necessary contextualization of extreme events in the context of EPF, and state-of-the-art models and frameworks that fit the desired purpose of modelling the highly volatile behavior of electricity price.

Theoretical background regarding the electricity market was done for understanding the importance of researching forecasting frameworks for this subject.

Research into state-of-the-art statistical and machine learning models was done afterwards, with the purpose of understanding what are the most suitable models and frameworks that are available to successfully create a forecasting model of EPF during extreme events.

Ultimately, the proposed solution is the development of a forecasting framework that incorporates data cleaning and transformation, the inclusion of a CNN architecture for feature extraction prior to the basic forecasting model.

This latter model is to be based on a LSTM/GRU architecture, with optimization. To better study the effects of extreme events in EPF, the additional inclusion of an ARIMA model will be added to the forecasting model, to compare the benefits of statistical model inclusion in hybrid neural network-based frameworks.

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