Electricity Price Forecasting

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Electricity price forecasting is of extreme importance for both governments and private companies. However, the price of electricity is very volatile, and its evolution depends on many external factors, which makes its prediction particularly challenging. Moreover, the development of renewable energy makes this prediction even harder and at the same time more relevant. Many methods have been developed since the last century to improve forecasting. The most widely used are statistical methods or methods based on Machine Learning and Deep Learning. The aim of this paper is to provide an overview of the main categories of these methods in order to highlight the general functioning of each of these categories and to understand their advantages and disadvantages. Furthermore, we provide in this paper a relatively simple implementation of four methods: ARIMA, MLP, CNN and LSTM, for hourly and day ahead predictions based on data from German electricity market. The results achieved could be improved by adding more complexity to model and adding more features. The objective is to illustrate the functioning, the implementation challenges, and the advantages of each of these methods. In our case, the results show that LSTM outperformed the other models in all our metrics.

Additional Key Words and Phrases: Electricity Price Forecasting, Statistical models, Deep Learning, Autoregressive Methods, LSTM, Neural Networks, Day ahead forecasting

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1 INTRODUCTION

In today's competitive market, forecasting the price of electricity has become of paramount importance. Electricity trading is done ubiquitously in Europe, Australia and North America employing market rules using spot and derivative contracts [1]. Electricity price forecasting is concerned with predicting the market value of electricity in wholesale electricity markets. This branch of energy forecasting focuses both on predicting the spot prices, where the price fixing and transaction is made immediately on spot; and forward prices of electricity, where the price is settled initially but the transaction is made at a later point in time. After the deregulation of electricity in the 1990s, the landscape of the energy sector has changed. Once a government centred monopoly, the electricity industry has now reshaped itself into a competitive market. Throughout Europe, North America and Australia it can be seen that the trade of electricity is conducted with proper application of market rules. The price of electricity is of interest to industries and it is subject to frequent changes. Needless to say that there are many factors that contribute to these changes. As we know, electricity production requires fossil fuels mostly. The statistical review of World Energy report published by BP indicated that 84% of electricity production still relies on fossil fuels [2]. Quite often it is seen that fossil fuel prices surge, which has its own plethora of reasons, somewhat directly impact electricity price. Moreover, transmission and distribution contributes to a big chunk of the electricity price. Weather is another unavoidable factor that greatly contributes to the change of electricity price. Adverse weather conditions increase the demand and in turn increases the price. Looking closely at data it can be inferred that seasons play key role in the change of electricity prices. For instance, in warm countries during the summer the demand and usage surges due to massive usage of air conditioning. Unlike other commodities electricity is very different when we take into account the fact that it can't be stored and the consumption and production needs to be in constant equilibrium. Apart from these, the price of electricity is also reliant on neighbouring energy markets. All these factors discussed make the price of electricity extremely volatile and difficult to predict. In this paper we are primarily concerned with the German electricity market. Not only is Germany among the biggest producers of electricity in Europe but also among the biggest exporters of energy [3]. 82.7 billion kWh electricity was exported by Germany in 2018 [4]. Germany happens to be the biggest exporter of electricity to Nordic countries. A price surge or increased consumption in Germany will therefore effect the electricity price in the Nordic market and this illustrates how volatile the electricity market actually is. It is of no surprise that such a volatile market is difficult to predict because there are way too many external factors. Despite the capricious state of the market it is very important and useful at the same time to be able to know which way the market is leading to. Predicting price beforehand can help companies and governments to take necessary decisions. There appears to be a few different methods in usage when it comes to modeling electricity price. According to Weron 2014, electricity price forecasting can be done in the following the methods [5] also mentioned in figure 1.

First comes the multi agent models which simulates the market using multiple agents interacting with each other in a game theory based approach to provide a qualitative assessment [1]. Fundamental models or structural models attempt to grasp the physical and economic relationships that exists in electricity production and trading [6]. The reduced-form approach leverages the statistical property of electricity price over time and tries to replicate it with the objective of derivatives valuation and risk management [6]. While this method does not concentrate on providing accurate hourly rates, but they try to replicate the properties of the electricity price

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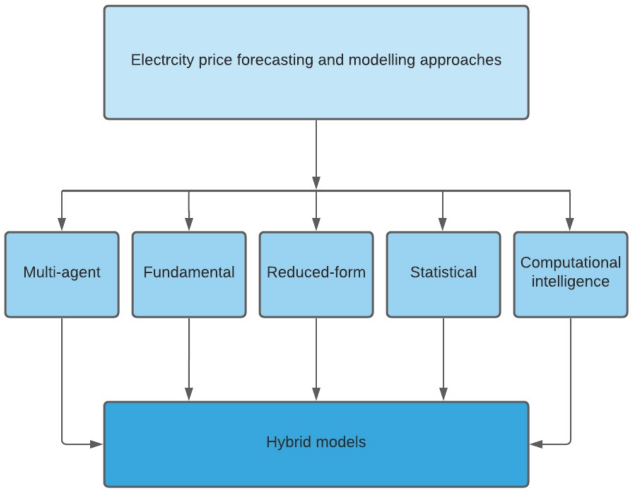

Fig. 1. Classification of methods in the domain of electricity price forecasting

such as price dynamics, correlation between commodity prices, marginal distribution at future time points. Statistical models try to estimate the price by using various statistical approaches such as regression methods [7], time series models such as AR, ARMA, ARIMA [8] and Heteroskedastic time series models such as GARCH AR-GARCH [9]. Statistical models are more popular than the aforementioned methods due to the fact that they allow system engineers to better understand the physical features. Then comes the computational intelligence models which are comprised of methods that leverage artificial intelligence and machine learning based methods namely artificial neural networks [10], fuzzy systems [11] and support vector machines [12]. These models are consider state of the art when it comes to electricity price forecasting as they perform far ahead compared to the previously mentioned methods. The fact that computational intelligence models are capable of handling non-linear and complex data is its prime advantage over statistical models. Finally comes the hybrid models which combines two or more of the techniques we have mentioned so far. We have extensively studied some research works where the authors have tried to estimate electricity price. We primarily put our attention on statistical and computational intelligence models with a deeper concentration on the later method, as these two methods have been empirically proven to yield the best results. In this paper we discuss about the papers we have studied in details and prior to that we provide a succinct introduction to the prior knowledge required to comprehend them properly. We have also implemented our own models to forecast electricity price for Germany. In this paper we describe our implementation in details and compare results of the models we have implemented.

2 LITERATURE REVIEW AND RELATED WORK

In this section we extend our discussion about electricity price forecasting by looking at the types and the horizons electricity price forecasting. Furthermore, we briefly discuss about the various methods used for forecasting and also briefly talk about some related works.

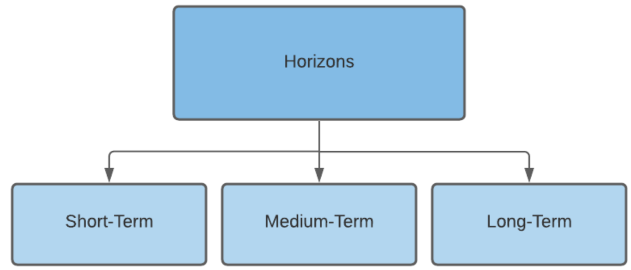

Fig. 2. Horizons of Electricity Price Forecasting

2.1 Electricity Price Forecasting Framework

2.1.1 Horizons: For electricity price forecasting there are mainly three types of horizons: short, medium, and long term as can be seen in the figure 2. Even though there is no agreed upon threshold that separate these three types in the literature there are some rules of thumb to be followed. Short term horizons vary from minutes to days. Usually, it corresponds to horizons where reliable meteorological prediction (such as fore temperature, wind speed, cloud cover) are available. Short term forecasting is mainly relevant for market operations [5]. It's suitable for intraday and day-ahead market prediction. In day ahead market, agents submit their bids and offers during each hour of the next day before a market closing time. On the other hand, in intraday market, participants trade continuously 24 hours a day with delivery on the same day. Medium term forecasting covers horizons beyond reliable meteorological predications. The medium-term horizon ranges from weeks to months or even years. Medium term predictions are impacted by deterministic demand patterns [13], prices for fuels used for conventional power generation, plans for changes in the power plant portfolio etc. Medium term forecasting is practical for maintenance scheduling, resources reallocation, bilateral contracting, derivatives valuation, risk management, and budgeting. Long term horizons range from few years to several decades. Long term predictions are impacted by all kind of factors (political economic and social etc.) which makes them hard to draw. These predications are useful for policy making and investment planning. It's noteworthy to mention that most electricity price forecasting literature focus mainly on short term forecasting.

2.1.2 Types of forecast: In this paper we will focus on point forecasting (where we predict a single value for each time point of the forecasting horizon), but it is important to note that there are other methods. The vast majority of electricity price forecasting methods are only concerned with point forecasts [5].However, in last decade probabilistic forecasting has gained momentum especially for energy systems planning and operations (Nowotarski and Weron, 2018). In probabilistic forecasting, there are mainly two approaches, the first and more popular one builds on the point forecast and the distribution of errors associated with it. The second approach directly considers the distribution of the prices. Another type of forecasting that is even less popular than probabilistic forecasting is ensemble forecasting. Ensemble forecasts do not focus on one point only for the prediction, instead, they predict an ensemble of m paths. These paths are also called, scenarios or trajectories.

2.1.3 Multivariate vs Univariate representation: For short term forecasting, there are two methods to represent the price series. The first modelling approach is to represent the prices data in multivariate fashion where the prices of day are represented with one 24 dimensional vector Pd = [Pd,1 ; … Pd,24]. The second modelling approach is to use a univariate representation of the price's series: Pt = P24d+h. The multivariate approach is more popular for day ahead forecasting since the prices for the 24 hours of the next day are disclosed at once in a specific time of the day (usually around noon), whereas the univariate approach is more popular for intraday markets [5]. The univariate approach is also more popular in the engineering electricity price forecasting where machine learning methods dominate. F. Ziel, R. Weron (2018) conducted an extensive empirical study to compare the two modelling approaches for short term electricity price forecasting [14]. The results show that despite a minor edge in predictive performance overall, multivariate approach does not outperform the univariate approach across all datasets, seasons, and times. For example, when analyzing model performance in the four seasons, the results show that the univariate modeling has an edge over the multivariate one in the Fall. This indicate that combining both modeling approaches could lead to an improvement of the forecasting accuracy.

2.2 Various Predictive Models

2.2.1 Multi Agent Models: In the pre-deregulation era, forecasting electricity prices generally concerned medium- and long-term time horizons, and focused mainly on matching supply to demand estimates. Multi-agent methods relied on the same principle but took into consideration the strategic bidding of the players. Multi-agent models also called game theoretic models are useful when predicting prices in markets where the prices history isn't available but the supply costs and market concentration (a function of the number of players and their respective shares of the market) are known. Some of the main multi-agent methods are the following:

- Nash-Cournot framework: in this framework, electricity is considered as a homogeneous good and the market equilibrium is determined with the capacity setting decisions of the suppliers. One of the main disadvantages of these methods is that they tend to provide higher prices than what is observed in reality [15].
- Supply function equilibrium: in this approach the price is modelled as the equilibrium of firms bidding with supply and demand curves in wholesale markets. The predications obtained with this method require some relatively complex calculation which is a considerable limitation.
- Strategic production-cost models: this approach takes agents' bidding strategies into account, based on conjectural variation. Each agent tries to maximize its profit while taking into consideration the behavior of other players. Compared to the previously mentioned methods, the strategic production-cost models require less computations [16].
- Agent-based simulation models: these models are an alternative to the previously mentioned methods where the modeler needs to solve complex equations in order to get to the 'equilibrium'. The basic tool of these models is a set of computational structures and rules for simulating the actions and interactions of autonomous players [17].

Multi-agent models are an extremely flexible tool for the analysis of strategic behavior in electricity markets. The main drawback of these models is that they require so many assumptions (about the players, their strategies, and interactions etc.) that are embedded in the simulation. Unfortunately, these assumptions do not usually hold. Besides, these models focus more on the qualitative analysis of the market rather than the quantitative results.

2.2.2 Fundamental Models: Fundamental models (also called structural models) describe the price dynamics by modelling the impact of basic physical and economical factors affecting the production and trading of electricity [18]. The functional association between fundamental drivers (such as loads, fuel prices, weather conditions etc.) are postulated and the fundamental inputs are modeled and predicted independently via statistical, reduced-form or machine learning techniques. Generally, there are two sub-classes of the fundamental models:

- Parameter rich fundamental models: these models are usually developed as in house product that use proprietary information; therefore, their details are not disclosed publicly.
- Parsimonious structural models of supply and demand that are built on publicly available information

The fundamental models present many challenges. First, the implantation of these model requires the availability of large amount data (such as plant capacities and costs, demand pattern and transmission capacities), which not guaranteed for all markets. Second, because of the nature of fundamental data, fundamental models are more suitable for medium- and long-term predictions.
Consequently, the application of these methods is generally limited to management and derivative pricing [19].

2.2.3 Reduced-form Models: Reduced form models (also called quantitative or stochastic models) are inspired from the financial domain. These models are not built to provide accurate hourly spot price forecasts, but rather to replicate the main characteristics of electricity prices (such as marginal distribution at the future time points, correlation between commodity prices etc.). This makes these models more adapted for risk management derivative pricing (as it is the case also for fundamental models).
Reduced form models provide a simplified, yet realistic to some extent price dynamics and are commonly used for computationally intensive derivatives pricing (e.g., of electricity futures and options) and value-at-risk calculations [20]. The two most popular model classes for the spot price dynamics include:

- Jump-diffusions, that are a combination of Brownian dynamics and Poisson-type point (jump) processes.
- Regime-switching models, typically involving a latent process describing the current state of the spot price (e.g., base regime

vs. spike regime) and Brownian dynamics in one or more regime.

These models work relatively well when it comes to volatility or price spikes forecasts. They can be built for both the forward and spot prices.

2.2.4 Statistical Models: The statistical approach is one of the six approaches defined by Weron in 2006 [21]. It is an evolution of the reduced model approach, which consists in building quantitative and stochastic models that highlight the statistical properties of the evolution of the price of electricity as a function of time, particularly for risk management. The statistical approach combines the application of statistical methods, signal processing techniques and the application of econometric models to the electricity market and is therefore much more suitable to forecast day-ahead electricity prices. With the statistical approach, the current electricity price is obtained by mathematically combining the old prices. Other variables can also be taken into account, such as production, consumption or weather conditions. The mathematical combinations used can be additive or multiplicative. The statistical approach is the approach that was historically used to make predictions in this area, before the development of Machine Learning/Deep Learning models. It is still sometimes used today, particularly as it is the approach that allows the most physical interpretations to be made. One of the limitations of this approach is that it is not very well suited to predicting non-linear behaviour. The greater the frequency of price changes, the worse the predictions. However, the price of electricity varies very quickly and the smaller the time window considered, the more the price tends to have a non-linear behaviour. For example, while the price of electricity over a year can be fairly well approximated by a linear model, this is no longer the case when the window considered is restricted to one day. Moreover, especially on a single day, the evolution of the electricity price shows large peaks, which are difficult to predict accurately in a statistical approach. In the presence of large peaks, the data must be filtered beforehand to obtain good performance, like it is done by Weron [21]. Furthermore, with the introduction of renewable energies, the price of electricity is becoming increasingly volatile, which will make the application of the statistical approach more difficult in the future. However, according to the comparative analyses carried out in Weron [5] and Lago [22], in most practical cases the performance of this approach is comparable to that of other approaches.

State of the art - classification of methods of the statistical approach:

In order to provide a state of the art of the main existing methods in the statistical approach and to better understand their advantages and limitations, we have classified them into different categories. For this purpose, we relied on the classifications of Weron [5] and Lago [22] and the methods presented by Ziel [23], McMenamin [24] and Karabiber and Xydis [25]. The figure 3 illustrates this classification. For the sake of clarity, we will not go into the details of all the models mentioned above but will simply explain the principles and limitations of each of the categories in the diagram. This diagram presents the main basic classical methods but is not exhaustive, many other variants exist.

I. Univariate statistical models:

A. Autoregressive models

Autoregressive models are time series models that uses observation, here power prices, from previous time steps as input to a regression equation to predict the value at the next time step. They model time correlation in the time series using a linear model. The ARMA method is the basic model. In order to be applied, the data must be stationary and not show any seasonality. ARIMA is an evolution of this method that can be applied to non-stationary data. Several variants of ARIMA were then developed to include seasonality such as SARIMA, or even double seasonality such as Double seasonal ARIMA. Wavelet-ARIMA is also an evolution of the ARIMA method. It starts with a pre-processing step that decomposes the initial signal into several components on which ARIMA is applied. As explained by Lago [22] and Ziel [23], these autoregressive models perform well for predictions. However, they can only be applied under certain constraints. Indeed, the data must respect the homoscedasticity property, which is not always respected by the evolution of the price of electricity. The application of these models therefore requires a prior statistical test or even a reprocessing of the data. In order to overcome this constraint of homoscedasticity, another variant of ARIMA can be used: the GARCH-ARIMA method. However, coupling the GARCH method to the ARIMA method adds a lot of complexity and GARCH cannot be used alone because, according to Lago [22], it would lead to very poor prediction performance.

B. Exponential Smoothing models

Exponential smoothing models use a family of algorithms that make using an exponentially weighted average of past observations. The key idea is to give more importance to certain values, to recent prices in the serie for instance. Some models use this property to give more weight to prices that reveal some seasonality in the data, such as double seasonal Holt-Winter (DSHW). This method uses additve trend and multiplicative seasonnality, where two seasonal components are multiplied together. Another well-known exponential smoothing method is the Trigonometric Seasonal Box-Cox Transformation with ARMA residuals Trend and Seasonal. It can be used with non-linear data thank to its Box-Cox transformation component. It has also two other components: an ARMA model for residuals and a trigonometric seasonal component. Such a model has a high complexity but can be applied even if the data have a high frequency. Thus, these models are interesting since they allow to work with non-linear data, which is not the case for general AR models. Nevertheless, they are harder to compute and, as explained by Karabiber and Xydis [25] who made experiments on electricity prices of the West-Danish market in 2016-2017, they don't always get better performances.

II. Multivariate statistical models:

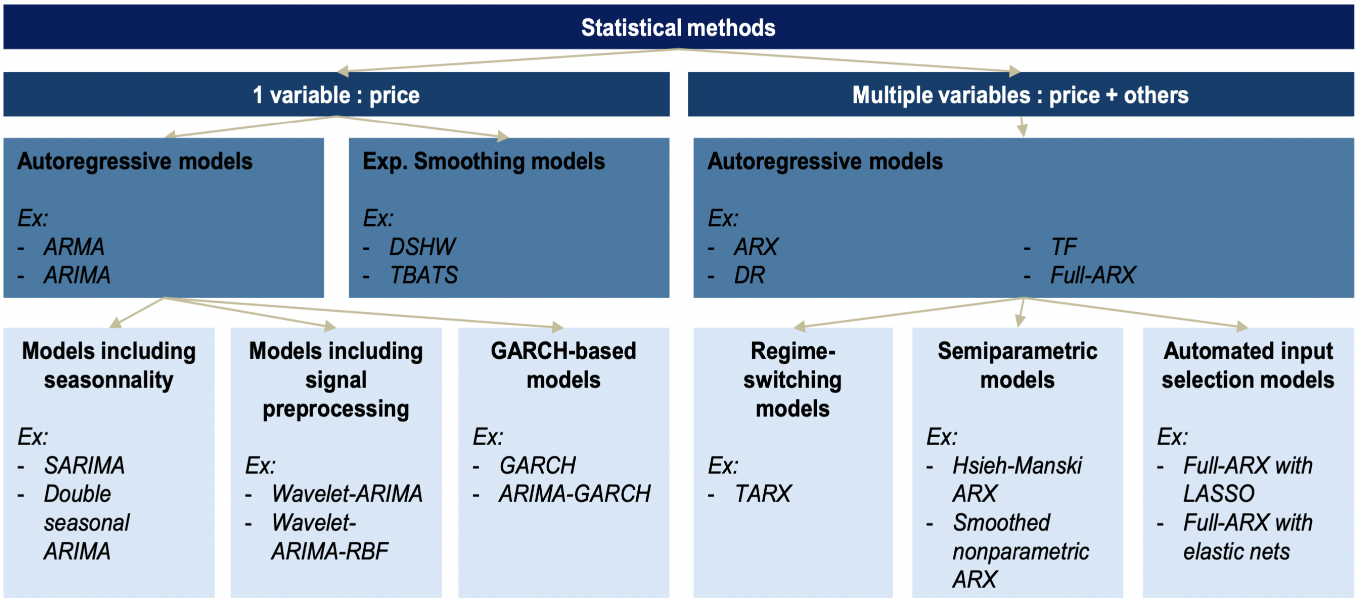

Fig. 3. Classification of statistical methods

A. Autoregressive models

The main idea of these models is the same than for univariate autoregressive models. In the multivariate models, regressors such as grid load, available capacity or ambient temperatures, for instance, are added to enhance the predictive accuracy. ARX is the basic models and some evolutions of this model have been made to improve performances.

- Regime-switching models: One of these evolutions is the regime-switching model. It consists in considering that the time series can be modeled by several regimes, which are in fact independent models, and combining them in switching models. For example, the TARX method models two regimes: one for the normal prices (stationary distribution) and one for the spiked prices, applies ARX with grid load for the exogenous variable, on each regime and then combine the results. Such a method improves the results especially for day-ahead forecasting as hourly prices and grid load distributions contains a lot of spikes, according to Lago [22]. These models allow to take into account both regimes and exogenous variables.
- Semiparametric models: A semiparametric model is a model using a nonparametric kernel density estimator, in other words, it is a model that relaxes some assumptions. For instance, in the smoothed nonparametric ARX model (SARX), the normality assumption need for the maximum likelihood estimation is relaxed. Thanks to such a property, the prediction performances of a semiparametric model are generally better with empirical data than theses of parametric distributions. According to Weron [5], SARX performs better than ARX in term of model error and they are able to perform well under different market conditions which leads to a bit more flexible and reusable models.
- Automated input selection models: As explained by Ziel [23], some autoregressive models, and in particular those that include exogenous variables, tend to do overfitting, which greatly reduces predictive performance because the model is no longer suitable for generalizing to other data. To solve this problem, regularization must be added to the model. Automatic selection of inputs consists in automatically selecting the important exogenous inputs and thus reducing the complexity of the model and this method therefore acts as regularization. For instance, full-ARX regularizes with Lasso uses Lasso to automatically reduce the contribution of unimportant inputs. According to the Lago's case study, full-ARX with LASSO gets better prediction performances than full-ARX [22].

Further study of autoregressive methods – focus on ARMA and ARIMA

For the implementation part, we chose to focus on autoregressive methods because they are currently the most used among statistical approaches and as explained in the state of the art, many variants exist including or not exogenous variables and allowing to reach similar performances or even better than in the other approaches. In the implementation, in order not to make the model too complex, we have implemented basic univariate statistical models: ARMA and ARIMA. (see implementation section). We will now present these methods in more detail. ARIMA, Autoregressive Integrated Moving Average Model, is a model used in time series analysis and is a generalization of the Autoregressive Moving Average (ARMA) model. These models are commonly used both to explore and analyze past data as input to the model and to make predictions about future points.

Definition:

A stationary process admits a minimal ARIMA(p,d,q) representation if it satisfies [26]:

$$\phi(L)(1-L)^d X_t = \Theta(L)\epsilon_t, \forall t \in Z$$

Under the following conditions:

(1) $\phi p \neq 0$ and $\theta q \neq 0$
(2) ϕ and Θ, polynomials of degrees p and q respectively, have no common roots and their roots are of moduli > 1
(3) $\epsilon\ t$ is a BB of variance $\sigma = 2$

ARIMA is particularly well suited to deal with time series. However, in order for the model not to be perturbed, the past time series input to the model must be stationary and show no sign of seasonality (deterministic component). Before applying this method, it is therefore necessary to carry out statistical tests to assess the stationarity of the data as well as the seasonality. If the data show signs of non-stationarity of the mean and/or seasonality, an initial differentiation and/or seasonal differentiation will be applied in order to remove these disturbing components from the model. These adjustments can be made either independently in the data preparation stage or in the implementation of the models. It is the "integrated" part of the ARIMA method that deals with stationarity of the mean, while a special model has been designed to deal with seasonality: SARIMA. SARIMA deals with seasonality by including multiple seasonality lags. For example, to handle monthly series with annual seasonality, SARIMA includes a lag of 12.

2.2.5 Computational Intelligence Models. Computation intelligence(CI) models are a varied group of nature-inspired computational techniques that have been developed to solve problems which traditional methods (e.g., statistical) cannot handle efficiently. CI combines elements of learning, evolution and fuzziness to create approaches that are capable of adapting to complex dynamic systems, and may be regarded as 'intelligent' in this sense. The main classes of computational intelligence models are artificial neural networks, fuzzy systems, support vector machines (SVM) and evolutionary computation(genetic algorithms, evolutionary programming, swarm intelligence). In the domain of electricity price forecasting artificial neural networks(ANN) consist of feed forward neural networks, convolutional neural networks and recurrent neural networks. We will not go deep into the other CI models but we will discuss briefly about the artificial neural network methods in the following subsections.

A.Feed Forward Neural Network

Feed forward neural network is the quintessential neural network architecture. The objective of a neural network is to map a feature vector x to a target output y. A neural network tries to estimate a function f^* that would map features x to a target y. This can be written as $y = f^*(x|\theta)$ where the parameter θ is learned to achieve the best approximation of the function [27]. The figure 4 illustrates the architecture of a very simple feed forward neural network with one hidden layer consisting of 4 nodes. Typically neural networks used in real life scenario have multiple hidden layers. The nodes of a hidden layer are basically non linear functions which take input from the previous layers and feeds the output to the next layer, hence, the name feed forward neural network. In the training, at first forward propagation is performed where the data is processed and fed forward throughout the network to predict an output. The predicted output then is compared to the ground truth data to calculate error. After that the neural network is optimized by performing backward propagation where the values of the θ parameters are updated throughout the network with respect to the gradients of the weights themselves. The forward and backward propagation is done throughout the entire data-set in multiple epochs until the error rate goes under an acceptable range. Then prediction is performed on novel data points using the model parameters of the trained model. The most common feed forward neural network is multi layer perceptron(MLP) where there are multiple hidden layers with the output of the previous layer being the input of the next layer and the output layer gives the predicted result. However, there exists another category of feed forward network called the radial basis function(RBF) network which has two layers and each node in the hidden layer employs a radial basis function as the activation function as opposed to MLP networks where the activation functions are non linear (e.g. sigmoid) or piecewise linear(e.g. ReLU). MLP networks are effective at capturing global data trends while RBF networks are good at exploiting local data trends [28]. In the works done by Chen, Dong,Meng, Xu, Wong, and Nagan (2012) [29]; Cruz et al.(2011) [30]; Garcia-Ascanio and Mate (2010) [31] the MLP architecture was used. The RBF network which is less popular than the MLP was used by Guo and Luh in 2003 [32] and also by Lin, Gow, Tsai (2010) [33].

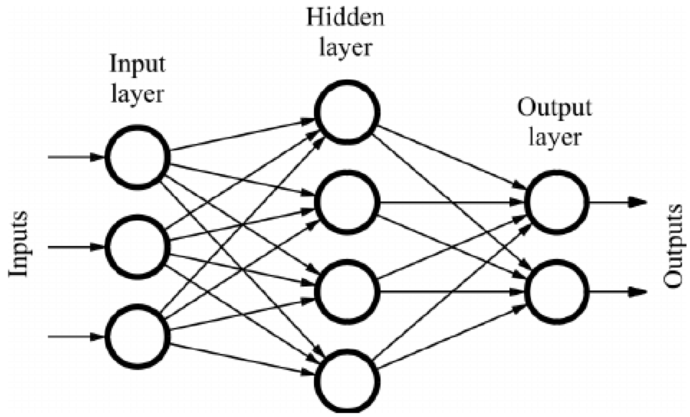

Fig. 4. A simple single layer feed forward network.

B. Convolutional Neural Network

Convolutional neural networks or CNNs are widely used in the domain of object detection, tracking and other computer vision applications. These neural network models are based on the convolution operation. In the figure 5 we can see a two dimensional array

I_{11}	I_{12}	I_{13}	I_{14}	I_{15}	I_{16}	I_{17}	I_{18}	I_{19}
I_{21}	I_{22}	I_{23}	I_{24}	I_{25}	I_{26}	I_{27}	I_{28}	I_{29}
I_{31}	I_{32}	I_{33}	I_{34}	I_{35}	I_{36}	I_{37}	I_{38}	I_{39}
I_{41}	I_{42}	I_{43}	I_{44}	I_{45}	I_{46}	I_{47}	I_{48}	I_{49}
I_{51}	I_{52}	I_{53}	I_{54}	I_{55}	I_{56}	I_{57}	I_{58}	I_{59}
I_{61}	I_{62}	I_{63}	I_{64}	I_{65}	I_{66}	I_{67}	I_{68}	I_{69}

K_{11}	K_{12}	K_{13}
K_{21}	K_{22}	K_{23}

Fig. 5. An image or 2D array I and kernel K

or image I on which a convolution operation will be performed using the kernel K. Let the dimensions of the image I and the kernel K be mxn and kxl respectively, then the output O of the 2D convolution operation is given by the equation 1:

$$O(i,j) = \sum_{k}^{m} \sum_{l}^{n} I(i+k-1, j+l-1) * K(k,l) \tag{1}$$

After a convolution operation is performed it is followed by a pooling a operation which reduces the dimensionality of the data and select the most prominent attribute. For instance, a 2x2 max pooling would choose the highest value in a 2x2 grid of the input to generate a new output image as illustrated in the figure 6. However, other form of pooling operations also exist such as average pooling. In

Image Matrix

2	1	3	1
1	0	1	**4**
0	6	**9**	5
7	1	4	1

Max Pool

2	4
7	9

Fig. 6. Illustration of a 2x2 maxpool operation

a CNN the convolution and pooling operations are performed to reduce dimensionality and extract the most useful features of the data and is followed by a fully connected layer to get the output prediction or value. Our implementation of the CNN is not concerned with two dimensional(2D) images. We are trying to estimate the value of electricity price which is a numerical value. Our implementation is concerned with using one dimensional(1D) tabular time series data of prices to predict future prices. As a result, our CNN models use 1D convolution operations and 1D pooling operations. In the paper titled "Deep Convolutional Neural Network Model for Short-Term Electricity Price Forecasting" authored by Cheng et al. convolutional neural networks were used to predict electricity price [34]. While convolutional neural networks are traditionally applied in the domain of imaging and vision and electricity price being a sequential time series data, this paper gives us an insight on how CNNs can also be used for time series data. For this research work, the authors have used data from 2015 to 2018 for New York city provided by ENGIE. Data from the years of 2015 to 2017 was used for training the model and the data of the year 2018 was used as the test data. As there is fluctuations in the prices of electricity over the seasons of a year, the authors have divided the data into 4 seasons categories Spring, Summer, Fall and Winter for each year in order to avoid the influence of fluctuating electricity prices. According to the authors, this was done to improve the predictive accuracy of the deep learning model. In the figure 7 we can see the architecture of the CNN model used by the authors to predict electricity price which taken from their paper. The authors have

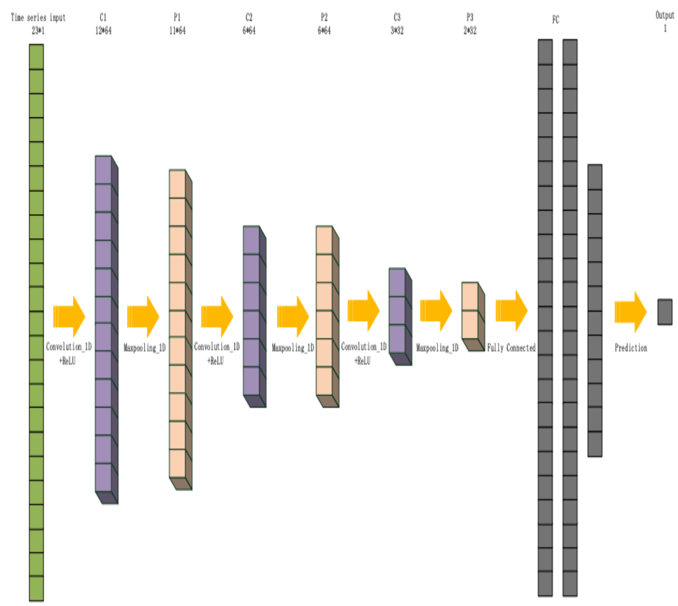

Fig. 7. Architecture of the proposed model by Cheng et al.

used 1D convolution layer with a rectified linear unit activation function (equation 2) which is followed by a pooling layer.

$$ReLU(x) = max(0, x) \tag{2}$$

The model takes 23 hours of electricity price as input. Convolution layers extract features from the data and the pooling layers select the prominent features. The very last layer of the model is a fully connected layer that gives a scalar output, the electricity price. The authors then compare their proposed CNN model with an LSTM(Long short-term memory) model and a feed forward neural network model. It was shown that their proposed CNN model had the least error among all the models with the performance of the

LSTM model being very similar to their proposed model.

C. Recurrent Neural Networks

Recurrent neural networks are a generalization of feedforward networks that uses the concept of internal memory. This concept allows the network to perform same operations on multiple inputs of a sequence thus making network capable of dealing with sequential data where inputs are not independent from each other. To perform a prediction for a particular input the recurrent neural network considers the computation performed for previous inputs. RNN are very popular for deal with sequential data, some of their applications are machine translation, video classification, sentiment analysis, time series prediction etc. Although, RNN are very appealing when dealing with sequential data, they suffer from long term memory problem due to exploding and vanishing gradient. This issue diminishes the capability of RNNs to deal with long sequences. Variants of RNN such as LSTM (long short-term memory) and GRU (gated recurrent units) are design to deal with this problem. The LSTM proposed in Hochreiter and Schmidhuber (1997) solved the short-term memory problem in vanilla RNN [35]. In the computation of an output, the LSTM relies on 3 inputs: the current input data, the short-term memory (hidden state) and cell state (also known as the cell state). LSTM also relies on the concept of gates to decide which information should be saved and which should be discarded. The internal architecture of an LSTM is shown in the figure 8

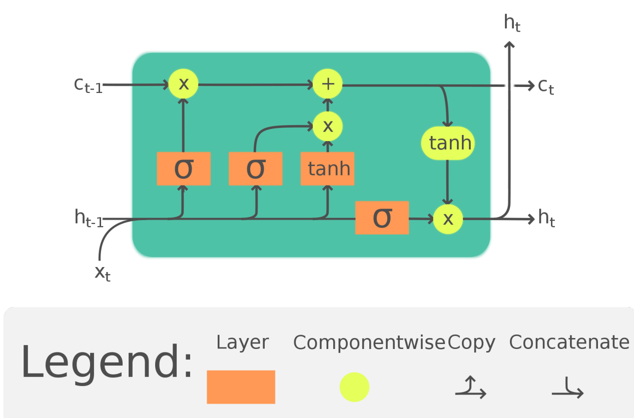

Fig. 8. The schematic diagram of an LSTM cell

The use of LSTM in the EPF area in the recent years is steadily increasing. In the Zhu et al (2018) paper, the authors used the LSTM for hourly price prediction on the New England and PJM day ahead market. The LSTM they designed uses the previous prices of a time window of length L (L in [4, 8, 12, 24]) to predict one hour prices and uses recursion to predict the prices for the following hours [36]. The study shows good results in comparison to Support vector machine and Decision trees models. In Bano et al (2020), the authors compare Multi-Layer Perceptron, SVM, Logistic regression and LSTM using one year of hourly data. The study concludes that LSTM performs better than MLP for the EPF problem [37]. The paper titled "Day-ahead electricity price prediction applying hybrid models of LSTM-based deep learning methods and feature selection algorithms under consideration of market coupling" authored by Li et al.predicts electricity price for the Nordic market which includes the countries Norway, Sweden, Finland and Denmark. The electricity price Nordic market is effected by cross border markets such as Germany since, electricity is imported from overseas markets. The authors Meticulously have tried to reduce the number of input features in this research work. LSTM models suffer in performance when the dimensionality of the input data is too high. This phenomenon is also called the dimensionality curse. As a result selection of the most appropriate features was a key goal of this research. The data used by the authors had 62 features, which included the day ahead prices, production, production prognosis, consumption, consumption prognosis etc of the different nordic zones and other countries like Poland, currency exchange rates, flow of electricity between the Nordic zones and a calculation feature called flow deviation of the zones. The authors have made different models which keep different features and drop others. The RFE-SVR-LSTM and LASSO-LSTM provided the best results.

D. Embedding

Ramentol et. al. provides a new approach to electricity price forecasting as they use the notion of embedding to capture calendar information and then feed this information to a neural network model to predict the prices [38]. This approach seems to outperform existing methods (such as LSTM) with the use of easier-to-understand model architectures. The study was conducted on the German electricity market, the results show that the used approach cut in half the forecast error compared to the existing default approach in short-term price forecasting. The results show also that this approach can be used in the forecasting of long-term electricity prices. In addition to these good results, this method provides good insight into the model's logic. In fact, using the embeddings we can gain economic understanding and analyse which calendar variables lead to similar behaviour of electricity prices

3 METRICS USED IN THE PAPER

For implementation of the models we have used some metrics to track the training and furthermore we have used several more to compare the results of the models. We have used Root Mean Squared Error(RMSE), Mean Absolute Error(MAE), Coefficient of Determination (R^2), Mean Squared Error(MSE) and Mean Absolute Percentage Error(MAPE). Following equations describe the metrics respectively:

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{3}$$

$$MAE = \frac{\Sigma_{i=1}^{n}|Y_i - \hat{Y}_i|}{n} \tag{4}$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\Sigma_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{5}$$

$$MSE = \frac{1}{n}\Sigma_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{6}$$

$$MAPE = \frac{100\%}{n}\Sigma_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}| \tag{7}$$

where:
n represents the number of data point
Y_i represents the actual value of the i^{th} data point
$\hat{Y}_i$ represents the predicted value of the i^{th} data point.

4 IMPLEMENTATION

As stated earlier, not only did we study the related work in the field of electricity price forecasting extensively, but we also wanted to have some working implementation of predictive models. The steps taken by us in implementation of the models is illustrated in the figure 9 and they are further elaborated in the following subsections. We implemented four methods: ARIMA, MLP, CNN and LSTM and compared the prediction results of these models .

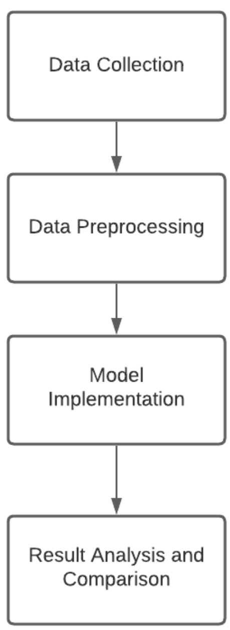

Fig. 9. Flowchart of the work methodology of our implementation

4.1 Data Collection

The evolution of the price of electricity as a function of time is a time series. A time series is a finite set of numerical values expressed in terms of a time index. The data we used for the implementation are hourly electricity prices expressed in euros/MWh. We focused on spot day-ahead prices because they are the ones for which predictions are most important. Forward prices correspond to contracts defined in advance, corresponding to the commitment to purchase a quantity of electricity fixed in advance at a price fixed in advance. These prices are therefore not determined by the same factors. The data collection was done from the smard.de website, which presents energy-related data in Germany on consumption, generation and the market. The collected data correspond to the wholesale electricity market prices in the Germany/Luxembourg segment. The exact definition of the collected price given by smard.de is "Weighted wholesale electricity price (day-ahead price on the exchange) for each hour [€/MWh] determined on the day-ahead auction that took place on the previous day - data is delivered no later than 2 hours after trading closes.

In order for all the implemented prediction models to be applied correctly, the training data must contain at least a whole period, i.e. a year. As the data is only available on the Germany/Luxembourg segment since 01/10/2018, we then collected it for 3 years: from 01/10/2018 00:00:00 to 30/09/2021 23:00:00. As 2020 was a leap year, the total number of data is 26,304. For training and testing split, we used 2 years for training and the remaining one year for testing.

4.2 Data Preprocessing

Before training and performing predictions with our models it is crucial to preprocess the data, otherwise, as seen practically, models tend to perform poorly. We perform hourly price prediction and day ahead price forecasting. For predicting hourly prices we have taken into account the price of electricity for the previous 23 hours. From the data we had we at first created a time series data-set where the first 23 hours are feature variables and the 24^{th} hour is the target. Using a sliding window approach we then discard the first hour and append the 24^{th} hour to the feature vector and take the 25^{th} hour as the target variable. By iterating through the basic tabular data we have created a time series sequence at first. We have taken a similar approach when it came to the day ahead price prediction. For the first tuple of the data-set, we have at first taken 24 hours of electricity price of 1 to n-1 days as feature and the 24 hours of the n^{th} day as target. Then for the next tuple, we remove the first day's value and append the value of the n^{th} day and take the $(n+1)^{th}$ day as target. We proceed through the data in an iterative manner to construct the data-set for day ahead electricity price forecasting. We can consider the 'n' as a hyperparameter that can be tuned to attain the best result. Furthermore we transform the values using the MinMax scaler which maps a set of input between 0 and 1. The transformation and inverse transformation are given by the following equations.

$$X_{scaled} = (X - X_{min})/(X_{max} - X_{min}) \tag{8}$$

$$X = X_{scaled} * (X_{max} - X_{min}) + X_{min} \tag{9}$$

Here in a vector X, X_{min} and X_{max} are the minimum and maximum values of X respectively. X_{scaled} is calculated using the equation 8. To obtain X form X_{scaled} we use the equation 9.

4.3 Preliminary Study and implementation of Statistical model ARMA and ARIMA

We at first use the statistical models ARMA and ARIMA for electricity price forecasting. Our approach is discussed below briefly.

4.3.1 General experimental approach: According to the theoretical part on the ARIMA model, the experimental approach to be followed in order to carry out an ARMA(p,q) or ARIMA(p,d,q) modelling is the following:

- Carry out an autocorrelogram of the data in order to check stationarity and determine the possible orders p and q and possibly d for ARIMA.
- Calculate the AIC or BIC to estimate the best possible p and q parameters among those that are plausible.
- Perform a diagnostic of the residuals on the past data input to the model (by statistical test, graphical representation or autocorrelogram).
- Confirm the model by testing it on a test sample not passed as input to the model.

4.3.2 Two approaches: To test the performances of this autoregressive method, we followed two approaches. The first is to calculate the statistical model for two years (2019-2020) and then make predictions for one year (2021). At first glance, this approach seems particularly well suited to statistical methods because the longer the time span considered, the more likely it is that the data can be considered stationary. As explained above, stationarity is a prerequisite for applying the ARMA method. In case of non-stationarity, the ARIMA method should be applied after determining the degree of non-stationarity, which is altogether more expensive than applying ARMA. Moreover, taking at least an entire as input can be useful to capture yearly or monthly patterns in the electricity price distribution if any. The second approach is more in line with what is currently done in the power industry. It consists of making predictions on a day-to-day basis, for 24 hours, based on the data of a few days preceding the day for which one wants to make. We have used a rolling window of 1 to 7 days and make predictions for the 24 hours of the next each time. This approach is certainly closer to reality but it is less suitable for the application of ARMA. Indeed, as the price of electricity is very fluctuating, the data considered in the rolling window are no longer always stationary, which implies using ARIMA.

4.3.3 Preliminary tests of stationarity and seasonality. Stationarity has been tested with the Ad-Fuller test. By performing it in the first approach, on the two first years of the dataset, we get the following results shown in the table 1. As the p-value « 5%, the input data of the first approach are stationary. In the second approach, as shown on the graph bellow in figure 10, as the number of days spent in input of the rolling window decreases, the percentage of data spent in input that is non-stationary increases. 90% of the data spent in input with a rolling window of 1 day (day-ahead prediction) is non-stationary. To test seasonality, we directly used the automatic research of the best ARIMA model (auto_arima of pmdarima) which takes the price distribution and output the ARIMA model with the best orders, including orders for seasonality. This revealed any seasonality in the first approach as well as in the second approach.

Test Statistics	-1.063689e+01
p-value	5.045508e-19
No. of lags used	4.400000e+01
Number of observations used	1.749900e+04
critical value (1%)	-3.430724e+00
critical value (1%)	-2.861705e+00
critical value (1%)	-2.566858e+00

Table 1. Results of dickey fuller test

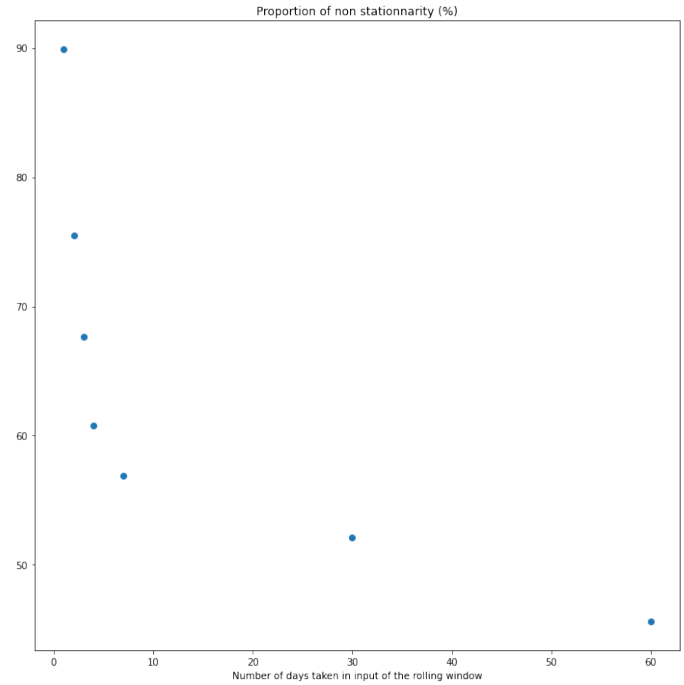

Fig. 10. Proportion of non-stationary data vs the number of days spent in input of the rolling window for the second approach

4.3.4 First approach results: In this model, as preliminary studies showed that the price distribution taken over 2 years was stationary and did not show any particular seasonality, we set d=0 and seasonal=False as parameters of auto_arima, in order to reduce the running time. The intervals for p and q were set to [0;8] and [0;3] respectively. According to auto_arima, the best orders for ARIMA was: ARIMA(8,0,1)(0,0,0). We fit this model using price distribution from 01-01-2019 00:00:00 to 31-12-2020 23:00:00. We obtained the following fit as shown in the figures 11 12 and 13.

Then, we applied this model to make predictions from 01-01-2021 00:00:00 to 30-09-2021 23:00:00. We obtained the following predictions as shows in the figures 14 15 16

We get the following errors measures for predictions made on the segment [01-01-2021 00:00:00 : 30-09-2021 23:00:00] as shown in the table 2: RMSE, MAE and R^2 is defined as shown in the equations 3 4 and 5:

4.3.5 Second approach results: In this model, we used a rolling window with 5 days in input and prediction for the following 24 hours. We used the same values as for the first approach for the parameters p,q and seasonal but we set d to None and the input data are no longer stationary.

We made the experiment on the segment [27-12-2020 00:00:00 : 30-09-2021 23:00:00] to get predictions on the segment [01-01-2021

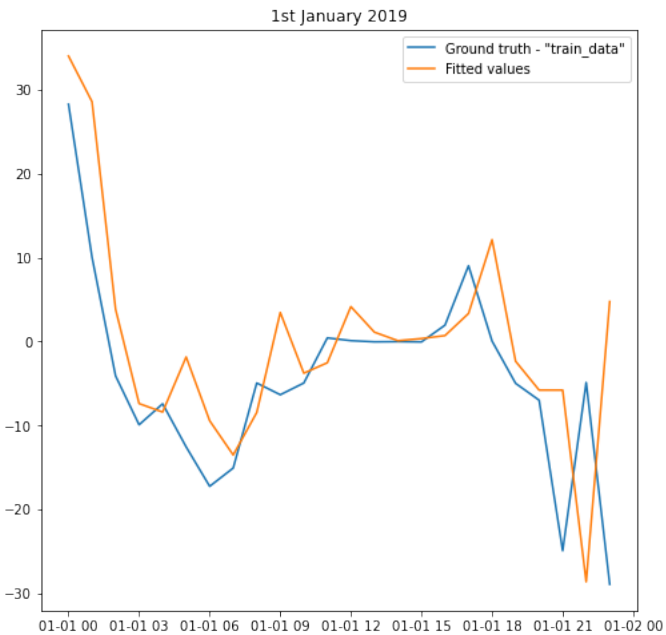

Fig. 11. Fitted vs ground truth value January 1 2019

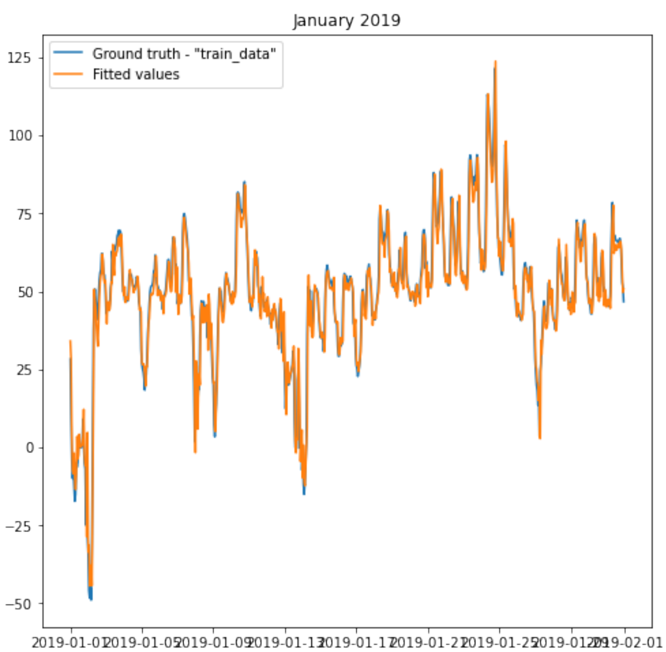

Fig. 12. Fitted vs ground truth value of January 2019

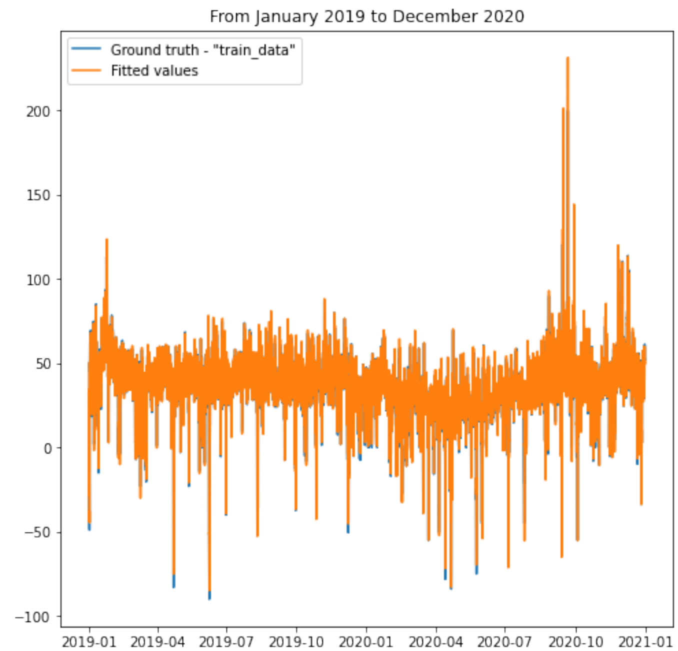

Fig. 13. Fitted vs ground truth value from 1/1/19 to 31/12/20

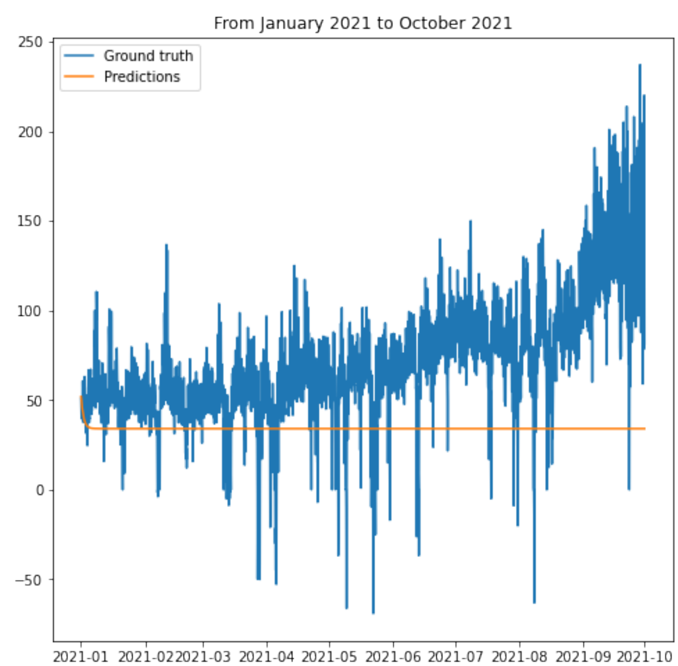

Fig. 14. Actual vs predicted value using the first method from January 2021 to October 2021

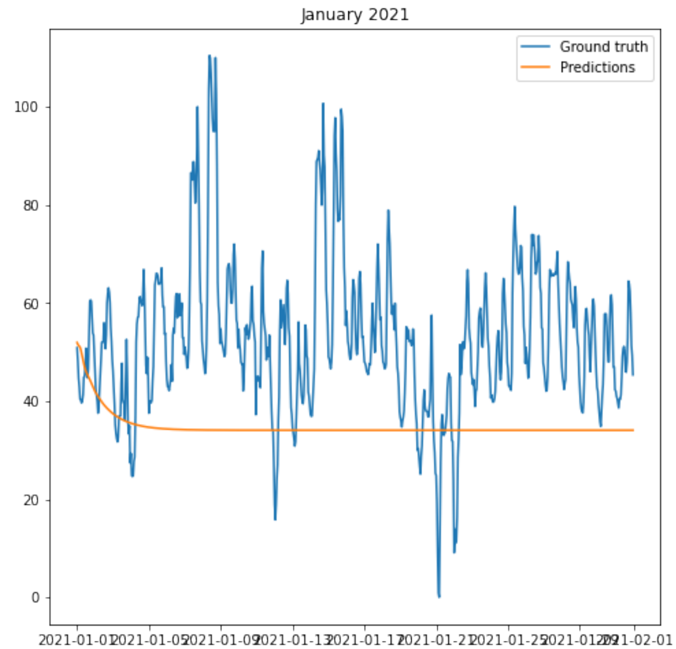

Fig. 15. Actual vs predicted value using the first method for January 2021

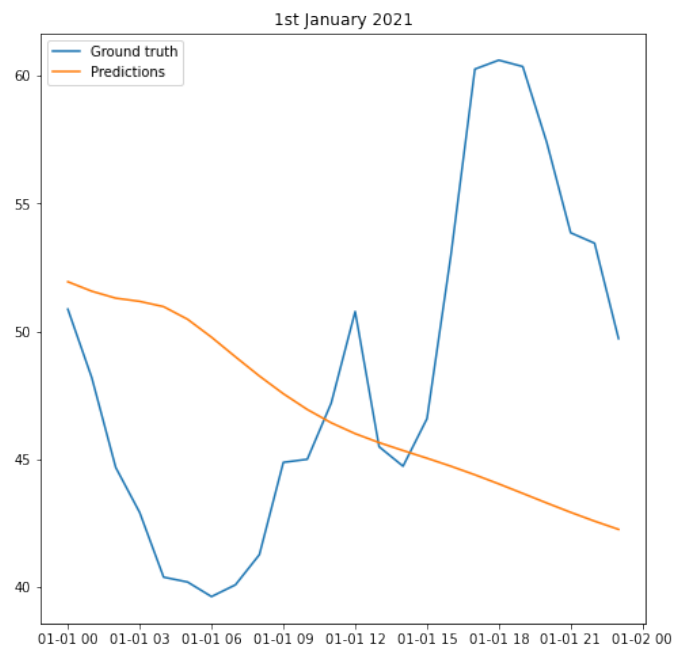

Fig. 16. Actual vs predicted value using the first method for 1st January 2021

RMSE	2422.5981988622348
MAE	39.15040279619834
R^2	-1.0339718088783831

Table 2. RMSE, MAE and R^2 score for prediction from 01-01-2021 00:00:00 to 30-09-2021 23:00:00 using the first method

00:00:00 : 30-09-2021 23:00:00] and be able to make comparison with the first approach.

We get the following predictions as shown in the figures 17 18 19

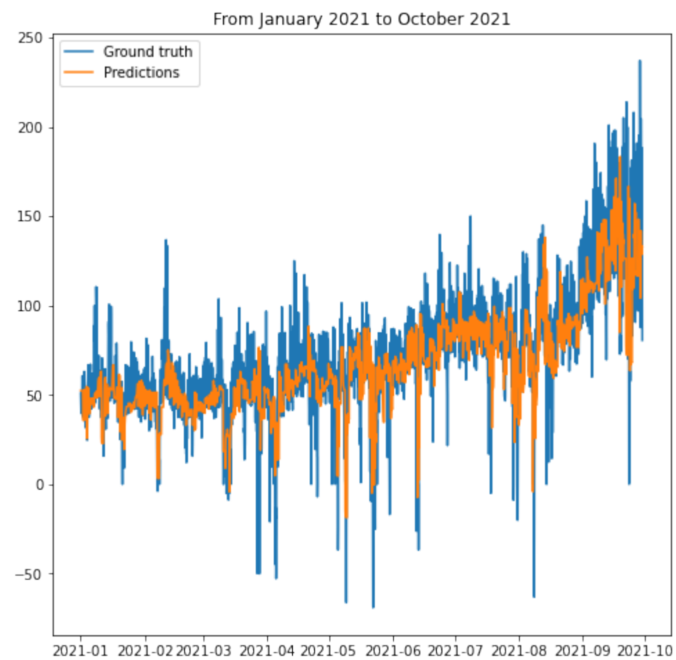

Fig. 17. Ground truth vs predicted value from 1/1/21 to 30/9/21 using the second approach

For the second approach we get the following error measures as shown in the table 3:

RMSE	520.676301740592
MAE	15.972385980549806
R^2	0.5588240814630461

Table 3. RMSE, MAE and R^2 score for prediction from 01-01-2021 00:00:00 to 30-09-2021 23:00:00 using the second method

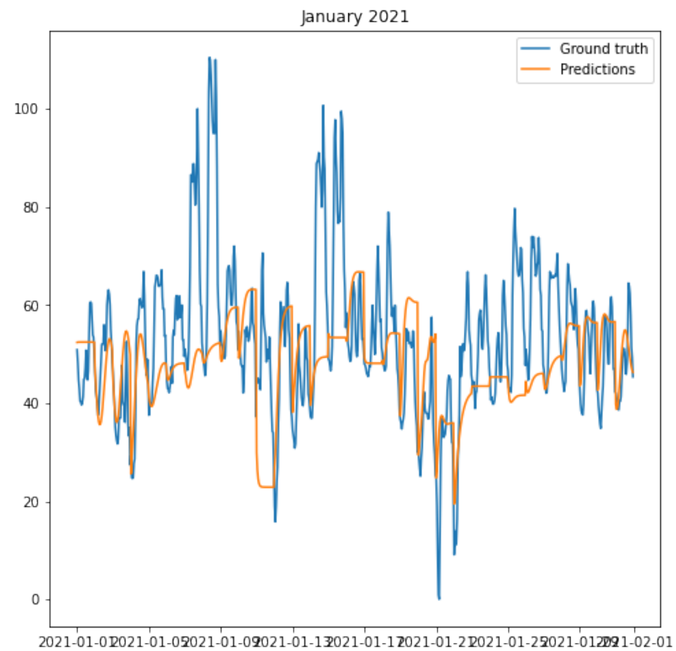

Fig. 18. Ground truth vs predicted value for January 2021 using the second approach

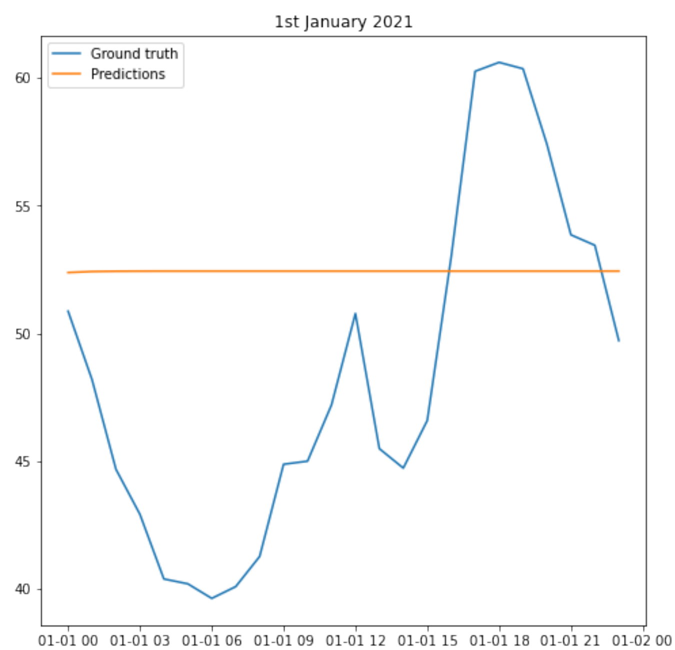

Fig. 19. Ground truth vs predicted value for 1/1/21 using the second approach

4.3.6 Conclusion – comparison of the two approaches: For each rolling window, the ARIMA model has to be recalibrated, which increases the complexity and the running of the model. Nevertheless, the first approach leads to almost constant electricity price predictions over the prediction segment which leads to very high prediction errors. The second approach is much more suitable than the first one to make monthly, daily or even hourly electricity price predictions, even if it predicts a constant hourly price over a day. Considering the same prediction segment, the prediction errors are much lower in the second approach. The first approach is rather suitable for understanding existing electricity price distribution profiles. In this implementation part, we find the same observations as those made in the literature review for statistical approaches, autoregressive methods and in particular those made with basic models such as ARMA or ARIMA are not well adapted to make predictions on non-linear distributions and with high frequencies of variations. We selected the second approach to make comparisons with the two other implementations.

4.3.7 Further investigations on the second approach: To compare the results with the two other implementations, we prepared the data in the same way. We applied MinMax() rescaling and we used an input segment input_days longer than the one used for predictions (cf. part on comparison between the 3 implementations). With these rescaled data, we also performed further investigations on the second approach by testing different sizes for the input_days variable. We get the following results as shown in figures 20 21 22 and 23.

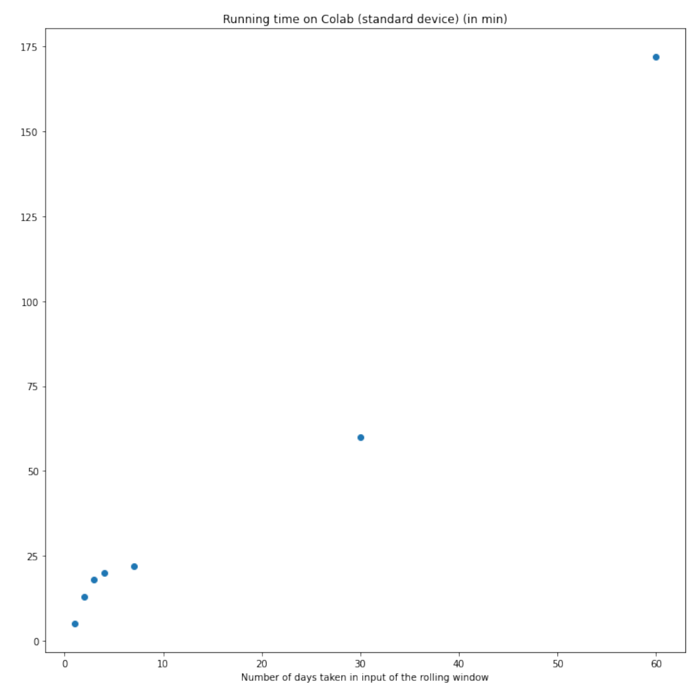

Fig. 20. Runtime on colab vs the number of days taken in the rolling window

As the graphs show, as the size of input_days increases, the running increases but the MAE and MSE errors decrease when we consider the entire prediction segment. When we took an input_days =

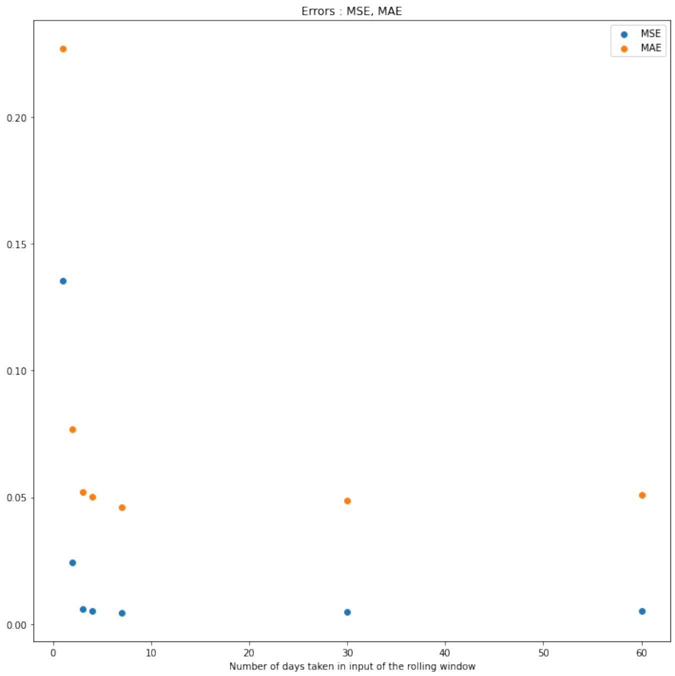

Fig. 21. MSE and MAE errors vs the number of days taken in the rolling window

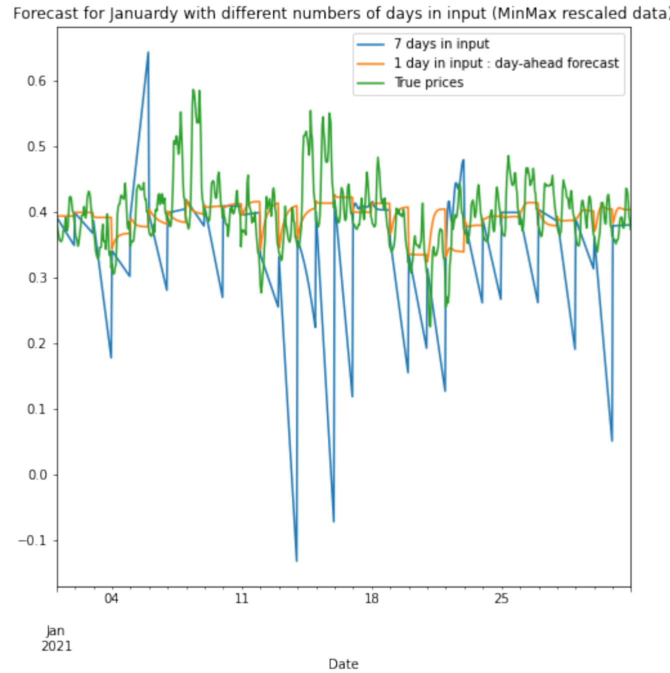

Fig. 23. True price vs forecasted price of January using various number of days as input

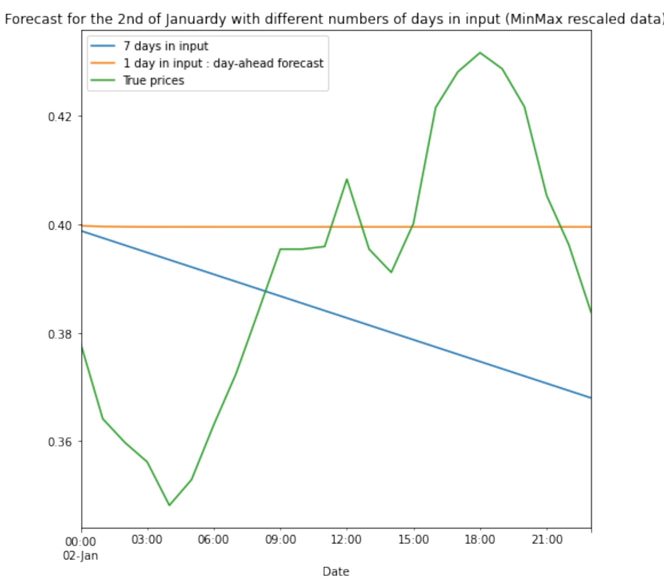

Fig. 22. True price vs forecasted price of 2nd January using various number of days as input

1, we reproduced a day-ahead model but the results are the worst. Therefore, this approach is not well fitted to perform day-ahead predictions. Such a model can be improved, as mentioned in the literature review part, by adding exogenous variables of performing preprocessing like, for example, wavelet decomposition.

4.4 Hourly Price Forecasting with Feed Forward Neural Network

We have two separate dense neural network implementations. In the first implementation we perform hourly prediction of electricity price. Our implementation is an uni-variate model where we take the price as the variable to predict future prices. The architecture of the multi-layer perceptron model is given in the figure 24.

4.5 Day Ahead Price Forecasting with Feed Forward Neural Network

For predicting day ahead price we have used 5 days prior data of electricity prices. The data is prepared to have 5x24 hours of prices as feature and the next 24 hours as the target. The input and output structure of the data is different and calls for a model with different architecture than the one used for predicting hourly prices. The architecture of the multi layer perceptron model for predicting day ahead prices is shown in the figure 25

4.6 Hourly Price Forecasting with Convolutional Neural Networks

As stated earlier for hourly price forecasting each data point has 23 previous hour price as features and one hour price as the target. As a result our convolutional neural network takes a 23x1 dimensional vector as input and we get a scalar value as the output. The

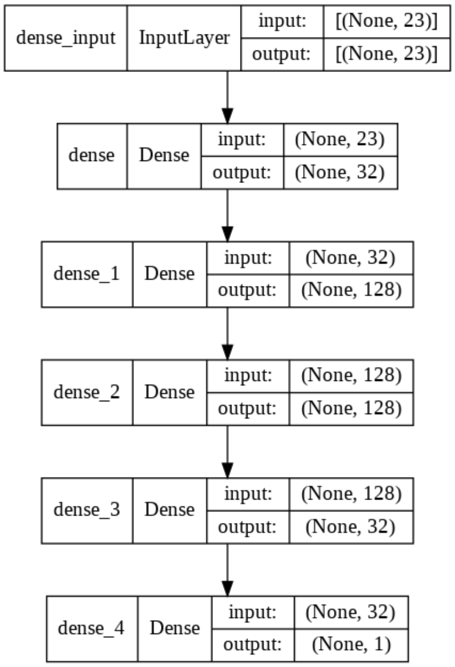

Fig. 24. Architecture of our feed forward neural network for predicting hourly prices

architecture of the convolutional neural network for hourly price prediction is illustrated in the figure 26

4.7 Day Ahead Price Forecasting with Convolutional Neural Networks

For day ahead price prediction we have used 5 days of previous prices to predict the next day's electricity price. In this case, the data points have 120 hours of prices as feature and 24 hours of prices as the target. Our convolutional neural network's architecture is changed to accept 120x1 dimensional vector as input and as output it gives a 24x1 dimensional vector as output. An illustration of the architecture of our convolutional neural network for day ahead price prediction can be seen in the figure 27.

4.8 Day Ahead Price Forecasting with Long Short Term Memory

We only constructed a model that performs day ahead price prediction using LSTM since in practical use cases it is more useful than hourly prediction.

- Feature engineering:
  - Network input: The input is the past prices of the previous 7 days: x(t-1) … x(t-7), the dimension of x(t) is 24 (which corresponds to one price value for each hour of the day)
  - Network output: x(t) which is a vector of dimension 24 containing the predicted prices for the 24 hours of the following day
- Network design:
  - Number of hidden Layers: 1,

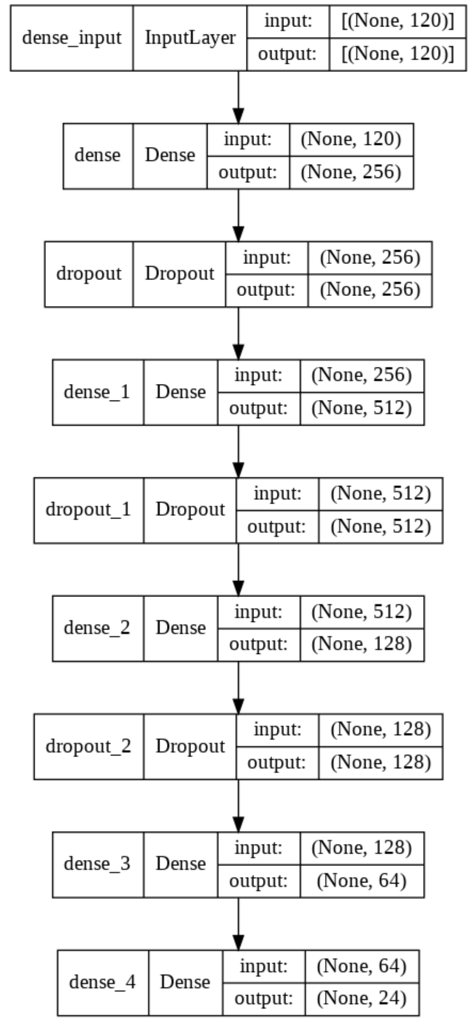

Fig. 25. Architecture of our feed forward neural network for predicting day ahead prices

  - Dimension of the hidden layer: 100
  - Number of LSTM cells: 1
  - Batch size = 1 (the number of training example in one forward/backward pass)
  - Learning rate: the learning rate was initialized at 0.003 and then at every 100 epoch it was modified such that: new learning rate = 0.5* old learning rate
  - Loss function: mean squared error
- Training and testing
  - Training epochs: 3000
  - Train/test split: 1/3 for testing and 2/3 for training

5 RESULT ANALYSIS AND COMPARISON

In this section we will present the results of our models and compare the results.

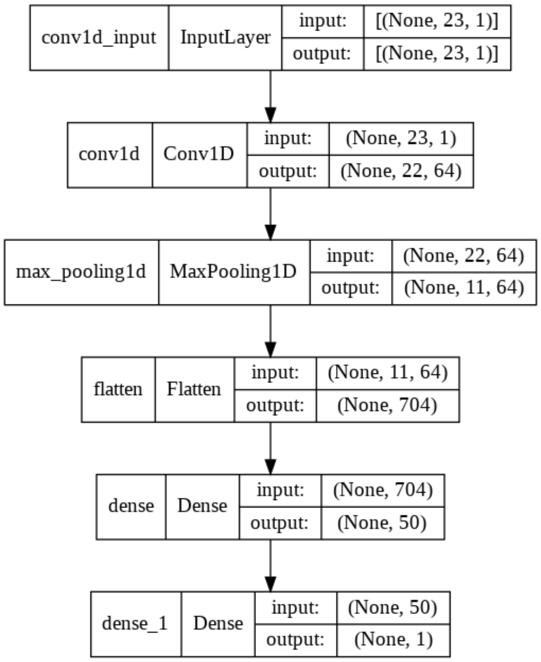

Fig. 26. Our convolutional neural network architecture for hourly price prediction with 23 dimensional vector input and a scalar output

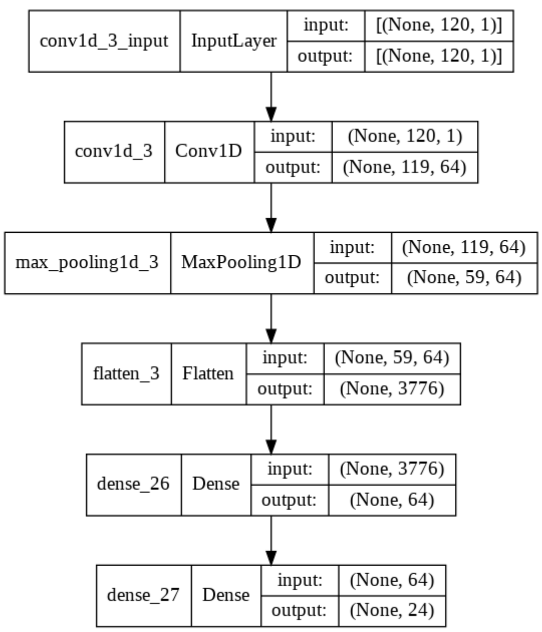

Fig. 27. Our convolutional neural network architecture for day ahead price prediction with a 120 dimensional vector input and a 24 dimensional vector output

The comparison is limited to day ahead predictions. We compared the statistical model and the computational intelligence models using various error metrics for the test data in table 4.

	ARIMA	LSTM	CNN	MLP
MSE	0.004389	0.003094	0.004875	0.007265
MAE	0.046003	0.035956	0.051046	0.068158
MAPE	146978513831.2562	0.077355	0.120015	0.151563

Table 4. The mean squared error, mean absolute error and mean absolute percentage error of our models on test data.

After that we predict randomly one week of electricity price from each of the four seasons using all of our models and compare it with the ground truth value. Prices vary with season as we stated in the introduction section. That is why we predict randomly a week from each of the seasons and see how the models compare as shown in the figures 28 29 30 and 31.

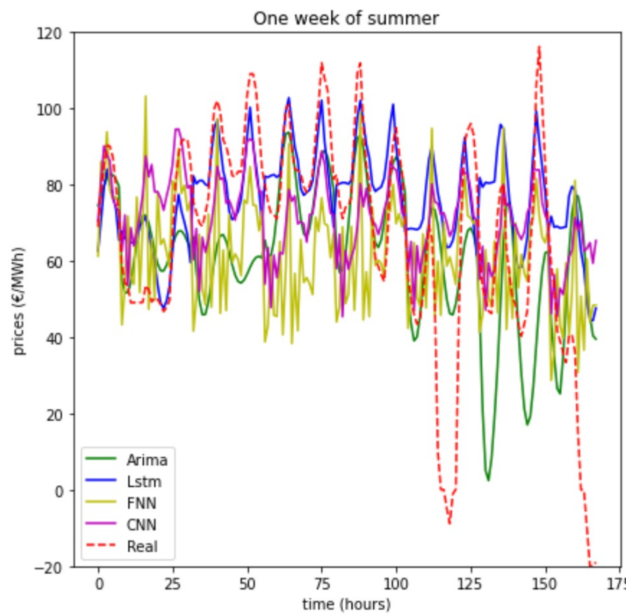

Fig. 28. Actual vs predicted value for a week in Summer for ARIMA, LSTM, CNN, FNN(MLP) models

In these figures we can see that there is a lot of fluctuations in electricity prices. Sometimes the prices spike and sometimes the prices see a precipitous fall. The predictions clearly show that the LSTM model performs the best among all other models whe trying to predict prices and comes closest to mimicking the ups and downs of the actual prices. The ARIMA model captures the overall behavior of price variation but fails to predict the rapid fluctuations and spikes. This is reflected in the scores of this model in table 4 , its MSE and MAE are relatively low while having a very high MAPE score (the MAPE score gets very high values when the prices are low and the difference between the prediction and real values is high). Nevertheless, it's important to note that due to practicality issues, we just implemented a simple ARIMA model that can be improved significantly by using wavelet-decomposition or by

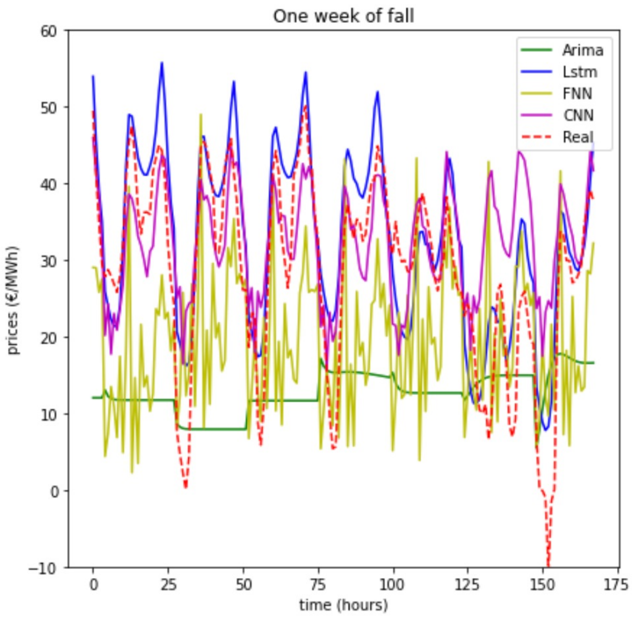

Fig. 29. Actual vs predicted value for a week in Fall for ARIMA, LSTM, CNN, FNN(MLP) models

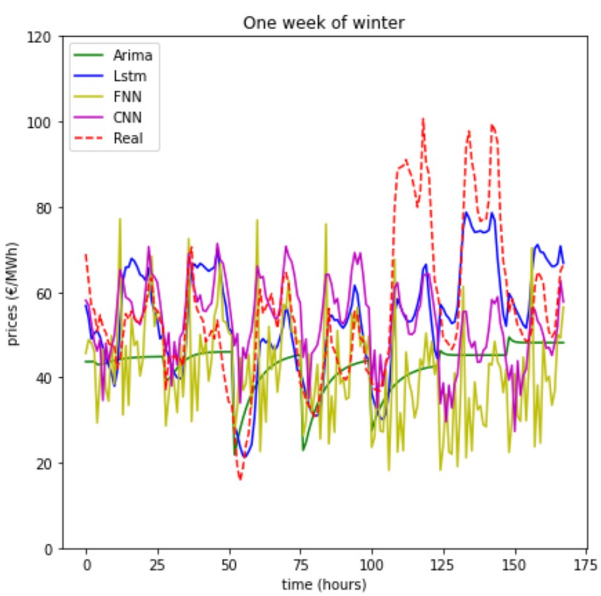

Fig. 30. Actual vs predicted value for a week in Winter for ARIMA, LSTM, CNN, FNN(MLP) models

adding exogenous features as explained in the literature review part.

In addition, it is important to note that the running time for making predictions with ARIMA was much longer than the running time for the training and testing stages of the FNN, CNN and LSTM

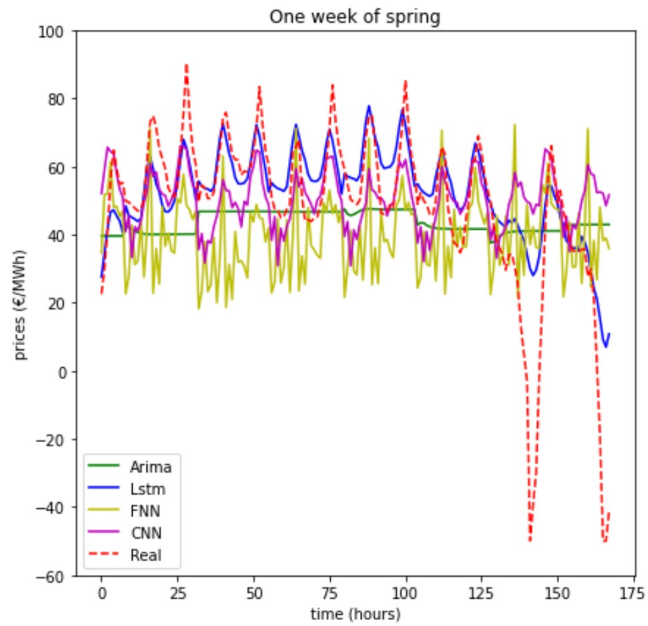

Fig. 31. Actual vs predicted value for a week in Spring for ARIMA, LSTM, CNN, FNN(MLP) models

methods. The running time of ARIMA was about 20 min while the running times of the other methods were about 5 min, on the same Colab notebook. Moreover, ARIMA is the only method that does not use a tensor and therefore its running time cannot be optimised with a GPU.

6 DISCUSSION AND CONCLUSION

This paper provides a review of the Electricity price forecasting research literature.

In the first part we described the framework of Electricity price forecasting by analyzing how the market is functioning, what are the horizons of the forecasts, what types of predictions are provided and what approaches are used to get these predictions.

Second, we studied the different modelling and predicting methods that have been the focus of electricity price forecasting research. We concluded that over the last three decades the methods used in this domain could classified into five main groups: multi-agent, fundamental, reduced form, statistical and computational intelligence methods, with the latter gaining more popularity in the last few years. For each of these methods we presented a few related research papers that utilized it for forecasting.

Finally, while focusing only on hourly and day ahead predictions, we implemented and compared four of the widely used and promising methods namely: ARIMA, Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). Our comparison was based on three years of German electricity market. We decided to use two years of data for training and testing the results on the remaining one year. Our results show that LSTM outperformed the other models according to the metrics we used. But it is noteworthy to mention that our comparison isn't perfect. During the implementation, many hyperparameters had to be manually chosen and different results could be achieved with different hyperparameter tuning.

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Electricity Price Forecasting

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Electricity price forecasting is of extreme importance for both governments and private companies. However, the price of electricity is very volatile, and its evolution depends on many external factors, which makes its prediction particularly challenging. Moreover, the development of renewable energy makes this prediction even harder and at the same time more relevant. Many methods have been developed since the last century to improve forecasting. The most widely used are statistical methods or methods based on Machine Learning and Deep Learning. The aim of this paper is to provide an overview of the main categories of these methods in order to highlight the general functioning of each of these categories and to understand their advantages and disadvantages. Furthermore, we provide in this paper a relatively simple implementation of four methods: ARIMA, MLP, CNN and LSTM, for hourly and day ahead predictions based on data from German electricity market. The results achieved could be improved by adding more complexity to model and adding more features. The objective is to illustrate the functioning, the implementation challenges, and the advantages of each of these methods. In our case, the results show that LSTM outperformed the other models in all our metrics.

Additional Key Words and Phrases: Electricity Price Forecasting, Statistical models, Deep Learning, Autoregressive Methods, LSTM, Neural Networks, Day ahead forecasting

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