HYBRIDISING NEUROFUZZY MODEL AND THE SEASONAL AUTOREGRESSIVE MODEL FOR ELECTRICITY PRICE FORECASTING ON GERMANY'S SPOT MARKET

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Abstract

Electricity price forecasting has become an area of increasing relevance in recent years. Despite the growing interest in predictive algorithms, the challenges are difficult to overcome given the restricted access to relevant data series and the lack of accurate metrics. Multiple models have been developed and proven to work in the area of EPF. This paper proposes a new univariate hybrid model, trained, and tested on German electricity market data, based on the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and the NeuroFuzzy-Local Linear Wavelet Neural Network (LLWNN). Although a series of complex challenges create difficulties in refining the model, the proposed algorithm significantly narrows the gap between predictions and actual prices. The ability to predict the dynamics of the price of electricity on the spot market is an important asset for both suppliers and consumers, with a view on prophylactic calibration of supply-demand ratios. The model can be extended and applied to any energy market with a stable structure.

Keywords: electricity price forecasting; Seasonal Auto-Regressive Integrated Moving Average (SARIMA); NeuroFuzzy-Local Linear Wavelet Neural Network (LLWNN); univariate hybrid model; German electricity market.

JEL Classification: Q47, C51, C52, C53, C55.

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Introduction

In a period dominated by crises, it becomes cardinal for states to anticipate consumption fluctuations and cost variations, considering the impact this resource has on both households and the business environment. The ability to forecast the price of electricity has been a constant concern in research, and efforts to create a model capable of accurately reproducing market fluctuations are of the utmost importance. The present article adheres to research efforts aimed at determining a correlation algorithm dedicated to forecasting the evolution of prices in the electricity market (Zema and Sulich, 2022).

Considering the easy access to current information, the degree of development, the relevance to the market of the entire Union, as well as the stability of the system, we used Germany's spot electricity market for the validation of the proposed model. The spot market, also known as the day-ahead market, is the place where firm hourly electricity transactions are carried out with delivery on the day following the trading day. In other words, the seller and buyer agree today at a price negotiated on the spot, and the quantity negotiated is delivered tomorrow at a certain time. Germany had the highest net electricity production in recent years. This was 20.5% of the total production of the European Union, closely followed by France with 19.1%. Italy (10.2%) was another EU member state with a double-digit share (Eurostat, 2022).

More than half of all the EU's net electricity production was generated from non-combustible primaries. A mere 41.3% of net electricity was generated from combustible sources, including natural gas, oil, and coal. Twenty-four percent of net electricity generation came from nuclear power plants, while hydropower plants (13.8%), and solar energy (5.3%) close the echelon. The clear trend towards a changing energy mix, along with complex geopolitical developments, will have a relevant impact on energy market price developments in the near future (European Commission's Directorate for Energy, 2022).

The present paper is proposing a new, univariate hybrid model to be used for electricity price forecasting, based on work already developed in the literature and proven to work in this area, based on the SARIMA (Seasonal Autoregressive Integrated Moving Average) model and the NeuroFuzzy-LLWNN (Local Linear Wavelet Neural Network) model.

The article begins with a chapter of theoretical considerations intended to place the topic in the context of specialised literature, while also bringing considerations regarding its relevance and topicality. Subsequently, a foray into the methodological plan is made, the two models, SARIMA and NeuroFuzzy-LLWNN, being explained, based on which the hybrid electricity price forecasting model will be developed. In the analysis chapter, the algorithm obtained is applied to the electricity spot market in Germany. In the last part of the paper, the forecast results are evaluated, demonstrating the accuracy of the developed hybrid model by referring to the independent operation of its basic components.

1. Theoretical considerations

Electricity Price Forecasting (EPF) is becoming a more and more pressing issue year by year, as shown in the bibliometric study done by Zema and Sulich (2022). As mentioned in their paper, some of the arguments for the importance of EPF range from the influence it brings on a company's stock (Tanasie et al., 2022) to influencing the operational decisions made by certain companies (Weron, 2014a).

A growing number of parametric and non-parametric models have been applied to the area of electricity price forecasting (EPF) in the research literature over the years (Weron; 2014b). Models such as SARIMA have already demonstrated to be very effective for the task of predicting electricity prices (Karabiber and Xydis, 2019), but of course, the fact that SARIMA models have a difficulty in predicting non-linear behaviour has to be taken into consideration.

For tackling this issue, the literature suggests the usage of Artificial Neural Networks (ANNs) with different kinds of variation in their architecture (Wang and Ramsay, 1998; Pao, 2007; Wang, et al., 2016). Models like these come with a series of initial advantages, such as handling the aforementioned non-linearity issue, improving the overall robustness of the analysis. However, ANNs can present some limitations when taking into account the choice of activation function (sigmoid), which can make the model converge to a point of local minima. Moreover, the random sampling of the initial weights can increase the training times significantly, which makes it even harder to iterate on the model architecture (Ben-Amor, Boubaker and Belkacem, 2018).

In order to solve the classical ANNs shortcomings, the literature suggests using LLWNNs instead, to try to forecast electricity prices (Pany and Ghoshal, 2015). LLWNN stands for Local Linear Wavelet Neural Network and represents a special solution to the multidimensionality problem of the WNN networks (Chen et al.; 2004) as originally developed by (Pati and Krishnaprasad, 1993). However, creating a hybrid model between LLWNN and the NeuroFuzzy Model, was proven to improve it when applied to price forecasting in FOREX (Forex, also known as FX or foreign exchange, is the exchange of one currency for another at an agreed price) markets by Mohapatra, Munnangi and Patra (2013), but was also successfully applied to electricity price forecasting by (Pany and Ghoshal, 2013).

Chen (2004), Dong, et al. (2011), Maciejowska and Nowotarski (2016) and Zhang, Tan and Wey (2020) have also addressed the issue of hybrid models in an attempt to solve the complex difficulties of forecasting electricity prices. In light of the proven effectiveness of hybrid models, we propose such a model using SARIMA for the regular components and a NeuroFuzzy-LLWNN for the irregular ones. Using a NeuroFuzzy-LLWNN instead of a more classical ANN approach, we solve the issues mentioned in the above paragraphs, thus improving the overall effectiveness of the model.

An approach to break down a signal into a number of intrinsic mode functions (IMF) and a residue that represents the trend is known as Empirical Mode Decomposition (EMD). EMD is a technique for obtaining instantaneous frequency data, performing well for data sets that are characterised by non-linearity and non-stationarity (Qiu, Suganthan and Amaratunga, 2017).

Ensemble empirical mode decomposition builds upon the classical EMD technique by combining the original timeseries with an ensemble of white noise data. Because the white noise has the effect of creating a consistent reference frame in the time-frequency domain, it captures the component of the signal with a similar scale into one IMF (Rilling and Flandrin; 2009). EMD has been successfully applied, using different model architectures, in the area of EPF by multiple authors (Qiu, Suganthan and Amaratunga, 2017; Buyukshain and Ertekin, 2019).

The aim of our paper is to create a hybrid model architecture based on previously proven statistical techniques that aims to solve the weaknesses present in the models when taken separately. This can be achieved by decomposing the time series and trying to predict its regular and irregular components separately.

2. Methodology

2.1. SARIMA Model

Because of the dependence on climate conditions that can affect changes in demand, electricity prices show seasonal features (Huurman, Ravazzolo and Zhou, 2012). The seasonal Autorregressive Integrated Moving Average Model (SARIMA) has been proven to work for predicting regular components of nonstationary time series, having been successfully applied in the area of electricity price forecasting (Buyukshain and Ertekin, 2019; Zhang, Tan and Wey (2020). George, Jenkins and Reinsel (1970) and Zhang, Tan and Wey (2020) describe the SARIMA model $(p,d,q)(P,D,Q)_S$ using the following:

$$\phi_p(B)\Phi_P\left(B^S\right)(1-B)^d\left(1-B^S\right)^D x_t=\theta_q(B)\Theta_Q\left(B^S\right)e_t \tag{1}$$

With

$$\begin{aligned}\varphi(B)&=1-\varphi_1 B-\varphi_2 B^2-,\cdots-\varphi_p B^p\\ \Phi_P\left(B^S\right)&=1-\Phi_S B^S-\Phi_{2S}B^{2S}-,\cdots-\Phi_{PS}B^{PS}\\ \theta_q(B)&=1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q\\ \Theta_Q\left(B^S\right)&=1-\Theta_S B^S-\Theta_{2S}B^{2S}-,\cdots-\Theta_{QS}B^{QS}\end{aligned}$$

Where:

D and *d* are the order of the seasonal and regular differences, respectively;

P and p represent the order of the periods taken into account in the autoregressive component (seasonal and regular);

Q and q represent the order of the periods considered in the moving average component, S is the number of periods in a year for which the seasonality of the time series repeats;

B being the lag operator;

and x_t and e_t represent the regular component and the white noise;

$\varphi($ (B) and $\varphi($ (B) represent the regular, respectively seasonal autoregressive components, and - θ (B) and θ (B) represent the regular, respectively seasonal moving average components.

2.2. NeuroFuzzy model

Ever since the creation of the LLWNN model by Whitcher (2004), it has shown more accuracy than the traditional WNN for time series forecasting. The main idea of LLWNN is to replace the connections between the hidden layer and the output with a local linear model. The advantages of this approach, as presented by (Mohapatra, Munnangi and Patra, 2013), include the good performance proven by the adoption of local linear models in several neurofuzzy systems, performing better than the standard LLWNN in terms of accuracy, error convergence speed, and its capability of handling uncertainties.

The general architecture for this neural network can be seen in (Figure no. 1). The model consists of 5 layers, starting with layer 1 which takes the form $u^{(1)}_i = x_i$, and just represents the plain input layer.

For the LLWNN side, the second layer represents the wavelet function for each node:

$$\phi = \left\{ \phi_i = |a_i|^{-1/2} \phi\left(\frac{x - b_i}{a_i}\right) : a_i, b_i \in R^n, i \in Z \right\} \tag{2}$$

a_i and b_i are the scale and translation parameters, and $i = 1,...,2n$. The third layer on the LLWNN side is represented by the two outputs of each part of the neural network.

Recall that the output of an LLWNN network is given by:

$$\begin{aligned} y &= \sum_{i=1}^{M} (w_{i0} + w_{i1}x_1 + \ldots + w_{in}x_n)\, \varphi_i(x) \\ &= \sum_{i=1}^{M} (w_{i0} + w_{i1}x_1 + \ldots + w_{in}x_n)\, |a_i|^{-1/2} \varphi\left(\frac{x - b_i}{a_i}\right) \end{aligned} \tag{3}$$

For the NeuroFuzzy component, the second layer is represented by the following equation that calculates the membership for a given input, using a Gaussian membership function:

$$u_{ij}^{(2)} = exp(\frac{-[u_i^{(1)} - m_{ij}]^2}{\sigma_{ij}^{(2)}}) \tag{4}$$

From the nodes of a set in layer 2, the nodes in layer 3 obtain one-dimensional membership degrees of the related rule. Here, the precondition function of the fuzzy rules is carried out using the product operator that is defined as:

$$u_j^{(3)} = \prod_i u_{ij}^{(2)} \tag{5}$$

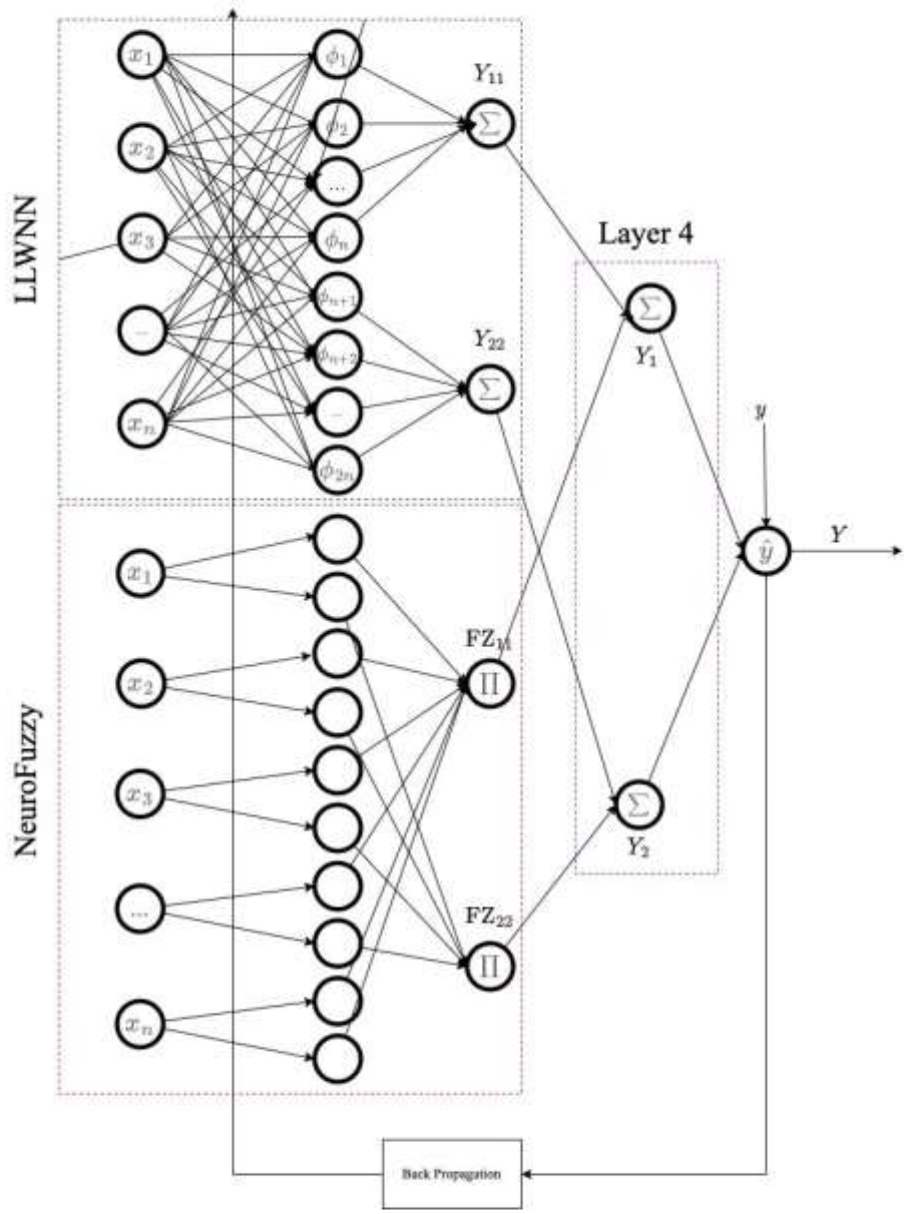

Figure no. 1. LLWNN-Neurofuzzy model architecture

Layer 4 is a layer that consists of consequent nodes, and they contain the NeuroFuzzy ouput from Layer 3, and the LLWNN output from layer 3, using the following equation:

$$u_j^{(4)} = u_j^{(3)} \sum_{k=1}^{M} w_{kj} \psi_k \tag{6}$$

where ψ_k is the functional expansion of the input and w_{kj} represents the weights of the LLWNN. The last layer of the neural network acts as a defuzzification one and takes as input the Layer 3 outputs of the LLWNN and NeuroFuzzy parts of the model, being represented by the following equation:

$$y = (y11.Fz11 + y22.Fz22)/(Fz11 + Fz22) \quad (7)$$

where y11 and y22 represent the output values of the LLWNN component and Fz11 and Fz22, respectively, represent the output values of the NeuroFuzzy component. More details regarding (1), (2), (3), (4), (5), (6), (7), internal architecture and backpropagation are presented by the authors in Mohapatra et al. (2013).

Taking this into consideration, we propose the usage of this model for the prediction of the irregular components in our final hybrid model.

2.3. Ensemble Empirical Mode Decomposition (EEMD)

As mentioned in Section 2, EEMD is an extension of EMD designed to solve the mode mixing problem. The data $x_{(t)}$ often consists of both the signal $s_{(t)}$ and the noise $n_{(t)}$:

$$x(t) = s(t) + n(t) \quad (8)$$

As mentioned in Khan et al. (2021), EEMD is a technique designed to remove the white noise from the data, since it is usually what obstructs it. To get rid of the noise in the data, EMD decomposes it by extracting a set of IMFs and a residual. Intrinsic Mode Functions are oscillatory, with variation in amplitude and frequency. By locating all local maxima and minima and linking them with cubic splines to construct the upper and lower envelope, a time series must first be divided into a number of IMFs. The envelopes' means are then calculated. The first IMF is then produced by subtracting the mean from the original data. The process repeats until a monotonic function is obtained. Given equation nr. 8, and according to Khan, et al. (2021), this process can be represented mathematically by:

$$x_{(t)} = \sum_{i=1}^{n} c_j + r_n \quad (9)$$

where r is the residue and n is the number of IMF extracted.

2.4. Stages of the hybrid univariate model

As previously shown, the main contribution of our paper is creating a hybrid model that combines SARIMA and NeuroFuzzy-LLWNN in order to forecast day-ahead electricity prices. Our proposed hybrid model consists of two steps, as described below (see also figure No. 2):

- The first step is Data decomposition. Different components with different characteristics should be extracted to better capture the complex features of electricity prices. Thus, Ensemble Empirical Mode Decomposition EEMD is used to convert the original electricity price into some regular and irregular component.

- The second step consists of selecting a suitable model for each component according to its own characteristics. Some components will exhibit regular characteristics. Thus, SARIMA is used for these regular components. Then the hybrid NeuroFuzzy model is selected for irregular components forecasting, which can capture the irregular changing trend.

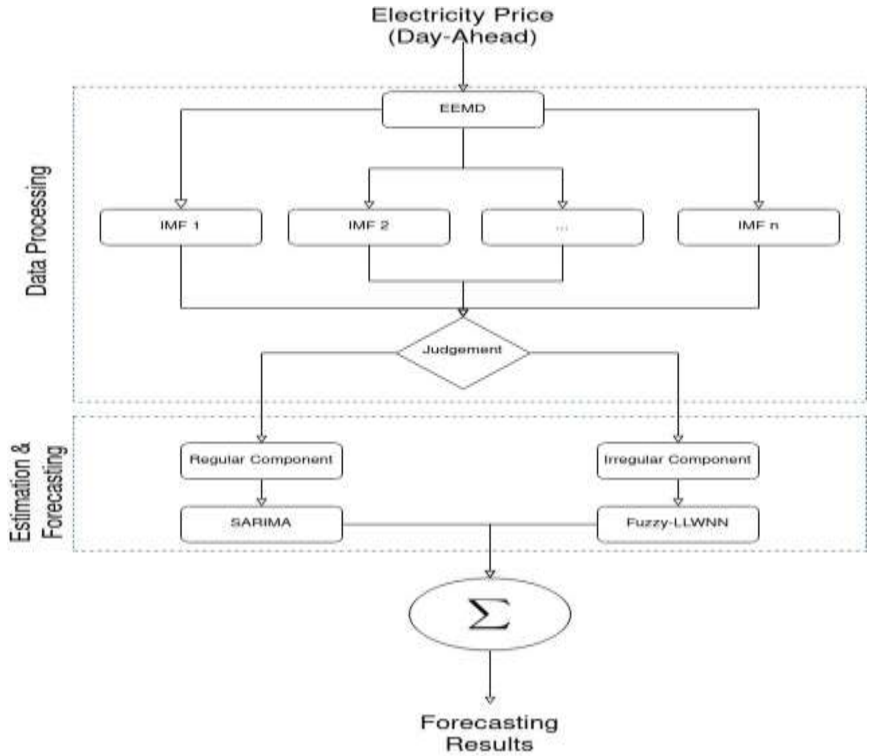

Figure no. 2. LLWNN-NeuroFuzzy model architecture

3. Analysis

3.1. Data

Our dataset consists of day-ahead electricity price data downloaded from the ENTSO-E transparency platform (see transparency.entsoe.eu). The dataset begins on 01.01.2015 and ends on 31.12.2021. In figure no. 3, we can see an overview of the full dataset. We can immediately deduct some special characteristics of the German electricity market, that being the occurrence of price spikes in both the positive and negative directions.

The model is applied to the German spot electricity market. This specific market was chosen for the implementation of the presented model, because it is considered to be a well-developed market, which is why the model could be generalised for other spot-type energy markets.

The proposed data set is divided into two subsets, the first being represented by energy prices between 2015 and 2018, used to estimate the parameters of the presented model, and the second, between 2019 and 2021, used to test its accuracy, this testing having been carried out outside the sample used for estimation .

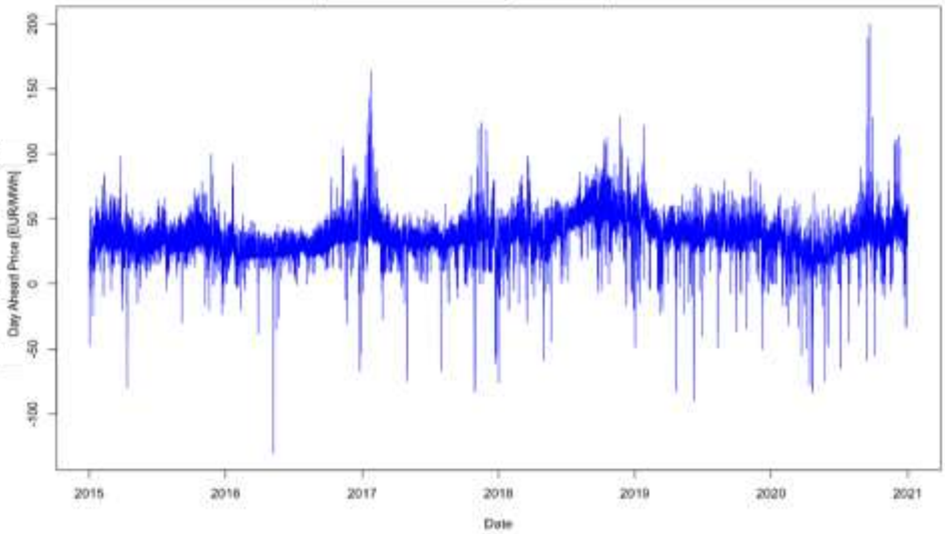

Figure no. 3. German electricity prices time series

3.2. Evaluation metrics and statistical tests

Every good EPF paper should have clear evaluation metrics. As already mentioned in (Lago et al.; 2021), the most commonly used evaluation metrics used to evaluate point forecasting models are the mean absolute error (MAE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE).

$$\text{MAE} = \frac{1}{24N_\text{d}}\sum_{d=1}^{N_\text{d}}\sum_{h=1}^{24}|p_{d,h}-\hat{p}_{d,h}|,$$

$$\text{RMSE} = \sqrt{\frac{1}{24N_\text{d}}\sum_{d=1}^{N_\text{d}}\sum_{h=1}^{24}(p_{d,h}-\hat{p}_{d,h})^2},$$

$$\text{MAPE} = \frac{1}{24N_\text{d}}\sum_{d=1}^{N_\text{d}}\sum_{h=1}^{24}\frac{|p_{d,h}-\hat{p}_{d,h}|}{|p_{d,h}|}, \tag{10}$$

with $p_{d,h}$ and $\hat{p}_{d,h}$ the real, respectively, forecasted prices on day d and hour h, and N_d representing the number of days in the test dataset.

However, MAPE is typically dominated by the times of low prices and is likewise not very instructive, because MAPE values grow very big with prices near zero (independent of the real absolute mistakes). To solve some of the issues that come from these facts, the symmetric mean absolute percentage error is defined as:

$$\text{MAPE} = \frac{1}{24N_{\text{d}}}\sum_{d=1}^{N_{\text{d}}}\sum_{h=1}^{24} 2\frac{|p_{d,h} - \hat{p}_{d,h}|}{|p_{d,h}| + |\hat{p}_{d,h}|} \tag{11}$$

Further improvements can be made to these metrics by scaling them. If we extrapolate MAE by an in-sample error of a naive forecast, we obtain the mean absolute scaled error (MASE).

$$\text{MASE} = \frac{1}{N}\sum_{k=1}^{N} \frac{|p_k - \hat{p}_k|}{\frac{1}{n-1}\sum_{i=2}^{n}\left|p_i^{\text{in}} - p_{i-1}^{\text{in}}\right|} \tag{12}$$

with the i^{th} price of the training dataset represented by p_i^{in}, and the naive forecase of p_i^{in}, represented by p_{i-1}^{in}. N is the number of training (in-sample) data points and n is the number of testing (out-of-sample) data points.

On top of that, if we normalise MAE with a naive forecast based on the out-of-sample dataset, we obtain the relative mean absolute error (rMAE).

$$\text{rMAE} = \frac{\frac{1}{24N_{\text{d}}}\sum_{d=1}^{N_{\text{d}}}\sum_{h=1}^{24}\left|p_{d,h} - \hat{p}_{d,h}\right|}{\frac{1}{24N_{\text{d}}}\sum_{d=1}^{N_{\text{d}}}\sum_{h=1}^{24}\left|p_{d,h} - \hat{p}_{d,h}^{\text{naive}}\right|} \tag{13}$$

As already argued by (Lago et al.; 2021), a good EPF paper should always use a combination of these metrics in order to provide a more accurate description of the developed model, the reason for which, we are considering these five metrics for evaluating our proposed model: MAE, RMSE, sMAPE, MASE, and rMAE.

4. Results and interpretation

4.1. Descriptive statistics

The density function of the dataset can be seen in figure no. 4, and it resembles a normal distribution, a fact which is confirmed by the Jaruqe-Bera test result, which can be seen in Table no. 1. The dataset consists of 52.608 observations of price, with a mean of 34.563 EUR/MWh, and a standard deviation of 16.608. We have also pre-conducted an ADF test which confirms that we are dealing with a stationary process of the price of electricity between 2015-2021 in Germany.

In the present case, an estimated measurement of *skewness* indicates that the distribution is not symmetric. Additionally, this time series displays lepto-kurtic behavior based on a high level of *kurtosis*. Also, the high value of the Jarque–Bera (JB) test confirms this significant deviation from normality. This means that the German electricity time series does not follow a normal distribution.

In addition, unit root tests, specifically Augmented Dickey-Fuller (ADF), were performed, which test the null hypothesis of non-stationarity (unit root) against the alternative hypothesis of stationarity in a time series. ADF testing of the German electricity time series indicates that it is significant to reject the null hypothesis, stating that the time series are non-stationary. Thus, this series is stationary and suitable for further tests related to this study.

Table no. 1. Descriptive statistics for the German next-day electricity price

Electricity price	
Observations	52.608
Mean	34.563
Standard	16.608
Minimum	-130.090
25%	25.920
50%	34.020
75%	43.590
Maximum	200.040
Kurtosis	7.808
Skewness	-0.216
Jarque_bera test	81047.046 (0.000)***
ADF test	-15.288 (0.000)***

Note: Levels of significance of Jarque-Bera and ADF tests are indicated between squared brackets.
*** Denotes significance at 1% level.

4.2. Forecasting results

4.2.1 Forecasting using SARIMA model

In Figure. no. 4 we can observe that SARIMA can handle the forecasting pretty well on its own, but since data can have some irregularities, SARIMA forecasts are far from perfect. The errors for the SARIMA model can be seen in Table no. 2.

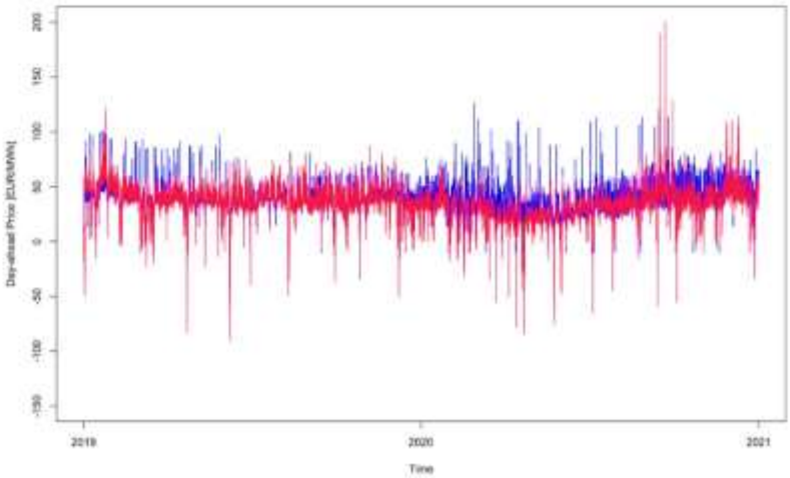

Figure no. 4. Original time series and SARIMA model predictions

4.2.2. Forecasting using the NeuroFuzzy – LLWNN model

The Fuzzy LLWNN model in figure no. 5, does not seem to perform much better than the SARIMA model, when taken separately. If we look at the errors in Table no. 2, they seem to confirm this behaviour, by showing only minor improvements.

Table no. 2. Error comparison between the component models and the final hybrid univariate model

Model	MAE	RMSE	sMAPE%	MASE	rMAE
SARIMA	16,060	20,281	43,825	1,682	2,204
Fuzzy-LLWNN	14,099	18,798	41,934	1,476	1,935
Hybrid	6,101	9,366	23,954	0,639	0,837

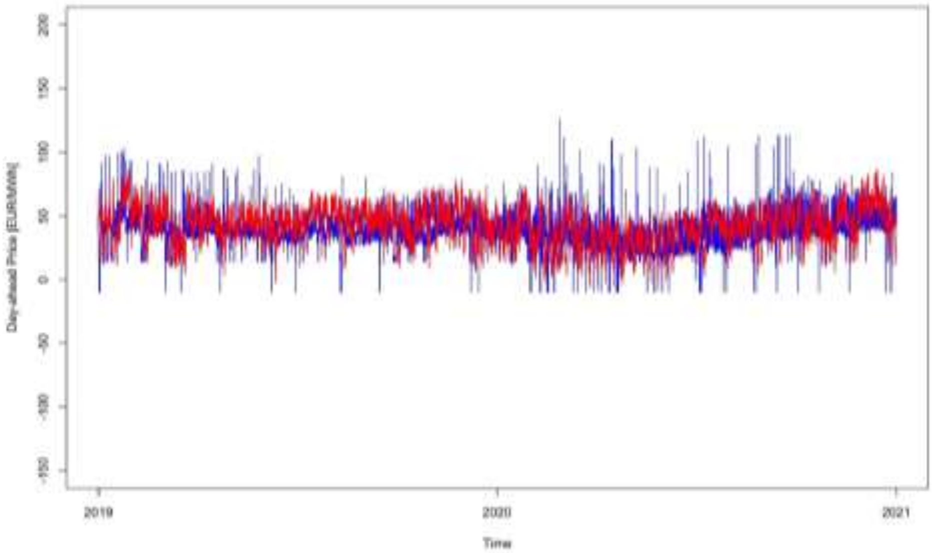

Figure no. 5. Original time series and Fuzzy-LLWNN model predictions

4.2.3. Forecasting based on univariate hybrid model

- *Ensemble Empirical Mode Decomposition Results (EEMD)*

This model shows the 9 Decomposed components or the intrinsic mode function (IMF). As we see here, the first component, i.e., IMF0, is the most complex component. We expected that the prediction accuracy of IMF1 will be the worst among all IMFs. And moving from IMF0 to IMF8, the prediction accuracy will be improved.

In the second stage, each IMF is considered an independent time series. By splitting the original series data into IMFs, that represent simpler components, the data is simplified, and the forecasting becomes more facile. In the third stage, the forecasted values of the IMFs are added together, in order to build the forecasted electricity price.

As seen in figure no. 6, regular behaviour is observed in IMF6 to IMF8, which can be attributed to the periodic features of electricity prices. Thus, the SARIMA model will be used to forecast these regular components. Besides, irregular behaviour is found in IMF1 to IMF5. Thus, the Fuzzy-LLWNN will be established to predict these irregular components.

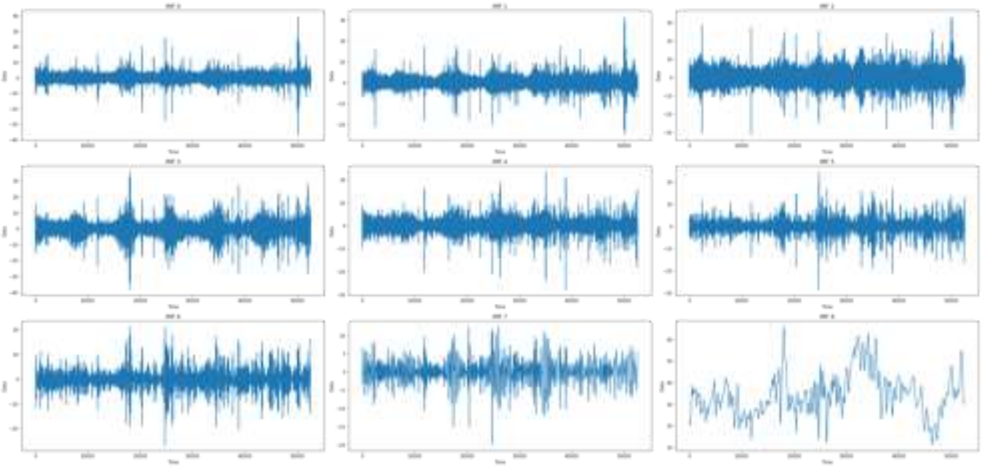

Figure no. 6. The original time series decomposed using the EEMD algorithm for 9 IMFs

- *Hybrid Forecasting*

The forecasting results of the hybrid model, obtained by applying the forecasts to each IMF described in the above paragraph, are clearly performing better than each model when taken separately, as can be seen in figure no. 7.

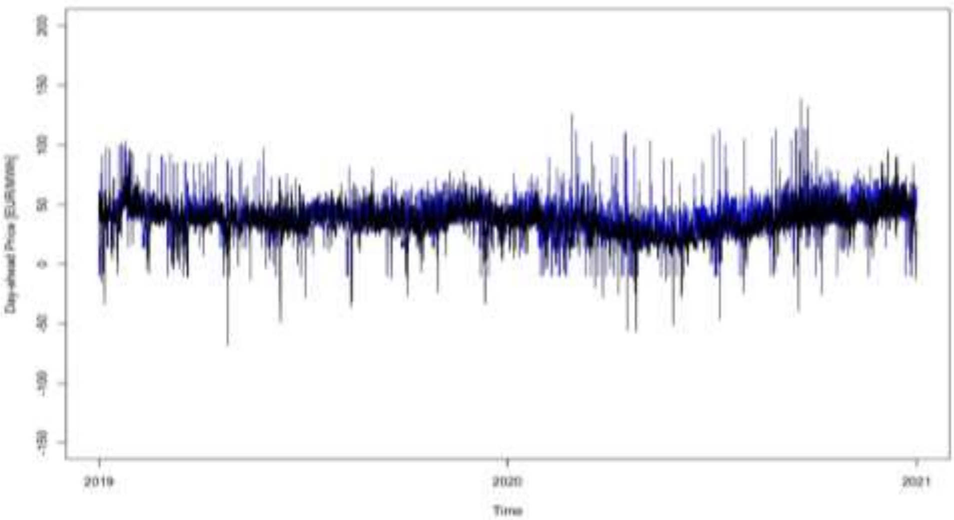

Figure no. 7. The original time series and the proposed hybrid model predictions

Moreover, this performance seems to be supported by the approximate halving of all of the errors.

Conclusions

The hybrid model developed in this paper demonstrates a remarkable performance, both by referring to the independent operation of its basic components, as well as from the perspective of a comparative evaluation made by means of the parameters that are widely used in specialised literature. This is simply a first step, as in the future improvements can be made by replacing SARIMA with a more complex, multivariate model, which can take into account more external variables or could even explain price changes that occur due to certain events on the international scene.

The proposed methodology brings an element of novelty to the specialised literature by choosing the components of the hybrid model itself. The obtained results have also been identified outside of the estimation sample, and this gives the methodology a degree of robustness for its use in future applications.

Accurate predictions represent a strong point of the hybrid SARIMA/Fuzzy-LLWNN methodology used in this article. The electricity price forecasting algorithm in the spot market in Germany can be hawked to applications already operational in the market, some of them obvious, such as the use of information for trading, others less obvious, such as the use of methodology predictions in order to improve the efficiency of electricity consumption according to the time interval, as well as within the "internet of things" type technologies.

The correlation matrix on the basis of which the evolution of the electricity market price developed in this model can be forecast is not infallible, as it works at an optimal level under normal market conditions. Beyond "black swan"-type events (very low-probability events, unpredictable) and various discontinuities, however, the systemic modeling capability provided by the hybrid SARIMA/NeuroFuzzy-LLWNN algorithm generates a high-fidelity picture of market evolution.

However, the proposed methodology also has more or less obvious limitations. First, it can only work on time series that exhibit the characteristics of the spot energy market. Time series relating to the prices of financial derivatives, including energy derivatives, cannot be subject to this methodology. Obviously, time series outside the field of electricity also have fundamentally different characteristics, which exclude them from the future application of the presented methodology.

Special, "black swan"-type events, such as the war in Ukraine, which led to an unprecedented increase in the prices of energy and energy products, are also limitations of the proposed methodology, which is why the data series used here stop in 2021. However, the presented application is considered important and should be used under normal market conditions.

The proposed model can work very well for spot energy data series and can be extended to more global spot electricity markets, depending on data availability, as future research directions.

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