MACHINE GENERATED TOOLS FOR SHORT-TERM FORECASTING OF THE PRICE OF THE ELECTRICAL ENERGY

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Abstract: In the contemporary context of energy markets, short-term electricity price forecasting plays a critical role for the efficient management of resources and optimization of energy systems. This paper explores the application of artificial intelligence and machine learning as tools for generating accurate short-term electricity price forecasts. We consider different algorithms, including neural networks, support vector machine learning, and time series, and analyze their accuracy and effectiveness in different real-world market conditions. The aim of the study is to provide a scientifically based view on the potential of machine-generated tools to improve the accuracy and reliability of short-term energy forecasts, which can contribute to greater stability and optimization of energy markets.

Key words: energy efficiency, electrical energy, forecasting, photovoltaic plant.

1. INTRODUCTION

Forecasting the use of electricity and its price is of considerable importance for various sectors of society, as well as from an economic point of view and ensuring the sustainability of the electricity system. One of the main problems that can be observed in this area is the management of costs, which affects both household consumers and industrial producers. For household consumers of electricity, forecasting the used electricity and its price allows for a more efficient use of resources, as well as reducing costs. For industrial consumers, this allows for the optimization of production costs, knowing at what point to increase or decrease production [1,2].

Another economic aspect that requires the development and use of electricity price forecasting is trading in energy markets. It is rational to implement optimization of electricity transactions, in which traders and suppliers have the opportunity to make adequate decisions for purchase and sale on the energy exchange, avoiding price risks.

Also, in this case, with the forecast prices made, the functioning of the energy market can be monitored and managed, thus ensuring transparency and stability [3,4].

From the point of view of the electricity system, it is necessary to ensure stability and sustainability of the provision of electricity. Forecasting electricity consumption could prevent interruptions, as various mathematical models of demand and supply are often included to reduce imbalances in the grids. Another significant problem is the large number of connected renewable energy sources, such as wind and photovoltaic power plants, which are highly dependent on external influences, as well as on weather conditions and regional characteristics. The possibility of obtaining advance information on the price of electricity a day ahead could encourage the use of more efficient and energy-saving measures, as well as investment in sustainable energy systems and ensuring reliable economic conditions in the future [5,6].

2. METHODOLOGIES

There are various methodologies that can be used to predict the consumed electricity and its price. Some of them are presented here, such as SARIMA, LSTM, and TCN [9-12]. Initially, it is necessary to evaluate the main metrics by which the prediction of the electricity price will be implemented. To validate the mathematical model, the input data used in the price prediction will be compared with the real output data at a specific time. This is necessary in order to determine the prediction error and after a certain number of iterations it can be reduced, which will lead to greater accuracy in the presented model.

There are several different analyses that can be used in this application. One of them is the correlation analysis, which uses Pearson's coefficient to determine the relative relationship between two independent variables. To determine the covariance of two independent variables, the following equation is used, in which the variables are divided by two by the product with a standard deviation [7,8]:

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

where $\rho_{X,Y}$ is always a value in the interval [-1;1]. The smallest value in this interval means negative correlation, and the largest value means full correlation.

Another commonly used analysis in forecasting and statistics is the Mean Squared Error (MSE). MSE is used to calculate the mean squared error over n number of trials. Equation (2) describes mathematically [9,10]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(A_t - F_t)^2 \tag{2}$$

Another problem encountered when using MSE is the graphical representation. To solve this problem, a similar analysis can be used, where the error is represented as a percentage in equation (3):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{3}$$

Where MAPE is Mean Average Percentage Error, A_t is real value and F_t is the forecasted value.

However, since using MAPE gives the same weighting function to all forecasts, to provide the percentage sum, WAPE can be used [11,12]:

$$WAPE = \frac{\sum_{t=1}^{n} |A_t - F_t|}{\sum_{t=1}^{n} |A_t|} \tag{4}$$

3. SIMULATION RESULTS

After implementing a simulation model, training of the neural network was implemented. Figure 1 shows a graph of the training and validation losses of a model during training for a certain number of epochs. The vertical axis (y-axis) shows the loss value, and the horizontal axis (x-axis) shows the number of epochs, from 0 to 50. The blue line represents the Training Loss. It drops sharply at the beginning and continues to decrease more smoothly as the number of epochs increases, indicating that the model is improving and minimizing the error in its predictions with respect to the training data.

The orange line represents the Validation Loss, which also decreases over time, although slightly more smoothly. This shows that the model is not only improving with respect to the training data, but also doing well with unseen data (the validation set), which is important for preventing overfitting.

Both the training and validation lines converge with each other over time, which shows good overall convergence of the model and indicates that it does not over-optimize to the training data, maintaining good generalization ability.

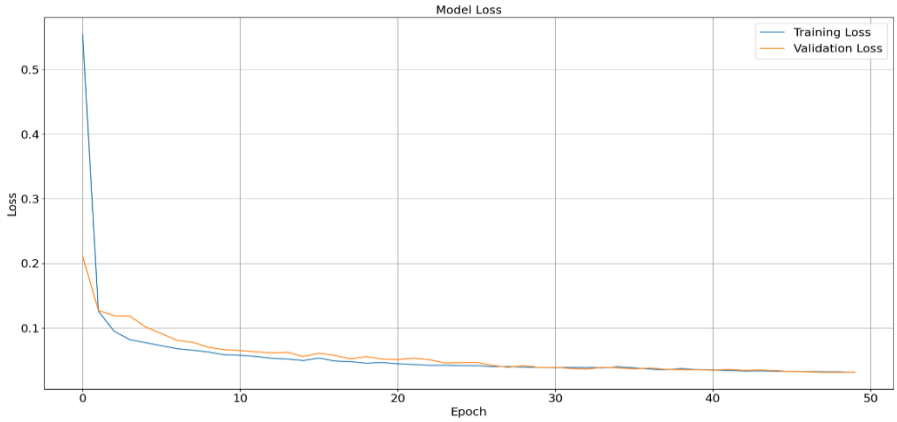

Figure 1. Training and validation loss

Figure 2 shows the graph used to forecast energy prices. From left to right, the horizontal axis (x-axis) shows dates and times, with the period from April 25, 2024 to May 31, 2024. The vertical axis (y-axis) shows prices in euros (EUR). Specifically, the graph shows two lines: The blue line shows historical energy prices for the period from April 25 to May 30. This line shows price fluctuations that reach over €150 at times. The orange line, which starts on May 30, shows the forecast energy prices for the next day,

May 31. This line shows an expectation of lower prices compared to historical data, with fluctuations appearing to be less pronounced than those used in training.

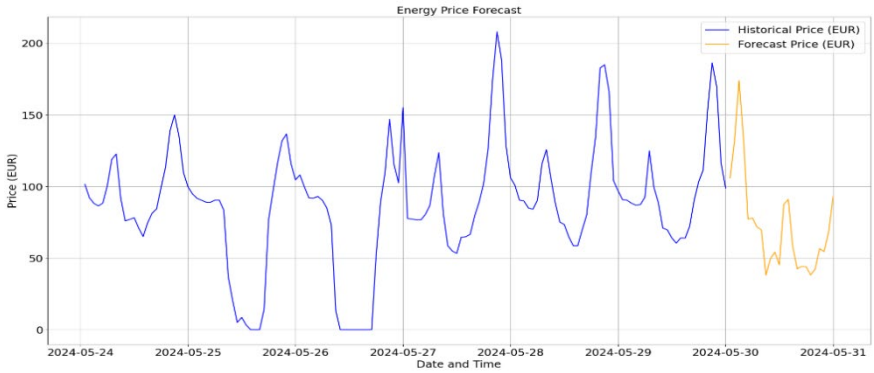

Figure 2. Historical price and forecasted prices in EUR

Figure 3 presents a comparison between the forecasted and actual electricity prices in leva per megawatt-hour (BGN/MWh) for the day 30.05.2024. The graph shows price fluctuations during different hours of the day. The forecasted price, shown in red, follows the general trend of the actual prices, depicted in blue, quite well, although there are some differences in the amplitude of the fluctuations and in the exact hours of the peak values. During the early hours of the day around 5 am, the forecasted price is higher than the actual one. There is a noticeable deviation around 2-3 pm, where the actual price reaches its peak, while the forecasted one shows a smoother approach. Late in the evening around 9 pm, it is again noticeable that the forecasted price is lower than the actual one. These differences can be further investigated to improve forecasting models, as accurate forecasts are critically important for optimizing the purchase and sale of electricity in the markets.

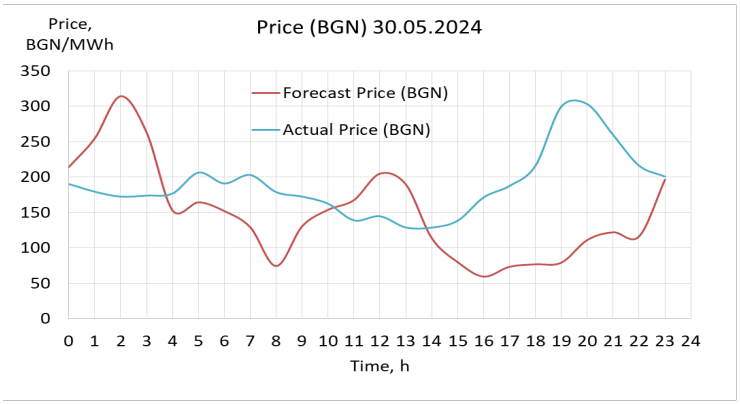

Figure 3. Forecasted and actual price of electrical energy in BGN/MWh for 24h

These differences can be further investigated to improve forecasting models, as accurate forecasts are critically important for optimizing the purchase and sale of electricity in the markets.

Figure 4 shows the forecast and actual electricity prices for the date 30.05.2024. The horizontal axis represents time in hours (from 0 to 24), and the vertical axis shows the price in euros per megawatt-hour with a range from 0 to 200. The graph shows that in the initial hours the forecast price is significantly higher than the actual price, reaching a peak around 3:00 a.m. After 6:00 a.m. the actual price remains relatively stable, while the forecast price varies and shows lower values. Around 7:00 p.m. the actual price reaches a second peak, while the forecast price remains at lower levels until the end of the day. The forecast and actual prices converge in some intervals, especially around 10:00 a.m. and 10:00 p.m. The graph presents a clear visualization of the differences between forecasted and actual electricity prices throughout the day.

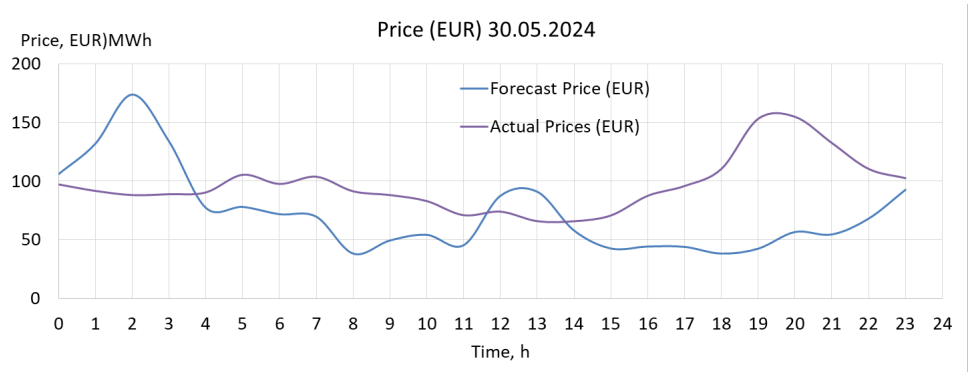

Figure 4. Forecasted and actual price of electrical energy in EUR/MWh for 24h

Figure 5 graph showing the forecast and actual volumes of electricity for the date 30.05.2024. The horizontal axis represents time in hours (from 0 to 24), and the vertical axis shows the volume in megawatt hours (MWh) with a range from 0 to 4000. The graph shows that at the beginning of the day the forecast volume is higher than the actual, with the forecast starting at around 3500 MWh, while the actual value is around 2500 MWh. After 6:00 a.m. the actual volume starts to increase and exceeds the forecast at around 7:00 a.m., reaching a peak around 8:00 a.m. After this point, the forecast volume remains relatively stable with a slight increase, while the actual volume shows significant fluctuations. Around 2:00 p.m. the forecast volume exceeds the actual, but towards the evening hours the actual values again exceed the forecast. The graph clearly demonstrates the dynamics and differences between the forecast and actual volume of electricity throughout the day, with in some intervals the forecast approaching the actual values, while in others significant deviations are observed.

When analyzing the relationship between the data in Figure 4 and Figure 5, the following conclusions can be drawn:

- At the beginning of the day (from 0 to 6 hours) the forecast price is higher than the actual one, while the volume shows the opposite trend - the forecast volume is higher than the actual one. This may mean that demand was lower than expected, which led to lower actual prices;

- Around 7:00 a.m. the actual volume exceeds the forecast, which coincides with a moment when the actual price approaches the forecast. This indicates that the increasing demand has led to the stabilization of prices relative to the forecast values;

- In the interval between 12:00 and 15:00 p.m. the actual volume falls below the forecast, and the actual price is below the forecast value. This may be due to lower than expected consumption, which has exerted downward pressure on prices.

- The evening hours (after 6:00 PM) show a significant increase in actual volume, exceeding the forecast, which coincides with an increase in the actual price above the forecast value. This is an indicator of increased demand during peak hours, leading to higher prices.

The analysis of the two graphs reveals a clear relationship between volume and price - when actual volume increases relative to the forecast, actual prices also increase, while when demand is lower than expected, prices decrease.

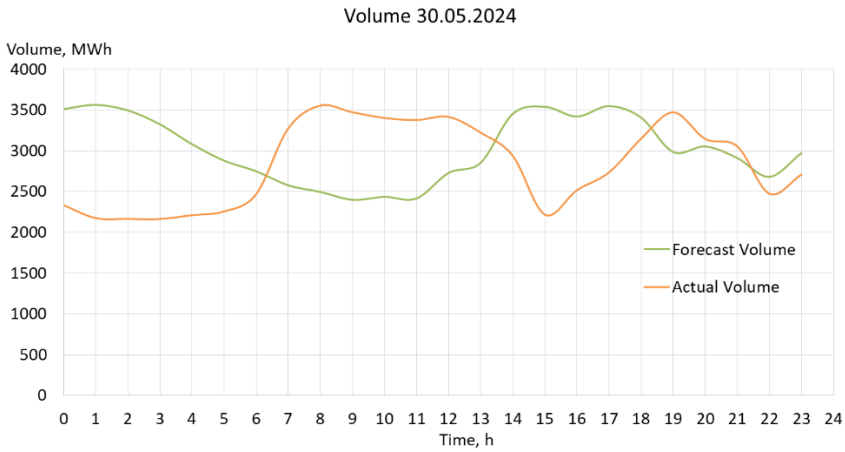

Figure 5. Forecasted and actual volume of electrical energy in MWh for 24h

Table 1 presents data on the actual and forecast price of electricity, as well as the volume of energy.

Table 1. Forecasted and actual prices in BGN and EUR

Forecast			***Actual Prices***		
Forecast Price (EUR)	***Forecast Price (BGN)***	***Forecast Volume***	***Actual Prices (EUR)***	***Actual Price (BGN)***	***Actual Volume***
106.036087	*214.249*	*3511.196*	*97.28*	*190.26*	*2331.8*
132.0522766	*254.796*	*3561.54*	*91.74*	*179.43*	*2174*
173.9834137	*314.3644*	*3493.888*	*88.18*	*172.47*	*2165.1*
133.9623718	*263.004*	*3323.533*	*88.94*	*173.95*	*2162.9*
77.2508316	*152.744*	*3080.226*	*90.44*	*176.89*	*2209.9*
78.05271912	*164.3412*	*2878.785*	*105.51*	*206.36*	*2255.5*
71.85353851	*151.9474*	*2747.844*	*97.67*	*191.03*	*2467*
69.7334671	*129.0454*	*2576.823*	*103.85*	*203.11*	*3272.8*
38.20581055	*74.24085*	*2495.057*	*91.4*	*178.76*	*3552.8*

49.43600464	130.4466	2398.434	88.2	172.5	3471.3
54.22951508	153.8077	2434.792	83.05	162.43	3401.7
45.36080551	167.59	2414.932	71	138.86	3376.6
87.54550171	204.9182	2728.273	74.02	144.77	3413.8
91.04020691	189.7111	2852.871	65.89	128.87	3221.1
57.91886139	113.8204	3451.767	65.82	128.73	2937.3
42.58245468	79.86469	3538.356	70.77	138.41	2216.3
44.24833298	59.38475	3418.64	87.57	171.27	2516.1
43.96012497	73.30128	3546.649	95.89	187.54	2734.5
38.22477341	76.77946	3405.545	110.46	216.04	3147.1
42.38970184	79.06448	2983.766	153.24	299.71	3470.8
56.65880966	111.0775	3052.235	155	303.15	3144.4
54.56725311	122.049	2910.037	132.68	259.5	3052.4
68.06983948	116.212	2679.94	110.51	216.14	2473.2
92.73459625	196.5146	2972.647	102.61	200.69	2707.7

The summary data from the information provided in Table 1 shows the following main features:

- The average forecast price of electricity is 72.92 EUR (149.72 BGN), while the average actual price is 96.74 EUR (189.20 BGN), which indicates that actual prices are usually higher than the forecast ones. The standard deviation for forecast prices is 34.86 EUR, while for actual prices – 23.55 EUR, which means that forecast prices are more volatile.

- The minimum forecast price is 38.21 EUR, while the minimum actual price is 65.82 EUR. Accordingly, the maximum values are higher for actual prices, which suggests that market conditions have led to higher than expected prices;

- As for the volume, the average forecast volume is 3019.07 MWh, while the actual average volume is 2828.17 MWh. This means that actual consumption is usually lower than forecasted. The lowest value of the forecast volume is 2398.43 MWh, and the actual – 2162.90 MWh. The maximum values show that in some cases the actual volume exceeds the forecast;

Overall, the data shows a trend towards higher actual prices and lower actual volumes compared to the forecast values, which may be due to various market factors such as demand, supply and external influences.

Table 2 provides the statistical data. The analysis of the provided statistical data on electricity prices and volumes reveals several key observations. The average price is 72.92 EUR (149.72 BGN), which indicates a moderate level of electricity costs during the observed period. The standard deviation of 34.86 EUR (66.89 BGN) indicates that there are significant fluctuations in prices. The minimum price is 38.21 EUR (59.38 BGN), while the maximum reaches 173.98 EUR (314.36 BGN), which indicates a wide range of fluctuations. The first quartile (25%) is 45.08 EUR (103.27 BGN), which means

that 25% of the observations are below this value. The median value (50%) is 62.99 EUR (141.20 BGN), which indicates that half of the data are below this value and the other half are above it. The third quartile (75%) is 88.42 EUR (191.41 BGN), which indicates that 75% of the data is below this value.

Table 2. Statistical summary

	Price (EUR)	***Price (BGN)***	***Volume***
count	*24*	*24*	*24*
mean	*72.92072*	*149.7197*	*3019.074*
std	*34.86417*	*66.8889*	*406.5308*
min	*38.20581*	*59.38475*	*2398.434*
25%	*45.08269*	*103.2743*	*2716.19*
50%	*62.99435*	*141.197*	*2978.207*
75%	*88.41918*	*191.412*	*3426.922*
max	*173.9834*	*314.3644*	*3561.54*

In the analysis of electricity volume, the average volume is 3019.07 MWh, which represents the typical level of consumption within the observed period. The standard deviation of 406.53 MWh shows a relatively high variation in volumes. The minimum volume is 2398.43 MWh, while the maximum reaches 3561.54 MWh, which indicates significant differences in consumption. The first quartile (25%) is 2716.19 MWh, which means that in 25% of the time the consumption was below this value. The median (50%) is 2978.21 MWh, which means that half of the time points have a volume below this value. The third quartile (75%) is 3426.92 MWh, indicating that 75% of the values are below this threshold.

The data analysis shows significant volatility in both prices and volumes of electricity, which can be due to factors such as market demand, seasonality, or regulatory changes. The difference between the minimum and maximum values is large, suggesting volatile market conditions. Half of the prices and volumes are concentrated around the median values, indicating relative stability over the long term. Looking at the quartiles, it is seen that in some cases prices can be significantly higher than the average values, suggesting peak periods of high demand. This analysis can help energy companies or consumers plan their costs and consumption more effectively by taking into account the peak and minimum values of prices and volumes.

4. CONCLUSION

In conclusion, the study demonstrates the significant potential of machine-generated tools for short-term electricity price forecasting. By applying various algorithms, including neural networks, support vector machines, and time series, it was found that these methods can provide high accuracy and reliability in predicting electricity prices in real market conditions. Analysis of forecast and actual values showed that although the forecasts follow the general trend of actual prices, there are deviations, especially in certain time intervals, such as early morning hours and peak periods during the day.

These differences highlight the complexity of market conditions and the need for more accurate forecasting models.

The results of the study confirm that the use of machine learning can significantly support the process of energy resource management by ensuring more efficient planning and allocation of electricity. Optimizing electricity trading through accurate forecasts helps to minimize financial risks and improve market transparency. For industrial users, this means the opportunity to better plan production processes, while for households, accurate forecasts can lead to cost reductions and more efficient use of resources.

The study also reveals some challenges related to factors such as the volatility of renewable energy sources, the impact of climate conditions and demand dynamics. These factors can affect the accuracy of forecasts and require improvements in the methods and models used. Future research could focus on developing hybrid models that combine different machine learning techniques and statistical approaches for more precise and adaptive forecasts.

The study makes it clear that the application of modern analytical methods and algorithms for forecasting electricity prices is not only necessary, but also inevitable for achieving higher efficiency and sustainability of energy markets. The integration of these technologies into energy systems can contribute to stability, lower costs and sustainable development of the sector in the long term.

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