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Electricity price forecasting on the day-ahead market using artificial intelligence algorithms

***Abstract**. This article presents the application of AI algorithms to predict hourly product prices in the uniform price auction system of the Polish Power Exchange. It involves analyzing the electricity price determination process, identifying factors shaping price curves, reviewing literature on AI methods for electricity price prediction, proposing a research methodology, and modeling solutions using artificial neural networks. Nine variants of multilayer perceptrons with backpropagation were optimized and compared using most common indicators. Results were compared with forecasts from foreign articles for other European markets to evaluate the effectiveness of using AI in predicting electricity prices in the Polish Day-Ahead Market.*

***Streszczenie.** W artykule przedstawiono zastosowanie algorytmów sztucznej inteligencji do predykcji ceny produktów godzinowych w notowaniach w systemie kursu jednolitego na rynku dnia następnego energii elektrycznej Towarowej Giełdy Energii. Przeanalizowano proces wyznaczania cen energii elektrycznej, identyfikację czynników kształtujących krzywe cenowe, dokonano przeglądu literatury dotyczącej zastosowania metod sztucznej inteligencji do predykcji cen energii elektrycznej, zaproponowano metodologię badań oraz zamodelowano rozwiązanie z wykorzystaniem sztucznych sieci neuronowych. Zoptymalizowano i porównano dziewięć wariantów perceptronów wielowarstwowych z propagacją wsteczną. W celu oceny skuteczności wykorzystania sztucznej inteligencji w prognozowaniu cen energii elektrycznej na polskim Rynku Dnia Następnego, otrzymane wyniki porównano z prognozami z artykułów zagranicznych dla innych rynków europejskich. (**Prognozowanie cen energii elektrycznej na rynku dnia następnego z wykorzystaniem algorytmów sztucznej inteligencji**)*

Keywords: artificial neural networks, electricity price forecasting, day-ahead market, TensorFlow
Słowa kluczowe: sztuczne sieci neuronowe, prognozowanie ceny energii elektrycznej, rynek dnia następnego, TensorFlow

Introduction

Predicting electricity prices enables better estimation of revenue from energy trading. This allows for conducting economic analyses for investments related to the power industry, where projected cash flows align more closely with reality. Energy companies, by having access to forecasts that accurately and precisely predict future electricity prices, can significantly shape their business strategies. In addition to traditional statistical methods, artificial intelligence methods and machine learning can be utilized for electricity prediction. The aim of this article is to examine the possibilities of effectively forecasting electricity prices for the Polish energy market using the artificial intelligence method based on historical data of hourly product prices in the uniform price auction system and data related to the operation of the power system.

Determination of electricity prices in the uniform price auction system on Day-Ahead Market

The Day-Ahead Market is one of the spot markets operating within the Commodities Exchange Market conducted by the Polish Power Exchange (Towarowa Giełda Energii S.A.) (TGE) [1]. In 2022, the total volume of electricity traded in the spot markets reached 33,026,770 MWh. Within the Day-Ahead Market, this trading volume accounted for 94% of the total volume in the spot markets, while the remaining 6% was attributed to the Intra-Day Market [2].

The uniform price in the Day-Ahead Market is determined with the assumption of maximizing the trading volume and minimizing the difference between the accumulated volumes of electricity in the buy and sell orders, while setting the lowest possible price for electricity [3]. All sell orders with a price limit lower than the prevailing price in a given hour will be fully executed. Similarly, all buy orders with a price limit higher than the prevailing price will be fully executed. In the case where sell or buy orders have a price limit equal to the prevailing price, these orders may be executed partially, fully, or not at all. This depends on the current supply and demand curves [1]. The submitted sell offers are sorted in ascending order of price, while buy offers are sorted in descending order. This process creates the supply and demand curves, also referred to as aggregate curves [4]. All accepted offers are executed at the same uniform price.

The uniform price in the market is determined daily for domestic offers at 10:30 a.m. (I fixing), and then again at 12:00 a.m. within the European market coupling mechanism, based on the last (highest-priced) accepted offer that corresponds to the intersection point of the supply and demand curves. In this way, prices are determined for the subsequent 24 hours. The delivery of electricity takes place on the following day after the resolution of which offers were rejected and which were accepted.

Factors influencing price from the supply side

To identify the factors influencing the supply of electricity, it is necessary to analyze the national electricity balance with a specific focus on the generation sub-sector. Based on the conducted analysis [5], [6], it has been determined that the majority of electricity in Poland is currently generated by conventional thermal power plants, primarily fueled by hard coal. The second most significant technology in terms of electricity production is conventional thermal power plants fueled by lignite. Wind power plants rank third, followed by conventional thermal power plants fueled by natural gas and photovoltaic power plants. The Polish power system also includes generation units such as biogas plants, biomass power plants, and conventional thermal power plants that co-fire biomass or biogas. This analysis of the generation sub-sector enables the determination of the factors influencing the supply of electricity in the Polish power system and the price of electricity on the day-ahead market.

The annual total costs of electricity generation for generating units consist of capital costs (e.g., depreciation costs, capital servicing costs) and operational costs, which are related to power plant operation. Operational costs can be divided into fixed costs (O&M costs - operating and maintenance costs, costs independent of the electricity production volume) and variable costs (dependent on the electricity production volume) [7]. These costs directly shape the price curve by influencing the prices of supply offers.

The impact of each cost component on the offered prices of electricity depends on the type of electricity generation technology and the type of fuel used:
- For conventional thermal power plants, all the mentioned cost components are present. The generation costs are strongly dependent on the price of coal [8], carbon dioxide emission allowances, fuel transportation costs, costs of other consumed raw materials, costs of self-consumed energy, and labor costs. Conventional power plants that use natural gas during electricity generation have lower carbon dioxide emissions, but the fuel price is significantly higher, which is why these power plants mainly operate during peak load periods,
- Biogas plants and biomass-based power plants are not subject to the provisions of the law [8]. Therefore, they do not incur costs related to the purchase of carbon dioxide emission allowances. However, they bear all the other costs similar to those of conventional thermal power plants,
- Other electricity generation technologies classified as renewable energy sources (wind, hydro, photovoltaic) do not incur variable costs associated with fuel purchase or carbon dioxide emission allowances. Hence, these technologies offer electricity at the lowest prices.

Photovoltaic and wind farms are capable of offering the lowest marginal price for electricity sales. Hydro and nuclear power plants can offer slightly higher prices, but significantly lower than conventional coal-fired power plants. Gas-fired power plants typically submit offers with the highest selling prices [9]. The volume of electricity offered for sale by different generation technologies also influences the price curve on the day-ahead market. Therefore, the following factors ultimately affect the supply curve:
- Weather conditions: Solar radiation intensity, wind speed, and rainfall (affecting river water levels) influence the volume of electricity offered by renewable energy generation units [10],
- Available capacity of centrally dispatched generating units.

If the sales offers from renewable energy generation units and coal-fired units cover a relatively small volume of electricity, the demand curve may align with the supply curve at high prices offered by gas-fired units.

Factors influencing price from the demand side

The factor shaping the aggregated demand curve (number of energy purchase orders and the total volume of energy in those orders) is the power demand. Power demand varies throughout different hours of the day and seasons. Based on an analysis of Poland's daily power demand for different days of the year, it has been observed that power demand is higher in winter months compared to summer months. Furthermore, the power demand on weekdays is higher than on non-working days. Throughout the day, the power demand fluctuates and is highest between 10:00 and 20:00. Such variations in power demand impact the volume of electricity in purchase bids, thus influencing the price. Considering only this aspect of price formation, it can be inferred that higher power demand leads to higher electricity prices on the day-ahead market.

The national annual electricity consumption in Poland between 1990 and 2021 [11] was analyzed. The data indicates that annual electricity consumption has been increasing over the years. This can be attributed to the development of the Polish economy and the growth of GDP, resulting in the establishment of a greater number of industrial facilities and commercial establishments.

The mechanisms managing the demand side have an impact on shaping the daily load curve, which in turn affects the number of electricity purchase orders on the day-ahead market and, consequently, the price of hourly products [12]. Among these mechanisms, the following can be distinguished:
- Actions aimed at increasing the efficiency of electricity utilization, thereby reducing energy consumption,
- Demand-side response programs.

Other factors

In addition to the factors influencing the demand and supply curves, which are based on the submitted electricity purchase and sale orders, there are other factors that are difficult to associate with just one type of influence on price. These factors can have a holistic impact on the power system and the functioning of energy markets. They are hard to predict but have a significant influence on the price curve of hourly products on the day-ahead market. These factors can include events in the macroeconomic environment, such as military and political conflicts, fuel embargoes, as well as legal and political changes. Additionally, extraordinary events like attempts to manipulate the market (artificial price inflation) can occur [13].

Data [11] regarding the Polish power system show a slight decrease in annual electricity consumption in 2020. This decrease can be attributed to the COVID-19 pandemic. The pandemic caused the slowdown of many sectors, leading to a reduction in electricity consumption for their needs, but it simultaneously increased electricity consumption in households. Overall, these changes resulted in a slight decline in electricity consumption compared to previous years. The daily distribution of power demand also changed. Events of this nature, such as the COVID-19 pandemic, which are difficult to predict, have an impact on electricity demand and the submitted purchase orders on the day-ahead market. Moreover, such events can also indirectly influence prices in the longer term. For example, they may delay the construction of new generation units [14, 15], which would ultimately lead to a decrease in electricity supply.

An example of how legislative changes affect the functioning of the TGE and the prices prevailing on the exchange (or the tendency of price increases or decreases) is the introduction of a directive [16]. The directive came into effect on April 8, 2018, and due to the increase in emissions allowances prices, the electricity price increased. In order to prevent the rise in electricity prices, preventive measures were implemented in Poland through a law [17]. The aim of these preventive measures was to prevent the increase in electricity prices for retail consumers and stabilize electricity prices on the wholesale market. The discussed legislative changes serve as an example of the impact of the legal environment on the functioning of the electricity market. This impact is not linear, and subsequent changes in the legal environment are difficult to predict.

The time horizon of factor impact

Factors influencing the price can be considered in terms of changes over a long time horizon (e.g., between consecutive months, in subsequent years) and a short time horizon (price changes between individual hours). Both types of interactions are important for forecasting electricity prices.

Factors that operate over a long time horizon do not affect the daily price curve but rather the overall trend of price increase or decrease between different days, months, and years. Among these factors, we can identify fuel prices, emission allowance prices, changes in the legal, political, and economic environment. Events that delay the increase in installed capacity in the power system can result in a situation where, despite the increasing average power demand, the balance between electricity demand and supply is achieved by more frequent utilization of expensive electricity generation technologies (e.g., gas-fired power plants). To maintain a stable, low price of electricity, it is crucial to increase the installed capacity of those generating units that can offer electricity at a low price (with low marginal costs).

Factors operating over a short time horizon shape the price curve throughout the day. The primary factors in this category are the power demand in a given hour of the day and weather conditions, which affect the generation of wind and solar power plants.

Choice of Artificial Intelligence Method for Electricity Price Prediction

Artificial intelligence methods are approaches that mimic the way the human brain works or certain aspects of human intelligence. Artificial intelligence is a broader concept than machine learning, although the terms are often used interchangeably. Machine learning is a means used within artificial intelligence methods. These methods utilize large datasets (training sets) consisting of input and output data (or just input data) to "train" the algorithm. Through algorithm training, patterns can be recognized, predictions can be made, and decisions can be autonomously made by the algorithm.

The classification of machine learning methods based on the learning criteria can be presented as follows:

- Supervised learning:
    - Support Vector Machines (SVM)
    - Decision trees and Random Forests (RF)
    - Neural Networks (NN)
- Unsupervised learning:
    - Unsupervised classification methods:
        - K-means algorithm
        - Density-Based Spatial Clustering of Applications with Noise (DBSCAN)
        - Hierarchical clustering
    - Anomaly detection and novelty detection:
        - One-Class SVM
        - Isolation Forest
    - Visualization and dimensionality reduction:
        - Principal Component Analysis (PCA)
        - Locally Linear Embedding (LLE)
        - t-Distributed Stochastic Neighbor Embedding (t-SNE)
    - Association rule learning:
        - Apriori algorithm
        - Eclat algorithm
- Partially supervised learning, e.g., Deep Belief Networks
- Reinforcement learning, with an example application being AlphaGo.

For electricity price forecasting, artificial intelligence methods such as artificial neural networks, random forests, and hybrid approaches combining artificial neural networks with other methods are commonly used [21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32]. Additionally, genetic algorithms can be used for training neural networks [25, 33, 34].

It has been decided that an artificial neural network – a multilayer perceptron with backpropagation of error - will be used for predicting prices of hourly electricity products on the day-ahead market in nine variants:

1. Multilayer perceptron with one hidden layer and two types of input data.
2. Multilayer perceptron with one hidden layer and three types of input data.
3. Multilayer perceptron with one hidden layer and four types of input data.
4. Multilayer perceptron with two hidden layers and two types of input data.
5. Multilayer perceptron with two hidden layers and three types of input data.
6. Multilayer perceptron with two hidden layers and four types of input data.
7. Multilayer perceptron with three hidden layers and two types of input data.
8. Multilayer perceptron with three hidden layers and three types of input data.
9. Multilayer perceptron with three hidden layers and four types of input data.

The choice of artificial intelligence method in the form of a neural network in these nine variants was based on a review of the relevant literature. The analysis revealed that this method is the most commonly used in international publications for electricity price prediction. However, there have been few publications on electricity price prediction using artificial neural networks based on data from the Polish electricity exchange [35, 36]. Moreover, these few publications only analyze neural networks using historical electricity price data as input.

Choice of Input Data

The artificial neural network will be trained in a supervised manner using data provided by Polskie Sieci Elektroenergetyczne S.A. (Polish transmission system operator) (PSE) on their website pse.pl under the "Praca KSE - Plan koordynacyjny 5-letni - wielkości podstawowe" (KSE Work - 5-year Coordination Plan - Basic Values) section, as well as data obtained from the TGE. The received data pertains to the date and time of electricity delivery, the prices of hourly products in the uniform clearing price system for fixing I on the day-ahead market, and the volume for this fixing during the period from January 1, 2015, to December 31, 2022. The hourly data available on the PSE website includes the following:

- Forecasted network demand,
- Required power reserve of the System Operator (TSO),
- Excess power available to TSO,
- Available power of generating units (JW) and energy storage facilities providing balancing services within the balancing market,
- Predicted generation of JW and energy storage facilities providing balancing services within the balancing market,
- Predicted generation of JW and energy storage facilities not providing balancing services within the balancing market,
- Forecasted cumulative generation from wind sources,
- Forecasted cumulative generation from photovoltaic sources,
- Planned cross-system exchange balance,
- Predicted level of unavailability resulting from network limitations in the transmission and distribution networks regarding electricity delivery,
- Predicted generation of generating resources not subject to capacity obligations,
- Capacity obligations of all capacity market units.

These data are available on the website of PSE for each hour of the year starting from January 1, 2021. Some of this data will be used as training data on the input layer side and subsequently as input data for prediction after training the network. The data obtained from the TGE will be used as training data for the neural networks on the output layer side for backpropagation of errors within the network. The selection of specific data from the mentioned ones, which are available on the website of PSE, will be based on an analysis of the impact of individual data on the accuracy of the forecast. Additionally, a prior analysis of factors influencing the formation of electricity prices will be taken into account. A separate price forecast will be conducted for each of the data variables. The training will be conducted for the period from January 1, 2021, to January 31, 2023, and the prediction will cover the period from February 1, 2023, to February 28, 2023. All data will be tested for the neural network with the same architecture. The network will have 1 input layer with 1 neuron, 1 hidden layer with 11 neurons, and 1 output layer with 1 neuron.

After performing 10 iterations of training the network and predicting the price, the Mean Absolute Percentage Error (MAPE) indicator (1) will be calculated for each data variable, followed by calculating the average MAPE value for 10 iterations (2).

$$\text{(1)} \qquad \mathrm{MAPE}(\mathrm{P},\widehat{\mathrm{P}}) = \frac{1}{\mathrm{n}} * \sum_{\mathrm{h}=1}^{\mathrm{n}} \frac{|\mathrm{P_h} - \widehat{\mathrm{P}}_\mathrm{h}|}{\mathrm{P_h}} * 100\%$$

$$\text{(2)} \qquad \mathrm{MAPE}(\mathrm{P},\widehat{\mathrm{P}})_{\mathrm{avg}} = \frac{1}{\mathrm{i}} * \sum_{\mathrm{j}=1}^{10} \frac{1}{\mathrm{n}} * \sum_{\mathrm{h}=1}^{\mathrm{n}} \frac{|\mathrm{P_{h,j}} - \widehat{\mathrm{P}}_\mathrm{h,j}|}{\mathrm{P_{h,j}}} * 100\%$$

Where: $\hat{P}_h$- predicted electricity price in hour h, P - actual electricity price in hour h, n - number of hours for which the prediction is made, i - number of iterations, equal to 10.

Based on the 10 iterations, 4 types of data will be selected. The average value of the MAPE indicator and the previously conducted analysis of the impact of individual factors on the electricity price will be taken into account when selecting the data.

When choosing the input data for the neural network, it is important to exclude as much as possible the use of data that has little influence on the electricity price. This will improve the accuracy of predictions in the target neural networks.

Based on the performed test predictions with one type of input data and the analysis of factors influencing the electricity price, the following input data will be used for the target predictions:

1. Predicted generation of generating units and energy storage facilities providing balancing services within the balancing market - due to achieving the lowest $\mathrm{MAPE_{avg}}$ and $\mathrm{MAPE_{min}}$ values, as well as the significant impact of this factor on the supply curve,
2. Forecasted network demand - due to achieving the third lowest $\mathrm{MAPE_{avg}}$ and the second lowest $\mathrm{MAPE_{min}}$ values. Additionally, this factor has the greatest influence on shaping the demand curve for the next day's market,
3. Forecasted cumulative generation from wind sources - due to having a relatively low $\mathrm{MAPE_{avg}}$ value and the second lowest $\mathrm{MAPE_{min}}$ value. Moreover, Chapter 2 showed that wind generation has a significant impact on shaping the market price for the next day,
4. Required power reserve of the transmission system operator - because for this input data, $\mathrm{MAPE_{avg}}$ had the second lowest value (16.630%), and $\mathrm{MAPE_{min}}$ had a value close to $\mathrm{MAPE_{avg}}$ (16.493%). This means that for these data, the prediction results in successive iterations were very similar (stable),

Neural network variants that assume only two types of input data will use the input data mentioned above with numbers 1 and 2. Variants using three types of data will use input data 1, 2, and 3 in a similar manner.

Tuning hyperparameters of the NN

The hyperparameters for each neural network, such as:
- the logic of initial connection weights between neurons,
- activation function for hidden and input layers,
- number of neurons in hidden layers,

were chosen based on the analysis of prediction results. The parameters were changed individually, and for each change, 10 iterations were performed. After completing 10 attempts for each modification of a hyperparameter, the MAPE indicator was calculated, and then the average value of this indicator was computed. Based on the average values of the indicator, optimal hyperparameters were selected for each neural network.

Other hyperparameters, such as:
- number of neurons in the input layer,
- number of neurons in the output layer,
- activation function for neurons in the output layer,

depend on the input data and expected output data and were predefined. They will not be optimized based on the optimization principles described above. Neural networks for each variant will have as many layers as the given variant assumes. The number of input neurons will be equal to the number of input data, while the number of neurons in the output layer for each variant will be 1. The optimizer for updating connection weights for each NN variant will be the Adam optimizer, which is one of the most effective optimizers combining the advantages of other solutions. The Adam optimizer is a variant of the stochastic gradient descent method that calculates adaptive learning rate coefficients for different parameters. The activation function for the output layer with one neuron will be the linear function. This function returns the input value of the neuron without modification as the output of the neuron [37], [38].

Selection of weight initialization method

The selection of weight initialization methods was carried out sequentially for each layer of the neural network, from the input layer to the output layer. Only one weight initializer was changed at a time. In the utilized Keras application programming interface (API) written in Python, various initializers are available, such as RandomNormal, RandomUniform, TruncatedNormal, Zeros, Ones, GlorotNormal, GlorotUniform, HeNormal, and HeUniform.

During the prediction process using different weight initializers for the input layer, all other layers have their weights set by default using the GlorotUniform algorithm [37] (selected by default in the absence of specifying this parameter in the code). During the prediction for subsequent layers, the initializers for the previous layers are defined in the code as the initializer with the lowest MAPEavg. A summary of the chosen methods for each layer and variant is presented collectively in Table 1

Table 1. The summary of the selected weight initialization methods for each layer and NN variants

NN Variant	Input Layer	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3	Output Layer
1	Ones	HeUniform	-	-	Ones
2	Ones	GlorotUniform	-	-	HeNormal
3	Ones	RandomUniform	-	-	HeNormal
4	Ones	GlorotUniform	HeUniform	-	Ones
5	Ones	HeNormal	HeNormal	-	RandomNormal
6	Ones	HeUniform	RandomNormal	-	HeNormal
7	Ones	RandomUniform	RandomNormal	Ones	GlorotUniform
8	Ones	HeNormal	GlorotUniform	GlorotNormal	HeNormal
9	Ones	GlorotUniform	GlorotNormal	HeNormal	HeNormal

Activation Function for Hidden Layers and Input Layer

The second parameter to be selected for each neural network variant was the activation function for the hidden layers and the input layer. The activation function was chosen based on the same assumptions as the selection of weight initialization methods. The assumptions also considered the use of the selected weight initialization method for each layer of the network. The available activation functions for neurons in the Keras API that can be used for the input layer and hidden layers are ReLU, Sigmoid, Softmax, Softplus, Softsign, Tanh, SELU, ELU, GELU.

It was assumed that the activation functions would be the same for all hidden layers as well as for the input layer [20]. Based on these assumptions, 10 iterations of hourly product price predictions were performed, and the MAPEavg error was calculated.

Based on the obtained results for each neural network variant, the activation functions for the input layer and hidden layers were selected. The summary of this selection is presented in Table 2.

Table 2. Summary of selected activation functions for the input layer and hidden layers for each NN variant

NN Variant	Activation Function
1	ReLU
2	ELU
3	ReLU
4	GELU
5	GELU
6	ELU
7	ReLU
8	ReLU
9	ReLU

Number of Neurons in Hidden Layers

The number of neurons in each layer was determined experimentally based on performing a test prediction using the same principles as the previous hyperparameters. The number of neurons was increased by 2 starting from 3 neurons in the first hidden layer and ending at 101 neurons. The number of neurons in subsequent hidden layers, if present in a particular variant, was half the size of the previous layer (rounded up).

Based on the conducted analysis, the number of neurons was determined for each variant of the artificial neural network in the respective hidden layers. The selection was made to achieve the lowest MAPEavg value. The summary of the selected number of neurons is presented in Table 3.

Table 3. Summary of the selected number of neurons in hidden layers for each variant

NN Variant	Number of Neurons		
	In Hidden Layer 1	In Hidden Layer 2	In Hidden Layer 3
1	17	-	-
2	29	-	-
3	31	-	-
4	17	9	-
5	69	35	-
6	33	17	-
7	33	17	9
8	51	26	13
9	95	48	24

Final Prediction

The neural networks in the final prediction were examined in a similar way to how the hyperparameters were selected. Ten iterations of model compilation, model training, and prediction of hourly product prices in the unified exchange rate system were conducted for each variant. The target prediction assumes the application of the selected hyperparameters, allowing for the analysis of neural network variants with the best network settings.

The target prediction was performed for a new set of test input data from March 1, 2023, to March 31, 2023. Based on previous test predictions for a different period, the hyperparameters were selected for each variant. However, to make the target prediction, it would be incorrect to use the same set of data that was used for parameter optimization [20].

To compare the accuracy of the prediction results (from March 1, 2023, to March 31, 2023) with the prediction results for foreign energy markets, the following indicators appearing in scientific publications will be calculated:

1. Mean Absolute Error (MAE) - equation (3) - one of the simplest indicators allowing the evaluation of forecast accuracy and neural network model quality [21, 22, 27];

$$\mathrm{MAE}(P,\hat{P}) = \frac{1}{n} * \sum_{h=1}^{n} |P_h - \hat{P}_h| \quad (3)$$

2. MAPE - equation (1) - the average absolute percentage error [21, 22, 26, 27, 28];

3. Symmetric Mean Absolute Percentage Error (SMAPE) - equation (4) - this indicator is a variation of the MAPE. Its application ensures that electricity prices predicted to be close to zero do not unnecessarily increase the value of the indicator [21], [22];

$$\mathrm{SMAPE}(P,\hat{P}) = \frac{1}{n} * \sum_{h=1}^{n} \frac{|P_h - \hat{P}_h|}{\frac{1}{2} * (|P_h| + |\hat{P}_h|)} * 100\% \quad (4)$$

4. Root Mean Square Error (RMSE) - equation (5) - the square root of the mean squared error [22], [24], [26];

$$\mathrm{RMSE}(P,\hat{P}) = \sqrt{\frac{1}{n} * \sum_{h=1}^{n} (P_h - \hat{P}_h)^2} \quad (5)$$

5. Mean Square Error (MSE) - equation (6) - the mean squared error [25];

$$\mathrm{MSE}(P,\hat{P}) = \frac{1}{n} * \sum_{h=1}^{n} (P_h - \hat{P}_h)^2 \quad (6)$$

Where: $\hat{P}_h$ - predicted electricity price in hour h, P_h - actual electricity price in hour h, n - the number of hours for which the prediction is made, with n equal to 744 for the prediction period from March 1, 2023, to March 31, 2023.

Results

Table 4 presents the results of target predictions in terms of calculated error indicators. To compare the prediction results with those for other European markets, the MAE and RMSE indicators were converted using the exchange rate of 4.70 PLN to 1 EUR.

Figures 1 and 2 depict the price prediction charts for hourly products compared to the actual prices for variants 1 (the variant with the highest MAPE indicator) and 3 (the variant with the lowest MAPE indicator). The prediction data represents the arithmetic average of 10 iterations, resulting in the presented data corresponding to the calculated average values from Table 4.

In March, the month for which the target prediction was conducted, there was a very low price of hourly product prices at 83.61 zł/MWh. The price curve in March exhibited significant fluctuations between consecutive hours, making it more challenging to predict compared to, for example, February, for which optimization predictions were performed. The results of the optimization predictions yielded lower MAPE values in the range of 8-10%. However, when the price of hourly product prices is very low in a particular hour, the MAPE value may be inflated, even though other indicators such as MAE or RMSE do not deviate significantly for that hour.

Table 3. Calculated error indicators for target prediction

NN Variant	MAPE [%]	MAE [PLN/MWh]	MAE [€/MWh]	SMAPE [%]	RMSE [PLN/MWh]	RMSE [€/MWh]
1	19,92	93,63	19,92	16,56	117,23	24,94
2	14,57	71,63	15,24	13,55	90,36	19,23
3	13,55	65,18	13,87	13,20	82,03	17,45
4	15,92	77,45	16,48	15,71	98,84	21,03
5	14,68	72,10	15,34	13,25	90,89	19,34
6	13,83	66,30	14,11	13,00	84,73	18,03
7	15,47	75,70	16,11	16,29	95,86	20,40
8	15,02	72,82	15,49	14,10	92,44	19,67
9	18,62	93,45	19,88	18,32	114,46	24,35

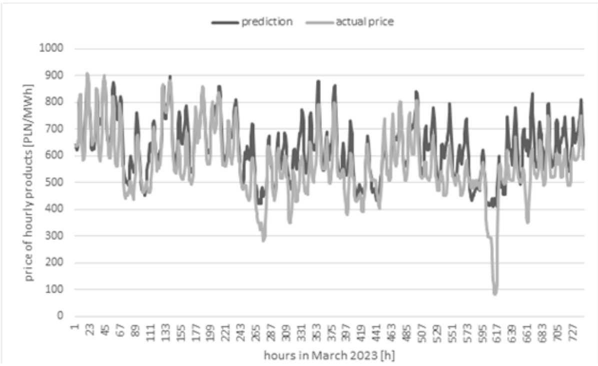

Fig. 1. Prediction of hourly product prices compared to the actual price for NN variant No. 1

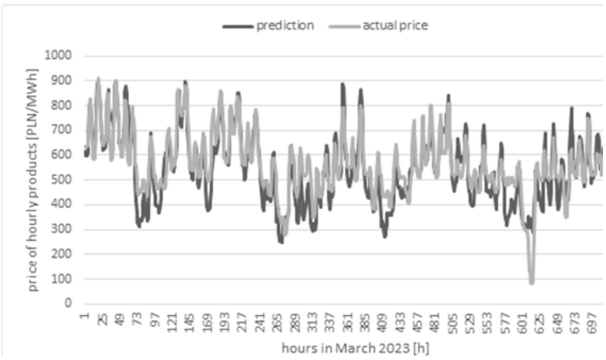

Fig. 1. Prediction of hourly product prices compared to the actual price for NN variant No. 3

All calculated error indicators, except for the SMAPE, were the lowest for NN variant No. 3. The second-best variant, providing the best prediction results, is variant 6. It achieved the lowest SMAPE value. The calculation of various error indicators is crucial for comparing the predictions made in this study with the electricity price predictions presented in scientific articles for foreign markets. Table 5 presents a comparison of indicators derived from scientific articles [21, 22, 24, 25, 26, 27]. In the case of many variants of analyzed artificial intelligence methods in a given article, the data for the best-performing variant were selected for comparison.

Table 5. Comparison of error indicators from scientific articles

Energy Market	Source	MAE [€/MWh]	MAPE [%]	SMAPE [%]	RMSE [€/MWh]
French	[21]	7,96	-	15,97	-
German		7,66	-	18,79	-
Belgian		11,86	-	21,65	-
French	[22]	4,063	15,160	11,488	11,880
German		3,716	77,145	14,970	6,796
Belgian		6,068	25,466	14,106	15,950
EPEX	[24]	-	-	-	6,58
Nord Pool	[26]	-	5,85	-	2,6697
Italian	[27]	5,80	-	-	-

Summary and Conclusions

The conducted research and analysis have demonstrated that it is possible to effectively forecast the prices of hourly electricity products in the next-day energy market using a unified price system. The obtained results are comparable to predictions made using artificial intelligence methods for other European markets.

The best analyzed variant of artificial neural network is variant 3, which is a single-layer feedforward multilayer perceptron with backpropagation and four types of input data. The second neural network variant that also yielded predictions closely aligned with the actual price formation was variant 6. This variant is a single-layer feedforward multilayer perceptron with backpropagation and two hidden layers, also with four types of input data. The worst results were obtained by variants with only two types of input data (variants 1 and 4) and variant 9 with three hidden layers and four types of input data.

Two of the most universal indicators for evaluating the quality of the predictions are MAPE and SMAPE. These indicators, by calculating the percentage error relative to the actual price, eliminate the influence of price differences between markets. However, it is also useful to analyze indicators such as MAE, which determines the average prediction error for a single hour, and RMSE, which determines the square root of the average squared error for a single hour.

Comparing the obtained predictions of the best artificial neural network variant for the Polish energy market with the best results for European markets, it can be concluded that the use of artificial intelligence methods for Polish conditions is justified and yields good results. The MAPE for the next-day market was 13.55%, and the SMAPE was 13.20%, which ranks second among the results presented in Table 5. The MAE for the Polish market was 13.87 €/MWh, and the RMSE was 17.45 €/MWh. These results are worse than those obtained for other European markets in Table 5. However, when comparing different energy markets, it is important to use indicators that eliminate the level of price formation in a specific market.

Creating an effective tool for predicting hourly product prices in the next-day market is highly valuable for energy companies engaged in electricity trading. Such a tool can also enable more accurate economic analysis for investments in the energy sector. Investigating the utility of artificial intelligence methods for this purpose is a key element in further developing this issue for the Polish market conditions.

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