Electricity Price Evolution and the Disruptive Economic and Geopolitical Context on the Spot Market. A Romanian Case Study

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Abstract

The current context of the electricity markets is marked by the lingering effects of COVID-19 and the conflict in Ukraine that have a significant influence on the European wholesale electricity markets. Both Day-Ahead Market (DAM) and balancing market have been heavily impacted by fluctuating prices. This trend started in October 2021 when the lockdowns were removed and the high request for commodities led to a higher inflation. Then in 2022, the conflict in Ukraine accentuated this evolution and even higher prices were recorded for electricity, gas, oil and other resources. In this paper, we analyze a set of fundamental variables and provide an electricity price forecast on DAM using a multiple regression model. The exogenous variables considered in this paper are the following: power system data (total consumption, total generation and its breakdown: renewables (RES) and Non-RES), economic data (inflation, interest rate), certificate price for CO2 emissions (EU-ETS), level of Danube River and other resources prices (oil, gas). Interesting insights can be extracted from a data set that consists of merged time series collected from January 2019 until August 2022. The results are measured using Mean Absolute Percentage Error (MAPE).

Keywords

Electricity price forecast, day-ahead market, multiple regression, emission price.

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Introduction

The electricity price evolution and forecast were extensively studied in the past as the electricity prices have a significant impact on the economies.

The motivation behind this study is related to the high price volatility that emerged by the end of 2021. For example, we show in Figure 1 two snapshots with the average prices on DAM in some European countries. The first snapshot is taken on 3rd on January 2022 and the second one is taken by the end of August (on 30th of August 2022).

One can notice that the prices increased from 100 Euro/MWh to 738 Euro/MWh, even seven times as is the case in Romania. Furthermore, impressive variations were recorded in France, Germany and in the neighbouring countries (Bulgaria, Serbia, Hungary). This evolution was the result of numerous factors, such as: rapid recovery after lockdowns and business dynamics that were left behind, European dependence on the Russian gas and oil resources, severe drought in some European countries, speculation on the market as market participant knew the economic and geopolitical context as well as the planned generation units outages.

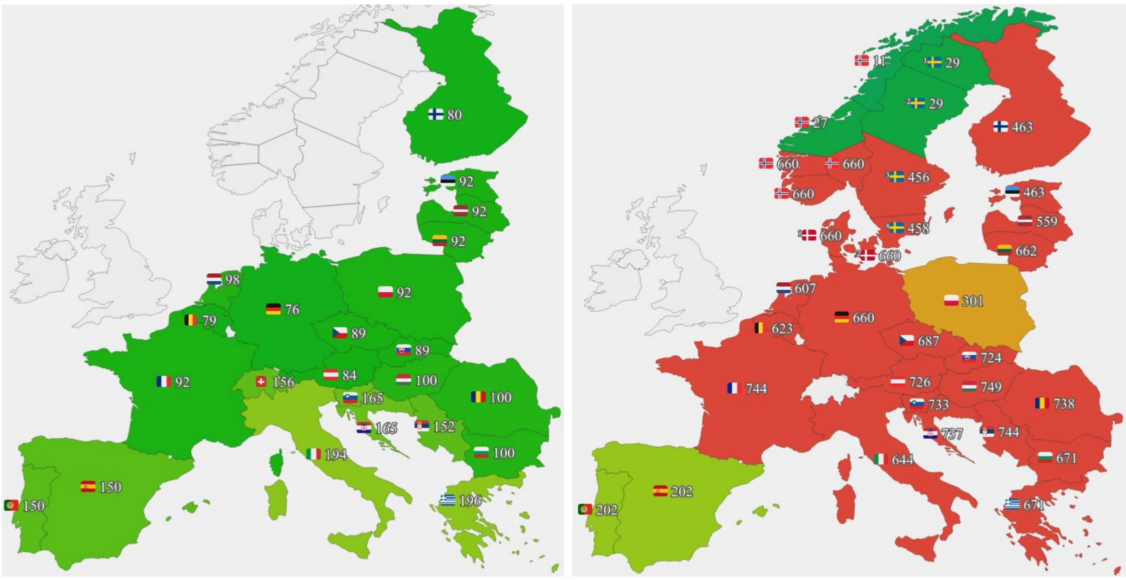

Figure no. 1. DAM prices in Europe 03 Jan. 2022 - 30 Aug. 2022

Source: https://euenergy.live

In the next section, we will investigate the input data set created to predict the electricity prices on DAM.

Literature review

The integration of the electricity price prediction was envisioned to estimate the electricity costs for commercial activities on mid-term (Busse and Rieck, 2022). Probably the most difficult aspect is to predict the electricity price spikes or sudden increase/decrease of the prices (Lu et al., 2005; Voronin and Partanen, 2013).

The financial impact of prediction low accuracy on the generation units (Kath and Ziel, 2018; Ugurlu et al., 2018), load schedule (Mathaba, Xia and Zhang, 2014) and storage facilities (Finnah, Gönsch and Ziel, 2022) was also studied. The impact of a higher volume of Renewable Energy Sources (RES), especially solar and wind, on the electricity prices on DAM was investigated by Alsaedi, Tularam and Wong (2020).

Numerous methods and models have been developed to cope with electricity price forecast, including naïve and regressive models (Nowotarski and Weron, 2015; Marcjasz, Uniejewski and Weron, 2020; Liu et al., 2022), neural networks (Abedinia et al., 2015; Keles et al., 2016; Lehna, Scheller and Herwartz, 2022), deep learning using Long Short-Term Memory (Li and Becker, 2021), Machine Learning (ML) – SVM (Razak et al., 2019) and hybrid models (Dong et al., 2011; Shikhin, Shikhina and Kouzalis, 2022).

Most of the studies related to the electricity price forecast on DAM focused on West-European countries (Spain - (Beltrán et al., 2022)), Australia (Yang et al., 2019), U.S.A. (Ontario - (Razak et al., 2019)) and Nordic countries (Danish market - Schütz Roungkvist, Enevoldsen and Xydis, 2020)), probably because the data sets are easily available.

Methodology

A similar analysis of the Romanian electricity prices and its prediction have not been performed yet. Therefore, for Romania, a data set was built merging open data sources such as from Transelectrica (https://www.transelectrica.ro/ro/web/tel/home) for Romanian power system data, INS (http://statistici.insse.ro/shop/?page=ipc1) for inflation or index price, OPCOM (https://www.opcom.ro/pp/grafice_ip/raportPIPsiVolumTranzactionat.php?lang=ro) for prices and traded quantities on DAM, Macrotrends for oil price, cursbnr (https://www.cursbnr.ro/robor) for interest rate (ROBOR3M), Romanian Commodities Exchange (https://www.brm.ro/piata-spot-gn/) for gas price on DAM). The various time series were merged based on date and hour, including level of Danube (https://www.cotele-dunarii.ro/Braila) at three locations (Turnu Măgurele, Brăila and Tulcea). We focused on the interval before COVID-19 and after the first waves of shock caused by the conflict in Ukraine. Thus, the data was extracted from 1st of January 2019 until end of August 2022. From the Romanian Transmission

System Operator - Transelectrica, we extracted several input variables, such as: the total consumption, generation and its breakdown (coal, oil and gas, hydro, nuclear, wind, PV, biomass generation), exchange with neighbouring power systems or sold. The prices for emissions EU-ETS (https://www.investing.com/commodities/carbon-emissions-historical-data) were also extracted as well as inflation in Europe that is actually highly correlated with inflation in Romania.

The electricity prices in Romania started to increase in October 2021 and kept an increasing pace until August 2022. The electricity price evolution on DAM is graphically depicted in Figure 2.

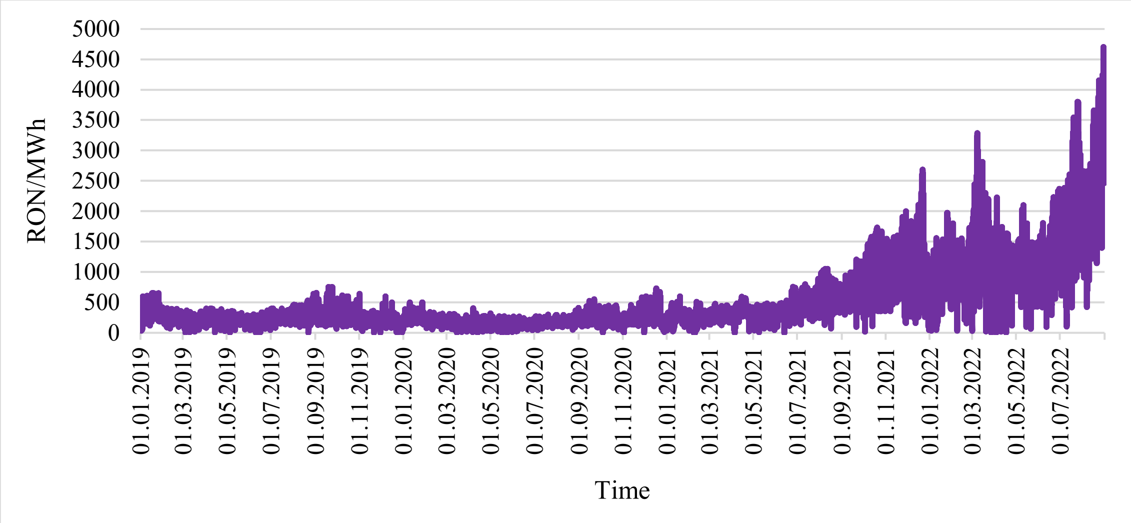

Figure no. 2. Price evolution in the analysed interval (Jan. 2019 - Aug. 2022)

For the analysed interval, Jan. 2019 - Aug. 2022, the correlation between electricity prices on DAM and the other variables is shown in Table 1. It is strongly correlated with gas price on DAM, inflation in Romania and Europe, interest rate (ROBOR3M), oil price and CO2 emissions certificate price (Price EUETS). A lower inverse correlation is registered between the electricity price on DAM and the level of Danube (-0.3 on average). Therefore, the droughts influence the electricity price on DAM: the lower the levels, the higher the prices.

Table no. 1. Correlations between target variable – electricity price on DAM (El_price_DAM) and other exogenous variables

Variable	2019-2022 El_price_DAM	2019 El_price_DAM	2020 El_price_DAM	2021 El_price_DAM	2022 El_price_DAM
El_price_DAM	1	1	1	1	1
El_quantity	0.196241	0.599123	0.312068	-0.13812	0.168683
Gas_price_DAM	0.89076	0.122353	0.443976	0.82858	0.757485
Gas_quantity_DAM	-0.14605	-0.03055	-0.1695	0.486406	0.334951
Inflation_RO	0.795821	-0.33964	-0.05012	0.789006	0.329347
Inflation_EU	0.814193	-0.16378	-0.07226	0.786641	0.454506
ROBOR 3M	0.664544	-0.31346	-0.07331	0.704966	0.586826
Oil_price	0.685848	-0.32092	0.423426	0.593899	0.042344
Level_Turnu Magurele	-0.28379	-0.31655	-0.11877	-0.55886	-0.44648
Level_BR	-0.32029	-0.27305	-0.0728	-0.57319	-0.55958
Level_TL	-0.26181	-0.26507	-0.09993	-0.5755	-0.54291
Consumption	0.131593	0.641255	0.765344	0.322032	0.193566
Generation	-0.04685	0.23874	0.536873	-0.03781	-0.1943
Coal_gen	-0.00101	0.405274	0.571223	0.132546	0.228913
Oil&Gas_gen	0.167736	0.366169	0.56547	0.414415	0.048759
Hydro_gen	-0.09151	0.024599	0.398181	-0.33788	-0.0179
Nuclear_gen	-0.0473	0.045853	0.07763	0.196464	-0.01421
Wind_gen	-0.07253	-0.15929	-0.17239	-0.00498	-0.3163
PV_gen	0.008701	0.074729	-0.11724	-0.09232	-0.00558
Biomass_gen	0.24985	0.242901	0.353651	-0.07165	-0.21031
Exchange	0.175975	0.293093	0.357552	0.306741	0.242605
Price_EUETS	0.763298	0.083855	0.442297	0.707506	0.004049

The variation in time of the correlations is shown in Figure 3:

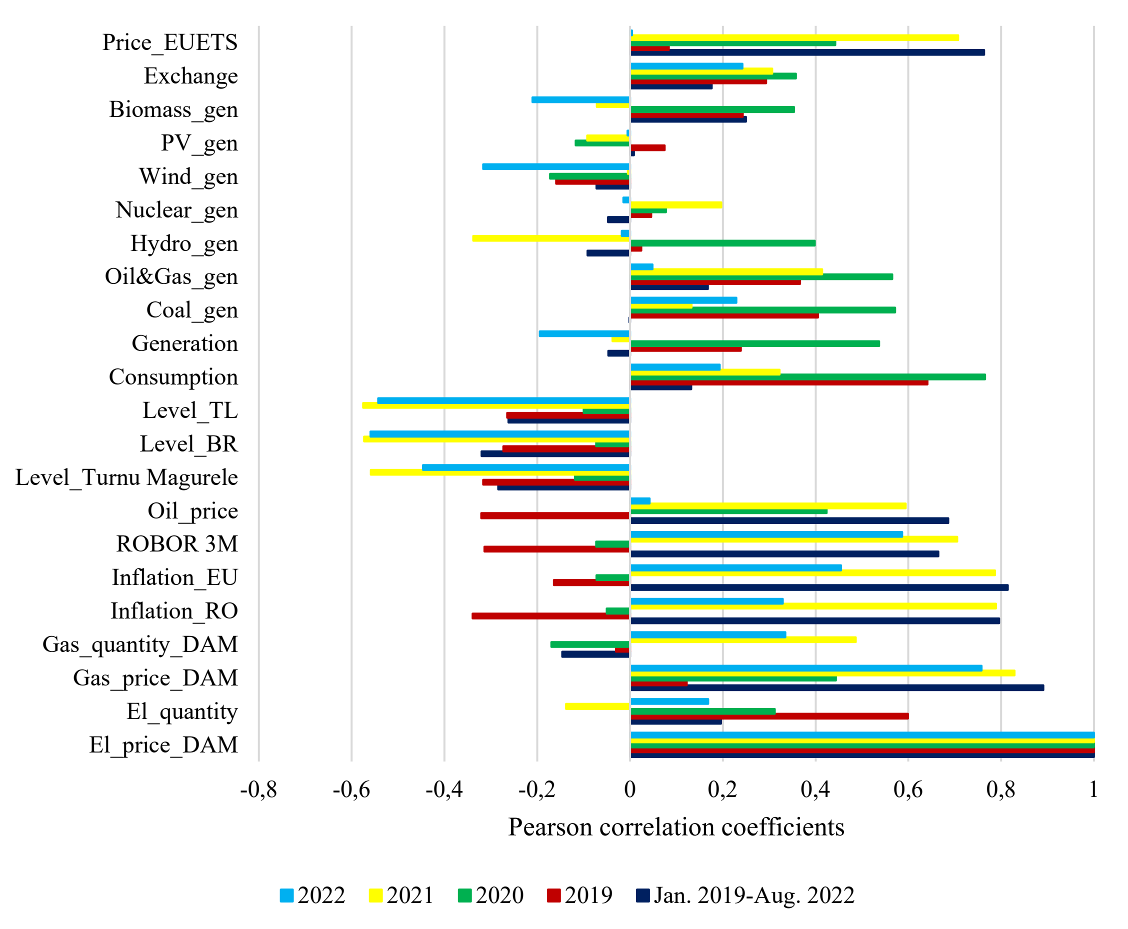

Figure no. 3. Pearson correlation coefficients

It is interesting to notice how some variables lost their importance (for instance, traded quantity on DAM, total consumption) and other gained more importance (gas price). The electricity price is more correlated with the prices of other resources (oil, gas) and less dependent on the consumption level. Inflation and interest rate have no significant influence in 2019 and 2020, but in 2021 they increased substantially.

For calculations, we considered several combinations of exogenous variables, and the best results are obtained using the variables shown in Table 2. The variation of electricity price is explained in proportion of 81% by the exogenous variables (as in Table 2): electricity traded quantity or volume on DAM (El_quantity), certificate price for CO2 emissions (Price_EUETS), gas price on DAM (Gas_price_DAM), inflation in Romania (inflation_RO), interest rate calculated at three months (ROBOR 3M) and brent crude oil price (Oil_price). The number of observations is 32,060 reflecting the hourly data in 3 years and half. All *p-values* are smaller than 0.05 threshold (as in Table 3). Therefore, the regression is statistically significant.

Table no. 2. Regression statistics

Regression Statistics	
Multiple R	0.899121
R Square	0.808419
Adjusted R Square	0.808383
Standard Error	241.1842
Observations	32060

Table no. 3. Regression coefficients and significance

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-197.787	8.935	-22.133	0.000	-215.301	-180.272	-215.301	-180.272

El_quantity	0.056	0.002	23.902	0.000	0.051	0.061	0.051	0.061
Price_EUETS	0.958	0.201	4.748	0.000	0.562	1.353	0.562	1.353
Gas_price_DAM	2.173	0.015	137.191	0.000	2.141	2.204	2.141	2.204
Inflation_RO	-43.997	1.797	-24.471	0.000	-47.521	-40.473	-47.521	-40.473
ROBOR 3M	85.749	2.404	35.659	0.000	81.036	90.463	81.036	90.463
Oil_price	1.566	0.133	11.699	0.000	1.303	1.828	1.303	1.828

The line fit plots associated to the exogenous variables are depicted in Figure 4.

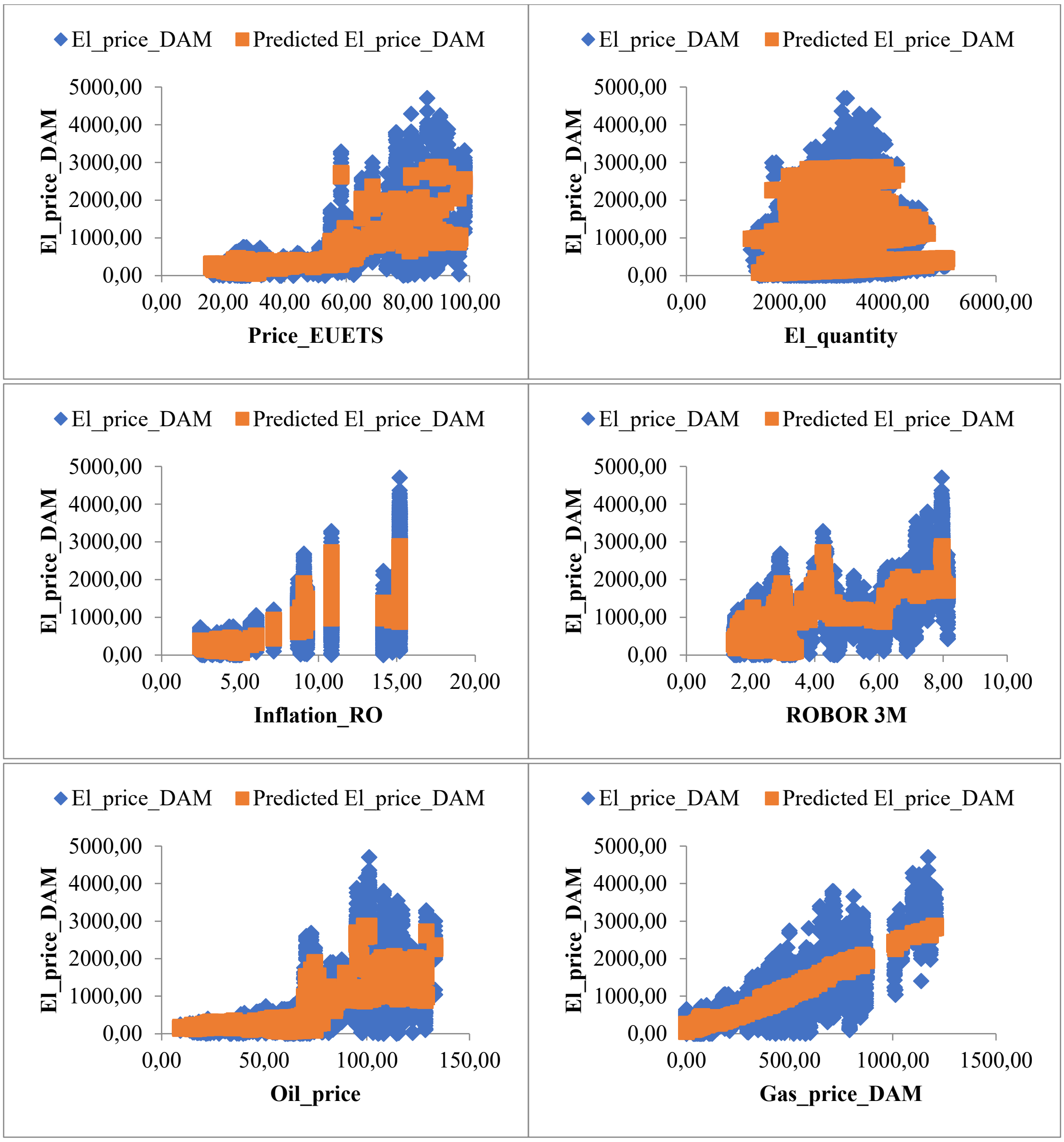

Figure no. 4. Line fit plots associated to the exogenous variables

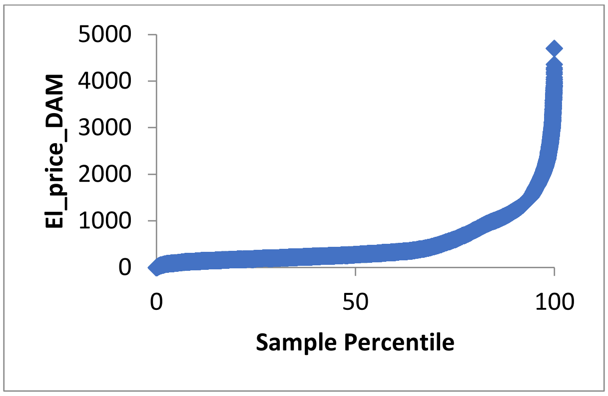

Figure no. 5. Normal probability plot

The residual plots are depicted in Figure 6. Residual is the difference between observed and predicted values.

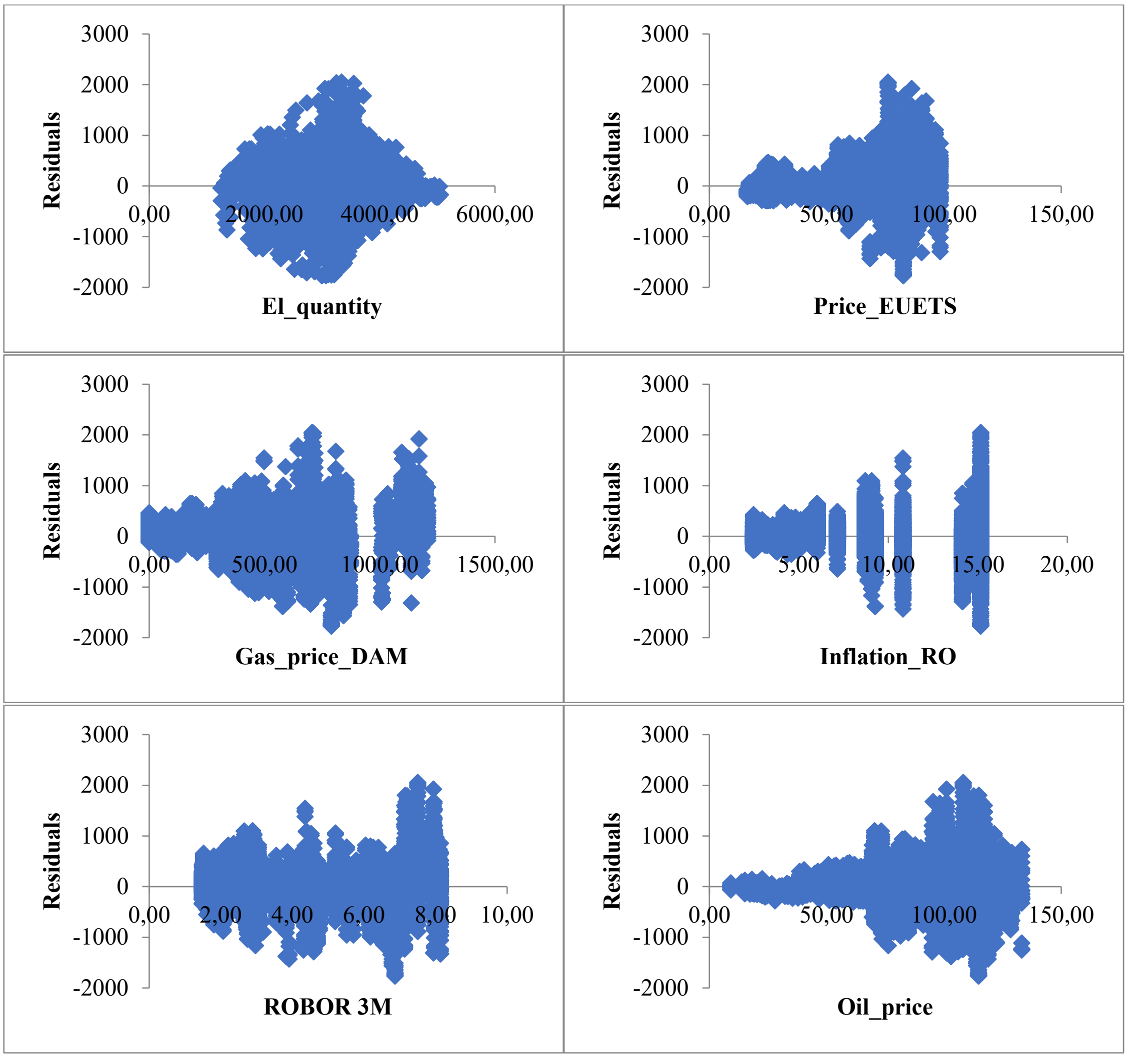

Figure no. 6. Residual plots

According to the results obtained in Table 3, one can predict the electricity price using the following equation:

$$\mathrm{El}_{\mathrm{price}_{\mathrm{DAM}}} = -197.787 + 0.056 \times \mathrm{El}_{\mathrm{quantity}} + 0.958 \times \mathrm{Price}_{\mathrm{EUETS}} + 2.173 \times \mathrm{Gas}_{\mathrm{price}_{\mathrm{DAM}}} - 43.997 \times \mathrm{Inflation}_{\mathrm{RO}} + 85.749 \times \mathrm{ROBOR}_{3\mathrm{M}} + 1.566 \times \mathrm{Oil}_{\mathrm{price}} \quad (1)$$

The results were measured using MAPE that is 6.17%, therefore the accuracy of the regression model is over 93%. The performance indicators except MAPE were calculated using FORECAST.ETS.STAT function from Excel. The values are presented in Table 4. MAPE was calculated using the following eq.:

$$MAPE = \frac{1}{T}\sum_{h=1}^{T}\frac{\left|y^h - \widehat{y^h}\right|}{\left|y^h\right|} \times 100\% \quad (2)$$

Where y^h is the observed value, $\widehat{y^h}$ is the predicted value and T is the interval.

Table no. 4. Performance indicators for predicting the electricity price on DAM using multiple regression

Metric	Value
MAPE	6.17099261
MASE	18.19563873
SMAPE	0.000263966
MAE	0.568033239
RMSE	4.070766716

MASE returns the mean absolute scaled error metric that is a measure of the accuracy of forecasts. SMAPE returns the symmetric mean absolute percentage error metric that is an accuracy measure based on percentage errors. MAE returns the symmetric mean absolute error metric an accuracy measure based on errors or a measure of the differences between predicted and observed values, whereas RMSE returns the root mean squared error metric.

Conclusion

In this paper, we aimed to analyse the electricity prices on the European spot markets (with a special focus on one of the East-European countries – Romania) and to predict them using a multiple regression model. Th contribution of this paper consists in identifying the variables that provide the best result as several regression models were run with different sets of six variable out of the total – 21 variables.

Therefore, we found out that electricity traded quantity or volume on DAM (El_quantity), certificate price for CO2 emissions (Price_EUETS), gas price on DAM (Gas_price_DAM), inflation in Romania (Inflation_RO), interest rate calculated at three months (ROBOR 3M) and brent crude oil price (Oil_price) represent the variables that allow us to predict the electricity price on DAM with an accuracy of 93%.

Compared with other approaches, such as ML, neural, networks, LSTM, our approach is simpler and assists us to understand the trend and potential evolution of the electricity prices on spot markets as well as factors that can influence these prices.

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References

Abedinia, O., Amjady, N., Shafie-khah, M. and Catalão, J.P.S., 2015. Electricity price forecast using Combinatorial Neural Network trained by a new stochastic search method. *Energy Conversion and Management*, 105, pp.642–654. https://doi.org/10.1016/j.enconman.2015.08.025.

Alsaedi, Y., Tularam, G.A. and Wong, V., 2020. Impact of solar and wind prices on the integrated global electricity spot and options markets: a time series analysis. *International Journal of Energy Economics and Policy*, 10(2), pp.337–353. https://doi.org/10.32479/ijeep.8939.

Beltrán, S., Castro, A., Irizar, I., Naveran, G. and Yeregui, I., 2022. Framework for collaborative intelligence in forecasting day-ahead electricity price. *Applied Energy*, 306, p.118049.

https://doi.org/10.1016/j.apenergy.2021.118049.

Busse, J. and Rieck, J., 2022. Mid-term energy cost-oriented flow shop scheduling: Integration of electricity price forecasts, modeling, and solution procedures. *Computers & Industrial Engineering*, 163, p.107810. https://doi.org/10.1016/j.cie.2021.107810.

Dong, Y., Wang, J., Jiang, H. and Wu, J., 2011. Short-term electricity price forecast based on the improved hybrid model. *Energy Conversion and Management*, 52(8–9), pp.2987–2995. https://doi.org/10.1016/j.enconman.2011.04.020.

Finnah, B., Gönsch, J. and Ziel, F., 2022. Integrated day-ahead and intraday self-schedule bidding for energy storage systems using approximate dynamic programming. *European Journal of Operational Research*, 301(2), pp.726–746. https://doi.org/10.1016/j.ejor.2021.11.010.

Kath, C. and Ziel, F., 2018. The value of forecasts: Quantifying the economic gains of accurate quarter-hourly electricity price forecasts. *Energy Economics*, 76, pp.411–423. https://doi.org/10.1016/j.eneco.2018.10.005.

Keles, D., Scelle, J., Paraschiv, F. and Fichtner, W., 2016. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. *Applied Energy*, 162, pp.218–230. https://doi.org/10.1016/j.apenergy.2015.09.087.

Lehna, M., Scheller, F. and Herwartz, H., 2022. Forecasting day-ahead electricity prices: A comparison of time series and neural network models taking external regressors into account. *Energy Economics*, 106, p.105742. https://doi.org/10.1016/j.eneco.2021.105742.

Li, W. and Becker, D.M., 2021. Day-ahead electricity price prediction applying hybrid models of LSTM-based deep learning methods and feature selection algorithms under consideration of market coupling. *Energy*, 237, p.121543. https://doi.org/10.1016/j.energy.2021.121543.

Liu, L., Bai, F., Su, C., Ma, C., Yan, R., Li, H., Sun, Q. and Wennersten, R., 2022. Forecasting the occurrence of extreme electricity prices using a multivariate logistic regression model. *Energy*, 247, p.123417. https://doi.org/10.1016/j.energy.2022.123417.

Lu, X., Dong, Z. and Li, X., 2005. Electricity market price spike forecast with data mining techniques. *Electric Power Systems Research*, 73(1), pp.19–29. https://doi.org/10.1016/S0378-7796(04)00125-7.

Marcjasz, G., Uniejewski, B. and Weron, R., 2020. Beating the Naïve—Combining LASSO with Naïve Intraday Electricity Price Forecasts. *Energies*, 13(7), p.1667. https://doi.org/10.3390/en13071667.

Mathaba, T., Xia, X. and Zhang, J., 2014. Analysing the economic benefit of electricity price forecast in industrial load scheduling. *Electric Power Systems Research*, 116, pp.158–165. https://doi.org/10.1016/j.epsr.2014.05.008.

Nowotarski, J. and Weron, R., 2015. Computing electricity spot price prediction intervals using quantile regression and forecast averaging. *Computational Statistics,* 30(3), pp.791–803. https://doi.org/10.1007/s00180-014-0523-0.

Razak, I.A.W.A., Ibrahim, N.N.A.N., Abidin, I.Z., Siah, Y.K., Abidin, A.A.Z. and Rahman, T.K.A. (2019), “A hybrid method of least square support vector machine and bacterial foraging optimization algorithm for medium term electricity price forecasting”, *International Journal of Integrated Engineering*, 11(3). https://doi.org/10.30880/ijie.2019.11.03.024.

Schütz Roungkvist, J., Enevoldsen, P. and Xydis, G., 2020. High-Resolution Electricity Spot Price Forecast for the Danish Power Market. Sustainability, 12(10), p.4267. https://doi.org/10.3390/su12104267.

Shikhin, V.A., Shikhina, A.V. and Kouzalis, A., 2022. Automated Electricity Price Forecast Using Combined Models. A*utomation and Remote Control*, 83(1), pp.153–163. https://doi.org/10.1134/S0005117922010118.

Ugurlu, U., Tas, O., Kaya, A. and Oksuz, I., 2018. The Financial Effect of the Electricity Price Forecasts’ Inaccuracy on a Hydro-Based Generation Company. *Energies*, 11(8), p.2093. https://doi.org/10.3390/en11082093.

Voronin, S. and Partanen, J., 2013. Price Forecasting in the Day-Ahead Energy Market by an Iterative Method with Separate Normal Price and Price Spike Frameworks. Energies, 6(11), pp.5897–5920. https://doi.org/10.3390/en6115897.

Yang, W., Wang, J., Niu, T. and Du, P., 2019. A hybrid forecasting system based on a dual decomposition strategy and multi-objective optimization for electricity price forecasting. Applied Energy, 235, pp.1205–1225. https://doi.org/10.1016/j.apenergy.2018.11.034.