energies

MDPI

Editorial

Price Forecasting in Energy Market

Yuriy Bilan [1,*], Serhiy Kozmenko [2] and Alex Plastun [3]

[1] Faculty of Management, Rzeszow University of Technology, 35-959 Rzeszow, Poland
[2] Institute of Management, University of Social Sciences, 90-113 Lodz, Poland
[3] Department of International Economic Relations, Sumy State University, 40000 Sumy, Ukraine
* Correspondence: y.bilan@prz.edu.pl

check for updates

Citation: Bilan, Y.; Kozmenko, S.; Plastun, A. Price Forecasting in Energy Market. *Energies* **2022**, *15*, 9625. https://doi.org/10.3390/en15249625

Received: 14 August 2022
Accepted: 19 October 2022
Published: 19 December 2022

1. Introduction

In autumn 2021, the world faced the first round of energy crisis. It was accompanied by the sudden spike in prices of energy assets (oil, natural gas, coal, uranium) and electricity. The second wave started when Russia invaded Ukraine. Disbalances in energy markets combined with uncertainty and sanctions caused another bout of price surges. The ripples are still settling, but some results are obvious now: inflation, shocks for global economy and for society, the threat of recession, etc. Governments were completely unprepared for this. At the same time, academics using "Energies" as a platform suggested different models and methods for price forecasting in the energy market. Standard "good-old" regression models evolved to machine-learning regressions and neural network-based models. This allowed for a reduction in information asymmetry around energy prices and better decision-making. Nowadays war is but an additional variable to be incorporated in models. All this makes for a promising research challenge here and now. As a result, some key ideas and messages related to price forecasting in energy markets were published recently in "Energies". Some papers and their contributions are presented below.

In Abadie [1], behavior of energy market prices during COVID-19 is explored. Pandemic has created a lot of challenges for the global economy. One of its consequences was the energy crisis at the end of 2021. However, before that crisis there were a lot of other disbalances: sudden drops in electricity consumption because of lockdowns, selloffs in the oil market with further extreme price growth, and other lesser but still important things. In this paper author explores electricity and natural gas prices during the first half-year of 2020 (first wave of lockdowns, the deadliest for the European economies, including the Spanish one) and compares them with price behavior in 2019. The actual aim of the paper was to show that pre-pandemic models cannot be applied in pandemic reality. The results are quite sound: wholesale electricity prices are found to be 60% lower than expected and natural gas prices were 62% lower than expected. The conclusions are very simple: you cannot effectively forecast prices in new reality using the models based and calibrated on "old reality" data. The paper is a very convincing illustration of market evolution and the necessity of constant re-calibration of models.

Another paper investigated connections between the number of COVID-19 cases and the energy commodity prices are assessed. In Dmytrów et al. [2], the idea is quite straightforward: as pandemic is an extremely important factor of influence for the energy market and its prices, this fact should be incorporated in the forecast models as a variable. The impact of pandemic can be measured and one of the best indicators for this is the number of daily cases parameter–a good proxy for the pandemic factor in the model. Authors try to prove this in theory. Using the Dynamic Time Warping (DTW) method, they analyze the similarity between the time series (energy commodity prices and the time series of daily COVID-19 cases). The key results indicate that prices for natural gas, palm oil, CO_2 allowances, and ethanol are strongly associated with the development of the pandemic; other energy assets (ultra-low-sulfur diesel, heating oil, crude oil, and gasoline) are weakly associated with COVID-19.

The fast penetration of renewables is another important factor having impact on electricity prices (Istudor et al. [3]; Rus et al. [4]).

Meanwhile, Viviani et al. [5] investigate a probabilistic method for electricity price forecasting. The issue of electricity price forecasting was never an easy task, because it is very specific market and unusual asset. You cannot store electricity economically, as a result there is a continuous balancing of production and consumption. Add weather conditions, seasonality, specifics of economic situation and you will have the extremely challenging task of price prediction in electricity market. Current energy crisis shows how vulnerable electricity prices are to external shocks. A multitude of unique variables, plenty of conditions and limitations exacerbated by overall uncertainty. No wonder traditional prediction models demonstrate low efficiency. Authors propose a solution: machine learning models. Neural networks approaches can be applied to existing statistical methods to derive a hybrid model for probabilistic type forecasting (Kelemen et al. [6]; Polishchuk et al. [7]). To prove that this solution really works German electricity prices data is analyzed. Tests provide evidence in favor of validity of this approach, both in terms of efficiency and precision of the model.

Kolcun and Rusek [8] analyzed Polish electricity market including the prices for electricity at the polish power exchange and the structure of production, energy consumption, power generation structure and energy exchange with foreign countries. Moreover, the existing markets and their nature, forming of turnover and prices mainly on the Day Ahead Market were discussed. In addition, the rules of Day Ahead Market application in terms of management in the power sector and its benefits was outlined.

The market structure of non-renewable resources can be characterized as imperfect. It follows that the directions of price trends attract the attention of financial markets, mineral and energy producers and policymakers alike (Butt et al. [9], Mahmood et al. [10]).

The issue of intraday electricity price forecasting is explored by Marcjasz et al. [11]. Motivation for intraday instead of more standard day-ahead market forecast is as follows: the rapid expansion of renewable generation is changing the electricity market and specifics of power generation.

More complexed deliberation on the energy market realities determine the global energy industry to redesign their business models towards renewable sources can be found in the elaboration by Androniceanu et al. [12] and Gavurova et al. [13]. They presented the components of renewable energy within the OECD countries and used 13 indicators in order to find out both the relations and the impact of main sectorial indicators and the global indicators of the OECD countries to their economic and social development. The main goal was to discover the main correlations between the renewable energies and the economic development of the OECD countries. The main findings of the PCA application are; (1) factor 1 was dominated by the main renewable energy sources: traditional biofuels, hydropower, solar, wind and other renewables, as well as energy products, energy exports, energy capacity and energy generation; (2) factor 2 was dominated positively by energy imports and negatively by primary energy supply and GDP per capita; (3) factor 3 measures electricity generation.

While previous studies have shown that German electricity market has weak efficiency and the best predictor is the most recent transaction price, in this paper the authors try to show that this is not the only option and there could be more efficient models developed. Using ID3-Price index (electricity price index in German intraday market), authors build the least absolute shrinkage and selection operator (LASSO) model. This model is based not on the most recent transaction price, but on a few hours-ahead prices, with a number of fundamental variables incorporated to increase the prediction power of the model. Authors start with a baseline model of 76 potential regressors and move further to the full model with up to 200+ explanatory variables. They claim that this model significantly outperforms the naïve forecast (where the most recent transaction price is used as a regressor).

The issues of forecasting accuracy are also raised by Jan et al. [14]. They point out that electricity prices are influenced by a number of specific factors such as jumps in volatility, seasonal patterns, calendar effects, nonlinearity, which makes accurate forecasting of electricity prices challenging. Many previous attempts were based on both linear (AR, ARMA, ARIMA, etc.) and nonlinear (ARCH, GARCH, etc.) time series models. Parametric and nonparametric regression-type models were applied, as were artificial intelligence models. Even a mixture of all methods mentioned above was used (so-called hybrid models); however, there is no unified methodology. The authors propose an original approach for short-term price forecasting in the electricity markets based on the functional autoregressive model. Testing of the model on the Italian electricity market has shown that the proposed method performs relatively better than the nonfunctional forecasting techniques such as autoregressive (AR) and naïve models.

Lucas et al. [15] showed that the opening of the European electricity markets provides significant changes to the electricity market and pricing there. Nowadays market participants are constantly balancing between bidding in a lower price day-ahead market with typically higher volume and higher returns in a lower volume market. As a result, price forecasting is vital for many, because it allows players to manage assets in an optimal way. A common way to forecast electricity prices is the use of time series analysis. In this paper, an alternative approach is proposed. Based on Loss of Load Probability (LOLP) approach, a number of variables are used to predict future prices. A total of 19 predictors are considered, including base production, system load, solar and wind generation, seasonality, day-ahead price, imbalance volume contributions, etc. The best machine-learning algorithm is chosen to be implemented for the real data analysis (the ELEXON Balancing Energy Market in the UK is explored in this paper). Real data testing shows that the peaks of the daily price fluctuation are well predicted by the model. Therefore, it appears that this approach could be used as an additional forecasting instrument for market participants to predict future electricity prices.

Browell and Gilbert [16] discuss the issue of electricity imbalance pricing. In general problem is as follows: in theory electricity market supply (constrained by the physics of complex transmission and distribution networks combined with the uncertain renewable energy production) must meet demand (which us extremely uncertain because of unstable economic conditions, weather etc.) continuously. However, in practice constant disbalances are present. They, in turn, cause price changes to fix these disbalances: imbalance pricing incentivizes market participants to minimize their imbalance volumes, i.e., to generate or consume what they have contracted. Authors of this paper choose very challenging task: to show that it is possible to forecast price disbalances. Very complex, non-trivia and sophisticated task. For these purposes 3 different forecast models are analyzed: Point Forecast Zero/Max model, Probabilistic Simple Hedge model, and Probabilistic Risk-Constrained model. The results from the Great Britain's balancing market show that imbalance prices and volumes can be forecasted using intraday and probabilistic forecasting: trading strategies based on these models have shown that they add value to risk-neutral and risk-constrained trading strategies, increasing revenue by up to 2% and 5%, respectively.

For an alternative approach to the imbalance market, the researchers should turn to Narajewski [17]. Using lasso with bootstrap, gamlss, and probabilistic neural networks for the case of German market a very short-term (30 min before the physical delivery) probabilistic forecasting model of imbalance prices is developed.

Despite good efficiency of the modelling (compared with naïve models) author concludes that the intraday electricity market is close to be efficient. This means it is difficult to predict prices there. As a result, author recommends market participants to avoid active trading based on forecasts in this market. Instead, they should minimize their imbalance. Anyway, probabilistic imbalance price forecasting can be used in other less efficient markets (with lower liquidity for example) with the aim to develop trading strategies and generate abnormal profits.

Oyewo et al. [18] discussed the issue of environmental risks caused by an increase in electricity production. Based on estimated environmental costs and modeled the marginal social costs associated with the lifespan of the coal power plants, optimum levels of electricity production are calculated.

In Wu et al. [19], the very challenging task of oil price forecasting is investigated. Really oil prices are influenced by a significant number of internal and external factors. It is quite hard to incorporate them all as well as their interactions properly in a single model. Authors used a number of neural network and self-learning models for these purposes. They apply complex step-by-step approach. First, they decompose the raw data (historical oil prices) into a group of sub data sets. Next, they use random vector functional link neural network to forecast the target values for each decomposed subseries individually with further optimization of parameters. On the final stage the predicted values of all decomposed components are assembled as the final predicted results using addition aggregation. Actually, this is implementation of so called "divide and conquer" framework, which is widely used in image processing, fault diagnosis, etc. This paper is a good illustration of the synthesis in science. Comparison with benchmark models showed significant outperformance of the proposed model.

Peng et al. [20] consider the same topic, suggesting an interesting idea. Overall, it is not a problem to create a trend model for oil prices. It even will be efficient for some time. However, then something will happen (OPEC+ deal, COVID-19, war etc.). A game-changing factor; in addition, the whole model will collapse. Authors provide original idea to fix situations such as this for the case of oil market which is extremely uncertain and unstable: the fluctuation trend approach. It means the use of different formal models for different fluctuation trends. Using nonlinearity autoregressive distribute lag approach (NARDL) model authors are trying to find the key influence mechanism characteristics of crude oil prices typical for different fluctuation trends. These characteristics can be related to different fundamental events and act as switchers between different trend models. Empirical tests based on event study model with dummy variables show a strong correlation between event shocks and event types in the evolution of crude oil price fluctuation. As a result, we have a better understanding of the nature of price changes and efficient mechanism of price forecasting even in conditions of unstable environment.

Another energy source is highlighted by Su et al. [21], who provide a set of arguments in favor of accurate price prediction in the natural gas market: energy management, economic development, and environmental conservation. Authors propose to use least squares regression boosting method for the purposes of natural gas spot prices forecasting. Using Henry Hub natural gas spot prices (daily, weekly and monthly) over the period January 2001 to December 2017 author developed and calibrated a forecasting model. Empirical testing on real data showed a high degree of fitting. To make sure that their linier model is best-in-breed, results from the most popular liner prediction models (linear regression, linear support vector machine, etc.) authors showed supremacy of the LSBoost-based model: a higher R-square and lower mean absolute error, mean square error, and root-mean-square error. Therefore, if you need a linier approach for price forecasting in the natural gas market, now you know what can be used.

Furthermore, Penisa et al. [22] explore the issue of price prediction of Lithium-Ion NMC battery packs. Renewable energy no matter whether it is based on wind or solar generation requires one key element: battery packs to storage generated energy. That is why Elon Musk first of all builds gigafactories. The economy of the pricing for the Lithium-Ion battery packs is rather complex: costs are non-linier because of the scale effect, innovation activity, installed capacity, mineral costs, demand and its elasticity etc. Previous attempts to model pricing for Lithium-Ion battery packs were rather fragmentary and unsuccessful. In this paper authors used multi-factor learning curve models. They incorporated different variables into models including previous Lithium-Ion NMC prices, Lithium-Ion NMC demand, patent cooperation treaty applications, raw material prices. Comparing modelling results with actual historical data the best parameters were detected. Price prediction for Lithium-Ion NMC battery packs up to 2025 are provided in the paper. Therefore, if you wantto find the best moment to invest in Lithium-Ion NMC battery packs, please, read this paper.

Finally, a carbon price prediction model is discussed in Zhou and Wang [23]. The rationale for the paper is as follows: sustainable development and SDGs achievement is impossible without carbon emission reduction. Nowadays carbon emissions are trading asset, so price forecasting is important issue and challenging task for academicians. Non-trivia task requires nonstandard steps. Authors propose original approach called a second decomposition carbon price prediction model. First step, a decomposition of carbon prices (both empirical and variational modes), is used as a part of the input of the prediction model. Next structural and nonstructural factors are defined (maximum correlation minimum redundancy algorithm is used for these purposes). The final step is the Sparrow search algorithm which optimizes the relevant parameters of Extreme Learning Machine with Kernel. Empirical tests of the model are performed for two typical carbon trading markets in China (Guangdong and Hubei markets). The results show superiority of the proposed model to other models.

2. Conclusions

In this overview we have discussed 23 papers related to different aspects of price prediction in energy markets ranging from the novel methods and approaches, to the specifics of energy market prices during COVID-19, from oil and natural gas price forecasting to electricity price prediction, from intraday data sets to daily, weekly and even monthly data, from "divide and conquer" framework to nonlinearity autoregressive distribute lag approach, from gigafactories to carbon emissions. New models and approaches combined with fresh ideas based on the latest challenges move the economic science forward.

Author Contributions: Writing—original draft preparation, A.P.; writing—review and editing, Y.B. and S.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Abadie, L.M. Energy Market Prices in Times of COVID-19: The Case of Electricity and Natural Gas in Spain. *Energies* **2021**, *14*, 1632. [CrossRef]
2. Dmytrów, K.; Landmesser, J.; Bieszk-Stolorz, B. The Connections between COVID-19 and the Energy Commodities Prices: Evidence through the Dynamic Time Warping Method. *Energies* **2021**, *14*, 4024. [CrossRef]
3. Istudor, N.; Dinu, V.; Nitescu, D.C. Influence Factors of Green Energy on EU Trade. *Transform. Bus. Econ.* **2021**, *20*, 116–130.
4. Rus, A.V.; Rovinaru, M.D.; Pirvu, M.; Bako, E.D.; Rovinaru, F.I. Renewable Energy Generation and Consumption Across 2030—Analysis and Forecast of Required Growth in Generation Capacity. *Transform. Bus. Econ.* **2020**, *19*, 746–766.
5. Viviani, E.; Di Persio, L.; Ehrhardt, M. Energy Markets Forecasting. From Inferential Statistics to Machine Learning: The German Case. *Energies* **2021**, *14*, 364. [CrossRef]
6. Kelemen, M.; Polishchuk, V.; Gavurová, B.; Szabo, S.; Rozenberg, R.; Gera, M.; Kozuba, J.; Andoga, R.; Divoková, A.; Blišťan, P. Fuzzy model for quantitative assessment of environmental start-up projects in air transport. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3585. [CrossRef]
7. Polishchuk, V.; Kelemen, M.; Gavurová, B.; Varotsos, C.; Andoga, R.; Gera, M.; Christodoulakis, J.; Soušek, R.; Kozuba, J.; Blišťan, P.; et al. A fuzzy model of risk assessment for environmental start-up projects in the air transport sector. *Int. J. Environ. Res. Public Health* **2019**, *16*, 3573. [CrossRef]
8. Kolcun, M.; Rusek, K. Analysis of prices for electricity at the polish power exchange. *Pol. J. Manag. Stud.* **2022**, *17*, 155–164. [CrossRef]
9. Butt, A.A.; Chughta, G.R.; Kabir, A.; Mahood, Z.; Jafri, Z.; Oláh, J. Analysis of Key Establishment Techniques for Secure D2D Communication in Emerging 5G Cellular Networks. *Acta Monast. Slovaka* **2021**, *26*, 395–403. [CrossRef]
10. Mahmood, A.; Zahoor, A.; Bai, Y.; Qiao, G.; Popp, J.; Oláh, J. Financial Inclusion, Technological Innovations, and Environmental Quality: Analyzing the Role of Green Openness. *Front. Environ. Sci.* **2022**, *10*, 851263. [CrossRef]
11. Marcjasz, G.; Uniejewski, B.; Weron, R. Beating the Naïve—Combining LASSO with Naïve Intraday Electricity Price Forecasts. *Energies* **2020**, *13*, 1667. [CrossRef]
12. Androniceanu, A.; Georgescu, I.; Dobrin, C.; Dragulanescu, I.V. Multifactorial components analysis of the renewable energy sector in the OECD countries and managerial implications. *Pol. J. Manag. Stud.* **2020**, *22*, 36–49. [CrossRef]

13. Gavurova, B.; Kovac, V.; Drabik, P.; Gomory, M. Exploration of Disparities in Environmental Activities of European Countries from Year 2006 to Year 2016. *Acta Montan. Slovaca* **2019**, *24*, 376–390.
14. Jan, F.; Shah, I.; Ali, S. Short-Term Electricity Prices Forecasting Using Functional Time Series Analysis. *Energies* **2022**, *15*, 3423. [CrossRef]
15. Lucas, A.; Pegios, K.; Kotsakis, E.; Clarke, D. Price Forecasting for the Balancing Energy Market Using Machine-Learning Regression. *Energies* **2020**, *13*, 5420. [CrossRef]
16. Browell, J.; Gilbert, C. Predicting Electricity Imbalance Prices and Volumes: Capabilities and Opportunities. *Energies* **2022**, *15*, 3645. [CrossRef]
17. Narajewski, M. Probabilistic Forecasting of German Electricity Imbalance Prices. *Energies* **2022**, *15*, 4976. [CrossRef]
18. Oyewo, T.; Olarewaju, O.M.; Cloete, M.B.; Adenuga, O.T. Environmental costs estimation and mathematical model of marginal social cost: A case study of coal power plants. *Environ. Econ.* **2021**, *12*, 90–102. [CrossRef]
19. Wu, J.; Miu, F.; Li, T. Daily Crude Oil Price Forecasting Based on Improved CEEMDAN, SCA, and RVFL: A Case Study in WTI Oil Market. *Energies* **2020**, *13*, 1852. [CrossRef]
20. Peng, J.; Li, Z.; Drakeford, B.M. Dynamic Characteristics of Crude Oil Price Fluctuation—From the Perspective of Crude Oil Price Influence Mechanism. *Energies* **2020**, *13*, 4465. [CrossRef]
21. Su, M.; Zhang, Z.; Zhu, Y.; Zha, D. Data-Driven Natural Gas Spot Price Forecasting with Least Squares Regression Boosting Algorithm. *Energies* **2019**, *12*, 1094. [CrossRef]
22. Penisa, X.N.; Castro, M.T.; Pascasio, J.D.A.; Esparcia, E.A., Jr.; Schmidt, O.; Ocon, J.D. Projecting the Price of Lithium-Ion NMC Battery Packs Using a Multifactor Learning Curve Model. *Energies* **2020**, *13*, 5276. [CrossRef]
23. Zhou, J.; Wang, S. A Carbon Price Prediction Model Based on the Secondary Decomposition Algorithm and Influencing Factors. *Energies* **2021**, *14*, 1328. [CrossRef]