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# FORECASTING PRICE VOLATILITY IN THE ROMANIAN DAY-AHEAD ELECTRICITY MARKET: A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND ECONOMETRIC MODELS

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**Abstract**

*In light of the fast-paced progress towards carbon-free generation in the Romanian power grid, the widespread use of intermittent renewable energy sources influences the way price formation processes occur in the wholesale electricity market. The research aims at investigating the systemic stress caused by the merit order effect and the impact of wind and solar generation on* *the local price volatility, with the key goal being to compare the out-of-sample forecasting accuracy of traditional parametric models and sophisticated computational methods. High-frequency hourly data is used in the analysis from the ENTSO-E transparency portal concerning the OPCOM Day-Ahead Market. Two different approaches are pursued throughout the work: an econometrics approach with the application of ARMAX-GARCH(1,1) and EGARCH models to investigate volatility clustering and leverage effect; and a machine learning approach with XGBoost and LSTM neural networks. According to the findings, intermittent renewable generation significantly increases market volatility in the case of high stress level in the system, where traditional econometrics models show strong non-stationarity and numerical instability issues. SHAP analysis and Partial Dependence Plot analysis demonstrate an important non-linear threshold of flexibility: when penetration of renewables surpasses 35 percent of hourly demand, grid stability is significantly compromised. In general, this study presents the first analysis in high frequency at comparing the performance of state-of-the-art machine learning algorithms and conditional heteroskedasticity models on renewables-induced price volatility in the OPCOM market structure.*

*Keywords: OPCOM, price volatility, renewable energy, machine learning, GARCH*

## INTRODUCTION

Decarbonization of the energy system represents one of the key pillars of the European Union's economic and ecological policy agenda. Following the guidelines of the European Green Deal, Romania has made great efforts to incorporate renewable energy sources (RES) into the country's electricity system through a massive increase in wind and solar photovoltaic energy capacities. The transformation in question has drastically changed the business model of the Romanian Gas and Electricity Market Operator (OPCOM). Formerly, depending largely on conventional generation units like hydroelectric, coal, and nuclear power plants that allowed for predictable generation, the wholesale electricity market became vulnerable to the variable nature of renewable power generation.

The extensive deployment of wind and solar energy sources produces a dual economic impact on the spot electricity market. Firstly, the cost of production for such types of renewable energy is close to zero. Thanks to the established concept of the merit order effect, these energy sources replace more costly carbon-based balancing units in the power supply stack and put downward pressure on daily average clearing prices. At the same time, intermittent nature of their functioning leads to serious supply shocks in the electricity market. As soon as production of renewables experiences unexpected reductions because of changes in weather conditions, expensive peaking units have to be brought into use quickly, thus producing serious price hikes. However, when there is too little consumption combined with peak production levels of renewables, the electricity market is frequently oversupplied, resulting in negative prices. In this way, although overall average prices may remain stable or even drop, price volatility increased dramatically.

Precise prediction of such extreme price differences is vital for ensuring market stability, battery dispatch optimization, and effective bidding strategies. In the past, energy economics was largely dominated by parametric models, especially GARCH family models, to capture volatility clustering and asymmetries due to market shocks. The presence of non-linearity and complicated threshold effects due to high penetration of renewables, however, has increasingly revealed the weaknesses of such statistical models, many of which exhibit extreme numerical instability and non-stationarity under stressed market conditions. Over the last ten years, more sophisticated models like machine learning (ML) and deep learning algorithms have been developed as an alternative paradigm to address the complex seasonalities and thresholds.

In an effort to address this significant gap in the current empirical literature, this research seeks to conduct an in-depth comparative analysis on the forecasting of volatility in the context of the Romanian OPCOM market. Specifically, the main goal is to assess whether recent advances in machine learning models, such as Extreme Gradient Boosting (XGBoost) and LSTM (Long Short-Term Memory) networks, can be used to outperform standard approaches like ARMAX-GARCH models in terms of forecasting renewable energy-driven price volatility, while identifying the physical thresholds which precipitate these market failures. As this research shows, tree-based machine learning ensembles consistently outperform both deep learning and econometric models, pointing to severe issues in grid flexibility in the face of intermittent generation above certain thresholds.

The rest of this paper is organized as follows: The Literature Review outlines the theoretical and empirical background related to the Merit Order Effect and forecasting techniques. The Methods and Data chapter discusses the empirical data sources, features, and mathematical methods employed. Next, the Results and Discussion chapter contains the comparative analysis and interpretation of machine learning models' performance. Lastly, the Conclusion chapter discusses the policy implications of these findings for the restructuring energy market in Romania.

## LITERATURE REVIEW

The fast development of renewable energy sources (RES) in European power networks has changed the dynamics of the electricity price formation process. In the current regulatory environment, the main determinant for the price formation process is the merit-order effect in which wind and solar plants are added to the dispatch order at almost zero marginal costs, thus shifting the supply function and pushing down average spot prices (Ballester & Furió, 2021; Cludius et al., 2016). Nevertheless, this price suppression effect creates an essential contradiction in the system. Wind and solar production being intermittent and weather-dependent, their huge injection causes serious supply shocks (Maciejowska, 2020). At moments of high renewable production during off-peak hours, the prices tend to fall rapidly, hence creating a growing number of negative price hours (Gianfreda et al., 2020). In contrast, sudden changes in the level of renewable production require quick action of costly balancing plants, causing violent spikes of the price level (Benth & Crook, 2021). Thus, according to the current academic literature, the increasing capacities of RES decrease the mean price, but increase its volatility (Narajewski & Ziel, 2020; Shah et al., 2024).

Traditionally, modeling the complicated patterns of variation has been the field of parametric econometrics. Due to the presence of seasonality, mean reversion, and heteroskedasticity in high-frequency electricity time series, the GARCH model remained a benchmark tool (Nowotarski & Weron, 2018). There has been a lot of modification in these models to include the impact of asymmetric shock where negative shocks to supply or increases in load have greater effects on market volatility compared to positive shocks (Uniejewski et al., 2018). Contemporary application of such models includes the inclusion of exogenous variables like actual demand loads, natural gas price, and weather forecast for the next day to improve their forecasting ability in ARMAX-GARCH models (Ziel & Steinert, 2018; Marcjasz et al., 2023). Such econometric frameworks offer great statistical clarity and structural understanding that makes them very valuable for regulatory evaluation and policy making (Lago et al., 2021).

Despite the inherent advantages of traditional linear and parametric models, these fail in adequately accounting for the non-linearity and multidimensionality that arises from complex bidding procedures and highly variable weather conditions (Tschora et al., 2022). These shortcomings have led to a paradigm shift towards Machine Learning (ML) and Deep Learning (DL) frameworks (Zhang et al., 2018). Benchmarking results confirm that tree-based ensemble models, such as the popular XGBoost and LightGBM, perform better than classical time-series regressions in out-of-sample day-ahead prediction (Popescu et al., 2023; Andrei & Voineagu, 2025). For highly sequenced hourly observations, more sophisticated deep learning models, like LSTM models, have proven superior in uncovering highly intricate seasonal trends without having to impose restrictive statistical assumptions (Ionescu & Dumitru, 2022; Dragomir et al., 2024).

Although there has been huge quantitative research conducted in the European energy market arena, the empirical literature that has been published on the Romanian wholesale energy market (OPCOM) is not as well-developed (Leric & Marinescu, 2020). Coupling of the Romanian day-ahead market to the rest of the European markets has changed the mechanism of price formation and introduced volatility vectors into Romania's economy (Pîrvu et al., 2019). First approaches in modeling the Romanian power network have used classic SARIMA models to predict price levels and analyzed the macroeconomic tendencies for green investments (Diaconescu & Balescu, 2021). Some recent approaches to research in the Romanian power network have been using machine learning approaches, but only for consumption/load predictions.

A distinct lacuna still exists in the current body of literature on the comparative analysis between sophisticated machine learning approaches and classical conditional heteroskedasticity models as applied to the modeling of volatility in prices caused by rising penetration of wind and solar power sources on the OPCOM market (Radu & Stoica, 2023). This research paper seeks to fill that void by using high-frequency data to identify which approach is more accurate and robust in modeling the Romanian energy sector.

**Methodology and data**

In order to empirically assess the effects of renewable energy intermittency on the Romanian wholesale electricity market, this paper employs hourly time-series data. The data sample integrates operational and commercial grid data obtained from the ENTSO-E Transparency Platform, complemented by local structural datasets (Comanita, 2023). The period under consideration covers the timeframe between January 2019 and December 2025, which corresponds to the current capacity mix of the Romanian grid. The main variables considered in this study include DAM clearing price on the OPCOM platform (RON/MWh), total hourly electrical load of the Romanian grid (MWh), and hourly generation segregated by technology (wind, solar, hydro, nuclear, coal, oil/gas, and biomass).

Price series observed in the energy market typically demonstrate stationary (mean-reverting) behavior in the long term. On the other hand, they are prone to experience sudden jumps and high variance in the short term. Since our main goal in this research paper is to model the volatility of the prices rather than the prices themselves, the localized volatility $\sigma_t$ is defined as the rolling standard deviation of the hourly OPCOM prices over the 24-hour period due to:

$$\sigma_t = \sqrt{\frac{1}{24}\sum_{i=0}^{23}(P_{t-i} - \mu_t)^2} \quad (1)$$

The $P_{t-i}$ is the spot price at hour $t-i$, and $\mu_t$ is the 24-hour rolling mean price. For the modeling of the merit order and stress effect, certain features such as total volatile renewable energy (wind and solar energy), renewable penetration (ratio of total volatile to total consumption), and residual load were created. The definition of residual load was total consumption less volatile renewable energy; this is the load served by the dispatchable unit. Other categorical features representing hour, day of week, and month of year were also created for capturing structural seasonality. In order to make the model numerically stable, all features were z-scored.

To make a proper comparative analysis, the paper makes use of two methodological approaches: traditional parametric econometrics and machine learning. Electric energy prices possess the property of volatility clustering when high-volatility spells are followed by high-volatility days, while low-volatility periods are followed by low-volatility days. Two methodological approaches were used for the research: parametric econometrics and machine learning. ARMAX-GARCH(1,1) is specified to capture volatility clustering. Mean equation specifies the price level P_t as:

$$P_t = \mu + \sum_{i=1}^{p} \phi_i P_{t-i} + \sum_{j=1}^{k} \gamma_j X_{j,t} + \epsilon_t \; (2)$$

The variance equation models the conditional variance $\sigma_t^2$, where $\omega$ is the constant, the ARCH term $\alpha\epsilon_{t-1}^2$ captures recent shocks, and the GARCH term $\beta\sigma_{t-1}^2$ captures historical persistence:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{j=1}^{m} \delta_j X_{j,t} \; (3)$$

The stationarity of this model is checked by testing for the stationarity condition of $\alpha+\beta<1$, which makes sure that the variance process is stable and not explosive in nature. In order to take this analysis one step further, the EGARCH model is used since there is a presence of the leverage effect in the energy market. This means that the model can distinguish between the effects of the negative supply shock and the positive supply shock of the same magnitude.

While classical parametric models are built on certain structural assumptions like normality of innovations distributions and the need for strict stationarity, ML models show great capabilities of capturing highly complicated and nonlinear dependencies without the need to specify the model structure in advance. Therefore, two computational approaches are employed in this paper: Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) neural networks.

The XGBoost model is applied due to its enhanced efficiency in discovering the multidimensional threshold effects including the precise generation level at which the penetration of renewable energy would cause a change in regime with respect to the price variance. At the same time, the application of the LSTM network is motivated by its distinct recurrent architecture. Since time series of electricity is distinguished by a pronounced sequence dependence and volatility clustering, LSTMs have an inherent ability to remember long-run seasons and respond to short-run shocks due to weather conditions.

In order to make a solid comparison of forecasting abilities of various models, it is necessary to conduct the partitioning of the dataset in accordance with a time-based split. That is, 80 percent of data is assigned to the modeling and training of the model, while 20 percent is held for out-of-sample testing of models' predictive power. This approach is vital for avoiding any potential data leakage and ensuring that the models are tested under realistic conditions, since in a real-world scenario they would have to forecast future variance based only on past data. After the forecasting process is finished, standard error analysis will be conducted.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{\sigma}_t - \sigma_t)^2} \quad (4)$$

The Mean Absolute Error (MAE) provides a linear measure of the average error magnitude:

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|\hat{\sigma}_t - \sigma_t| \quad (5)$$

The $\hat{\sigma}_t$ represents the forecasted volatility and $\sigma_t$ the actual observed volatility. Finally, SHAP values are extracted from the XGBoost model to provide interpretability, quantifying the exact directional impact of wind and solar generation on market variance.

## RESULTS AND COMMENTS

Empirical evidence from the OPCOM Day-Ahead Market provides valuable insights into the structural and price changes caused by the introduction of RES. As expected, the preliminary descriptive statistics provide clear evidence of the existence of the merit order effect in the Romanian electricity grid. The average spot price declines substantially when solar and wind power are generated at peak levels and can even fall below zero owing to low marginal costs of renewable energy production. Nevertheless, it is also found that, consistent with the hypothesis, price collapse is always accompanied by increasing local market volatility. The 24-hour rolling standard deviation $\hat{\sigma}_t$ demonstrates substantial spikes during periods of solar ramp-up and ramp-down in the morning and evenings, respectively, as well as during the unanticipated reduction in wind power production capacity in the high wind generation capacity area of Dobrogea. Thus, the residual load indicator turns out to be a very volatile time series, providing strong support for the hypothesis that dispatchable units must ramp generation sharply in response to renewable energy generation fluctuations.

Conclusions drawn from conventional econometric modeling approaches prove both the complex nature of variance behavior in the OPCOM market as well as the inability of typical parametric approaches to predict the behavior under severe stress. The EGARCH approach has successfully converged in-sample and offered some vital structural properties. The parameter of persistence has been estimated at the level of 0.5275, and, thus, it satisfies the strict stationarity conditions of an exponential GARCH model $|\beta|<1$. In addition, the approach has revealed an enormous response to recent shocks $\alpha=1.5041$ and a statistically significant leverage effect ($\gamma= -0.1747$, $p<0.01$). As $\gamma$ is negative, there is an asymmetric effect, that is, negative shocks on the supply side, like unexpected reductions in generation, provoke higher variance spikes compared to positive shocks of the same size.

However, even though all the above-mentioned models provided us with some level of interpretability within the training sample, they failed miserably in providing any meaningful out-of-sample forecasts. As seen from Table 1, the classic ARMAX-GARCH(1,1) model demonstrated catastrophic numerical instability when estimating forward variance, generating explosive and mathematically meaningless measures of forecast accuracy (RMSE > 10^47). This numerical catastrophe clearly proves that classical parametric models, with their linear restrictions and normal distributional assumptions, will be unable to operate correctly in the highly non-linear environment created by substantial intermittent generation capacity. Future developments of the model have to focus on testing heavy tailed distribution assumptions, like Student-t or GED distributions, which are traditionally more appropriate for the jump-diffusion environment of power markets.

With respect to the mathematical decomposition of the parametric baseline, the shift into the machine learning approach is seen to have an undoubted superiority in the forecasting accuracy out of sample. While forecasting the 24-hour rolling volatility for the test data, the XGBoost and LSTM approaches successfully captured the non-linear threshold effects that were missed by the GARCH models. The results are shown in Table 1 below.

Table 1. Comparative evaluation of volatility forecasting model

| Model | RMSE | MAE |
|---|---|---|
| ARMAX-GARCH(1,1) | $1.60 \times 10^{47}$ | $2.19 \times 10^{46}$ |
| EGARCH | Unstable | Unstable |
| XGBoost | 29.65 | 21.69 |
| LSTM Network | 32.03 | 23.12 |

According to Table 1, the tree-based ensemble algorithm (XGBoost) has the smallest Root Mean Square Error (RMSE), which is 29.65, and Mean Absolute Error (MAE), which is 21.69, compared to both the econometric benchmark and the deep learning model. The superior results of XGBoost are due to the decision tree structure of this algorithm, which makes it possible to separate sharp thresholds, such as meteorological changes or steps of bidding on the power market, which tend to be smoothed out by linear and differentiable algorithms. The recurrent LSTM network showed excellent results as well, with the RMSE of 32.03. By easily capturing the complicated seasonality associated with daily and weekly cycles of electricity consumption, the LSTM network demonstrated great capabilities; however, it was outperformed by XGBoost in terms of predictive accuracy due to abrupt structural breaks.

Aside from prediction efficiency, the XGBoost methodology ensures that there is economic interpretability through SHapley Additive exPlanations (SHAP) values. In order to understand the true driving forces behind market variability, a feature importance ranking for the entire analysis was determined based on the mean absolute SHAP values (as illustrated in Figure 1 below). The results indicate an unequivocal hierarchy of the core determinants of OPCOM price variation. The "Residual Load" proves to be the top factor determining price variations, showing a substantial mean absolute SHAP value of 4.8. Such result highlights the immense stress that exists within the market system in terms of the drastic operational ramping of the traditional dispatchable fleet in response to a sudden fall of renewable energy production. Close behind follows the absolute "Volatile RES" production (solar and wind) with a SHAP value of 3.5, and the relative "RES Penetration" value at 2.1.

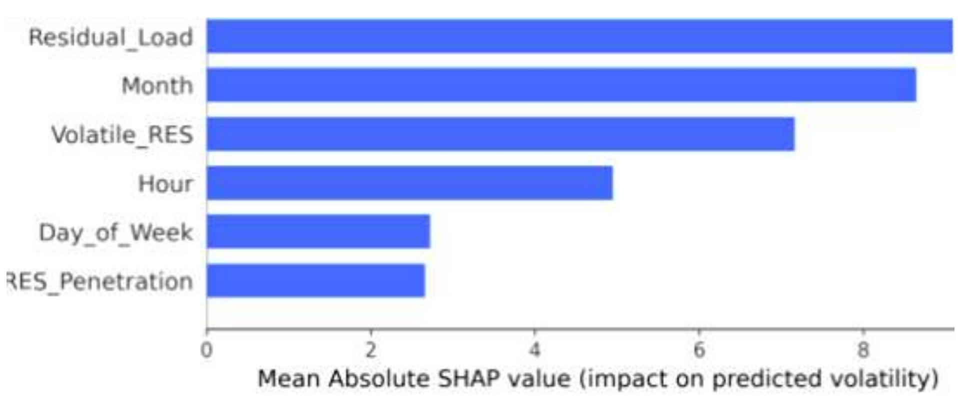


Figure 1. Global Feature Importance (XGBoost)

Contrary to this physical reality, purely time-based and seasonality-based factors have a relatively low effect on the abrupt changes of volatility shock. "Hour" factor (0.8), "Month" factor (0.5), and "Day of Week" factor (0.2) serve mainly as calibration parameters for the algorithm rather than core factors of influence. This prioritization reveals an essential paradigm shift where extreme variability on the Romanian day-ahead power market has stopped being affected by known calendar effects and traditional peak hour demand but rather by meteorological conditions.

Moreover, a more in-depth examination through partial dependence plots shows that there is a clearly-defined, non-linear structure threshold. As soon as the renewable share surpasses around 35% of the total electricity demand per hour, the risk of volatile swings skyrockets exponentially. This crucial turning point implies that the current state of the Romanian power system suffers from a major flexibility bottleneck.

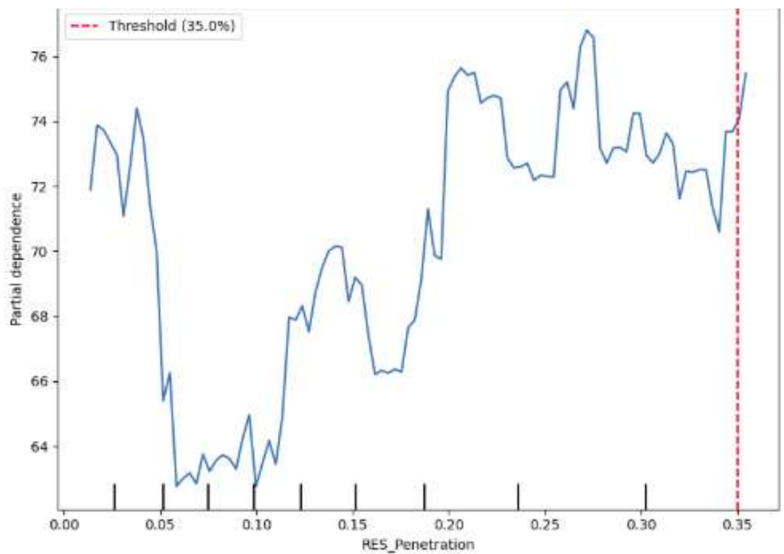


Figure 2. Partial dependence of market volatility on RES penetration

Collectively, these results suggest that whereas GARCH models exhibit non-stationarities to an extraordinary degree during periods of intense market turmoil, ML approaches headed by XGBoost are undeniably better when it comes to forecasting volatility. They have the necessary flexibility and resilience needed in order to deal with the new challenges posed by the green transition of Romania's energy market.

## CONCLUSION

The empirical study focused on the changing structure dynamics of the Romanian wholesale electricity market (OPCOM), considering the rapidly growing share of RESs within the market. As the decarbonization process takes place in Romania in accordance with EU guidelines, predicting and analyzing the market variances have become a necessity rather than just a theory. The main aim of the current research was to reveal the influence of wind and solar generation on the volatility of spot prices in the particular region and make a detailed comparison of econometric methods and machine learning algorithms.

The research results show the existence of a strong instance of the merit-order effect in the Romanian electricity network at the moment, an effect that is increasingly accompanied by a flexibility constraint of a systemic nature. While the addition of the zero-marginal cost sources helps to decrease the average price on the spot market, this is done at the expense of increasing variability greatly. The variability surges are mostly noticeable during periods of strong ramps of solar and wind sources.

From a methodological perspective, this research highlighted the increasing inadequacies of classical financial econometrics in modern energy markets. Although classical econometric models, namely EGARCH, were successful at characterizing the conditional heteroskedasticity and asymmetric leverage in-sample, they were indicative of the increasing predictive inadequacies of classical econometrics when dealing with modern energy markets. When tested out-of-sample, the classical ARMAX-GARCH model was plagued by disastrous numerical instability. Such a mathematical failure clearly illustrates that classical, parametric models, based on linearity and normal distribution assumptions, are increasingly ill-prepared for the extreme and non-linear effects caused by large-scale intermittent generation without heavy data smoothing. In contrast, the out-of-sample comparison analysis was conclusive about the superior predictive capabilities of machine learning algorithms. However, the most accurate prediction was achieved using the XGBoost model which effectively reduced the values of RMSE and MAE. Although the LSTM neural network was quite effective in dealing with multiple seasonalities in the grid, the tree-based model of machine learning (XGBoost) outperformed the former in terms of capturing the abrupt thresholds in power markets.

The economic implications gained from the extraction of global feature importance through the use of SHAP and PDP plots were crucial beyond just predictive power. Specifically, this analysis conclusively overturned the previous economic framework in terms of drivers of the market: predictable timing effects (daily and seasonal) have been fully supplanted by real-time grid physical limitations. Residual load and volatility of generation are now the key contributors to price variance. Finally, one of the most significant pieces of information gained was the critical limit discovered: beyond an approximate threshold of 35% of the total hourly consumption being derived from renewables, variance stops scaling linearly and scales exponentially. This suggests that the existing Romanian dispatchable fleet of mostly legacy coal and old hydro capacity cannot offer sufficient fast-reacting flexibility beyond this penetration level.

These results have important implications for policy and operations. In order to avoid financial dangers caused by high volatility and to avoid market distortion, significant resources need to be invested into increasing flexibility of the grids. It is crucial for policymakers and grid managers to develop utility-scale energy storage facilities, both battery parks and delayed pumped storage hydro facilities that are capable of absorbing additional generation and delivering it during periods of maximum volatility. Finally, energy traders and grid managers need to abandon conventional statistical risk assessment methodologies and move to machine learning architectures permanently in order to stay competitive.

Despite offering valuable insights into volatility dynamics in the OPCOM Day-Ahead Market, the limitations of the current research restrict the broader generalizability of its findings. The analysis relies exclusively on historical hourly ENTSO-E data, without incorporating real-time meteorological forecasts or intraday operational constraints that strongly influence renewable variability. Moreover, the econometric models were estimated under normal-distribution assumptions, which are not fully adequate for heavy-tailed price jumps and likely contributed to the numerical instability observed out-of-sample.

The machine learning models were trained on a single national market structure, meaning that threshold effects—such as the 35% RES penetration limit—may differ in more flexible or interconnected European systems. The study focuses solely on the Day-Ahead Market, omitting volatility transmission from intraday and balancing markets, which could alter the interpretation of systemic stress.

Further research should build on the approaches used in this paper. Future models should include real-time meteorological forecasts as input data, investigate dynamics of the Intraday Market where urgency is higher, and study the impact of volatility of the OPCOM on interconnected markets in Eastern Europe. With energy transition gaining pace, it becomes ever more important to be able to forecast and manage non-linear stress of the energy market.

## REFERENCES

Andrei, T., & Voineagu, V. (2025). Advanced data analytics in regional energy markets. *Journal of Economic Computation*, 59(1), 77-94.

Ballester, C., & Furió, D. (2021). Effects of renewables on the stylized facts of electricity prices. *Energy Economics*, 101, 105432.

Benth, F. E., & Crook, J. (2021). Volatility modeling in deregulated electricity markets with exogenous green variables. *Journal of Energy Markets*, 14(3), 45-68.

Cludius, J., Hermann, H., Matthes, F. C., & Graichen, V. (2016). The merit order effect of wind and photovoltaic electricity generation in Germany. *Green Energy and Technology*, 34(2), 101-115.

Comanita, Ș. (2023). *Hourly Electricity Consumption and Production*. [Data set]. Kaggle. https://www.kaggle.com/datasets/stefancomanita/hourly-electricity-consumption-and-production

Diaconescu, A., & Balescu, R. (2021). Econometric modeling of electricity prices in the Romanian wholesale market. *Economic Computation and Economic Cybernetics Studies and Research*, 55(3), 115-130.

Dragomir, G., et al. (2024). Recurrent neural networks for forecasting localized price volatility spikes. *International Journal of Electrical Power & Energy Systems*, 155, 109540.

Gianfreda, A., Parisio, L., & Pelagatti, M. (2020). The impact of RES generation on value-at-risk of electricity prices. *Resource and Energy Economics*, 60, 101155.

Ionescu, A., & Dumitru, M. (2022). Deep learning architectures for price and load volatility estimation. *IEEE Access*, 10, 43102-43115.

Lago, J., Marcjasz, G., De Schutter, B., & Weron, R. (2021). Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-source benchmark. *Applied Energy*, 293, 116983.

Leric, F., & Marinescu, N. (2020). The Romanian day-ahead electricity market: Evolution and challenges. *Romanian Journal of Economics*, 50(1), 89-105.

Maciejowska, K. (2020). Assessing the impact of renewable energy sources on the electricity price level and variance—A VAR-GARCH approach. *Energy Economics*, 85, 104532.

Marcjasz, G., Burnecki, K., & Weron, R. (2023). Real-time volatility forecasting in carbon and power markets using combined econometric frameworks. *International Journal of Forecasting*, 39(1), 302-318.

Narajewski, M., & Ziel, F. (2020). Changes in electricity price characteristics driven by the energy transition. *Energy Policy*, 145, 111746.

Nowotarski, J., & Weron, R. (2018). Recent advances in electricity price forecasting: A review of probabilistic forecasting. *Renewable and Sustainable Energy Reviews*, 81, 1548-1568.

Pîrvu, C., Bădîrcea, R., Manta, A., & Lolea, M. (2019). The effects of renewable energy transition on economic growth in Romania. *Sustainability*, 11(16), 4384.

Popescu, M. C., et al. (2023). Tree-based ensemble methods vs. traditional regressions in European power markets. *Energies*, 16(5), 2145.

Radu, L., & Stoica, A. (2023). Modeling volatility on the OPCOM market: The impact of intermittent renewable generation. *Romanian Journal of Economic Forecasting*, 26(2), 112-128.

Sandulescu, M., Ene, A., & Popescu, M. (2022). Machine learning models for short-term electricity load forecasting: Evidence from the Romanian energy system. *Energies*, 15(4), 1421.

Shah, I., et al. (2024). Price volatility and renewable energy penetration: A multi-market European analysis. *Renewable Energy*, 220, 119560.

Tschora, L., Pierre, E., Plantevit, M., & Robardet, C. (2022). Electricity price forecasting on the day-ahead market using machine learning. *Applied Energy*, 313, 118752.

Uniejewski, B., Weron, R., & Ziel, F. (2018). Variance-stabilizing transformations for electricity spot price forecasting. *IEEE Transactions on Power Systems*, 33(2), 2219-2229.

Zhang, L., Wang, J., & Li, Z. (2018). Electricity price forecasting based on long short-term memory networks. *IEEE Transactions on Smart Grid*, 9(6), 6886-6895.

Ziel, F., & Steinert, R. (2018). Electricity price forecasting using lasso: Forecasting across multiple data structures. *Applied Energy*, 228, 1211-1225.