MODELLING ENERGY MARKET DYNAMICS IN ALBANIA: A COMPARATIVE STUDY OF ADVANCED FORECASTING TECHNIQUES

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Abstract

Prediction models play a critical role in understanding dynamic relationships within energy markets, providing insights into price fluctuations and trading volumes. By capturing these complex interactions, advanced forecasting techniques enable better decision-making and strategic planning. The establishment of the Albanian Power Exchange (ALPEX) has introduced a structured energy market in Albania, fostering transparency and competitiveness in electricity trading. This study focuses on modelling energy market dynamics in Albania by analysing key indicators, including Market Clearing Prices (MCP), energy volumes traded, and energy production and consumption. Using daily data from May 2023 to May 2024, the study employs both statistical and machine learning models to forecast MCP as a univariate time series. By comparing the predictive performance of traditional statistical approaches such as ARIMA with advanced machine learning techniques like XGBoost and Neural Network Autoregressive, the research aims to identify the most accurate methodologies for forecasting MCP. The findings aim to guide stakeholders in utilizing data-driven models for market analysis and strategic development.

Key words: *energy, market, seasonal, statistical analysis, demand, production.*

Përmbledhje

Modelet e parashikimit luajnë një rol kritik në kuptimin e marrëdhënieve dinamike brenda tregjeve të energjisë, duke ofruar njohuri mbi luhatjet e çmimeve dhe vëllimet e tregtimit. Duke kapur këto ndërveprime komplekse, *teknikat e avancuara të parashikimit mundësojnë vendimmarrje dhe planifikim strategjik më të mirë. Krijimi i Bursës Shqiptare të Energjisë (ALPEX) ka prezantuar një treg të strukturuar energjie në Shqipëri, duke nxitur transparencën dhe konkurrencën në tregtimin e energjisë elektrike. Ky studim fokusohet në modelimin e dinamikave të tregut të energjisë në Shqipëri duke analizuar treguesit kryesorë, qe përfshijnë çmimet kleruese të tregut, vëllimet e energjisë të tregtuara si dhe prodhimin e konsumin e energjisë. Duke përdorur të dhëna ditore nga Maji 2023 deri në Maj 2024, studimi përdor modele statistikore dhe algoritme machine learning për të parashikuar çmimet kleruese të tregut. Duke krahasuar saktësinë e modeleve parashikuese statistikore tradicionale si ARIMA me modelet e avancuara machine learning si XGBoost dhe Neural Network Autoregressive, studimi synon të identifikojë metodologjitë më të sakta për parashikimin e çmimit klerues të tregut. Rezultatet synojnë të drejtojnë palët e interesuara në përdorimin e modeleve të bazuara nga të dhënat për analizën e tregut dhe zhvillimin strategjik.*

Fjalë kyçe: *energji, treg, sezonalitet, analizë statistikore, kërkesë, prodhim.*

1. Introduction

The energy market in Albania has undergone significant transformations in recent years, driven by the liberalization of energy policies, integration into regional markets, and the increasing importance of renewable energy sources. Albania’s energy sector is characterized by a high reliance on renewable energy, particularly hydropower, which accounts for around 95% of the country’s electricity generation. Albania is working toward the full liberalization of its energy market, allowing for the separation of generation, transmission, and distribution activities. The Albanian Power Exchange (ALPEX) was officially established in October 2020 through the signing of a shareholder agreement[1] between Albania's Transmission System Operator (OST) and Kosovo's Transmission System Operator (KOSTT).

This agreement marked a significant step towards the creation of a joint electricity market between the two countries. It operates the day-ahead and intra-day markets for both countries, promoting market coupling and

[1] https://alpex.al/corporate/governance/

integration with neighbouring markets in line with EU regulations. ALPEX aims to enhance market transparency, facilitate cross-border trading, and improve energy security through regional cooperation and real-time data on prices and volumes. These developments have heightened the need for accurate forecasting models to ensure market stability, optimize resource allocation, and support decision-making for stakeholders. Traditional statistical models have been used for a long time in energy market analysis, but the complexity and volatility of modern electricity markets demand more advanced methodologies.

This study aims to explore the dynamics of Albania's energy market by employing a comparative analysis of advanced forecasting techniques, including statistical, machine learning, and hybrid models. By evaluating their predictive accuracy and applicability in the context of Albania's unique energy landscape, this research seeks to provide actionable insights for improving market efficiency and fostering sustainable energy practices.

Over the years, significant advancements have been made in electricity price forecasting, reflecting the evolving complexity of energy markets and the increasing need for precise predictive models. Early work by (Contreras et al., 2003), established the foundation using ARIMA models to predict next-day electricity prices with hourly data from the Spanish power market. This study highlighted the effectiveness of statistical methods in capturing temporal patterns and seasonal effects, establishing a baseline for forecasting methodologies. Advancing from this point, (Singhal & Swarup, 2011) demonstrated the potential of artificial neural networks (ANNs) for electricity price forecasting.

By employing a feedforward neural network with backpropagation, their study illustrated the ability of ANNs to model nonlinear relationships and adapt to the volatility of energy markets, using data from the Indian market. Moving the field forward, (Yan & Chowdhury, 2013) introduced a hybrid approach by integrating Least Squares Support Vector Machines (LSSVM) with ARMAX models for mid-term market clearing price forecasting. Their framework emphasized the importance of hybrid models in leveraging the strengths of complementary techniques, effectively addressing both linear and nonlinear features in price data. Moreover, (Yang et al., 2017) combined wavelet transforms, ARMA, and kernel-based extreme learning machines, achieving notable improvements in accuracy for complex and high-frequency electricity price data.

Their innovative methodology underscored the value of hybrid models in handling intricate data dynamics. While these studies primarily focused on methodological advancements, (Hong et al., 2020) provided a broader perspective by offering a comprehensive review of energy forecasting methodologies. They identified emerging trends, such as the integration of data-driven approaches with domain expertise and outlined future directions for research. Adding a market-specific dimension, (Pinhão et al., 2022) explored electricity spot price forecasting by modelling supply and demand curves. Their work highlighted the critical role of incorporating market dynamics and behavioural patterns into predictive models, offering a more holistic understanding of price movements. In the context of the German market, (Poggi et al., 2023) presented a comparative analysis of statistical and deep learning methods. Their study balanced interpretability and precision, using traditional models like ARIMA and GARCH as benchmarks while deploying Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and hybrid architectures to address nonlinearities and temporal dependencies in price data. Moving focus to renewable energy, (Gjika et al., 2019) evaluated hybrid models for forecasting water inflows in Albania.

Their work demonstrated the applicability of hybrid techniques for renewable energy forecasting, underscoring the importance of tailored solutions for unique market structures. In a later study (Gjika et al., 2021) analysed the impact of climatic factors on hydropower energy production in the Drin River cascade in Albania, focusing on seasonal patterns. Various models, including ARIMA, ETS, TBATS, STLM, and neural networks, were tested, with neural networks effectively capturing seasonality and providing accurate monthly energy forecasts. The authors acknowledged the inherent uncertainty and emphasized the potential of hybrid models for improved predictions. Classical time series and deep learning models for short- and medium-term energy load prediction, using three years of hourly and daily data was presented by (Gjika & Basha, 2022). Average temperature was included as an external variable, with load dynamics correlated to temperature. Models were evaluated using accuracy metrics (MSE, RMSE, MAPE, AIC, BIC) and statistical test graphics, showing competitive performance.

The findings provided insights for stakeholders to optimize energy management and forecasting. Expanding on this, (Benti et al., 2023) reviewed recent advancements in machine learning and deep learning for renewable energy generation forecasting, emphasizing their adaptability and predictive accuracy. Advanced methods were also presented by (Qosja et al., 2024a; 2024b) where they compare machine learning approaches—Radial Basis Function (RBF), feedforward neural networks, and recurrent neural networks—for forecasting daily electricity consumption in Tirana and extended to five regions in Albania. Performance was evaluated across four scenarios involving different training/testing splits, historical data usage, and hyperparameter optimization. Results show that the RBF ARX model outperformed others in accuracy and computational efficiency, highlighting its effectiveness for electricity consumption forecasting.

Collectively, these studies form a robust framework for understanding and improving energy market dynamics. They underscore the necessity of combining statistical, machine learning, and hybrid approaches, particularly in regions like Albania, where distinct market structures and renewable energy potentials require customized forecasting strategies.

1.1 Data

In our work we use daily time series data of energy load, production, market clearing prices and total energy volumes traded for a period of one year (May 2023-May 2024). The dataset includes 366 days with no missing values or outliers. Daily energy load (consumption), production and total volumes are measured in MWh, while market clearing prices are measured in Euro/MWh. Load and production energy hourly data are taken from Transmission System Operators of Albania, while hourly market clearing prices and total energy volumes traded in the day-ahead market are obtained from ALPEX[2]. Hourly data from ALPEX is published daily in Excel files. The files are processed and merged to extract the necessary indicators, with the hourly data further aggregated into daily summaries.

[2] https://alpex.al/day-ahead-market/

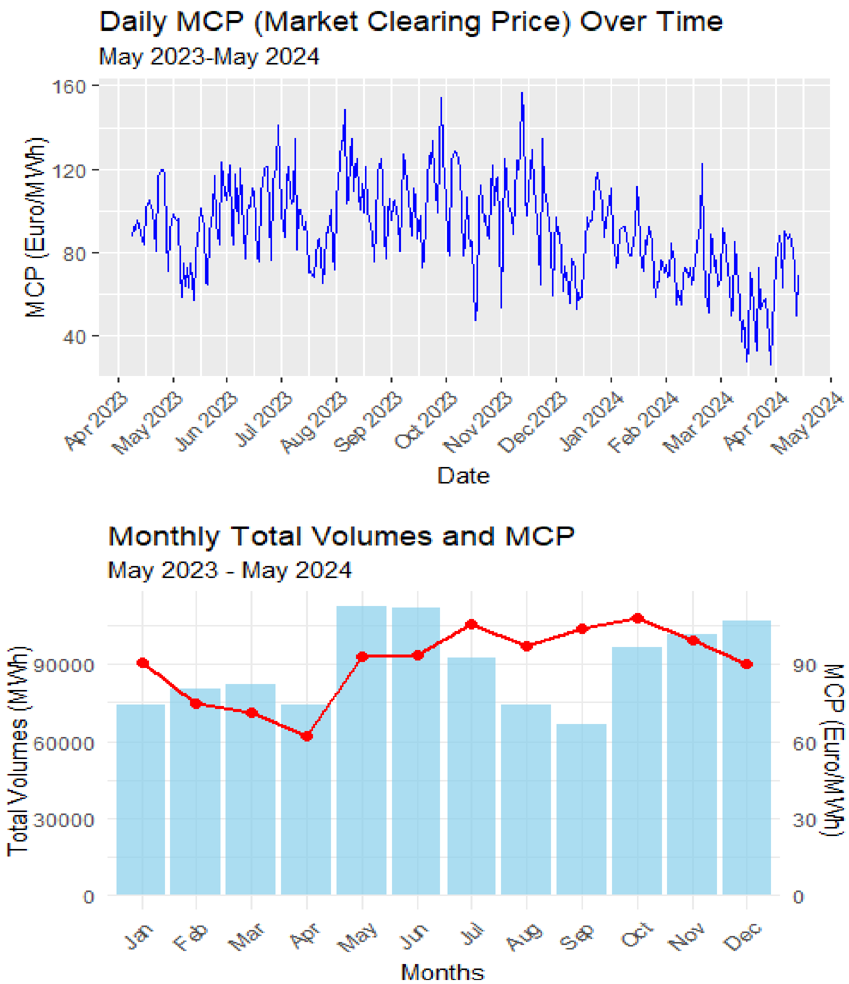

Figure 1. (a) Market electricity prices over time; (b) Monthly total energy volumes traded (blue bars) vs electricity prices (red line)
Source: Authors

Daily market electricity price lacks clear patterns, making it unpredictable and challenging to forecast. Related to total volumes traded we can observe from Figure 1(b) that lower MCP values typically occur in winter months with higher energy production due to rainfall and snow melting. Higher MCP values correspond to lower energy volumes traded (July-October), suggesting that when supply is constrained, prices rise.

This pattern aligns with the basic economic principle of supply and demand, where reduced supply leads to price increases, and abundant supply drives prices down.

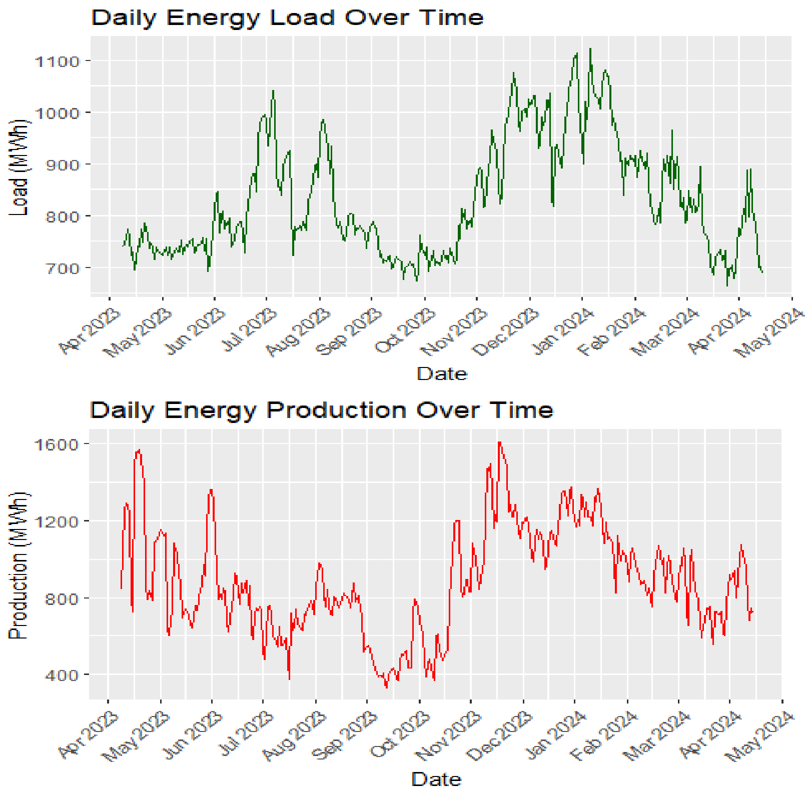

Figure 2. Daily energy load and production over time (Period: May 2023 to May 2024) Source: Authors

In Figure 2, time series data for electricity load and production shows strong seasonality influenced by summer and winter patterns. During summer, energy demand increases due to the widespread use of cooling systems, while production may decline, due to the reliance on hydropower, as reduced rainfall lowers water availability. In contrast, winter sees both high demands, driven by heating needs and shorter daylight hours, and higher production, as increased precipitation boosts hydropower. These seasonal imbalances between supply and demand significantly affect market dynamics, leading to price fluctuations and requiring careful forecasting and grid management to ensure stability.

1.2 Relationship between variables

There are periods during a year when we have more demand than supply or otherwise. We have calculated the energy balance and we added a categorical variable in the dataset which takes three values: *Deficit* when the difference between production and load is negative; *Surplus* when the difference is positive; *Balanced* when the difference is equal. We are interested to see the relationships between electricity price with load and production during the periods of deficit and surplus.

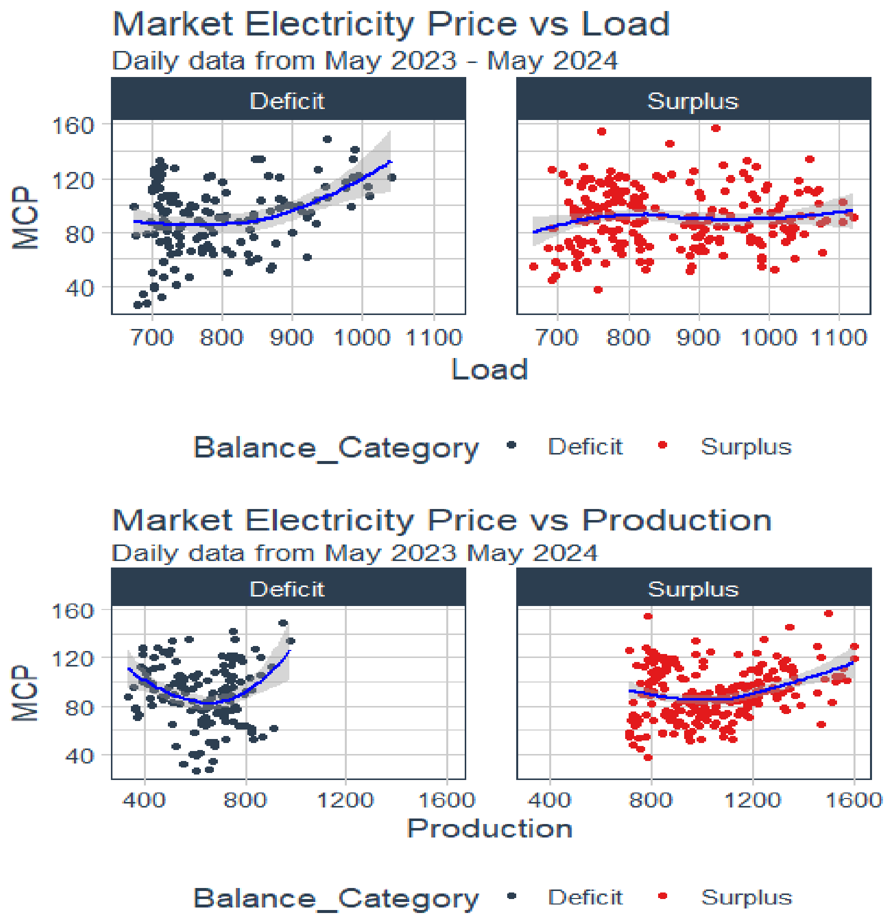

Figure 3. (a) Correlation between MCP and load; (b) Correlation between MCP and production, during different periods of deficit and surplus
Source: Authors

As observed in Figure 3(a), during periods of electricity deficit, when demand for power increases significantly, there is a corresponding rise in electricity prices. This phenomenon occurs due to the stronger competition for limited energy resources, which drives prices upward. On the other hand, during periods of energy surplus, when supply exceeds demand, electricity prices generally remain more stable or even decrease. However, if demand increases alongside production during energy surplus, (Figure 3(b)), the effect on price may be neutral or even positive, as the equilibrium price depends on both supply and demand. These dynamics underscore the complex relationship between supply, demand, and pricing in the electricity market.

High-demand periods often coincide with peak consumption hours or extreme weather events, where the balance between supply and demand becomes tense. Studying electricity prices under these conditions allows us to evaluate how efficiently the market responds to stress and understand the pricing mechanisms that influence consumer behaviour.

In order to see the correlation between different variables we use a correlation funnel plot, which is a data visualization technique used to identify the strength and direction of relationships between variables. Numeric data are binned into categorical data, then all categorical data is one-hot encoded to produce binary features. Our goal is to analyse the relationship between binary features (such as months, periods of deficit or surplus, and particularly price) and the target variable, which represents high electricity demand.

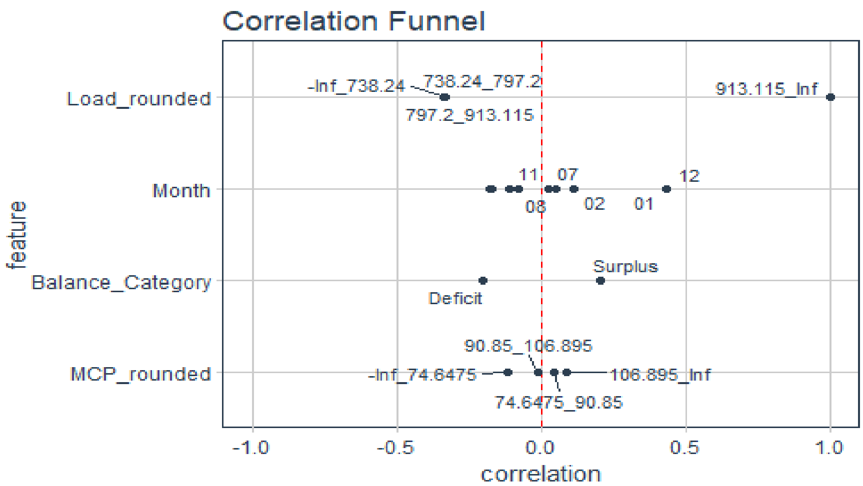

Figure 4. Correlation funnel between different variables
Source: Authors

As observed in Figure 4, when the energy load exceeds 913.115 MWh, there is a positive correlation with the winter months (December, January and

February). These months correspond to surplus in electricity balance, because of the increased rainfall that supports hydropower generation. The higher energy load, indicative of increased demand, also aligns with electricity prices exceeding 106.895 Euro/MWh.

2. Methodology

The methodology of this study combines classical statistical modelling with advanced machine learning techniques for electricity price forecasting. We use the Autoregressive Integrated Moving Average (ARIMA) model, known for capturing seasonality and trends in time series data, alongside the Extreme Gradient Boosting (XGBoost) model, which handles non-linear relationships and complex interactions. Additionally, we apply the NNAR (Neural Network AutoRegressive) model designed to uncover intricate dependencies and dynamic patterns in time series data. By combining lagged observations as inputs with the flexibility of neural networks, it is particularly effective for modelling seasonal trends and handling non-stationary data, making it a valuable tool in energy forecasting. The dataset was organized into training (80% of data) and testing (20% of data). The models' performance is compared through accuracy metrics.

2.1 ARIMA model

The ARIMA methodology, introduced by Box and Jenkins (1976), is a statistical approach designed to analyse and build forecasting models that effectively represent time series data. By capturing the underlying correlations within the data, ARIMA models (Weiss, 2000; Hyndman & Athanasopoulos, 2018) offer a robust framework for time series prediction. Notably, these models rely solely on historical data from the time series, enabling them to generalize forecasts and enhance predictive accuracy while maintaining simplicity and efficiency. The complete ARIMA model can be expressed as:

$$y_t^{(d)} = c + \varepsilon_t + \phi_1 y_{t-1}^{(d)} + \cdots + \phi_p y_{t-p}^{(d)} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-p} \quad (1)$$

Where y_t is the observed time series at time t, ϕ_1 is the autoregressive coefficient, θ_1 is the moving average coefficient, ε_t is white noise error term at time t and d is the degree of differencing to achieve stationarity.

2.2 STL+ARIMA model

Statistical approaches like ARIMA, artificial neural networks (ANNs), and machine learning techniques have been widely used in energy forecasting. (Leite Coelho da Silva et al., 2022; Karabiber & Xydis, 2019) have used statistical and deep learning methods for load and price electricity forecasts. Another method used among researchers is STL + ARIMA model, a hybrid approach that combines the strengths of seasonal decomposition and time series forecasting. The STL (Seasonal and Trend decomposition using LOESS) method decomposes the time series into three components: seasonality, trend, and residuals, allowing each component to be analysed and modelled separately. The residual (remainder) component, which contains the irregular and non-seasonal variations, is then modelled using an ARIMA (Autoregressive Integrated Moving Average) model to capture linear dependencies and make forecasts. This combination allows STL + ARIMA to effectively handle complex seasonal patterns and trends, providing accurate forecasts for time series with strong seasonal structures.

2.3 XGBoost Model

XGBoost is an effective tree-based ensemble learning algorithm. It is based on gradient boosting architecture (Chen & Guestrin, 2016; Bentéjac et al., 2020), which uses various complement functions to estimate the results using

$$\overline{y_i} = y_i^0 + \eta \sum_{k=1}^{K} f_k(U_i) \tag{2}$$

Where, $\overline{y_i}$ - indicated the predicted output for the ith data with the parameter vector U_i, K - denotes the number of estimators corresponding to independent tree structures for each f_k, y_i^0 - display the primary hypothesis (mean of the original parameters in the training data), η – learning rate, f_k - represents the leaves weight that is established by reducing the objective function of the kth tree.

$$f_{obj} = \gamma T + \sum_{a=1}^{T} \left[g_a \omega_a + \frac{1}{2}(h_a + \lambda)\omega_a^2 \right] \tag{3}$$

Where T – denotes the quantity of leaf nodes, γ – denotes the complexity parameter, λ – constant coefficient, ω_a^2 - leaf weight from 1 to T, g_a and h_a are the summation parameters for the entire dataset associated with a leaf of the initial and previous loss function gradient. In order to build the kth tree, a leaf is distributed into several leaves.

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} + \frac{(G_L+G_R)^2}{H_L+H_L+\lambda}\right] \quad (4)$$

Where G_L and H_L - division of the left leaf, G_R and H_R - division of the right leaf. When the gain parameter is approximated to zero, the division criteria are generally assumed.

2.4 NNAR model

The NNAR (Neural Network AutoRegressive) model (Veloz et al., 2016; Hyndman & Athanasopoulos, 2018) is a hybrid approach combining the autoregressive framework with the flexibility of neural networks to forecast time series data. It uses lagged observations as inputs, with a feedforward neural network capturing non-linear relationships and predicting future values. The model is denoted as NNAR(p,k), where p is the number of lags and k is the number of hidden neurons, or NNAR(p,P,k) for seasonal data. Unlike traditional AR models, NNAR does not assume linearity or stationarity, making it suitable for capturing complex patterns, trends, and seasonality in data. It is trained by minimizing a loss function (e.g., Mean Squared Error) using gradient-based optimization. In the NNAR model, the inputs into each hidden layer neuron are combined linearly:

$$h_j = \alpha_j + \sum_{i=1}^{N} \omega_{i,j} x_i \quad (5)$$

Where h_j is the j-th hidden layer neuron, N is the number of input layer neurons, α_j is the intercept of the j-th hidden neuron, $\omega_{i,j}$ represents the weights assigned to the connection between the input and the hidden layer, x_i are the observations of the input layer. Non-linear activation functions in the hidden layers enable the model to capture intricate patterns and the relationships in the data. The activation function is given by:

$$g(h) = \frac{1}{1+e^{-h}} \quad (6)$$

2.5 Accuracy metrics

Evaluation metrics play a vital role in measuring the performance of forecasting models, helping to ensure their accuracy and reliability. Commonly used metrics in time series forecasting include Mean Absolute

Error (MAE), which quantifies the average size of prediction errors; Root Mean Squared Error (RMSE), which gives greater weight to larger errors by squaring the differences; and Mean Absolute Percentage Error (MAPE), which represents errors as a percentage of the actual values. These metrics offer valuable insights into the model's accuracy, consistency, and robustness, making them essential for comparing and selecting the most effective forecasting method. Mathematically, these metrics are defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \text{ (mean absolute error)} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \text{ (root mean squared error)} \quad (8)$$

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - y_i|}{|y_i|}\right) \cdot 100\% \text{ (mean absolute percentage error)} \quad (9)$$

Where x_i are real values, y_i are predicted values and $f(\cdot)$ - some function that transforms both the predicted and observed values. The authors (Hyndman & Koehler, 2006) propose the Mean Absolute Scaled Error (MASE) as a scale-independent metric that effectively addresses challenges arising from zero demand values, making it especially suitable for analyzing intermittent demand data. In contrast, the study from (Reich et al., 2016) introduces the relative Mean Absolute Error (relMAE) as a useful metric for evaluating point predictions, enabling consistent comparisons of similar modeling approaches across different time series datasets. These accuracy metrics, mathematically are represented as:

$$MASE = \frac{MAE}{MAE_{in-sample,naive}} \text{ (mean absolute scaled error)} \quad (10)$$

$$relMAE = \frac{1}{T}\sum_{i=1}^{T}|f(x_i) - f(y_i)| \text{ (relative mean absolute error)} \quad (11)$$

3. Results and discussions

In our work, we utilized STL + ARIMA, along with ARIMA, NNAR, and XGBoost, to evaluate their performance in forecasting electricity prices. The models were trained on the training dataset and then evaluated on the test dataset. The data were processed in R using as the main forecasting library the package: *modeltime* (Dancho, 2024). The full time series with the main parts of: train and test can be seen in Figure 5.

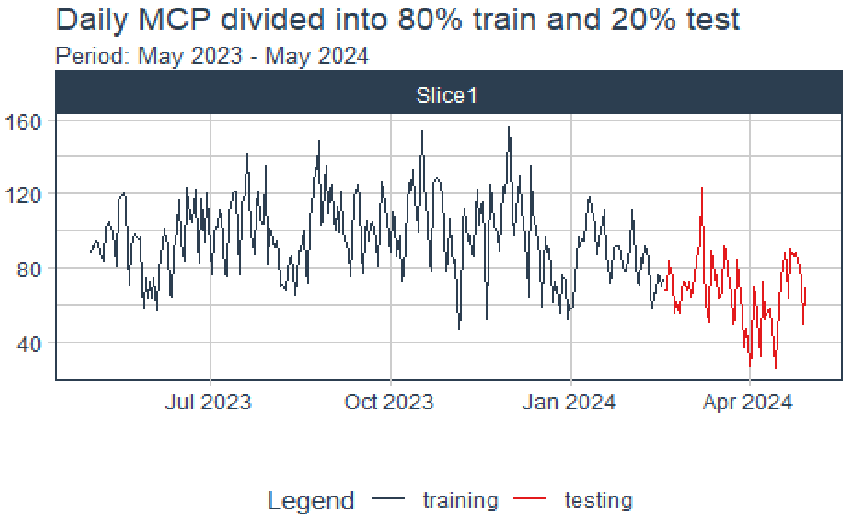

Figure 5. MCP divided into train and test
Source: Authors

In STL+ ARIMA we used three seasonal periods: 7, 30, 60 for weekly and monthly seasonality. Since the pattern in price electricity was visible every two months we used also period 60. For XGBoost model we performed hyperparameter tuning and the best parameters elected were 200 trees, with learning rate equals to 1.02 and minimal node size 2. The results of accuracy metrics for the test dataset are presented in Table 1, offering a comparative analysis of model performance.

Table 1. Accuracy metrics for out of sample data using different models

Metrics	ARIMA	STL+ARIMA	XGBoost	NNAR
RMSE	26.9	18.2	17.0	19.1
MAPE	42.9	27.2	23.2	29.1
MASE	1.92	1.21	1.13	1.28
MAE	22.2	14.0	13.0	14.8

Source: Authors

The table clearly shows that the XGBoost model outperforms all other models across all evaluated accuracy metrics, demonstrating its ability to provide the most reliable and precise predictions for day-ahead electricity prices. To further illustrate the accuracy of the predictions, a comparison of actual versus predicted values is presented in Figure 6.

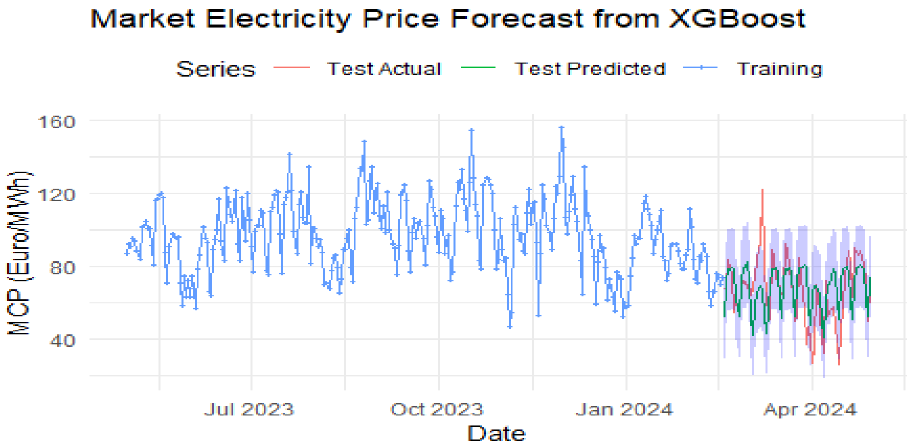

Figure 6. Forecasts of market electricity price from XGBoost model
Source: Authors

The Figure 6 reveals that the XGBoost model struggles with predicting sharp spikes in electricity prices, which often occur due to sudden market changes or extreme conditions that are challenging to model. However, for the remainder of the test data, the model demonstrates strong predictive capability, closely aligning with the actual values. This indicates that XGBoost is effective at capturing the general patterns and trends in electricity prices but may benefit from further fine-tuning or the incorporation of additional features to improve its performance in forecasting these sudden changes.

Conclusions

In our study, we explored various models to forecast day-ahead electricity prices in Albania, aiming to evaluate their accuracy and effectiveness. Both classical statistical models and advanced machine learning techniques were employed and compared using standard evaluation metrics applied to the test dataset. Among the models tested, XGBoost demonstrated superior performance, delivering more accurate predictions compared to other methods. In addition to price forecasting, we also analyzed the relationship between energy load and production, recognizing their critical influence on market dynamics. Understanding these relationships provides valuable insights into the factors influencing price fluctuations and serves as a foundation for future studies. Our subsequent research will incorporate these findings to refine forecasting models and improve the accuracy of electricity price predictions by integrating load and production dynamics into the modeling process.

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