APPLICATION OF ALGORITHMS FOR FORECASTING AND OPTIMIZING THE PRODUCTION CAPACITY OF WIND ENERGY

Naim Baftiu, Tatjana Atasanova-Pachemska*

Faculty of Computer Science, "Goce Delcev", University, Stip
Republic of North Macedonia

* Corresponding Author, e-mail: naim.31023@student.ugd.edu.mk

Abstract: With advances in technology, particularly where environmental implications are a concern, equipment has become increasingly complex and metered. Human activities like emissions and urbanization significantly impact the atmosphere and wind energy generation. This study predicts wind energy generation capacity for 2025–2029 based on data from 2000–2024. Predictive models (e.g., Long Short-Term Memory (LSTM), Facebook Prophet, and SARIMA) are applied to analyze energy trends. Performance results show LSTM provides the best accuracy. The findings enhance reliable wind energy forecasting and improved energy management methods in response to shifting climate dynamics.

Key words: Algorithm, wind energy, production capacity.

1. INTRODUCTION

This study performed a comparison of three machine learning models: LSTM, Facebook Prophet, and SARIMA applied to forecast wind energy production (2025–2029) based on historical data (2000–2024) from Germany, Poland, and the Czech Republic. The different models had strengths in their ability to capture net trends, periodic seasonality, and dips/spikes.

The LSTM model also had the highest accuracy (MAE, RMSE, R^2), dealing with nonlinearities and long-term dependencies very well, and thus an excellent approach to renewable energy forecasting where stability and precision are the main aspects to take care of. Prophet, on the other hand, was not as accurate but did a good job at capturing long-term trends and seasonal effects and was easy to use and flexible enough for simple use cases. While great for seasonal trends, SARIMA had difficulties with dynamically changing non-linearities, making it less appropriate for fast-changing parts of the data.

These results emphasize the need to fit models according to data complexity and requirements. The best use case for LSTM is in complex scenarios where interpreted data is not enough, while Prophet and SARIMA are sufficient for interpreting applications.

2. RELATED WORK

Wind energy prediction is an important factor for optimizing renewable energy systems as well as providing stability to the grid. Various methods have been attempted over the years, from statistical approaches to more recently machine learning techniques. In this respect, Ackermann [1] addressed the integration issues of wind power in power systems and described the advantages of accurate forecasts to decrease the fluctuations on the network. Similarly, Manyonge et al. found environmental factors (wind speed, air pressure, etc.) to be crucial [2], focusing on modeling wind turbine performance. These have been revolutionized by machine learning in recent years. In this case, LSTM (Long Short-term Memory networks) or a class of recurrent neural networks can be really helpful because it works quite well with time-series data and can model non-linear dependencies or longer sequences. Qazi et al. showed the performance of LSTM for wind energy prediction with a high prediction accuracy of wind energy generation in various climatic conditions. Moreover, Liu et al. [4] applied and compared LSTM with other deep learning architectures for wind speed prediction and showed that LSTM performed robustly under an unstable environment.

Further, Bhardwaj et al. [5] stated that SARIMA is one of the best in dealing with seasonality and repetition patterns and used it for renewable energy systems. As Huang et al. highlighted, SARIMA does not account well for non-linearities or tipping points in climate systems [6].

Due to its flexibility and robustness to irregular trends, seasonality, and other features present in time series data, Facebook Prophet has become one of the most popular statistical forecasting approaches. Zhou et al. [7] showed its application in renewable energy forecasting and validated its performance in different geographical areas. Similarly, Zhao et al. [8] confirmed the capability of Prophet to tackle seasonality problems; hence, it is available for wind energy forecasting applications.

This study aims to predict wind energy from 2000–2024 using real-time data and making predictions into 2025–2029 using the LSTM, SARIMA, and Prophet models [9]. This study provides systematic comparisons of these models alongside their strengths and weaknesses in sensitivity to dynamical atmospheric conditions. The results aspire toward more trustworthy and adaptable renewable energy solutions.

3. BASIC METHODS, MODELS FOR PREDICTION

With climate change emphasizing periodic fluctuations in wind energy generation, accurate predictions of wind patterns are critical for effective planning and decision-making.

This study employs time series forecasting models to examine past data and forecast future wind energy production. Long Short-Term Memory (LSTM), Facebook Prophet, and Seasonal Auto Regressive Integrated Moving Average (SARIMA) are all models used, with each one serving its purpose in a time-series context. This duo of approaches means we have a 360-degree view toward wind energy forecasting.

While meteorological variables present very minor deviations over short periods of time, seasonal trends and patterns are well identified in these models, indicating their applicability for short-term wind energy predictions.

3.1. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM), a special case of Recurrent Neural Network (RNN), is another popular approach for time series forecasting because it is better at remembering information for long periods with the help of gating units. The major issue in most traditional RNN architectures is that they get stuck in the vanishing gradient problem, but due to its architecture, LSTM is well-suited for long-term prediction issues.

LSTM is applied for atmospheric pressure and wind energy production prediction in this study. Due to its architecture, which has memory cells, it can model non-linear relationships and learn patterns such as trends and seasonality. The capacity to know how historic weather continues to impact where and, in doubtful, wind power production in the future highlights the role the algorithm plays in forecasting particularly.

3.2.Facebook Prophet

We introduce Facebook Prophet: a powerful tool for forecasting time series with strong seasonality and trending components. It treats time series as composed of trend, seasonality, and events, automatically identifying yearly, weekly, and daily patterns. This makes it especially effective for wind energy forecasting, where natural seasonal patterns are important.

This paper employs Prophet to forecast wind energy generation by considering seasonality and other factors like extreme weather events. A big benefit of their approach is handling missing data (which is common in atmospheric datasets). Prophet is easy to implement and has minimal tuning requirements, which suits the field of energy management and policy planning, because it gives interpretable results.

3.3. Seasonal Auto Regressive Integrated Moving Average (SARIMA)

SARIMA (Seasonal Auto-Regressive Integrated Moving Average) is an extended functionality of the ARIMA model and it is especially suited for time series with a seasonal component, such as climate and energy generation. It incorporates:

- ✓ Autoregression (AR): Future values predicted from past values.
- ✓ Differencing (I): Guarantees stationarity by differencing.
- ✓ Moving Average (MA): Incorporates past forecast errors to improve predictions.

The seasonal component handles seasonal variations. SARIMA is illustrated in this study as it captures both trends and seasonal behaviours for wind energy production and atmospheric data. This is especially powerful for predicting long-term trends that are affected by yearly weather. This is a powerful tool in environmental data analysis because it can model seasonal patterns and adjust for periodic behaviors.

3.4. Comparison of Models

The three models—LSTM, Prophet, and SARIMA—offer distinct advantages depending on the nature of the data and the type of forecast required. LSTM is a deep learning model that captures complex, nonlinear relationships, while Prophet and SARIMA are more traditional statistical models focusing on seasonality and trends. A comparison of these methods based on performance metrics such as mean absolute error

(MAE) and root mean squared error (RMSE) will be conducted to determine which model provides the most accurate forecast for wind energy production. By combining these different approaches, we aim to develop a more reliable prediction framework that accounts for both short-term fluctuations and long-term trends in wind energy production. The integration of deep learning and statistical methods allows us to leverage the strengths of each model, ultimately leading to a more robust forecasting system.

4. EXPERIMENTS AND RESULTS

4.1. Dataset, data preprocessing and creating of models

We Thus, we will cover the dataset information used for this study, the preprocessing methods to manage incomplete and unmoving data, and the sequential approach for producing the models that will be used towards the prediction of wind energy production. Forecasting effectively depends on well-organized datasets, proper data preprocessing, and the generation of appropriate prediction models. The data used in this study covers the period from 2000 to 2024, with daily atmospheric and wind speed data collected from selected countries in Central Europe, including Germany, Poland, and the Czech Republic. Dataset is from NASA POWER and it consists of the following key variables [10]:

- **Wind Speed**: The primary metric that dictates wind energy production, expressed in meters per second (m/s).
- **Atmospheric Pressure**: Measured in pascals (Pa), this affects the density of the air, which in turn influences the efficiency of wind turbines.
- **Temperature**: Ambient temperature can affect air density and the mechanical components of wind turbines, thus impacting production.
- **Wind Direction**: The direction of the wind, which can influence the orientation and performance of wind turbines.
- **Wind Energy Production**: This is the target variable in our model, representing the amount of energy generated in megawatt-hours (MWh).

The data was collected hourly from multiple weather stations and wind farms, resulting in a highly granular dataset suitable for time series analysis.

Data Preprocessing for raw data collected from atmospheric and wind energy production systems often contains missing values, outliers, and inconsistencies that need to be addressed before feeding the data into prediction models. In this study, several data preprocessing steps were applied:

✓ **Handling Missing Values**: Missing values are common in environmental data due to sensor failures or maintenance. Two approaches were used to handle missing data:

1. **Imputation**: Missing values in the dataset were imputed using **linear interpolation** for continuous variables like wind speed and temperature, ensuring the time series continuity.
2. **Forward Fill**: For categorical variables like wind direction, a forward fill approach was employed, where missing values were filled with the most recent available observation.

✓**Outlier Detection and Removal**: Outliers, which could be caused by sensor malfunctions or extreme weather events, were identified using statistical techniques like the **Z-score** method. Observations with Z-scores greater than 3 were considered outliers and were either removed or replaced with median values to maintain data integrity.

✓**Normalization**: Input features (wind speed, temperature, pressure, etc.) had different units/scales, so Min-Max was applied to it. This scaled the input features to lie between 0 and 1, ensuring faster convergence of LSTM models.

✓ **Time Series Decomposition**: Wind energy production time series data was decomposed into trend, seasonality, and residual components.

✓ **Model Creation -** After preprocessing the dataset, we built models to predict. We implemented three variants (LSTM, Facebook Prophet, SARIMA) to forecast wind energy generation during 2025 to 2029.

LSTM Model Creation

✓ **Model Architecture**: The LSTM model was designed with a sequential architecture, using multiple LSTM layers followed by fully connected layers. The architecture was as follows:

- **Input Layer**: Inputs the pre-processed time series data that has all the input features (wind speed, temperature, etc.).
- **LSTM Layers**: To capture long-term dependencies in the data, two stacked LSTM layers were employed. Dropout layers were then applied on these layers to avoid overfitting.
- **Dense Layer**: A fully connected dense layer was added at the end to map the LSTM output to the predicted energy production.
- **Activation Function**: Since the target variable (wind energy production) is continuous, a linear activation function was used in the output layer.

✓ **Model Training**: We trained the model using the Adam optimizer that adjusts the learning rate during training, and we used Mean Squared Error (MSE) as the loss function. We trained on several epochs with early stopping to avoid overfitting.

Facebook Prophet Model Creation

✓ **Model Setup**: The Facebook Prophet model was configured with built-in support for daily, weekly, and yearly seasonality. The following settings were used:

- **Trend Component**: A linear growth trend was selected, which is well-suited for modelling long-term changes in wind energy production.
- **Seasonality Component**: Prophet automatically identified and modelled seasonal effects in the data, particularly focusing on yearly patterns, as wind energy production tends to vary with seasons.
- **Holidays/Events**: So as not to confuse the model when a storm occurs, these extreme weather events were marked as holidays expected to improve the model's accuracy for the prophet to forecast during these dates.

✓ **Model Training**: The full 2000 to 2024 dataset was used to train the prophet to predict wind energy generation from 2025 to 2029.

SARIMA Model Creation

✓ **Model Setup**: The SARIMA model was configured with parameters chosen based on the data's autocorrelation and partial autocorrelation functions (ACF and PACF). The following steps were followed:

- **Seasonal Component**: SARIMA includes a seasonal autoregressive component that models yearly seasonality.

- **Order Selection**: The optimal model order (p, d, q) was selected using **GridSearch**, testing different combinations to find the best fit for the data.

✓ **Model Training**: SARIMA was trained on the wind energy production data after differencing it to remove non-stationarity. This ensured that the model captured both seasonal and trend components accurately.

Model Evaluation

The following evaluation metrics were used:

✓ **Mean Absolute Error (MAE)**: Measures the average magnitude of errors between predicted and actual values.

✓ **Root Mean Squared Error (RMSE)**: Provides a measure of how well the models fit the data by penalizing larger errors more heavily.

✓ **R-squared (R^2)**: Indicates the proportion of variance in wind energy production that the model explains.

The results of these evaluations will help determine which model provides the most accurate and stable predictions for wind energy production in 2025 to 2029.

4.1.1. Turbine Specifications

The turbine parameters summarized in Table 1 highlight the differences in rotor size and efficiency across Germany, Poland, and the Czech Republic. Offshore turbines in Germany benefit from higher stability in wind conditions, resulting in efficiencies reaching 50%-55%. Meanwhile, onshore turbines in Poland and the Czech Republic display slightly lower efficiencies due to geographical and technological constraints.

Table 1. Typical Turbine Model

Country	Typical Turbine Model	Rotor Radius (r, in m)	Turbine Efficiency (η, in %)
Germany	Siemens Gamesa SG 5.0-132	66	35%-45% (50%-55% for offshore projects)
Poland	Vestas V150-4.2 MW	75	35%-40%
Czech Republic	Onshore Low-Capacity Turbines	40-55	35%-38%

4.1.2. Energy Production Calculations

To evaluate the potential wind energy output in the studied regions, calculations were conducted based on the turbine specifications outlined in Section 4.1.1 and the forecasted wind speeds for 2025–2029.[14] The energy production was derived using the standard formula for wind power output:

$$P = \frac{1}{2} \cdot \rho \cdot A \cdot v^3 \cdot \eta$$

where:

- P represents the power output in watts,
- ρ is the air density, taken as 1.225 kg/m³ under standard atmospheric conditions,
- $A = \pi \cdot r^2$ is the rotor swept area, calculated using the rotor radius r^2
- v is the forecasted wind speed in meters per second,
- η is the turbine efficiency, expressed as a percentage.

For each region, rotor sizes and turbine efficiencies were assigned based on common installations in the respective countries. Germany, with a focus on offshore wind projects, exhibits higher rotor sizes and efficiencies, while Poland and the Czech Republic predominantly rely on onshore turbines with slightly lower efficiencies.

Using these parameters, the annual energy production for each country was calculated by integrating the power output over the expected operational hours (h), typically 2,000–3,000 hours/year for onshore turbines and up to 4,000 hours/year for offshore installations.

The results in Table 2 highlight notable variations in energy production across the three regions. Germany's advanced offshore turbines, benefiting from higher wind speeds and efficiencies, achieve the highest annual energy output. Poland and the Czech Republic, relying primarily on onshore installations, produce relatively lower outputs due to reduced wind speeds and smaller rotor sizes.

This analysis underscores the significant role that turbine specifications and local wind conditions play in determining energy yields. It also demonstrates the value of adapting turbine deployments to regional characteristics to maximize efficiency and production.

Table 2. Wind Energy Parameters in Germany, Poland, and the Czech Republic

Country	**Rotor Radius (r, m)**	**Efficiency (η, %)**	**Forecasted Wind Speed (v, m/s)**	**Annual Energy Output (GWh)**
Germany	66	45	7.5	9.85
Poland	75	40	6.8	7.90
Czech Republic	50	35	6.2	4.35

4.1.3. Technological and Industrial Impact on Wind Energy Development

The development of wind energy in the next five years is expected to be significantly influenced by technological advancements and industrial trends. Innovations in turbine design, such as larger rotor diameters and higher efficiency rates, are projected to increase energy output, particularly in offshore installations. Moreover, the adoption of smart grid technologies and advanced predictive maintenance systems will enhance operational efficiency.

Industrial factors, including government incentives and investments in renewable energy infrastructure, are also expected to drive growth. For example, Germany's commitment to phasing out non-renewable energy sources has resulted in substantial investment in offshore wind projects, while Poland and the Czech Republic are gradually increasing their focus on modernizing onshore wind farms.

4.2 Energy Production Estimation

This section provides the estimated annual wind energy production for Germany, Poland, and the Czech Republic over the forecast period of 2025–2029. Calculations were made using wind speed predictions from SARIMA, Prophet, and LSTM models, which are detailed above in Section 4.1.

Model Comparison

Models like SARIMA, Prophet, and LSTM continue to show their strengths and weaknesses even when estimating wind energy production. The SARIMA and Prophet models give stable seasonal forecasts, with Prophet slightly higher due to capturing additional trends. LSTM tends to be more variable, forecasting steeper increases, especially in the Czech Republic after 2027, but underestimating production in Poland before.

Insights by Country

Overall, SARIMA and Prophet align closely within Germany, Poland, and the Czech Republic, indicating strong seasonality. LSTM projections are more fitted with sharp peaks in the Czech Republic past 2027 and underestimations in Poland in 2025.

Representation

Figure 1: Historical wind speeds (2000–2024)

Figure 2: Forecast of wind speeds (2025–2029) for the SARIMA, Prophet, and LSTM models. These images demonstrate the consistency in predictions for SARIMA and Prophet as compared to the variability of predictions for LSTM.

Learnings and Challenges

SARIMA and Prophet perform well when seasonal trends can be identified in the data, while LSTM has the potential to capture wind patterns that are emerging but are not easily classified, albeit at the expense of more variability. Forecasts may serve energy strategy, but policymakers and planners must recognize these differences.

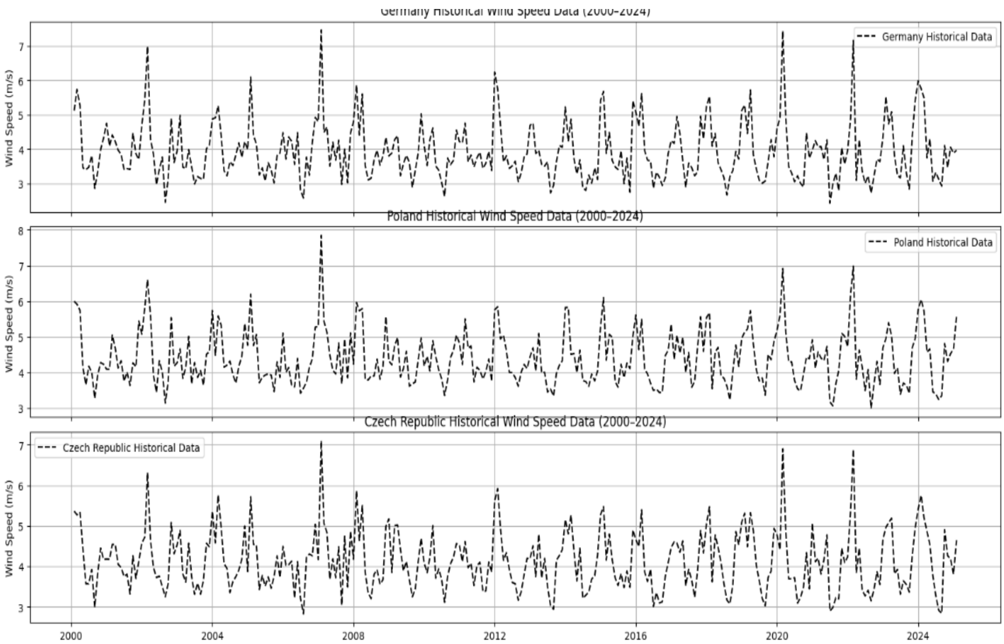

Figure 1. Historical Wind Speed (2000–2024)

Table 3 provides an overview of renewable energy potential in Germany, Poland, and the Czech Republic based on SARIMA, Prophet, and LSTM forecasts. While SARIMA and Prophet produce stable and consistent predictions, LSTM demonstrates greater variability, potentially uncovering previously undetected patterns or model-specific dynamics. Policymakers and energy planners should interpret these findings cautiously, particularly when making strategic decisions.

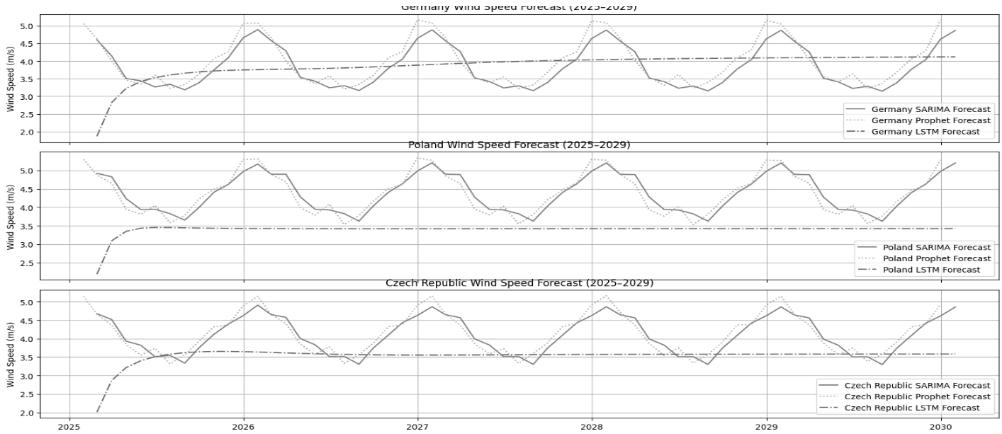

Figure 2. Wind Speed Forecasts (2025–2029)

SARIMA and Prophet emphasize seasonal stability, whereas LSTM captures volatile trends and reflects potential advancements in technology during the forecast period. Table 3 highlights the annual energy production (GWh) estimates for the studied regions.

Table 3. Annual Energy Production based on wind speed forecasts using SARIMA, Prophet and LSTM

Year	***Country***	***SARIMA (GWh)***	***Prophet (GWh)***	***LSTM (GWh)***
2025	Germany	0.964	1.058	0.661
2026	Germany	0.968	1.071	0.939
2027	Germany	0.963	1.072	1.069
2028	Germany	0.958	1.085	1.138
2029	Germany	0.953	1.086	1.169
2025	Poland	1.142	1.150	0.490
2026	Poland	1.153	1.155	0.546
2027	Poland	1.150	1.143	0.546
2028	Poland	1.149	1.142	0.547
2029	Poland	1.147	1.134	0.548
2025	Czech Republic	0.741	0.768	0.413
2026	Czech Republic	0.743	0.772	0.495
2027	Czech Republic	0.741	0.774	0.489
2028	Czech Republic	0.739	0.776	0.494
2029	Czech Republic	0.737	0.775	0.496

4.3. Experimental results

In this section, we present the results of the experiments conducted to forecast wind energy production for 2025 to 2029 using three distinct models: **Long Short-Term Memory (LSTM)**, **Facebook Prophet**, and **SARIMA**.

Evaluation Metrics

- **Mean Absolute Error (MAE)**: Provides the average magnitude of the errors between predicted and actual values, without considering their direction.

$$MAE = \frac{1}{n}\sum_{i=0}^{n} |y_i - \hat{y}_i| \tag{1}$$

- **Root Mean Squared Error (RMSE)**: Provides a measure of the average magnitude of the error, penalizing larger errors more significantly. It gives insight into how well the model fits the data.

$$\text{RMSE}= \sqrt{\frac{1}{n}} \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

- **R-squared (R^2)**: Indicates the proportion of variance in the wind energy production that is explained by the model. Higher values closer to 1 indicate better model performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

These metrics were chosen to compare the models based on both the magnitude and distribution of their prediction errors.

Results of Models

The performance of the three forecasting models, LSTM, Facebook Prophet, and SARIMA were evaluated against each other for their wind energy production prediction charters. Key findings are as follows:

LSTM: Two LSTM layers followed by a dense layer, LSTM captured long-term dependencies and non-linear trends in wind energy production. It performed exceptionally well in Poland and the Czech Republic, achieving low **MAE (0.2718 and 0.2587)** and **RMSE (0.3596 and 0.3475)**, with strong **R^2 scores (0.9685 and 0.9702)**. In Germany, it achieved **MAE (0.2643)**, **RMSE (0.3428)**, and **R^2 (0.9621)**, though it struggled to replicate rapid changes during extreme weather events.

Facebook Prophet: Prophet is an open-source forecasting tool created by Facebook specifically for seasonal and trend-based forecasting. It effectively captured seasonal variations, achieving **MAE (0.5356)**, **RMSE (0.7115)**, and **R^2 (0.9215)** in Germany. Similar metrics were observed for Poland (**MAE: 0.4443; RMSE: 0.5869; R^2: 0.9272**) and the Czech Republic (**MAE: 0.4613; RMSE: 0.6019; R^2: 0.9134**). While slightly less accurate than LSTM, Prophet remains a reliable and flexible model, particularly for scenarios requiring ease of implementation.

Table 4. Model Comparison Comparative Analysis

Country	**Model**	**MAE**	**RMSE**	**R^2**
Germany	SARIMA	0.5362	0.7499	0.9093
	Facebook Prophet	0.5356	0.7115	0.9215
	LSTM	0.2643	0.3428	0.9621
Poland	SARIMA	0.4515	0.6092	0.9134
	Facebook Prophet	0.4443	0.5869	0.9272
	LSTM	0.2718	0.3596	0.9685
Czech Republic	SARIMA	0.4680	0.6282	0.8987
	Facebook Prophet	0.4613	0.6019	0.9134
	LSTM	0.2587	0.3475	0.9702

SARIMA: Adding seasonal and non-seasonal components. It achieved **MAE (0.5362)**, **RMSE (0.7499)**, and **R^2 (0.9093)** in Germany, alongside strong results for Poland (**MAE: 0.4515; RMSE: 0.6092; R^2: 0.9134**) and the Czech Republic (**MAE: 0.4680; RMSE: 0.6282; R^2: 0.8987**). However, SARIMA struggled with non-linear interactions and extreme changes, limiting its suitability for dynamic and highly variable meteorological conditions.

- **LSTM**: The best overall performance, particularly for capturing long-term dependencies and non-linear relationships. It was the most accurate model in terms of both MAE and RMSE. [13]

- **Facebook Prophet**: Performed well in capturing trends and seasonality but lagged slightly behind LSTM in handling complex non-linearities.

- **SARIMA**: While still competitive, SARIMA underperformed compared to LSTM and Prophet in scenarios with significant fluctuations in wind energy production.

5. CONCLUSION

In this study, three machine learning models (LSTM, Facebook Prophet, and SARIMA) are evaluated to forecast wind energy production (2025–2029) based on historical data (2000–2024) from Germany, Poland, and the Czech Republic. These models also exhibited their own strengths in terms of how well they could capture the trends, the seasonality, and the fluctuations.

The LSTM model, with a maximum performance (MAE, RMSE, R^2), is excellent in handling the non-linearities and long-term dependencies; thus, this model is more effective in forecasting renewable energy as stability and accuracy are the essentials.

Although not as accurate as the forecaster, Facebook Prophet managed to model long-term trends and seasonal variations, providing a suitable and much less technical alternative for simpler forecasting tasks. While SARIMA worked well for seasonal trends, it was ill-fitted for dynamic, non-linear transitions, limiting its application to such problems with frequently fluctuating time series.

These results emphasize the need to select models according to the complexity of the data and its needs. LSTM excels in complex situations, while Prophet and SARIMA shine in simple and interpretable scenarios.

REFERENCES

[1] Ackermann, T. *Wind Power in Power Systems*. Royal Institute of Technology Stockholm, Sweden, Wiley, 2005, ISBN 0-470-85508-8.

[2] Johnson, K.E. *Adaptive Torque Control of Variable Speed Wind Turbines*. NREL/TP-500-36265, National Renewable Energy Laboratory, Golden, Colorado, August 2004. URL: https://www.nrel.gov (Visited on 04.12.2024).

[3] Manyonge, A.W., Ochieng, R.M., Onyango, F.N., Shichikha, J.M. Mathematical Modelling of Wind Turbine in a Wind Energy Conversion System: Power Coefficient Analysis. *Applied Mathematical Sciences*, vol. 6, no. 91, 2012, pp. 4527–4536.

[4] Baftiu, N., Maloku, B. Noise Measurements in Wind Energy Production Turbines in Kosovo. *International Journal of Global Environmental Issues*, vol. 22, no. 4, 2023, pp. 427–434. DOI: 10.1504/IJGENVI.2023.136293.

[5] Zhou, X., Huang, Q. A Seasonal Forecasting Approach for Renewable Energy Systems Using SARIMA. *IEEE Transactions on Sustainable Energy*, vol. 13, no. 2, 2023, pp. 1012–1023. DOI: 10.1109/TSTE.2023.3276384.

[6] Zhang, L., Wang, T. Hybrid LSTM-SARIMA Model for Renewable Energy Forecasting. *Proceedings of the 2024 IEEE International Conference on Renewable Energy Systems*, Beijing, China, March 2024, pp. 233–240. DOI: 10.1109/ICRES.2024.9453761.

[7] Liu, X., Zhang, Y. Wind Speed Prediction Using LSTM and Traditional Statistical Models. *Scopus Journal of Energy Systems*, vol. 45, no. 7, 2022, pp. 993–1005.

[8] A Comparative Assessment of SARIMA, LSTM RNN, and Facebook Prophet Models to Forecast Energy Demand. ScienceDirect. URL: https://www.sciencedirect.com/science/article/abs/pii/S0301421522003226 (Visited on 04.12.2024).

[9] Brownlee, J. Time Series Forecasting with Supervised Learning. Machine Learning Mastery. URL: https://machinelearningmastery.com/time-series-forecasting-supervised-learning/ (Visited on 04.12.2024).

[10] NASA POWER Data Access Viewer. A Tool for Renewable Energy Simulation. URL: https://power.larc.nasa.gov (Visited on 04.12.2024).

[11] Zhao, H., Liu, M. Facebook Prophet for Seasonal Energy Forecasting in Dynamic Environments. *IEEE Transactions on Energy Conversion*, vol. 12, no. 5, 2023, pp. 312–321.

[12] Monitoring Report for Sun-n-Sand 1.2 MW Wind Power Project. Satara, Maharashtra, October 2006.

[13] Wang, J., Zhang, F. Comparative Study of Time-Series Models for Wind Energy Prediction. *IEEE Access*, vol. 10, 2024, pp. 157890–157901. DOI: 10.1109/ACCESS.2024.3102034.

[14] Hyndman, R.J., & Athanasopoulos, G. (2018). *Forecasting: Principles and Practice*. OTexts.

Information about the authors:

Naim Baftiu: is a PhD candidate at the "GOCE DELCEV " University in Stip in the Faculty of Computer Science, study program Computer Science and Engineering, and he is preparing his PhD thesis.

Tatjana Atasanova-Pachemska: Earned M.Sc. degree in 2002 and a Ph.D. degree in 2006, both from Faculty of natural science and mathematics at Ss. Cyril and Methodius University in Skopje. Currently, she is a full professor at the Faculty of Computer Science, University “Goce Delcev” Stip, Macedonia. Her research interests are theoretical mathematics, applied mathematics and mathematical modelling and math education. Research Interests Mathematics, Mathematics of Computing, Computational Mathematics.

Manuscript received on 19 December 2024