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A transformer-based time series forecasting model with an efficient data preprocessing scheme

Kyrylo Yemets[1], Michal Gregus[2]
[1]Department of Artificial Intelligence, Lviv Polytechnic National University, Lviv, Ukraine
[2]Department of Information Management and Business System, Faculty of Management, Comenius University Bratislava, Bratislava, Slovak Republic

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ABSTRACT

Time series forecasting with cyclicality is key to the development of green energy, particularly wind energy, due to its high volatility. Accurate forecasting allows for optimal use of energy storage systems and balancing of power grids. In this article, the authors have developed a model for forecasting time series in wind energy through the combined use of Fourier transform and an adapted transformer architecture to solve the time series forecasting problem. The use of Fourier transform provided the ability to detect and account for hidden periodicities that may not be obvious in simple time series analysis, and allowed for the separation of random fluctuations from significant cyclical components, contributing to more accurate data analysis. The use of transformer architecture made it possible to effectively account for both short-term fluctuations and long-term trends in wind patterns, creating more accurate and reliable forecasts of wind energy production. The results show that the model outperforms methods such as transformers, long short term memory (LSTM), LSTM with Fourier transform, and DeepAR in forecast accuracy, taking into account seasonal, weather, and daily cycles of wind data.

Corresponding Author:

Kyrylo Yemets
Department of Artificial Intelligence, Lviv Polytechnic National University
Kniazia Romana str., 5, Lviv 79905, Ukraine
Email: kyrylo.v.yemets@lpnu.ua

1. INTRODUCTION

Time series forecasting plays a critical role in the development of green energy, particularly in the fields of wind and solar energy [1]. These renewable energy sources have a unique characteristic: their production is not constant and depends on variable natural conditions [2]. This feature creates significant challenges for energy systems, particularly in the areas of energy storage and grid balancing [3], [4].

Wind and solar energy are characterized by unstable generation [1]. Wind turbines produce electricity only when there is sufficient wind speed, and solar panels generate electricity only when there is adequate solar radiation [5], [6]. These factors can fluctuate significantly throughout the day, season, or year [7], [8]. Such variability poses serious challenges for energy systems that must ensure a stable supply of electricity to consumers. In this context, accurate energy production forecasting becomes not just useful but a necessary tool for effective energy system management [9]-[11]. Forecasts help energy system operators anticipate periods of low production and prepare for them in advance, which is particularly important in the context of energy storage.

Energy storage systems, such as large-capacity batteries or pumped-storage power plants, play a key role in balancing electricity supply and demand [12]. They allow the storage of excess energy during periods of high generation and its use when production decreases. However, effective use of energy storage systems requires accurate forecasting of both energy production and consumption [13], [14].

In the context of time series forecasting for wind energy, selecting an appropriate model is critically important for achieving high accuracy results [15], [16]. Traditional time series forecasting methods, such as autoregressive integrated moving average (ARIMA) models [17], have limitations in their ability to account for long-term dependencies and nonlinear relationships in the data [13], [14]. Recurrent neural networks (RNNs) [18] and their variants, such as long short term memory (LSTM) [19], can show better results in processing sequential data, but still face challenges when working with very long sequences due to difficulties in training on large time scales [20]. Transformers, originally developed for natural language processing tasks [21], have proven to be extremely effective in time series analysis, particularly in forecasting wind energy production. Their ability to efficiently process long-term dependencies in data through the self-attention mechanism allows the model to consider relationships between different time points regardless of their distance in the sequence [15]. Parallel data processing significantly speeds up training and inference compared to sequential models like RNNs. An important advantage of transformers is the absence of the vanishing gradient problem, which often arises in recurrent architectures when working with long sequences [22].

Therefore, after thorough analysis and comparison of different approaches, transformers were chosen as the most promising architecture for this task. The flexibility of the transformer architecture allows easy adaptation of the model to the specific features of wind energy forecasting. Additionally, their ability to efficiently process multivariate time series provides the opportunity to consider various factors that affect wind energy production [23]. It is important to note that the effectiveness of transformers in wind energy production forecasting is significantly enhanced by prior data preprocessing.

Wind data has a complex cyclic structure that depends on different time scales [24]. Seasonal cycles associated with changes in the seasons affect general weather conditions and wind patterns. Daily cycles caused by temperature differences between day and night lead to changes in wind speed and direction [25], [26]. Weekly and monthly patterns are also observed, which may be related to broader meteorological phenomena. Fourier transformation allows these cyclic components to be effectively extracted from the time series, representing them in the frequency domain [27]. This approach has several important advantages [16]. In particular, it helps to reveal hidden periodicities that may not be obvious in a simple time series analysis [28]-[30]. Additionally, this transformation allows for the separation of random fluctuations from significant cyclic components, contributing to more accurate data analysis.

The combination of Fourier transformation with transformer architecture creates a powerful tool for wind energy forecasting. Transformers, receiving input data preprocessed by Fourier transformation, can effectively account for both short-term fluctuations and long-term trends in wind patterns. This enables the creation of more accurate and reliable energy production forecasts, which is critically important for the effective management of wind power plants and the optimization of energy systems.

Therefore, the main contribution of this article is:

- We developed a time series forecasting model in the field of wind energy by jointly using Fourier transformation for transitioning from the time domain to the frequency domain and an adapted transformer architecture for solving the time series forecasting task, which allowed us to account for the complex nature of wind data and achieve high forecasting accuracy on large datasets.
- We compared our developed model with a number of existing state-of-the-art methods and demonstrated its advantages based on various performance indicators, ensuring further sustainable development and efficient use of renewable energy sources, particularly wind energy.

The next section describes the adapted transformer architecture for solving the time series forecasting task, presents the basic principles and mathematical formulations of Fourier transformation for transitioning (transforming input data) from the time domain to the frequency domain, and provides a detailed description of the proposed model's joint use of Fourier transformation and transformers. For better visualization of the proposed model's functionality, a flowchart of its work is presented. The third section is devoted to modeling the model's performance. It describes the dataset used for modeling, presents the mathematical formulations of the performance indicators used to evaluate the model's accuracy, and collects the obtained results. The fourth section compares the effectiveness of our developed model with a number of existing state-of-the-art methods and demonstrates its advantages based on various performance indicators. The conclusions based on the results of the conducted research are presented in the final section.

2. METHOD

2.1. Transformer architecture for time series forecasting

The transformer architecture has gained significant popularity in the field of machine learning, particularly in natural language processing [15]. This technology finds wide application in various tasks, from text translation to sentiment analysis, due to its ability to efficiently process long sequences of data and identify relationships between distant elements. The key components of a transformer are the encoder and decoder, which allow the model to grasp the context and structure of the input information.

The application of transformers has also proven to be promising in the field of time series forecasting. This is especially valuable when it is necessary to analyze multiple time series related by a common theme, such as meteorological conditions. In the context of weather forecasting, we deal with various parameters—temperature, humidity, atmospheric pressure, precipitation—that interact in complex ways and depend on time. Transformers demonstrate the ability to capture these complex relationships, which contributes to improving the accuracy of forecasts.

To adapt to the tasks of time series forecasting, the classical transformer architecture has undergone certain modifications. For convenience, we have depicted the transformer architecture in the form of a flowchart. The architecture of the transformers for solving the given task is shown in Figure 1.

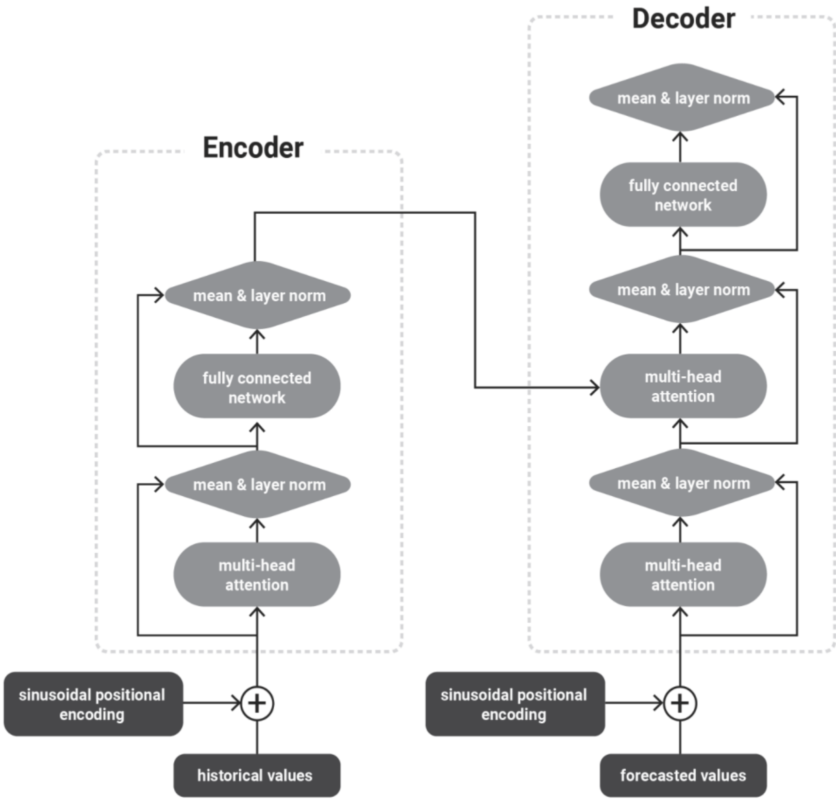

Figure 1. The adapted architecture of the transformer model to solving time series forecasting task

For adaptation, components such as tokenization and embedding were removed from the classical transformer architecture, simplifying the model and reducing its computational complexity. Instead of standard positional encoding, sinusoidal encoding was introduced, which better reflects the features of time sequences, giving more weight to recent events and preserving the temporal ordering of data. An important element of adaptation also involved the use of layer normalization instead of batch normalization. This approach ensures greater stability in the training process, as normalization is based on the statistical metrics of individual layers rather than the entire batch of data. Such a methodology allows for more effective consideration of seasonal and cyclic components of time series, which is crucial for accurate forecasting. Overall, the adapted transformer architecture demonstrates significant potential in the field of time series analysis and forecasting, offering an innovative approach to solving complex tasks in this area, especially when analyzing large time series or multiple time series [15].

2.2. Fourier transformation-based data preprocessing

Fourier transformation is an important mathematical tool that allows a time signal to be represented as a combination of sinusoidal waves of different frequencies [31]. This transformation is used to transition from the time domain, where the signal is represented as a function of time $x(t)$, to the frequency domain, where the signal is described as a function of frequency $X(f)$. Formally, Fourier transformation is defined as (1) [15], [16]:

$$X(f) = \int_{-\infty}^{\infty} x(t)\, e^{-2\pi i f t} dt \tag{1}$$

The formula shows how each frequency f in the signal spectrum is related to the integration of the initial signal $x(t)$ after its modulation by a complex exponential function [32]. After applying this transformation, the signal is no longer represented as a time function but becomes a frequency function. When it comes to time series, Fourier transformation allows for the exploration and analysis of the frequency components in the data [27]. By applying Fourier transformation to a time series, we can see which frequencies dominate the signal, i.e., which oscillations are most prominent in the given time series. Often, after obtaining the frequency spectrum, the primary frequency components can be identified, which correspond to the main trends or cycles in the data [33], [34]. This allows us to focus on the significant components of the signal by filtering out less important or noisy frequencies. To achieve this, filtering is used in the frequency domain, where certain frequencies are removed or attenuated.

Fourier transformation has several important applications in time series forecasting [35], [36]. First, it allows for the extraction of the main frequency components, simplifying the model and reducing the risk of overfitting since only the most significant oscillations are taken into account. Second, it helps identify cyclic or seasonal components, which can be used as additional predictors in forecasting models. Finally, frequency spectrum analysis can help detect anomalies, i.e., oscillations that do not align with the overall trend.

2.3. A transformer-based time series forecasting model with FFT-based data preprocessing

In this article, the authors have developed a time series forecasting model for wind energy by jointly utilizing Fourier transformation and an adapted transformer architecture to solve the time series forecasting task. The flowchart of the proposed model is described in Figure 2.

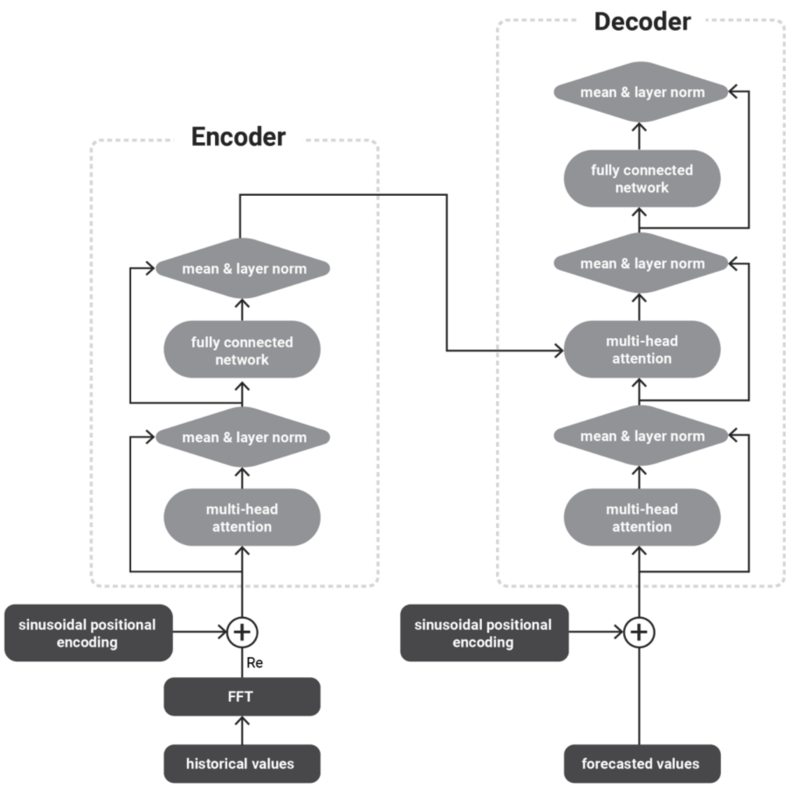

Figure 2. Transformer model with FFT preprocessing

To facilitate understanding of the operation of all procedures of the developed model depicted in Figure 2, the algorithm has been divided into several steps, each with its own specificity.

Step 1. Transition from the time domain to the frequency domain through Fourier transformation, which allows for the analysis of the frequency composition of the time series. For each contextual window in the time series x(t), which represents a limited sequence of values, we apply the discrete Fourier transform (DFT):

$$X(f) = \sum_{t=0}^{N-1} x(t)\, e^{-2\pi i \frac{ft}{N}} \tag{2}$$

where N is the size of the contextual window, t are the time indices, and f are the frequency indices. This transformation allows the time series to be represented as a set of harmonic components, with each frequency having its own complex value.

Step 2. The obtained frequency components, which are complex numbers, require further processing. We take only the real part of the complex number:

$$X(f) = \mathrm{Re}(X(f)) \tag{3}$$

This real component is the primary characteristic of the frequency that we use for further forecasting.

Step 3. Before passing this data to the model, we normalize it to improve the stability and accuracy of the forecast [37], [38]. Normalization can be done using standard methods, such as min-max normalization or standardization, to bring the frequency components into a specified range of values [30]. The time series itself is normalized in the same way. In this work, the following normalization scheme is used [37], [38]:

$$X_{std} = \frac{X(f) - \min(X(f))}{\max(X(f)) - \min(X(f))} \tag{5}$$

$$X(f) = X_{std} \times (\max(X(f)) - \min(X(f)) + \min(X(f))) \tag{6}$$

Step 4. After the frequency components have been normalized, they are fed into the transformer (replacing the time sequence samples with frequency components):

$$x(t_1), x(t_2), x(t_3) -> X(f_1), X(f_2), X(f_3) \tag{7}$$

Thus, instead of returning the data to the time domain using inverse Fourier transformation, the model forecasts the already normalized time series [39]. This simplifies the process and allows the transformer to fully leverage its architecture for data processing without the need to handle frequency attributes at the output. The "encoder-decoder" architecture of the transformer enables the model to effectively work with normalized time series, bypassing the inverse Fourier transformation step.

3. RESULTS AND DISCUSSION

3.1. Dataset descriptions

To test the effectiveness of the developed model, this article uses a dataset available in an open repository [40]. This dataset contains a single very long time series representing wind power production in megawatts (MW), recorded every 4 seconds, starting from 01/08/2019. It was downloaded from the online platform of the Australian Energy Market Operator (AEMO). The length of this time series is 7,397,147 data points.

3.2. Performance indicators

The effectiveness of the model was evaluated based on the following indicators [41]-[43]:

Mean average error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - x_i| \tag{8}$$

Mean square error (MSE):

$$MSE = \sum_{i=1}^{n} \frac{(y_i - x_i)^2}{n} \tag{9}$$

Root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - x_i)^2}{n}} \quad (10)$$

Symmetric mean absolute percentage error (SMAPE):

$$SMAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - x_i|}{(|y_i| - |x_i|)/2} \quad (11)$$

Mean absolute scaled error (MASE):

$$MASE = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - x_i|}{|x_i - x_{i_{n-1}}|} \quad (12)$$

The comprehensive consideration of all the above indicators provides a holistic assessment of the time series forecasting results when using all the investigated models [44].

3.3. Results

Experimental studies on the effectiveness of the developed time series forecasting model for wind energy through the joint use of Fourier transformation and an adapted transformer architecture were carried out by selecting a contextual window size of 60 values. This choice was determined by the specific data and task. The results of the developed model based on metrics (8)-(12) are presented in Table 1. The results from Table 1 were used to compare the effectiveness of the developed model with a number of existing models.

Table 1. Efficiency estimates of the transformer model in solving the time series forecasting task

Performance indicator	Value of the performance indicator
MASE	0.94
SMAPE	0.691
MAE	2.041
MSE	17.606
RMSE	2.832

3.4. Comparison and discussion

To compare the performance of the proposed model, which combines a transformer with Fourier transformation, several other approaches were used: baseline transformer [45], LSTM [17], LSTM with Fourier transformation [46], and DeepAR [47]. This selection of state-of-the-art methods is justified as follows. LSTM is a type of RNN specifically designed to work with sequential data. It is capable of effectively capturing long-term dependencies in data due to its internal architecture, which includes memory cells and forget mechanisms. This makes LSTM particularly useful for time series forecasting, where it is important to consider both short-term and long-term trends. However, due to its recurrent nature, LSTM may face difficulties in processing very long sequences, especially when the data exhibits complex cyclicality or seasonality. In the LSTM-based forecasting method with Fourier transformation, the latter procedure is also used for data preprocessing, helping to isolate the frequency components of the time series, which simplifies the forecasting task for LSTM. This approach slightly improves forecasting accuracy but is more suitable for relatively short time sequences. The DeepAR architecture is based on RNN and is well-suited for time series forecasting at the group series level. DeepAR models the dependencies between different time series, allowing for more accurate forecasts for each individual series by considering information from other similar series. This model is particularly effective when working with large datasets containing multiple time series, as it allows for the consideration of general trends and structures common to the entire group of series. Although the RNN on which DeepAR is based work well with short-term dependencies, they may struggle to process long-term dependencies in sequential data, which can reduce forecasting accuracy.

The study conducted a series of experimental evaluations on the effectiveness of each of the above-mentioned state-of-the-art methods in solving the given task. Specifically, Table 2 summarizes the numerical values of metrics (8)-(12) for each of the existing models, as well as for the model developed in this study.

Table 2. Efficiency comparison for all investigated models in solving the time series forecasting tasks

Model title	MASE	SMAPE	MAE	MSE	RMSE
Proposed model (transformer+FFT)	0.931	0.686	3.046	12.83	3.581
Transformer [17]	0.954	0.705	3.071	12.955	3.599
LSTM+FFT [37]	0.971	0.76	3.346	14.178	3.765
LSTM [15]	0.976	0.786	3.371	14.354	3.788
DeepAR [38]	0.964	0.752	3.203	13.83	3.718

The results obtained from Table 2 show that the model developed in this article demonstrates the best results among all the tested models. For example, the RMSE value for this approach is 0.931, which is the lowest among other models, indicating its high accuracy. Even compared to the baseline transformer model, which shows an RMSE of 0.954, the additional application of Fourier transformation, characteristic of the developed model, provides a noticeable improvement. The MASE value for the developed model is also the lowest, at 0.686, which is significantly lower than the results of other models, such as LSTM+FFT with a MASE of 0.76 or classical LSTM with a MASE of 0.786. This demonstrates that Fourier transformation significantly enhances the model's effectiveness for this metric. However, when considering MAE, both the baseline transformer and the proposed model show nearly identical results, with a slight improvement for the proposed model: 3.046 versus 3.071, respectively. This indicates that while Fourier transformation helps reduce the mean absolute error, the effect is less pronounced than for RMSE and MASE. In terms of the SMAPE metric, the proposed model also demonstrates the best results, with a value of 12.83, which is lower than other models, such as LSTM (14.354) and LSTM+FFT (14.178). This indicates that FFT helps significantly reduce the SMAPE. For visualizing the comparison results, they are summarized in Figure 3 for all the investigated models based on metric (9).

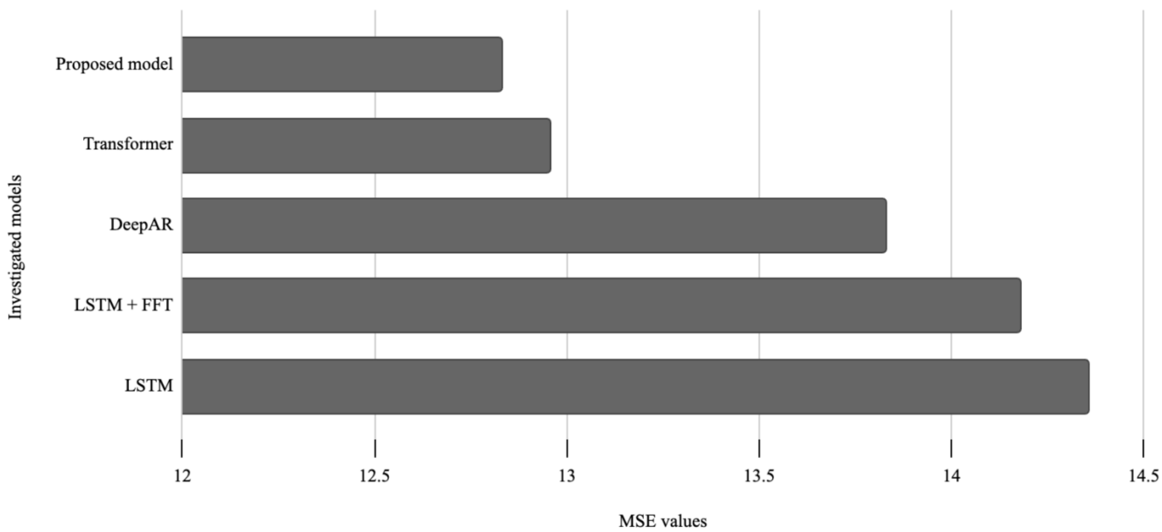

Figure 3. Comparison of the mean squared error of all investigated neural network models used for solving the given task

The graph illustrates a comparison of the mean squared error of different models used for time series forecasting. The lowest MSE is observed in the proposed model, at approximately 16.5, indicating its high accuracy compared to other approaches. The LSTM model combined with Fourier transformation also shows good results, approaching an MSE of around 17.0. This serves as additional evidence supporting the combined use of frequency analysis with neural network architectures. The DeepAR model holds a middle position with an MSE of around 17.5, indicating its competitiveness, although it lags behind the proposed model in terms of accuracy. The baseline transformer shows a significantly higher MSE, reaching approximately 18.5, indicating lower accuracy compared to the other approaches. The worst results are shown by the LSTM model, with an MSE of around 19.0, indicating its lower effectiveness in this context.

The implications of these results are significant for both the field of wind energy and computer science. Notably, the following points stand out:

a. The proposed preprocessing technique for cyclical time series—replacing time series values with the real part of a complex number derived from the fast Fourier transform (FFT)—has demonstrated a substantial increase in the effectiveness of deep learning neural networks for forecasting wind energy production.
b. The time series forecasting model developed in this paper, which combines Fourier transformation with an adapted transformer architecture, provides more precise forecasts for wind energy production. This precision is crucial for optimizing energy generation and grid management.
c. The forecasting accuracy achieved allows energy providers to make better-informed decisions regarding energy distribution, storage, and consumption. This can lead to a more reliable energy supply and reduced reliance on fossil fuels.
d. The model's ability to effectively handle large datasets suggests that it can be applied across various geographical locations and conditions, enhancing its real-world applicability.

Overall, the contributions of this research have the potential to advance the field of wind energy forecasting significantly, improving the reliability and sustainability of renewable energy systems. However, there are still opportunities for further improvement of the proposed model. Notably, three promising avenues for future research include:

a. Employing both the real and imaginary parts of the complex numbers obtained from the FFT to replace the time series values. This approach would significantly expand the input space of the problem, providing additional information for the artificial neural network approximator, which could enhance forecasting accuracy when analyzing cyclical time series.
b. Conducting experimental studies on the effectiveness of the proposed preprocessing method with other state-of-the-art neural network architectures. The goal would be to identify simpler models with fewer parameters that can achieve the same forecasting accuracy as demonstrated in this paper.
c. Creation of an ensemble model and optimizing model parameters using the state-of-the-art optimizers [48] to achieve even greater forecasting accuracy.

4. CONCLUSION

Time series forecasting plays an important role in the energy sector, particularly in forecasting wind energy production. This task is critical for the effective planning of energy resources and ensuring the stability of energy systems. Forecasting allows system operators to optimize energy production and distribution processes, minimizing losses and improving economic efficiency.

In this paper, a time series forecasting model was developed based on the combined use of transformers and FFT to improve forecast accuracy. The authors conducted modeling using a large dataset to forecast wind energy production based on time series and compared the effectiveness of the developed model with various existing state-of-the-art methods. Specifically, the effectiveness of using this approach was investigated.

The modeling results showed that the developed model produces the best results among all the models studied. For example, the RMSE value for this approach is 0.931, which is the lowest among other models. The use of FFT also provides significant improvements in MASE and SMAPE metrics, indicating its ability to significantly enhance forecasting accuracy. Although LSTM- and DeepAR-based models showed competitive results, they could not outperform the developed model. This confirms the advantage of the approach that combines frequency analysis with the powerful capabilities of transformers. The results presented in this paper contribute significantly to the research field by offering a robust methodology for wind energy forecasting, which enhances economic efficiency and stability within energy systems. This work underscores the critical role of time series forecasting in the energy sector, particularly in optimizing wind energy production.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Kyrylo Yemets	✓	✓	✓			✓			✓	✓	✓			
Michal Gregus				✓	✓		✓	✓		✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [Zenodo] at https://doi.org/10.5281/zenodo.4656032, reference number [32].

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BIOGRAPHIES OF AUTHORS

Kyrylo Yemets is a Ph.D. student at the Department of Artificial Intelligence of Lviv Polytechnic National University, Ukraine, and a machine learning engineer. He received an M.Sc. degree in Computer Science from the National Technical University "Kharkiv Polytechnic Institute", Ukraine in 2021. His research interests include time series, natural language processing, transformers, and ensemble methods where he is the author/co-author of over 10 research publications. He can be contacted at email: kyrylo.v.yemets@lpnu.ua.

Prof. Michal Gregus is a Professor of the Faculty of Management, Comenius University Bratislava, Bratislava, Slovak Republic. He finished his university studies with summa cum laude and obtained his Ph.D. degree in the field of mathematical analysis at the Faculty of Mathematics and Physics at Comenius University in Bratislava. He has been working previously in the field of functional analysis and its applications. At present, his research interests are in management information systems, in modelling of economic processes, and in business analytics. He can be contacted at email: Michal.Gregus@fm.uniba.sk.