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Hybrid Transformer Forecasting for Renewable Microgrids

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ABSTRACT

Study aimed to develop an intelligent system for short-term forecasting of electricity generation by wind and solar power stations, based on hybrid transformer neural networks, with a view to improving the efficiency and stability of microgrids in western Ukraine, particularly within the Volyn region. During the study, empirical data on meteorological parameters – such as wind speed, solar irradiance, temperature and humidity – were collected, along with historical generation data from renewable energy facilities in the Volyn region over three years. A hybrid model of transformed neural networks was developed and trained, combining the advantages of different architectures for processing time series. The main results showed that the proposed system achieved an average absolute error in forecasting wind power generation of 4.2% and solar generation of 3.8% over a horizon of 1 to 6 hours. This is 25% better than standard neural networks and 31% better than statistical models. Testing of the system on a real microgrid in the Volyn region with a capacity of up to 10 MW demonstrated a 36% improvement in the microgrid's operational stability, a 21% reduction in peak load deviations, a 17.6% reduction in power system balancing costs, and the maintenance of the grid frequency within the regulatory limits (±0.05 Hz). Furthermore, thanks to optimisation, the share of renewable energy sources was increased by 14% without the risk of overloading the equipment. The results obtained demonstrated the high efficiency of hybrid transformable neural networks under the variable weather conditions of western Ukraine. Practical value of results lies in the possibility of directly implementing the developed system into existing microgrids in the Volyn region; furthermore, microgrid operators and energy companies can utilise the hybrid transformer model for short-term forecasting of wind and solar generation.

Keywords: Generation data, renewable energy sources, reserve control, forecast integration, operational stability.

Mathematics Subject Classification: 62M10, 90B50, 94A12

Computing Classification System: I.2.6

1. INTRODUCTION

An increase in the share of renewable energy sources within the electricity supply mix is accompanied by significant volatility in electricity generation due to dependence on meteorological factors. Wind and solar power stations are characterised by high variability in generation, which complicates power balancing and the maintenance of frequency and voltage in the grids, and also leads to increased costs for reserve regulation and a reduction in the reliability of the power supply. In Ukraine, where the share of renewable energy sources continues to grow following the energy transition strategy, these issues are particularly pressing in regions with high potential for wind and solar energy, particularly in the western part of the country, where climatic conditions favour the development of such facilities.

Existing approaches to forecasting generation from renewable energy sources include both statistical methods and artificial intelligence-based models. Neural networks are effective in handling non-linear relationships of time series data, as shown in the literature (Guliyev, 2024; Hadasik et al., 2025). Talaat et al. (2023) specifically used artificial intelligence to integrate and control hybrid renewable energy sources in microgrids, which resulted in improved forecasting accuracy, optimised deployment and control of energy storage systems, reduction of power losses and enhanced stability. Gangwar et al. (2024) proposed deep learning models for the integration of renewable sources into microgrids and the optimisation of their operation in smart grid environments. Mahjoub et al. (2023) proposed an energy management strategy for a microgrid consisting of a photovoltaic system, wind turbines and batteries. The authors used an LSTM network-based forecasting algorithm, which achieved low root mean square error (RMSE 0.0221-0.0790) for PV power and battery state of charge, and reliable power balancing in the experiments. Mittal and Karuna (2024) used swarm intelligence algorithms for optimisation of hybrid wind-solar microgrids. Using particle swarm optimisation (PSO) they achieved 80% renewable energy penetration and cut operating costs by 15%. Zafar et al. (2024) proposed a hybrid model based on convolutional neural network, autoencoder and LSTM for solar generation forecasting in smart grids. This approach delivered higher accuracy compared with standalone LSTM models or a combination of CNN-LSTM, thanks to better capture of complex time-series patterns and a significant reduction in errors.

Ukrainian research addressed adaptation of modern artificial intelligence methods to local climatic and technical conditions. Kholyavka (2025) developed information technology models and methods for assessing the condition of microgrids with renewable energy sources. The author integrated hybrid forecasts based on a bidirectional LSTM network (BiLSTM) with fuzzy logic, which ensured effective classification of microgrid states and decision-making under conditions of uncertainty. Ambraschuk (2025) investigated artificial intelligence methods for forecasting energy generation from alternative sources. Comparison of different machine learning models in isolated power systems, where a significant improvement in forecast accuracy was demonstrated compared with statistical methods, particularly under conditions of limited data and unstable generation, was emphasised. A methodology for optimising the training of LSTM networks for forecasting solar generation using a Bayesian approach was proposed by Zinkevich et al. (2025). Bayesian hyperparameter optimisation made it possible to improve the model's generalisation ability and reduce the effect of overfitting, which proved effective for short-term forecasting of power output from photovoltaic plants under variable weather conditions. Moreover, Bobeyko (2025) studied energy efficiency measures for the green transition for Ukraine. The paper presents algorithms for adaptive consumption control based on Internet of Things (IoT) technologies that enable real-time monitoring and dynamic load regulation. The results demonstrate the potential of smart systems to reduce the total energy consumption of the transition to renewable energy sources.

However, the application of hybrid transformer architectures to forecast short-term wind and solar generation simultaneously according to regional metrological characteristics is still lacking. The majority of the studies focus on individual sources or generic models without profound integration of the optimisation of microgrids in a specific climatic zone. There is a lack of empirical research on the use of transformer models with real-world data from the western region of Ukraine to directly evaluate the impact on the stability and economics of microgrids.

The goal of the research was to create and evaluate an intelligent system for forecasting the short-term electricity generation of wind and solar power stations using hybrid Transformer neural networks to improve the efficiency and stability of microgrid management in the western region of Ukraine. It was assumed that the use of the attention mechanism of the Transformer together with the elements of the recurrent and convolutional layers will cause a significant decrease in the error of the forecast in comparison with the traditional neural networks in the aspect of weather variability in the Volyn region.

2. MATERIALS AND METHODS

The study was conducted during 2022-2025 based on data on real renewable energy facilities in the Volyn region. This included a microgrid of up to 10 MW capacity made up of solar and wind power stations and local energy storage systems. The empirical part of the study was conducted in the temperate continental climate of Western Ukraine with a high variability of weather parameters. Data used in the work were obtained from the archives of the Borys Sreznevsky Central Geophysical Observatory (2026), the ERA5 database (Copernicus Climate Change Service, Climate Data Store, 2023), publicly available and local meteorological stations in the locations of the studied facilities in the cities of Lutsk, Kovel and Volodymyr (Meteopost, 2026). Historical generation data were collected from microgrid operators and NEURC registers (National Commission for State Regulation in the Fields of Energy and Utilities, 2024) for three years with a sampling interval of 15 minutes, which resulted in a sample size of 105,120 observation points for each source type. The sample was selected on the basis of the completeness of the data and representativeness of the seasonal and diurnal cycles (excluding periods of emergency outages). The sampling method was a non-random sample stratified by season and source type.

The hybrid transformer neural network model combined convolutional layers with a recurrent LSTM block of 128 units and an 8-head multi-head attention mechanism. The input vector was built from lag values of the generation up to 24 steps, meteorological parameters and cyclical time signals in the form of sine and cosine waves of daily and annual periods. The model was trained on 70% of the dataset using the Adam optimiser with a learning rate of 0.0005, a batch size of 64, and early stopping. Ablation analysis method was used to evaluate the individual contribution of the components and stress testing was performed to verify the robustness of the system to anomalies by adding Gaussian noise. Forecasting accuracy was evaluated on the basis of MAE and RMSE metrics, the coefficient of determination R^2 and the mean absolute percentage error (MAPE) in a 1-6 hour horizon.

The methodology for assessing economic efficiency was based on a comparative analysis of the baseline and experimental scenarios during three months of online tests. The baseline case was the microgrid operation with the standard algorithms of the operator without the use of intelligent forecasts. The experimental scenario involved the integration of forecasts from a hybrid model into a control optimiser using linear programming. Total balancing costs have been calculated as the sum of fuel costs for backup generators, the notional cost of battery degradation, the financial losses from forced generation curtailment and costs of unscheduled manual interventions by dispatchers. Financial and operational data were available from the microgrid operator's internal records, fuel consumption logs, technical data concerning the number of battery charge and discharge cycles, the use of backup generators and the extent of forced generation curtailment. The savings percentage of 17.6% was calculated as the difference of the costs between the two scenarios divided by the costs of the baseline scenario. The absolute monthly savings of more than 20,000 UAH were defined as the arithmetic mean of the difference in cost for the total observation period. To determine statistical significance ($p<0.05$), Pearson's correlation coefficient was used in a correlation analysis of the relationship between the reduction of the forecast error and the amount of funds saved, presented as daily aggregated data over the 90-day observation period. Statistical analysis of the results also included application of Student's paired t-test to test the significance of the difference in forecasting errors between the models. All computations were done in Python with the pandas and numpy libraries (McKinney, 2022; VanderPlas, 2016). The model was validated in the online forecasting mode on a real microgrid and updated on a monthly basis to adapt to seasonal variations.

3. RESULTS

Worldwide trends in renewable energy development show a growing share of decentralised energy systems, with generation largely covered by wind and solar power stations. At the same time, the integration of such sources into local energy systems is accompanied by an increase in uncertainty of operating modes due to dependence on short-term changes in meteorological parameters. The generation forecast accuracy is important for providing stability and economic efficiency in microgrids where the power balancing is done at a small scale with minimal reserves (Hernández-Mayoral et al., 2023; Karimzada and Donato, 2024; Massenio et al., 2023). The problem of accurate forecasting is especially important in regions with a very changeable weather regime, such as the western part of Ukraine. Under such conditions, traditional statistical forecasting methods, in particular ARIMA and its modifications, often demonstrate insufficient accuracy due to the pronounced non-linear nature of the relationships between meteorological variables (wind speed, solar radiation, cloud cover, temperature) and actual electricity generation. The non-linearity of these relationships is further complicated by inertial processes at the power generation facilities themselves and rapid short-term changes in weather parameters. Under such complex conditions, the use of hybrid artificial intelligence models – combining attention mechanisms, recurrent structures and convolutional elements – can substantially improve quality of forecasts (Wan et al., 2023; Zinkevich et al., 2025; Zhangabay et al., 2023a). Such models can simultaneously cover short-term fluctuations in parameters, long-term seasonal and diurnal cycles, as well as complex non-linear relationships between various meteorological factors. As a result, hybrid architectures demonstrate better generalisation ability and adaptability compared to homogeneous models (Saltos et al., 2026; Salman et al., 2024; Tursunbaev et al., 2025). The effectiveness of such hybrid models depends to a large extent on the representativeness and quality of the input data. The training dataset must cover a wide range of weather scenarios – from calm periods and heavy cloud cover to strong gusts of wind and clear, sunny days, as well as various operating modes of power plants throughout the year (Doroshkevich et al., 2017b; Fioretto et al., 2013a). Only under such conditions can the model learn to respond appropriately to the actual variability in generation typical of regions with a temperate continental climate.

An analysis of empirical data collected in the Volyn region during the period 2022-2025 clearly demonstrated the significant variability in electricity generation from renewable sources, which is characteristic of regions with a temperate continental climate and highly variable weather conditions. In the western part of Ukraine, the wind speed varies from 1.2 m/sec in calm periods to 12-15 m/sec during the passage of weather fronts (Meteopost, 2026). The wind and solar energy potential in this part of Ukraine is one of the highest in the country. Such dynamics directly affect microgrid stability, which results in more complex power balancing and higher possibility of the grid frequency to deviate from the regulation limit of ±0.05 Hz. The dataset is highly representative, with only emergency outages or scheduled maintenance periods (less than 4% of the data) excluded, and with uniform stratification across seasons and generation types. Table 1 summarises the main features of the collected meteorological and generation data, which are used for training and testing the model.

Table 1. Characteristics of the volume and composition of empirical data for the Volyn Oblast for the period 2022-2025

Data type	Number of records	Average value
Wind speed (m/s)	105.120	4.7
Solar radiation (W/m²)	105.120	312
Temperature (°C)	105.120	8.9
Wind power generation (MW)	105.120	2.4
Solar power generation (MW)	105.120	1.8

Source: compiled by the authors based on Copernicus Climate Change Service, Climate Data Store (2023), Earth Data (2026), and ENTSO-E Transparency Platform (2026).

The results in Table 1 confirmed the high representativeness of the empirical data collected. The mean values of meteorological parameters and generation were calculated directly from the processed dataset, which comprises over 105,120 records for each source type. Verification of the results using Student's paired t-test confirmed the absence of a statistically significant difference ($p>0.05$) between actual generation volumes and forecast values, demonstrating the model's high adequacy. The results obtained correspond to the actual capacities of the microgrid under study, up to 10 MW, where wind generation predominated during the cold season and solar generation during the warm season. The sample structure reflects the meteorological characteristics of the Volyn region, in particular the correlation between wind speed and solar irradiance, which was used to model microgrid's operation across all operating modes. The high representativeness of the three-year empirical data obtained, covering daily and seasonal cycles of generation variability, ensured the validity of the hybrid neural network training process and provided an objective basis for verifying the accuracy of the forecasting models.

The LSTM layers stored long-term information about the system's previous states, enabling the model to effectively account for the inertial characteristics of power generation inherent in both wind and solar power stations. In particular, a change in wind speed does not always lead to an immediate corresponding change in power output due to the mechanical inertia of the turbine rotor and delays in the control system (Rahmanov et al., 2017; Palmieri et al., 2018; Zhang et al., 2025), whilst solar generation depends significantly not only on the current level of solar irradiance, but also on the cumulative effect of previous changes in cloud cover, the speed at which clouds move, and the duration of periods of reduced sunlight (Anyanwu et al., 2025; Halko et al., 2021; Lyubchyk et al., 2015). Convolution blocks, in turn, ensured the effective extraction of local short-term patterns in time series, such as impulse fluctuations in power, short-term gusts of wind or rapid changes in solar irradiance. As a result, the model was able to respond more accurately to high-frequency variations typical of the region. This is especially true for the Volyn region, where sharp changes in cloudiness, the passage of atmospheric fronts and instability of winds are often observed in spring and autumn, creating significant difficulties for traditional forecasting models (Doroshkevich et al., 2017a; Meteopost, 2026).

The input vector was built from lagged generation values (up to 24 steps before), a full set of meteorological variables and cyclical time signals (sine and cosine of the diurnal and annual cycles) which improved resilience to seasonal variations. This approach took into account both short-term fluctuations and long-term cyclical trends, which is important for areas with strong seasonality, such as the Volyn region. Training was performed on 70% of the sample using the Adam optimiser with a learning rate of 0.0005, a batch size of 64 and early stopping based on validation error. The process terminated at epoch 87, when the loss on the validation set stabilised at 0.031, showing that there was no overfitting despite the presence of noise in the real-world data from the Volyn Oblast. This approach was directly based on principles tested in modern hybrid models for artificial neural networks and improved generalisation compared to homogeneous architectures (Brescia et al., 2023; Zemouri et al., 2025). Eight attention heads were used to identify relationships between different meteorological variables, and the 128 units in the LSTM layer retained context for up to 24 hours. This number of parameters proved sufficient for modelling complex non-linear dependencies, whilst at the same time not leading to an excessive increase in computational complexity. A convolutional layer with a kernel size of 3 filtered out local noise effects, which is relevant in the Volyn region, where sudden changes in wind speed and cloud cover are a common occurrence and can cause short-term peak fluctuations in generation. As a result, the model demonstrated increased resilience to anomalies in the data, which is critical for real-world microgrids, where data gaps and noise spikes are inevitable.

The addition of a multi-head attention mechanism can be used to dynamically identify the most relevant segments of a sequence and establish more effective relationships between variables, even when the time series is of considerable length (Brescia et al., 2024; Dai et al., 2023). This is important when dealing with tasks with high frequency and unevenly distributed patterns in time series. In addition, the CNN component can identify short-term local patterns in time series, which is a significant advantage over models that only use recurrent layers (Agga et al., 2022; Abdullayev and Karimzada, 2013). Convolutional layers guarantee efficient capture of local dependencies and data features, which complements the recurrent networks and enhances the overall quality of complex time series modelling (Ahmed et al., 2023; Savastio et al., 2025). Thus, the model can better capture abrupt changes in the intensity of solar radiation or wind gusts, which are often important for accurate generation forecasting. Therefore, the selected architecture combines the advantages of the three approaches, which has guaranteed its high performance.

The proposed hybrid transformer model has demonstrated high accuracy in short-term forecasting of electricity generation from wind and solar sources. The mean absolute error values increase systematically as the forecast horizon lengthens; however, even over a six-hour interval, they remain at a level acceptable for operational management (Biliuk et al., 2022b; Hashimov et al., 2019). The results obtained confirmed the effectiveness of the proposed architecture under the conditions of variable weather factors in the Volyn region. The forecasting accuracy was assessed using an independent test sample for horizons ranging from 1 to 6 hours. The main metrics used were the mean absolute error, the root mean square error, the coefficient of determination and the mean absolute percentage error. To summarise the results of the accuracy assessment of the hybrid model across different time horizons in the Volyn region's microgrid, Table 2 presents the values of the relevant metrics.

Table 2. Accuracy metrics for the hybrid model across different forecast horizons in the Volyn region

Horizon	MAE wind (%)	MAE solar (%)	RMSE (MW)	R^2	MAPE (%)
1 hour	3.2	2.8	0.31	0.97	4.1
3 hours	4.1	3.6	0.42	0.95	5.2
6 hours	5.4	4.9	0.58	0.93	6.7
Average	4.2	3.8	0.44	0.95	5.3

Source: compiled by the authors.

The results in Table 2 demonstrate the model's high effectiveness under the real-world conditions of changeable weather in the western region. The forecasting error increased as expected with a longer forecast horizon; however, over a 6-hour interval, it exceeds 6%. This accuracy is important especially for areas with high frequency of short-term weather variations, where even small errors can lead to unwelcome deviations in the power balance and an increased demand for reserve sources. For the forecast horizons of interest (1 to 6 hours), the average absolute error was 4.2% for wind generation and 3.8% for solar generation. The coefficient of determination R^2 ranged between 0.95 depending on the time horizon, indicating the high explanatory power of the model concerning variations in actual generation. The model was able to explain more than 93% of the variation in generation with a coefficient of determination greater than 0.93 for all the time horizons considered. This is a big step forward compared with traditional recurrent approaches. In classical LSTM models, the R 2 value is often confined to the region of 0.85-0.90 for a longer forecast horizon, which shows the restricted ability of these models to properly capture the complex non-linear relationships within time series (Neagoe et al., 2025; Zhangabay et al., 2023b). The obtained results show that the proposed architecture is better adapted to fast changes in the weather conditions, and provides a more stable forecast quality over a larger time range. Experimental testing of the contribution of individual architectural components confirmed that the use of the multi-head attention mechanism reduced the mean error during periods of sharp meteorological fluctuations by 12% compared with the baseline LSTM model. This demonstrated the system's superior generalisation ability and its adaptability to the changing weather conditions characteristic of the Volyn region. The model's robustness to anomalies in the input data was confirmed by the continued stability of the forecasts when noise was artificially introduced into the meteorological parameter vectors, with accuracy deviations not exceeding 0.5%.

A comparative analysis of accuracy was conducted using identical data from the Volyn region with standard LSTM and CNN-LSTM models, as well as the ARIMA statistical model. The practical effectiveness of the authors' development – which consists of a specific topology involving the sequential connection of convolutional layers, long short-term memory (LSTM) blocks and the integration of a Multi-head Attention layer at the feature aggregation stage – was confirmed by specific quantitative comparison metrics. Thanks to the attention mechanism's ability to dynamically recalculate the weight coefficients of meteorological parameters depending on the current generation mode, the proposed hybrid model achieved an average absolute error of 4.3% for wind power generation and 3.9% for solar power generation over time horizons ranging from 1 to 6 hours. This approach significantly outperformed existing alternatives: forecasting accuracy was 24-27% higher than that of standard LSTM networks, 18-22% higher than that of the baseline CNN-LSTM architecture, and 29-34% higher than that of the ARIMA statistical model. The application of Student's paired t-test confirmed that the observed reduction in error compared with alternative approaches is statistically significant ($p<0.05$). The proposed hybrid transformer model demonstrated a significant advantage, achieving a 19-32% reduction in the mean absolute error compared with alternative approaches. This reduction in forecasting error significantly reduces uncertainty in the operation of the microgrid, which directly affects the levels of operational reserves required and improves accuracy of determination of optimal modes of buffer capacity utilisation, battery charge-discharge strategies and the deployment of reserve sources (Boralessa et al., 2022; Balato et al., 2015; Davlatshoevich et al., 2022). In practical terms, this leads to significantly less frequent use of expensive diesel or gas-fired backup generators and a reduction in the number of battery charge–discharge cycles, which helps to extend their service life and substantially reduce overall operating costs (Balog and Davoudi, 2021; Rabat et al., 2018). Furthermore, the improved accuracy of forecasts reduces the frequency of situations where the microgrid operator is forced to intervene manually to correct the power balance (Fioretto et al., 2013b; 2014; Qiu et al., 2025). This not only reduces the operational workload on staff but also enhances the overall stability of the microgrid's operation, particularly in the context of sudden weather changes characteristic of the western region of Ukraine.

The integration of forecasts into the control system was accomplished through a linear programming optimiser, where the forecast generation acted as either a hard or soft constraint, depending on the optimisation scenario. This approach formalised the trade-off between minimising reserve costs, maintaining regulatory frequency levels and battery lifetime. The optimiser took into account technical constraints (SOC constraints, generator response times, time windows) and economic considerations in real time and could therefore produce a practical course of action for operators (Biliuk et al., 2020; 2022a; Brescia et al., 2026). The online testing of the microgrid in the Volyn region confirmed the decrease in the number of corrective interventions, and the increase in predictability of operating modes. This was quantified by comparative indicators before and after integration. Simply by improving forecast accuracy, the stability was increased by 36% and peak deviations reduced by 21% without any new equipment or further investment in infrastructure modernisation. This demonstrates that even technically limited local power systems can achieve significant improvements simply by optimising control algorithms and improving the quality of forecast data. The developed system's application resulted in a decrease of the average monthly balancing costs by 17.6% compared to the baseline situation for the three-month observation period. The microgrid under the study with a capacity of up to 10 MW has savings of more than 20,000 UAH per month, which is confirmed by the internal operational records of the microgrid operator. This was achieved by reducing the cost of fuel for backup diesel generators, minimising battery depreciation by optimising charge-discharge cycles, avoiding financial losses from forced curtailment, and minimising unscheduled manual interventions by dispatchers. The received indicators of economic efficiency are directly related to the accuracy of the developed algorithm for time horizons from 1 to 6 hours. Statistical analysis confirmed a strong linear relationship (Pearson's correlation coefficient $r=0.84$, $p<0.05$) between the percentage reduction in the mean absolute forecast error and the amount of funds saved on capacity reserving. Practical tests in microgrid environment confirmed the fact that the proposed intelligent system provides full coverage of typical operating modes of renewable energy facilities (including periods of prolonged calm, sudden atmospheric fronts and peak insolation) translating theoretical advantages of hybrid architecture into a measurable reduction in operating costs and an increase in the stability of the local power system. These savings begin to accrue within the first few months of the system's implementation. The share of renewable energy sources has increased by 14%, indicating more efficient use of available generation capacity and a reduction in instances of curtailment. This also means a reduction in reliance on diesel or gas reserves, which has a positive impact on both the economic performance and the environmental performance of the microgrid.

The results of the study confirmed the hypothesis regarding the effectiveness of hybrid transformer neural networks for short-term forecasting of wind and solar generation. An average error of 3.8-4.2%, combined with a 14-36% improvement in the operational performance of the microgrid, demonstrates the significant scientific and practical contribution of this research. To summarise the results, it can be stated that the proposed hybrid transformer model ensures high accuracy in short-term forecasting of generation from wind and solar power stations in regions with high meteorological variability. The accuracy metrics and operational improvements obtained confirm the feasibility of integrating such models into microgrid control systems. Further development of the system may include expanding the set of input data, implementing adaptive online learning, and testing over longer forecasting horizons, which will enhance the efficiency of energy system planning and management.

4. DISCUSSION

The results of this empirical study confirm the high effectiveness of hybrid transformer neural networks for short-term forecasting of wind and solar generation in microgrids in the Volyn region. The proposed model has demonstrated significant scientific and practical potential under real-world operating conditions. A comparison with other studies has revealed both similarities and differences related to regional characteristics, model architecture and forecasting horizons. In a study dedicated to forecasting solar and wind generation for the transition to green energy, Mohsin et al. (2022) developed a hybrid model based on LSTM and a gated recurrent unit (GRU), incorporating a wavelet transform for signal decomposition. The authors achieved a MAPE of 6.8-9.2% for hybrid systems using real-world data from Pakistan. In the present study, the MAPE did not exceed 6.7% even over a six-hour horizon, whilst for one- and three-hour intervals it was 4.1-5.2%, indicating the superiority of transformer attention mechanisms over classical recurrent architectures under conditions of high data volatility in the Volyn region, where frequent changes in cloud cover and gusts of wind require better capture of global dependencies.

To forecast hybrid solar-wind systems in urban environments in Pakistan, Javaid et al. (2024) developed a hybrid model combining a CNN, an LSTM and an attention mechanism with data pre-processing using empirical mode decomposition. The authors achieved an RMSE of 0.45-0.72 MW for time horizons of up to 4 hours. In the results of this study, the RMSE ranged from 0.31 to 0.58 MW over similar time horizons, indicating greater accuracy due to a larger number of attention heads (8) and the integration of cyclical time features, which better account for diurnal and seasonal patterns in the temperate continental climate of western Ukraine.

A hybrid model based on LSTM with the Fourier SynchroSqueezed Transform for forecasting photovoltaic generation in Spain was proposed by Rajah et al. (2025). The authors obtained an average error of 4.1-5.6% over time horizons of 1-8 hours after applying frequency analysis to identify periodic components. The results of the analysis (MAE 2.8-4.9% for solar generation) demonstrate similar accuracy over short time horizons, but outperform it over a six-hour interval, which is explained by the greater adaptability of the transformer architecture to the simultaneous forecasting of two types of sources without the need for separate pre-processing of frequency components, and by better handling of non-linear relationships between meteorological variables. Furthermore, a hybrid deep learning model with hyperparameter optimisation using a genetic algorithm for very short-term forecasting of wind power in Bangladesh was applied by Faruque et al. (2024). The authors achieved a MAPE of 5.2-7.8% over horizons of up to 30 minutes. The MAPE values for wind power generation obtained in this study (4.1-6.7%) are superior, particularly for time horizons exceeding 3 hours, confirming the advantage of integrating attention mechanisms to capture the non-linear relationships between wind speed and generation under a temperate continental climate characterised by more frequent medium-term frontal changes.

Prabha et al. (2025) developed hybrid photovoltaic-wind microgrids using a swarm optimisation algorithm to tune the parameters and a supplemented physics-informed neural network for forecasting and control. They achieved a 28-32% improvement in stability and a 13-18% reduction in costs in simulations. In the present study, stability increased by 36%, whilst peak balance deviations decreased by 21%, indicating greater efficiency in integrating transformer-based forecasts into a linear programming optimiser compared with swarm optimisation algorithms under real-world microgrid conditions in the Volyn region with limited computational resources.

The control of a hybrid microgrid incorporating photovoltaics, wind power and energy storage systems in South African conditions was optimised by Michael et al. (2023) using a model based on mixed-integer linear programming (MILP) with forecasts generated by an artificial neural network (ANN). The authors achieved a cost reduction of 12-16%. The results obtained (a 17.6% reduction in balancing costs) exceed this figure, which is explained by higher forecast accuracy and the direct integration of forecast values into the optimiser's objective function without additional assumptions regarding probabilistic scenarios. Abdelghany et al. (2023) proposed coordinated optimal operation of a grid-connected wind-solar microgrid with the integration of hybrid energy storage systems. The authors developed a comprehensive control strategy that combines generation forecasting with the optimisation of charge-discharge cycles for hybrid storage devices (batteries and supercapacitors). As a result, they succeeded in reducing power fluctuations by 18-25% and lowering operating costs by 14-19% under simulation conditions. The empirical results of the study exceed these figures: microgrid stability increased by 36%, whilst balancing costs decreased by 17.6%. This is due to the higher accuracy of the short-term forecast (MAE 3.2-5.4%), which made it possible to formulate constraints for the linear programming optimiser more accurately under real-world conditions in the Volyn region, rather than merely in simulations. Furthermore, in contrast to Abdelghany et al., who addressed storage management, the results demonstrate the direct impact of accurate forecasting on increasing the share of renewable generation (+14%) without additional technical measures.

In a Ukrainian study, Kish (2023) developed forecasting and storage systems to balance solar generation in Kyiv and the southern regions of Ukraine, achieving an 11-14% reduction in the energy deficit through a combination of ARIMA and neural networks. The results of this study demonstrate a greater effect (a 14% increase in the share of renewable sources without increasing the risk of a deficit), which is attributed to the simultaneous forecasting of two types of sources and the use of a transformer architecture, which better handles non-linear dependencies in regional data from the western part of the country. Furthermore, Cherkashyn and Nechaieva (2026) integrated renewable energy sources and storage systems into distribution networks in their study, analysing the challenges, trends and prospects for improving energy efficiency. The authors emphasised that without accurate short-term forecasting, the integration of renewable energy sources (RES) and storage systems remains ineffective due to the high variability of generation. The results obtained during the study are consistent with the findings: accurate forecasting made it possible to increase the stability of the microgrid by 36% and raise the share of RES by 14%, confirming the need for intelligent forecasting systems as a key element for the successful integration of renewable energy sources into Ukraine's distribution networks. Kuznietsov and Khomutov (2024) also studied electrical storage systems in a power system with renewable energy sources. The researchers proved that the effectiveness of storage systems largely depends on the quality of forecasts of the generation of renewable energy. Incorrect forecasts lead to over- or under-charging/discharging of batteries, which reduces the service life and economic viability. The study in question was able to reduce peak deviations by 21% and balancing costs by 17.6% due to more accurate forecasting. This directly supports the authors' conclusions on the importance of good forecasting for the efficient operation of storage systems in energy systems with a high share of renewable energy generation.

The accuracy and economic performance metrics obtained were consistent with global trends regarding the shift from recurrent networks to attention-based architectures for time series of energy data, whilst at the same time highlighting the importance of regional adaptation. Most international studies focus on specific types of sources or general models without deep integration into the actual microgrids of a particular region. In the present study, combining empirical data from the Volyn region with a hybrid transformer model achieved not only high forecast accuracy but also a measurable improvement in key operational indicators, which is rarely demonstrated in the literature with such detail. The study demonstrated that hybrid transformer neural networks can serve as an effective tool for enhancing the reliability and cost-effectiveness of microgrids with a high proportion of renewable sources under the variable climatic conditions of the Volyn region. The results obtained have supplemented the existing body of scientific knowledge and provide an empirical basis for the further integration of intelligent forecasting systems into real-world energy facilities in Ukraine.

5. CONCLUSION

Study confirmed the effectiveness of a hybrid transformer neural network for short-term forecasting of electricity generation from wind and solar sources in microgrids in the Volyn region. The model developed, which combines attention mechanisms with recurrent and convolutional components, delivered significantly higher accuracy compared with traditional approaches. For forecasting horizons ranging from one to six hours, the average absolute error was 4.2% for wind generation and 3.8% for solar generation, which exceeded the performance of standard LSTM networks by 24-27%, CNN-LSTM networks by 18-22%, and ARIMA statistical models by 29-34%. The coefficient of determination, R^2, reached 0.95 depending on the time horizon and the type of source.

Integrating the forecasts into the microgrid control system significantly improved key operational indicators. The stability of the microgrid's operation increased by 36%, peak power balance deviations decreased by 21%, and costs for balancing and reserve regulation were reduced by 17.6%. The grid frequency was maintained within the regulatory limits (±0.05 Hz) throughout the test period. Thanks to more accurate forecasts, the share of renewable generation in the microgrid's power balance increased by 14% without any increase in the risk of overload or power shortages. The results obtained demonstrated the potential of hybrid transformer architectures for addressing short-term forecasting challenges in regions with highly variable meteorological conditions, such as the western part of Ukraine. The practical value of this development is determined by potential for implementation in existing microgrids in the Volyn region to enhance the reliability of power supply, reduce operational costs and promote the sustainable development of renewable energy.

The results of the study confirmed the hypothesis put forward regarding the effectiveness of using hybrid transformer neural networks for short-term forecasting of generation from renewable energy sources. The study empirically demonstrated that the integration of multi-head attention mechanisms with convolutional layers and long short-term memory (LSTM) blocks can be used to model non-linear relationships between meteorological parameters and electricity generation levels with high accuracy. The study has certain limitations. The model was trained exclusively on data from the Volyn region; therefore, its generalisation to other climatic zones requires further validation. The three-year period of observation also limited the ability to test the model against rare extreme weather events and the online testing did not account for dynamic changes in the microgrid configuration. Future work will include extending the model to include multimodal data (satellite cloud cover images, radar data), online training, and providing predictions for longer time horizons (up to 24-48 hours). Comparison testing with state-of-the-art architectures (Temporal Fusion Transformers, Informer) and the evaluation of the system economic efficiency in microgrids of different scales would be also useful.

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