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Optimizing the Integration of Wind and Solar Power for Hybrid Electrical Energy in High-rise Building Energy Systems

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Abstract

The optimization of wind and solar energy utilization in high-rise building energy systems represents an innovative approach to sustainable energy management. This study examines the environmental factors influencing energy production from wind turbines and photovoltaic panels, utilizing machine learning models including bidirectional long short-term memory (Bi-LSTM), stacked long short-term memory (stacked LSTM), convolutional neural network-long short-term memory (CNN-LSTM), and attention LSTM to forecast energy output. The findings indicate that CNN-LSTM outperforms other models with the lowest mean absolute error (MAE) of 23.72, mean squared error (MSE) of 896.10, and Root mean squared error (RMSE) of 29.93 for photovoltaic (PV) power prediction, alongside the highest R-squared (R^2) value of 0.9971. For wind power prediction, CNN-LSTM also achieved an MAE of 11.40, MSE of 213.28, RMSE of 14.60, and an R^2 of 0.9988. The analysis shows that wind power output is exponentially correlated with wind speed, while PV power output has a linear relationship with solar irradiation. The highest recorded energy production occurred in August, with PV generating 720 kWh, whereas wind power remained relatively stable, averaging 310 kWh throughout the year. The monthly and daily energy production patterns clearly demonstrate the benefits of integrating wind and solar systems for a more reliable energy supply. These findings emphasize the significance of optimizing energy systems based on location and showcase the potential of artificial intelligence in enhancing the accuracy of renewable energy forecasting.

Keywords: Optimization Energy; Wind and Solar Energy; Renewable Energy; High-rise Building.
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1. Introduction

The solution to the energy crisis and environmental problems caused by the use of fossil fuels is to realize renewable energy.[1,2] Wind and photovoltaic energy are renewable sources with the most significant potential to meet global energy needs.[3,4] This energy is very abundant and environmentally friendly. Renewable energy has been widely applied as an additional energy source in households and large industries.[5] However, the production of these two energy sources is highly dependent on uncertain weather conditions. Highly fluctuating weather conditions lead to uncertain energy production and impact the balance between energy production and demand.

In urban areas, high-rise buildings have become a common sight. The potential for renewable energy production in high-rise buildings can be realized using wind and solar energy. This integration is a strategic step in realizing self-sufficient energy to fulfill the building's energy needs. Some researchers have combined systems by optimizing system size and analyzing their reliability.[6,7] The configuration of solar panel tilt and turbine hub height has been investigated to predict the generated energy empirically.[8,9] The configuration of solar panel tilt and turbine hub height has been investigated to predict the generated energy empirically. Additionally, various methods are used for optimization, such as grid methods, stochastic approaches, iterative techniques, and artificial intelligence. Distributed photovoltaic-wind (PV-wind) turbine hybrid systems have been proposed due to the complementary nature of wind and wind power in terms of temporal and

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spatial patterns.[10-12] Integrating wind and solar energy on the roof can maximize the space to generate renewable energy.[13] To maximize the utilization of this energy, it is necessary to optimize the use of hybrid systems in high-rise buildings.

Research on optimizing design with multi-objective systems in urban or rural residential buildings has been conducted without considering space constraints.[14-16] Saturation of resources as an optimization factor parameter has been proposed in hybrid systems with storage batteries.[17,18] The influence of daily and seasonal factors on wind and solar power makes it difficult to assess the potential of this system to be applied on roofs as a hybrid system.[19] The use of machine learning as an optimization step has also been initiated recently.[20,21] Prediction accuracy has been achieved using conventional neural networks (CNN), which results in significant improvements in predictions on hybrid models for solar-hydrogen photovoltaic.[22,23] The use of the long short-term memory (LSTM) model to predict solar energy on buildings has been carried out under certain conditions.[24] The analysis of monthly and daily energy production patterns highlights the complementary nature of wind and solar energy, demonstrating the advantages of integrating these systems for a more stable energy supply.[25] These findings underscore the importance of location-based energy system optimization and the potential of artificial intelligence in improving renewable energy forecasting accuracy.[26,27] Research on the prediction of solar energy potential using LSTM for solar electric vehicle applications in Cameroon was also conducted. This study was limited to using only the LSTM model and using only two parameters, irradiation and temperature.[28] Wang *et al.* conducted a study in China on wind power and solar energy predictions with 85% accuracy results with 1 month of data.[29] While Xiu *et al.* conducted research on the predictions of wind energy and photovoltaic energy in the economic sector, this research was limited to data presented on one day.[30] So there is a gap in conducting the integration of wind and solar power systems, which can provide a more consistent and resilient energy supply compared to relying on a single renewable energy source. Therefore, optimization of environmental influence on energy production within a year needs to be investigated further.

This research aims to optimize the hybrid system by examining energy production over the course of a year. The analysis is conducted by looking at monthly energy as well as daily ranges. Weather conditions, time, and seasons are the focus of this research. The hybrid system is applied to supply energy to high-rise buildings with an energy storage concept, and it examines the system's performance in the morning, afternoon, evening, and night. Additionally, the parameters of environmental influence on energy production are also considered.

2. Methods

This study systematically collected various environmental parameters that influence energy production from wind turbines and solar panels, including air temperature, relative humidity, air pressure, wind speed and direction, rainfall, and solar radiation. Additionally, energy production data from the renewable energy systems was gathered for further analysis. The collected data was utilized to investigate the relationship between environmental factors and energy generation, as well as to develop predictive models for estimating the power output of renewable energy systems. This approach provided deeper insights into the factors affecting wind and solar energy efficiency, thereby facilitating the optimization of renewable energy-based power generation systems. This system is made in a hybrid manner for power generation, as shown in Fig. 1.

This study employed artificial intelligence-based modeling techniques to forecast the electrical power output of solar panels and wind turbines. The predictive models utilized included Bi-LSTM, stacked LSTM, CNN-LSTM, and attention LSTM. These models were chosen for their ability to handle sequential data and nonlinear patterns often found in renewable energy predictions.[31,32] The results of the evaluation demonstrate that the CNN-LSTM model outperformed the other approaches, exhibiting lower mean absolute error, mean squared error, and root mean squared error metrics, in addition to a higher coefficient of determination (R^2) value, suggesting that this model can more effectively capture the patterns in energy production.[33] The advantage of CNN-LSTM lies in its ability to extract spatial features from data before using them in time-series analysis, making it more effective in handling complex energy fluctuations.[34] Conversely, the Attention LSTM model showed higher prediction errors, particularly at extreme data points, suggesting a tendency for the model to overfit certain patterns.[35] With accurate energy prediction modeling, renewable energy systems can be optimized to improve efficiency and reliability under various environmental conditions.

3. Results and discussion

The production value of wind and solar power (PV) is predicted using several models to see their accuracy. The models used are Bi-LSTM, stacked LSTM, CNN-LSTM, and attention LSTM. The prediction results are compared with the actual values. The analysis is carried out with a time span of one year. The energy unit used in this study is watt.

Fig. 2 shows the results of power prediction on wind energy. The actual wind power shown with a dashed black line is compared to the predicted results. The results show that each

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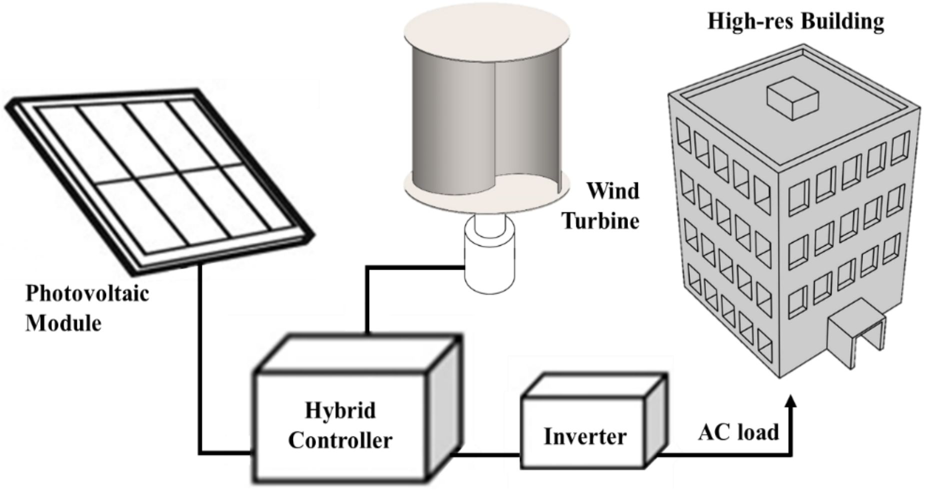


Fig. 1: Hybrid PV-wind energy system.

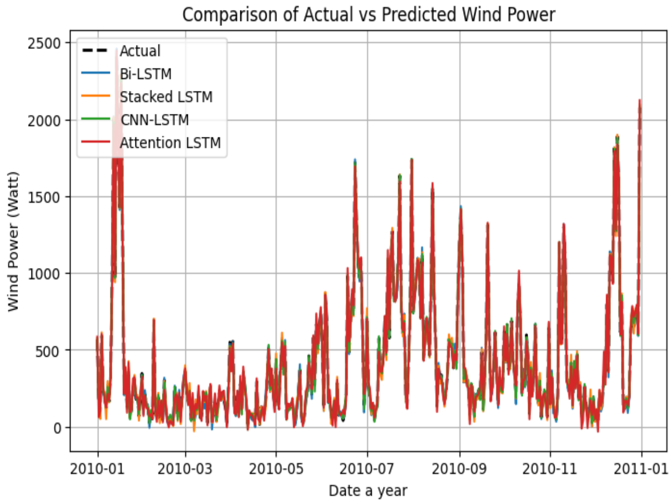


Fig. 2: Wind power prediction for a year in tropical countries.

line representing the predicted results overlaps with the actual line. This shows that the prediction model has successfully captured the pattern well. In more detail, the CNN-LSTM model shows more accurate results compared to other models. The accuracy of this model is proven by the results of the metric evaluation where the CNN-LSTM model has an mean absolute error (MAE) value of 11.40, mean squared error (MSE) of 213.28, and root mean squared error (RMSE) of 14.60 recorded as the lowest among other models besides also having an R^2 value of 0.9988 which is the highest compared to others as shown in Fig. 3. This model is able to capture trends and patterns of daily power results with more precision.[36,37]

Meanwhile, the solar energy predictions produced are shown in Fig. 4. The trend of the prediction results shows a similar pattern, where CNN-LSTM has better accuracy than other models. The conformity of the results with the actual data proves that the model can capture fluctuating PV power patterns. The CNN-LSTM model produces MAE results of 23.72, MSE of 896.10, and RMSE of 29.93, while the R^2 value reaches 0.9971 and is recorded as the highest among other models. This proves that the accuracy of the CNN-LSTM model is the best. These results are consistent with Singhal *et al.*[38] (2024), which showed that this model has advantages in processing data with time series data formats and complex special parameters.[39]

On the other hand, Attention LSTM is the model with the worst performance. Attention LSTM has shown a similar trend where this model has shortcomings in capturing seasonal patterns with high fluctuations so it is too sensitive to noise, besides over-fitting occurs.[40,41] In addition, Stacked LSTM also shows high deviation due to high model complexity resulting in over-fitting. Stacked LSTM requires a larger dataset and parameter tuning to produce lower deviation.[42,43] Electric power prediction using CNN-LSTM model and successfully with high accuracy using seven weather variables as parameters. The prediction results are influenced by several parameters used. The influence of these parameters can be seen from the correlation between environmental variables and energy production. The temperature parameter has a negative correlation with relative humidity of -0.91, while it has a positive correlation with irradiation of 0.82. This shows that when temperature increases, humidity tends to decrease, and this is caused by the increase in sunlight, which is shown in Fig. 5.

In terms of energy production, wind speed and wind direction have a positive correlation with turbine power (0.85 and 0.15). This shows that the higher the wind speed, the greater the power produced. This relationship is non-linear in nature, where at low speeds (0-2 m/s) the power produced is small. However, the power produced increases exponentially when the wind speed increases above 3 m/s, as shown in Fig. 6(a). PV power prediction also has a similar trend, a high positive correlation with irradiation (0.82). This proves that the solar energy received determines the production of electrical energy from solar panels. This relationship is linear in nature, where at low irradiation (0-25 W/m^2) the power produced is low, while when irradiation increases, the power produced also increases proportionally, as shown in Fig. 6(b).

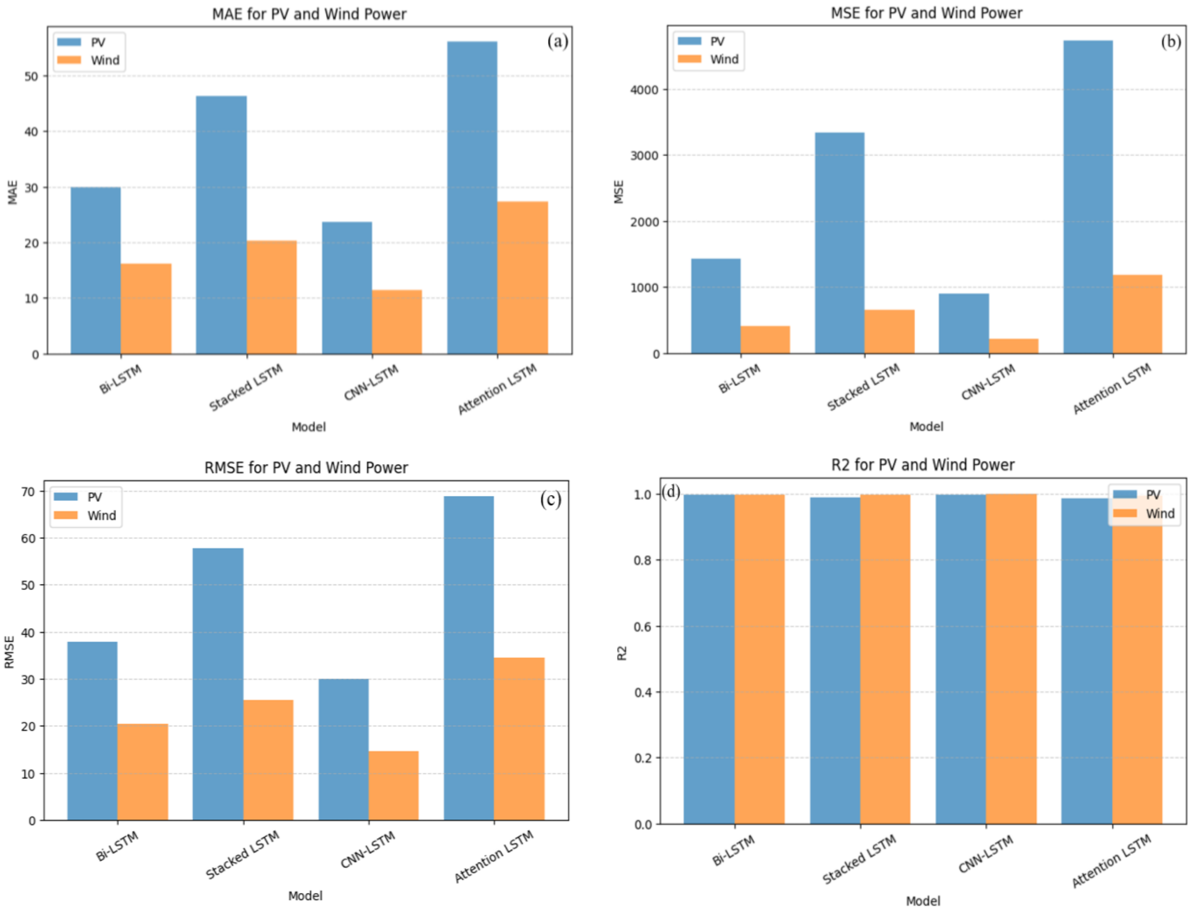


Fig. 3: Evaluation metrics for PV and wind power (a) MAE, (b) MSE, (c) RMSE and (d) R^2.

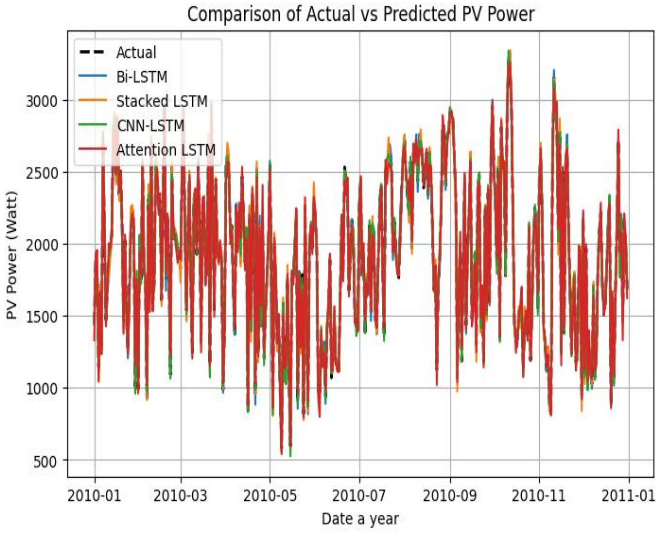
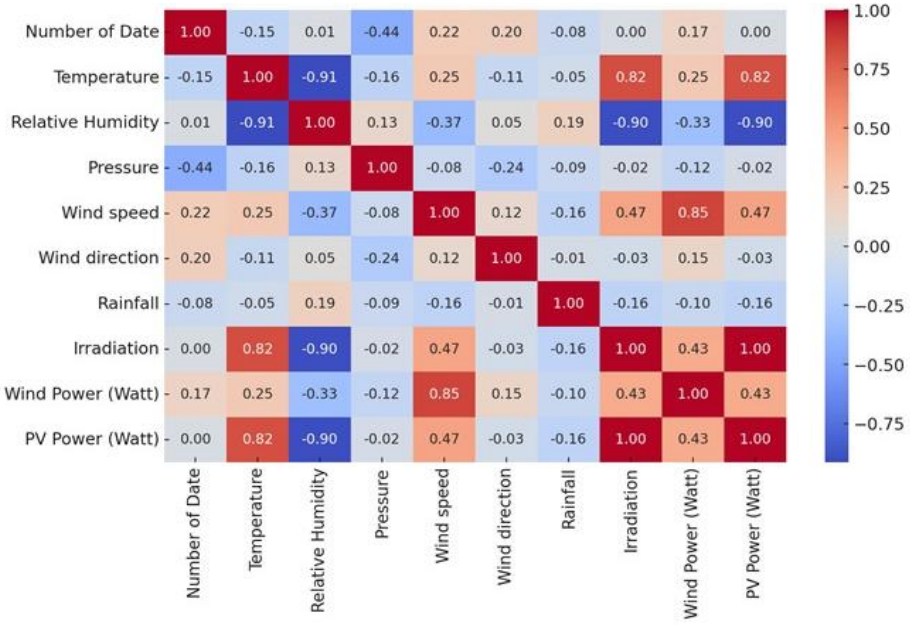


Fig. 4: Photovoltaic (PV) power prediction for a year in tropical countries.

Therefore, the utilization of wind energy is more optimal in locations with high wind speeds, while solar panels are more effective in areas with high levels of solar irradiation. These results are relevant to Tjahjana *et al.*[44] research where the increase in electrical energy is directly proportional to wind speed, and Maduabuchi *et al.*[27] found that irradiation is directly proportional to photovoltaic energy production.

Fig. 7 illustrates the total monthly energy generated by PV and Wind throughout the year. In general, PV production (blue) dominates over Wind (orange) in every month, indicating that solar energy serves as the primary source in this system. The peak production occurs in August, where the total energy generated reaches its highest point of the year, likely due to higher solar radiation intensity during the summer season. Conversely, the lowest energy production is observed in May and June, potentially caused by weather factors such as increased cloud cover or the rainy season, which reduces solar radiation. Meanwhile, energy production from wind remains relatively stable throughout the year, although its contribution is significantly lower than that of PV. Certain months, such as July, August, and December, show a slight increase in Wind energy production, which may be attributed to seasonal wind pattern variations. This production pattern indicates that energy fluctuations are primarily influenced by PV, as it depends on daylight duration and solar intensity, which vary throughout the year. Therefore, the combination of PV and wind can enhance energy supply stability, particularly when PV production declines in certain months. By understanding these seasonal patterns, strategies such as energy storage or increasing Wind capacity can be implemented to optimize the renewable energy system, ensuring a more stable and reliable energy supply throughout the year.



	Number of Date	Temperature	Relative Humidity	Pressure	Wind speed	Wind direction	Rainfall	Irradiation	Wind Power (Watt)	PV Power (Watt)
Number of Date	1.00	-0.15	0.01	-0.44	0.22	0.20	-0.08	0.00	0.17	0.00
Temperature	-0.15	1.00	-0.91	-0.16	0.25	-0.11	-0.05	0.82	0.25	0.82
Relative Humidity	0.01	-0.91	1.00	0.13	-0.37	0.05	0.19	-0.90	-0.33	-0.90
Pressure	-0.44	-0.16	0.13	1.00	-0.08	-0.24	-0.09	-0.02	-0.12	-0.02
Wind speed	0.22	0.25	-0.37	-0.08	1.00	0.12	-0.16	0.47	0.85	0.47
Wind direction	0.20	-0.11	0.05	-0.24	0.12	1.00	-0.01	-0.03	0.15	-0.03
Rainfall	-0.08	-0.05	0.19	-0.09	-0.16	-0.01	1.00	-0.16	-0.10	-0.16
Irradiation	0.00	0.82	-0.90	-0.02	0.47	-0.03	-0.16	1.00	0.43	1.00
Wind Power (Watt)	0.17	0.25	-0.33	-0.12	0.85	0.15	-0.10	0.43	1.00	0.43
PV Power (Watt)	0.00	0.82	-0.90	-0.02	0.47	-0.03	-0.16	1.00	0.43	1.00

Fig. 5: Correlation heatmap between various environmental variables and power output.

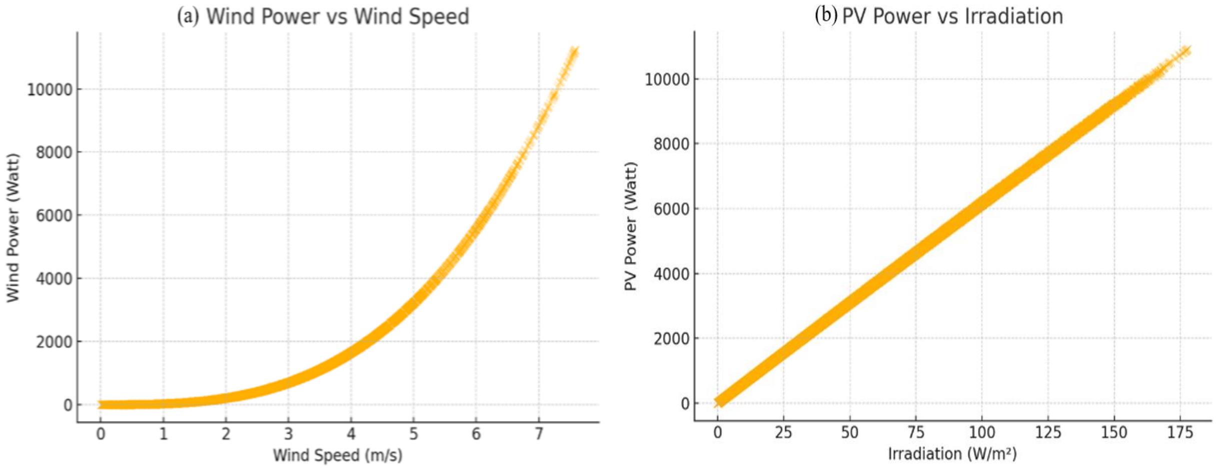


Fig. 6: Power correlation with (a) wind speed and (b) irradiation.

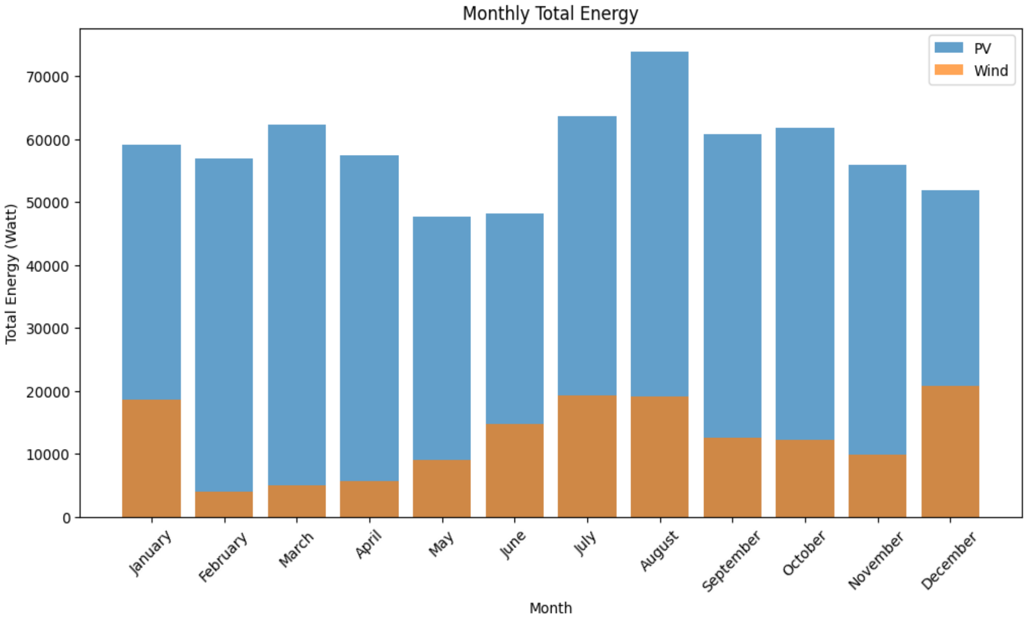


Fig. 7: Monthly total energy generation.

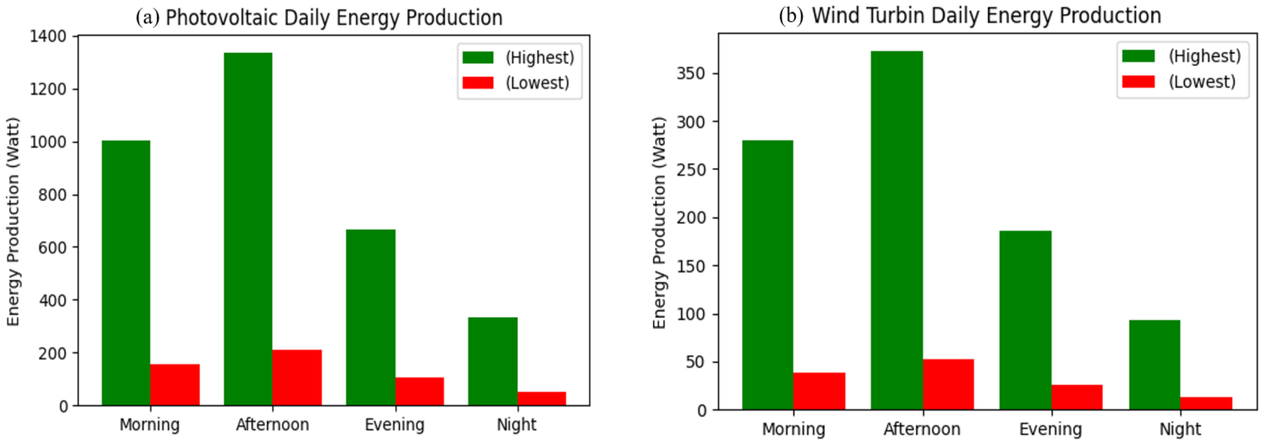


Fig. 8: Daily energy production of (a) photovoltaic and (b) wind turbine.

Fig. 8 illustrates the comparison of daily energy production from photovoltaic (PV) and wind turbine systems based on time of day. In the PV graph (left), energy production peaks during the afternoon (12:00–18:00) when solar radiation is at its highest. Production starts to increase in the morning (06:00–12:00), then gradually declines in the evening (18:00–00:00), with nearly no production at night (00:00–06:00) due to the absence of sunlight. On days with the lowest energy production, the output remains consistently low across all time periods, highlighting the PV system's dependency on solar radiation. This result is in line with previous findings where the highest energy production occurs at midday.[24]

Conversely, in the wind turbine graph (right), energy production is more evenly distributed throughout the day, although it still exhibits a peak around afternoon (12:00–18:00). Energy output remains relatively high in the morning (06:00–12:00) and continues into the evening (18:00–00:00), with only a slight decline. Unlike PV systems, wind turbines can still generate energy during nighttime hours (00:00–06:00), albeit at a lower output. On days with the lowest energy production, wind turbines still generate energy across all time periods, though at significantly reduced levels. This pattern is similar to research conducted by Idogho *et al.*, where production starts to increase in the morning and decreases after sunset, confirming that PV is only effective when there is direct sunlight.[45]

The comparison between PV and wind turbines indicates that PV systems are highly dependent on sunlight, whereas wind turbines can provide more consistent energy generation throughout the day. A combination of both systems could offer a more stable energy solution, where wind turbines can continue operating when solar panels are inactive, such as during nighttime or overcast conditions.

4. Conclusion

This study provides an in-depth analysis of wind and solar energy utilization for high-rise building energy systems, emphasizing the role of environmental factors in energy production. The results indicate that wind speed and solar irradiation are the primary determinants of energy output, with wind power increasing exponentially and PV power increasing linearly with respective environmental factors. The evaluation of predictive models demonstrated that CNN-LSTM had the best performance, recording the lowest MAE (23.72 for PV, 11.40 for wind), MSE (896.10 for PV, 213.28 for wind), RMSE (29.93 for PV, 14.60 for wind), and the highest R^2 values (0.9971 for PV, 0.9988 for wind), outperforming Bi-LSTM, stacked LSTM, and attention LSTM models.

Furthermore, seasonal and daily energy generation patterns reveal that integrating wind and solar energy sources enhances energy stability, ensuring a more reliable power supply. The monthly energy production analysis showed that PV energy dominates throughout the year, with peak production in August at 720 kWh, while the lowest production was observed in May and June at approximately 450 kWh. Wind energy remained relatively stable, with an average monthly production of 310 kWh, contributing to overall system reliability. The combination of both energy sources allows for optimization strategies, such as energy storage and adaptive capacity expansion, to mitigate fluctuations in renewable energy availability. These findings underscore the importance of advanced forecasting techniques in improving renewable energy efficiency, supporting the transition toward more sustainable and resilient energy systems. Future research should explore the integration of additional renewable energy sources and real-time adaptive control systems to further enhance optimization strategies.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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