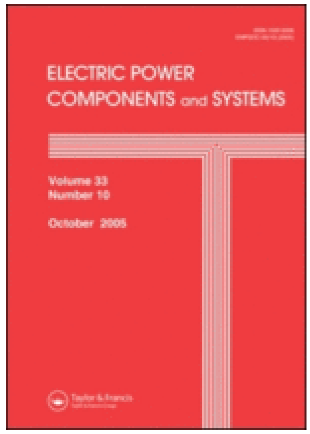

Data-Driven Wind Power Forecasting using LSTM

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DATA-DRIVEN WIND POWER FORECASTING USING LSTM

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ABSTRACT

Due to the erratic nature of the wind, it is hard to eliminate forecasting error in the production of wind power. Understanding the potential uncertainties associated with estimating wind power production and utilising this knowledge to create a precise and trustworthy prediction are essential for successful power grid integration. The many wind power forecasting models currently in use are examined in this study. It draws attention to both their benefits and drawbacks. It also provides a thorough examination of an LSTM model utilising data acquired in 2022–2023 from the Indian Palladam Wind Farm. A wind farm's ability to produce wind energy is influenced by a variety of factors. Every element, including wind speed and turbine characteristics, has a different effect on the output. The study goes into great detail about the advantages of various components and explains why the LSTM method ultimately proves to be the most successful. The model is run just for the most important factors after a careful investigation and analysis, producing the best results.

1. KEYWORDS

Long Short Term Memory (LSTM) model, Machine Learning, Wind power forecasting, Forecasting error, Power grid integration, Wind power production, Wind power forecasting models, Data analysis, Renewable energy, Energy production, Energy generation

2. INTRODUCTION

The global energy demand is enormous and growing rapidly, with an annual power consumption of roughly 15 terawatts (TW).[1]By 2050, according to present patterns, this will have doubled, and by the end of the century, it is anticipated to have tripled. One of the most significant sources of electricity in the electrical power system today is wind energy. Because wind properties are unpredictable, extremely variable, and influenced by numerous factors, predicting wind speed is challenging.[2]Wind power is becoming more important as a source of renewable energy as the worldwide wind sector experiences significant growth. Consider carefully using the energy that is already available or finding alternate energy sources as two possible ways to lessen this hazard. The primary energy sources, fossil fuels, are rapidly running out of fuel and may not be able to meet this enormous demand for very long due to the development of energy-hungry technology and the growing global population. This is true even with focused energy conservation and improvements in the efficiency of the current systems. Reliable forecasts of wind power production are crucial for the effective integration of this variable resource onto the power system as wind generation increases.[3] Accurate wind energy estimations are essential for the development and administration of wind farms, as well as for managing power generation and system stability. In order to predict wind, numerical weather prediction models are essential. These models simulate atmospheric processes and forecast future weather using mathematical calculations.[4]

The pattern of wind power is also highly irregular due to the pattern of wind speed. Outliers are more frequent as a result of abrupt wind gusts. As a result, precise predictions cannot be made using direct statistical models. In most literary works, hybrid models—which blend statistical, intellectual, and physical models—are used. [5]

To produce precise forecasts of wind direction and speed, these models combine physical and chemical models of the atmosphere and seas. As technology and our understanding of atmospheric processes have advanced throughout time, so have numerical weather prediction models.[6] For certain sites, such as wind farms, these models are used to produce wind energy predictions. Forecast mistakes still remain, despite advances in numerical weather prediction methods. Numerous things, including the models' low resolution, unpredictability of the initial conditions and boundary conditions, and biases within the models themselves, might be blamed for these inaccuracies.

Researchers have explored various modeling approaches to improve wind energy predictions and reduce forecast errors. Different models like Support Vector Regression, Decision Trees, Random Forests, RNN (Recurrent Neural Networks) and LSTM (Long Short-Term Memory) have been researched upon each having their own merits and demerits. [7]

Short-Term Wind Energy Forecasting Using Support Vector Regression by Oliver Kramer and Fabian Gieseke makes an effort to capture a diversified dataset by using datasets from three separate sites. They believe that using an insensitive loss function enhances the model's accuracy for situations including wind resource. However, the model still works well for short-term forecasts of two hours because it showed significant deviations in forecasts of just ten minutes, and when the dataset was multiplied, the high collection of data produced disturbances that resulted in high error values of up to 2.984. [8]

The team of Behnam Mohamaddi-Ivaltoo's Long-Term Wind Power Forecasting Using Tree-Based Learning Algorithms trained their model to predict up to six months ahead. To find the best model that will meet their model requirements, they compare different machine learning algorithms such decision trees, Bagging, and XGBoost. They have also collected data from a variety of sites at varying altitudes to further test their model. But the only parameters used in their model are standard deviation and average wind speed. This does not give a holistic perspective because there are many more aspects than those mentioned above that should be present.[9]

The aim of Xiaoou Li and team's wind energy forecasting using multiple ARIMA models is short-term prediction using the noise estimation method. It integrates several models, including ARIMA, wavelet transformation, neural networks, etc. However, employing the ARIMA model has its own set of issues because it has trouble handling seasonal components. We believe that ARIMA isn't the best option for forecasting in a field like wind energy, where seasons have a significant impact on the ambient temperature and other important variables.[10]

Nomman shabbir and team's Wind Energy Forecasting Using Recurrent Neural Networks, the model is compared to the Elering algorithm employed by Estonia's energy regulating authority. They utilise an LSTM model comparable to ours as it has been proven to be the best option for wind energy forecasting. Their model can forecast up to three days ahead. Our paper takes a similar strategy as theirs, but the number of elements included in ours is significantly bigger in an attempt of successfully enhancing accuracy.

This paper proposes a new forecast model for wind speed prediction with deep learning algorithm using LSTM technique, taking in various factors which influence the energy generated.

Expanding on the discussion of wind energy and its critical role in the global power landscape, the immense and escalating demand for energy globally necessitates a comprehensive exploration of sustainable energy sources. As of now, the annual power consumption stands at approximately 15 terawatts (TW), a staggering figure that is expected to double by 2050 and triple by the end of the century, based on current consumption patterns. Addressing this surging demand requires a strategic shift towards renewable energy sources, with wind energy emerging as a substantial contributor to the global electrical power system. [11] However, the unpredictability and variability of wind properties present significant challenges in accurately predicting wind speed, emphasizing the importance of reliable wind energy predictions to effectively integrate this variable resource into the power system as its utilization grows [12]

Efforts to mitigate this challenge include optimizing the utilization of existing energy resources and exploring alternative energy sources. Fossil fuels, which constitute a primary energy source, are depleting rapidly and may fall short in meeting the escalating energy demand, exacerbated by advancements in energy-hungry technologies and a burgeoning global population. Despite concentrated efforts on energy conservation and enhancing the efficiency of current systems, the sustainability of relying predominantly on fossil fuels remains questionable. [13] Consequently, there is an urgent need to transition towards sustainable, renewable energy sources like wind power to bridge the energy demand-supply gap. Numerical weather prediction models play a pivotal role in predicting wind power production by simulating atmospheric processes and forecasting future weather through mathematical calculations. These models, however, grapple with challenges owing to the irregular pattern of wind power, marked by frequent outliers due to abrupt wind gusts. Direct statistical models often fall short in delivering precise predictions, prompting the adoption of hybrid models that amalgamate statistical, intellectual, and physical models. Hybrid models have shown promise in capturing the irregularities of wind power patterns and enhancing prediction accuracy

3. RELATED WORKS

Slama and Lahouar in their study *Hour-ahead Wind Power Forecast Based on Random Forests* explore hour-ahead wind power forecasting using Random Forests, providing insights into the application of machine learning for short-term wind power prediction.[14] Biswas et al investigate short and mid-term wind power prediction techniques, including ARIMA models and hybrid approaches, which is relevant to our understanding of existing forecasting methods[15]. Gershenson and Santamaría-Bonfil propose a wind speed forecasting method based on Support Vector Regression, offering valuable insights into modeling wind farm behavior.[16] Apart from these, ensemble machine learning models for wind power prediction and wind turbine power prediction provided by Kayisli et al. and Kramer et al provided valuble insights for the base of the model building. Chen et al. present a combined CNN-RNN model for wind speed forecasting, offering insights into neural network-based approaches for renewable energy prediction and Obeidat et al.[17] [18] [19] explored wind power forecasting using artificial neural networks, aligning with our focus on neural network techniques for wind prediction.

The reviewed literature provides a comprehensive understanding of wind power prediction models, machine learning approaches, and neural network models relevant to our research. The insights gained from these studies will serve as a foundation for the development and evaluation of our autoencoder LSTM-based wind power prediction model.

4. CONTRIBUTIONS

From the previous methods, we have concluded that LSTM method with an autoencoder will provide best results for predicting wind energy. Since our wind power prediction predicts for a smaller time gap, by incorporating a sliding window approach, we can increase accuracy by increasing relevance of the data used for prediction. This sliding window approach has not been widely used for wind power prediction and by incorpoarting this in our method, we were able to see a significant rise in accuracy levels.

5. ARTIFICIAL NEURAL NETWORK

A group of machine learning models known as Artificial Neural Networks are modelled after the structure and operation of the human brain. An input layer, one or more hidden layers, and an output layer are the three layers that make up an artificial neural network (ANN). In order to learn from data, each connection between neurons has a weight that is changed throughout training. Since nonlinear correlations within data are frequently present in intricate systems like wind energy prediction, ANNs are particularly adept at modelling them. These distinctions could be difficult to capture using conventional linear models. ANNs eliminate the need for manual feature engineering by automatically extracting pertinent features from the input data. The capacity to handle huge and complicated datasets requires this competence. ANNs are suitable for dynamic systems like weather and energy production that display seasonality and other fluctuations because they can adapt to changing data patterns over time. On parallel computing hardware, ANNs may be effectively trained and deployed, allowing for quicker model construction and real-time predictions.The ANN does not require retraining because it learns from analysed data. It also goes by the label ”blackbox model” and offers little insight into how the models would behave in practise. All that is required of the user is input, observation, and waiting for output. All that is required of the user is input, observation, and waiting for output. ANNs are viewed as simple mathematical models that can improve current data processing techniques.

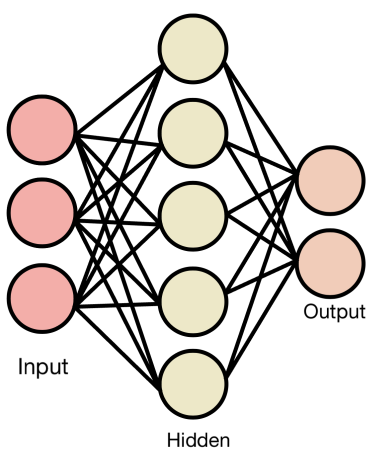

Fig. 1. Architecture of ANN

6. LONG SHORT TERM MEMORY MODELS (LSTM)

Long short-term memory (LSTM) is a recurrent neural network (RNN) development. The output of the previous layer is combined by a single Tanh function in typical RNN modules, but memories are stored in LSTMs via a feedback loop and gates. A cell, an input gate, an output gate, and a forget gate comprise each of the four interactive NN layers present in LSTMs. While the three additional gates regulate the flow of information into and out of the cell, the cell recalls values at self-assertive time intervals. The LSTM can add to or subtract from the main chain of data flow, the module state, using sigmoid gates.

As was already said, the output of wind energy can be influenced by a wide range of technical and arbitrary factors. The factors included in wind power forecasting models include wind speed, wind direction, ambient temperature, relative humidity, renewable capacity, and curtailment of renewable energy sources. They go further than this as well. Hydraulic group pressure, the normal generator speed, and gearbox bearing temperature are other factors that influence the output. A detailed analysis was used to narrow down the maximum participation of these components to a manageable quantity, which we subsequently used in our LSTM technique.

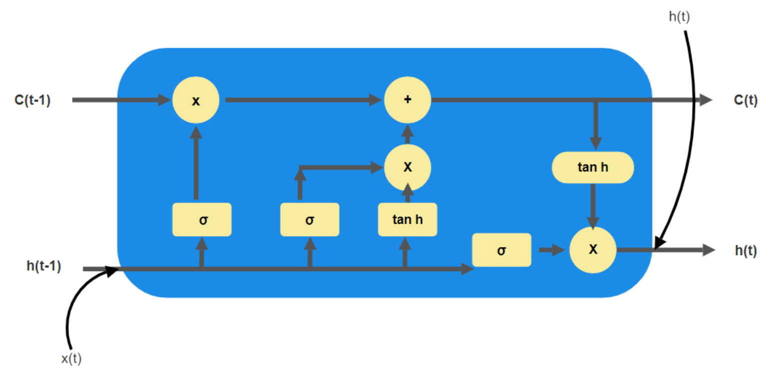

Fig. 2. LSTM model diagram

7. AFFECTING FACTORS

7.1. Hydraulic group pressure

The hydraulic group pressure of a wind turbine indirectly affects the quantity of wind energy produced by adjusting the pitch angle of the blades. The pitch angle may be adjusted for the best absorption of wind energy. It establishes the location of the blades in relation to the wind. The pitch angle is altered by the hydraulic group pressure by spinning the blades while applying pressure to hydraulic fluid. If the hydraulic group pressure was too low, the blades wouldn’t be able to rotate at the correct angle, which would reduce the turbine’s efficiency. The appropriate hydraulic group pressure must be kept constant for the longest lifespan and greatest turbine performance. The hydraulic group pressure indirectly affects wind energy generation by controlling pitch angle.

7.2. Average generator speed

A wind turbine’s hydraulic group pressure indirectly affects the quantity of wind energy produced by controlling the pitch angle of the blades. The pitch angle may be adjusted for the best absorption of wind energy. It establishes the location of the blades in relation to the wind. The pitch angle is altered by the hydraulic group pressure by spinning the blades while applying pressure to hydraulic fluid. If the hydraulic group pressure was too low, the blades wouldn’t be able to rotate at the correct angle, which would reduce the turbine’s efficiency. The appropriate hydraulic group pressure must be kept constant for the longest lifespan and greatest turbine performance. The hydraulic group pressure indirectly affects wind energy generation by controlling pitch angle. Maintaining the proper average generator speed is crucial for maximizing wind power generation because wind turbines are designed to operate within a specific generator speed range to achieve optimal performance.

7.3. Gearbox bearing Temp

The production of wind energy may be significantly impacted by the gearbox bearing temperature of a wind turbine. The gearbox, an essential part of the turbine that transmits the rotational energy of the blades to the generator, is supported and operated smoothly by the bearings, which also serve to support the gearbox shafts. The performance and dependability of the turbine may be impacted if the bearing temperature is either too high or too low.

A high bearing temperature can result in lubrication issues like oil evaporation or degradation, which can increase friction and wear on the bearings. This could lead to the bearings failing early, costing the turbine money in repairs and downtime. On the other hand, if the bearing temperature is too low, the lubrication may become overly viscous, decreasing the gearbox's efficiency and raising the possibility of bearing damage.

The gearbox bearing temperature must be kept within a certain range to ensure optimal wind energy generation. By keeping an eye on the temperature and modifying the lubrication system as necessary, this can be accomplished. The turbine can operate at peak efficiency, lowering maintenance costs and increasing power generation by maintaining the proper bearing temperature.

7.4. Average Ambient temperature

The amount of wind energy produced by a wind turbine can be significantly impacted by the ambient temperature. Temperature has an impact on air density, which has an impact on the aerodynamics of the blades and the amount of wind energy that can be captured.

In general, colder temperatures lead to denser air, which makes it possible to extract wind energy more effectively. This is so that the generator can produce more power because the blades can produce more lift. Warmer temperatures, on the other hand, lead to less dense air, which can lower the airflow through the blades and the amount of power that can be produced.

But operating a wind turbine in extremely cold weather can also be difficult because ice buildup on the blades can have an adverse effect on its aerodynamics and even result in damage. Additionally, extremely high temperatures have the potential to impair the cooling and electronic systems of the turbine.

Wind turbines are typically made to operate within a specific temperature range in order to maximize the generation of wind energy. Based on the current temperature and wind speed, the turbine's control system can also change the blade pitch and rotor speed to optimize performance. The production of wind energy can be increased and maintenance costs can be decreased by tracking and managing the ambient temperature and how it affects the turbine's operation.

7.5. Average Rotor speed

The output of a wind turbine's wind power generation is significantly influenced by its average rotor speed. The amount of wind energy that is captured by the turbine's blades and transformed into electricity by the generator is directly influenced by the rotor speed.

Usually, the turbine's controller regulates the rotor speed by altering the blade pitch in order to maintain the desired rotor speed. The turbine may not be producing as much power as it could if the rotor speed is too low because not enough rotational energy is being transferred to the generator. On the other hand, if the rotor speed is too high, it might harm the turbine's generator or other parts.

Wind turbines are typically built to operate within a certain range of rotor speeds that maximize power output while avoiding hazardous conditions in order to maximize wind power generation. The controller for the turbine continuously checks the rotor speed and modifies the blade pitch as necessary to keep it at the right speed for the current wind conditions.

Wind turbines can perform at their best and produce their maximum amount of power by maintaining the proper average rotor speed. In order to ensure optimal power generation and reduce maintenance costs, rotor speed, a crucial component of wind turbine operation, should be carefully monitored and managed.

7.6. Average wind speed

One of the most important elements affecting the production of wind energy is the average wind speed in the area around a wind turbine. A small increase in wind speed can result in a much larger increase in power output because the power output of a wind turbine is directly proportional to the cube of the wind speed.

The performance of wind turbines depends on the prevailing wind conditions and is designed to operate within specific wind speed ranges. If the average wind speed is too low, the turbine may not turn at all because the blades won't rotate quickly enough to produce enough power. The turbine may need to stop operating if the wind speed is too high in order to prevent damage or unsafe operating conditions.

In order to maximize the output of power while avoiding harmful conditions, wind turbines are typically built to operate in a narrow range of wind speeds. The controller for the turbine constantly checks the wind speed and modifies the blade pitch and rotor speed as necessary to maintain the best speed under the current wind conditions.

Wind turbines can operate at their peak efficiency and produce the most power by maintaining the proper average wind speed. In order to ensure optimal power generation and reduce maintenance costs, wind speed—a crucial parameter for wind turbine operation—should be closely monitored and controlled.

8. COMPARISON OF MODELS

8.1. Decision Trees

Long-term wind power prediction utilising tree-based algorithms involves employing methods like random Forests, Gradient Boosting,XGBoost and Bagging.[20] These algorithms make use of historical wind-related data to forecast wind power over extended time frames[14]. Random forest is an ensemble learning method that combines decision trees using bagging(bootstrap aggregation). The main advantage of bootstrap aggregation is its immunity to noise, thus generating non-correlated trees through different training samples[21]. Another advantage is the reduction of computational complexity, which can serve helpful on very large datasets[22]. Decision tree refers to a tree based handling multi output problems with little data preparation. Bagging and boosting methods convert weak learners into powerful learners, AdaBoost, a well known subset begins by training a decision tree in which each sample is assigned an equal weight. Next, weights weights of the samples are correcting their past performance. The effectiveness of Wind Power Forecasting algorithms can be measured using Mean Absolute Error which measures the difference between the observation and prediction without deeming the errors' direction. Other methods include formulating the Root Mean Square Error and the Coefficient of Determination[17].

Decision Trees are computed as the average of the subsets of the training data. The intervals are mutually exhaustive and completely exhaustive. When computing, this roughly computes to the following formula where y_1 to y_n are the training observations.

$$\hat{f}(\tilde{t}) = \frac{1}{|\{y_s, s \in \{1;\ldots;T\} \cap I_T\}|} \sum_{s=1}^{T} y_s \cdot \mathbb{I}_{s \in I_T}$$
$$\text{for all } \tilde{t} \geq T$$

8.2. SVR

Long term wind power forecasting through Support Vector Regression(SVR) involves employing a machine learning technique that aims to predict wind power based on historical data, meteorological factors and geographical attributes.[23] The grid search method for SVR optimises two kernal functions,radial basis function(RBF) or polynomial function(PF) such that the accuracy of forecasting results is improved.[24] SVR establishes a hyperplane that best captures the relationship between input variables and wind power output in a high-dimensional space.Commonly tuned by an exhaustive search technique, deterministic and stochastic methods have also been proposed, where Genetic Algorithms (GA) have obtained good results SVR can be computationally intensive, while dealing with large datasets or complex kernel functions.[18] On the other hand, SVR can effectively capture complex non-linear relationships between input variables and wind power output, thus offering predictions even in situations where linear models might fail.[25]

8.3. RNN

Utilising their capacity to recognise temporal correlations in previous wind data, recurrent neural networks (RNNs) are used to predict wind[26]. These networks forecast future wind conditions using sequences of historical measurements of wind speed and direction. RNNs are well suited for short- to medium-term wind forecasts because they are particularly good at simulating the dynamic nature of wind patterns[27]. RNNs can recognise patterns, trends, and seasonality in wind behaviour by being trained on large historical datasets.[28] This enables more precise forecasts for a variety of applications, including the optimisation of renewable energy generation and severe weather forecasting.[19]Time-series data's temporal dependencies are exceptionally well captured by RNNs. RNNs naturally take into account this sequential information, allowing them to generate accurate predictions based on prior patterns. Wind behaviour is strongly dependant on previous conditions.Because of the interaction of numerous variables, including local geography, terrain, and weather systems, wind patterns frequently display non-linear behaviour. RNNs are suited for modelling these complex connections because they can learn complex non-linear correlations.Recurrent neural networks (RNNs) for wind prediction have many advantages, but they also have significant restrictions and potential downsides.[29] Particularly in deep architectures or when working with lengthy sequences, RNNs may experience vanishing or ballooning gradient difficulties. Because of this, it may be difficult for RNNs to accurately capture long-term dependencies, which are essential for wind prediction.

8.4. ARIMA

For predicting wind power, the Autoregressive Integrated Moving Average (ARIMA) model is frequently employed. A statistical time series model was used to appropriately represent the conditional mean of wind power.[15] .Time series forecasting involves predicting future values of a variable based on its past values.ARIMA models are widely used in various fields such as finance, economics, and engineering for forecasting purposes.The ARIMA model is a combination of three components: autoregression (AR), differencing (I), and moving average (MA).The autoregression component involves predicting future values based on past values of the same variable.The differencing component involves transforming the time series data to make it stationary, which means that its statistical properties such as mean and variance remain constant over time.The moving average component involves predicting future values based on past errors or residuals of the model.ARIMA models are useful for forecasting time series data that exhibit trends, seasonality, and other complex patterns.The accuracy of ARIMA models depends on various factors such as the quality and quantity of data, the choice of model parameters, and the forecasting horizon.ARIMA models can be combined with other techniques such as artificial neural networks (ANNs) to improve their forecasting accuracy.[30]

In a more detailed explanation, their method entailed the examination of a value Y at a specific time t. They would then adjust this value by either increasing or decreasing it, taking into account the Y values from earlier time points (like t-1, t-2, and so on). Additionally, they factored in the inclusion of error terms from prior time points to make these adjustments. The formula is computed as follows Where "e" is an error term and "c" is a constant.

$$Y_t = c + \phi_1 y_{dt-1} + \phi_p y_{dt-p} + \ldots + \theta_1 e_{t-1} + \theta_q e_{t-q} + e_t$$

9. DATA USED

The data utilized in this research project was gathered from the Palladam wind farm situated near the city of Thirupur, Tamil Nadu, India. This dataset is a valuable resource for understanding and analyzing the performance of wind turbines and their relationship to environmental conditions in this specific region.

The recorded dataset encompasses a variety of parameters, which were measured at regular intervals of every 5 minutes over the full year during 2022.

To gain insights from this dataset, graphs were plotted and analysed illustrating trends, correlations and patterns dicovered in the data.

Of the data, only the parameters that were relavent to predicting the reactive power were taken into account. The parameters that were taken into account were

- Actual Generator Phase 1 Temperature
- Actual Generator Phase 2 Temperature
- Actual Generator Phase 3 Temperature
- Generator Speed
- Temperature in Generator Slip Ring Chamber
- Total Active Power
- Temperature Outside Nacelle
- Temperature Inside Nacelle
- Wind Speed Outside Nacelle

9.1. Actual Generator Phase 1 Temperature

This data parameter refers to the real-time temperature measurement of the first phase of a wind turbine generator. Monitoring this temperature is crucial to ensure the efficient operation and longevity of the generator, as excessive heat can lead to equipment damage.

9.2. Actual Generator Phase 2 Temperature

Similar to the first parameter, this data point pertains to the temperature of the second phase of the wind turbine generator. Accurate monitoring of all phases ensures the generator's reliability and safety.

9.3. Total Active Power

Total active power represents the electrical power output of the wind farm. This data is vital for assessing the farm's energy production efficiency and overall performance.

9.4. Actual Generator Phase 3 Temperature

This parameter tracks the temperature of the third phase of the generator. Monitoring all three phases collectively helps detect any imbalances or overheating issues, which are critical for maintaining operational efficiency.

9.5. Generator Speed

Generator speed is a fundamental data point for wind farms, as it indicates the rotational speed of the generator's rotor. It directly correlates

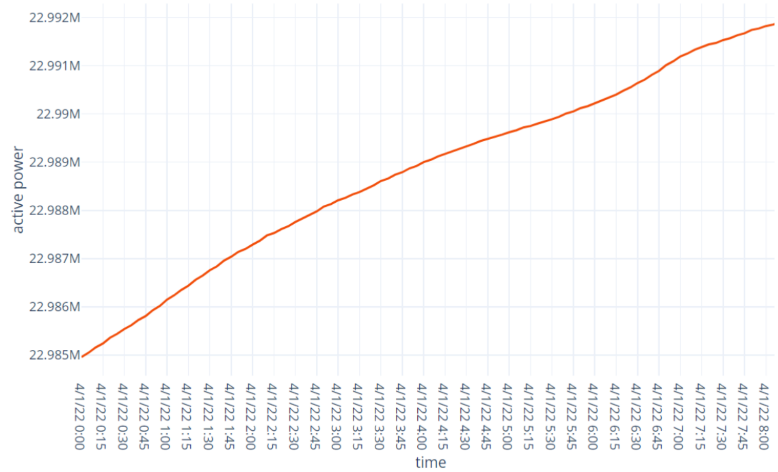

Fig. 3. Variation of Active Power

with power generation, and wind farm operators use this data to optimize energy production while safeguarding equipment.

9.6. Temperature in Generator Slip Ring Chamber

This data parameter measures the temperature inside the generator slip ring chamber. Keeping this temperature within a specified range is essential to prevent electrical issues and maintain the integrity of the electrical connections.

9.7. Temperature Inside Nacelle

The temperature inside the nacelle is an important parameter for monitoring the wind turbine's internal environment. Maintaining an optimal temperature ensures the longevity and efficiency of the equipment.

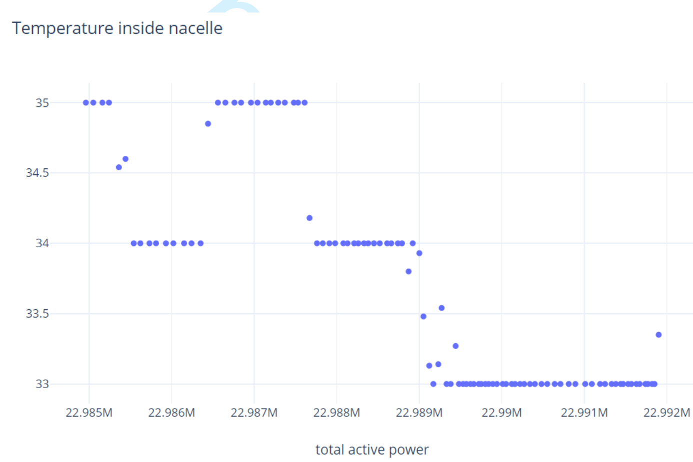

Fig. 4. Variation of Temperature Inside Nacelle

9.8. Wind Speed Outside Nacelle

Wind speed outside the nacelle is a critical data point for wind farm operators. It helps them understand the wind conditions the turbines are exposed to and aids in adjusting the turbine's orientation for optimal power generation.

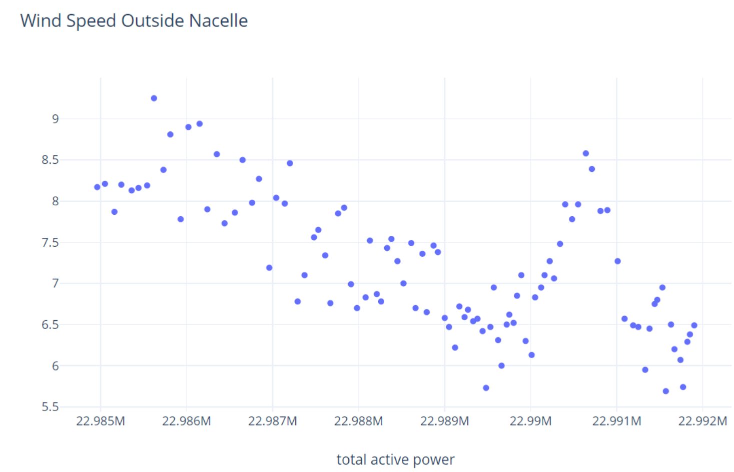

Fig. 5. Variation of Wind Speed Outside Nacelle

9.9. Temperature Outside Nacelle

This data measures the external temperature around the wind turbine nacelle. Tracking this information is crucial for understanding the external environmental conditions that impact the turbine's performance and efficiency.

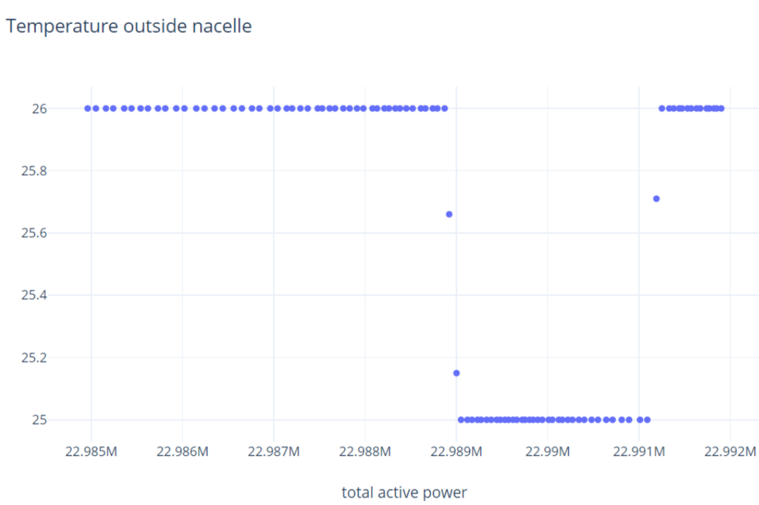

Fig. 6. Variation of Temperature Outside Nacelle

10. PROPOSED METHODOLOGY

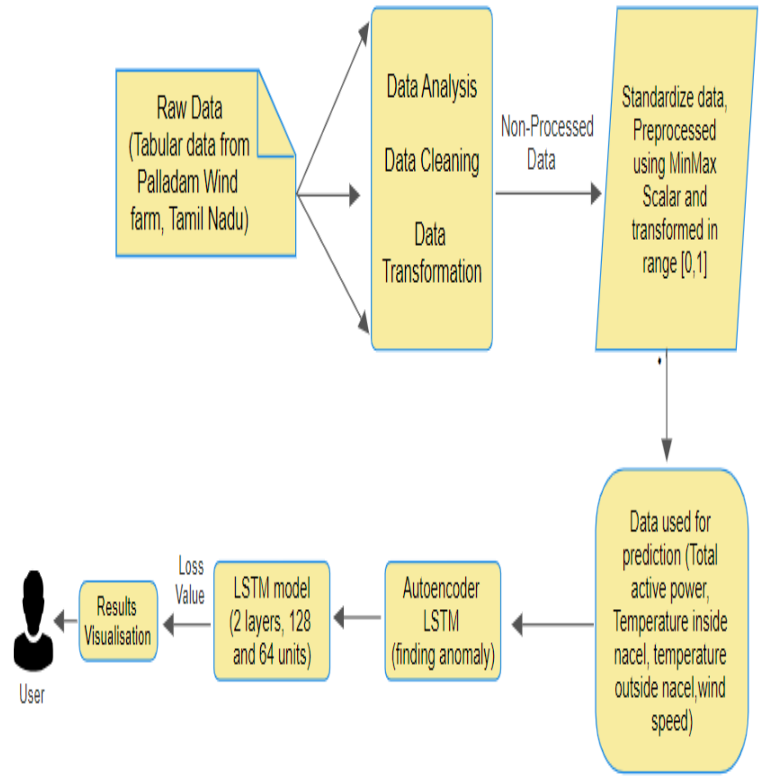

Fig. 7. Proposed System design using LSTM

In this research, a comprehensive framework for predicting wind power utilizing Long Short-Term Memory (LSTM) neural networks is presented. The preprocessed dataset, consisting of input features and the target variable 'TotalActivepower,' was loaded and subjected to data preprocessing steps, including Min-Max scaling. A train-test split was performed to partition the data, and feature scaling was applied to ensure consistency. To conform to the LSTM model's requirements, the data was reshaped into a suitable format. The core of the research lies in the definition of the LSTM model architecture, which incorporates two LSTM layers with dropout regularization to prevent overfitting. The model was compiled with an adaptive learning rate strategy using the Adam optimizer and Mean Squared Error (MSE) loss function. To optimize training, early stopping and learning rate scheduling was introduced as callbacks. After training, its performance was evaluated on a test dataset, and the resulting Mean Squared Error is reported. Additionally, the code saves the best-performing model, which is later used to make predictions on test data. The predictions are then transformed back to the original scale for interpretability. This code serves as a foundation for accurate wind power prediction, particularly in the context of renewable energy forecasting, showcasing the practical implementation of LSTM neural networks in regression tasks.

Model	Testing	Loss Value (Reconstruction Loss)
Autoencoder LSTM to check anomaly and predictions using LSTM	Predicting 3 hours in advance	0.00346

Table 1. Results Tabulated

11. RESULTS

The results are plotted as a graph which is given in Fig.7. The performance of the developed Long Short-Term Memory (LSTM) neural network model for wind power prediction was rigorously evaluated to assess its accuracy and predictive capabilities. The model was trained on a dataset comprising historical wind-related features and corresponding wind power generation values. The training process, as detailed in the methodology section, included 50 epochs with batch sizes of 32, guided by early stopping and a learning rate scheduler. Upon completion of training, the model was subjected to evaluation using a separate test dataset. The primary evaluation metric employed was the Reconstruction Loss value and was calculated as 0.003, indicating the model's accuracy to estimate wind energy.

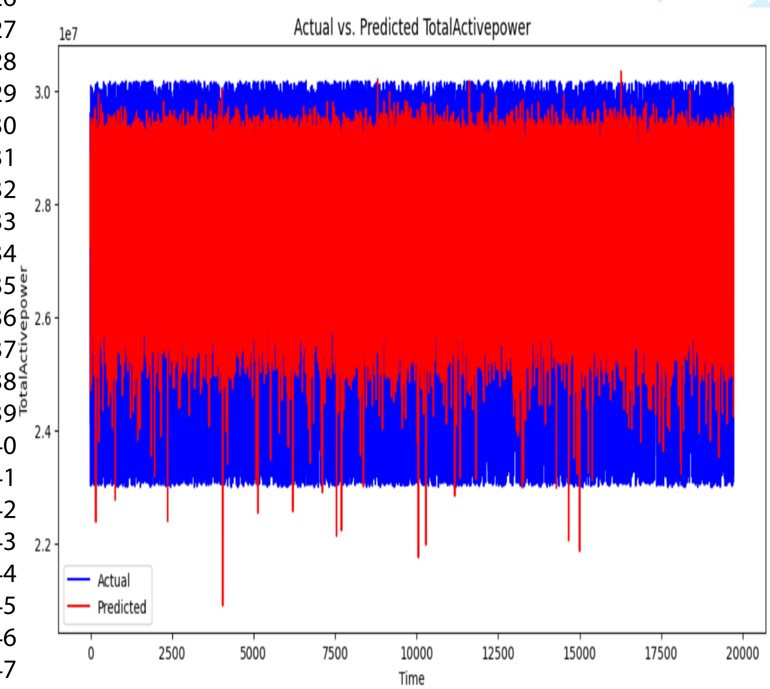

Fig. 8. Results

These results underscore the model's potential in aiding the optimization and management of wind energy resources, contributing to the advancement of renewable energy systems. However, it is essential to acknowledge the possibility of further model fine-tuning and validation across diverse datasets and operational conditions for comprehensive applicability. The tabular column tabulates the results. Here it is seen that by including a sliding window approach, the data becomes more relavant and thus makes better predictions.

To improve accuracy, By incorporating the sliding window approach.The sliding window size or "look-back" window size is determined by the time steps variable. This variable is set to 12 meaning a history of 12 steps is used to make the prediction of the next step. The sliding window approach is explained in the flowchat as shown.

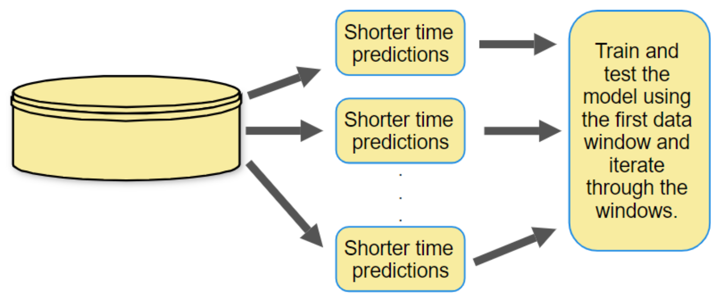

Fig. 9. Sliding window Algorithm

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