Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

A Comparative Study on Wind Power Forecasting Models Based on the Use of LSTM

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Abstract: In the context of wind power generation's growing significance, this research tackles the critical problem of improving power system stability by reducing peak load and frequency control pressures using sophisticated wind power forecasting methods. Using the rapidly developing area of artificial intelligence and neural networks in particular, the study explores the efficacy of Long Short-Term Memory (LSTM), a recurrent neural network designed for event forecasting in time series data with long intervals and temporal delays. The research presents a novel forecasting model, LSTM that enhances prediction accuracy. This is corroborated by the calculated Root Mean Squared Error (RMSE) of 0.6782 and Mean Absolute Error (MAE) of 0.4614. The sustainability and dependability of wind energy integration into power systems may be enhanced by these findings, which highlight the possibility for more efficient and rapid convergence processes in wind power forecasting.
Keywords: Wind Power Forecasting, LSTM-based Models, Renewable Energy Prediction, Time Series Forecasting

1. Introduction

Wind power has limitless economic potential as a renewable energy source, and so does study of associated forecasting technology. The intermittency, volatility, and unpredictability of wind resources, however, have posed significant difficulties for the reliable running of the electricity grid. The following issues can no longer be adequately addressed using conventional methods of wind power forecasting. This is why it is critical to implement the latest innovations in artificial intelligence right now. Simulation, extension, and expansion of human intellect are the goals of artificial intelligence research and development in the field of computer science known as artificial intelligence (AI). Rapid advancements in machine learning, deep learning, and other areas of artificial intelligence have opened up new avenues of inquiry and application in the quest for more accurate methods of predicting the output of wind turbines.

Estimating wind speed is essential for predicting wind power. Accurate forecast of wind power is very difficult due to the cyclical, daily pattern and strong stochastic unpredictability. Since local and regional temperatures, terrain, and obstructions like buildings all impact wind energy, it is evident that effective translation and application of the wind energy resources need accurate and thorough information on the wind properties of the area. Different models have been presented by researchers in recent decades to make predictions based on past wind speed data. These models may be roughly categorized as physical, statistical, intelligence learning, or hybrid.

Over the course of many years, the global electricity sector, and the supply industry in particular, has undergone a number of significant structural and systematic shifts. These shifts have been driven primarily by two factors: the trend toward privatization (reforms) in the industry and the shift in electricity generation towards clean, pollution-free renewable energy sources. With the climate constantly changing, energy forecasting has become a crucial part of power grid management. Planning, scheduling, and real-time balancing of the power grid's resources all benefit greatly from accurate forecasts. Modern power systems have three main forecasting challenges: electrical load, pricing, and renewable energy sources. The wind power business has grown exponentially and emerged as a frontrunner among the newly-emerging renewable energy sources (solar energy).

Moreover, renewable power is quickly turning into a critical piece of the power network and is generally viewed as a practical elective energy source. Wind power is one of the quickest developing renewable energy sources, and in certain nations it has even supplanted petroleum products altogether. Likewise, the capacity to create power from the wind is dynamic, stochastic, intermittent, and connected to the development of other slope occasions. Notwithstanding this, it is one of the most deep-rooted renewable energy options in contrast to the customary energy assets since it is a uninhibitedly available and contamination free wellspring of energy. Toward the finish of 2016, the worldwide introduced nameplate limit with regards to wind power would have reached 486.8 GW, an increment of 12.5% from 2015. It is anticipated that toward the finish of 2021, wind power would have developed to around 817 GW, addressing a yearly development pace of 10.4 percent. Electric power frameworks in view of a huge lattice and related interconnections utilize these wind limit establishments. Solar, geothermal, and tidal energy are now rapidly expanding as additional eco-friendly electricity production options.

Vulnerabilities in wind power come from those in its subordinates, for example, projections of wind speed and course. Compelling wind power creation forecasting philosophies are required pair with the fast advancement of wind ranches. The specialized and monetary ramifications for the effective administration and activity of power frameworks range from highs (as expanded steadfastness) to lows (as diminished save upkeep costs). Figures of wind power (WPF) demonstrate the way that much energy can be created from the wind at a specific second from here on out. With regards to carrying out and running on wind power, WPF is critical. The WPF has been finished on a long-term, medium-term, and short-term premise.

Wind power is very variable, unpredictable, and intermittent since it is so dependent on external factors such as the weather, the seasons, and the passage of time. Because of these factors, wind power is receiving a lot of attention. Therefore, unlike power generated with conventional facilities, energy produced by wind cannot be readily matched to electrical demand. The electricity grid faces additional issues as the percentage of wind power used to fulfil demand increases.

1.1. Integration with Grid

The main challenge of wind power's grid integration is the control of its intermittent production. The transmission provider's remit ends at the grid level, where demand and supply must be balanced. Therefore, planning the supply ahead of time is essential to accommodate the load profile. The load represents the aggregate demand for electrical service in a certain region. Load forecasting methods are often used to predict future loads. For load forecasts a day or a week out, the Mean Absolute Percentage Error (MAPE) ranges from 0.87 to 1.34 percent. The performance of load forecasting models and approaches is still being actively worked on by academics and practitioners alike. This means that the study has progressed to an advanced level.

1.2. Integration with Electricity Markets

In most cases, two processes work together to construct the power market. The first is the Day Ahead market, where the cost of generating the energy needed to meet the anticipated demand for the next day is exchanged. Electricity pricing and generation may be settled for the different bidding hours via an auction procedure and subsequent bidding. The second mechanism is the auxiliary service market, also known as the intraday market, in which the disparities between expected and actual output and consumption are exchanged (for example, when a power plant goes down or when wind power supply is intermittent). The ancillary service sector spans several time periods and is crucial to the reliable functioning of the electricity grid. As a result, both customers and providers benefit from anticipatory knowledge of the power price. Electricity price forecasting, like load forecasting, is still in the early stages of development, with a stated error rate (MAPE) of 3.96–4.92%.

Therefore, precise information on the time and quantity of power output from these variable sources is crucial for a successful integration of significant quantities of wind power into the electrical supply system.

Wind power forecasting needs vary depending on the forecasting horizon, with one step ahead, many lead hours ahead, and probabilistic forecasting all being viable options. In multistep forecasting, the inaccuracy multiplies with each lead hour estimate, making the process more difficult; in probabilistic forecasting, various statistical elements add complexity and further complicacy to the process. It also has an obvious impact on a utility's bottom line.

2. Literature Review

According to (Abdel-Aal 2009), accurate predictions of future wind speeds are crucial for a variety of industries, including wind farm management and conservation, power grid integration, shipping, and aviation. Improved power grid security, increased stability of power system operation and market economics, and a significant boost in wind power penetration may all be attributed to the availability of precise wind speed predictions. Greenhouse gas emissions and other pollutants released as a consequence of using traditional energy sources will be greatly reduced as a result.

Several statistical and learning-based techniques have been used to construct models for predicting wind speed. Using an auto regressive model and independent component analysis, Firat et al. (2010) introduced a fresh mathematical technique. Results showed that the proposed strategy outperformed direct forecasting in terms of accuracy. Auto regressive moving average (ARMA) of time series is a strong fit for forecasting wind speed because of the wind's excellent progression and unpredictability.

Foreseeing wind speed and direction, Erdem & Shi (2011) offered four strategies based on the ARMA technique. According to the findings, the created model outperforms the ARMA model in predicting wind direction, whereas the opposite is true for wind speed prediction.

In order to forecast wind speed, Li et al. (2011) introduced an ARMA model integrated with a wavelet transform. In order to separate the low and high frequency components of the total wind speed, the wavelet transform is used. The ARMA model makes predictions about the wind speed based on smooth data. The forecast accuracy is enhanced by this combination model.

Time series estimation of wind power production using a radial basis function neural network was previously reported by Chang (2013). The anticipated and actual values show a high degree of agreement. The collected findings demonstrated the accuracy and dependability of the proposed forecasting system.

In order to predict wind speed, Li & Shi (2010) looked at three common forms of ANN: adaptive linear elements, back propagation, and radial basis functions (RBF). The findings of a comparison between three different kinds of ANN demonstrate that, even when using the identical wind dataset, no one ANN model consistently beats the others. In addition, the quality of the available data will determine which ANN variant is selected.

An SVM-based approach to forecasting wind power was reported by Zeng and Qiao (2011). National Renewable Energy Laboratory provides real-time data on wind speed and wind power, which is used in simulation research. In comparison to the persistence model and the RBF neural work-based model, the suggested SVM approach shows substantial improvement.

In order to predict wind speeds one day in the future, Zhou et al. (2011) detailed a comprehensive investigation of the parameters of least-squares support vector machines (LSSVM) models. Multiple SVM kernels are available for use, including linear, gaussian, and polynomial kernels. It is discovered that LSSVM techniques can often outperform the persistence model.

Short-term wind power forecasting using neuro-fuzzy networks was reported and tested by Xia et al. (2010) on a real wind farm in China. The evaluation results highlighted the trained neuro-fuzzy networks' prominence for wind power prediction.

Using evolutionary optimization methods for automated neural network definition and closest neighbor search, Jursa and Rohrig (2008) unveiled a novel short-term prediction approach. The results of the experiments validated the effectiveness of the suggested automated specification technique in reducing forecasting mistakes.

3. Model Architecture

LSTM networks were planned explicitly to beat the long-term reliance issue looked by repetitive brain networks RNNs (because of the evaporating inclination issue). LSTMs have criticism associations which make them different to more conventional feedforward brain organizations. This property empowers LSTMs to deal with whole successions of data (for example time series) without treating each point in the succession freely, yet rather, holding valuable data about past data in the arrangement to assist with the handling of new data focuses. Accordingly, LSTMs are especially great at handling arrangements of data like text, discourse and general time-series.

A LSTM organization can realize this example that exists each 12 periods in time. It doesn't simply utilize the past expectation but instead holds a longer-term setting which assists it with beating the long-term reliance issue looked by different models. It is quite important that this is an exceptionally oversimplified model, yet when the example is isolated by significantly longer timeframes (in long sections of text, for instance), LSTMs become progressively valuable.

The working of LSTM can be envisioned by understanding the working of a news channel's group covering a homicide story. Presently, a report is worked around realities, proof and explanations of many individuals. Whenever another occasion happens you make both of the three strides.

LSTMs deal with both Long Term Memory (LTM) and Short Term Memory (STM) and for making the calculations simple and effective it uses the concept of gates.

- **Forget Gate:** Forget gate is where LTM sends irrelevant data to be forgotten.
- **Learn Gate:** In order to apply what we've just learnt from STM to the present input, we combine it with the event (the input at hand).
- **Remember Gate:** combines non-forgotten LTM data with STM and Event to serve as an improved LTM.
- **Use Gate:** Similarly to how an updated STM utilizes LTM and STM and Event to forecast current event output, this gate does the same.

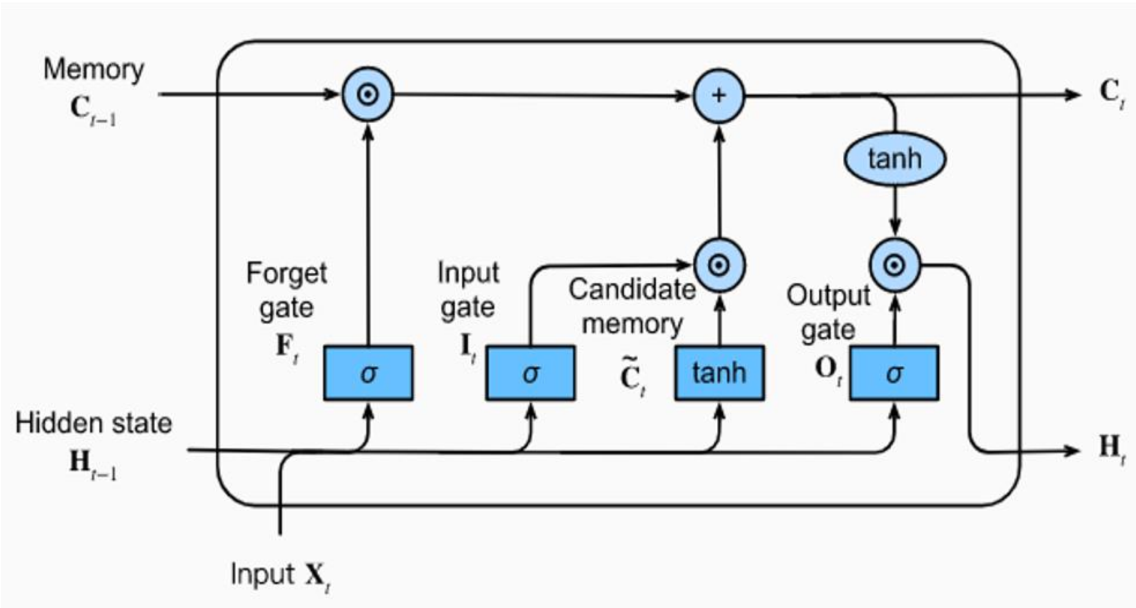

Fig 1: Architecture of LSTM

4. Data Collection

Kaggle's Wind Turbine Scada Dataset was used to analyze wind power generating data and evaluate the efficacy of a suggested method.

SCADA (Supervisory Control and Data Acquisition) systems in wind turbines collect and store data points every 10 minutes. This data is essential for tracking and improving wind turbine efficiency. The following information is gathered and saved in a file by a wind turbine in Turkey's SCADA system:

Each data point is given a time stamp, which is recorded as a date/time every ten minutes.

LV ActivePower (kW): Indicates the current kinetic energy output of the turbine.

A wind turbine's electrical output is directly proportional to the wind speed at the turbine's hub height, which is indicated by the parameter "Wind Speed" (m/s).

For a particular wind speed, the turbine's theoretical power output is provided by the Theoretical_Power_Curve (KWh). The maker of the turbine decides on these figures, which are expressed in kilowatt-hours.

The wind direction is measured in degrees relative to the turbine's hub height. Wind turbines will automatically face this way. Degrees are used to describe the direction of wind.

5. Exploratory Data Analysis

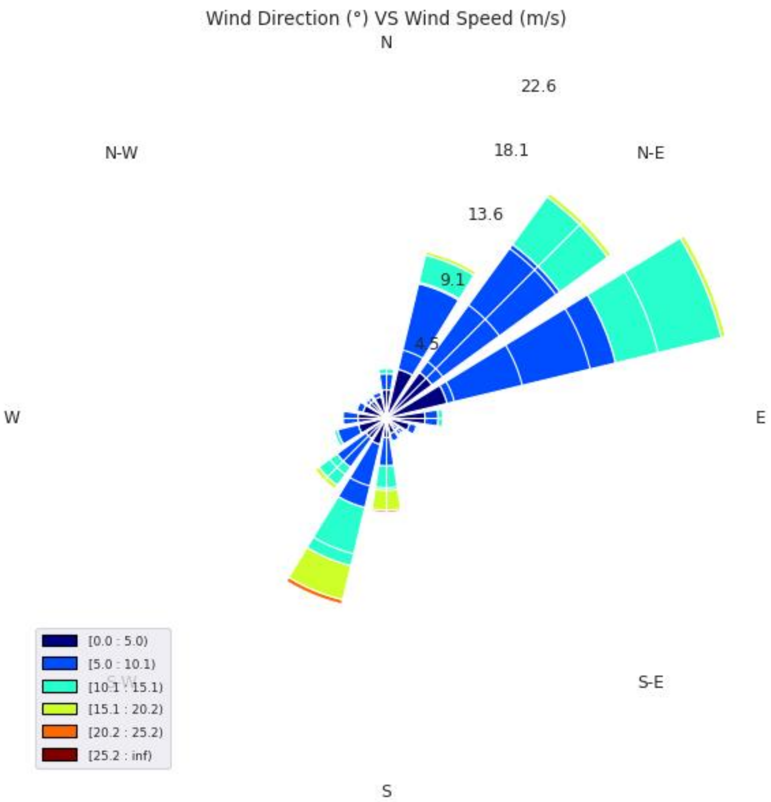

Fig 2: Relationship between wind direction and wind speed

Figure 2 depicts the correlation between wind direction and local wind speed. The spokes in the diagram stand for the wind's direction, with north at the top and the others grouped clockwise around it. The length of the spokes provides a visual representation of the wind's velocity, with greater velocities being associated with longer spokes.

According to the data, winds are strongest while coming from the west. Since the west spoke is the longest, we might infer that this is the direction from which the wind most often blows. Less wind comes from the other directions, as shown by the shorter spokes.

The wind is often strongest toward the west and southwest, as seen by the graph. If you look at the graph, you'll see that the longest spokes are located in the west and southwest, where the wind is often strongest. The opposite directions often have weaker winds.

The graph illustrates that the majority of the time, the strongest winds are coming from the west, followed by the southwest.

Here is a more detailed interpretation of the graph:

- The most common wind direction is west, followed by the southwest, the northwest, and finally the east.
- The strongest winds come from the west and southwest, then the northwest, and finally the east.
- The southeast has the least frequent wind, followed by the south and the northeast.
- The southeast, south, and northeast have the lightest winds.

This graph should be seen as a snapshot of the wind conditions at the given place and time. The wind may be quite different in different places and at different times. The direction and velocity of the wind, for instance, may vary depending on the time of day, the season, and the weather conditions.

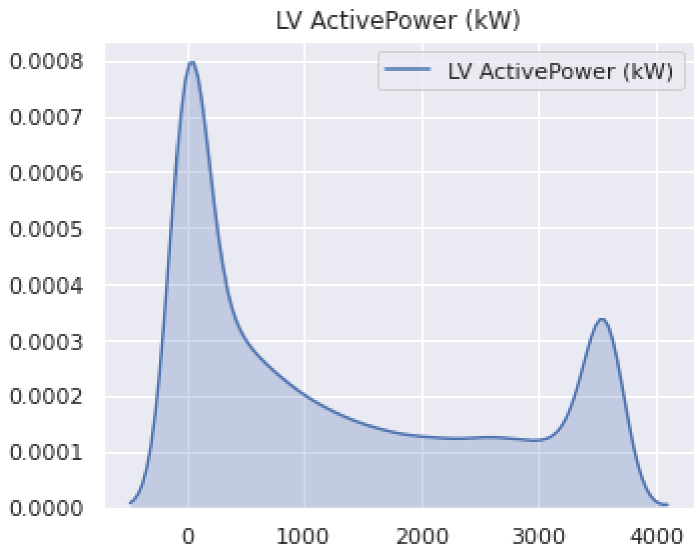

Fig 3: Active power consumption (in kW) of a household over a 24-hour period

Household active power use (in kW) during a 24-hour period is shown in Fig. 3. Time, on the x-axis, is juxtaposed with actual power used, on the y-axis.

The graph depicts a day in which active power usage is lowest in the morning and rises steadily until late afternoon. The evening hours, namely between 6 and 10 p.m., saw the largest peak in active power use. Then, when night falls, the amount of electricity actually used begins to drop.

The graph further reveals many peaks in the active power use at various times of the day. Air conditioners, refrigerators, and washing machines are probably to blame for these spikes.

The graph depicts a typical day in the life of a household's active electricity usage, with consumption peaking in the evening.

Here is a more detailed interpretation of the graph:

- Between 2 and 6 in the morning, active power use is at a minimum. Most people are sleeping and there is less going on in the home at that time, so it seems sense that this would be the case.
- After 6 a.m., the daily power usage starts to rise steadily. Probably because people are getting up and going about their normal morning routines, which include things like cooking breakfast, getting dressed, and turning on appliances.
- Between the hours of 8 and 9, the active power usage is at its highest. The widespread use of home cooking machines like microwaves, toasters, and blow dryers is probably to blame.
- After reaching a second high between 12 and 1 p.m., active power usage drops marginally. This is probably because to the widespread use of microwaves and ovens as people prepare their lunches.
- After then, it drops until the third peak, which occurs between 6 and 10 at night. This is probably because when people go home from work, they turn on their air conditioners, fridges, and washers.

After then, active power usage drops progressively throughout the night, reaching a new low between 2 and 6 in the morning.

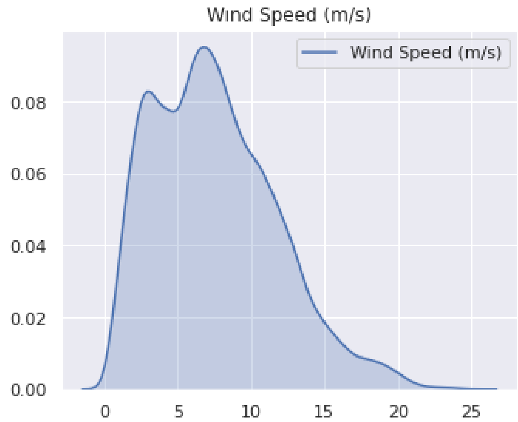

Fig 4: Density plot of wind speed at a particular location

The chart you included shows the density of wind speeds across time and space. Wind speed, in meters per second (m/s), is shown along the x axis, while data density, in terms of the number of points at each wind speed, is plotted along the y axis.

According to the data, an average wind speed of around 5 m/s is recorded here. There is also a substantial quantity of information at wind speeds between 10 and 15 meters per second. Wind speeds over 25 m/s see a drop in data density, although readings are still available.

The average wind speed at this site is shown to be quite low by the graph, with occasional strong gusts. Here is a more detailed interpretation of the graph:

- The typical wind speed here is around 5 meters per second. This indicates that this is the typical wind speed, as opposed to a less common speed. There is also a substantial quantity of information at wind speeds between 10 and 15 meters per second. This indicates that winds of this velocity occur often.
- The data density diminishes with increasing wind speed, although information is available for gusts up to 25 m/s. This suggests that winds of this strength are possible, albeit uncommon.
- •The distribution of wind speeds has a lengthy tail at higher speeds, as seen by the graph. This implies there is a remote possibility of very strong wind speeds.

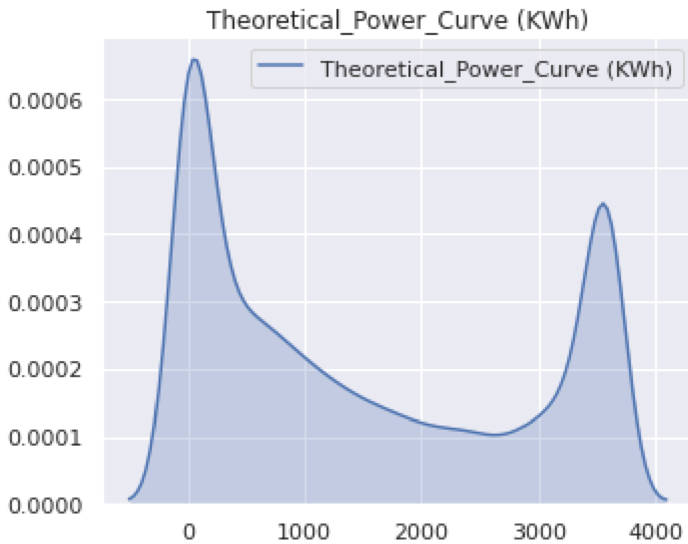

Fig 5: Theoretical power curve of a wind turbine

The theoretical power curve of a wind turbine is shown in the graph you submitted. Power output in kilowatts (kW) is plotted against wind speed in meters per second (m/s) on the x axis.

According to the data, the wind turbine generates more electricity as the wind speed rises. Although there is a correlation between wind velocity and generated power, the connection is not linear. The power output rises gradually at low wind speeds. However, the power output rises more sharply with increasing wind speed.

The graph also reveals that the wind turbine's greatest power production occurs at a certain wind speed. This wind velocity is referred to as the cut-out wind speed. The maximum allowable wind speed is set to prevent damage to the wind turbine.

The graph demonstrates, in general, that a wind turbine's power production is proportional to the speed of the wind. A wind turbine's power output at a given wind speed may be estimated using the graph.

Here is a more detailed interpretation of the graph:

- A wind turbine's maximum power production as a function of wind speed is shown on a graph called the theoretical power curve.
- Several assumptions, including the wind turbine's efficiency and the site's typical wind conditions, are used to derive the theoretical power curve.
- Wind turbulence and mechanical losses in the wind turbine may reduce the actual power production relative to the predicted power output.

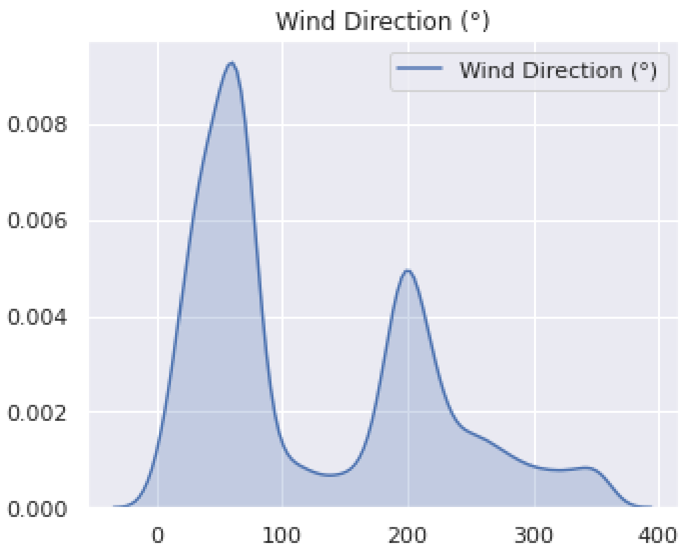

Fig 6: KDE of wind direction

Fig 6 illustrates how the prevailing winds in a given area vary in both direction and velocity. Each wind direction is represented by a spoke in the wheel, with the length of the spoke corresponding to the frequency with which that wind direction blows. High winds are represented by darker spoke colors, and low winds by lighter ones.

According to the wind rise diagram, winds are strongest when coming from the west. Wind is most prevalent from the West, as seen by the longest spoke on the graph, which points in that direction. Less wind comes from the other directions, as shown by the shorter spokes.

The wind rise also reveals that the strongest winds come from the west and southwest. The windiest directions are toward the west and southwest, where the graph's darkest spokes may be seen. The opposite directions often have weaker winds.

In general, the wind rise diagram indicates that the strongest winds are coming from the west, namely the western and southwestern quadrants.

Here is a more detailed interpretation of the graph:

- The most common wind direction is west, followed by the southwest, the northwest, and finally the east.
- The strongest winds come from the west and southwest, then the northwest, and finally the east.

- The wind is calmest toward the southeast, and then the south, and then the northeast, and its speed is lowest in those directions.

6. Power Generation According To Temperature

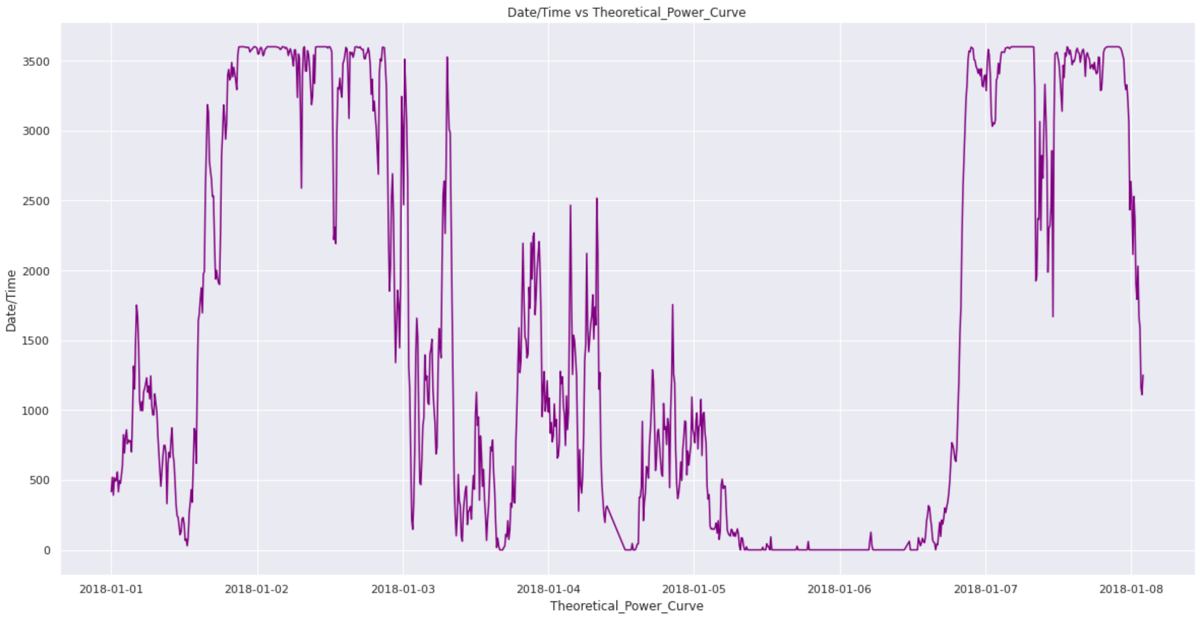

Fig 7: Power Generation v/s Date/time

Mean daily temperature and wind speed are shown against month on the x-axis, and month on the y-axis.

The graph illustrates that the summer months of June, July, and August have the greatest daily mean temperature, while the winter months of December, January, and February have the lowest. March through May has the greatest average daily wind speed, followed by June through August with the lowest.

A broad inverse link between temperature and wind speed is also shown by the graph. So, while it's hot outside, the breeze is weak, and vice versa. Reason being, when temperatures are high, the atmosphere becomes more stable, reducing the strength of the winds.

The average daily temperature and average daily wind speed at this site exhibit noticeable seasonal variation in the graph. Highs in the summer and lows in the winter characterize the seasonal temperature range. The spring months see the greatest average wind speed, while the summer months see the lowest. Additionally, there is often an inverse link between temperature and wind velocity.

- The daily mean temperature is highest in the summer months (June, July, and August), with average temperatures above 25 degrees Celsius.
- The daily mean temperature is lowest in the winter months (December, January, and February), with average temperatures below 10 degrees Celsius.
- The daily mean wind speed is highest in the spring months (March, April, and May), with average wind speeds above 5 meters per second.
- The daily mean wind speed is lowest in the summer months (June, July, and August), with average wind speeds below 3 meters per second.

There is a general inverse relationship between temperature and wind speed. This means that when the temperature is high, the wind speed is low, and vice versa. This is because high temperatures tend to create stable atmospheric conditions, which suppress wind speeds.

7. Data Preprocessing

7.1. Handling Missing Values

When working with a dataset, "handling missing values" refers to the steps taken to address and rectify situations where data is either missing or incomplete.

We dealt with and managed missing and incomplete data points during the first stage of data preparation. We were able to do this by eliminating from our dataset those rows with missing values. Since missing data might create mistakes and complexities during analysis, ensuring data completeness and maintaining the quality of the dataset was the goal. For reliable analysis and data integrity, it is essential to deal with missing values.

7.2. Date-Time Format Conversion

Time and Date Format The term "conversion" is used to describe the method by which a dataset's values for dates and times are transformed into a uniform format.

In the second stage, we focused on normalizing the date-time column in our dataset to the 'YYYY-MM-DD HH:MM:SS' format. The time and date information is represented consistently and analytically in this style. This standardization of time makes the converted data appropriate for a wide range of analytical methods and visual representations.

7.3. Eliminating Irrelevant Columns

Identifying and deleting columns in a dataset that do not contribute directly to the research topic or analysis is the process of "eliminating irrelevant columns," which streamlines the dataset for improved relevance.

During the last round of data preprocessing, we focused on streamlining the structure of the dataset by erasing irrelevant columns. To do this, we had to remove the decomposed date-time characteristics ('Year,' 'Month,' 'Day,' 'Time Hours,' 'Time Minutes') and the 'Wind Direction (°)' column. These rows were disregarded since they had nothing to do with the study's main objectives. As a result, we hoped that the dataset would be more suitable for further analysis and modeling since it would be more compact and focused on the most significant attributes.

8. Model Configuration

Long Short-Term Memory (LSTM) networks were used extensively as a cornerstone in our data analysis and predictive modeling, and we took a methodical approach by predefining particular values for critical parameters. These constants were selected with care to guarantee repeatability and consistency of findings. For example, we fixed the number of training epochs at 15, which determined how long the training would take; we kept the number of units in a network layer at 10; we were strict about keeping the number of data points to forecast at 1000; and we defined the time window for time series analysis as 24. At the same time, we used long short-term memory (LSTM), a recurrent neural network, as a central component of our investigation strategy. When working with time series data, LSTM networks shine because to their proficiency with sequential data. This feature helped us successfully record intricate temporal connections and unearth hidden patterns in our data. In particular, LSTM proved important in handling the complex issues posed by time-varying data. Our research endeavors were successful because of this smart mix of set parameter values and LSTM design.

9. Results & Discussions

9.1. Evaluation Metrics: NMAE and NRMSE

Maldonado-Correa et al. (2021) [3] state that the mean absolute error (MAE) and root-mean-squared error (RMSE) are the most used ways of assessing error in wind power prediction models. Two measures were used to evaluate the accuracy of several wind power prediction models in this research. Explanations of the MAE and RMSE are provided below.

9.1.1. MAE

The observed value, Oi, is substituted into equation for the experimental value, Pi, and the sample size, n. Therefore, MAE is defined as the typical absolute deviation from the expected value. The optimal value is 0, and performance degrades as the value increases. The extent of the mistake is accurately represented in the final number with MAE since it uses the absolute value of the error. In other words, it is an appropriate indication when there are numerous outliers or when the loss due to mistake grows linearly. Since the error is quantified, it's also possible to compare the precision of various wind power plants and compensate for the scale-dependent limitations of root-mean-squared error (RMSE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(|O_i - P_i|)$$

9.1.2. *RMSE*

As shown in Equation , the root-mean-squared error (RMSE) is calculated by squaring the error between the observed value (Oi) and the projected value (Pi) and then averaging the results. As the value rises, the accuracy of the predictions decreases. Since the mistake is squared, a greater error has a greater proportional impact. When the cost of making a mistake climbs exponentially, this indicator becomes useful. Additionally, although it is a technique to assess the precision of a representative prediction model, it suffers from the drawback of being very sensitive to size.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2}$$

The extent of the inter-plant discrepancy varied according to the maximum power generating quantity of each wind power facility. The MAE and RMSE indicators were converted to their nominal counterparts, nMAE and nRMSE, by dividing the MAE and RMSE indicators by the installed capacity of each wind power plant (its maximum power generation), respectively, so that errors could be compared in the same unit. The nMAE (percent) and nRMSE (percent) were calculated by multiplying the respective values by 100 for ease of numerical comparison.

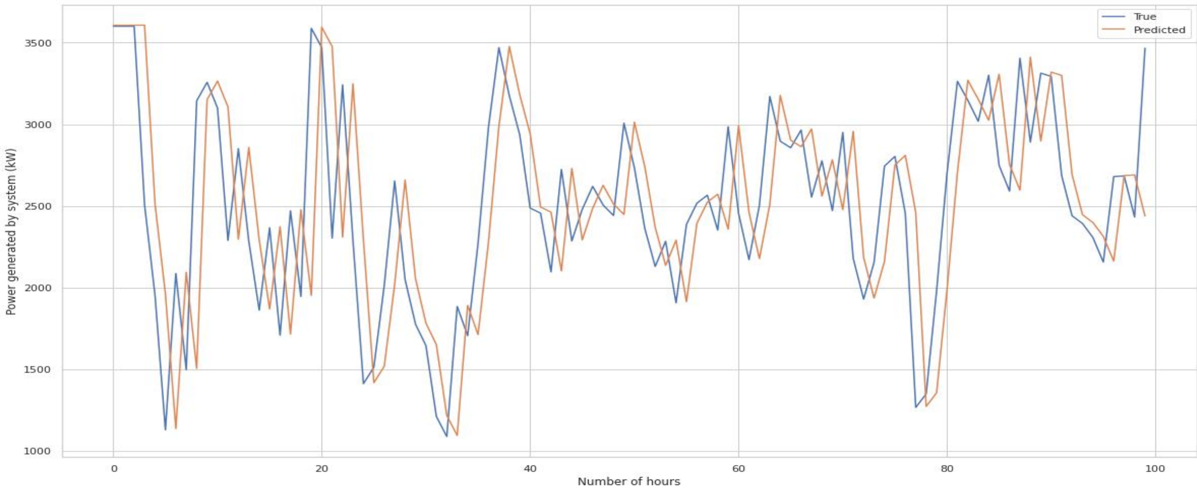

Fig 8: True values and Predicted values of LSTM

In the instance of LSTM forecasting, the differences between the actual and anticipated speeds are shown in Figure 11. The LSTM outputs results that are used to create the performance graph. The RMSE number and the MAE are presented as performance indicators for LSTM.
For LSTM, the RMSE and MAE are 0.6782 and 0.4614.

10. Conclusion

After careful examination of the output, it is clear that the LSTM achieves its goals. LSTM has a lower error rate than other forecasting methods, allowing it to be employed more often. Since LSTM is capable of remembering patterns for extended periods of time, it may be used with deep learning to improve forecasting methods. Hybridization with various models may improve the accuracy and prediction power of LSTM. Based on the data, it seems that LSTM is useful for making predictions. Therefore, organizations may use LSTM to make more accurate weather predictions by applying it to bigger data sets, taking use of the model's patternremembrance characteristic. It may be used to keep the gap between power production and power use constant in the event of wind power forecasts.

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