Environmental Challenges 11 (2023) 100722

Contents lists available at ScienceDirect

Environmental Challenges

journal homepage: www.elsevier.com/locate/envc

Short-term forecasting of wind power generation using artificial intelligence

Shezeena Qureshi[a], Faheemullah Shaikh[a], Laveet Kumar[b], Farooque Ali[a], Muhammad Awais[a], Ali Etem Gürel[c,d,*]

[a] Department of Electrical Engineering, Mehran University of Engineering & Technology, Jamshoro, Pakistan 76062
[b] Department of Mechanical Engineering, Mehran University of Engineering & Technology, Jamshoro, Pakistan 76062
[c] Department of Mechanical Engineering, Düzce, Türkiye, 81620
[d] Clean Energy Resources Application and Research Center, Düzce University, Düzce, Türkiye, 81620

ARTICLE INFO

Keywords:
Wind power forecasting
gated recurrent unit
autoregressive integrated moving average
artificial intelligence
short-term forecasting

ABSTRACT

As global warming is increasing due to conventional sources the government and the private sectors introduce policies to minimize it, renewable energy has been developed and deployed because of these strategies. Among the various renewable energy sources, wind energy is the fastest-growing and cleanest energy resource in the world. However, predicting wind power is not easy due to the nonlinearity in wind speed that eventually depends on weather conditions. To reduce these issues improved forecasting models have been used to get the correct results and improve the performance and stability of the power system and thereby its reliability and security.

In this work, two models are used to predict the “Output of Wind Turbine” to improve the prediction accuracy of short-term wind power generation. The two models namely the Gated Recurrent Unit (GRU) from the deep learning model and Autoregressive Integrated Moving Average (ARIMA) from Statistical Learning. The data used in this research is collected from the wind power plant, Located in Jhimpir Pakistan. This study compares the accuracy metrics of deep learning models and statistical models to determine which model is the most effective for producing wind power.

The results are obtained by using python programming in Jupyter Notebook software and the accuracy metrics of each algorithm are compared with each other as a result Gated recurrent unit (GRU) is the best model among others with the least possible errors and high accuracy. i.e., up to 0.047 root mean square error, 0.89 coefficient of metrics, and 0.03 mean absolute error. Hence, due to its advanced features, then other deep learning, and statistical models the Gated recurrent unit (GRU) Model is suitable for the prediction of wind turbine output power.

1. Introduction

Nowadays the world is diverted towards renewable energy due to its tremendous growth in the power sector i.e., depleting fossil fuels, environmental impacts, and costs of production. Wind energy provides the cleanest and fastest-growing energy in different countries throughout the world. Therefore, improved forecasting models are used to estimate the accurate power for the proper maintenance, reliability, and optimization of the power supply system. Many energy experts think that we are only using a tiny fraction of the renewable energy that is currently accessible and that the energy industry should be considered more fully utilized than it currently is. For example, if we could simply use a little portion of the sun’s energy that is currently available, that would be more than enough to meet the world’s energy needs several times. Renewable energy sources are advantageous not only from an energy standpoint but also from an ecological one since they allow us to preserve our environment for future generations. The two renewable energy sources that are currently receiving the most attention are wind and sun, and many believe that they will take center stage in the years to come. One of the advantages of renewable energy is that these energies are free from greenhouse gas emissions because if these gases will not be reduced it results in the production of heat due to the rising temperature and it can dangerously affect our world’s circumstances. Therefore, the use of wind and sun as renewable energy sources in the world will surely reduce these impacts.

There are multiple types of renewable energy sources available throughout the world, wind and solar energies are widely available when compared to other renewable energy sources. We are particularly

* Corresponding author.
E-mail address: alietemgurel@duzce.edu.tr (A.E. Gürel).

https://doi.org/10.1016/j.envc.2023.100722
Received 13 January 2023; Received in revised form 15 April 2023; Accepted 27 April 2023

predicting the "Output of Wind Turbine" in this research because there are various advantages of wind power over solar power, wind energy is available throughout the whole day while solar energy is only available during the daytime and in cloudy conditions. Hence, it cannot be harnessed. Some research shows that wind turbines release less amount of CO_2/kWh when it is compared with solar panels.

Now, coming towards what is the need to forecasts wind energy? The demand for an efficient power source to run modern industry has risen dramatically in past years. Therefore, the generated power from renewable power resources is difficult to be predicted. With consideration of the stochastic nature of wind power, this work addresses the three main issues, first, it discusses the factors on which wind power depends i.e., wind pressure, wind speed, non-linear behavior of output, temperature, and the humidity of the surrounding atmosphere. Second, it examines how the power system's generation and consumption of electricity are balanced. Third, it performs an assessment of various forecasting methods, and the performance of the different models is compared with each other, and the output of the wind turbine is predicted for the proper functioning of the power system.

Due to the growth of the world's population, the demand for consumers is growing as well, as a result, the supply must increase to meet the demand of various consumers. Hence, forecasting wind power generation is a significant problem. The chaotic fluctuation of wind energy makes it difficult to predict wind power and assessing the model's accuracy is not easy. Therefore, errors in wind power generation could cause problems with electricity transmission and distribution to different consumers. Accurate forecasting methods are used to forecast wind power and it can be achieved by using different algorithms of artificial intelligence and statistical methods.

2. Literature

Most of countries around the world are facing Economical and environmental issues during the generation of electrical power and to overcome these problems, renewable energy sources are used by different countries, especially wind energy. Wind energy is rapidly increasing and due to fluctuating nature and intermittence nature of wind and different patterns of weather especially wind speed and its direction, researchers and policymakers have become aware of the importance of wind energy and to overcome these problems. Different models and algorithms are used to predict the accurate results of wind turbine power output, and this can be achieved by using different models of artificial intelligence because these models provide accurate results with fewer errors. In this section, we have discussed the research of various scholars in this field and then analyze the overall comparison of different models together.

Peiris et al., performed research work which is done based on the "Pawan Danawi" wind farm, located in Sri-Lanka. Researchers have applied multiple numerous, statistical and Machine Learning methods and they found out that Artificial Neural Networks (ANN) were highly popular and efficient methods in the field of wind power prediction. And the model showed the validation percentage of 15% produced the most accurate results (Peiris et al., 2021). Delgado and Fahim, performed data analysis to comprehend the characteristics of the wind and forecast the generated power. Long Short-Term Memory (LSTM), a Recurrent Neural Network (RNN) variation is utilized for wind turbine prediction because it can overcome nonlinear dynamics and long-term dependencies using information received by SCADA systems When Long Short-Term Memory (LSTM) is compared to Moving Average Techniques (MA) and Multilayer Perceptrons, a comparative analysis reveals that it produces the lowest error scores. The created RNN model is more effective than other models at capturing the dynamic behavior of wind energy (Delgado and Fahim, 2020). Guot et al., discuss three different types of Machine Learning methods used for load forecasting Support Vector Regression (SVR), Random Forest Regression (RFR), and Long Short-Term Memory (LSTM). The results show that Support Vector Regression (SVR) model performs better when it is compared to traditional Short Term Load Forecasting (STLF), The research shows the comparison of advantages and disadvantages of Support Vector Regression (SVR), Random Forest Regression (RFR), and Long short term memory (LSTM).The Random Forest model used in this research has many advantages over many existing model of load forecasting/prediction, because of its simplicity, fast to train, and low over fitting tendency. The capacity factor which is the ratio of real power to the rated power is used to measure the performance of the wind farm. The performance measures Mean Squared Error (MSE) and Mean Absolute are calculated to obtain the accuracy of the trained model. The measured error is varies from 7.3% to 3.6% and accuracy found up to more than 87% (Guot et al., 2020). Rashid et al., predicted the output of wind turbine by using Random Forest Regressor algorithm. The Supervisory Control and data Acquisition System (SCADA) data of two years is collected from a wind form located in France. The Random Forest model used in this research has many advantages over many existing model of prediction, because of its simplicity, fast to train, and low over fitting tendency. The capacity factor which is the ratio of real power to the rated power is used to measure the performance of the wind farm (Rashid et al., 2020). Chakrabortty et al., analyzed two datasets from two separate wind farms located in Australia and predicted the very short-term wind power generation for the Bodangora wind farm and Capital wind farm. He performed a comparative study between Autoregressive integrated moving average (ARIMA), Support Vector Machine (SVM) and Hybrid deep learning models. He concluded that the Bodangora wind farm could experience, up to 1.59% in MAE, 3.73% in Root Mean Square Error (RMSE), and 8.13% in Mean Absolute Percentile Error (MAPE). In comparison to the Recurrent neural network (RNN) model, the suggested model reduces Mean Absolute Error (MAE) by 2.11 percent, Root Mean Square Error (RMSE) by 0.72 percent, and Mean Absolute Percentile Error (MAPE) by 16.88 percent when predicting CWF power generation. The majority of the error remains as low as less than 10% of the total generation capacity. The relative size of the forecasting errors for the wind farm can be observed on average as 9.94% of its power generation capacity (Chakrabortty et al., 2020). Lal et al., proposed three different models namely long short term Memory (LSTM), Multilayer Perceptron (MLP), and Convolutional Neural Network, to learn the relationship in the time series. The models are proposed to improve the Short-Term Load Forecasting (STLF), Medium Term Load Forecasting (MTLF), and Long-Term Load Forecasting (LTLF) accuracy. The Long short term Memory (LSTM) model and MLP model shows excellent results with Mean Absolute Percentile Error (MAPE) and Root Mean Squared Error (RMSE) with 9.77% and 11.66% respectively (Lal et al., 2020). Liu et al, when they compared the physical and statistical algorithms to estimate wind power, he discovered that the physical method's accuracy was low because they were analytical yet user-friendly techniques. But for his research, he employed statistical techniques including Autoregressive integrated moving average (ARIMA), Support Vector Machine (SVM), and Recurrent Neural Network (RNN). By applying these algorithms, he stated the issues with Recurrent Neural Networks (RNN), such as the disappearing gradient and exploding gradient, and to reduce these issues, he used the Deep Learning Long Short term Memory (LSTM) algorithm. He collected the data from three different wind farms, including farm 1 in Inner Mongolia, farm 2 in the Netherlands, and farm 3 in Yunnan, China, and found that each farm's data was unique. The RMSE of the DWT RNN, DWT BP, LSTM, RNN, and BP was successively reduced by 33.01%, 37.63%, 63.80%, 64.90%, and 65.87%. The MAPE of the DWT RNN, DWT BP, LSTM, RNN, and BP was consecutively reduced by 11.73 percent, 37.94 percent, 37.29% percent, 41.78% percent, and 45.5 Comparing DWT LSTM's prediction accuracy to the other five prediction methods, a significant improvement was seen (Liu et al., 2019). Alencar et al, forecasted wind power generation for the ultra-short, short, medium, and long term and gathered data from the National Institute of Space Research's National Organization System of Environmental Data (SONDA) (INPE). For an accurate wind power estimate, he employed a variety of models and compared the outcomes. From his research, he found that

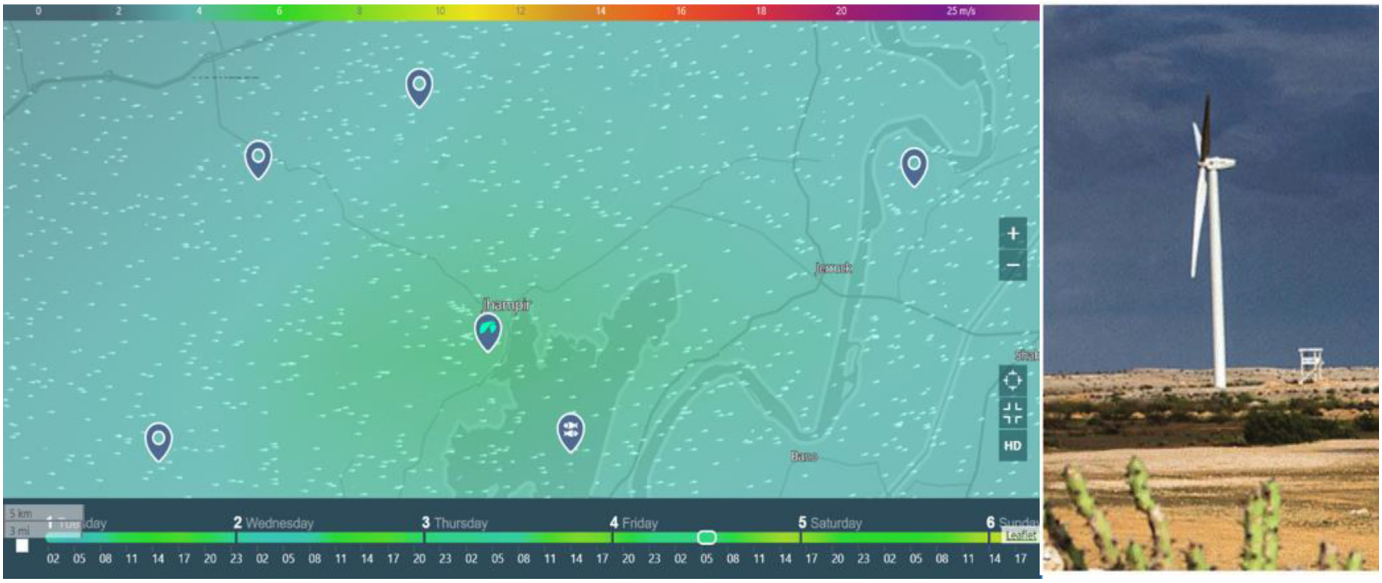

Fig. 1. Data Collection from Wind Farm located at Jhimpir Pakistan for wind power Forecasting.

it was not possible to predict the wind power by utilizing individual models hence utilized a mixture of two or three models together. He applied ARIMA, NN, ARIMA +NN1+NN2, and ARIMA +NN1 models. He found that, among these models, ARIMA+NN1+NN2 produced the best results with the fewest mistakes in the forecasting of wind speed over all forecast horizons. The hour horizon had the highest response with a result of 0.180. The hour horizon had the best reaction (mean absolute percentage error, or MAPE) with 2.571%, and the week horizon had the lowest response, 5.796% (Alencar et al. (2017).

By conclusion the above research that is based on different locations and the chosen data must be varied on the basis of the location. As the input of each research is varied the results that are output can also be varied. As, we know that the input always depends upon the output, here input is the data that we are feeding the model that is not fixed due to the change in the location and output is the prediction of the active power. Our research is based on the prediction of the active power of wind turbines located in the wind power plant at Jhimpir, Pakistan. And in our research, we are using two models i.e., Autoregressive integrated moving average “ARIMA” (Statistical Model) and Gated Recurrent Unit “GRU” (Deep Learning Model) lastly comparison of these two models gives the suited model for this research.

3. Methodology

This section explains the main methods which are used to achieve the goal of this research which is explained in the introduction section. The estimation of the wind power of wind turbines can be achieved by using improved forecasting models to get higher accuracy and reliability so that the overall cost of the system can be reduced. For this purpose, Artificial Intelligence and Statistical methods are used to get accurate results and actual power which is fed to various customers to the utility of the power sector.

3.1. Study area and weather data

The first step is to collect data from wind farms where wind turbines and Supervisory Control and Data Acquisition (SCADA) system are installed in it which collect the data from different sensors.

At the time of collection of data, the environmental conditions need to be focused on because the behavior of the environment on the operation of the wind turbines is emphasized.

The environmental factors- wind speed, wind direction, weather, temperature, humidity, pressure, precipitation, Air density, blade radius, and lightning directly or indirectly, independently or in combination with others affect wind energy generation. Wind turbines need to be in areas with a lot of wind on a regular basis, which is more important than having occasional high winds. One month dataset is used in this research, and it is obtained from the Wind power plant at Jhimpir Pakistan (Fig. 1)

3.2. Flow chart of the proposed methodology

To achieve the desired output, we need to follow some steps that are mentioned in the flow chart below which describes the procedure of the methodology. The results of this article can be achieved by programming. Programming contains some fixed set of instructions and commands that is necessary to be followed step by step, otherwise, the command shell shows the error output. During the coding, the first and initial step is to import the data or input. But In python to read that data we need to import the libraries in order to get the data from the Jupyter Notebook. After importing the data, we split the data into two halves i.e., training and testing data sets. Because the models can be used in the testing data sets therefore it is necessary to split the data. By using the model, we will get the desired output but then we check the accuracy and errors of the models if it shows the least error then it is fine otherwise the cycle follows the repetitive iterations to reduce the errors. Which is the goal of this project to find out the least error and high accuracy model for the wind turbine. For a better understanding, the flow chart is shown in Fig. 2.

3.3. Procedures of the proposed approach

3.3.1. Data Preprocessing

The collected data is now processed to remove the unwanted data that is not needed for the proposed model so that the accuracy of the model is not compromised. The unwanted data includes the separation of positive and negative values, null entries, and the duration of the period during which the data is collected. The boxplot of data is given in Fig. 3.

The data preparation process is presented in Fig. 4. The tasks involved in creating the data set that will be used in the modeling step are all included in the data preparation stage. These involve cleaning up

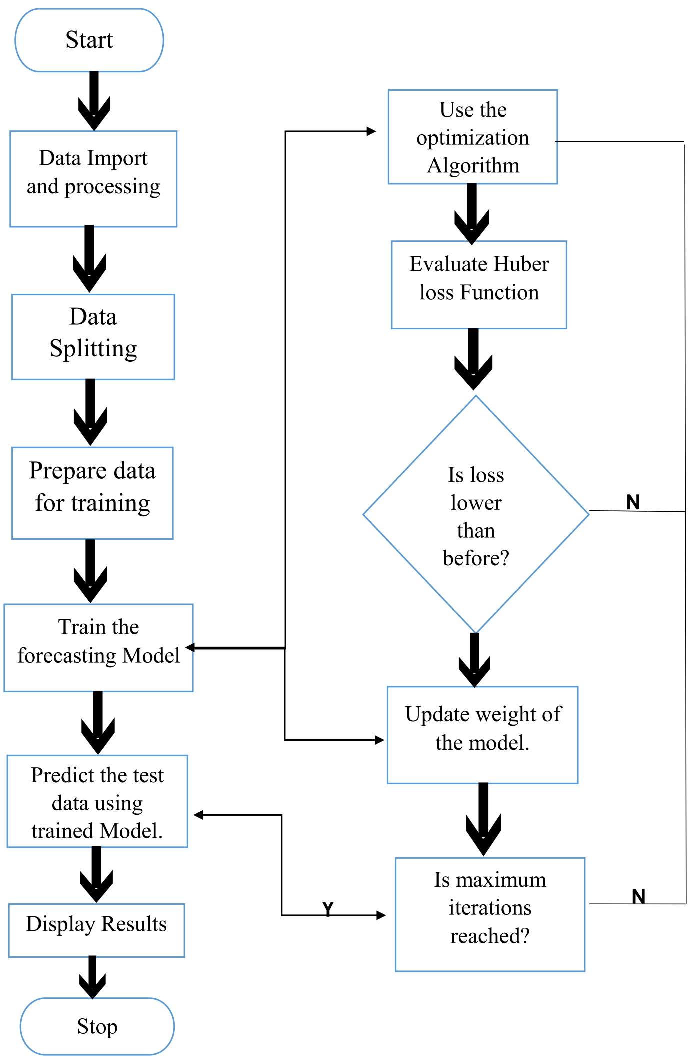

Fig. 2. Flow chart of the Prediction Model.

data, fusing information from many sources, and turning information into more practical variables. By choosing the data that will be most helpful for our work, we can prepare it by completing certain operations like data cleaning and data transformation before moving on to the modelling stage.

3.3.2. Data Splitting

The cleaned data is split into two halves i.e., training and testing data. The separation of training and testing data is done in a continuous way in order to avoid over-fitting risk, which reduces the accuracy of the model. The data is divided in such a way that training data consists of 80% of the preprocessed data and the remaining 20% comes in the category of testing data. The data splitting is shown below in Fig 5a and 5b.

4. Forecasting Models

This section describes the machine learning and statistical algorithms that are used to accurately predict the performance of wind turbines. These include gated recurrent unit (GRU) and autoregressive integrated moving average (ARIMA). This model is obtained by using python software that uses a coding of various algorithms and then comparing the performance of accuracy matrices of each algorithm to predict the correct and best model for the prediction of wind turbine output. The model that shows high accuracy is said to be the best model for forecasting renewable energy, which would not be possible without machine learning and deep learning techniques. The flow chart for forecasting wind turbine output using Artificial Intelligence (AI) is shown in Fig. 6.

4.1. Gated Recurrent Unit (GRU)

A gated recurrent unit is an advanced version of a recurrent neural network. It was introduced by Kyunghyun Cho et al in the year of 2014. It is used to solve the vanishing gradient problem faced by the Recurrent neural network (RNN). Gated recurrent units (GRU) are very similar to Long Short-term Memory (LSTM) and use gates to control the flow of information. But unlike a Long Short-term Memory (LSTM) it has only two gates i.e update and a reset gate. Gated recurrent units (GRU) are more efficient than Long Short-term Memory (LSTM) as it takes less time for training. Due to their more straightforward construction, they provide certain improvements over Long Short-term Memory (LSTM).

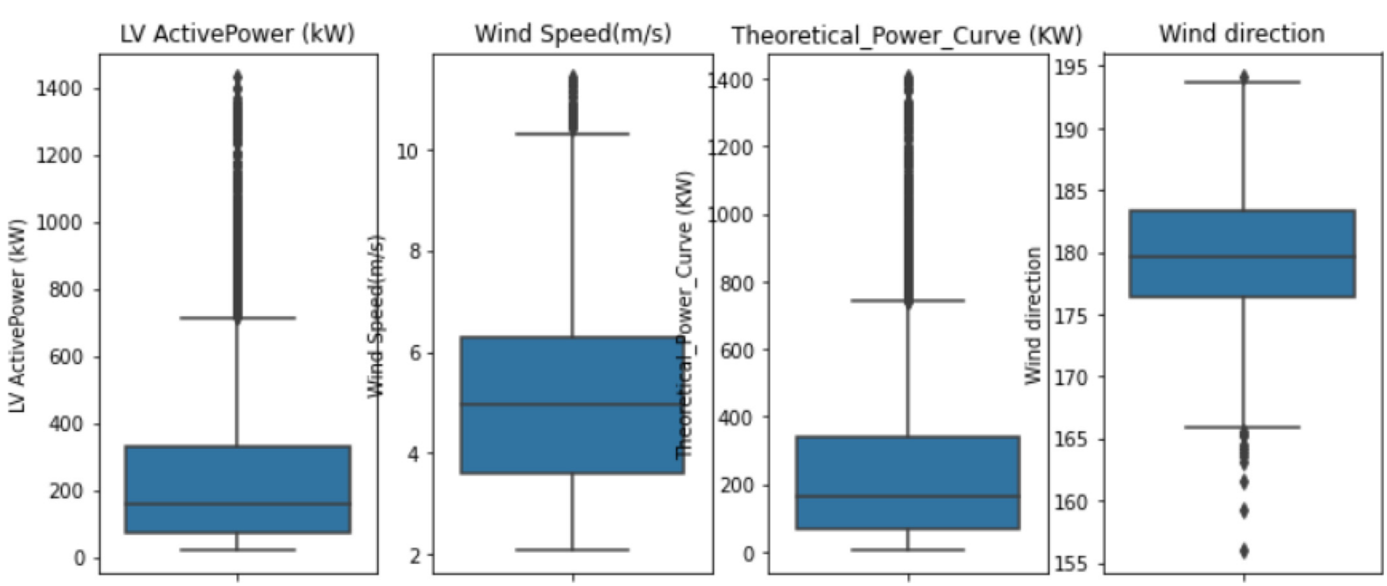

Fig. 3. A scenario of the data is plotted in form of a Boxplot in Jupyter Notebook.

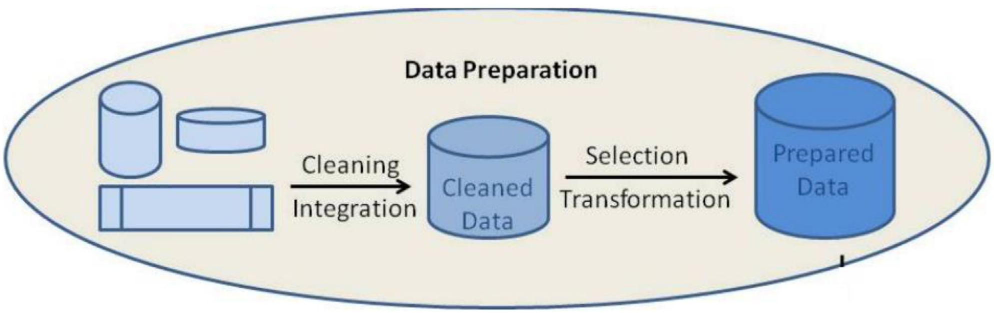

Fig. 4. A sliding window approach to preparing data for Training.

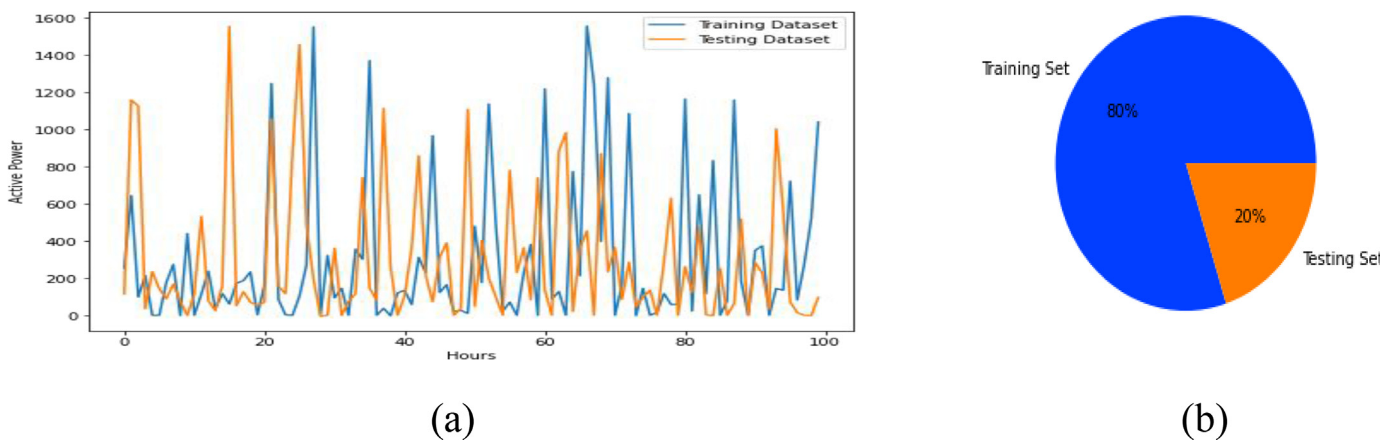

Fig. 5. Data Splitting into Training and Testing (a) Active power vs time (b) Pie plot.

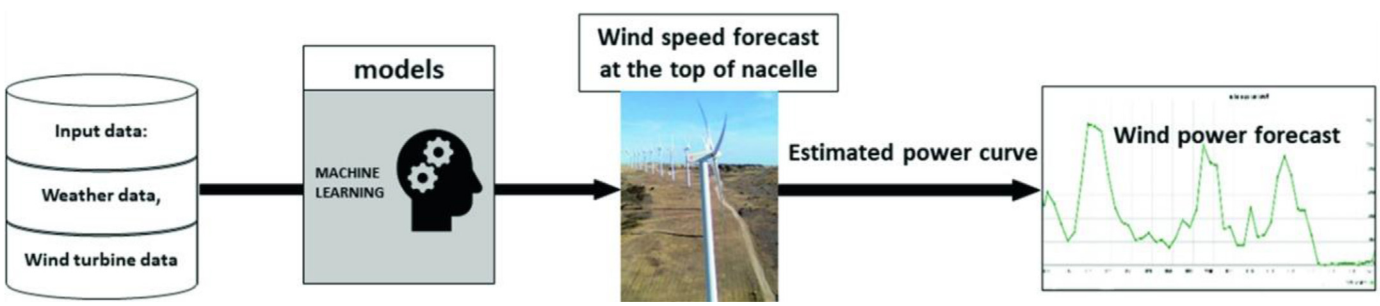

Fig. 6. Wind Power Forecasting using Artificial Intelligence (AI).

Gated recurrent units (GRU) consist of the only hidden state while Long Short-term Memory (LSTM) consists of both hidden and cell states. It is the reason that Gated recurrent units (GRU) are faster to train. Let's understand the working of Gated recurrent units (GRU) in detail by considering the above figure. At each timestamp "t" it requires an input x_t and the hidden state h_{t-1} from the preceding timestamp t-1. The next timestamp is assigned a new hidden state, h_t, which then generates an output. A Gated recurrent units (GRU) currently only has two gates as compared to the Long Short-term Memory (LSTM) cell's three gates. The first gate is known as the update gate and the second gate is known as the Reset gate.

4.1.1. Update Gate

The update gate is also known as long-term memory, and it defines in Eq. (1).

$$z_t = \sigma\left(x_t W^{(Z)} + U^{(Z)} h_{t-1}\right) \tag{1}$$

The current input x_t is multiplied by its own weight $W^{(Z)}$ and the result is added with the product of the previously hidden layer h_{t-1} and its own weight $U^{(Z)}$ (Fig. 7). Following the above scheme shows the equation in a graphical way. The model is aided by the update gate in deciding how much historical data from earlier time steps should be sent to the future. This is very helpful since the model can decide to replicate all the historical data, so removing the possibility of a vanishing gradient.

4.1.2. Reset Gate

In essence, the model uses this gate to determine how much of the past data should be forgotten. It is calculated using with Eq. (2).

$$r_t = \sigma\left(x_t W^{(r)} + U^{(r)} h_{t-1}\right) \tag{2}$$

This formula is the same as the one for the update gate. The difference comes in the weights and the gate's usage. The reset gate is responsible for the short-term memory. Fig. 8 shows the clear representation of the Eq. (2).

4.1.3. Candidate hidden state

The reset gate output r_t is multiplied by the input and hidden state from timestamps t-1. The result of providing all of this information to the tanh function is the hidden state of the candidate. The key to this equation is how we use the value of the reset gate to estimate how much the previous hidden state can influence the candidate state. When r_t equals

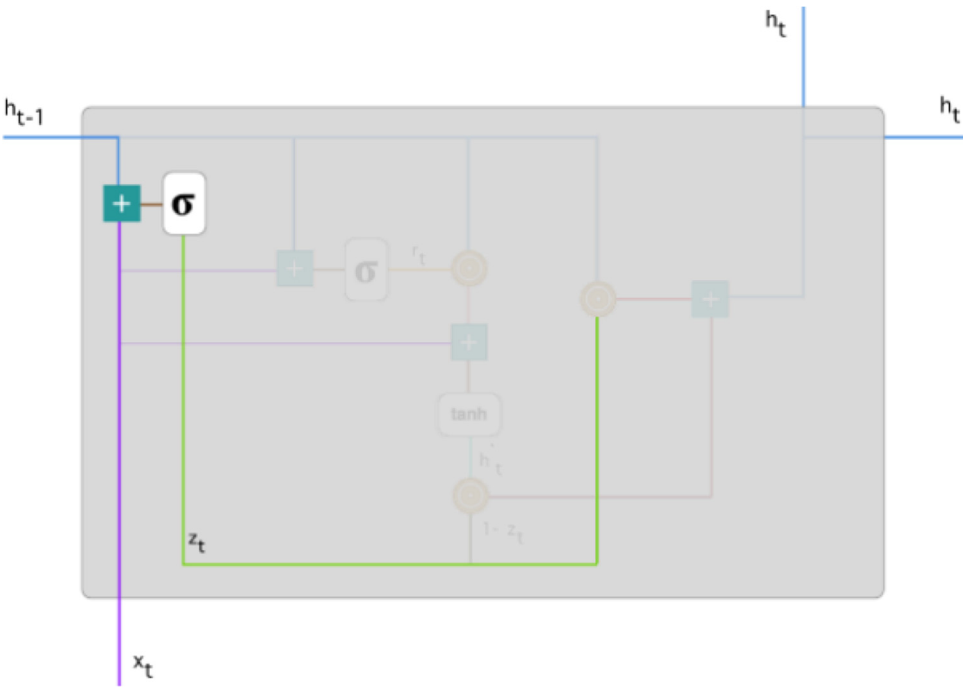

Fig. 7. Formation of update gate.

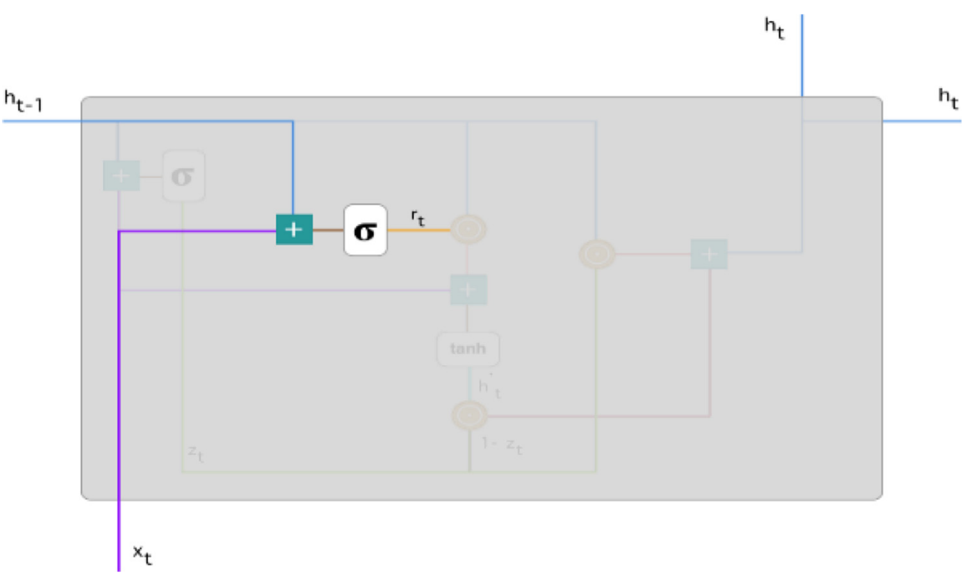

Fig. 8. Formation of reset gates.

1, all of the data from the preceding hidden state ht-1 is considered. Similarly, if the value of r_t is 0, the information from the previous hidden state will be completely ignored.

4.1.4. Hidden state

Once we have obtained the candidate state, it is used to generate the current hidden state, h_t. Here, is when the update gate enters the picture. We employ a single update gate in GRU to govern both the historical information (h_{t-1}) and the new information, as opposed to using two gates like in LSTM (from the candidate state). It is calculated using with Eq. (3).

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h_t^{'} \tag{3}$$

The formation of the hidden state is given in Fig. 8. If z_t is close to 0, the first term in the equation will vanish, indicating that there won't be much information left over from the previous hidden state in the current hidden state. On the other hand, the second component merges into one and provides the hidden state at the current timestamp which only contains information from the candidate state. Similarly, if z_t is on the second term, the current hidden state will be totally dependent on the first term, i.e., the information from the hidden state at timestamp t-1. As a result, the value of z_t in Eq (3). is quite important, as it might range from 0 to 1.

Fig. 9

The basic structure of Gated recurrent units (GRU) is formed by combining all the preceding processes, as indicated in the diagram (Fig. 10.)

4.2. Autoregressive integrated and moving average (ARIMA)

ARIMA an abbreviation for Autoregressive integrated and moving average is a combination of two models AR (Autoregressive) and MA (Moving average) by adding integration in the time series data. Both of these algorithms are used to predict future events in the time series data.

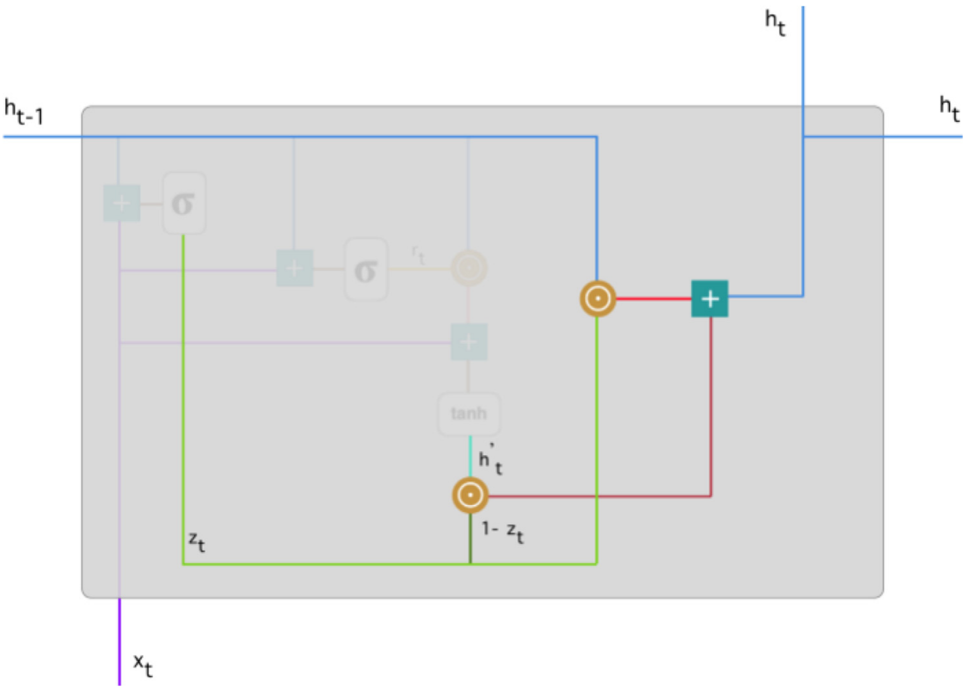

Fig. 9. Formation of hidden state.

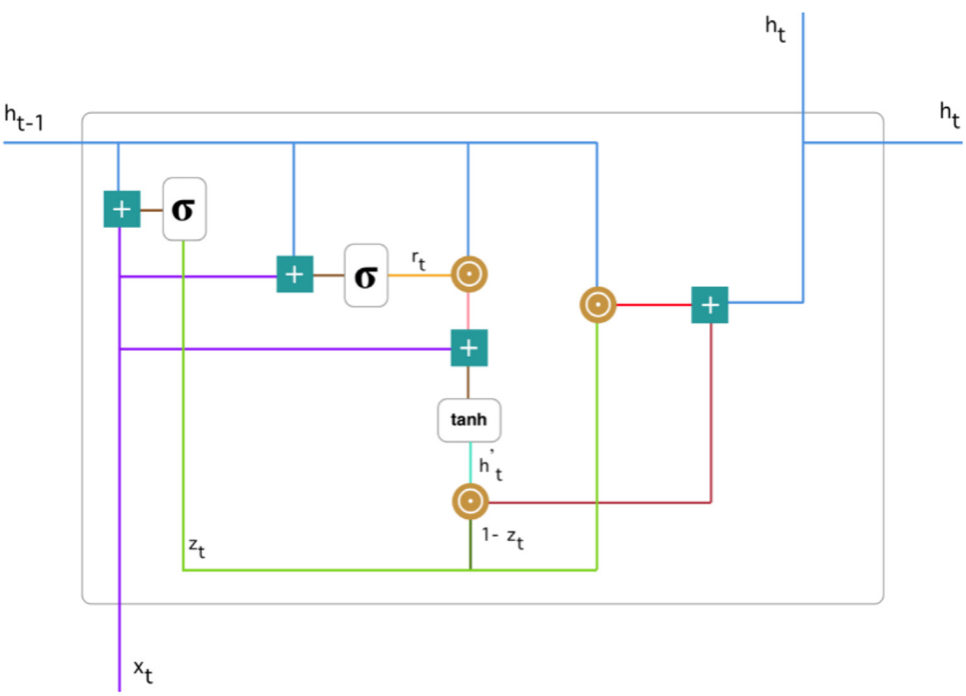

Fig. 10. Basic Structure of Gated recurrent Units (GRU).

The type of regression analysis called Autoregressive integrated and moving average (ARIMA) demonstrates the strength of a dependent variable in relation to other variables that are subject to change. By focusing on the differences in the series values rather than actual values, the model's primary goal is to forecast future time series movement. When there is evidence of non-stationarity in the data, Autoregressive integrated and moving average (ARIMA) models are used.

The trend and seasonal components are two common causes of non-stationary data in time series. The differencing process is used to convert non-stationary data into stationary data. To remove the trend component in the data, one or more times of differencing steps can be used.

The Autoregressive integrated and moving average (ARIMA) model is generally represented as p, d, q, and parameter p, d, q is defined in Fig. 11.

The model's capacity to forecast the true value by obtaining the expected output is determined by the loss function and the performance itself. The function's output demonstrates the applicability of the created model. For instance, a high output value denotes a model that performs poorly, whereas a low number denotes a model that performs well, Forecast the result. Mean Squared Error (MSE), Mean Absolute Error (MAE), and Huber are the three most frequently used loss functions in machine learning. Loss given that it has an impact on learning is crucial to train the model with the proper loss function. In certain ways.

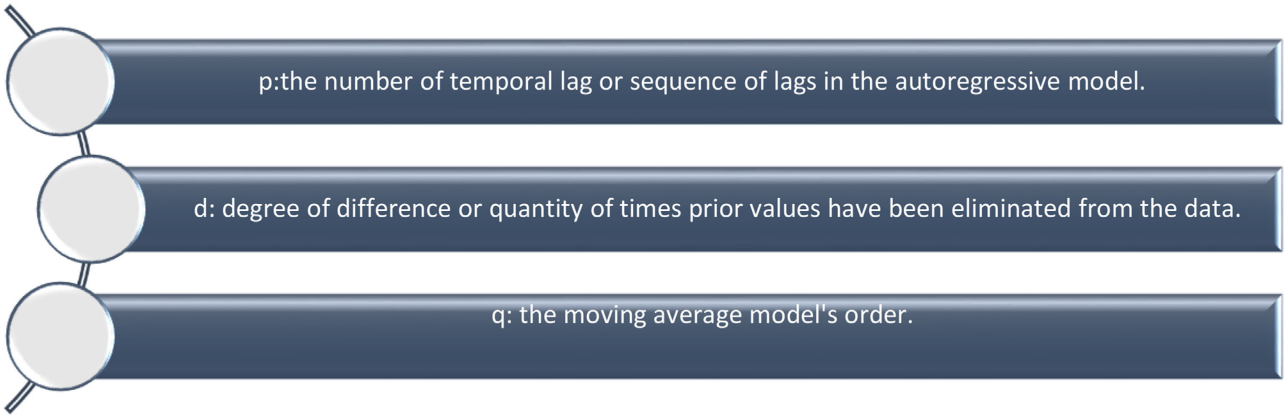

Fig. 11. Parameters for Autoregressive integrated and moving average (ARIMA) model.

For instance, when there are outliers in the Mean Absolute Error (MAE), Mean Squared Error (MSE) prioritizes adequate model training. This is helpful for avoiding outliers when the model is being trained.

5. Evaluation Metrics

The performance of the proposed model for the short-term prediction has been measured by using statistical parameters/indices i.e., Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentile Error (MAPE), Mean Squared Error (MSE), Coefficient of Determination (R^2) to achieve the goal of the project. The aim was to fix the models for wind speed forecasting applications with better accuracy and minimal statistical error.

5.1. Mean Squared Error (MSE)

The average of the squares of the deviations, which is the difference between the estimator and what is estimated, is measured by the mean squared error of an estimator in statistics. The difference between the actual value and the anticipated value results from either the prediction curve being over-fitted or under-fitted, which decreases the model's accuracy.

The Mean Equared Error (MSE) is a measure of the quality of an estimator it is always positive, and values closer to zero are better (Karaman et al., 2021; Geetha et al., 2022). It can be calculated by Eq. (4):

$$MSE = \frac{1}{n}\sum_{i=0}^{n}\left(y_i - y'_p\right)^2 \tag{4}$$

5.2. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is the difference between two continuous variables, which are referred to as the actual and anticipated values, which are represented by y and y' in statistics. By comparing the estimator and the estimated value, we may determine the error between these two variables as well as the accuracy of the metrics (Wu et al., 2022). It can be determined by Eq. (5).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_p\right| \tag{5}$$

5.3. Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) presents information on the short-term performance of the prediction models. Root Mean squared Error (RMSE) value is always positive and is desired to be close to zero (Ağbulut et al., 2021; Kadad et al., 2022). The Root Mean Squared Error (RMSE) is calculated using Eq. (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_p\right)^2} \tag{6}$$

5.4. Mean Absolute Percentile Error (MAPE)

The Mean Absolute percentile Error (MAPE), or Mean Absolute Error (MAE) in percentage, calculates how far the model's forecasted values are, on average, from their actual values. This approach is unaffected by outliers like Mean Absolute Error (MAE) because it also uses the absolute value. Since both Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) have values ranging from zero to positive infinity, this method can be used to analyze the performance of the model by scaling predicted values against the true value. Mean Absolute Percentile Error (MAPE) can be calculated by using Eq. (7) (Ağbulut et al., 2021; Teke et al., 2015).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_p}{y_i}\right| \tag{7}$$

5.5. Coefficient of Determination

This metric presents knowledge about how well a model can predict a set of measured data. The value of R^2 varies between 0 and 1. The R^2 value approaching 1 is an indication of better performance (Gürel et al., 2021). R^2 value is obtained by Eq. (8).

$$R^2 = 1 - \frac{\sum_{i=0}^{n}\left(y_i - y_p\right)^2}{\sum_{i=0}^{n}\left(y_i - y^-\right)} \tag{8}$$

6. Results and Discussion

This section describes the results obtained by the models that are discussed in the above section in Jupyter Notebook by using Python Programming. For that reason, the various libraries are imported according to the type of model being used in the Anaconda shell, and then data can be loaded by using the pandas' library, after performing these steps the major step is to clean the data in order to remove the unwanted rows, columns or some Nan values from the dataset. After cleaning the dataset, the dataset can be Split into training and testing by a ratio of 80% and 20%. The model is trained in 80% of the data and then algorithms are used on 20% of the testing dataset. The results can be obtained on the testing dataset by using statistical, artificial intelligence algorithms which are explained in detail below:

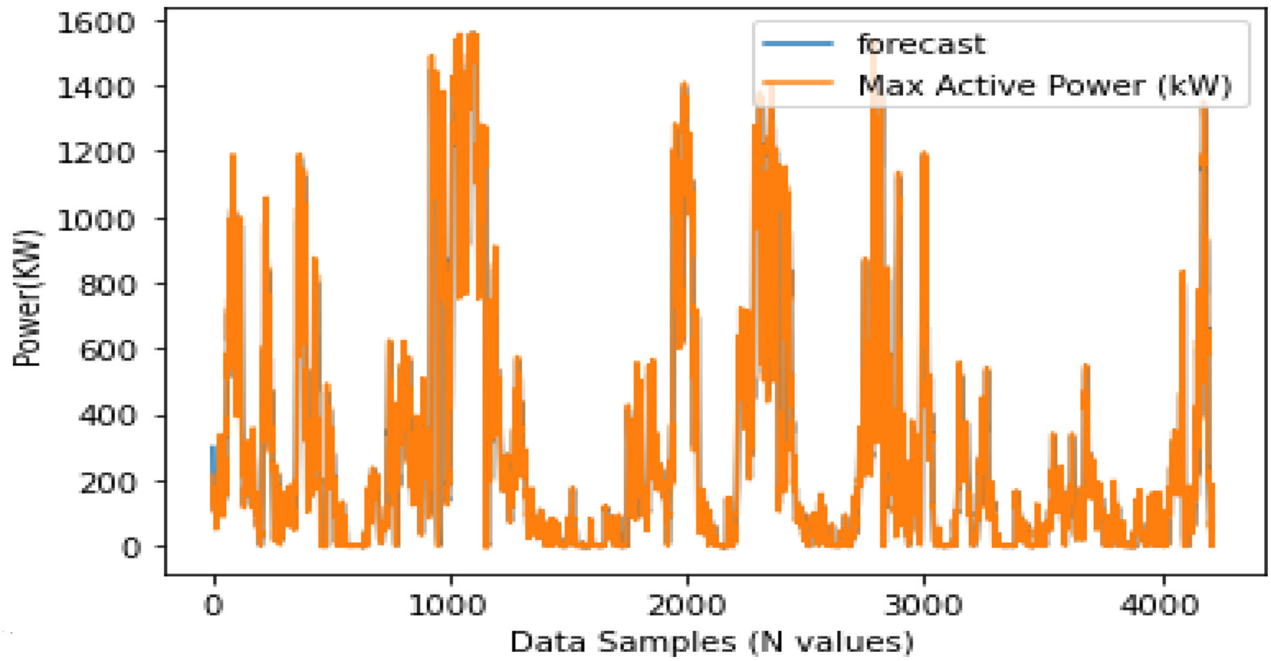

Fig. 12. Forecasted and Actual Power (KW) of Autoregressive integrated moving average (ARIMA).

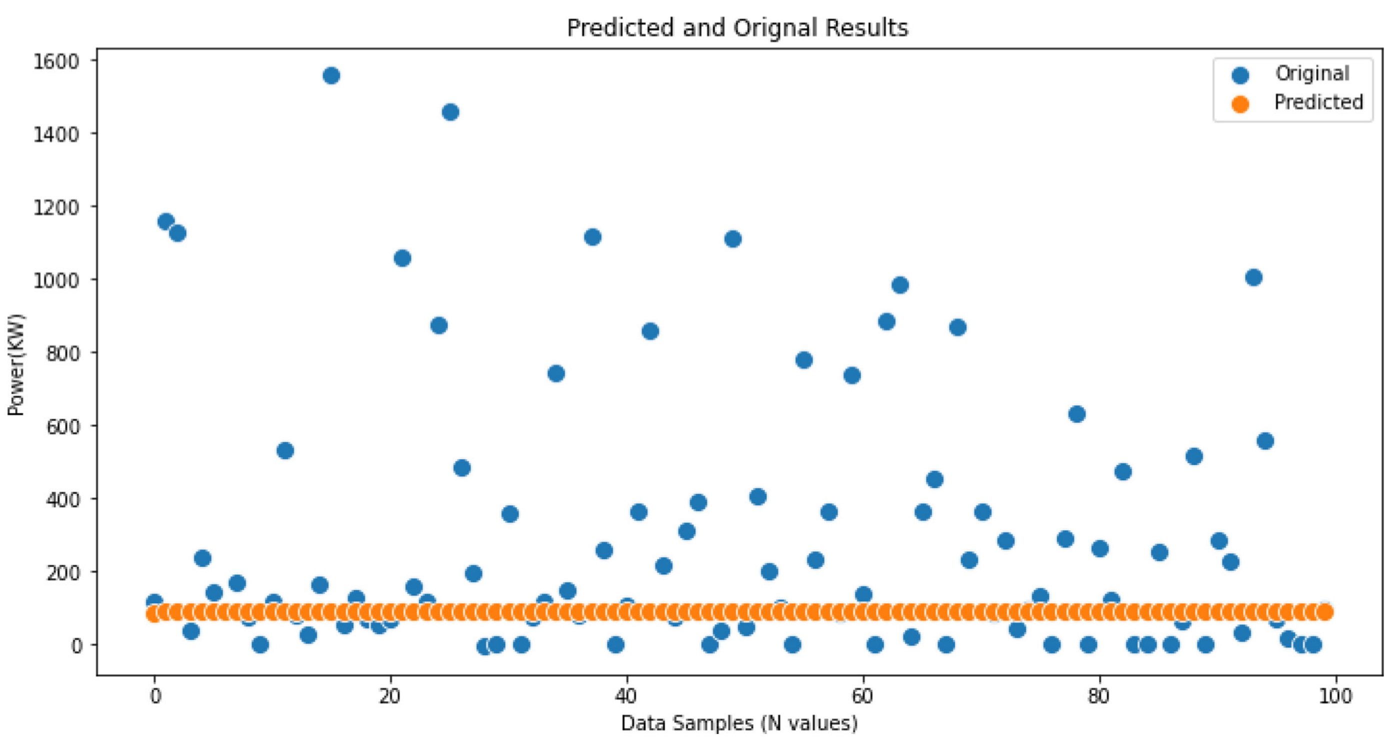

Fig. 13. . Forecasted and Actual Power (KW) of Autoregressive integrated moving average (ARIMA).

6.1. The Results for Autoregressive integrated moving average (ARIMA)

It is a statistical and time series algorithm, the detail about this model is already mentioned in the chapter modeling section. The output of the wind turbine is predicted and the plot between actual and predicted values of the Wind turbine is shown in Fig. 12. This figure shows the output of the wind turbine by taking all the datasets together that's why the plot shows to be denser.

By taking some portion of the dataset the scattered plot is generated between actual and predicted values of wind turbine output as shown in Fig. 13.

Autoregressive integrated moving average (ARIMA) is a simple yet powerful method to forecast the output, but it depends upon the seasonality and trend of the function so without knowing this we can't predict the output. Hence it does not show accurate results in such cases and is usually avoided. During the training of the model, residual errors can be plotted in the Autoregressive integrated moving average (ARIMA)

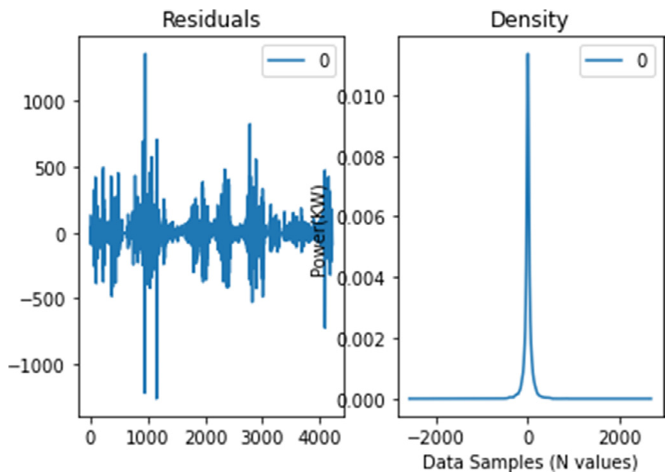

Fig. 14. Residual Errors of Autoregressive integrated moving average (ARIMA) Model.

Table 1
Statistical metrics of Autoregressive integrated moving average (ARIMA) Model.

Metric	Value
MAPE %	-475.7425
ME %	-179.75
MAE%	226.558
MPE%	-476.49
RMSE%	397.639
CORR%	0.03
MINMAX%	0.655

Table 2
Statistical Metrics of Gated Recurrent Unit (GRU) Model.

Metric	Value
R^2	0.891
MSE	0.0022
MAE	0.03
RMSE	0.047

Model that shows the values of the curve in the zero value, and the curve of density is plotted in the range of -2000 to 2000. Where a spike is generated at 0 value. The plot is shown in Fig. 14.

The power curve shows the relationship between wind speed and wind power, by mathematically wind power is directly proportional to the cube of the wind speed of the turbine. This relationship is plotted with the help of python coding in Jupyter Notebook in Autoregressive Integrated Moving Average (ARIMA) Model as shown in Fig. 15.1.

The performance measures show the performance of model and the behavior of the model. The values of the various accuracy metrics of the Autoregressive integrated moving average (ARIMA) model are shown in Table 1.

6.2. The results for Gated Recurrent Unit (GRU)

It is a deep learning neural network algorithm. During the data spiting the plot is generated between training and testing in Gated Recurrent Unit (GRU) model and the output is shown in Fig. 16.

The output of the wind turbine is predicted and the plot between the actual and predicted values of the wind turbine is shown in Fig. 17.

By taking some portion of the dataset the scattered plot is generated between actual and predicted values of wind turbine output as shown in Fig. 18.

The Performance measures show the performance of the model and the behavior of the model. The values of the various accuracy metrics of the Gated Recurrent Unit (GRU) model are shown in Table 2.

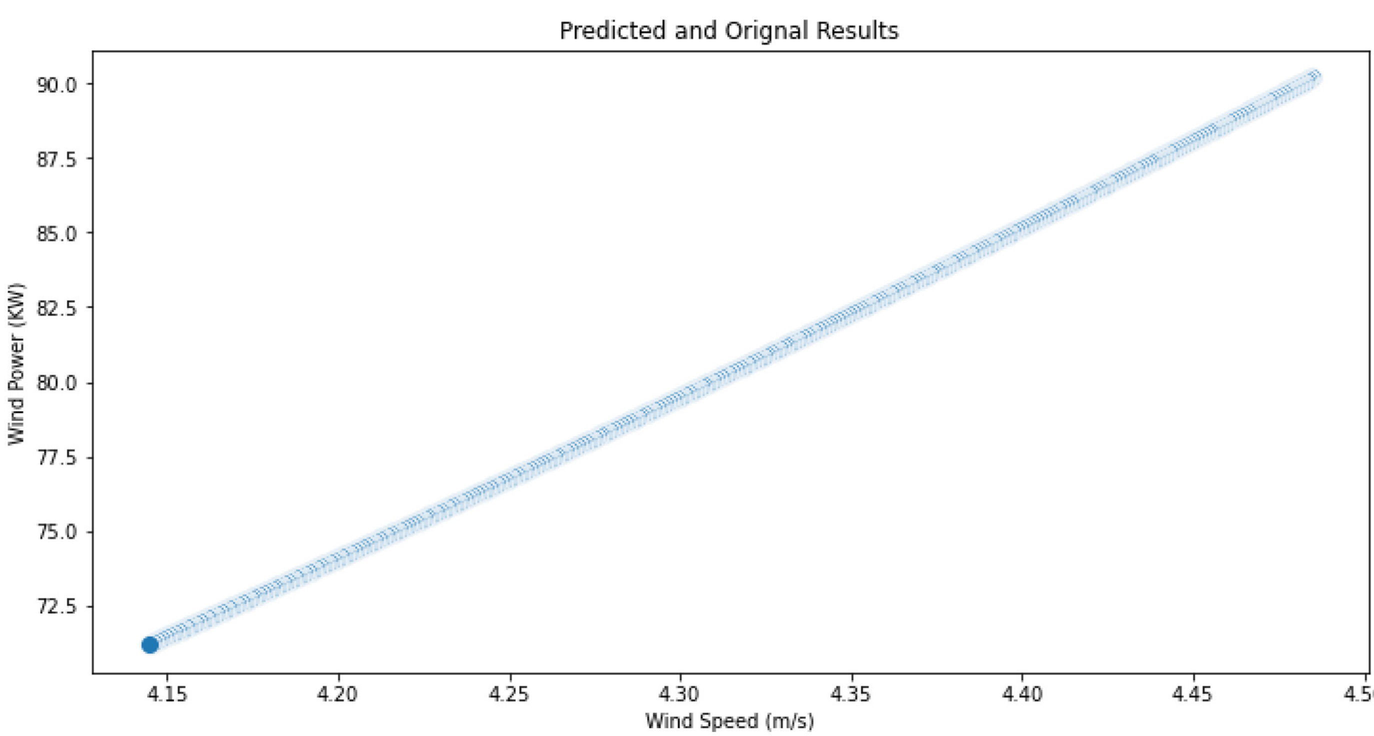

Fig. 15. Power Curve of wind turbine.

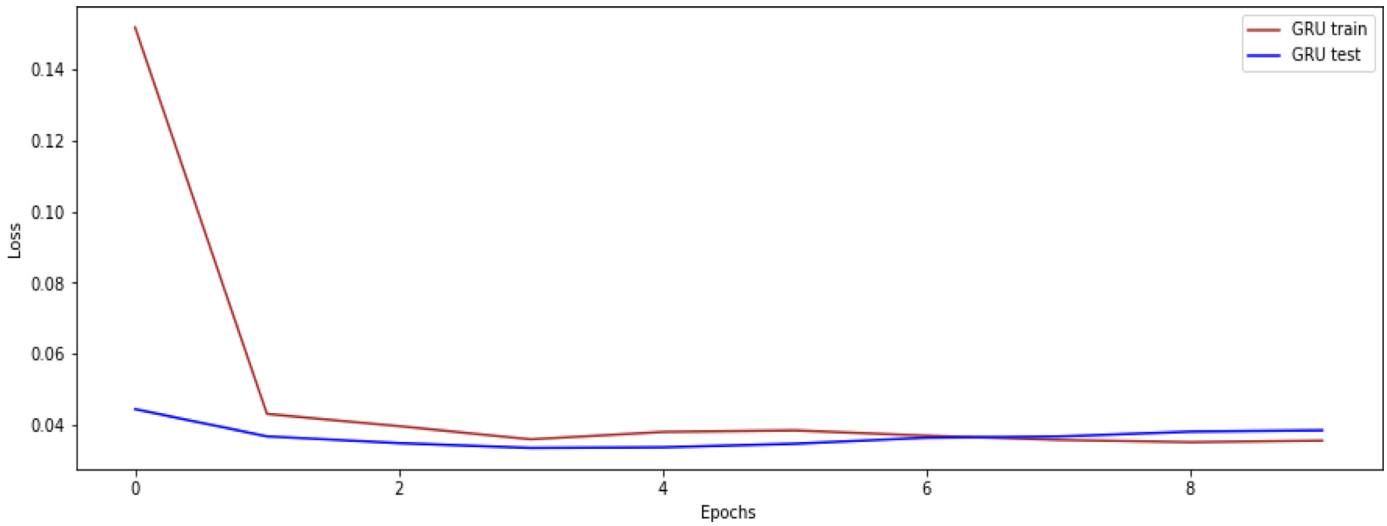

Fig. 16. Training and testing of the Gated Recurrent Unit (GRU) Model.

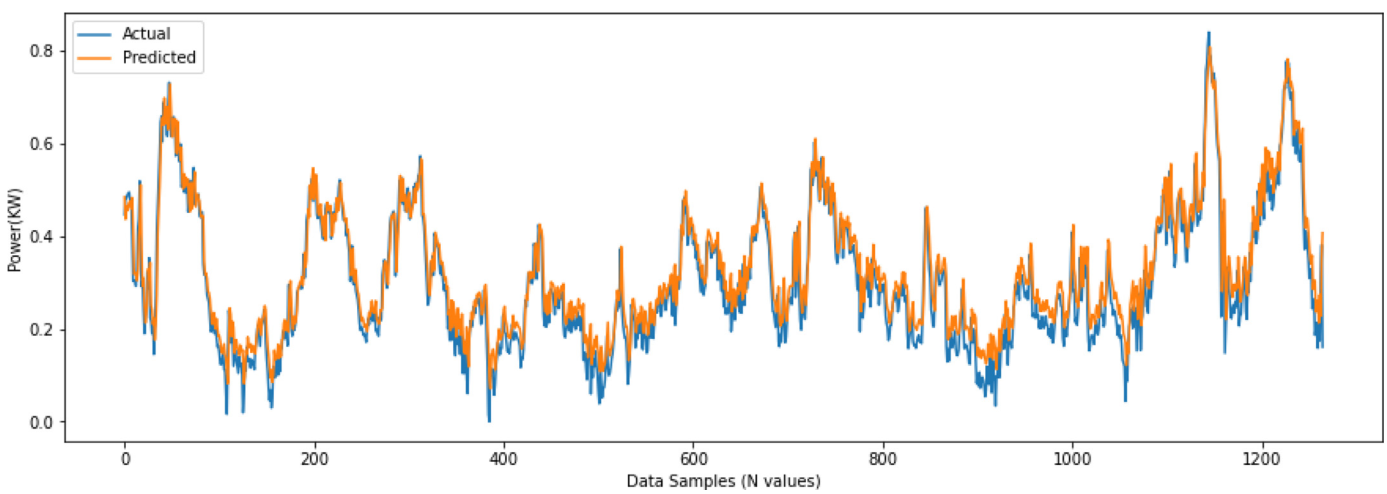

Fig. 17. Forecasted and actual power (kW) of Gated Recurrent Unit (GRU) Model.

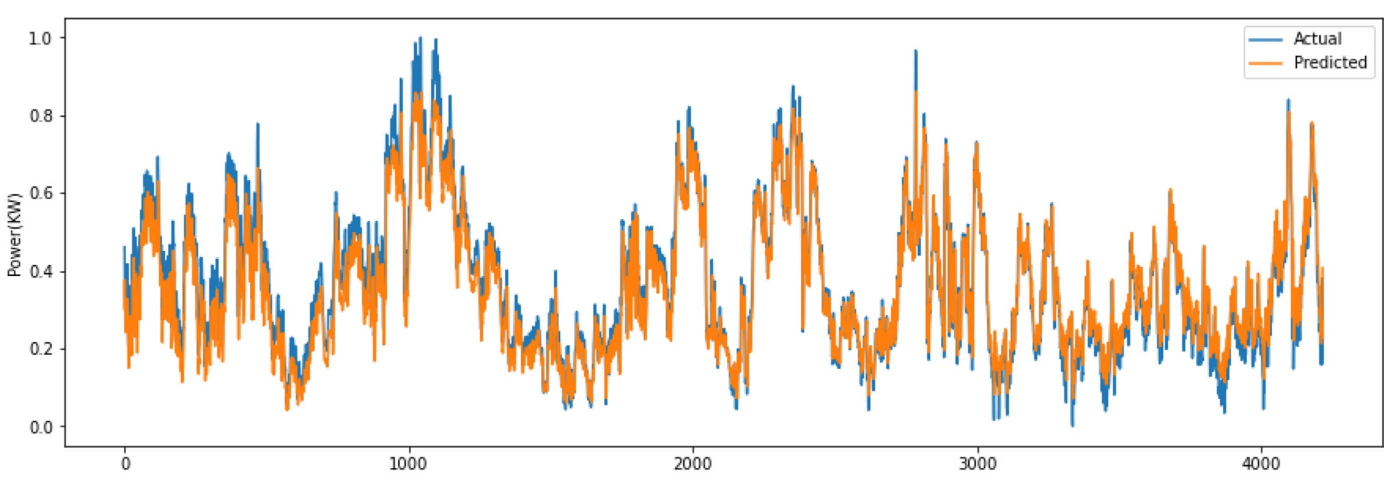

Fig. 18. Forecasted and actual power (kW) of Gated Recurrent Unit (GRU) Model.

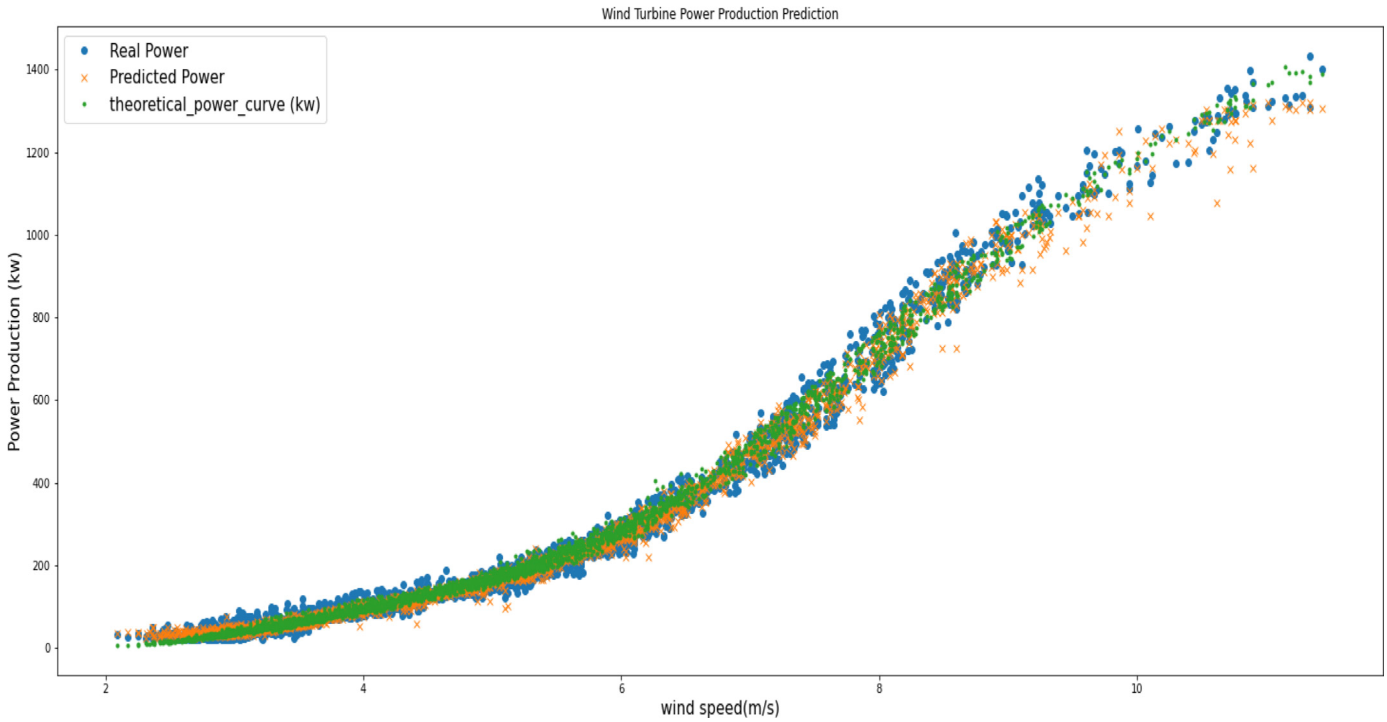

Fig. 19. Power curve of Gated Recurrent Unit (GRU) model.

Table 3
Advantages and disadvantages of models.

Advantages	**Autoregressive integrated moving average (ARIMA)** 1. It performs a time series forecasting 2. Its training time is high. 3. Robustness 4. Strong generalization capacity.	**Gated Recurrent Unit (GRU)** 1. It is a deep neural network that consists of hidden layers. 2. Its training time is low. 3. Robustness. 4. Avoid overfitting.
Disadvantages	**Autoregressive integrated moving average (ARIMA)** 1 It highly depends on seasonality and trends. 2 Complex model. 3 It does not have a memory to store the data. 4 Usually Avoided.	**Gated Recurrent Unit (GRU)** 1 Faster. 2 Less Complex as it has two gates. 3 It has the memory to handle long-term dependencies. 4 Highly preferred.

Table 4
Accuracy of forecasting models.

Models	Mean Absolute Percentile Error (MAPE)	Mean Error (ME)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)
Autoregressive integrated moving average (ARIMA)	475.74	226.55	397.639	226.55
Gated Recurrent Unit (GRU)	0.456	0.037126	0.0479	0.037126

The power curve shows the relationship between wind speed and wind power, by mathematically Wind power is directly proportional to the cube of the wind speed of the turbine. This relationship is plotted with the help of Python coding in the Jupyter Notebook in the Gated Recurrent Unit (GRU) Model as shown in Fig. 19.

The results of the study show that both models evaluated have advantages and disadvantages. Table 3 was created so that these advantages and disadvantages can be better understood by the reader.

The statistical metrics of each algorithm is compared with each other and those models who has least errors and high accuracy are said to be the accurate or best forecasting model for the wind power plant at Jhimpir Pakistan. Those model whose value of accuracy metrics is nearer to the 1 are known as accurate models, whereas those models whose value of accuracy metrics is larger are known as worst model. The accuracy of the forecasting models is shown in the Table 4.

7. Conclusion

- In this article, we have analyzed the prediction of wind power by using some historic data from the wind turbine data. We tested two algorithms namely ARIMA (Autoregressive integrated moving average) from statistical models, and GRU (Gated recurrent unit) from deep learning models by using Python Programming. We compared different parameters of the Huber Loss Function with another algorithm in the form of accuracy matrices and graphs. In this study, we concluded that Gated Recurrent Unit (GRU) shows us the best output against the Autoregressive integrated moving average (ARIMA).

- Initially, the data is collected, then pre-processed, then we developed the forecasting module that needs to be tested, in the third step we trained the model by taking some part of the input data and feed into the model, and in the last step, we got our output in the form of performance measuring parameters. In the literature review, we found that different researchers proposed the study about different methods of predicting the algorithms, and the efficiency of models varies with the amount of data given to the different models. In this study, we found out that Gated Recurrent Unit (GRU) gives the best results when compared to Autoregressive integrated moving average (ARIMA).
- The model is developed on the Jupyter Notebook Software using Python language as it is the most dominating and easiest language in the world nowadays.
- In the future, by using Hybrid models of Artificial Intelligence, the generated result can be more accurate and predicts the exact output of the wind turbine with the least possible errors and produces high Accuracy. The predicted Output of the wind turbine can be changed by using more data points, as data is the first and foremost important step of this research.
- These models can be deployed on a higher level by using Flask Software and are useful for real-time applications just as web development, and web desktop applications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Ağbulut, Ümit, Gürel, Ali Etem, Biçen, Yunus, 2021. Prediction of daily global solar radiation using different machine learning algorithms: Evaluation and comparison. Renewable and Sustainable Energy Reviews 135, 110114.

Delgado, I., Fahim, M., 2020. Wind turbine data analysis and LSTM-based prediction in SCADA system. Energies 14 (1), 125.

Geetha, A., Santhakumar, J., Sundaram, K.M., Usha, S., Thentral, T.T., Boopathi, C.S., Sathyamurthy, R., 2022. Prediction of hourly solar radiation in Tamil Nadu using ANN model with different learning algorithms. Energy Reports 8, 664–671.

Gürel, A.E., Ağbulut, Ü., Biçen, Y., 2020. Assessment of machine learning, time series, response surface methodology and empirical models in prediction of global solar radiation. Journal of Cleaner Production 277, 122353.

Kadad, I.M., Ramadan, A.A., Kandil, K.M., Ghoneim, A.A., 2022. Relationship between ultraviolet-b radiation and broadband solar radiation under all sky conditions in kuwait hot climate. Energies 15 (9), 3130.

Karaman, Ö.A., Ağır, T.T., Arsel, İ., 2021. Estimation of solar radiation using modern methods. Alexandria Engineering Journal 60 (2), 2447–2455.

Liu, Y., Guan, L., Hou, C., Han, H., Liu, Z., Sun, Y., Zheng, M., 2019. Wind power short-term prediction based on LSTM and discrete wavelet transform. Applied Sciences 9 (6), 1108.

Peiris, A.T., Jayasinghe, J., Rathnayake, U., 2021. Forecasting wind power generation using artificial neural network: "Pawan Danawi"—A case study from Sri Lanka. Journal of Electrical and Computer Engineering 2021.

Rashid, H., Haider, W., Batunlu, C., 2020. Forecasting of wind turbine output power using machine learning. In: 2020 10th International Conference on Advanced Computer Information Technologies (ACIT). IEEE, pp. 396–399.

Teke, A., Yıldırım, H.B., Çelik, Ö., 2015. Evaluation and performance comparison of different models for the estimation of solar radiation. Renewable and sustainable energy reviews 50, 1097–1107.

Wu, J., Fang, H., Qin, W., Wang, L., Song, Y., Su, X., Zhang, Y., 2022. Constructing High-Resolution (10 km) Daily Diffuse Solar Radiation Dataset across China during 1982–2020 through Ensemble Model. Remote Sensing 14 (15), 3695.