Materials Today: Proceedings xxx (xxxx) xxx

Contents lists available at ScienceDirect

Materials Today: Proceedings

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

Wind power forecasting based on time series model using deep machine learning algorithms

V. Chandran [a], Chandrashekhar K. Patil [b], Anto Merline Manoharan [a], Aritra Ghosh [c], M.G. Sumithra [a], Alagar Karthick [d,*], Robbi Rahim [e], K Arun [f]

[a] Department of Electronics and Communication Engineering, KPR Institute of Engineering and Technology, Arasur, Coimbatore 641407, Tamilnadu, India
[b] Department of Mechanical Engineering, Brahma Valley College of Engineering & Research Institute, Nashik 422 213, Maharashtra, India
[c] College of Engineering, Mathematics and Physical Sciences, Renewable Energy, University of Exeter, Cornwall TR10 9FE, UK
[d] Department of Electrical and Electronics Engineering, KPR Institute of Engineering and Technology, Arasur, Coimbatore 641407, Tamilnadu, India
[e] Department of Informatics Management, Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Sumatera Utara 20219, Indonesia
[f] Udhaya Semiconductors Limited, Avinashi Road, Coimbatore 641062, Tamilnadu, India

ARTICLE INFO

Article history:
Received 25 March 2021
Accepted 31 March 2021
Available online xxxx

Keywords:
GRU
RNN
LSTM
Wind power forecasting
Deep Machine learning

ABSTRACT

Wind energy is a created due the uneven heating of the earth surface and Coriolis acceleration. Wind energy source is capable of continuously and sustainably producing energy from renewable sources (RES). However, energy generation from the wind power plant has number of issues, such as initial investment costs, wind power plant stationary properties and difficulty in identifying wind power zones. Three deep learning algorithms are utilized in the study for predict short-term wind power generation from wind speed data. We suggested a system that would effectively predict wind power values of wind power by utilizing machine learning algorithms. The machine algorithms adopted for this study is Long Short-Term Memory (LSTM), Gated Reference Unit (GRU) and Recurrent Neural Network (RNN). The models proposed are applied in six times to the projection of wind farm output. The error analysis to balance performance and other approaches is carried out. More concerns are also discussed on short-term wind energy forecasts accuracy improvement. Furthermore, the results have shown that machine learning models can be used in locations other than models. This research showed that, if the basic location model is reasonable, machine learning algorithms could be efficiently used before installation of the wind power plants in an unknown geographical area.

Selection and peer-review under responsibility of the scientific committee of the 12th National Conference on Recent Advancements in Biomedical Engineering.

1. Introduction

Wind energy has gained enormous interest in many countries, on account of environment deterioration, fossil fuels depletion and the increasing need for electricity. Indeed, wind energy is increasingly growing renewable energy source [1–5]. The variable nature of wind energy, however, could jeopardise electricity system reliability, stability and efficiency [6,7]. The wind resources assessment is a vital way in which wind turbines are built efficiently, wind farms are built. This problem is the manner in which we forecast and model statistics. Machine training and algorithms for artificial intelligence are also successful [8–12]. In the near future, one of the most critical problems for the global energy market is ensuring operational security by increased integration of renewable energy resources [13–18]. For potential global energy supply and demand, high RE integration tools will be major challenges. Wind energy utilization is clearly sustainable, renewable, unavoidable and cost effective [19–23] among the numerous RE sources like geothermal, tidal energy and solar. Although wind power uses are still confronted with many hurdles, it is an unreliable source of energy in grids, and in these references, it provides spatial and temporal variables [24–27]. The ranges and applications of energy prediction models are relatively broad [11,12,28–30] and the state-of-the-art prediction model's usage and application in different areas in real time are highlighted in the carried-out research. Profound awareness and expert regulatory trend for energy-saving buildings in the field of air conditioning and cooling

* Corresponding author.
E-mail address: karthick.power@gmail.com (A. Karthick).

https://doi.org/10.1016/j.matpr.2021.03.728
2214-7853/
Selection and peer-review under responsibility of the scientific committee of the 12th National Conference on Recent Advancements in Biomedical Engineering.

Please cite this article as: V. Chandran, C.K. Patil, A. Merline Manoharan et al., Wind power forecasting based on time series model using deep machine learning algorithms, Materials Today: Proceedings, https://doi.org/10.1016/j.matpr.2021.03.728

[31]. The energy management strategy was evaluated for the HPS framework as well as the cell temperature estimates for energy characterisation in large solar cell modules [32–40]. Multiclass Approaches and Model regression are the two of the three supervised learning algorithm types in machine learning. The binary results (1 in 2 expedient groups are predicted using ML algorithms with binary distribution technology. ML models with Multi-class predicament utilized for different groups to be made (Fig. 1 or more than two outcomes) prediction. The regression algorithms ML model a numerical forecast. In order to train the regression algorithm Amazon ML is using the industry algorithm called multiple linear regression functions. Multiple Linear regression functions which is known as industry algorithm is utilized by Amazon ML to train the regression algorithm. Linear regression algorithms are further classified into two groups, uncontrolled ML models is one of the two classified group of linear regression algorithm [41]. For the estimation of electrical loads, the deep-believing network Boltzmann machine (RBM) is used. With low run-time [42], the network reduced the forecast error. Hong et al. uses Volatile Artificial Bee Colony (CABCA) and the SRSVR model integrated hybrid model to predicts the strength of Southeast China. In contrast to the ARIMA (Auto-Regressive Integrated Moving Average) model, the effectiveness of the model is validated [43]. According to the GWEC, the installed wind energy industry in 2018 was 51.3 GW [44], according to the Global Wind Statistics-2018 study (Table 1).

On the basis of the above discussion the work looks to eliminate the formation problem and better prediction of wind power series by introducing deep learning model. Contributions of this paper are: (1) a novel deep-interval prediction method is developed that represents Long Short-Term Memory (LSTM) proof of the prediction; (2) loss functions are optimised for the application of the root average square back propagation and comparative experiments are carried out to fully test and compare the proposed model with traditional models such as Gated recurrent units (GRU), LSTM and Recurrent Neural Network (RNN). The rest of the paper is summarised as follows: Section 2 sets out theoretical histories for the LSTM network, the RNN network and the GRU networks Section 3 sets out a new methodology for the wind power interval forecasting process. Section 4 sets out the specifics of the experiment and the effects. Finally, the Section summarises the findings.

Ping Jiang et al. introduced a hybrid system for wind speed forecasting prediction for wind energy production. The hybrid proposed prediction system consists of forecasting system evaluation, optimal sub-model selection, distribution fitting-based interval forecasting and modified multi-objective optimization-based point prediction. The hybrid model predicts the interval forecasts and wind speed point more accurately than the existing systems in short term prediction. The datasets are obtained from china's Shandong peninsula. The accurate prediction

Table 1
Forecast methods.

Forecasting approach	Remarks	Ref
Time-series models (Persistence, AR, ARMA, ARX, ARIMA, GARCHetc.)	It uses meteorological data which are easily available, for most reliable .forecasting approach	[45–46]
NWP approach	Optimal for long-term forecasting	[47]
SVM-based approaches	Exhibits better generalization capabilities.	[48]
ANN-based approaches	Adjustable for wide range of parameters	[49–50]
	Highly non-linear models such as wind speeds	[51]
Artificial intelligence-based hybrid approaches	To attain better accuracy and robustness in wind forecasting these approaches reduces the computational complexity, limitations by using the superior features of the above-mentioned individual methods of forecasting.	[52]

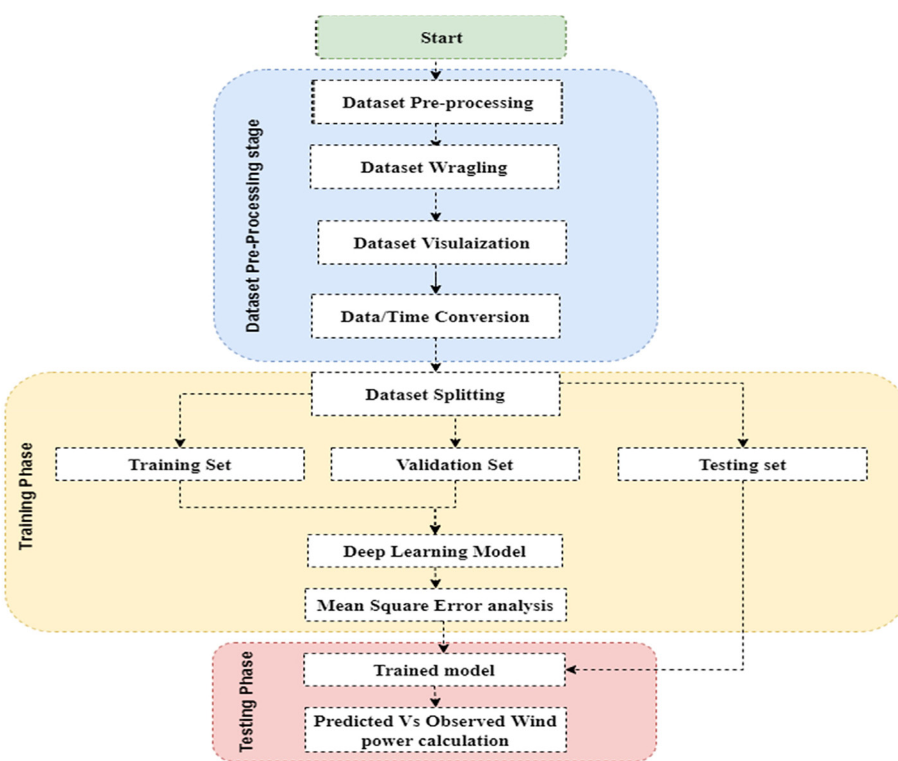

Fig. 1. Overall workflow of the proposed deep learning models.

of the point forecasting and interval prediction helps to determine rotary reserve capacity and wind turbine count and also helps in programming the power grid [53,54]. Wenlong Fu et al. proposed an MHHOGWO based model for optimization of parameters and feature selection. The author works by combining various models to predict the wind speed more accurately. The predictions obtained from the model is the combination of all the integrated modules for multi-step short term wind prediction. The proposed model is tested with four different datasets from two real sites at a different time interval. The combined proposed model gives a more accurate result in prediction [55]. Kijem Nam et al. described a detailed survey about the energy forecasting model for various renewable energy such as fuel from plants, wind farms, IGCC and HSS. It proposed a GRU forecasting model-based on deep-learning for energy forecasting which predict the required electricity and reduce the insufficient of electricity supply in Jeju Island Korea. It is utilizing SWOT assessment for economic environment, technological circumstance of the renewable energy weakness, threats, benefits and its opportunity along with the above-mentioned circumstance [56]. J. J. Yang et al. proposed DRL rainbow algorithm for predict the uncertainty in the wind power and electricity price. The algorithm increases the efficiency of the data-driven controller which in turn reduces the loss in the revenue of the country to Wind Power Producer. The results are validated at Jiangsu province, China through simulated results. It optimizes the uncertainty and overcome the conventional method difficulties by taking discrete input. It also focusses on energy storage system. And purchase reservations [57]. George et al. introduced a model based on Radial Based Functions Neural Networks (RBFNN) to solve non-linear complex problem in solar and wind forecasting. The model improves accuracy of the prediction for performance improvement w.r.t state of art prediction methods. The RBFNN divided into two-part Cluster and Regressors. The cluster part clusters the input data through which the neighbour clusters activated for ensemble prediction and individual prediction. A kernel is used to analyse the input vector with its complimentary parts. The validation of the proposed model is carried out by utilizing two solar and two wind forecasting case study. The main advantage of the model is it solves the regional forecasting non-linear problem and provide high accuracy for even larger sets of data [58].

Hui-li designed a MEC- MMADapGA-MODWT- EOD model which is constructed using integrated deep learning with neural network model. The proposed model combines three modules such as data processing methods, error correction methods and ensemble optimization methods. The proposed method fulfils major drawback in these areas in existing systems. The hybrid model shows improved performance and the model is verified using four real time wind speed data. The real time data is given as an input to neural network model. The performance and accuracy of the deep model in multistep forecasting is higher than the existing models of forecasting [59]. Hui lu et al. proposed a model to enhance the performance of wind speed forecasting prediction. The proposed model consists of three parts in that the input dataset is decomposed into sub-series by EWT the dataset given as an input are non-stationary dataset. The EWT method reduce the uncertainty of non-stationary wind speed data input. Then the output of the EWT is given to the deep learning model which process the sub-series for accurate prediction. Q-algorithm is used to connect the three deep model and also provide optimization better than the conventional optimization methods. LSTM-DBN-ESN are the three deep models. The author compared the adaptability and predictability of the proposed method with sixteen traditional methods and three state of art methods. From the analysis, the proposed model shows better performance in adaptability and prediction than the existing models. The parameter should be updated at regular interval to eliminate the accuracy reduction after long run [60]. Gholamreza et.al designed a model for LSTM based prediction model for wind speed forecasting with mutual information and entropy-based feature selection, crow search algorithm, wavelet transform. The accuracy of the prediction is improved which is validated by applying the model in real-time in several areas. The errors in the forecasting prediction such as RMSE, MAE and MAPE are calculated for the proposed model. The proposed hybrid model optimized WT-FS-LSTM model shows improved performance than MLP,WT-FS,MLS,LSTM,WT-LSTM, WT-FS-LSTM. The proposed model is optimized using two algorithms crow search algorithm and PSO. While comparing the crow search algorithm and PSO optimization method former outperforms the latter method. The proposed model is multi adaptable model which is also used to forecast power load, price and reserve etc. [61]. Ceyhum Yildiz et al. proposed a two-module model for forecasting wind power based on deep learning. The first module, the features extracted are carried out by variational mode decomposition (VMD) the images are created using extracted features, deep convolutional neural network (CNN) based on enhanced residual method is used to forecast the wind power. The results are compared with GoogleNet, Alex net, VCGG-16, ResNet-18, Squeeze net type of state of art existing modules. The proposed model outperforms the other compared models. The proposed model eliminates some errors such as pixel disappearing and gradient by processing the 2D features in every layer of down sampling to improve the accuracy. In the proposed model, the parameter usage is lesser than the existing Resnet 18 model. For more accurate the proposed model is preferrable than the compared existing methods [62].

Zhingun Peng et al. introduces a WSTD model that incorporate with GRU model for forecasting the wind speed data. GRU deep learning model is used to extract the information of time series for forecasting the data. The WSTD model i.e wavelet soft threshold demonising the redundant information to geo accurate forecasting result from the wind speed data set. The introduction model combined with LSTM and the result of forecasting is analyzed. The accuracy of WSTD model with GRU outperforms the other thirty-four existing model. The major drawback wind energy forecasting is depending upon wind speed prediction. The prediction forecasting of wind speed is affected by its unpredictable nature, fluctuation and randomness. The proposed model is 8.02% to 33.82% improves that accuracy then WSTD-LSTN model. The adoptability of the proposed model in multistep is higher than other models [63]. Hamed H.H. aly et al. analysed the performance of various artificial intelligent learning models which are formed by combine various filters such as Recurrent Kalman Filter (RKF), Fourier Series (FS), Artificial Neural Networks (ANN) and Wavelet Neural Network (WNN). By shuffled combination of these four models twlve different models are formed and analysed. These are clustered models for deep learning analysis for wind speed and power forecasting. From the results, WNN models with RKF is topped in performance and forecasting among the other hybridlike combined models. It is concluded from the results that 40 neurons are the best number, 4 is hidden layer with the models provide improved accuracy and 4 cluster segments are the optimal value for higher performance. For the validation of the proposed model is carried out by K-fold cross validate method. The models are tested using novel dataset and the accuracy of the prediction is calculated. These hybrid combination models calculate the wind power and speed with more accuracy and gives better performance [64].

Shuai Zhang et al. introduces a model for the time series forecasting of wind power which improves production of electricity from the renewable wind energy. Deep learning methods are used to analyse time series characteristics data set. In the proposed model, the modules are designed such as ensemble model, EDNN boosting deep learning method incorporate ADAboost algorithm and dynamic error correction method along with Enhanced Multi-Population No- Dominated Sorting Genetic Algorithm-II (MPNSGA-II). LSTM, CNN, MLP are the deep learning models used in combination ode for time series forecasting. The designed model is used to forecast wind speed, $PM_{2.5}$ concentration and electricity price. The deep learning models combined ensemble learning which are used to extract the implicit features from the data set. The ensemble modes improve robustness and generalization of the model. It uses Adaboosting algorithm for sample weight updating and loss function which can be achieved by forecasting effectiveness metrics. DEC is for error prediction and correction for the time series forecasting models. MPNSGA-II is used for ensemble pruning of multi-objective time series forecasting. KRR is used as a meta predictor. Exploitation ability and exploration of the NSGA is enhanced by cross-population inter-crossing and opposite population initialization method. The proposed model is verified with two real time data sets. The improved accuracy of the proposed model is analyzed by using 16 baseline models and six datasets. The main drawback of the model is for multi-dimensional variating input the forecasting capability is not achieved. Therefore, the future scope of the model is work on to improve the accuracy for the multi-dimensional variating input [65].

Farah Sahid et al. proposed a new model for wind power prediction with long short-term memory (WN-LSTM) based on wavelet kernels. The model LSTM combines Ricker, Morelet, Shanon and Gaussian Activation kernels for prediction of power distinguish the model. The wavenet model uses the deep learning modules very well for vanishing gradient and for non-linear mapping in utilize the wavenet transformations. The model is implemented in seven wind farms for short term memory in Europe. The efficiency of the model is calculated by Mae, MAPE error. These errors give the difference between the predicted value and actual value of the real-world farms. WN-LSTM is established using one-way ANOVA at the confident level of 955. For MAE 30% improvement is detected. The difference in the actual and predicted value for the proposed model is obtained as 0.02. Machine learning paradigm is used in this work to establish the strength of the proposed LSTM with wavenet. The proposed model makes used to tackle the market demand for power because of it is high accuracy [66]. Zheuri ma et al. introduce a prediction model with deep learning algorithms, error correction strargy and double decomposition. The adaptive noise and variational mode are the decomposition methods for error series and original wind speed series. Nine modes are analysed with four forecasting data in the proposed method. The CEEMDAN-Error-VMD-LSTM model having high accuracy than the other single models. The error correction is improved about 60–70% in the proposed models. The randomness and complexity of the error series is adjusted by LSTM for better prediction. The accuracy, reliability of the predictors is improved in the proposed model. it is used to maintain the wind plant and the turbine adjustments easily. The humidity, temperature, pressure are the factors the author mentioned in future scope [67]. Rajtha meka et al. developed state of art temporal convolution network known as TCN model to predict the power generated by wind turbine by using metrological data. The TCN is integrated with LSTM. The hyperparameters of the TCN model is optimized using Taguchi experiment for design based orthogonal array tuning method. The proposed model analyses the data for 50 min which is less than 1 h, very difficult to analyse because of lack of data and variation of it. OATM optimize amount of input history, the kernel size, number of filters and residual stack amount. The implemented model is analysed along with existing models such as CNN + LSTM, MLR + NRMSE and NMAE. The proposed model given 90% confident interval prediction. Air density, surface heat flux, surface temperature and relative humidity are the variables of the meteorology whose correlation with the wind power production is demonstrated in the method. The method provided high accuracy than the existing model.

2. Wind forecasting using deep learning models algorithms

2.1. Proposed methods

The proposed model for predicting the power produce by the wind turbines are explained in three parts in this section. In the first part the dataset construction process in the input layer under the consideration of operating condition of the variable is detailed. The remaining sections are describing the RNN, LSTM and GRU frameworks in details. Table 2 various ranges of wind power in different forecasting range.

Fig. 1 shows the overall workflow for the wind power prediction. The proposed workflow contains the three steps dataset pre-processing stage, training phase and testing phase. In the dataset pre-processing stage dataset are formatted and cleaned to fit into the deep learning model. In training phase the dataset is splitted into the validation set, testing set and training set. Then the deep learning model is developed and trained and validated using the training and validation dataset. The performance of the model is validated by calculating mean square loss. In the testing phase the trained model is tested with testing dataset and the predicted and observed value is plotted.

2.1.1. RNN – recurrent neural network

Recurrent neural networks are the leading paradigm for solving time-dependent problems. One of the most important features of RNN models is the ability to memorise information from previous data. The information in the RNN model will be processed over time using a feedback loop. The fundamental structure of recurrent neural networks is shown in the Fig. 2. Feedforward networks principle is adopted in RNN but it maintains the state information and iterating sequence elements for the sequence process in extremely minimized version. RNN is the neural network having internal loop connection. Between the process the RNN state is reset among two different independent sequences. RNN takes the inputs as a sequence of vector, which is encoded as 2D tensor (timestamps, input features). At each time step, the output t is obtained from combination of the input and current state at t is taken as input. It iterated over time steps. The pseudo code of RNN is given by,

Pseudo code RNN

state_t = 0 *the state at t

for input_t in input sequence: *iterates over sequence elements

output_t = f (input_t, state_t)

state_t = output_t *for the next iteration the previous output is given as an input.

Block A in the figure above shows the basic structure of the RNN, where the feedback loop v implies that the data provided in block h will be recursively used. Block B denotes its analogous chain structure, where the output of the previous layer is fed into

Table 2
Classification of forecasting range.

Forecasting Range	Range	Applications
Very short term	Few seconds to 30 min	Wind turbine control
Short Term	30 min to 48 h	Economic loan dispatch planning
Medium Term	48 h to 1 week ahead	Unit commitment decision
Long Term	1 week to 1 year or more period	To build the wind farm

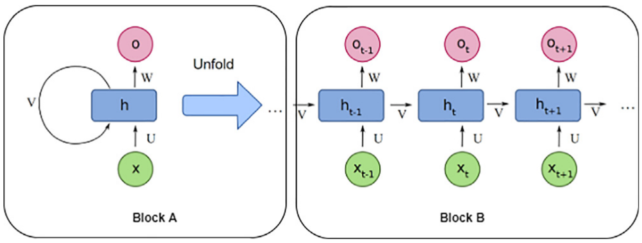

Fig. 2. Recurrent Neural Network Architecture.

the next layer. If the model relies on long-term temporal dependency, RNN is vulnerable to gradient problems of descent. The output sequence of the RNN is determined on the basis of the h_t

The current state equation

$$h_t = f(h_{t-1}, X_t) \tag{1}$$

After applying the Activation Function,

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}X_t) \tag{2}$$

W = weight
h = single hidden vector, W_{hh}= previous hidden layer weight, W_{xh}= current input state weight

Output of the RNN model

$$y_t = W_{hy}h_t \tag{3}$$

y_t = output
W_{hy} = weight at the output state

2.1.2. LSTM – Long Short-Term Memory networks

The LSTM network [23] is part of the deep recurrent neural network (RNN) family. In Standard RNNs gradient problem of vanishing is one of the main drawbacks which is eliminated in LSTM by integrating self-connected "gates" in the hidden units. LSTM main purpose is to solve the gradient disappearance issue. The LSTM is primarily used for time series deep learning. Weather conditions, which are a form of time series, are used to generate wind power. As a result, we can use the LSTM model to forecast wind energy. In any form, deep learning can approximate complex functions. Examine nonlinear data for linear relationships. You can delve into the secret relationships between data and fully utilise data's potential. Traditional machine learning does not have the benefits that deep learning does. This section introduces the LSTM theory. The LSTM network consists of simple units called memory cells. Fig. 3 shows the LSTM cell structure. Long-term memory has the benefit of retaining long-term reliance on information. Back-propagation algorithm is used to trained the LSTM models. The LSTM model comprises of one output gates, three input gate and a forgotten gate. The input gate will receive the input sequence and refresh the memory. The sigmoid function in the input gate will decide whether to accept the signal through its condition statement 0,1, and the tanh function will accept the signal ranges from-1 to 1 to determine their essential levels. Long-term memory has the benefits of long-term information retrieval. The LSTM model has been trained using a back-propagation algorithm. The LSTM model consists of three input gates, an output gate and a forgotten gate.

Pseudo code for LSTM architecture

1. Output_t = activation (dot (state_t, U0) + dot (input_t, W0) + dot (C_t, V0) + b0)
2. i_t = activation ((dot (state_t, Ui) + dot (input_t, Wi) + bi)
3. f_t = activation ((dot (state_t, Uf) + dot (input_t, Wf) + bf)
4. k_t = activation ((dot (state_t, Uk) + dot (input_t, Wk) + bk)
5. C_t + 1 = i_t * k_t + c_t* f_t

Where, i_t is the input gate equation of the LSTM Network, f_t is the forgot gate equation of the LSTM Network, k_t is the output gate equation of the LSTM network. The present information of the data and new information update in the carry track is given by i_t and k_t. In carry dataflow the irrelevant information's are intentional forget by multiplying c_t and f_t at any time.

The input gate will receive the input sequence and refresh the memory. The sigmoid function in the input gate will decide whether to accept the signal through its condition statement 0,1, and the tanh function will accept the signal ranges from-1 to 1 to determine their essential levels.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i \tag{4}$$

$$C_t = \tanh(W_c.[h_{t-1}, x_t] + b_C \tag{5}$$

The Forgot Gate in LSTM is used to discard the information of the block. The sigmoid function is determined. In the cell state Ct − 1 for each number the material input (Xt) and previous state (ht-1) and the outputs a number between 0(omit this) and 1(keep this) to be consider.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{6}$$

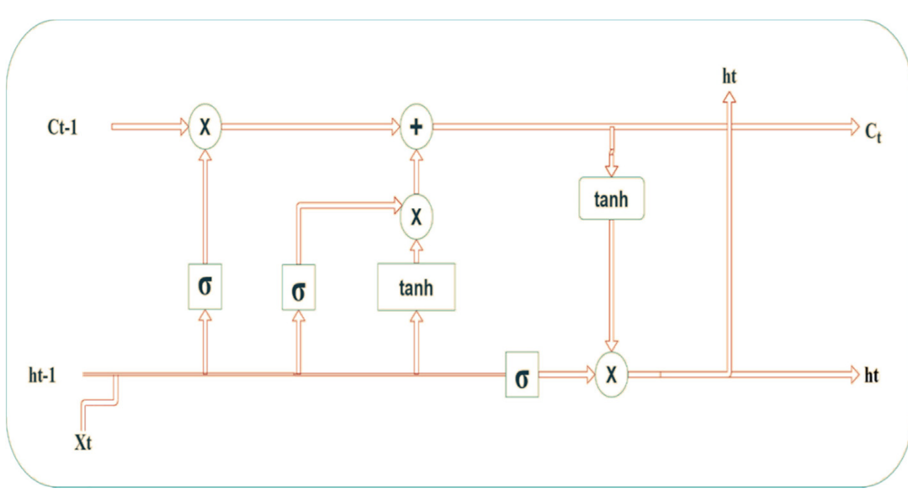

Fig. 3. Long Short-Term Memory Architecture.

The output decision is made by output gate using memory of the block and the input. The values to be passes through, is decided by sigmoid function and the level of importance of the values passed is ranged from −1 to 1 is determined by the weighting of the value which is given by the tanh function and multiplied by the sigmoid production.

$$O_t = \sigma(W_0[h_{t-1}, x_t] + b_o) \quad (7)$$

$$h_t = O_t * tanh(C_t) \quad (8)$$

2.1.3. GRU – Gated recurrent units

In recurrent neural network the gating system strategies such as Gated recurrent units are utilized. The GRU is like a long, short-term memory with a forgotten gate, but it has very few parameters than the LSTM, since it lacks the output gate. RNN gradient problem loss is managed by these designs and for broad time step distances it provides better capture dependency for time series. The distinguishing features of GRU gates are: When processing subsequent inputs, a recurrent neural network (RNN) retains the previous information status and transfers it to the next time stage. In WPF activities, RNN is used because wind power data is time-dependent. The disappearing and bursting gradient problems plague the training of RNN models. X_t and H_t denote the current input and output at phase t, respectively, while Rt and Z_t denote the reset and update gates. GRU's main structures are both gates, each of which is a simple neural network. The activation candidate for the output H_t is Ht. The update gate Z_t and reset gate R_t, on the surface, appear to calculate a correlation match between previous state knowledge and next phase forecasting. The former decides how much data from the historical state can be used in forecasting, while the latter determines how much original data should be retained. Adaptive short-cut connections are formed in this regard, bypassing multiple temporal phases. The knowledge at the current state can be saved and used to influence the values of future measures using this structure. The gated recurrent unit structure is shown in the Fig. 4.

Update gate:

The update gate (Zt) is in charge of calculating how much previous data (prior time steps) required to shifted to the next state. It's a crucial component. In the network unit X_t is act as a input vector which is multiplied with parameter weight (W_z) matrices. The t_1 in H (t_1) denotes that it contains the previous unit's knowledge and is multiplied by its weight. After that, the sigmoid activation function is used to combine the values from these parameters. The sigmoid function will produce between the values 0 and 1 in this case.

Reset gate:

The model's reset gate (r_t) is utilized to determine the amount of past knowledge should be ignored. The update gate's formula is the same as this one. Their weights and gate use vary, as discussed in the following section. The reset gate is depicted in the diagram below. X_t and H_{t-1} are the two inputs. Multiply by their weights, then add point-by-point and run through the sigmoid function.

In time Series,

Short-term dependencies capture is aided by Reset gate;

Long-term dependencies capture is aided by Forgot gate;

The GRU gates having reset gate and update gate, the reset R_t and update gate Z_t are computed as

$$R_t = \sigma(X_t W_{Xr} + H_{t-1} W_{hr} + b_r) \quad (9)$$

$$Z_t = \sigma(X_t W_{Xz} + H_{t-1} W_{hz} + b_z) \quad (10)$$

Wxr,Wxz ∈ Rd × h, and Whr,Whz ∈ Rh × h are weight parameters, br,bz ∈ R1 × h are the biases. The sigmoid function is used to transform input values to the interval (0,1).

3. Data description

The SCADA database which is investigated in the work is the 2.3 MW power rated three bladed upwind turbine recorded database which is located 109 m (length from hub height to sea level) above the sea level in brussel Belgium. The wind turbine having jacket type support structure. The dataset contains the date/time of the data recorded in the wind turbine, ambient temperature, direction of the wind flow, speed of the wind and wind power generated from the wind turbine. The total dataset consists of 50,530 data entries. The dataset is represented in the floating point 64 bit. The dataset is visualized with the help of sea born python library. The dataset relationship is plotted and shown in the Fig. 5 below.

3.1. Data pre-processing

In the processing of wind power forecasts any data may be detected and omitted from the SCADA database. It may indicate the variable measurements or mistake detections, deviating from standard observations. This paper uses the LSTM algorithm to discovers data points that varies from the general wind power measurement pattern, a form of decision-making tree set system. There was a strong difference between these two trends. In the

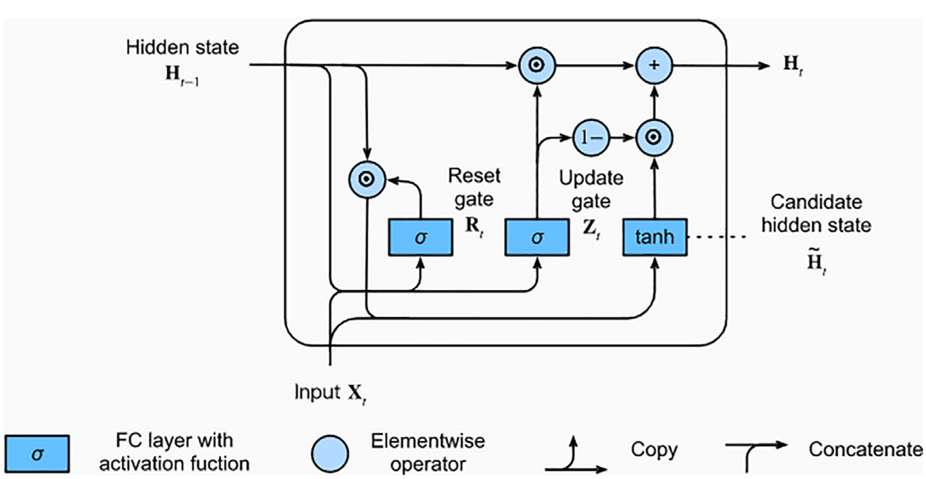

Fig. 4. Gate recurrent units.

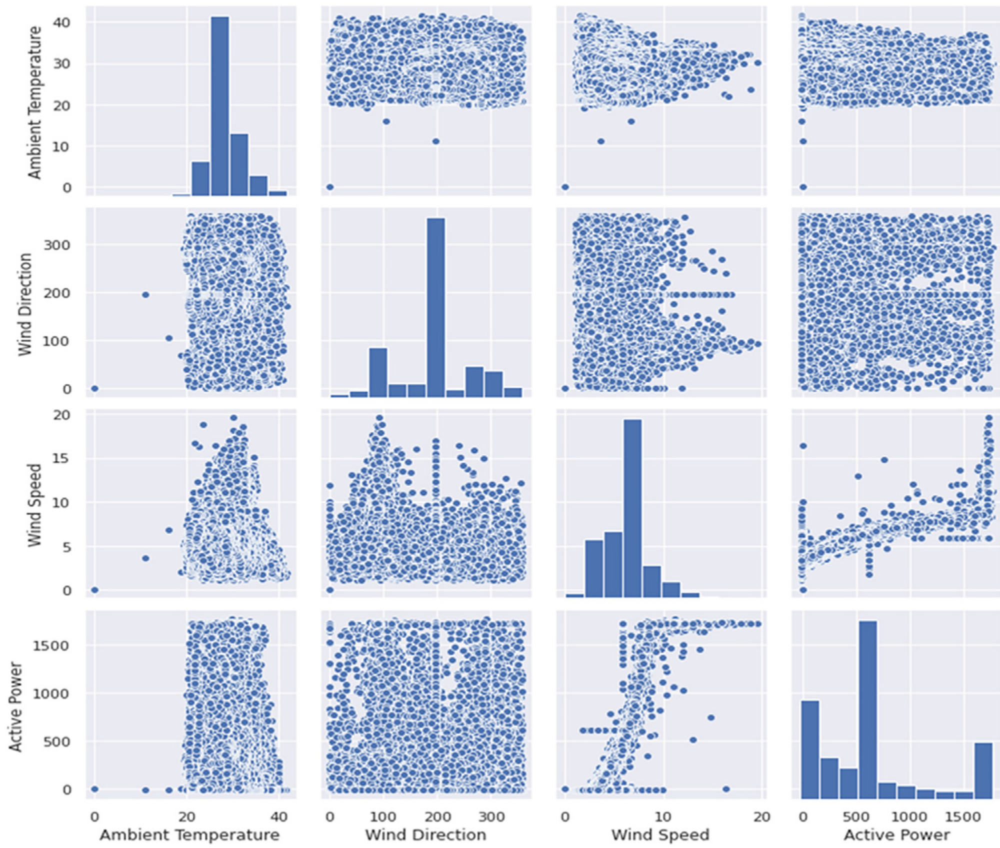

Fig. 5. data visualisation.

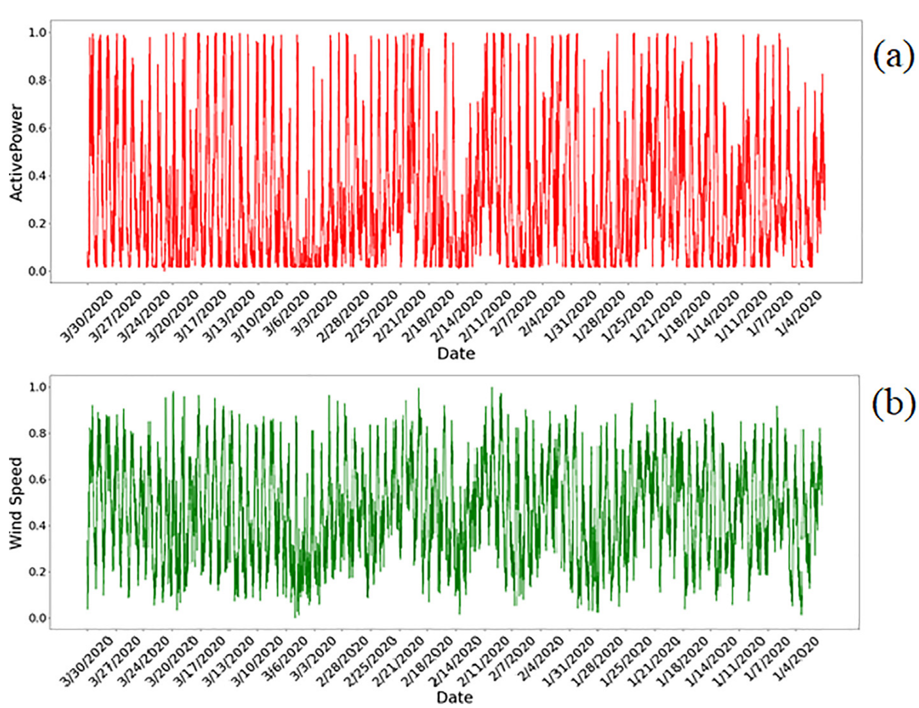

Fig. 6. Wind production (Before Normalization) Wind speed (Before Normalization).

Fig. 6 (a-b) for scenario before normalisation of the active power and wind speed.

Stage 1: The wind speed in the bottom of the power curve is above 3.5 m/s, but the corresponding active force is almost zero, due to the induced downtime of the turbines in a horizontally dense cluster.

Stage 2: The production of wind turbine is decreased in the outermost group which is dense clustered centre at the centre of the power curve. Lack of demand at a instance, high capacity wind power storage difficulties, limitations of grid supply are some of the reasons triggered the operators for wind restrictions.

Stage 3: The outliers of this sort are distributed allegedly around the power curve, triggered by a sensor failure (under or over measured wind speeds) and possible noise during signal processing.

The filtering LSTM is shown in the Fig. 7, the majority of outliers found at the border of the model were removed immediately. The SCADA dataset filtered in the target database for the deep learning model.

3.2. Histogram distribution and Auto correlations

The histogram of each feature is presented in Fig. 8. The ambient temperature, wind direction, wind speed and active power is presented in the Fig. 7(a-d). In the current database, the rated wind speed of the target wind turbine is 7.2 m/s, while the mean and median of the recorded wind speeds are 7 and 6.7 m/s, respectively (see the histogram of wind speed in Fig. 8 (c).

The extent to which the parameters in the SCADA database have a greater influence on wind power generation than others is equally important to find and calculate. It is worth noting that these relationships are difficult to describe explicitly in the SCADA database since several variables simultaneously affect power generation. Fig. 8 shows in the form of a thermal map, where the individual coefficients contained in the matrix are represented by colours, and a graph of the correlations of all the input functions of the active power. For each function of the displayed heat map, which is one of the most common strength measures in a linear relationship between any two variables, Pearson product-moment correlation coefficients have been established. This form of correlation is defined by the corresponding standard deviation covariance between the target variables. It shows values of +1 to

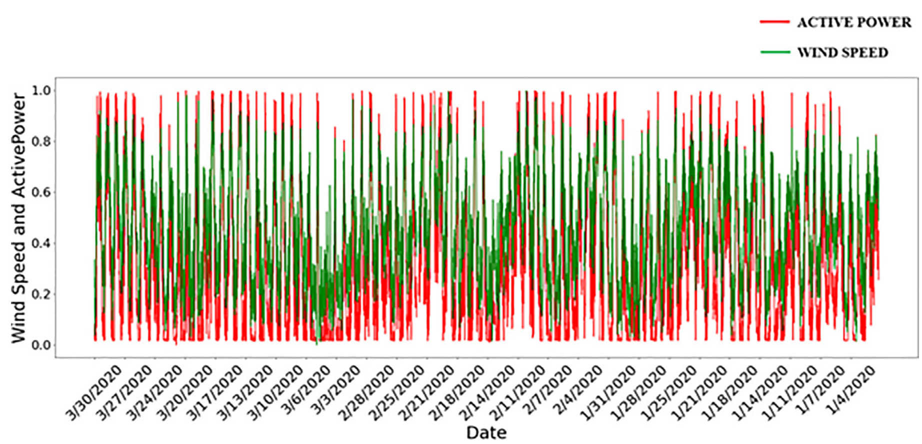

Fig. 7. Wind speed and production (Normalized).

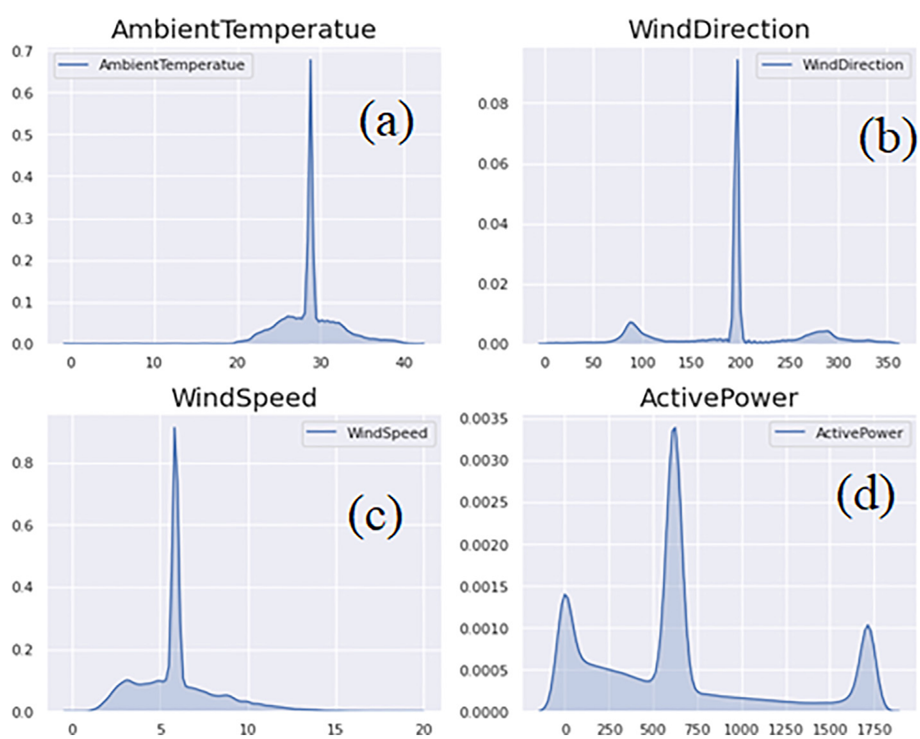

Fig. 8. Histogram Distribution.

−1, with a fully positive linear correlation of +1, 0 shows no linear correlation, and −1 implies a totally negative linear correlation. The wind speed and wind direction ratios to active power are positive, indicating that these three variables are strongly correlating in values and rising in the same direction. Fig. 9 shows that the values of these 3 variables are strongly interlinked. On the other hand, the correlations between the other ambient temperature and the active power is closer to zero, which means that they are not very much in line with the power produced. Note that the coefficients of correlation only consider linear ties. In other words, this method can be used only for preliminary assessments and can totally neglect non-linear relations. And can totally neglect non-linear relations.

The wind rose diagram is plotted to understand and to provide succinct view of how wind speed and direction are typically distributed at particular location. Wind roses were historically the forerunners of the compass rose (found on charts), since there was no distinction between a cardinal direction and the wind that blew from that direction. The frequency of winds over a time span is plotted by wind direction using a polar coordinate method of gridding, with colour bands showing wind speed ranges. The wind direction with the highest frequency is shown by the direction of the longest spoke. The wind rose diagram for the dataset discussed in shown in the Fig. 10.

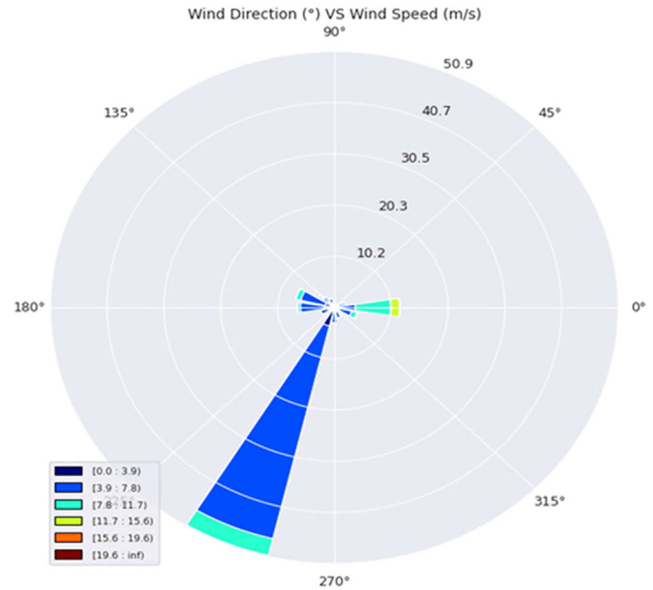

Fig. 10. Wind rose diagram to determine the wind direction and speed at the particular region.

4. Result and discussion

For wind speed forecasting the combination of GRU, RNN and LSTM networks are utilized. The proposed model are implemented and tested in the Intel i9 processor with NVIDIA Quadro RTX 6000. The different algorithms such as LSTM, GRU and RNN is developed and trained on the wind speed dataset. The total dataset of 50,530 is divided in the ratio of 75% of training set, 15% validation set and 10% of testing dataset. The proposed models are trained with mean square error loss function and with the training parameter of epoch 20, batch size of 64. The rate of learning of the proposed model is fixed as 0.001. The adaptive momentum estimation (ADAM) optimizer is used as training algorithm. The Adam optimizer combines the properties of AdaGrad and RMSProp to handle the sparse gradients on noisy problems. The models are trained on the training set and validated using the validation dataset. The graph is plotted with validation loss with epoch and training loss with epoch for the LSTM, GRU and RNN shown in the Fig. 11. Table 3 gives the validation results of the model. The mean square error of the RNN, GRU and LSTM are 0.143, 0.130 and 0.135 respectively. From the results it is clearly showing that the Gated Recurrent Unit (GRU) is showing better results than the other models with 0.130 value of mean square error. The mean square error is given by the equation

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

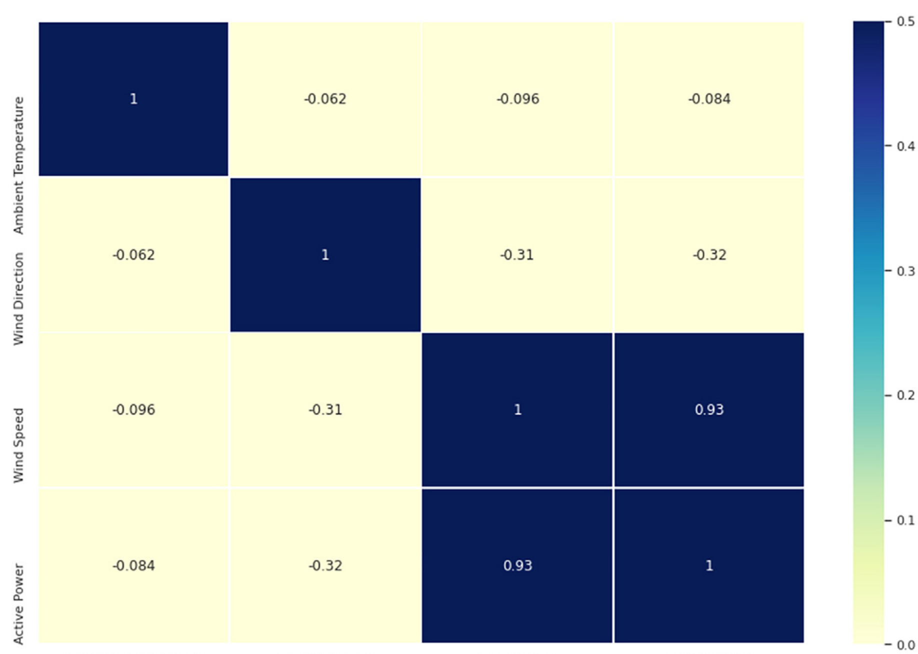

Fig. 9. Autocorrelation Wind Production.

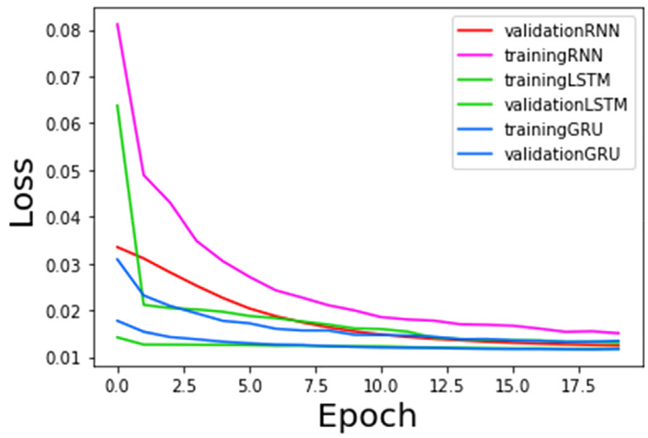

Fig. 11. Overall training and validation loss of the used models.

where,

MSE = mean squared error
n = data point's number
Y_i = observed values
$\widehat{Y}_i$ = predicted values

The trained and validated model is tested with the testing data to predict the wind power from the ambient temperature, wind direction, wind speed. The estimated output power from the LSTM, GRU and RNN model is plotted with the predicted output power from the dataset is shown in the Fig. 12. It is clearly shown that the GRU model is provided the output power closely to the predicted output power. The LSTM model is also performing better when compared to RNN and very close to the GRU prediction. The RNN performance is not up to the other models due to its vanishing gradient problem occurred during the training phase.

For the generation and management of wind energy, the wind power forecasting is of significance, providing fundamental support for wind turbine control and the preparation of hybrid wind power systems. Accurate and stable forecasts of wind power are commonly understood to play an important role in generating wind turbines. The wind interval prediction will calculate the range of changes in forecast performance, in comparison with the point prediction, due to unknown faith-level variables, which assess the preview range at the value observed, and provide a comprehensive guidance on power system planning. For design and operation of the power grid, including the wind farm, the comprehensive functions of the wind interval are summarised as follows; Secondly, deep-learning models can provide decision makers interested in producing wind turbines with extensive knowledge. Decision-makers can then create an extensive plan for the modification of wind turbines so that wind power production is optimised. Secondly, it is important to balance supply and demand, which play a central role in the sustainable management of energy and in economically efficient activities. Overload would, on the contrary, have a detrimental effect on energy efficiency, rendering it unable to fulfil normal power requirements and possibly weaken the safety and stability of the grid, and will lead to a surge of production costs and long-term costs due to the inherent problems of energy saving.

5. Conclusion

Modern wind energy planning systems are used to forecast difficult problems in operating loads, to minimise risks and to improve performance. Deep learning techniques have recently appeared in advanced prediction as efficient methods. The authors of this paper were urged for statistical model implementation without using NWP inputs by the need for accurate predictive models. This paper provides an HDLS-oriented hybrid deep learning approach oriented on EEMD and the LSTM network. The efficient LSTM noise technique was utilised by extracting noisy data to prepare the input and significantly increase predictive precision. The wind speed prediction is improved further through the GRU network which has been better designed to extract complex data and extremely nonlinear features from the real time series data collection. Concerning to predict difficult operation problems and minimise risk and improve efficiency, modern electrical power systems are using wind energy forecasts. Profound learning approaches have recently become effective prediction methods.

Table 3
Model validation.

Model	Epoch	Learning rate	Loss function	Batch Size	Training Loss	Validation Loss	Mean Square Error
LSTM	20	0.001	Mean Square error	64	0.0134	0.0116	0.1358
GRU	20	0.001	Mean Square error	64	0.135	0.0117	0.130
RNN	20	0.001	Mean Square error	64	0.0151	0.0124	0.143

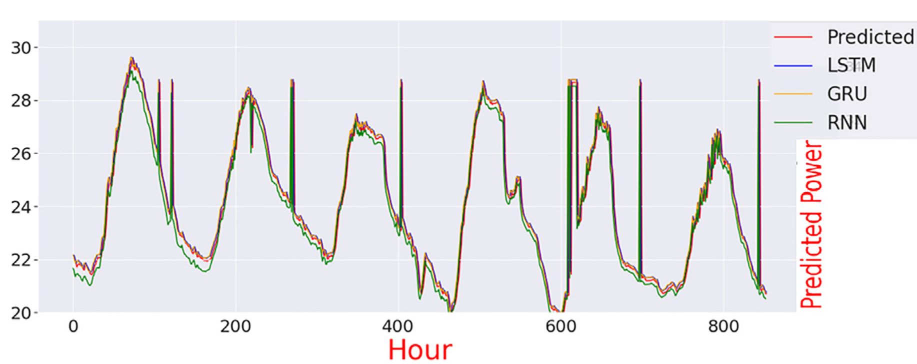

Fig. 12. wind power forecast using LSTM, GRU and Simple RNN.

The need for exact prediction models led to a statistic model. For pre-processing the input and significantly improved predictive accuracy by eliminating noise data, successful loudness technique LSTM was used. The GRU network is better suited to extract extremely non-linear and complex data from an input data set in real time to boost the wind speed prediction even further.

CRediT authorship contribution statement

V. Chandran: Formal analysis, Writing - review & editing. **Chandrashekhar K. Patil:** Writing - original draft, Formal analysis, Writing - review & editing. **Anto Merline Manoharan:** Writing - original draft. **Aritra Ghosh:** Methodology, Formal analysis, Supervision, Validation. **M.G. Sumithra:** Writing - original draft. **Alagar Karthick:** Methodology, Formal analysis, Supervision, Validation, Formal analysis, Writing - review & editing. **Robbi Rahim:** Formal analysis, Writing - review & editing. **K Arun:** Formal analysis, Writing - review & editing.

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.

References

[1] A. Karthick, K.K. Murugavel, L. Kalaivani, U.S. Babu, Performance study of building integrated photovoltaic modules, Adv. Build. Energy Res. (2017), https://doi.org/10.1080/17512549.2016.1275982.
[2] A. Karthick, K. Kalidasa Murugavel, L. Kalaivani, Performance analysis of semitransparent photovoltaic module for skylights, Energy. 162 (2018) 798–812, https://doi.org/10.1016/j.energy.2018.08.043.
[3] P.R. K, M.V.N.S. Gupta, S. Nundy, A. Karthick, A. Ghosh, Status of BIPV and BAPV System for Less Energy-Hungry Building in India—A Review, Appl. Sci. 2020, Vol. 10, Page 2337. 10 (2020) 2337. 10.3390/APP10072337.
[4] A. Karthick, M. Manokar Athikesavan, M.K. Pasupathi, N. Manoj Kumar, S.S. Chopra, A. Ghosh, Investigation of inorganic phase change material for a semi-transparent photovoltaic (STPV) Module, Energies 13 (2020) 3582, https://doi.org/10.3390/en13143582.
[5] A. Karthick, K. Kalidasa Murugavel, A. Ghosh, K. Sudhakar, P. Ramanan, Investigation of a binary eutectic mixture of phase change material for building integrated photovoltaic (BIPV) system, Sol. Energy Mater. Sol. Cells. 207 (2020). 10.1016/j.solmat.2019.110360.
[6] N. Manoj, M. Samykano, A. Karthick, Case studies in thermal engineering energy loss analysis of a large scale BIPV system for university buildings in tropical weather conditions: a partial and cumulative performance ratio approach, Case Stud. Therm. Eng. 25 (2021), https://doi.org/10.1016/j.csite.2021.100916 100916.
[7] V. Chandran, C.K. Patil, A. Karthick, D. Ganeshaperumal, R. Rahim, A. Ghosh, State of charge estimation of lithium - ion battery for electric vehicles using machine learning algorithms, World Electr. Veh. J. 12 (2021) 38.
[8] V.S. Chandrika, A. Karthick, N.M. Kumar, P.M. Kumar, B. Stalin, M. Ravichandran, Experimental analysis of solar concrete collector for residential buildings, Int. J. Green Energy. 00 (2021) 1–9, https://doi.org/10.1080/15435075.2021.1875468.
[9] C.S. Dhanalakshmi, P. Madhu, A. Karthick, R.V. Kumar, Combination of Woody and Grass type Biomass : Waste Management , Influence of Process Parameters , Yield of Bio-oil by Pyrolysis and its Chromatographic Characterization, 80 (2021) 172–180.
[10] B. Stalin, M. Ravichandran, G.T. Sudha, A. Karthick, K.S. Prakash, A.B. Asirdason, S. Saravanan, Effect of titanium diboride ceramic particles on mechanical and wear behaviour of Cu-10 wt% W alloy composites processed by P/M route, Vacuum. 184 (2021), https://doi.org/10.1016/j.vacuum.2020.109895 109895.
[11] S. Senthilkumar, A. Karthick, R. Madavan, A. Arul Marcel Moshi, S.R. Sundara Bharathi, S. Saroja, C. Sowmya Dhanalakshmi, Optimization of transformer oil blended with natural ester oils using Taguchi-based grey relational analysis, Fuel. 288 (2021) 119629. 10.1016/j.fuel.2020.119629.
[12] V.S. Chandrika, M.M. Thalib, A. Karthick, R. Sathyamurthy, A.M. Manokar, U. Subramaniam, B. Stalin, Performance assessment of free standing and building integrated grid connected photovoltaic system for southern part of India, Build. Serv. Eng. Res. Technol. (2020), https://doi.org/10.1177/0143624420977749.
[13] C.S. Dhanalakshmi, P. Madhu, A. Karthick, M. Mathew, R. Vignesh Kumar, A comprehensive MCDM-based approach using TOPSIS and EDAS as an auxiliary tool for pyrolysis material selection and its application, Biomass Convers. Biorefinery (2020), https://doi.org/10.1007/s13399-020-01009-0.
[14] A. Karthick, K. Kalidasa Murugavel, K. Sudalaiyandi, A. Muthu Manokar, Building integrated photovoltaic modules and the integration of phase change materials for equatorial applications, Build. Serv. Eng. Res. Technol. 41 (2020) 634–652, https://doi.org/10.1177/0143624419883363.
[15] A. Karthick, K.K. Murugavel, P. Ramanan, Performance enhancement of a building-integrated photovoltaic module using phase change material, Energy. 142 (2018) 803–812, https://doi.org/10.1016/j.energy.2017.10.090.
[16] V. Krishnavel, A. Karthick, K.K. Murugavel, Experimental analysis of concrete absorber solar water heating systems, Energy Build. 84 (2014) 501–505, https://doi.org/10.1016/j.enbuild.2014.08.025.
[17] P. Manoj Kumar, K. Mylsamy, K. Alagar, K. Sudhakar, Investigations on an evacuated tube solar water heater using hybrid-nano based organic phase change material, Int. J. Green Energy. 17 (2020) 872–883, https://doi.org/10.1080/15435075.2020.1809426.
[18] A. Karthick, P. Ramanan, A. Ghosh, B. Stalin, R. Vignesh Kumar, I. Baranilingesan, Performance enhancement of copper indium diselenide photovoltaic module using inorganic phase change material, Asia-Pacific, J. Chem. Eng. 15 (2020), https://doi.org/10.1002/apj.2480.
[19] P. Ramanan, K. Kalidasa Murugavel, A. Karthick, K. Sudhakar, Performance evaluation of building-integrated photovoltaic systems for residential buildings in southern India, Build. Serv. Eng. Res. Technol. 41 (2020) 492–506, https://doi.org/10.1177/0143624419881740.
[20] P. Ramanan, K.M. K., A. Karthick, Performance analysis and energy metrics of grid-connected photovoltaic systems, Energy Sustain. Dev. 52 (2019) 104–115. 10.1016/j.esd.2019.08.001.
[21] R. Pichandi, K. Murugavel Kulandaivelu, K. Alagar, H.K. Dhevaguru, S. Ganesamoorthy, Performance enhancement of photovoltaic module by integrating eutectic inorganic phase change material, Energy Sources, Part A Recover. Util. Environ. Eff. (2020), https://doi.org/10.1080/15567036.2020.1817185.
[22] M.E.H. Attia, A. Karthick, A.M. Manokar, Z. Driss, A.E. Kabeel, R. Sathyamurthy, M. Sharifpur, Sustainable potable water production from conventional solar still during the winter season at Algerian dry areas: energy and exergy analysis, J. Therm. Anal. Calorim. (2020), https://doi.org/10.1007/s10973-020-10277-x.
[23] M.K. Pasupathi, K. Alagar, P. Michael Joseph Stalin, M.M. Matheswaran, G. Aritra, Characterization of hybrid-nano/paraffin organic phase change material for thermal energy storage applications in solar thermal systems, Energies. 13 (2020). 10.3390/en13195079.
[24] S. Sebastin, A.K. Priya, A. Karthick, R. Sathyamurthy, A. Ghosh, Agro Waste Sugarcane Bagasse as a Cementitious Material for Reactive Powder Concrete, Clean Technol. 2020, Vol. 2, Pages 476-491. 2 (2020) 476–491. 10.3390/CLEANTECHNOL2040030.
[25] A. Karthick, K. Kalidasa Murugavel, L. Kalaivani, U. Saravana Babu, Performance study of building integrated photovoltaic modules, Adv. Build. Energy Res. 12 (2018) 178–194, https://doi.org/10.1080/17512549.2016.1275982.
[26] R. Sathyamurthy, A.E. Kabeel, A. Chamkha, A. Karthick, A. Muthu Manokar, M. G. Sumithra, Experimental investigation on cooling the photovoltaic panel using hybrid nanofluids, Appl. Nanosci. (2020), https://doi.org/10.1007/s13204-020-01598-2.
[27] S. K, K. Alagar, V.K. R, M.P. VJ, M. P, Performance and emission characteristics of diesel engine fueled with ternary blends of linseed and rubber seed oil biodiesel, Fuel. 285 (2021) 119255. 10.1016/j.fuel.2020.119255.
[28] M.E.H. Attia, Z. Driss, A.E. Kabeel, A. Afzal, A.M. Manokar, R. Sathyamurthy, Phosphate bed as energy storage materials for augmentation of conventional solar still productivity, Environ. Prog. Sustain. Energy. (2021), https://doi.org/10.1002/ep.13581.
[29] V.K. Ramalingam, A. Karthick, M.P.V. Jeyalekshmi, A.M.M.A.J. Decruz, A.M. Manokar, R. Sathyamurthy, Enhancing the fresh water produced from inclined cover stepped absorber solar still using wick and energy storage materials, Environ. Sci. Pollut. Res. (2021), https://doi.org/10.1007/s11356-020-12030-1.
[30] S.D. Kumar, M. Ravichandran, A. Jeevika, B. Stalin, C. Kailasanathan, A. Karthick, Effect of ZrB2 on microstructural, mechanical and corrosion behaviour of aluminium (AA7178) alloy matrix composite prepared by the stir casting route, Ceram. Int. (2021), https://doi.org/10.1016/j.ceramint.2021.01.158.
[31] A. Karthick, V.K. Chinnaiyan, J. Karpagam, V.S. Chandrika, P.R. Kumar, Optimization of PV-wind hybrid renewable energy system for health care buildings in smart city, Hybrid Renewable Energy Systems 213–228 (2021), https://doi.org/10.1002/9781119555667.ch8.
[32] K. Alagar, S. Thirumal (2021). Standalone PV-Wind-DG-Battery Hybrid Energy System for Zero Energy Buildings in Smart City Coimbatore, India. Advanced Controllers for Smart Cities: An Industry 4.0 Perspective, 55-63.
[33] A.M. Manokar, A. Karthick, Review on progress in concrete solar water collectors, Environ. Sci. Pollut. Res. (2021), https://doi.org/10.1007/s11356-021-13415-6.
[34] R. Naveenkumar, M. Ravichandran, B. Stalin, et al., Comprehensive review on various parameters that influence the performance of parabolic trough collector, Environ. Sci. Pollut. Res. (2021), https://doi.org/10.1007/s11356-021-13439-y.
[35] V. Mohanavel, K.S. Ashraff Ali, S. Prasath, T. Sathish, M. Ravichandran, Microstructural and tribological characteristics of AA6351/Si_3N_4 composites manufactured by stir casting, J. Mater. Res. Technol. 9 (6) (2020) 14662–14672.
[36] Vinayagam Mohanavel 2020 Mechanical and microstructural characterization of AA7178-TiB2 composites Materials Testing 62 146-50.

[37] V. Mohanavel, K. Rajan, M. Ravichandran, Synthesis, characterization and properties of stir cast AA6351-aluminium nitride (AlN) composites, J. Mater. Res. 31 (2016) 3824–3831.
[38] V. Mohanavel, M. Ravichandran, Experimental investigation on mechanical properties of AA7075-AlN composites, Mater. Testing 61 (2016) 554–558.
[39] V. Mohanavel, M. Ravichandran, Influence of AlN particles on microstructure, mechanical and tribological behaviour in AA6351 aluminum alloy, Mater. Res. Exp. 6 (2019) 106557.
[40] M. Paidar, K.S. Ashraff Ali, V. Mohanavel, S. Mehrez, M. Ravichandran, O.O. Ojo, Weldability and mechanical properties of AA5083-H112 aluminum alloy and pure copper dissimilar friction spot extrusion welding-brazing, Vacuum 187 (2021) 110080.
[41] T. Ahmad, H. Chen, A review on machine learning forecasting growth trends and their real-time applications in different energy systems, Sustainable Cities Soc. 54 (2020) 102010.
[42] A. Dedinec, S. Filiposka, A. Dedinec, L. Kocarev, Deep belief network based electricity load forecasting: an analysis of Macedonian case, Energy 115 (2016) 1688–1700.
[43] G.W.E. Council, Global wind report 2018, annual market update released on april 2019.
[44] O. Karakuş, E.E. Kuruoğlu, M.A. Altınkaya, One-day ahead wind speed/power prediction based on polynomial autoregressive model, IET Renewable Power Generation 11 (11) (2017) 1430–1439.
[45] O.B. Shukur, M.H. Lee, Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA, Renewable Energy 76 (2015) 637–647.
[46] E.M. Larsen, P. Pinson, F. Leimgruber, F. Judex, Demand response evaluation and forecasting—Methods and results from the EcoGrid EU experiment, Sustainable Energy, Grids Networks 10 (2017) 75–83.
[47] Z. Tian, S. Li, Y. Wang, X. Wang, Wind power prediction method based on hybrid kernel function support vector machine, Wind Eng. 42 (3) (2018) 252–264.
[48] A. Aghajani, R. Kazemzadeh, A. Ebrahimi, A novel hybrid approach for predicting wind farm power production based on wavelet transform, hybrid neural networks and imperialist competitive algorithm, Energy Convers. Manage. 121 (2016) 232–240.
[49] M. Santhosh, C. Venkaiah, D.V. Kumar, Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction, Energy Convers. Manage. 168 (2018) 482–493.
[50] H. Liu, X. Mi, Y. Li, Comparison of two new intelligent wind speed forecasting approaches based on wavelet packet decomposition, complete ensemble empirical mode decomposition with adaptive noise and artificial neural networks, Energy Convers. Manage. 155 (2018) 188–200.
[51] G. Le Ray, P. Pinson, Online adaptive clustering algorithm for load profiling, Sustainable Energy Grids Networks 17 (2019) 100181.
[52] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (8) (1997) 1735–1780.
[53] P. Jiang, Z. Liu, X. Niu, L. Zhang, A combined forecasting system based on statistical method, artificial neural networks, and deep learning methods for short-term wind speed forecasting, Energy 217 (2021) 119361.
[54] W. Fu, K. Wang, J. Tan, K. Zhang, A composite framework coupling multiple feature selection, compound prediction models and novel hybrid swarm optimizer-based synchronization optimization strategy for multi-step ahead short-term wind speed forecasting, Energy Convers. Manage. 205 (2020) 112461.
[55] K. Nam, S. Hwangbo, C. Yoo, A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: a case study of Korea, Renewable Sustainable Energy Rev. 122 (2020) 109725.
[56] J.J. Yang, M. Yang, M.X. Wang, P.J. Du, Y.X. Yu, A deep reinforcement learning method for managing wind farm uncertainties through energy storage system control and external reserve purchasing, Int. J. Elec. Power Energy Systems 119 (2020) 105928.
[57] G. Sideratos, N.D. Hatziargyriou, A distributed memory RBF-based model for variable generation forecasting, Int. J. Elec. Power Energy Systems 120 (2020) 106041.
[58] H. Liu, R. Yang, T. Wang, L. Zhang, A hybrid neural network model for short-term wind speed forecasting based on decomposition, multi-learner ensemble, and adaptive multiple error corrections, Renewable Energy 165 (2021) 573–594.
[59] H. Liu, C. Yu, H. Wu, Z. Duan, G. Yan, A new hybrid ensemble deep reinforcement learning model for wind speed short term forecasting, Energy 202 (2020) 117794.
[60] G. Memarzadeh, F. Keynia, A new short-term wind speed forecasting method based on fine-tuned LSTM neural network and optimal input sets, Energy Convers. Manage. 213 (2020) 112824.
[61] C. Yildiz, H. Acikgoz, D. Korkmaz, U. Budak, An improved residual-based convolutional neural network for very short-term wind power forecasting, Energy Convers. Manage. 228 (2021) 113731.
[62] Z. Peng, S. Peng, L. Fu, B. Lu, J. Tang, K. Wang, W. Li, A novel deep learning ensemble model with data denoising for short-term wind speed forecasting, Energy Convers. Manage. 207 (2020) 112524.
[63] H.H. Aly, A novel deep learning intelligent clustered hybrid models for wind speed and power forecasting, Energy 213 (2020) 118773.
[64] S. Zhang, Y. Chen, W. Zhang, R. Feng, A novel ensemble deep learning model with dynamic error correction and multi-objective ensemble pruning for time series forecasting, Inf. Sci. 544 (2021) 427–445.
[65] F. Shahid, A. Zameer, A. Mehmood, M.A.Z. Raja, A novel wavenets long short term memory paradigm for wind power prediction, Appl. Energy 269 (2020) 115098.
[66] Z. Ma, H. Chen, J. Wang, X. Yang, R. Yan, J. Jia, W. Xu, Application of hybrid model based on double decomposition, error correction and deep learning in short-term wind speed prediction, Energy Convers. Manage. 205 (2020) 112345.
[67] R. Meka, A. Alaeddini, K. Bhaganagar, A robust deep learning framework for short-term wind power forecast of a full-scale wind farm using atmospheric variables, Energy 221 (2021) 119759.