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Designing of Novel Wind Power Prediction Framework using Dilated Echo State Network with Gelu Activation Function

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Abstract: Globally, wind power generation gained huge attention due to its nature of clean, green, and renewable energy. Huge advancements are presented in wind energy production, but they face more issues as wind power generation is stochastic, unstable, and intermittent which creates more complications for power grid dispatch. So, it is important to tackle these issues by predicting the wind power and speed. In the wind power forecast, different processing schemes are employed to decrease the prediction miscalculations generated by nonlinearity and non-stationary wind power time series. However, these kinds of issues are not able to be addressed due to the disorganized characteristics of wind power time series. The grey model is a widely used technique for these uncertain systems presented with minimal information and also it requires minimal operational data. However, these techniques affect the prediction accuracy of the system. Hence, it is essential to overcome multiple limitations presented in the conventional wind prediction models. In the developed wind power prediction framework, essential wind power data required for the validation is collected from the benchmark resources. Next, the gathered wind power data is offered to the wind power prediction phase. In this phase, a developed Dilated Echo State Network with Gaussian Error Linear Unit Activation Function (DilESNet-GeluAF) is employed to predict the wind power. Finally, the wind power predicted outcome is attained from the developed DilESNet-GeluAF. Later, several validations will be executed in the developed framework over the conventional techniques to verify its efficiency.

Keywords: Wind Power Prediction; Dilated Echo State Network; Gelu Activation Function; Performance Measures.

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Nomenclature

Abbriviation	Expansion
DilESNet-GeluAF	Dilated Echo State Network with Gaussian Error Linear Unit Activation Function
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
ARMA	Auto-Regressive Moving Average
RFR	Random Forest Regressor
DTR	Decision Tree Regressor
KNNR	K-Nearest Neighbors Regressor
MLPR	Multiple-Layer Perception Regressor
CEEMD	Complementary Ensemble Empirical Modal Decomposition
KELM	Kernel Extreme Learning Machine
ISCASO	Improved Snake Optimization Algorithm
STGNN	Spatio-Temporal Graph Neural Network
GNN	Graph Neural Network
EFRCN	EncoderForest-Temporal Convolutional Network
PCC	Pearson Correlation Coefficients
SVR	Support Vector Regression
GRU	Gated Recurrent Unit
BDL	Bayesian Deep Learning
CCNQR	Composite Conditional Nonlinear Quantile Regression
CNN	Convolutional Neural Network
DBN	Deep Belief Network
MASE	Mean Absolute Scaled Error
MEP	Mean Effective Pressure
SMAPE	Symmetric Mean Absolute Percentage Error
MAE	Mean Absolute Error
RMSE	Root Mean Square Error

1. Introduction

Presently, the world facing major issues like environmental pollution, climate change, and resource shortages. So, sustainable enhancements are essential to execute the global energy transition, which is the process that helps to shift from fossil energy resources to renewable energy resources [1]. The global energy transition helps to minimize environmental damage

with sustainable enhancement. In renewable energy resources, wind energy is the clean energy resources that effectively minimize carbon emissions. Wind energy plays a major role in contributing to sustainability, energy security, and coping with climatic changes [2]. Globally, wind energy resources are rich, and also developing countries utilize wind energy to promote clean energy. Due to several growths in the wind power units, the proportions of wind power linked with the grid are also improved and it needs constant operation in the power units [3]. The ultra-short-term wind power forecasting models organize the power generation plan of the wind farms. The outcome curves recognized by the wind farms are tuned in the conventional units by reducing the operational costs.

The variation patterns presented in the wind power prediction techniques explain the dissimilarity patterns of wind power outcomes and also compute the advancements in terms of reliability, safety, and controllability [4]. Various research works are developed by considering the short-term wind prediction procedures. The prediction techniques have the efficiency to predict future power outcomes by observing historical information. More precise wind power prediction assists in decreasing the imbalance issues that the wind resources owners are paying [5]. Higher wind power prediction accuracy permits the system operator to improve market efficiency and operational reliability in enormous power systems. Artificial intelligence techniques are complicated techniques that are widely used in wind power prediction [6]. Among all, an ANN technique offers better performance. The RNN models need more operation time, which makes the implementation expensive. Hence, tackling multiple complications associated with the existing framework is essential, so, a novel wind power prediction framework is developed.

Core Objective: The core objectives of the developed framework are to design an efficient wind power prediction mechanism for providing better balancing between supply and demand. In this research work a novel framework DilESNet-GeluAF is designed for predicting wind power, which effectively enhances the wind power forecasting efficiency and also reduces the operating cost. Using the developed DilESNet-GeluAF framework helps to reduce the errors in the network by improving the prediction accuracy with reliability that helps to enhance the profit of the wind farm owners.

Organization of the Work: The remaining parts of the developed work included related theories in Section II, methodology in Section III, empirical results in Section IV, and conclusion and future direction offered in Section V.

1.1. Wind Power Forecasting Methods

Presently, different types of wind power forecasting techniques have been designed by researchers to predict wind power accurately without any misclassifications.

Short-term Wind Power Prediction: These kinds of research work provide better decision-making outcomes for the grid operators and also aid in stabilizing the energy system. In 2024, Yang *et al.* [7] designed a novel weighted-voting-based and multi-parameters similarity matching procedures for enhancing accuracy in short-term wind power prediction techniques. This framework utilized 96h-time-scale samples to execute the similarity matching. In 2022, Dong *et al.* [8] developed a new multi-class ARMA technique for predicting short-term wind power to execute better training in every class. The suggested model gained superior training efficiency with minimal parameters. In 2022, Mogos *et al.* [9] developed an ensemble framework using RFR, DTR, KNNR, and MLPR to predict very short-term wind power. In 2022, Zhao and Zhou [10] designed a multi-step short-term wind prediction technique using ensemble techniques. Here, decomposition was executed by CEEMD. Significant parameters in the KELM were tuned by the ISCASO.

Ultra-Short-term Wind Power Prediction: These techniques are widely utilized as they effectively reduce the uncertainty issues generated when wind power is integrated. In 2024, Liu *et al.* [11] suggested an STGNN with power fluctuation patterns for ultra-short-term wind prediction. Here, the statistical validations were executed in the extreme points and then cluster power was separated into various fluctuation slots. In 2023, Liao *et al.* [12] recommended an ultra-short-term wind power prediction technique with GNN for collecting the spatio-temporal characteristics among the nodes. In 2024, Sun *et al.* [13] proposed an EFRCN that helped to collect complicated patterns and also arrange the minimal frequency information.

Two-Step Wind Power Prediction: This process helps to enhance the scheduling procedures in the power system and also it minimizes the complications achieved while wind power fluctuations are attained. In 2022, Zhang *et al.* [14] proposed a two-step wind power

prediction framework. Here, an ensemble empirical mode decomposition technique was used in the long time-scale phase and also the deep deterministic policy gradient approach was employed in the short time-scale phase.

Machine learning-based Wind Power Prediction: These techniques were employed to identify the relationship without considering any existing structural data with the meteorological variables. In this category, in 2024, Ye *et al.* [15] recommended a novel wind power output prediction mechanism using time-series generative adversarial networks. This work utilized the PCC and SVR to correct the errors in the power prediction techniques. In 2023, Sheng *et al.* [16] designed a hybridized wind power prediction model with a GRU for predicting the sub-sequence components in different time scales. In 2024, Liu *et al.* [17] proposed a BDL model for predicting wind power with multi-source heterogeneous prior data. In 2022, Zhou *et al.* [18] recommended the CCNQR technique to offer higher reliability to the power system. The performance of the power intervals was enhanced by considering the adaptive boundary quantiles.

Deep Learning-based Wind Power Prediction: These techniques were employed to eliminate the information loss and also to validate the sequential information. In 2023, Yang *et al.* [19] suggested a novel probability prediction model for wind powers. Here, the dilated causal CNN was used to accomplish more accurate wind power prediction outcomes. In 2024, Li *et al.* [20] recommended a Hammerstein system using a DBN for predicting the wind powers in separable signals. The dynamic linear and static nonlinear blocks were employed to design the Hammerstein system.

2. Related Theories

2.1. Recurrent Neural Networks

RNN [21] is an ANN model, which has a unit connection with the current cycles. The recurrent connections permit the targets to analyze the input functions in prior time instants. Moreover, the RNN has the efficiency to collect the temporal patterns in a series nature. In the RNN, the input sequence is considered as $Z(1), Z(2),..., Z(A)$ in every $\Re^q$. The hidden state sequences are validated as $X(1), X(2),..., X(A)$ at all $\Re^w$. Finally, the prediction sequences are provided as $\hat{C}(1), \hat{C}(2),..., \hat{C}(A)$ in each $\Re^e$. Then, the iterating of these equations is offered in Eq. (1).

$$X(a) = V\left(B^{[r]}.Z(a) + B^{[u]}.X(a-1) + N_X\right) \quad (1)$$

$$\hat{C}(a) = M\left(B^{[y]}.A(a) + N_t\right) \quad (2)$$

Matrices weights for the input layer are offered as $B^{[r]}$, hidden layers are provided as $B^{[u]}$, and outcomes layers are given as $B^{[y]}$. Biases are indicated as N_X and N_t, vector values of pre-defined functions are represented as $V(.)$ and $M(.)$ in the above equation, which is well-defined Jacobian with non-linear functions. Here, a predefined value $X(0) = X_0$ is fixed in the state of the network. The objectives of RNN in single (Z, C) pairs are specified as $S\left(\hat{C}, C, \theta\right)$. Distance function S is used to validate the prediction deviation $\hat{C}$ from the target outcomes C and also the model parameter vectors are given as θ. The RNN model is efficient in unfolding the recurrent networks to n-times into the past with hidden layers and the RNN structure is offered in Fig. 1.

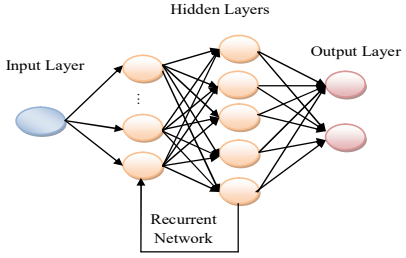


Fig 1. Architectural Presentation of RNN

2.2. Echo State Network

ESNet [21] is a kind of reservoir computer that holds the RNN linked with hidden layers and also easily handles the sequential information. These ESNet techniques are widely used in signal-processing applications. Using ESNet in the wind power prediction model helps to ease the training procedures and also helps to study the temporal dependencies. The ESNet techniques utilized the reservoir computing paradigm with alternative gradient descent techniques. The major goal of the reservoir computing process is to employ the hidden layers generated by the enormous sparsely linked neurons that help in transforming the input information to the higher dimensional space for performing specific tasks. Implementation procedures of ESNet are simple and it has three layers such as input, output, and hidden layers. In this phase, the hidden layers act as reservoirs that are formed by considering the neuron counts. Moreover, they attained minimal connectivity among the self-connections.

In ESNet, weights presented in the reservoir are not updated and also the training process is performed in the output layer. Here, the weights are connected in the last layer with the reservoir and this pattern is termed as ridge regression. In this case, the reservoirs work as a non-linear dynamic filter to map the inputs to the higher dimensional region without executing any training in the weights of hidden layers. The structural illustration of the ESNet model is given in Fig. 2.

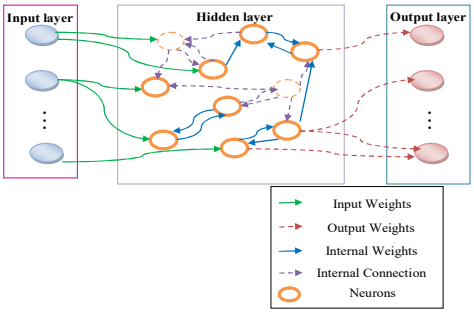


Fig 2. Pictorial Presentation of ESNet

3. Methodology

3.1. Proposed Model Overview

In the developed research work, an efficient wind power prediction technique is designed using deep learning techniques. Initially, the required data for the validation are gathered from benchmark resources. Using high-quality data for the validation helps to enhance the wind power prediction efficiency without any errors. Next, the gathered wind power prediction data are fed into the developed DilESNet-GeluAF for predicting wind power. The developed DilESNet-GeluAF is the integrated version of ESNet and GeluAF with a dilated layer. ESNet helps to make the wind power prediction process simple and also it has enormous memory to collect the temporal dependencies. GeluAF helps to observe the complicated patterns and relationships presented in the data. Moreover, it helps to eliminate the overfitting issues and enhance the robustness of the developed system. Finally, the wind prediction outcomes are attained from the developed DilESNet-GeluAF technique. Later, various analyses are performed to verify the wind power prediction performance of the suggested technique over existing models.

3.2. DilESNet-GeluAF for Wind Power Prediction

An efficient framework named DilESNet-GeluAF is designed in this research work to predict wind power effectively by enhancing the reliability of the power system operation. Here, the developed DilESNet-GeluAF technique is implemented by fusing the ESNet with a dilated layer and GeluAF. The developed framework utilized ESNet as it uses simple training procedures with higher robustness. Moreover, the implementation of ESNet is easy and also eliminates the non-converging issues in the network. But, its hyperparameters are highly sensitive and also they easily fall into the vanishing gradient issues. In some cases, it didn't have the efficiency to process the data presented in the velocity fields. So, tackling multiple disadvantages presented in the existing ESNet is significant to attain better wind power prediction outcomes in the network. To tackle these issues in ESNet, the dilated layer is used

in the developed wind power prediction model. The validation efficiency of the dilated layer is good and also it can be used in the larger receptive fields without any coverage loss. Several advancements in the dilated layers help the developed wind power prediction technique to provide better outcomes. Later, the GeluAF is employed in the suggested wind power prediction technique to enhance the efficiency while analyzing the complicated patterns and also enhancing the generalization rate. Hence, the newly developed wind power prediction technique is termed DilESNet-GeluAF, which effectively eliminates the vanishing gradient issues and enhances the convergence issues. In the developed DilESNet-GeluAF technique, the dilated layer is included with the ESNet and also the normal activation function of ESNet is replaced with GeluAF. Finally, the suggested DilESNet-GeluAF technique helps to obtain high-quality wind power prediction outcomes. The structural illustration of the developed DilESNet-GeluAF-based wind power prediction framework is offered in Fig. 3.

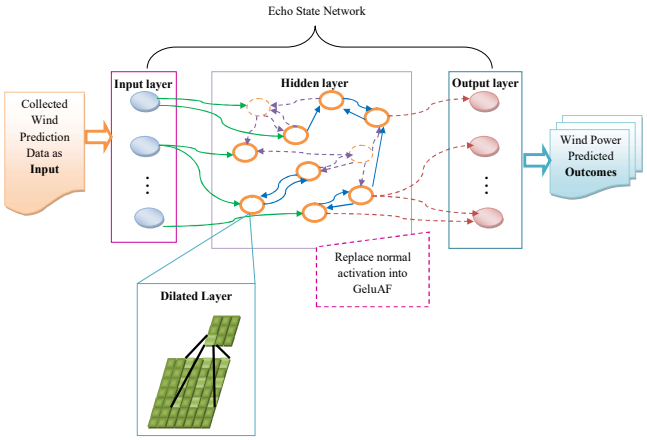


Fig 3. Pictorial Illustration of Developed DilESNet-GeluAF-based Wind Power Prediction Framework

3.3. Analysis Measures

In this phase, various performance measures utilized for analyzing the performance based on the prediction of wind power are discussed as follows. Performance measures used in the analysis are MASE, MEP, SMAPE, MAE, and RMSE.

SMAPE *Smape* is demonstrated in Eq. (3).

$$Smape = \frac{100\ \%}{z}\sum_{x=1}^{z}\left\|\frac{\hat{C}_a - C_a}{|C_a| + |\hat{C}_a|}\right\| \tag{3}$$

MAE *Mae* is signified in Eq. (4).

$$Mae = \frac{1}{z}\sum_{x=1}^{z}\left\|C_a - \hat{C}_a\right\| \tag{4}$$

One Norm ON_1 is given is Eq. (5).

$$ON_1 = \sum_{x=1}^{z}|R_x| \tag{5}$$

RMSE *Rmse* is specified in Eq. (6).

$$Rmse = \sqrt{\frac{1}{z}\sum_{x=1}^{z}\left(C_a - \hat{C}_a\right)^2} \tag{6}$$

Two Norm ON_2 is provided in Eq. (7)

$$ON_2 = \left(\sum_{x=1}^{z} R_x\right)^2 \tag{7}$$

MASE *Mase* is offered in Eq. (8).

$$Mase = S\left[\frac{|\hat{C}_a|}{\frac{1}{z-1}\sum_{x=1}^{z}|C_{ax} - C_{ax-1}|}\right] \tag{8}$$

MEP *Mep* is provided in Eq. (9).

$$Mep = \frac{100\ \%}{z}\sum_{x=1}^{z}\left\|\frac{C_a - \hat{C}_a}{C_a}\right\| \tag{9}$$

The infinity norm is presented in Eq. (10).

$$ON_{\infty} = \underset{1 \le x \le z}{Max} \left| R_x \right| \tag{10}$$

Here, the predicted sample counts are given as z, a real value of the response variable is offered as C_a, the predicted value is specified as $\hat{C}_a$, matrixes is represented as R, and also mean value is termed as S.

3.4. Empirical Results

An efficient wind power prediction technique DilESNet-GeluAF was designed and executed in Python. Classical wind power prediction schemes employed for the validations were CCNQR [18], STGNN [13], EFRCN [8], and KELM [10]. Here, the developed framework DilESNet-GeluAF was analyzed over various error measures.

3.5. Data Sources

The developed framework utilized the publically available dataset for the validation collected from the European wind farm and the link "https://zenodo.org/records/5525065: Access Date 2024-11-09". This dataset holds the data collected from the offshore wind farms with two offshore turbine and meteorological mast details. The dataset holds 1440 samples that are collected in 10-minute intervals.

3.6. Analysis of Actual and Predicted Values

In the developed wind power prediction model, the actual and predicted value of the developed DilESNet-GeluAF is offered in Fig. 4. Here, the actual value and the predicted value are contrasted over the wind power and number of steps ahead values. Executing actual and predicted value analysis helps to verify the efficiency of the suggested framework in wind power prediction. Moreover, this analysis helps to identify the difference between the training and optimization parameters. Moreover, this validation helps to visualize the performance of developed DilESNet-GeluAF in the actual and predicted cases.

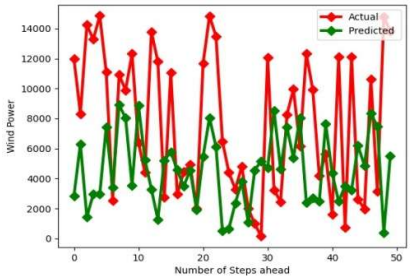
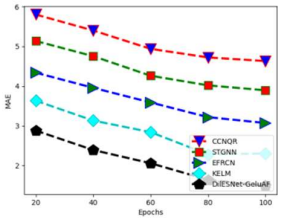


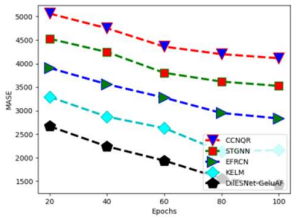
Fig 4. Actual and Predicted Value Analysis on Developed DilESNet-GeluAF-based Wind Power Prediction Model

3.7. Performance Analysis on Suggested Framework

In this phase, the efficiency of the suggested DilESNet-GeluAF-based wind power prediction model is validated over different performance measures are given in Fig. 5. In this phase, the developed DilESNet-GeluAF-based wind prediction model is varied over epochs to verify its efficiency. In the error metrics analysis, the suggested technique gained minimal error rates than the classical wind power prediction techniques. Reducing the errors in the suggested DilESNet-GeluAF helps to overcome the misclassification issues and also helps to accomplish superior wind power prediction outcomes. Increasing the epoch count up to 100 effectively reduced the errors to the initial count of 20. Eliminating the outcome variation issues and errors in the suggested DilESNet-GeluAF helps to reduce the implementation cost and also improves the prediction efficiency in a complicated environment.



(a)



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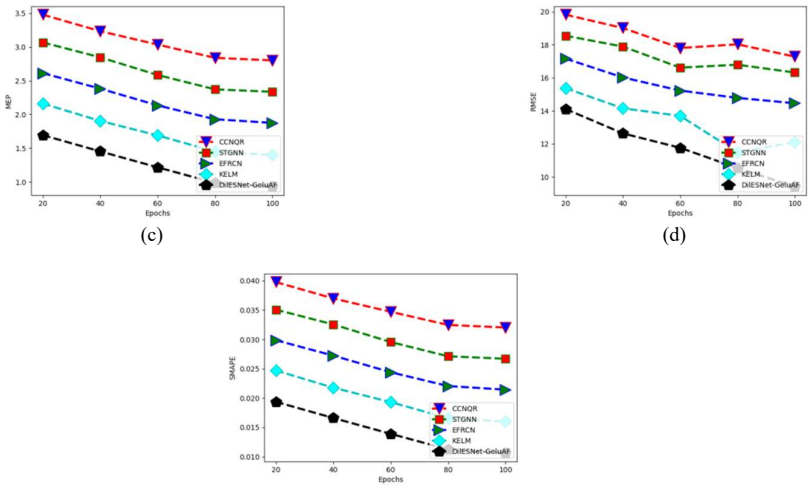

Fig 5. Performance Analysis on Developed Wind Power Prediction Framework over "(a) MAE, (b) MASE, (c) MEP, (d) RMSE, and (e) SMAPE"

3.8. Overall Efficiency Analysis of Recommended Technique

Overall performance analysis on the suggested DilESNet-GeluAF-based wind power prediction techniques over classical power prediction models is offered in Table I. In this phase, various validations are executed by considering the error measures. In the RMSE validation, the suggested DilESNet-GeluAF-based wind power prediction technique gained a minimal error rate of 9.41% than the classical techniques like CCNQR, STGNN, EFRCN, and KELM, respectively. Here, the MEP validation is executed in the suggested technique to attain better decision-making outcomes in the wind power prediction techniques and also it helps to verify the predicted errors over the actual power percentage. The overall performance of the developed wind power prediction technique displayed that the suggested technique effectively reduces the error than the classical techniques and also it accomplishes more precise results than the traditional models.

Table 1. Overall Performance Validation Of Developed Wind Power Prediction Model Over Existing Techniques

Performance Measures	CCNQR [18]	STGNN [13]	EFRCN [8]	KELM [10]	DilESNet-GeluAF
MEP	2.80214	2.336528	1.875148	1.400223	0.929532
SMAPE	0.032024	0.026703	0.02143	0.016003	0.010623
MASE	4114.455	3525.812	2834.07	2161.419	1423.215
MAE	4.630857	3.893786	3.068476	2.300837	1.484361
RMSE	17.28464	16.32116	14.46179	12.11171	9.413912
One-Norm	136753.9	114987.4	90615.17	67946.02	43834.67
Two-Norm	2970.294	2804.723	2485.199	2081.347	1617.742
Infinity-Norm	369.25	512.25	512.25	403.25	325.5

4. Conclusion and Future Directions

An efficient wind power prediction technique named DilESNet-GeluAF was designed in this research work. In this framework, essential wind prediction data utilized for the validation were gathered from the standard resources and offered to the DilESNet-GeluAF-based wind power prediction model. Here, the collected data were processed in developed DilESNet-GeluAF and attained the wind power prediction outcomes. Later, multiple observations were executed in the suggested wind power prediction technique to observe its performance over the existing framework. MEP validation executed in the recommended DilESNet-GeluAF-based wind power prediction technique gained superior efficiency as 66.82%, 60.21%, 50.42%, and 33.61% better than the classical techniques like CCNQR, STGNN, EFRCN, and KELM respectively. Thus, the analysis displayed that the suggested wind power detection model DilESNet-GeluAF gained comparatively higher prediction effectiveness than the conventional techniques.

Future Directions: In the future, the developed framework will be extended with ensemble techniques for predicting wind power. Moreover, online wind power prediction data

will be considered for validation in the upcoming research, which will help to further improve the prediction accuracy.

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