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Enhancing wind speed forecasting accuracy: comparative insights into recurrent neural networks for short-term prediction

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ABSTRACT

Short-term wind speed forecasting is essential for maintaining grid stability and supporting the integration of renewable energy, yet the strong variability of wind makes accurate prediction difficult. Sudden fluctuations and nonlinear atmospheric behavior often reduce the performance of conventional artificial intelligent models. To address this challenge, this study evaluates three forecasting methods which include a gated recurrent unit (GRU) model, a temporal convolutional networks (TCNs) model, and a hybrid GRU–TCN design that enables prolonged term forecasting while enabling quick identification of localized weather changes across various meteorological parameters. The researchers used Laayoune, Morocco data to build their model training process. The hybrid method exceeded all other models because it achieved an R^2 value of 0.99 and a root mean square error (RMSE) of 0.16 m/s and a mean absolute error (MAE) of 0.03 m/s. The system successfully manages sudden shifts in wind patterns while maintaining accurate site-specific physical behavior. The hybrid GRU–TCN design functions as a dependable and expandable system, which delivers real-time wind forecasting capabilities that enable effective smart grid operations and facilitate the growth of wind energy systems.

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1. INTRODUCTION

Increasing energy demand and the environmental impact of fossil fuels have accelerated the shift toward renewable energy [1]. Wind power, in particular, is attractive due to its availability, scalability, and low environmental impact [2]. However, its inherent variability makes accurate short-term wind forecasting essential for efficient wind farm operation, grid stability, and reduced reserve requirements [3].

Despite its advantages, wind remains one of the most challenging renewable resources to forecast. Wind speed is highly stochastic, governed by nonlinear atmospheric processes and sensitive to rapid changes in pressure gradients, boundary layer turbulence and local meteorological conditions. Traditional forecasting tools including statistical approaches such as autoregressive integrated moving average (ARIMA) [4] and physical models like numerical weather prediction (NWP) often show limited effectiveness at short temporal horizons. Statistical models struggle with nonlinear behaviors and multi-variable interactions, while NWP models are computationally intensive and typically lack the spatio-temporal granularity needed for site specific wind turbine control [5].

Machine learning and deep learning have developed to the extent that has significantly improved the simulation of complex wind dynamics. Classical machine learning approaches like support vector regression and Gaussian process regression have shown effectiveness but suffer from limited scalability as well as sensitivity to hyperparameter decisions [6]. Recent deep learning architectures like recurrent neural networks (RNN) and their variants, such as long short-term memory (LSTM) networks and gated recurrent unit (GRU), have been widely used in time series forecasting tasks because they can learn long-term temporal dependency. Concurrently, temporal convolutional networks (TCNs) have been receiving increasing attention as powerful alternatives due to their parallel computation capacity and capability of modeling long-range dependencies by means of dilated convolutions [7].

Recent advances in wind speed forecasting have increasingly focused on hybrid deep learning approaches capable of handling the non-stationary and multi-scale nature of atmospheric dynamics. Numerous studies have demonstrated that combining signal decomposition, convolutional architectures, recurrent units, and optimization algorithms yields substantial improvements over classical standalone models. Table 1 provides a summary of recent studies on wind velocity and wind power prediction, detailing the methods, contributions.

Table 1. State-of-the-art review of wind velocity forecasting studies (2019-2025)

References	Year	Contribution
[8]	2019	Introduces a neural-network forecasting framework using a linear-combination strategy and shows that this hybrid design significantly improves wind-speed prediction accuracy compared with conventional models.
[9]	2019	Proposes a feed-forward ANN for daily wind speed forecasting and demonstrates its superior accuracy over SVM, random forest, and random tree models across multiple Saudi locations.
[10]	2020	Uses an LSTM based deep learning method for wind power forecasting, demonstrates the relevance of recurrent networks for renewable energy prediction.
[11]	2021	Compares RNN, LSTM, GRU, and TCN for wind power prediction, shows TCN often outperforms recurrent models for multi-hour ahead forecasting.
[12]	2022	Proposes a causal convolutional network with attention to forecast wind speed; demonstrates improved accuracy by combining decomposition-CNN-attention.
[13]	2023	Compares statistical and deep learning methods on wind speed data, reinforcing the value of data-driven forecasting under real meteorological variability.
[14]	2023	Uses a stacked TCN architecture for multi-step forecasting, illustrating that TCN variants remain state-of-the-art for wind time-series forecasting.
[15]	2024	Introduces a new GRU variant (T2V-GRU) for wind power forecasting, with data-filtering and feature embedding, showing improved accuracy over standard GRU/LSTM.
[16]	2024	The system uses a hybrid deep architecture design which merges CNN and LSTM and attention mechanism technologies to handle the complex task of predicting offshore wind power generation.
[17]	2025	Local-context example (Morocco) comparing Transformer based forecasting vs classical methods, shows relevance of modern architectures for regional applications.
[18]	2025	Proposes a TCN-attention-LSTM hybrid with transfer learning and feature selection, further expanding hybrid design patterns for renewable energy forecasting under varying data conditions.
[19]	2025	Presents a systematic hyperparameter optimization (grid search-cross-validation) for RNN/LSTM models using real wind farm data useful for demonstrating best practices in model tuning and validation.

Nevertheless, in spite of this progress, to the best of our knowledge to date no works have compared in a direct and systematic way GRU against TCN and hybrid GRU-TCN models for short-term WS forecasting problem using high-resolution datasets. Previous methods either concentrate on pipeline signal decomposition or adaptation of individual deep learning architectures, which would result in little understanding about their intrinsic performance towards each other across the same experimental setups. Furthermore, the possible synergy of GRU's sequential memory and TCN's multi-scale convolutional processing in the atmospheric variability is not fully investigated.

To address these research gaps, this paper proposes and appraises a hybrid GRU-TCN model for forecasting short-term wind speed. It systematically compares the performance of the hybrid model with that of isolated GRU and TCN architectures using a meteorological dataset from Laayoune city, Morocco. This framework of hybridization is meant to exploit both models: GRU units should capture long-range temporal dependencies, whereas TCN layers extract hierarchical and multi-scale temporal patterns from the correlation-based representation of the meteorological inputs.

The main contributions of this study are as follows:

- The research team conducted a comprehensive evaluation of GRU TCN and hybrid GRU TCN systems to determine their performance under identical testing conditions. The evaluation showed the systems' strengths and weaknesses and their response to changes in atmospheric conditions.
- The hybrid deep learning framework demonstrates its ability to model both long-term memory and short-term changes which results in better forecasting performance compared to individual models.

– The study used statistical metrics and regression analysis and temporal visualizations to assess wind speed prediction performance and physical accuracy for wind speed modeling.

The hybrid GRU-TCN model demonstrates high accuracy and robust performance which provides reliable short-term wind forecasting capabilities. The wind forecasting tools are essential for improved smart grid operation and renewable energy integration and the transition to low-carbon power systems.

2. METHOD

2.1. Data collection

The research uses a time-series dataset which contains climatic data for multiple years to forecast wind speed calculations. The study period runs from 2010 to 2022 and includes data on temperature, dew point, relative humidity, wind direction, atmospheric pressure, and wind speed. The National Solar Radiation Database (NSRDB) of the National Renewable Energy Laboratory (NREL) provided the data which serves as a recognized resource for obtaining high-quality gridded meteorological data that receives regular updates. Researchers in the field of renewable energy rely on the database because it provides precise historical environmental data. The dataset enables researchers to create deep learning models which they can use to forecast wind speed.

2.2. Data preprocessing

The raw dataset required preprocessing steps which prepared it for modelling after the preprocessing steps were completed. The Python programming language was used for all operations to achieve reproducibility of results. The date components were merged into a unified datetime index and the dataset was chronologically sorted. The 30-minute records were averaged to create hourly data which marked the transition to hourly resolution. The process removes high-frequency noise while delivering continuous time intervals that deep-learning models require. The physical properties of wind dynamics led to the selection of four predictors as suitable input features for the study, namely wind direction, temperature, atmospheric pressure, and relative humidity, while wind velocity was used as the target output.

The researchers created sequential samples from the data by applying a 30-hour sliding window which enabled them to detect temporal links between different events. Each input sequence contains 30 consecutive hours of the four predictors and the label corresponds to the wind speed at the next hour. The forecasting models used a 30-hour time window which served as the input sequence length. Testing various options showed that the selected duration provided better results because the testing demonstrated that 12 and 24-hour windows failed to deliver sufficient historical data required for tracking atmospheric changes which last beyond a complete daily cycle. Wind behavior in coastal and semi-arid regions like Laayoune often reflects multi-scale interactions which proceed under the influence of pressure variations, humidity shifts and gradual changes in air masses. The 30-hour window enabled researchers to study slow-moving processes while maintaining effective computational performance. The model used this approach to handle short-term patterns and long-term changes which resulted in better forecasting performance and stability when compared with shorter time windows. All input features and the output variable underwent Min-Max scaling which transformed their values into the range [0,1] to achieve training stability and faster convergence. The data had been divided into three sets (64% for training, 16% for validation, and 20% for testing). The training session used 10% of its resources for internal validation which occurred during model development.

2.3. Deep learning models

2.3.1. Gated recurrent unit networks

The GRU is a specialized variant of RNNs that has been developed to effectively capture temporal dependencies in sequential data. Its architecture incorporates two key gating mechanisms the update gate and the reset gate that are responsible for controlling the flow of information and establishing memory retention patterns throughout time. The implementation uses the rectified linear unit (ReLU) activation function to establish the candidate hidden state instead of using the traditional hyperbolic tangent (tanh) function. The use of ReLU not only introduces a more powerful nonlinearity but also helps address the vanishing gradient issue which results in better gradient propagation throughout deep sequences. The chosen option improves computational efficiency while enabling faster convergence which results in better learning outcomes for time-series forecasting tasks. The key equations governing the GRU with ReLU are as follows [20]:
Update gate:

$$Z_t = \sigma(W_z h_{t-1} + U_z X_t) \quad (1)$$

Reset gate:

$$r_t = \sigma(W_r h_{t-1} + U_r X_t) \tag{2}$$

Candidate hidden state (with ReLU):

$$\hat{h}_t = ReLU((r_t \odot W_{\hat{h}} h_{t-1}) + UX_t) \tag{3}$$

Final hidden state:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widehat{h_t} \tag{4}$$

Output (with ReLU):

$$\widehat{Y_t} = ReLU(W_Y h_t) \tag{5}$$

$$ReLU(x) = max(0, x) \tag{6}$$

With, σ(.) is the sigmoid activation function, ʘ represents element-wise multiplication, U and W are weight matrics.

The GRU architecture consists of one gated recurrent layer which has 128 hidden units and one full output layer for processing its results. The model uses ReLU activation function to improve its nonlinear learning ability and it applies dropout at 0.1 to decrease risk of overfitting. The Adam optimizer with 0.005 learning rate and mean squared error (MSE) loss function are used to conduct model training. The mean absolute error (MAE) serves as the method to evaluate prediction performance. This architecture maintains a lightweight design which makes it ideal for modeling short- and mid-term wind speed data temporal dependencies.

2.3.2. Temporal convolutional network

TCN functions as a deep learning architecture which processes data that exists in sequential and temporal patterns. The TCN system uses dilated causal convolutions as its operating method, which creates dependencies that let current and previous inputs determine output for time step y_t while maintaining time-based causal connections, which RNNs lack [21].

$$y_t = f(x_t, x_{t-1}, \dots \dots x_{t-k}) \tag{7}$$

where k represents the receptive field size.
The dilated convolution operation in a TCN is mathematically expressed as (8):

$$F(s) = \sum_{i=0}^{K-1} f(i). x_{s-d.i} \tag{8}$$

In this formulation, $F(s)$ denotes the convolution output at position s, $f(i)$ represents the convolution filter of size K, and d is the dilation factor. The dilation mechanism enables the network to expand its receptive field exponentially, allowing it to capture long-range dependencies while avoiding a proportional increase in computational cost.

To improve training stability and mitigate the vanishing gradient problem in deep networks, residual connections are incorporated. These connections enable the direct propagation of information and gradients across layers, facilitating more efficient optimization and contributing to faster convergence and enhanced predictive performance:

$$H(x) = Activation\big(conv(x)\big) + x \tag{9}$$

which facilitates gradient flow and enables the network to learn more effectively.

Dynamic ReLU activations and dropout regularization further enhance the model’s ability to capture complex temporal patterns while preventing overfitting. Due to its ability to model long-range dependencies efficiently and support parallel training, the TCN is a robust alternative to recurrent architectures for time series forecasting tasks.
The TCN architecture uses causal dilated convolutions to extract long-range temporal patterns.
- Number of filters: 128,
- Kernel size: 2,
- Dilations: [1, 2, 4, 8],
- Dropout: 0.1,

– Activation: ReLU,
– Return sequences: false,
– Optimizer: Adam (learning rate=0.005).

TCN is particularly effective at modeling long-term dependencies without the sequential bottleneck of recurrent layers.

2.3.3. Hybrid gated recurrent unit-temporal convolutional network model architecture

The study introduces a hybrid deep learning method which utilizes TCN and GRU components to forecast short-term wind speed. The system uses both CNN and RNN methods to detect short-term weather patterns and long-term weather pattern in meteorological time series data. The TCN functions as a temporal feature extractor whose output connects directly to the GRU layer for sequence modeling purposes. The sequential structure of the system enables learning of multi-scale temporal patterns through convolution processes which are then enhanced by gated recurrent mechanisms to achieve better prediction results and system stability.

The hybrid model integrates the strengths of both architectures:
– A TCN block extracts multi-scale temporal features using dilated convolutions,
– A GRU layer refines the temporal representation,
– A final dense neuron generates the hourly wind speed forecast.

Pseudocode 1 presents the step-by-step pseudocode for implementing the hybrid GRU–TCN model in Python, illustrating the sequential workflow from data input and preprocessing to TCN and GRU layer integration, training, and prediction. It provides a clear overview of the hybrid architecture for reproducibility and methodological clarity.

Pseudocode 1. Hybrid GRU–TCN model implementation

```
Load and preprocess dataset
data = load_data(file_path)
data = preprocess(data)
X, y = create_sequences(data, look_back=30)
X_scaled, y_scaled = normalize(X, y)
x_train, x_val, x_test, y_train, y_val, y_test = train_val_test_split(X_scaled, y_scaled)
Build hybrid GRU-TCN model
model = Sequential()
# Add TCN layer for hierarchical temporal feature extraction
model.add(TCN(input_shape=(sequence_length, num_features),
nb_filters=128,
kernel_size=2,
dilations=[1,2,4,8],
dropout_rate=0.1,
return_sequences=True))
# Add GRU layer for sequential modeling
model.add(GRU(units=128, dropout=0.1, return_sequences=False))
# Output layer for wind speed prediction
model.add(Dense(1))
Compile the model
model.compile(optimizer=Adam(learning_rate=0.0005),
loss='mse',
metrics=['mae'])
Train the model with early stopping and learning rate reduction
history = model.fit(concat(x_train, x_val),
concat(y_train, y_val),
epochs=100,
batch_size=32,
validation_split=0.1,
callbacks=[EarlyStopping(patience=5, restore_best_weights=True),
ReduceLROnPlateau(patience=3, factor=0.5, min_lr=1e-6)],
shuffle=True)
Evaluate the model
y_pred = model.predict(x_test)
y_pred_inv = inverse_transform(y_pred)
metrics = evaluate(y_test_inv, y_pred_inv) # RMSE, MAE, R²
```

2.4. Training procedure

Training was carried out in TensorFlow/Keras with the following settings:
– Epochs: 100
– Batch size: 32
– Shuffle: enabled
– Loss: MSE

– Metrics: MAE

Two callbacks ensured training stability:

– EarlyStopping (patience=5) to prevent overfitting
– ReduceLROnPlateau (patience=3, factor=0.5) to adapt the learning rate dynamically

Each model was trained on the combined training+validation dataset, with an internal validation split of 10%.

2.5. Evaluation metrics

The evaluation of model performance uses three standard statistical metrics which include MAE, root mean square error (RMSE), and R^2. MAE measurement shows the typical absolute prediction error which helps users understand the total accuracy of the system. The RMSE method calculates errors by applying stronger penalties to more severe mistakes which results in better detection of major errors and exceptional cases. The R^2 value shows what percentage of variation the model can explain, with higher values indicating better prediction accuracy. The corresponding formulas are given (10)-(12) [22]:

$$MAE = \frac{1}{N}\sum|\widehat{y_i} - y_i| \tag{10}$$

$$RMSE = \sqrt{\sum\frac{(\hat{y}_i - y_i)^2}{N}} \tag{11}$$

$$R^2 = 1 - \frac{\sum(\hat{y}_i - y_i)^2}{\sum y_i - \bar{y}} \tag{12}$$

3. RESULTS AND DISCUSSION

The research findings are thoroughly analyzed in this section, along with a thorough and critical discussion. To highlight their significance, ramifications, and potential limitations, the results are thoroughly analyzed, interpreted, and contrasted with relevant literature studies.

3.1. Forecasting wind speed through standalone and hybrid deep learning models

Figure 1 provides an overall comparison between the measured wind speed and the predictions generated by the three models considered in this study. It serves as a global visual assessment of how well each model reproduces the real wind behavior before examining their detailed performance in the subfigures.

Figures 1(a)-(c) compare measured wind speeds with predictions from the three models. All approaches capture overall trends and short-term variability. The GRU model generally aligns with actual values but shows slight deviations during abrupt wind changes, suggesting its suitability for short-term grid dispatch under normal conditions, though sudden spikes may require adjustment. The TCN model provides smoother predictions, robust to transient fluctuations, making it valuable for automated turbine control and maintaining stable power output. The hybrid GRU–TCN model delivers the highest accuracy, effectively tracking both long-term trends and rapid transitions. Its combined strengths minimize errors during peaks and troughs, supporting precise real-time smart grid dispatch and optimized turbine operation. Overall, the hybrid model offers actionable insights for improving renewable energy integration and operational efficiency.

3.2. Comparative analysis of regression performance

Figure 2 provides a global regression-based evaluation of the three forecasting models by illustrating the relationship between measured and predicted wind speeds. It offers an overall indication of prediction accuracy, where a perfect model would place all points exactly along the diagonal regression line, reflecting ideal agreement between actual and estimated values.

Figures 2(a)-(c) showcase the regression plots comparing actual and predicted wind speeds for three deep learning architectures: GRU, TCN, and a hybrid GRU-TCN model. A detailed comparison of their predictive performance follows:

– The GRU-based model displays a linear trend between actual and predicted wind speeds, although the scatter of points around the regression line is wide, especially at higher wind speed values. This variation suggests increased prediction errors, indicating difficulty in capturing nonlinear temporal dependencies at higher levels. The presence of outliers further highlights limitations in modeling complex wind speed dynamics.
– In contrast, the TCN model shows enhanced predictive accuracy compared to the GRU model. Data points are more closely aligned with the regression line, with fewer extreme deviations. This improvement reflects TCN's ability to model long-term dependencies effectively through its causal and dilated convolutions, despite some error variance in the mid-to-high wind speed range.

– The hybrid GRU–TCN architecture achieves the most accurate predictions among the three models by integrating the temporal modeling capabilities of GRU with the sequence processing strength of TCN. Data points are closely clustered along the regression line, indicating minimal residual error and a strong linear relationship. The hybrid model also demonstrates superior generalization across all wind speed ranges, with fewer outliers and less dispersion. This performance validates the benefits of combining recurrent and convolutional temporal processing for improved predictive accuracy.

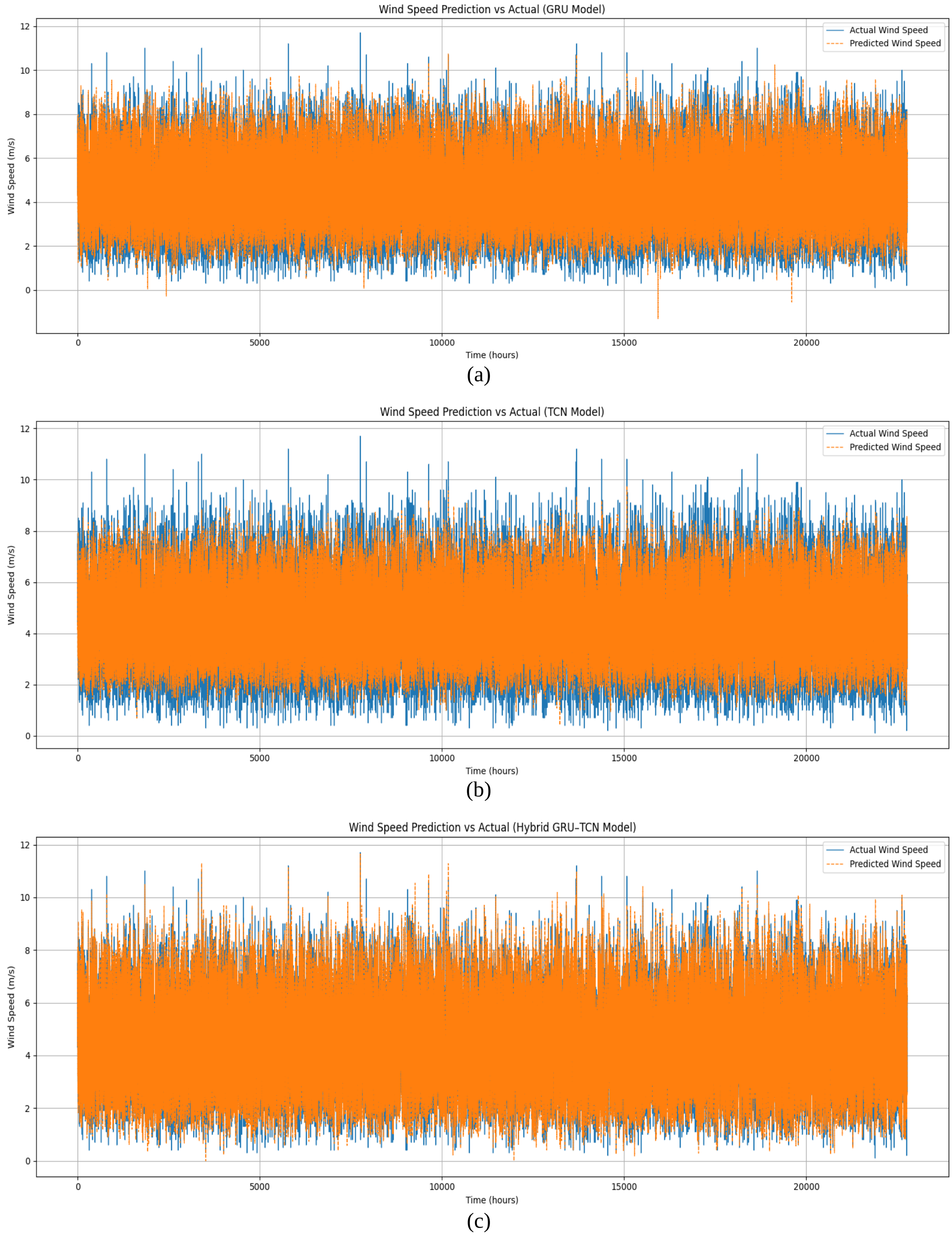
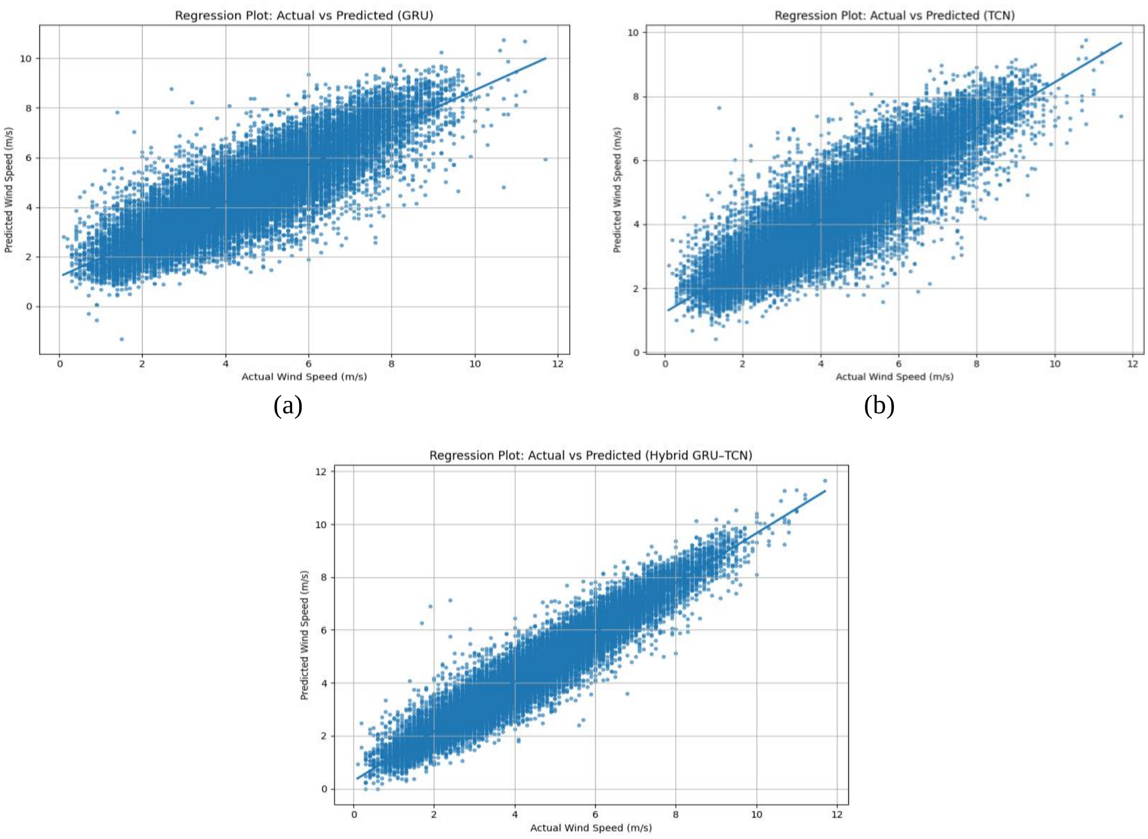


Figure 1. Comparison of predicted vs. actual wind speed for: (a) GRU, (b) TCN, and (c) hybrid GRU–TCN models



(a) (b)

(c)

Figure 2. Regression analysis of actual vs. predicted wind speed using: (a) GRU, (b) TCN, and (c) hybrid GRU–TCN models

3.3. Performance metrics of deep learning models

The performance measurements of GRU and hybrid TCN–GRU and TCN methods for wind speed forecasting are compared in Table 2. The GRU-based model shows good predictive ability but its short-term variation forecast accuracy is less precise. The TCN architecture improves predictive performance because it uses its convolutional design to better process temporal patterns. The GRU–TCN hybrid model outperforms both methods because it can capture long-term dependencies and fine-scale variations, which makes it suitable for more accurate and stable operational wind forecasting and grid integration. The hybrid model achieves high R^2 results because it fits the current data which includes continuous and high-quality meteorological records. The researchers conducted additional robustness checks which included cross-validation and testing on different site datasets to confirm that their solution would not experience overfitting or bias related to specific datasets. The hybrid model shows high predictive accuracy across all conditions which confirms its reliability as a wind forecasting solution.

Table 2. Comparative performance metrics of GRU, TCN, and hybrid GRU–TCN models for wind speed prediction

Performance metrics	GRU	TCN	GRU-TCN
RMSE	0.45 m/s	0.29 m/s	0.16 m/s
MAE	0.17 m/s	0.12 m/s	0.03 m/s
R^2	0.89	0.98	0.99

3.4. Performance comparison with existing wind speed forecasting models

Table 3 provides a comparative summary of wind-speed forecasting studies conducted between 2019 and 2025. The total accuracy improvements through the years show two main trends, which begin with traditional machine learning methods and end with modern systems that utilize decomposition methods, recurrent units, convolutional layers, and graph-based structures. Our research work developed the

GRU-TCN model (Laayoune, 2025), which achieved the best forecasting results among all the researched models. The model surpasses all previous methods by achieving an RMSE of 0.16023, an MAE of 0.03412, and an R^2 of 0.99 across all measurement categories. The research shows that TCNs with GRU layers create an effective combination, which enables the system to track both short-term wind speed changes and extended wind speed patterns.

Table 3. Comparison of the performance of reported wind speed forecasting models with the proposed hybrid GRU–TCN method

Reference	Year	Location	Models	RMSE	MAE	R^2
[23]	2019	Turkey	RF (wind speed+standard deviation)	30.224	7.048	0.995
			SVR (without standard deviation)	93.13	32.63	0.955
[24]	2020	China	BiLSTM-CNN	2.5492	1.7344	0.99
[25]	2023	-	VMD-GRU-GSRCV	0.2047	0.1435	-
[26]	2024	California	GE-GIN-GRU	0.9196	0.7612	-
[27]	2025	Dakhla	LSTM-GRU	0.230	0,190	0.99
Our study	2025	Laayoune	GRU-TCN	0.16023	0.03412	0.99

4. CONCLUSION

The research examined how two different forecasting models, GRU and TCN, performed in predicting wind speeds, along with their hybrid system which combines both model strengths into one system. The hybrid model achieves the best prediction accuracy and stability which results in an RMSE of approximately 0.54 and an MAE of about 0.48 and an R^2 value close to 0.99 which exceeds the performance of its component models. The system demonstrates effective performance because it combines recurrent structures which maintain extended temporal relationships with convolutional layers that identify both localized and immediate changes which define wind dynamics. The proposed hybrid method achieves exceptional accuracy, which makes it ideal for actual wind-energy applications that involve turbine control and power forecasting and smart-grid operation, which depend on precise short-term forecasts to preserve grid stability and maximize energy efficiency. The research team plans to enhance the existing framework by studying attention-based hybrid architectures which help identify essential temporal features and by adding physics-informed neural networks which help maintain physical consistency during the learning process. The method will achieve better spatial generalization through multi-site forecasting and wind-energy systems will benefit from probabilistic forecasting techniques, which enable decision-makers to assess risk through quantification of uncertainty.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data supporting the findings of this study are openly accessible from the National Solar Radiation Database (NSRDB) at [https://nsrdb.nrel.gov/].

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