EasyChair Preprint

№ 11968

Forecast of Wind Speed Using GRU Neural Network in Tetouan City

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February 7, 2024

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Abstract

Wind speed prediction is crucial for efficient electricity production from wind energy sources. Previous methods, particularly artificial intelligence techniques, have been established for wind speed prediction. This study employs a Gated Recurrent Unit (GRU) model to predict daily wind speeds in Tetouan City northern Morocco, leveraging five years of historical meteorological data.

We aim to develop a reliable forecasting tool that enhances our understanding of wind patterns in the region, contributing to more efficient energy management."

Utilizing the MATLAB interface and the Adam optimization algorithm, the GRU is trained to ensure robust performance.

Performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the correlation coefficient (R), were calculated to assess the accuracy of the forecasting model. The achieved values for MSE, RMSE, and R stand at [insert values here]. These metrics demonstrate the effectiveness of the GRU model in providing precise wind speed predictions.

Introduction

In pursuit of sustainability goals, the pivotal role of renewable energy sources becomes evident. Shifting from fossil fuels to renewable energy not only allows for a substantial reduction in greenhouse gas emissions but also serves as a powerful means to combat climate change and minimize our environmental impact[1].

Our study will focus on wind energy as a renewable source in Tetouan, a city located at approximately 35.57°N latitude and 5.37°W longitude in northern Morocco[2].The accurate prediction of wind speed is vital for keeping the electrical grid safe and ensuring efficient functioning of wind power systems. Precise forecasts not only enhance the reliability of wind energy systems but also contribute to stable energy supply, cost-effective operations, and progress toward carbon neutrality goals[3].

The intermittent and variable nature of wind necessitates advanced predictive models to optimize energy production and grid management.

In this study, we focus on harnessing the power of deep learning, specifically the Gated Recurrent Unit (GRU), to forecast wind speeds for Tetouan City over five years.

Traditional forecasting methods often fall short of capturing the intricate temporal dependencies present in meteorological data. GRU, a type of recurrent neural network (RNN), excels in modeling sequential data while addressing challenges such as vanishing gradients. This research builds on the strengths of GRU to create a predictive model capable of adapting to the dynamic nature of wind behavior[4].

Our methodology involves meticulous data preprocessing to ensure the quality of the input data, feature selection to identify influential variables, and training the GRU model on historical meteorological data. The objective is to provide a reliable tool for anticipating wind speed variations, contributing to the development of sustainable practices and informed decision-making in Tetouan City.

Methodology

Variable Selection for the Prediction Model

To forecast wind speed, we processed data for Tetouan from the year 2017 to 2022, sourced from the following website https://power.larc.nasa.gov/data-access-viewer/. The correlation coefficient will be calculated using Equation (7) to understand the relationship between each pair of variables. In our study, the dew temperature and wind temperature exhibit a correlation coefficient equal to **0.826927** as mentioned in Table 1. This figure indicates that these two variables share similar climatological characteristics, allowing us to eliminate one in favor of the other to avoid computationally expensive calculations[5].

Table 1 : The correlation coefficients between the variables.

	PS	RH	TS	TDEW	PREC	WD	WS	WSMI	WSMA
PS	1	0,157821	-0,35449	0,3495	-0,39874	-0,06033	-0,20111	-0,08493	-0,26979
RH		1	-0,72575	-0,23228	0,340876	0,050718	0,211798	0,213016	0,199688
TS			1	**0,826927**	-0,21575	-0,15158	-0,05444	-0,06767	-0,04312
TDEW				1	-0,07033	-0,21128	0,080361	0,061427	0,083182
PREC					1	0,130835	0,26872	0,157904	0,34112
WD						1	-0,30552	-0,29751	-0,24541
WS							1	0,89754	0,945285
WSMI								1	0,759987
WSMA									1

GRU model

The Gated Recurrent Unit (GRU) is a type of recurrent neural network and one of the simplified models of LSTM proposed by Cho et al.(Gate-Variants of Gated Recurrent Unit (GRU) Neural Networks). It's particularly effective for processing sequential data where dependencies exist across different time steps. And designed to address the vanishing gradient problem in traditional RNNs.

GRU has two gates: an update gate and a reset gate as mentioned in Figure 1. The update gate determines how much of the past information to carry into the future, and the reset gate decides how much of the past information to forget.

The update and reset gates are controlled by sigmoid activation functions, and the candidate activation is computed using a hyperbolic tangent function. The equations for a GRU are as follows[6]:

$$Zt = \sigma(Wz \cdot [Ht - 1, Xt]) \quad (1)$$

$$Rt = \sigma(Wr \cdot [Ht - 1, Xt]) \quad (2)$$

$$\check{H}t = tanh(W \cdot [Rt \odot Ht - 1, Xt]) \quad (3)$$

$$Ht = (1 - Zt) \odot Ht - 1 + Zt \odot \check{H}t \quad (4)$$

Where:

- Zt is the update gate output.
- Rt is the reset gate output.
- $\check{H}t$ is the candidate activation.
- Ht is the hidden state at time t.
- Wz , Wr , and Wh are weight matrices.
- σ is the sigmoid activation function.
- $\odot$ denotes element-wise multiplication.

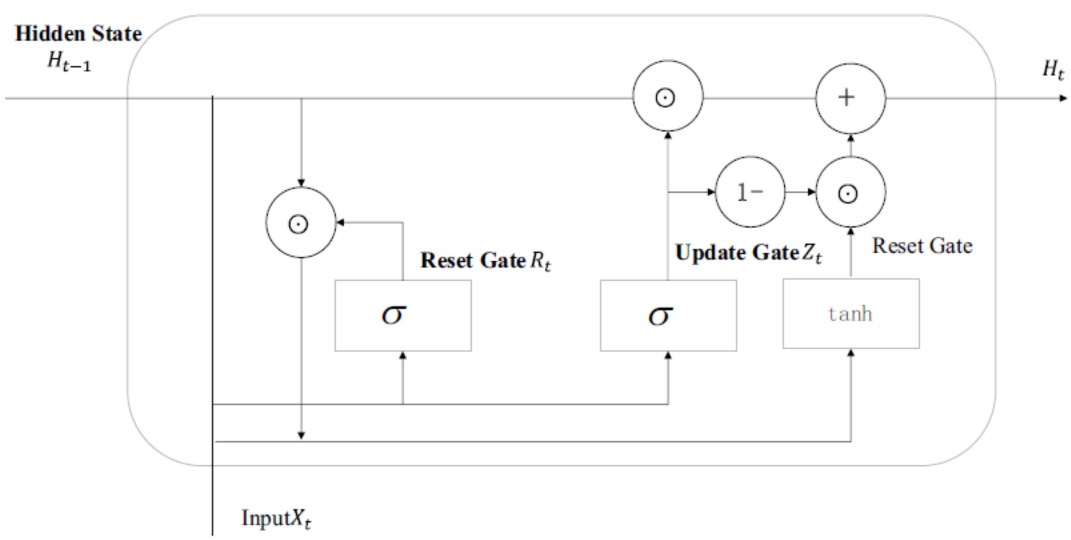

Figure 1: GRU structure[6].

Training GRU in MATLAB

Data division

To train the Gated Recurrent Unit (GRU) model in MATLAB, the dataset is divided into 70% for training allowing the model to learn from the majority of the dataset, and 15% for validation helps fine-tune parameters to prevent overfitting. Finally, the remaining 15% of the data forms the testing set, serving as a critical measure to assess the model's generalization performance on unseen data. (Multivariate Statistical Machine Learning Methods for Genomic Prediction).

Model Performance

Evaluation metrics such as Root Mean Square Error (RMSE), Mean Squared Error (MSE), and correlation coefficient (R) are selected to quantify the disparity between the actual and predicted results as shown in the equations below[7].

$$\mathbf{MSE}=\frac{1}{n}\sum_{i=1}^{n}(yi-\hat{y}i)^2 \qquad (5)$$

$$\mathbf{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi-\hat{y}i)^2} \qquad (6)$$

$$\mathbf{R}=\sqrt{1-\frac{\sum_{i=1}^{n}(yi-\hat{y}i)^2}{\sum_{i=1}^{n}(yi-\bar{y})^2}} \qquad (7)$$

Where:

yi represents the actual values.

$\hat{y}i$ represents the predicted values.

$\bar{y}$ is the mean of actual values.

Results and discussions

Figure 2 represents wind speed data over five years for Tetouan City, and offers a visual snapshot of the variations observed in Tetouan. This illustration provides insight into the temporal dynamics of wind speed in the region, allowing for a qualitative understanding of how these speeds fluctuate throughout the specified duration.

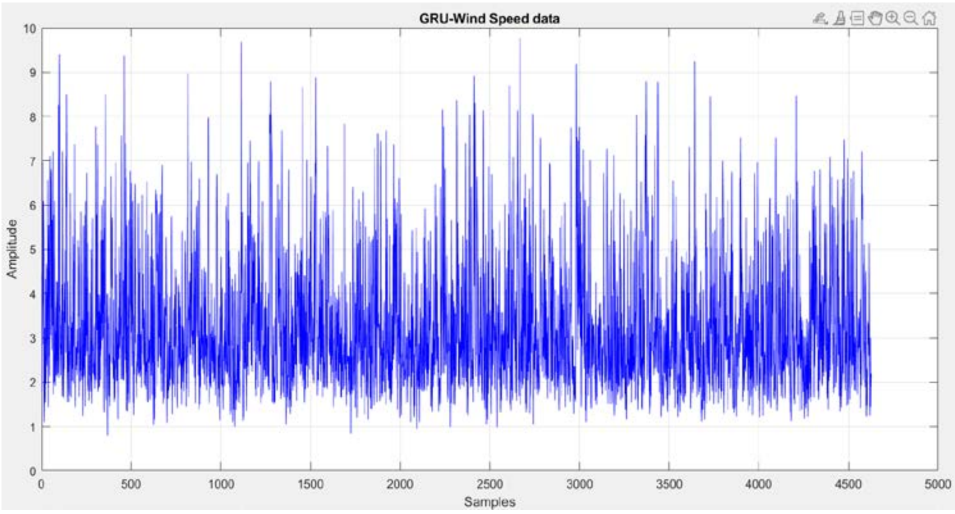

Figure 2: Wind speed data over five years for Tetouan City

we systematically varied the number of neurons, recording the corresponding values of Mean Squared Error (MSE), Root Mean Square Error (RMSE), and correlation coefficient (R) as mentioned in Table 2. Through this iterative process, the architecture employing 250 neurons consistently delivered commendable results. This finding underscores the effectiveness of the configuration with 300 neurons in enhancing the GRU model's predictive accuracy for wind speed data in Tetouan.

Table 2:Training phase metrics

Hidden units	100	200	250	300
RMSE	0,4079	0,2942	0,2509	0,2539
MSE	0.1664	0.0866	0.0630	0.0645
R	0.96663	0.98038	0.98582	0,98544

Applying the chosen GRU model with 250 neurons to forecast wind speed for the next ten days using new data resulted in accurate predictions as shown in table 3, further establishing the model's reliability for short-term forecasting in Tetouan[8].

Table 3:prediction of wind speed for August 2022

Original wind speed	Predicted wind speed
4.3300	3.7840824
4.5100	4.3150544
1.4900	2.1320496
1.6700	2.2029073
1.2300	1.8307570
1.2300	2.0918059
2.0300	2.3851404
2.3000	2.3083563
1.4800	1.8808231
2.3100	2.1985528
2.1200	2.3033011

3.3800	2.9887688
2.8500	2.6435132
2.9700	2.9222593
3.0700	3.0898049
3.3000	3.1771216
2.9600	3.0442715
2.5900	2.6985466
5.1400	5.0015702
4.1000	4.2691374
3.1900	2.5936532
2.5500	2.2622468
1.4800	1.5436649
1.2500	1.8244233
1.8700	2.1726320
3	2.8274927
1.4500	1.8176749
1.9500	1.7915848
1.8900	1.8256583
2.2000	2.5225320
2.1100	2.1279218

Beyond the technical aspects, the discussion delves into the practical implications of these results for renewable energy planning and the challenges posed by the intermittent nature of wind. The nuances of these discussions contribute to a comprehensive understanding of the model's performance and its applicability in real-world scenarios[9].

Conclusion

our study demonstrates the efficacy of the GRU model in capturing complex temporal dependencies and providing reliable predictions.

The obtained metrics values demonstrate the efficacy of the GRU model in capturing complex temporal dependencies and providing reliable predictions.

- RMSE: 0,2509

- MSE: 0.0630

- R: 0.98582

These results underscore the potential of the GRU model as a valuable tool for anticipating wind speed variations in Tetouan. The model's high accuracy contributes to the advancement of sustainable practices and informed decision-making in the realm of renewable energy. The findings highlight the significance of leveraging advanced deep learning techniques, such as the GRU model, for enhancing the precision and reliability of wind speed forecasting.

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