Stacked Gated Recurrent Unit Approach for Wind Speed Forecasting in the Region of Adrar

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ABSTRACT

Wind power has seen increased growth and development in recent years as a clean, low-cost renewable energy type. Wind speed forecasting has been playing an important role in the generation of wind power as a key to improving the accuracy of wind power and the integration of renewable energy within the main electrical grid and its stability. This paper proposes a stacked gated recurrent unit SGRU model for short-term wind speed forecasting in the Adrar wind station, using the NASA dataset. The suggested method efficacy is evaluated using data from the Adrar wind farm. In comparison to existing deep learning-based approaches, the suggested strategy is appropriate for wind speed forecasting and achieves superior forecasting performance in terms of several index errors.

Keywords: Forecasting, Wind speed, GRU

1 Introduction

In general, Artificial intelligence (AI) techniques work well with time series and non-linear problems such as wind speed forecasting. This study examines the use of the stacked gated recurrent unit (SGRU) deep learning model for predicting wind speed. In particular, the suggested strategy attempts to incorporate additional layers of GRU rather than the feed-forward layer to reduce dataset complexity by utilizing a gating mechanism for accurate short-term wind speed forecasts [1].

2 Model and Method

2.1 Staked gated recurrent unit SGRU

GRU or gated recurrent unit is also an enhanced version of the conventional RNN. In 2014, it was launched by Kyunghyang Cho [2]. It is extremely similar to LSTM in that both are built on gating methods to regulate the flow of information, but GRU employs only two gates as opposed to three equations (1, 2). It is possible to regulate how much of the new state is identical to the old state, allowing the update gates to effectively capture long-term dependencies in sequences. While the second gate, known as the reset gate, is responsible for determining how much of the prior state to retain. In addition to these gates, there is a state known as Hidden state H_t equations (4) [3].

$$R_t = \sigma(X_t w_{XR} + h_{t-1} w_{hR} + b_R) \quad (1)$$

$$U_t = \sigma(X_t w_{XU} + h_{t-1} w_{hU} + b_U) \quad (2)$$

$$\widehat{H}_t = \tanh(X_t w_{XH} + (R_t \odot h_{t-1}) w_h + b_h) \quad (3)$$

$$H_t = (U_t h_{t-1} + (1 - U_t) \odot \widehat{H}_t) \quad (4)$$

Where σ is the sigmoid function, X_t is the input given to the gate, w_{XR}, w_{XU} , w_{hR}, and w_{hU} are respectively the weight parameters for the reset gate, the update gate, the hidden state. The Stacked GRU is an extension of this model that has multiple hidden GRU layers to make the model deeper and increase wind speed forecasting accuracy.

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3 Experiments

Initially, the dataset undergoes preprocessing, followed by its division into training and testing sets, with 80% and 20% of the data allocated to training and testing, respectively. Employing a configuration of 10 hours as the step count and incorporating four input variables wind speed at 50 m, relative humidity at 2 m, temperature, and wind speed at 10 m, to predict wind speed one hour ahead the process is described in figure 1. Subsequently, for wind speed forecasting, the recommended SGRU model undergoes training with specified parameters: a learning rate of 0.001, a batch size of 250, and 250 epochs.

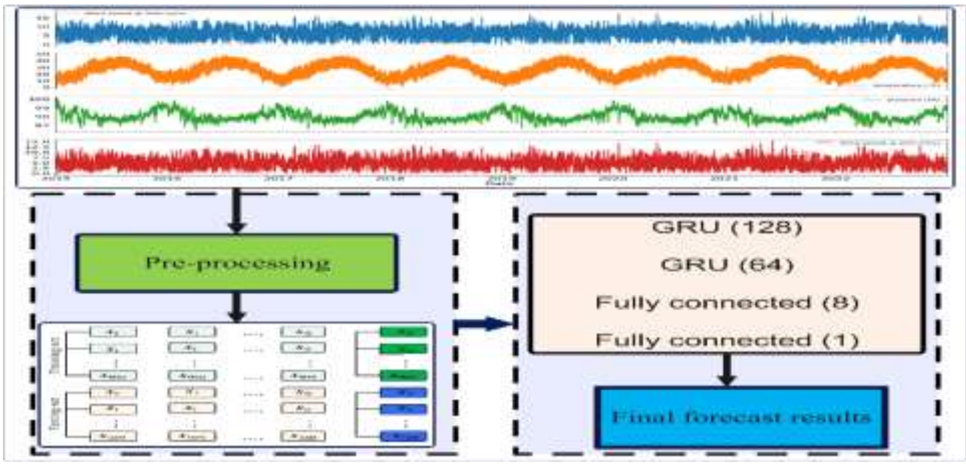

Figure 1: *Architecture of the deep Stacked GRU network.*

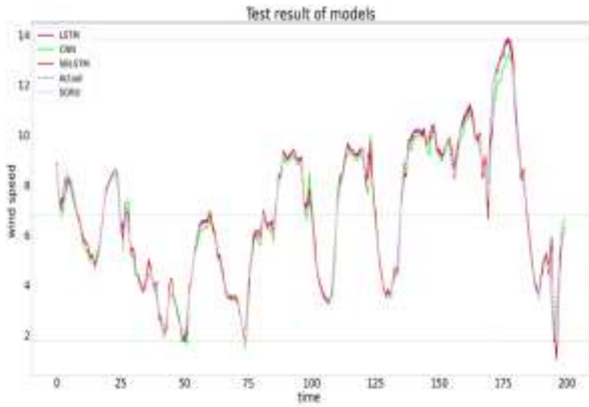

Figure 2: *Results of SGRU and other forecasting models*

4 Results and Discussion

Table 1: *Error forecasting result of the four models*

model	MAE	MSE	R^2	RMSE	MAPE (%)
LSTM	0.25	0.17	0.975	0.42	57.72
CNN	0.29	0.22	0.966	0.47	62.67
SBLSTM	0.26	0.18	0.974	0.41	58.28
SGRU	**0.23**	**0.15**	**0.98**	**0.39**	**55.28**

Table 1 and figure 2 demonstrates that the SGRU forecasting model has the lowest errors in comparison to the other models, with the lowest RMSE and MAE, indicating that the SGRU has a strong resolution in dealing with wind speed fluctuations. Furthermore, SGRU provided a lower R2 and MAPE, suggesting that the proposed approach achieved better forecasting precision.

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5 Conclusion

This paper offers a deep learning model for short-term wind speed forecasting utilizing SGRU to enhance the low accuracy of classical deep learning in wind speed forecasting models. It is advised that future study continue to incorporate a range of forecasting methodologies to increase wind speed forecasting accuracy.

How to Cite

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