



Wind Speed Forecasting Using Wavelet Analysis and Recurrent Artificial Neural Networks Based on Local Measurements in Singida Region, Tanzania

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Abstract

High accuracy wind speed forecasting is essential for wind energy harvest and plays a significant role in wind farm management and grid integration. Wind speed is intermittent in nature, which makes the forecasting to be a big challenge. In the present study, three hybrid single-step wind speed forecasting techniques are proposed and tested by local measurement data in Singida region, Tanzania. The three techniques are based on Wavelet Analysis (WA), Back Propagation (BP) optimization algorithm, and Recurrent Neural Network (RNN). They are referred to as WA-RNN, BP-RNN, and WA-BP-RNN. The model results showed that WA-BP-RNN outperforms the other two proposed techniques, with minimum statistical errors of 0.56 m/s (BIAS), 6.89% (MAPE) and 0.53 m/s (RMSE). Furthermore, the WA-BP-RNN technique has shown highest correlation value of 0.95, which indicates that, the strength of a linear association between the observed and forecasted dataset of the wind speed. In addition, the deployment of the BP optimization algorithm in the proposed technique showed improvements of the model results.

Keywords: Wind speed, Forecasting, Wavelet analysis, Recurrent Neural Network, Back Propagation algorithm.

Introduction

The increased energy demands due to the growing global economy and the environment concerns combined with sustainability of fossil fuels have encouraged the search for clean, sustainable and environmentally friendly sources of energy. Renewable energy resource is often regarded as the best alternative of the fossil fuels (Fazelpour et al. 2015). Among all the renewable energy sources, wind power due to its safety for the environment as well as its sustainability has become more conspicuous and fastest growing renewable energy source in recent years (Keyhani et al. 2010). Within

a short period of 18 years, the wind energy industry has transformed into a major player in the global electricity demands. It has experienced an outstanding expansion in recent years, which is projected to continue in the future. The global cumulative installed capacity rose from 23.9 GW in 2001 to 744 GW in 2020 (GWEC 2021).

However, the main challenge with wind energy is its intermittent nature, which makes the output power of wind farms difficult to control (Kaur et al. 2014). The best way to solve this problem is to predict the future values of wind power production, for which the most important factor responsible is the

local wind speed. The forecasted variations of wind speed, is important in the wind energy industry for design, performance analysis, and running cost estimations of the industry (Yao et al. 2013, Saini and Ahuja 2017, Zhang et al. 2019, Wei 2019). For appropriate and effective applications of the wind energy, it is useful to know the statistical distribution, persistence, availability, diurnal variations, and forecasting of the wind speed. Knowing the wind speed characteristics are important for site selection, operation performance and planning of wind farms (Keyhani et al. 2010, Saini and Ahuja 2017, Noman et al. 2021). However, wind speed has strong randomness and volatility, which makes forecasting challenging. Accurate forecasting of the wind speed is needed in wind power performance and safe operations of wind farms (Zhang et al. 2019). Consequently, wind speed forecasting has become an area of interest for the researchers in the wind energy industry recently.

In the past few decades, different methods to address the forecasting of the wind speed have been proposed. Generally, these techniques can be divided into statistical techniques (Ma et al. 2009), Physical techniques (Landberg 1999, Al-Deen et al. 2006, Negnevitsky and Potter 2006, Lange and Focken 2009) and combination of both statistical and physical techniques (Guo et al. 2010, Zhang et al. 2014, Zhang et al. 2019). In recently years, Artificial Intelligence (AI) gains popularity in wind speed forecasting (Kisi et al. 2011, Filik and Filik 2017, Lopez et al. 2020). These studies show that, AI techniques appear to be more accurate compared to the traditional statistical models. Artificial Neural Network (ANN) is the one of the AI techniques that have been extensively employed in meteorological forecasting. In recently years it has been applied in wind speed prediction for wind energy industry. Conventional ANN use the gradient descent method to compute the input weights, output weights, and hidden-node bias, which converge slowly during the computation process and tend to get stuck in local minima easily (Zhang et al. 2019). To

solve this problem, some studies employed Wavelet Neural Network (WNN) as a substitute to the conventional ANN. The method has shown promising results compared with conventional ANN (Yao et al. 2013, Wei 2019). The combination of Wavelet Analysis (WA) and ANN has been widely applied on wind speed forecasting (Saini and Ahuja 2017, Berrezzek et al. 2019, Faniband and Shaahid 2020). However, the accuracy of the results highly depends on the optimization mechanisms.

In recent years, Recurrent Neural Network (RNN) has been applied in wind speed forecasting (Elsaraiti and Merabet 2021). However, it is found that the disappearance or explosion of gradient information during the training process by RNN is the main problem. To solve this problem, this study proposes the use of Wavelet Analysis (WA), dynamic Back Propagation (BP) optimization algorithm and Recurrent Neural Network (RNN) to forecast the mean monthly wind speed of Singida region in Tanzania, which has indicated to be one of the potential sites for large scale wind energy potential (Kumwenda 2011). Specifically, three hybrid single-step models that use the dynamic BP optimization algorithm for parameter optimization are proposed. These models include WA-RNN, BP-RNN and BP-WA-RNN.

Materials and Methods

Data and study Area

The wind speed data used in this study as a training dataset to the WA-RNN, BP-RNN and BP-WA-RNN models were provided by the Tanzania Meteorological Authority (TMA) from Singida region, for the period of 10 years from 2010 to 2019 on monthly basis. The data are available for 10 m above ground level from the meteorological station in Singida region located at 4.82° S 34.75° E and is 1547 m above the sea level. Although the data are not good enough for the commercial wind energy production, but they provide a clear picture of the wind status at the site, which is very important for wind energy project. The location and topographic of the region are indicated in Figure 1.

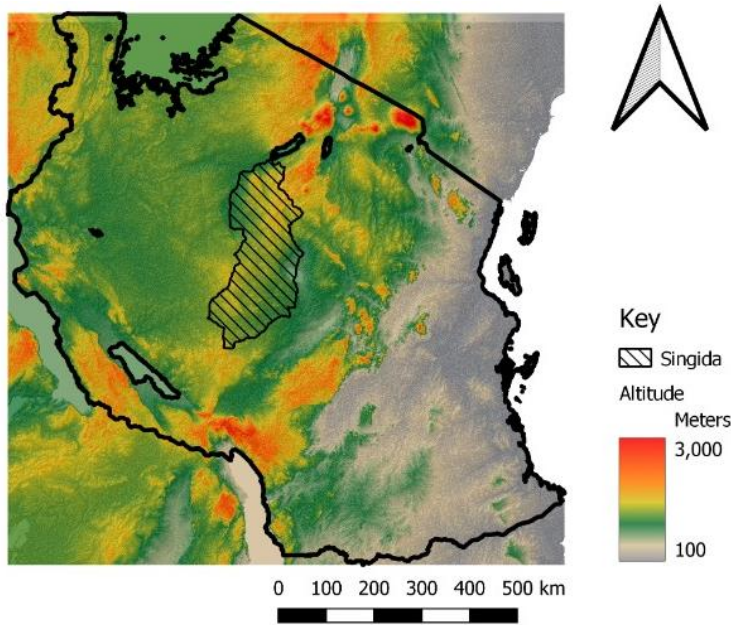


Figure 1: Topography (shaded) of Tanzania and the location of Singida region.

Wavelet Decomposition

The wavelet transformation is a mathematical method used to decompose a continuous-time data into multiscale components. Generally, two major decomposition algorithms are widely employed: Continuous Wavelet Transformation (CWT) and Discrete Wavelet Transformation (DWT) (Liu et al. 2018). In this study, the DWT is applied for the wavelet decomposition of the series wind data in a similar fashion with Liu et al. (2018) and Berrezzek et al. (2019). This methodology has proved to give good results especially when the signal has high frequency components for short durations and low frequency components for long durations. Generally, the DWT uses discrete $a = 2^j$ and $b = k \cdot 2^j$ as follows (Berrezzek et al. 2019):

$$DWT(j, k) = \frac{1}{\sqrt{2^j}} \int x(t) \psi_{a,b}^*(t) \left(\frac{t - k2^j}{2^j} \right) dt \quad (1)$$

where, $x(t)$ represents the signal to be processed, $\psi_{a,b}^*(t)$ is complex conjugate of the basic wavelet $\psi_{a,b}(t)$, scaled by a factor $a > 0$ and shifted by the parameter b , which is given as:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t - b}{a} \right). \quad (2)$$

Practically, the M^{th} level DWT decomposition of sampled signal $x(t) = (x_1, x_2, x_3, \dots, x_N)$ is computed by passing the signal through M low-pass (h) and high-pass (g) filters, resulting in one approximation coefficient vector A_m and M detail coefficient vector D_m , respectively, such that $1 \leq m \leq M$. Figure 2 represents the DWT decomposition as expressed by:

$$x(t) = A_M(t) + \sum_{m=1}^M D_m(t) = \sum_n a_{M,n} \phi_{M,n}(t) + \sum_{m=1}^M \sum_n d_{m,n} \psi_{m,n}(t) \quad (3)$$

where, $a_{M,n}$ and $d_{M,n}$ are, respectively, the approximation and detail coefficients of the wavelet expansion.

The functions $\phi_{m,n}(t) = 2^{m/2}\phi(2^m t - n)$ and $\psi_{m,n}(t) = 2^{m/2}\psi(2^m t - n)$, form orthogonal basis (Berrezzek et al. 2019). Here m is a scale factor and a signal decomposed over a set such that m ranges from 1 to M . It can be shown that the decomposition coefficients can be recursively computed by a pair of low-pass and high-pass digital filters whose impulse response are $h[n]$ and $g[n]$, respectively (Yan et al. 2014). Equation (4) represents the multi-resolution decomposition algorithm.

$$\begin{aligned}
 a_{m+1,n} &= \sum_k h[k-2n]a_{m,n} \\
 d_{m+1,n} &= \sum_k g[k-2n]a_{m,n}
 \end{aligned}
 \tag{4}$$

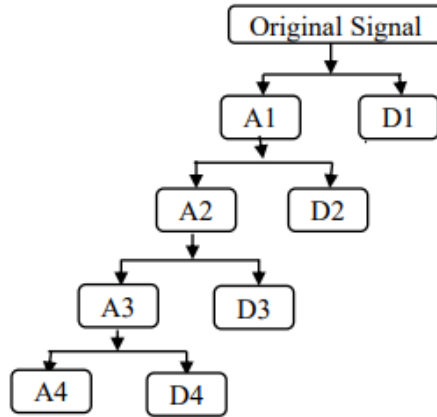


Figure 2: Wavelet multiresolution decomposition.

The reconstruction of the signal is computed as a sum of decomposed components of the original signal. From Figure 1, the reconstruction signal is calculated as:

$$x = A_1 + D_1 = A_2 + D_2 + D_1 = A_3 + D_3 + D_2 + D_1 = A_4 + D_4 + D_3 + D_2 + D_1 \tag{5}$$

Recurrent Artificial Neural Network (RNN)

Recurrent Artificial Neural Network (RNN) is the second kind of Artificial Neural Network (ANN) where the output of the previous step is fed as an input to the new step. In the traditional ANN, all the inputs and outputs are independent of each other. Different with the traditional ANNs, RNN has recurrent layers in which neurons are

linked (Figure 3). Therefore, the information from a neuron is transferred to the neurons in the same and next layers (Elsaraiti and Merabet 2021). RNN calculates new states by employing its activation functions to the prior states and new inputs recursively. At a time step, t there is a hidden state value (h_t) which is computed as:

$$h_t = f(w_x x_t + u_h h_{t-1} + b) \quad t = 0, \dots, N \tag{6}$$

where x_t is the inputs at time t , h_{t-1} is the hidden states of the previous step ($t - 1$), w_x and u_h are weight for the input and for the previous state value, respectively. Moreover, f is the activation function applied to the hidden state of current time and b is the bias.

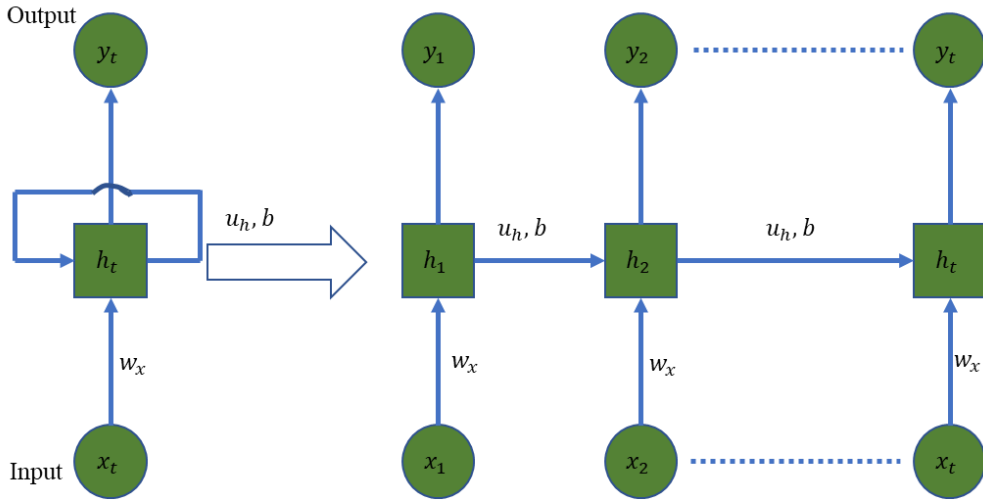


Figure 3: The sketch of a Recurrent Artificial Neural Network, RNN.

Forecasting Validation

To validate the model and quantitatively evaluate its performance, three statistical parameters were considered, namely the bias (BIAS) in Equation (7), the mean absolute percentage error (MAPE) in Equation (8), the root mean square error (RMSE) in Equation (9), and the Pearson correlation coefficient (*r*) in Equation (10) (Zhang et al. 2018).

$$BIAS = \frac{1}{T} \sum_{t=1}^T (X_t - \hat{X}_t) \tag{7}$$

$$MAPE = \frac{1}{T} \sum_{t=1}^T \left| \frac{X_t - \hat{X}_t}{X_t} \right| \times 100\% \tag{8}$$

$$RMSE = \left[\frac{1}{T} \sum_{t=1}^T (X_t - \hat{X}_t)^2 \right]^{\frac{1}{2}} \tag{9}$$

$$r = \frac{T \sum_{t=1}^T \hat{X}_t X_t - \sum_{t=1}^T \hat{X}_t \sum_{t=1}^T X_t}{\sqrt{\left[T \sum_{t=1}^T \hat{X}_t^2 - \left(\sum_{t=1}^T \hat{X}_t \right)^2 \right] \left[T \sum_{t=1}^T X_t^2 - \left(\sum_{t=1}^T X_t \right)^2 \right]}} \tag{10}$$

where \hat{X}_t represents the forecasting value, and X_t represent the observation value, and T is the total number of forecasting periods. The BIAS either describes the forecasted results overestimate or underestimates the observation values. The MAPE and RMSE used to evaluate the overall deviation value and its relative value between the forecasted results and observation results, respectively. The Pearson correlation coefficients used to account the strength of a linear association between the observation results and the

forecasted dataset (Zhang et al. 2019).

All simulation activities for the three proposed hybrid single-step techniques (WA-RNN, BP-RNN and BP-WA-RNN) were conducted in MATLAB/SIMULINK platform.

Results and Discussions

The comparison of the average wind speed from three forecasting techniques (WA-RNN, BP-RNN, and WA-BP-RNN) and the measurement data at the observation

site is shown in Figure 4. It can be noted from Figure 3 that the wind speed is well resolved by the model simulations compared with the observed data in BP-RNN, and WA-BP-RNN techniques. The comparison between models results and observations is quite good for the two techniques (BP-RNN, and WA-BP-RNN) and relatively bad for WA-RNN technique. Both three techniques (WA-RNN, BP-RNN, and WA-BP-RNN) have a tendency to give higher wind speed than the observation data.

The statistical forecasting results of the wind speed from the three techniques (WA-RNN, BP-RNN, and WA-BP-RNN) are presented as the values of evaluation metrics in Table 1, where the best performance is highlighted in bold. The statistical results

indicate that the simulated results are likely to overestimate the wind speed as all biases are positive. All the wind speed MAPEs are less than 20% and the worse MAPEs are obtained only with WA-RNN technique. Except Pearson correlation coefficient (r), BIAS, MAPE and RMSE has shown to be lowest in WA-BP-RNN technique compared to the rest of the techniques presented in this study. Wind speed RMSEs are all less than 1.5 m/s, and much lower in WA-BP-RNN technique. The values of RMSE show that the WA-BP-RNN model performs better than the WA-RNN model and the BP-RNN model. Thus, the accuracy of the WA-BP-RNN approach is potentially improved compared with the WA-RNN technique.

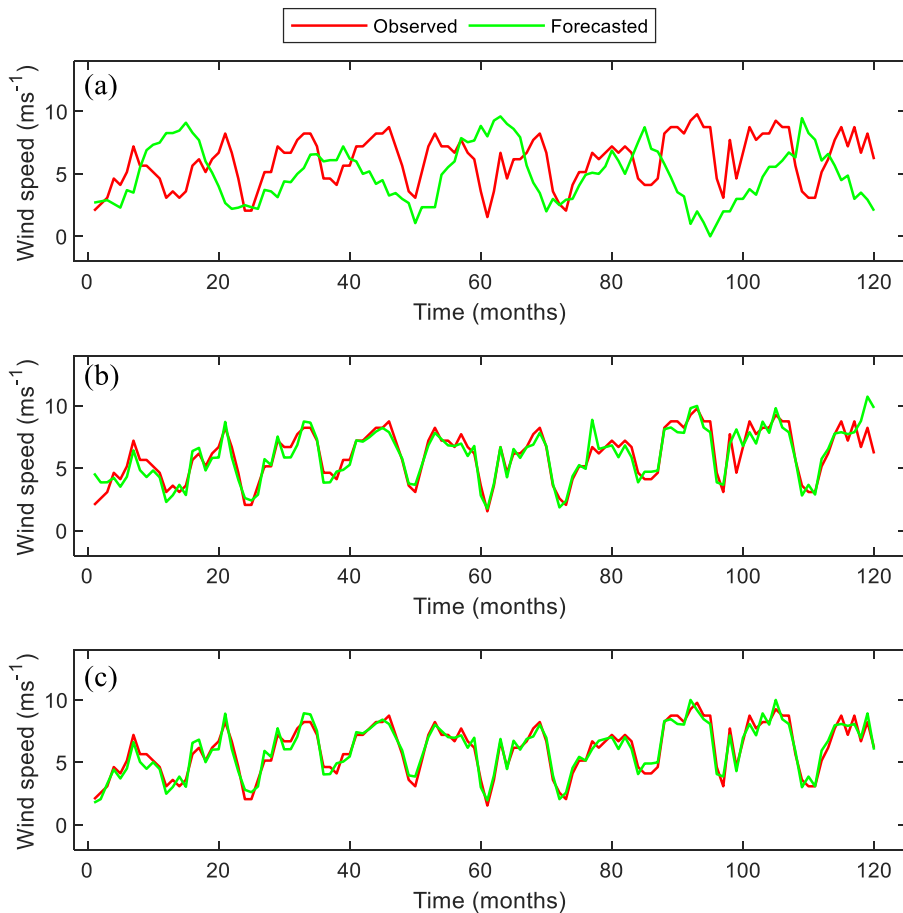


Figure 4: Wind speed comparison between the observed and forecasted results for (a) WA-RNN, (b) BP-RNN and (c) WA- BP-RNN.

In the scatter plots for wind speed, the forecasted results for the three techniques are represented against the observation values as depicted in Figure 5. It can be noted from Figure 4 that, many of the points represented in both three techniques (WA-RNN, BP-RNN, and WA-BP-RNN) are nearby to the diagonal. The spread of the points shows a high accuracy on the WA-BP-RNN technique compared to the WA-RNN and BP-RNN techniques. However, as previously seen from the BIAS and RMSE values as tabulated

in Table 1 computed for both three techniques, the scatter plots show same tendency of overestimate the forecasted results compared with the observation data. The Pearson correlation coefficients for the wind speed between the forecasted and the observations are high on both three cases (WA-RNN, BP-RNN, and WA-BP-RNN) with values ranging from 0.8727 to 0.9490 (Table 1). The highest correlation coefficient is found in WA-BP-RNN technique compared to the other two techniques.

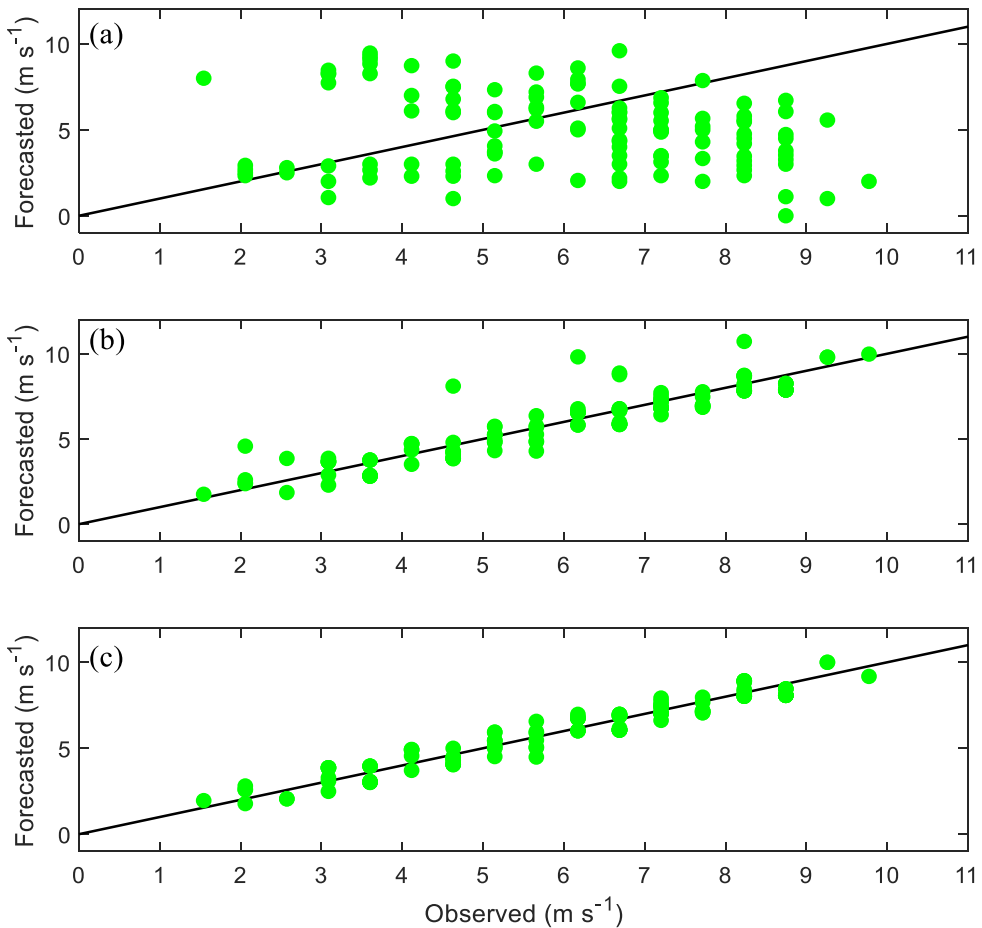


Figure 5: Comparison of the forecasted and observation wind speed results by using scatter plots, (a) WA-RNN, (b) BP-RNN and (c) BP-WA-RNN.

Table 1: The average bias, mean absolute percentage error, root mean square error and Pearson correlation coefficient for the wind speed in WA-RNN, BP-RNN, and WA-BP-RNN techniques.

	BIAS (m/s)	MAPE (%)	RMSE (m/s)	<i>r</i>
WA-RNN	0.92	10.02	1.08	0.87
BP-RNN	0.85	8.73	0.91	0.93
BP-WA-RNN	0.56	6.89	0.53	0.95

Compared to other wind speed models proposed earlier shown in Table 2, the proposed model (BP-WA-RNN) outperforms and achieves better minimal statistical errors. Therefore, the proposed BP-WA-RNN offers good forecasting results. Further comparison

of the performance metrics among the different wind speed prediction methods demonstrated merits of the proposed approach are very effective minimum error and simple implementation.

Table 2: Comparison of the proposed method with previous approaches

S. No	Forecasting model	Methodology	Performance metrics	Parametric values
1	Xie et al. 2021	MV-LSTM	BIAS	----
			MAPE (%)	7.36
			RMSE	1.33
			<i>r</i>	0.92
2	Yuan and Shen 2020	ARIMA	BIAS	-----
			MAPE (%)	10.06
			RMSE (m/s)	1.03
			<i>r</i>	0.80
3	Zhang et al. 2019	CS-WD-ANN	BIAS	---
			MAPE (%)	8.96
			RMSE	0.99
			<i>r</i>	0.85

Conclusions

In the present study, three hybrid single-step wind speed forecasting techniques (WA-RNN, BP-RNN, and WA-BP-RNN) were designed. The models combine Wavelet Analysis (WA), Recurrent Neural Network (RNN) and optimized by dynamic Back Propagation (BP) algorithm. The WA-RNN technique deploys wavelet analysis to decompose the original dataset into several sub-series dataset, and then applied to the RNN functions for each sub-series dataset to obtain the forecasting variables. In BP-RNN, the BP algorithm is applied to the RNN functions to obtain the forecasting variables. Finally, for WA-BP-RNN technique, the original dataset is decomposed by the method of wavelet analysis into sub-series waveforms

at different frequencies. These waveforms are used as the input in the RNN. The dynamic BP algorithm is applied to optimize the variables of each RNN to obtain the forecasting result. The observational data from the meteorological station in Singida region were used as an input for the designed techniques.

The results show that, WA-BP-RNN technique performs best compared to other three proposed hybrid techniques, with lowest computed variables of BIAS, MAPE, and RMSE, and highest values of *r*. The WA-RNN technique performs the least among the three proposed hybrid techniques. Application of the BP algorithm in our proposed hybrid techniques shows more advantages concerning the forecasting results

compared with one which did not apply BP algorithm. For example, comparison between WA-RNN, and WA-BP-RNN techniques shows that the errors in WA-BP-RNN are smaller than in WA-RNN.

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Conflict of Interest

We declare no conflict of interest in this research work.

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