Vertical Wind Speed Extrapolation Using Regularized Extreme Learning Machine

H. Nuha
Assistant Professor
HUMIC, School of Computing
Telkom University
Indonesia

M. Mohandes
Professor
EE Department and Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS)
King Fahd University of Petroleum & Minerals, Dhahran-31261
Saudi Arabia

S. Rehman
Interdisciplinary Research Center for Renewable Energy and Power Systems (IRC-REPS)
King Fahd University of Petroleum & Minerals, Dhahran-31261
Saudi Arabia

Ali A-Shaikhi
Associate Professor
Department of Electrical Engineering
King Fahd University of Petroleum & Minerals, Dhahran-31261
Saudi Arabia

The cost of measuring wind speed (WS) increases significantly with mast heights. Therefore, it is required to have a method to estimate WS at hub height without the need to use measuring masts. This paper examines using the Regularized Extreme Learning Machine (RELM) to extrapolate WS at higher altitudes based on measurements at lower heights. The RELM uses measured WS at heights 10-40 m to estimate WS at 50 m. The estimation results of 50 m are further used along with the measured WS at 10-40 to estimate WS at 60 m. This procedure continues until the estimation of 180 m. The RELM's performance is compared with the regression tree (RegTree) method and the standard 1/7 Power Law.
The proposed algorithm provides an economical method to find wind speed at hub height and, consequently, the potential wind energy that can be generated from turbines installed at hub height based on measurements taken at much lower heights. Moreover, these methods' extrapolated values are compared with the actual measured values using the LiDAR system. The mean absolute percentage error (MAPE) between extrapolated and measured WS at the height of 180 m using measurements at the height of 10-40 m using RELM, RegTree, 1/7 Power Law, and Power Law with adaptive coefficients is 13.36%, 16.76%, 33.50%, and 15.73%, respectively.

Keywords: *Wind Speed; Vertical Extrapolation; Regularized Extreme Learning Machine; Regression Tree.*

1. INTRODUCTION

Globally increasing energy requirements and environmental concerns due to the burning of fossil fuels to meet power demands have led people from all walks of life to utilize clean and renewable energy sources. The renewable sources of energy that are being given attention include wind, solar, geothermal, biomass, and ocean. The wind is one of the most commonly used energy sources in the present scenario due to its commercial acceptance and technological maturity. Saudi Arabia is also installing wind farms and has an extensive capacity buildup program by 2030. So, to best utilize the wind resources, its variability on a time scale (from minutes to hours to days, etc.) is critical to managing wind power economically. Among all the meteorological parameters, wind speed is the most fluctuating parameter. It changes with time of the day, day of the year, location, and height. Wind speed increases with height, specifically onshore, due to several near-surface human activities, air density, trees, buildings, surface roughness, topographical features, etc. [1]. However, these effects weaken with increasing height, and wind speed usually increases with height.

Figure 1 shows the LiDAR system based on measured wind speeds at different heights at the Dhahran site for around 100 hours during the data collection period. It is to be noted that wind speed values at different heights follow the trend with time and show its fluctuating nature. Wind speed at 20 m is the lowest while 180 m is the highest.

The figure shows that WS increases with height. It is to be noted that wind speed values at different heights also follow the trend with time.

In general, higher wind speed (WS) yields higher energy produced by the wind turbine. Therefore, wind turbines with higher hub heights are chosen [2]. This leads to measuring WS at hub heights using wind masts or LiDAR-type devices to estimate energy sources accurately. However, both measurements require high costs and skilled technicians for aerodynamic and wind farm layout optimization [3–5]. For example, the price of 60 m and 80 m turbine masts are about US$45,000 and US$85,000, respectively [6]. Generally, the hub heights of modern commercially available wind turbines vary from 80 m to 180 m for both onshore and offshore installations. Therefore, accurate methods are needed to estimate WS at a certain height using measurements at lower heights to make the installation investment advantageous and profitable.

Several methods have been proposed to estimate WS at higher heights based on measurements at lower heights. Logarithmic and power-law methods were found to perform well only under stable atmospheric conditions [7]. Machine learning approaches have been used for temporal predictions of wind speed and pressure-correction algorithms for fast convergence [8]–[10]. However, the estimation of WS at higher heights

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Correspondence to: Dr. A. Al-Shaikhi
King Fahd University of Petroleum & Minerals,
Dhahran-31261, Saudi Arabia
E-mail: shaikhi@kfupm.edu.sa
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based on measurements at lower heights is very limited. Turkan et al. [11] compared the performance of seven different machine-learning methods to find WS at 30 m height based on measurements at 10 m height. The seven methods are Support vector machine regression, multi-layer perceptron, radial basis function neural networks, Kstar, locally weighted learning, decision stump, and random tree. Daily average WS values at 10 m and 30 m heights for one year at Kutahya city in Turkey were used in this study. Data from 11 months were used for training, and the data for one month was used for testing. The support vector machine performed the best among the 7 analyzed methods. However, the study was limited to using WS at one level (10 m) and extrapolating it to one level (30 m).

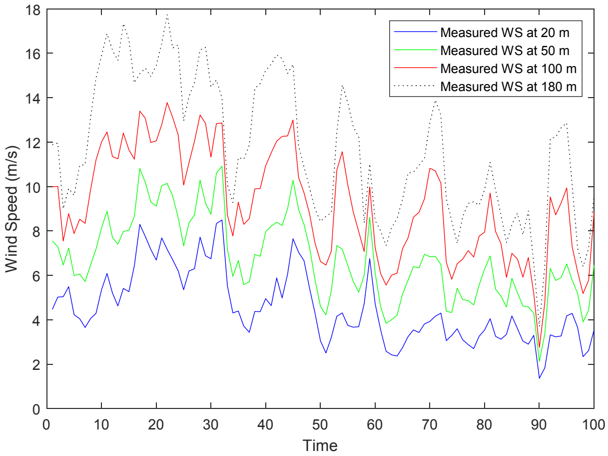


Figure 1. Samples of measured WS at various heights

Saiful Islam et al. used two hybrid neural networks to estimate WS at 100 m based on measurements at 10-40 m heights [12]. The first hybrid method used a genetic algorithm to find initial weights and biases, followed by MLP to estimate the WS at higher heights. The second hybrid method used particle swarm optimization to find the initial weights and biases, followed by MLP for WS extrapolation. The two-hybrid methods performed equally well and outperformed the MLP network alone. However, in the study, there were no measured values beyond a height 40 m, and results were compared to each other but not to the actual values. Bañuelos-Ruedas et al. [13] reviewed several classical non-machine learning methods to estimate WS at higher heights. Most of the papers dealt with WS vertical extrapolation for medium heights (100-120 m).

Mohandas and Rehman used Restricted Boltzmann Machine (RBM) to estimate WS up to a height of 120 m based on 10-40m[3]. The restricted Boltzmann Machine (RBM) is a probabilistic model with two layers. Each RBM represents a pair of layers in a deep neural network (DNN). The RBM must be exposed to the training data in an unsupervised fashion (input data only, without target) using contrastive divergence by updating the weights using the difference between states on the same layer after taking the samples from another layer's distribution. Stacking the trained RBMs provides near-optimal weights for DNN and prevents vanishing gradient problems by stacking the RMBs layer by layer.

This paper proposes using the regularized extreme learning machine (RELM) method for extreme height (up to 180 m) WS vertical extrapolation. The proposed method is simple because the algorithm is only required to optimize the output weights. The main practical app–lication of the proposed algorithm is to predict the WS ahead of time for power estimation to manage the grid properly. The results of the proposed method are compared with the regression tree, the standard 1/7 Power Law, and the Power Law with adaptive coeffi–cient methods for low, medium, and high height extrapolations.

2. METHODOLOGY

The extrapolation in this study uses the regularized extreme learning machine (RELM) method to optimize the model based on a single-hidden layer feed-forward neural network (SLFN), as depicted in Figure 2[14]. The extrapolation problem can be considered a reg–ression problem with N training samples $\{(x_i, y_i)\}_{i=1}^{N}$, with input vector $x_i \in \mathbb{R}^M$ and the corresponding desi–red output $y_i \in \mathbb{R}$. Each input vector consists of M elements representing the number of WS measured at the lower altitude. The output of the SLFN has a single output y representing the WS at height $M + 1$.

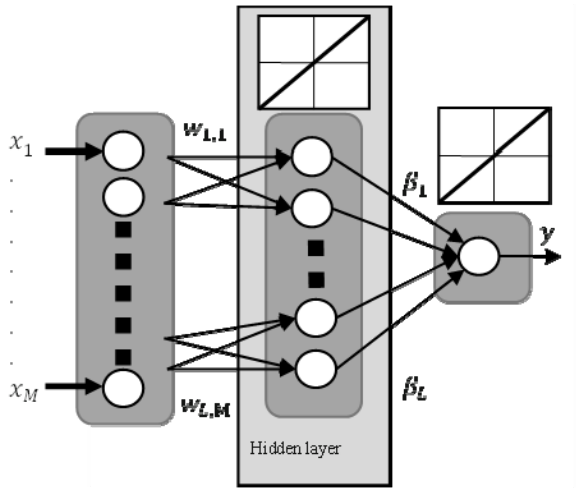


Figure 2. RELM for Estimation

Assuming that the model perfectly satisfies the relationship between x_i and y_i, the SLFN with L hidden units is modeled by the following summation:

$$\sum_{j=1}^{L} \beta_j \left(w_j x_i \right) = y_i, i = 1, 2, \ldots, N \tag{1}$$

where $w_j = [w_{j1}, w_{j2}, \ldots, w_{jM}]^T$ is randomly initialized input weight vector that connects M input units to the j-th hidden unit, and β_j represents the weight that connects the j-th hidden unit to the output unit. The output unit uses a linear activation function without any bias. The N equations in (1) can be concisely expressed as the following linear system:

$$H\beta = y \tag{2}$$

with the output weights $\boldsymbol{\beta} = [\beta_1, \beta_2, \ldots, \beta_L]^T$ and outputs $\boldsymbol{y} = [y_1, y_2, \ldots, y_N]^T$. The hidden layer output values is given by the matrix $\mathbf{H}$

$$\mathbf{H}\left(w_1,\ldots,w_L,x_1,\ldots x_N\right)=\begin{bmatrix} h_{1,1} & \cdots & h_{1,L} \\ \vdots & \cdots & \vdots \\ h_{N,1} & \cdots & h_{1,L} \end{bmatrix}_{N\times 1} \tag{3}$$

Where

$$h_{i,j} = w_i x_i \tag{4}$$

It can be observed from the equation above that all weights in $\boldsymbol{H}$are fixed, and we need to find the output weights $\boldsymbol{\beta}$ as solutions to the linear equation in (2) [15]. So, the output weights $\boldsymbol{\beta}$ are given by:

$$\hat{\beta} = \begin{cases} \left(\mathbf{H}^T\mathbf{H} + \dfrac{\mathbf{I}}{D}\right)^{-1}\mathbf{H}^T y, & \text{if } N > L \\ \mathbf{H}^T\left(\mathbf{H}\mathbf{H}^T + \dfrac{\mathbf{I}}{D}\right) & \text{otherwise} \end{cases} \tag{5}$$

where D is a regularization constant to prevent overfitting[16]. The RELM method has been applied successfully for predictions[17], [18].

The experiment was carried out by dividing the data into 75%, 5%, and 20% for training, validation, and testing. There is no iteration in the RELM since the output weights β is obtained analytically with a single calculation (equation 5) given hidden layer values H got using equation 4 and training data. In addition to pre–venting the over-fitting problem, the regularization parameter (D) is also used to enhance the generalization performance. Selecting the appropriate D is performed by trial and error. The validation is used to determine the regularization parameter D by comparing the perfor–mance (Equation 9) using the validation data. The output weights β are calculated in equation 5 using the training data. At the same time, the validation data is only used in selecting β with minimum error and is not included in calculating β. The performance of the validation data shows that the model with the regu–larization constant $D = 10^{-7}$ and the number of hidden units $M = 5$ achieves the best and most robust result (Table 1).

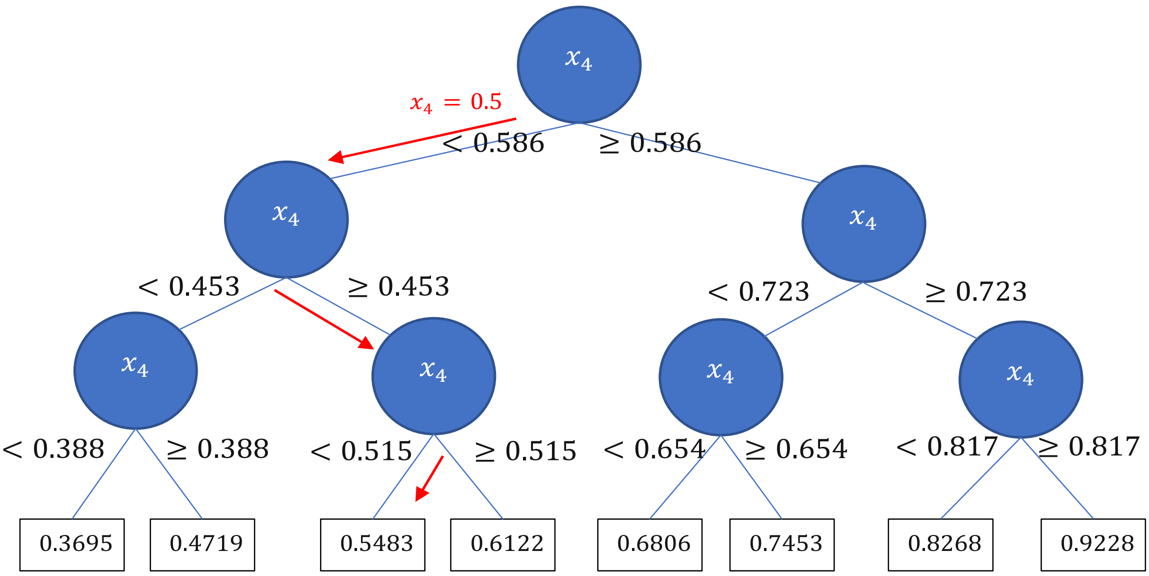


Figure 3. A trained regression tree sample with nodes (circle) and leaves (rectangle)

Table 1 Preliminary experiments to determine RELM configurations

D	10^{-10}	10^{-9}	10^{-8}	10^{-7}	10^{-6}	10^{-5}	10^{-4}	10^{-3}	10^{-2}	10^{-1}	1	10	10^{2}	10^{3}
M = 7	2.50	2.50	2.76	15.2	11.4	30.1	172.7	29.1	662.9	5.10	19.2	6.63	71.43	6.69
M = 6	2.50	2.50	2.51	2.48	74.4	118.0	18.66	13.54	13.04	21.26	28.19	11.05	111.53	19.35
M = 5	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50	2.50
M = 4	3.00	3.00	4.37	2.60	2.62	3.96	4.16	4.28	4.98	2.68	2.61	2.61	2.61	2.61
M = 3	4.10	5.46	9.95	3.00	6.11	6.21	4.42	2.65	2.89	4.30	2.58	2.57	3.41	3.69

Table 2. The results of the WS estimation at 50-180 m heights based on measured WS at 10-40 m heights

Heights (m)	MSE				MAPE (%)				R^2 (%)			
	RELM	RegTree	1/7 PL	A-PL	RELM	RegTree	1/7 PL	A-PL	RELM	RegTree	1/7 PL	A-PL
50	0.04	0.05	0.15	0.05	2.61	3.01	6.08	3.19	98.94	98.37	98.76	98.76
60	0.15	0.21	0.65	0.19	4.75	5.72	11.38	5.53	96.10	93.67	95.41	95.41
70	0.27	0.40	1.27	0.37	6.04	7.41	14.94	7.02	93.56	89.39	92.31	92.31
80	0.46	0.70	2.17	0.61	7.37	9.22	18.24	8.60	89.93	83.35	87.98	87.98
90	0.68	1.04	3.17	0.89	8.46	10.62	20.86	9.85	86.29	77.73	83.74	83.74
100	0.96	1.48	4.41	1.25	9.54	11.96	23.31	11.06	81.88	71.60	78.72	78.72
110	1.22	1.88	5.58	1.58	10.25	12.87	25.18	11.96	78.63	67.13	74.96	74.96
120	1.52	2.35	6.93	1.97	10.99	13.84	26.94	12.86	74.89	62.33	70.75	70.75
130	1.79	2.76	8.18	2.30	11.44	14.48	28.34	13.49	72.24	58.98	67.74	67.74

140	2.10	3.25	9.60	2.69	11.95	15.17	29.67	14.11	69.18	55.25	64.37	64.37
150	2.36	3.65	10.90	3.03	12.32	15.60	30.76	14.58	67.17	52.69	62.03	62.03
160	2.67	4.11	12.36	3.42	12.74	16.09	31.82	15.05	64.76	50.05	59.34	59.34
170	2.90	4.42	13.57	3.71	13.04	16.36	32.67	15.38	63.40	48.49	57.82	57.82
180	3.17	4.84	14.90	4.05	13.36	16.76	33.50	15.73	61.65	46.38	55.96	55.96

2.1 Regression Tree

The regression tree (RegTree) method [19] is used as a non-parametric method for estimating continuous dependent output y with continuous inputs xw; here, data is divided into nodes based on conditional binary comparisons[20]. RegTree builds a tree consisting of nodes and leaves (terminal-nodes) representing the conditional distribution of output y given inputs $x = \{x_1, x_2, \ldots, x_n\}$ as shown in Figure 3. The main steps in the RegTree method are[21]:

1) Starting from the root node, the method evaluates all possible partitions for each of the estimators by applying an impurity function $\gamma(t)$ to each partition t and calculating the impurity diffe–rence. The impurity function $\gamma(t)$ is given by:

$$\gamma(t)=\sum_{n=1}^{N}\left(y_i(t)-\bar{y}(t)\right)^2 \tag{6}$$

where $y_i(t)$ and $\bar{y}(t)$ denote the outputs and the corresponding mean at node t, respectively.

2) Determine the best partition by calculating the goodness function $\delta(t)$ and split the data set into right and left child nodes. The goodness function $\delta(t)$ is given by:

$$\delta(t)=\gamma(t)-\gamma(t_R)-\gamma(t_L) \tag{7}$$

where $\gamma(t_R)$ and $\gamma(t_L)$ denote the impurity function of the right and left child nodes of node t, respectively.

3) Repeat steps 1-2 for each non-leaf until the maximum number of nodes.

4) Prune the tree and select a sequence of sub-tree that achieves the best result on the validation data.

Figure 3 shows a trained subtree using normalized WS from heights 10 to 40 m to predict WS at 50 m. Therefore, each input vector x consists of 4 elements x_1, x_2, x_3 and x_4, corresponding to WS at 10 m, 20 m, 30 m, and 40 m, respectively. It can be noticed that the root node is built using the fourth element x_4 (WS at 40 m) since it is the most correlated to WS at 50 m. The full regression tree containing nodes using other input elements (x_1, x_2 and x_3) is very large and is not feasible to be displayed. Based on the figure, the prediction is calculated by comparing the input element x_4 at the root node until one of the leaves. For example, if $x_4 = 0.5$, then the output value will follow the red line to reach $y = 0.54$. The final output is further denormalized by multiplying it by the maximum value.

2.2 1/7th Power Law

In addition to the RegTree method, several previous studies used 1/7 Power Law [22] which is simple but very useful for vertical WS extrapolation. As shown in Figure 1, higher locations tend to produce higher WSs [12]. Therefore, the 1/7 Power Law states that the incremental relationship between WS and height, i.e., WS v_{M+1} at height h_{M+1} can be calculated by the following equation:

$$v_{M+1}=v_M\left(\frac{h_{M+1}}{h_M}\right)^{\frac{1}{7}} \tag{8}$$

where v_M is the wind speed at height h_M and the roughness coefficient is set to $\alpha = 1/7$. In addition to the standard 1/7 PL, the power-law with an adaptive coef–ficient (A-PL) is also used for vertical extrapolation. The coefficient is selected by trial and error on the vali–dation data. The experiments show that the coefficients α = 0.34, 0.45, 0.5, 0.3, 0.5, 0.45, 0.4, 0.4, 0.35, 0.4, 0.35, 0.4, 0.35 and 0.35 for height 50 m, 60 m, … 180 m extrapolations achieve the best performance at the analyzed location.

2.3 Performance Measures

In this study, three performance measures are employed based on the difference between the actual values (y) and the predicted outputs ($\hat{y}$), including mean squared error (MSE), mean absolute percent error (MAPE), and the coefficient of determination (R^2). These performance measures are calculated using the following equations:

$$MAPE=\frac{1}{N}\sum_{n=1}^{N}\left|\frac{y_n-\hat{y}_n}{y_n}\right| \tag{9}$$

$$MSE=\frac{\sum_{n=1}^{N}\left(y_n-\hat{y}_n\right)^2}{N} \tag{10}$$

$$R^2=1-\frac{\sum_{n=1}^{N}\left(y_n-\bar{y}\right)^2}{\sum_{n=1}^{N}\left(y_n-\hat{y}\right)^2} \tag{11}$$

where $\bar{y}$ denotes the mean of the measured data.

3. EXPERIMENTAL RESULTS

In general, WS are measured using masts up to 40 meters, so the WS must be extrapolated to the desired heights. The 1/7 power law method has low accuracy for vertical extrapolation. Therefore, in addition to the fixed coefficient, the power-law with adaptive coef–ficient, machine learning, and statistical-based approaches are used for vertical extrapolation. This paper used two real datasets to confirm the robustness of the RELM.

3.1 Numerical Results from the first dataset

The first WS data were measured in Dhahran, Saudi Arabia, between 20 June 2015 and 29 February 2016 using a LiDAR system. The WS data was stored for an average of 10 minutes. Then, the average WS value is calculated at an altitude of 10-180 m. The RELM described above was used to estimate WS at higher elevations. WS at heights of 10-40m is used to estimate the value of WS at altitudes of 50-180 m. During the training, all data is normalized between 0 and 1 by dividing the data by the maximum value.

The extrapolation process is carried out by training RELM using WS values at heights of 10, 20, 30, and 40 m as inputs and WS at the height of 50 m as an output. Next, the WS was measured at heights10-40 m, and the extrapolated WS at the height of 50 m was used to train a new RELM with 5 inputs to estimate the WS at60 m height. These steps, which use the measured and estimated WS values at lower elevations to calculate the WS value at one level higher height, are continued until the estimation of the WS at the height of 180 m.

Table 2 shows the performance of the RELM, RegTree, and 1/7 Power Law methods in terms of MSE, MAPE, and R^2. RELM achieves MAPE values ranging from 2.61% at 50 m to 13.36% at 180 m, 1/7 Power Law achieves 3.01% at 50 m to 16.76% at 180 m of MAPE values, and 1/7 Power Law achieves 6.08% at 50 m to 33.50% at 180 m of MAPE values. The same trends were observed in the case of MSE where RELM, RegTree, and 1/7 Power Law yield 0.04 to 3.17, 0.05 to 4.84, and 0.15 to 14.90, respectively. These values indicate that the performance of all methods deteriorates with more heights, as shown in Figure 4. Despite having better MSE and MAPE than 1/7 Power Law, the RegTree R^2 score is lower than the R^2 score of 1/7 Power Law, as shown in Figure 5. The proposed method outperforms the other methods and achieves a higher R^2 score than that of the RegTree and 1/7 Power Law for all heights.

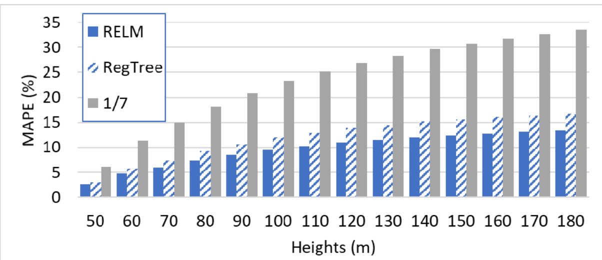


Figure 4. MAPE between different methods

Despite having better MSE and MAPE values than the 1/7 Power Law (Table 2 and Figure 4), the RegTree R^2 score is lower than the R^2 score of the 1/7 Power Law, as shown in Figure 5. The proposed algorithm outperforms the other methods and achieves the highest R^2 score for all heights.

The extrapolation results are displayed for only three heights, namely 50, 100, and 180 m, representing low, medium, and extreme heights, respectively. Figures 6(a) and 6(b) at low height WS estimation show the WS esti–mated using RELM and RegTree, respectively. Each line in figure 6(a), for example, shows the measured WS at heights 10-40 m and the corresponding extrapolated WS at 50 m. Figure 6(c) shows the scatter plot for WS mea–sured and estimated for a height of 50 m using RELM with an R^2 score of 98.94%, Figure 6(d) is a scatter plot for RegTree with an R^2 score of 98.37%, and Figure 6(e) is a scatter plot for 1/7 Power Law with an R^2 score of 98.76%. Figure 6(e) shows that many points on the scatter plot for 1/7 Power Law are above the diagonal line, indicating that the estimated values are too low compared with the measured values. This is by the WS value calculated using RELM and LWSE for a height of 50 m shown in Figure 6(f) for the same interval. Some samples of the 1/7 Power Law estimated values are below the measured values.

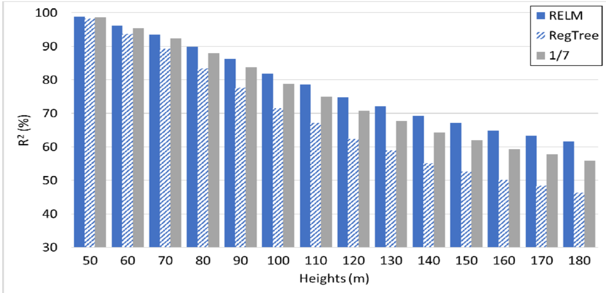


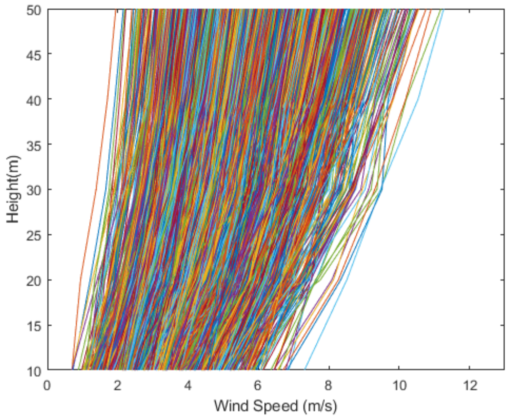
Figure 5. R^2 between different methods

In the estimation results for medium height (100 m), the superiority in the performance of the RELM is also shown in Figure 7. RELM, RegTree, and 1/7 Power Law methods use the 10-40 m measurement results and the 50-90 m estimation results to estimate the WS at the 100 m height. All methods' performance (MSE, MAPE, and R^2) decreased when compared to the estimation performance at the height of 50 m. However, for all aspects of accuracy, RELM still outperforms the other methods; for example, the coefficients of determination for RELM, RegTree, and 1/7 Power Law are 81.88 %, 71.6 %, and 78.72 %, respectively. The scatter plot for 1/7 Power Law also shows that many points are located far above the diagonal line, which indicates that the 1/7 Power Law estimation result is too low.

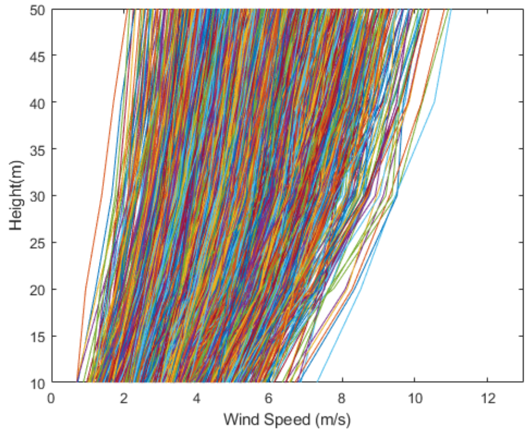
Figure 8 shows the extrapolation of WS to the maximum height. The results of the WS measurements at an altitude of 10-40 m and the estimated values at altitudes of 50-170 m are used to estimate the WS at the height of 180 m. MSE, MAPE, and R2 for all methods (RELM, RegTree, and 1/7 Power Law) are worse than the estimation results at low (50 m) and medium (100 m) heights. This is due to the increasing use of the estimated WS values for the estimated height of 180 m. Even so, the extrapolation using RELM outperforms that of RegTree and 1/7 Power Law.

3.2 Numerical Results from the second dataset

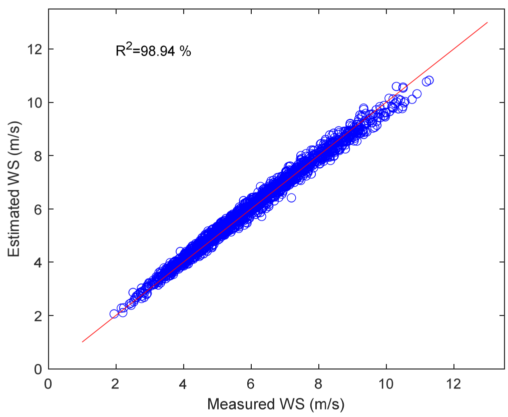
The second WS dataset was collected from 1 March 2017 to 31 March 2018 using a LiDAR device installed at the King Fahd University of Petroleum & Minerals (KFUPM) beach at the same heights as the first dataset. Table 3 summarizes the numerical results obtained using the same methods evaluated using the same assessment measures. It can be noticed that the results confirmed the superiority of the RELM method for all heights and performance measures. The A-PL has a significant performance improvement over the standard 1/7 power law. On average, the A-PL also outperforms the RegTree at higher heights (over 80 m). The main drawback of the A-PL is that the best coefficient must be determined empirically. The error also increases with heights as more estimation error accumulates.



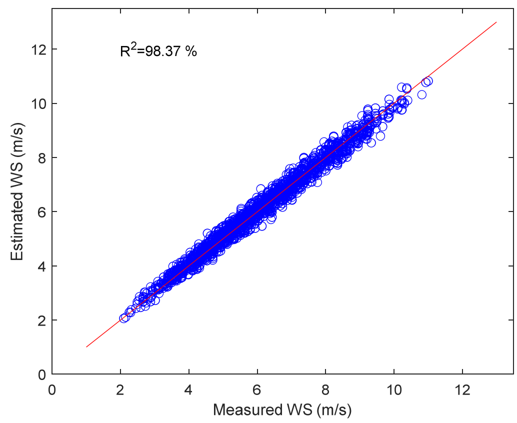
(a)RELM estimated WS at a height 50 m



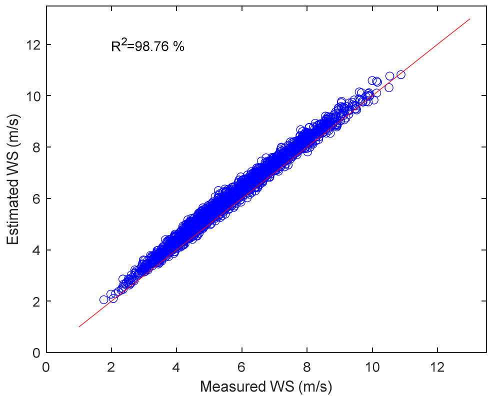
(b)RegTree estimated WS at height50 m



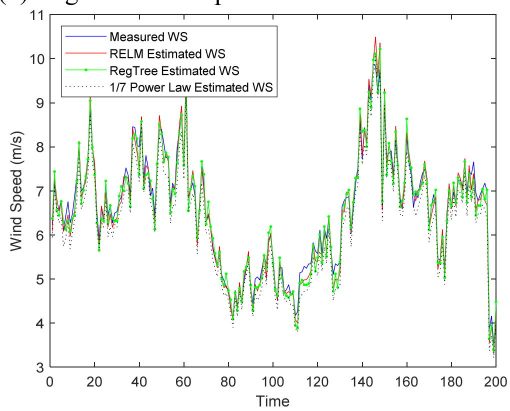
(c) RELM Scatter plot of estimated WS at 50 m



(d) RegTree Scatter plot of estimated WS at 50 m

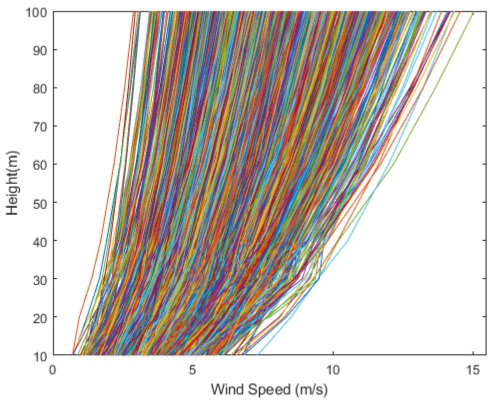


(e) 1/7 power low scatter plot of estimated WS at 50 m

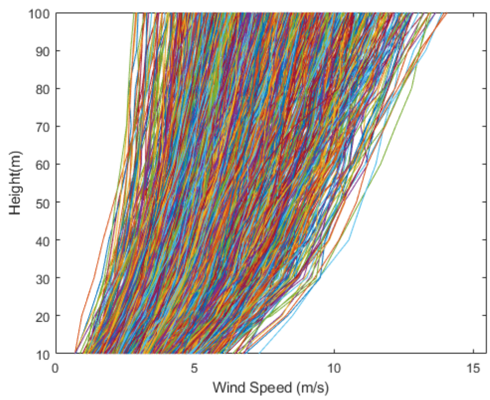


(f) Sample of measured and estimated WS at 50 m

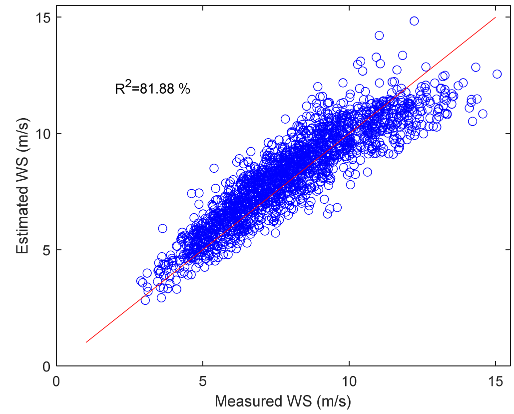
Figure 6. Performance of RELM, RegTree, and 1/7 power law on the estimation of WS at 50 m based on measurements between 10-40 m



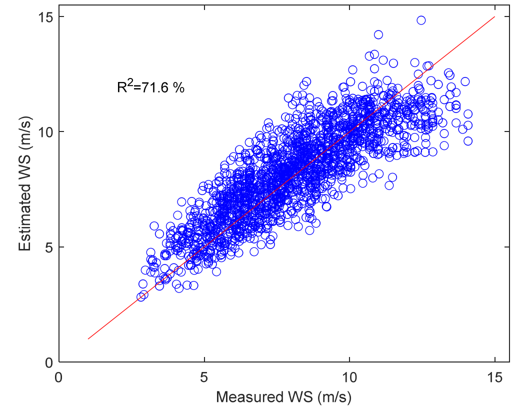
(a) RELM estimated WS at heights 50-100 m



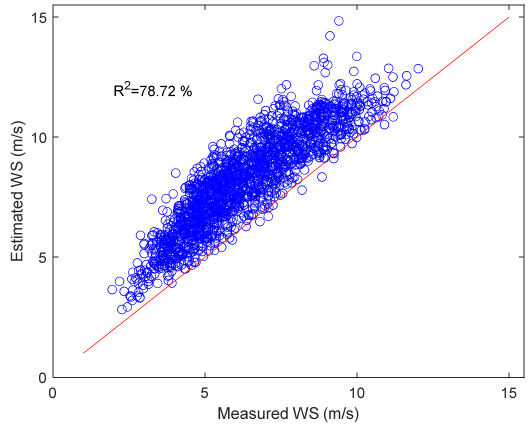
(b) RegTree estimated WS at a height 50-100 m



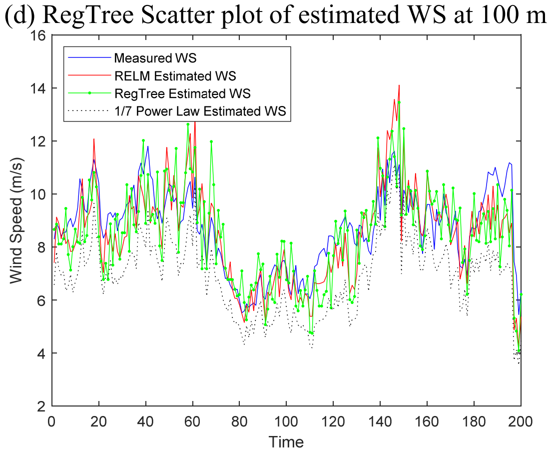
(c) RELM Scatter plot of estimated WS at 100 m



(d) RegTree Scatter plot of estimated WS at 100 m

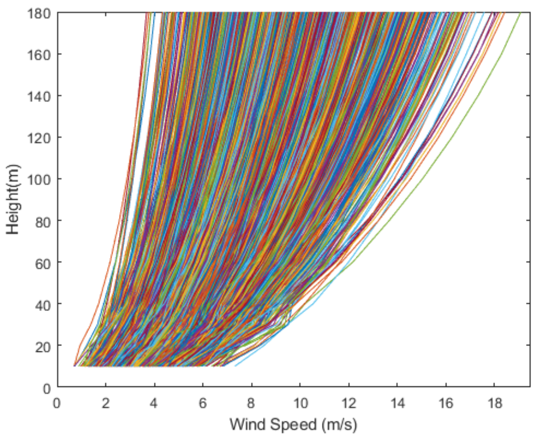


(e) 1/7 power low scatter plot of estimated WS at 100 m

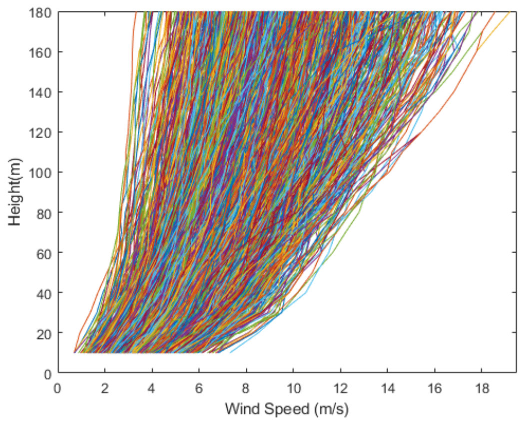


(f) Sample of measured and estimated WS at 100 m

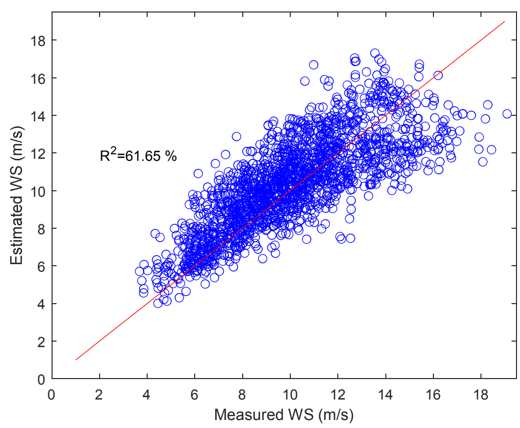
Figure 7. Results for estimation of WS at 100 m based on WS measurements at heights 10-40 m and estimated at 50-90 m.



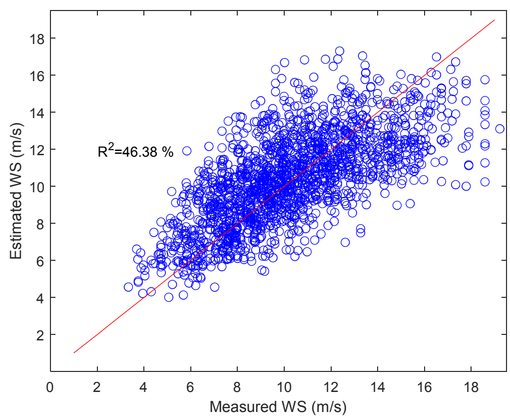
(a) RELM estimated WS at heights 50-180 m



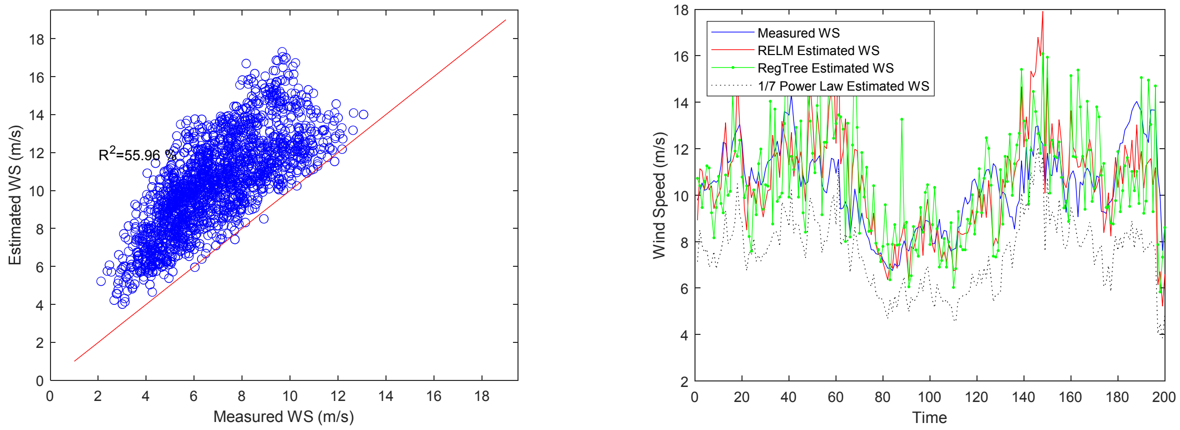
(b) RegTree estimated WS at a height 50-180 m



(c) RELM Scatter plot of estimated WS at180 m



(d) RegTree Scatter plot of estimated WS at 180 m



(e) 1/7 power low scatter plot of estimated WS at 180 m

(f) Sample of measured and estimated WS at 180 m

Figure 8. Results for estimation of WS at 180 m based on measurements WS at heights 10-40 m and estimated at 50-170 m.

Table 3. Estimated WSs at 50-180 m heights based on measurements at 10-40 m heights using the second dataset

Heights (m)	MSE				MAPE (%)				R^2 (%)			
	RELM	RegTree	1/7 PL	A-PL	RELM	RegTree	1/7 PL	A-PL	RELM	RegTree	1/7 PL	A-PL
50	0.03	0.06	0.16	0.07	2.48	3.15	5.63	3.56	98.95	98.07	98.02	98.02
60	0.12	0.21	0.54	0.23	4.41	5.63	9.83	6.00	96.83	93.98	94.38	94.38
70	0.24	0.44	1.07	0.46	5.96	7.90	13.12	8.01	94.23	88.41	90.54	90.54
80	0.43	0.79	1.83	0.72	7.52	10.23	16.15	9.47	90.66	81.37	85.68	85.68
90	0.61	1.15	2.61	0.99	8.65	11.80	18.52	10.62	87.87	75.35	81.97	81.97
100	0.86	1.62	3.59	1.35	9.83	13.49	20.73	11.86	84.38	68.77	77.65	77.65
110	1.08	2.03	4.53	1.67	10.66	14.70	22.51	12.70	81.64	63.80	74.49	74.49
120	1.37	2.53	5.63	2.04	11.52	15.90	24.20	13.57	78.45	58.68	70.97	70.97
130	1.60	2.96	6.65	2.36	12.03	16.69	25.60	14.08	76.24	54.84	68.43	68.43
140	1.89	3.47	7.82	2.74	12.67	17.58	26.94	14.71	73.58	51.01	65.52	65.52
150	2.12	3.91	8.96	3.06	13.04	18.18	28.14	15.16	71.96	48.20	63.47	63.47
160	2.41	4.49	10.24	3.47	13.52	18.99	29.28	15.70	69.88	44.80	61.05	61.05
170	2.62	4.85	11.32	3.76	13.77	19.30	30.29	16.05	68.62	42.68	59.50	59.50
180	2.89	5.31	12.53	4.12	14.10	19.73	31.24	16.46	66.84	40.26	57.53	57.53

4. CONCLUSION

Wind turbine hub heights are usually available up to 180 m. Therefore, the WS should be measured or extrapolated to the desired height with the smallest possible error. However, due to cost and expertise limitations, WS measurements are only carried out at much lower heights. This is because the cost of wind measurement masts increases significantly when the height is increased. This paper examined the extrapolation of WS to a certain turbine mast height using the WS values measured at lower heights. The model is trained to estimate WS at the next level of heights. The extrapolated data and measurement data at lower altitudes are used to estimate the WS at the next altitude level. The procedure was carried out up to WS at the height of 180 m. The estimated WS values are compared with the actual measured values in terms of MSE, MAPE, and R^2 performance measures. Experimental results showed that RELM produces more accurate estimates than the RegTree and the standard 1/7 Power Law in all three measures. The MAPE between extrapolated and measured WS from the first dataset at the height of 180 m was obtained using measurements of 10-40 m, and RELM, RegTree, 1/7 Power Law, and A-PL methods are 13.36%, 16.76%, 33.50%, and 15.73 %, respectively. The corresponding MSE values are 3.17, 4.84, 14.90, and 4.05, while the corresponding R^2 scores are 61.65%, 46.38%, 55.96%, and 55.96%. The numerical results from the second dataset showed a similar trend where the RELM outperforms the other methods. Similar results are expected at any climate and location where WS is measured at 10-40 m heights by following the same method explained in this paper. The training of the developed networks may be updated every few years to follow any meteorological cyclic change.

COMPUTER PROGRAMS

The program is written using Matlab and is available at (https://github.com/hilalnuha/RELMverticalWS).

ACKNOWLEDGMENT

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NOMENCLATURE

A-PL	Adaptive Power Law
WS	Wind speed
RELM	Regularized extreme learning machine
RegTree	Regression tree
SLFN	Single-hidden layer feed-forward neural net
MSE	Mean squared error
MAPE	Mean absolute percentage error

R^2 Coefficient of determination
LiDAR Light detection and ranging

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ЕКСТРАПОЛАЦИЈА ВЕРТИКАЛНЕ БРЗИНЕ ВЕТРА КОРИШЋЕЊЕМ РЕГУЛАРИЗОВАНЕ МАШИНЕ ЗА ЕКСТРЕМНО УЧЕЊЕ

Х. Нуха, М. Мохандес, С. Рехман, А. А-Шеики

Цена мерења брзине ветра (ВС) значајно расте са висином јарбола. Због тога је потребно имати метод за процену ВС на висини главчине без потребе за коришћењем мерних стубова. Овај рад испитује коришћење Регуларизоване машине за екстремно учење (РЕЛМ) за екстраполацију ВС на већим висинама на основу мерења на нижим висинама. РЕЛМ користи измерени ВС на висинама 10-40 м да би проценио ВС на 50 м. Резултати процене од 50 м се даље користе заједно са измереним ВС на 10-40

за процену ВС на 60 м. Овај поступак се наставља до процене од 180 м. Перформансе РЕЛМ-а се упоређују са методом стабла регресије (РегТрее) и стандардним законом 1/7.

Предложени алгоритам обезбеђује економичан метод за проналажење брзине ветра на висини чворишта и, последично, потенцијалне енергије ветра која се може генерисати из турбина инсталираних на висини чворишта на основу мерења на много нижим висинама. Штавише, екстраполиране вредности ових метода се пореде са стварним измереним вредностима коришћењем ЛиДАР система. Средња апсолутна процентуална грешка (МАПЕ) између екстраполованог и измереног ВС на висини од 180 м коришћењем мерења на висини од 10-40 м коришћењем РЕЛМ, РегТрее, 1/7 Повер Лав и Повер Лав са адаптивним коефицијентима је 13,36%, 16,76%, 33,50% и 15,73%, респективно.