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Comparative analysis of Artificial Neural Networks with conventional methods for extrapolation of wind speed at an elevated height

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Abstract. Due to rapidly increasing pollution, it becomes necessary to substitute fossil fuels, and as wind energy is available quite easily and in abundance, researches are carried out in this area. These facts make it imperative to know about the variables and the problems involved behind it. The wind speed is a random variable, and it depends on atmospheric factors like pressure, relative humidity, wind dispersion & wind direction. This paper introduces the method to effectively predict wind speed by making use of the Levenberg-Marquardt backpropagation algorithm in artificial neural network (ANN) and by conventional means like power law & log law in MATLAB. Data from the Gulf of Khambhat, Gujarat provided by LIDAR for a period of 8 months, was used to prepare valid data set to train the neural network and to build a model to predict wind speed. After obtaining a histogram of the predicted values by log law, power law and ANN, it was seen that wind speed values obtained by ANN were quite close to actual values than the values obtained through the other methods. A comparison in terms of root means square error and percentage of the number of data indicates that developed neural network gives less root mean square error and a higher percentage of data whose absolute error lie between -0.2 and 0.2.

1. Introduction

As the population and standard of living of human increases, the energy consumption rises and the need for energy expands rapidly. If we continue to produce energy in the same conventional ways, then we are in turn contaminating the environment. So in order to meet the increased energy demands and environmental factor we have to have some alternative energy sources. Among the renewable energy resources, wind energy is a more feasible and easily available energy source, and it is also cheaper than solar energy resource [10]. The target of 15 percent of renewable power by 2020 can be achieved only if the wind energy sector is allowed to grow [8]. The wind turbine design is dependent on the wind speed at the turbine hub height [11]. Overdesigning the turbine blade which leads to an increase in the size of the blade is a big issue in terms of financial investment [7]. So to design particular wind turbines accurate wind speed is required at the turbine hub height. Moreover, in many cases measuring the wind speed at elevated height is difficult. So wind speed needs to be extrapolated at elevated height by taking reference of wind speed at a lower height. Accurate extrapolation of the wind speed over different elevation is a complex problem. To extrapolate the wind speed at elevated heights, generally, two conventional methods are used. One is extrapolation using power law and the second one is extrapolation using log law. These methods depend upon constant exponents, which does not consider



the change in environmental condition and other change in wind-related parameters which are directly or indirectly affects the wind speed at different heights. At lower altitudes wind speed follows the logarithmic trend but when the data of surface roughness is not available, then it is challenging to predict the wind speed accurately with the log-law approach. Wind shear coefficient is dependent on environmental stability and wind characteristics [9], which states that wind speed is also dependent on those parameters. Neural networks approach can consider environmental factors on which wind speed is dependent. A Neural Network can develop an algorithm which can predict accurate outputs by initially training the network with the known data in which dependent parameters are taken into consideration. ANN can learn and adapt to complex and nonlinear data, and most importantly ANN does not impose any restriction on input data variables. In this study a Feedforward Neural network is developed using the 8-month dataset at 40m, 60m, 80m and 87m heights at 10 minutes time interval by considering six input parameters. LIDAR collects these data at the location of Gulf of Khambhat, Gujarat, India. In this study wind speed is extrapolated over 100m to 200m height thorough three different extrapolation method and results have been compared in terms of the root mean square errors and percentage of the given data for which absolute errors lies within the range of [-0.2,0.2].

Nomenclature					
v_{ext}	Extrapolated Velocity	m/s	w	Weight	
v_{ref}	Velocity at the reference height	m/s	B	bias	
z_{ext}	Extrapolation Height	m	y_n	Predicted output using Neural Network	
z_{ref}	Reference Height	m	n	Index of output data	
e	Absolute Error	m/s	k	Index of Iteration	
z_o	Roughness Length	mm	E	Absolute error Matrix	
v_{tr}	Training Dataset Velocity	m/s	N	Total output data	
z_{tr}	Training Dataset height	m	J	Jacobian Matrix (Partial Derivative of the Error function with weights and bias)	
MSE	Mean Square Error	(m/s) ²	α	Wind Shear Coefficient	
RMSE	Root Mean Square Error	m/s			
v	Actual Velocity of the dataset	m/s			

2. Collected Data

The input variable plays a vital role to achieve accurate results. To estimate the wind speed accurately study of the effect of the different input parameter is essential. The LIDAR based measurement was conducted in Gulf of Khambhat, Gujarat, India by National institute of Wind Energy Chennai and wind related data in 10 minute time interval were collected in time span of November 2017 to June 2018. The data consist of parameters such as Pressure, Relative Humidity, Height, Wind dispersion, Wind Direction and wind speed from November 2017 to June 2018. LIDAR collects these data at the location of Gulf of Khambhat, Gujarat, India. The data is of total eight-month duration and at the interval of 10 minutes. Wind speed varies from season to season, and even from day to night, it is because of the change in the temperature and pressure gradient. As the difference gets higher, the speed of the wind also increases [12].

3. Methodology

The Speed of height ranging from 100m to 200m are extrapolated using two conventional methods and also with a developed feed-forward neural network approach. These extrapolated Speed values are compared with the actual ones, and overall RMSE is obtained. After that RMSE value of all three methods is compared to conclude which method is best suitable for the given problem.

3.1. Power Law

Power law method is one of the most common and conventional methods used to extrapolate wind speed over different heights. Here it is used to extrapolate wind Speed from 100m to 200m height. The Speed is extrapolated over a dataset of 8 months with 10 minute time interval at 100m, 107m, 120m, 140m, 160m, 180m and 200m using power law.

As a reference, 8-month data at 10 minutes time interval of 40m is taken into consideration to extrapolate wind speed at different heights. The wind shear coefficient (α) is taken as 1/7. The following equation is used for Extrapolation of Speed from 100m to 200m height [1].

$$v_{ext} = v_{ref} \times \left(\frac{z_{ext}}{z_{ref}} \right)^{\alpha} \quad (1)$$

3.2. Log Law

Log law method is another commonly used conventional method to extrapolate wind speed over different heights. The Speed is extrapolated over the same dataset of 8-months with 10 minute time interval at 100m, 107m, 120m, 140m, 160m, 180m and 200m with log law.

Corresponding 8-month data at 10 minutes time interval of 40m is considered to extrapolate the wind speed over different elevated height. As per the NIWE report of LIDAR wind resource assessment, the average value of surface roughness is taken as 0.2 [12]. The following equation is used for Extrapolation of wind speed over 100m to 200m height [1].

$$v_{ext} = v_{ref} \times \frac{\ln\left(\frac{z_{ext}}{z_o}\right)}{\ln\left(\frac{z_{ref}}{z_o}\right)} \quad (2)$$

3.3. Neural Network

The main objective of using a neural network approach is to improve the performance of extrapolated wind speed by taking factors like time horizon, two environmental conditions (Temperature and pressure), two wind-related parameters (Wind dispersion and wind direction) and height into consideration. A feed-forward neural network was created and trained using Levenberg-Marquardt backpropagation algorithm considering eight-month training data of 60m, 70m, 80m and 87m with six

input variables and one output variable as wind shear coefficient. The developed feed forward neural network is used to predict wind shear coefficient for 100m, 107m, 120m, 140m, 160m, 180m, and 200m height. The predicted wind shear values are used to calculate the wind speed at 100m, 107m, 120m, 140m, 160m, 180m, and 200m altitude

3.3.1. Feed Forward Network. A feed-forward neural network consists of six input layer neurons, eight hidden layer neurons, and one output layer neuron. Six input layer neurons are taken since we have six desired input variables, which are Time Horizon, Pressure, Relative Humidity, Height, Wind dispersion and Wind Direction. One output neuron is considered for wind shear coefficient as it is the only output variable. After many iterations for training the networks, the decision to take eight number of hidden layer neurons was finalized to develop neural network optimally.

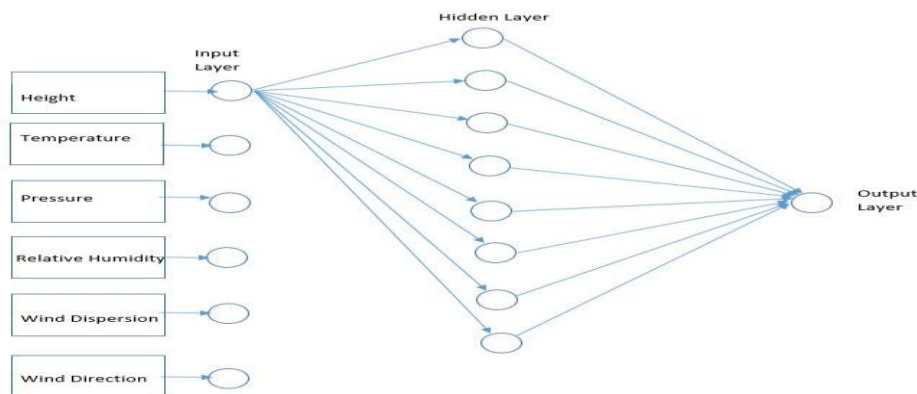


Figure 1. Schematic Diagram of Feed Forward Network

For representation purpose only one input neuron connections with all hidden neurons are shown in Figure 1.

Actual network has all input and hidden neurons are connected in forward direction.

Table 1. Feed Forward Neural Network Selected Parameters

Neural Network Parameter	Parameter value/function
Number of Input Layer Neurons	6
Number of Input Layer Neurons	8
Number of Input Layer Neurons	1
Hidden layer transfer function	tansigmoid
Hidden layer transfer function	purelinear

3.3.2. Preparing a training target. Wind shear coefficient is taken as an output variable of a feed-forward neural network. For training the data, the exact values of wind shear coefficient are required. These values are calculated for an eight-month training dataset of 60m, 70m, 80m, 87m at 10 minutes time interval by keeping α as a subject in power law equation [7]. Values of α are calculated for all N number of data available at each height.

$$\alpha = \frac{\ln v_{tr} - \ln v_{ref}}{\ln z_{tr} - \ln z_{ref}} \quad (3)$$

3.3.3. Training Neural Network. After creating a feed-forward neural network an eight-month training dataset of 60m, 70m, 80m, 87m at 10 minutes time interval was taken to train and validate the feed-forward neural network. The training algorithm used was the Levenberg-Marquardt backpropagation algorithm.

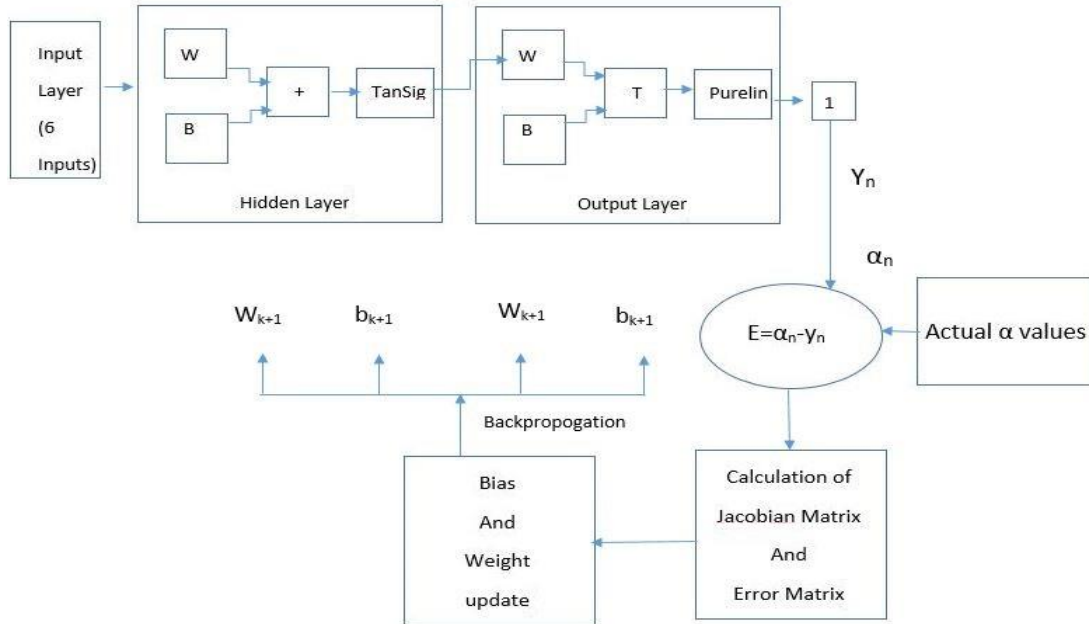


Figure 2. Schematic Diagram of Training phase

Training starts with randomly initialization of weight and bias between neurons of input layer-hidden layer and Hidden layer-Output layer. In the first iteration taking into consideration of all input variable values multiplies with corresponding weight and adding each bias of each neurons gets added and gives output to the upcoming neuron through assigned transfer function. During this only forward propagation a certain output at output neuron is generated. This output is compared to the actual values of training dataset in terms of error function MSE [5]. Then during back propagation at each neuron absolute error and partial derivatives of absolute error with respect to weights and bias are calculated, forming jacobian matrix (J) and absolute error matrix (E). And the new weights and bias at each neurons are updated using following equation [2]. In each k th iteration jacobian matrix and absolute error matrix gets updated. Combination Coefficient is taken as 0.1.

$$e_n = \alpha_n - y_n \quad (4)$$

$$MSE = \frac{\sum_{n=1}^N e_n^2}{N} \quad (5)$$

$$w_{k+1} = w_k - [J_k^T J_k + \mu I]^{-1} J_k^T E_k \quad (6)$$

3.3.4. Calculation of extrapolated wind speed. The trained neural network is used to predict the wind shear coefficient (α) by feeding the input parameters of a dataset consisting of 100m, 107m, 120m, 140m, 160m, 180m, and 200m height. The predicted α values are fed into the power law equation to extrapolate wind speed over these heights.

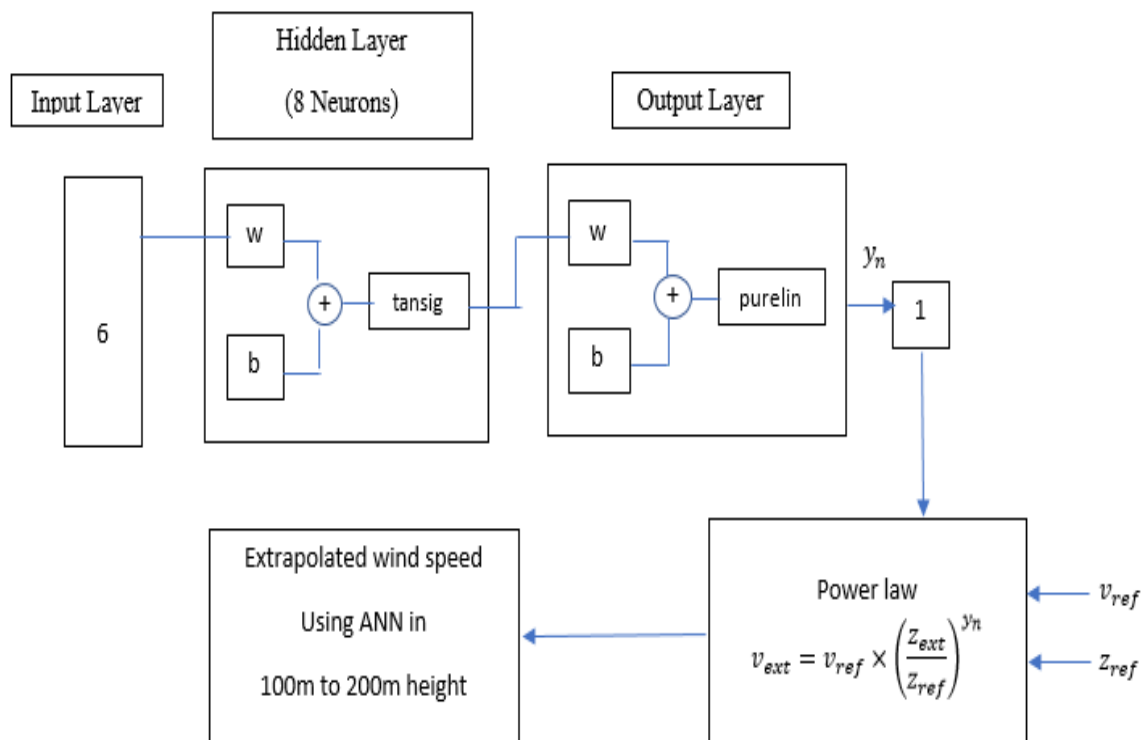


Figure 3. Schematic Diagram of Extrapolation of wind speed using trained Neural Network

3.4. Error Comparison

RMSE calculates the square root of the averaged squared errors between actual output and extrapolated output by a particular method, and it is more useful for more significant errors [5]. So among the standard comparison methods, RMSE and the absolute error is selected to compare three different extrapolation methods. After extrapolating wind speed of eight-month dataset at 100m, 107m, 120m, 140m, 160m, 180m and 200m height using power law, log law and developed Feed-forward neural network, at each height for N data an absolute error and RMSE [5] between extrapolated wind speed and actual wind speed were calculated.

$$e_n = v_n - y_n \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{n=1}^N e_n^2}{N}} \quad (8)$$

4. Results

To compare the performance of three extrapolation methods two comparison parameter was used. First one is RMSE and the second comparison parameter is the percentage of the given data for which absolute error lies in the range of [-0.2, 0.2].

4.1. Result containing RMSE

RMSE gives information about the overall error of specific data; that is why it gives a better understanding of the comparison of the performance of different methods [5]. After extrapolating wind

speed of eight-month dataset at 100m, 107m, 120m, 140m, 160m, 180m and 200m height using power law, log law using equation (1) and (2) respectively, at each height for given data the actual wind speed and extrapolated wind speed was given to the equation (8), and RMSE value was obtained between extrapolated wind speed and actual wind speed for N data at each height.

After finding RMSE using two conventional methods, a trained neural network was used to predict α at 100m, 107m, 120m, 140m, 160m, 180m, and 200m height. Extrapolated wind speed was calculated Using equation (1) at each height. The extrapolated wind speed and Actual wind speed are put into equation (8) to get RMSE at each height 100m, 107m, 120m, 140m, 160m, 180m, and 200m. Calculated RMSE at each height using three various extrapolation methods is shown in Table 2. The RMSE at 100m, 107m, 120m, 140m, 160m, 180m and 200m for three extrapolation methods are also represented graphically in Figure 4.

Table 2. RMSE for Extrapolation of wind speed using three different methods at various height.

Training Data in Neural Network	Extrapolated Height in Neural Network (m)	Root Mean Square Error (m/s)		
		Log Law	Power Law	Feed Forward Neural Network
60m to 87 m	100	0.989	1.041	0.936
	107	1.078	1.155	1.006
	120	1.232	1.273	1.153
	140	1.44	1.522	1.359
	160	1.639	1.732	1.553
	180	1.817	1.938	1.734
	200	1.968	2.070	1.878

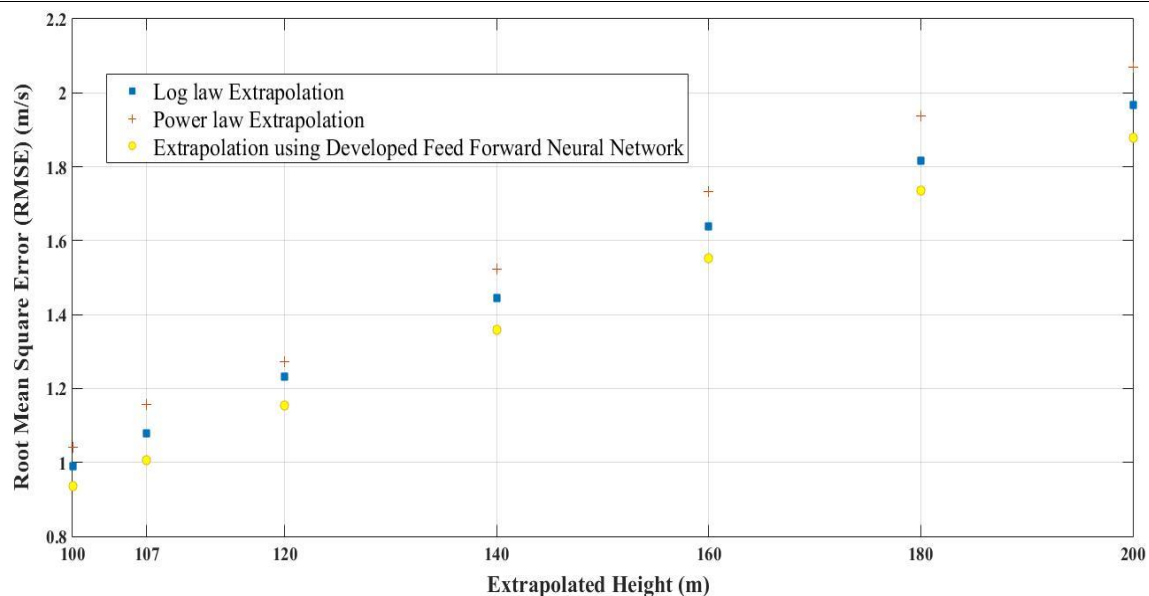


Figure 4. Scatter plot of RMSE (m/s) in all extrapolation methods.

From Table 2. And Figure 4., it was observed that at every height the overall RMSE for extrapolated velocities over various heights is Highest for conventional power law method while the feedforward neural network method gives least overall RMSE at all heights. Log law has slight higher RMSE error value compared to neural network approach, but it is better than the power law approach for extrapolation. Power law seems to give the worst result of RMSE compared to other two

extrapolation method approach. It was observed that the performance of all three methods decreases with an increase in height

4.2. Results containing % Data with error in the range $[-0.2, 0.2]$

It is also essential to find the absolute error between extrapolated values and actual values. A method whose absolute errors are near to zero is expected to give more accurate results. An absolute error has been calculated using equation (7) just by taking the difference between extrapolated and actual wind speeds for each height.

Similarly after finding absolute error using two conventional methods a trained neural network has been used to predict α at 100m, 107m, 120m, 140m, 160m, 180m, and 200m height. Using equation (1) extrapolated wind speeds were calculated at each height. The extrapolated wind speed and Actual wind speed are fed into equation (7) to get the absolute error (e) at each height 100m, 107m, 120m, 140m, 160m, 180m, and 200m. Calculated absolute errors of all heights combined are represented graphically as a histogram using three various extrapolation methods.

Also since it is essential to know how much-extrapolated data are accurate (error within $[-0.2, 0.2]$) percentage of data with error within $[-0.2, 0.2]$ is also calculated and represented in all three histograms with three different extrapolation method. Percentage of data with error within $[-0.2, 0.2]$ for each technique is also described in Table 3.

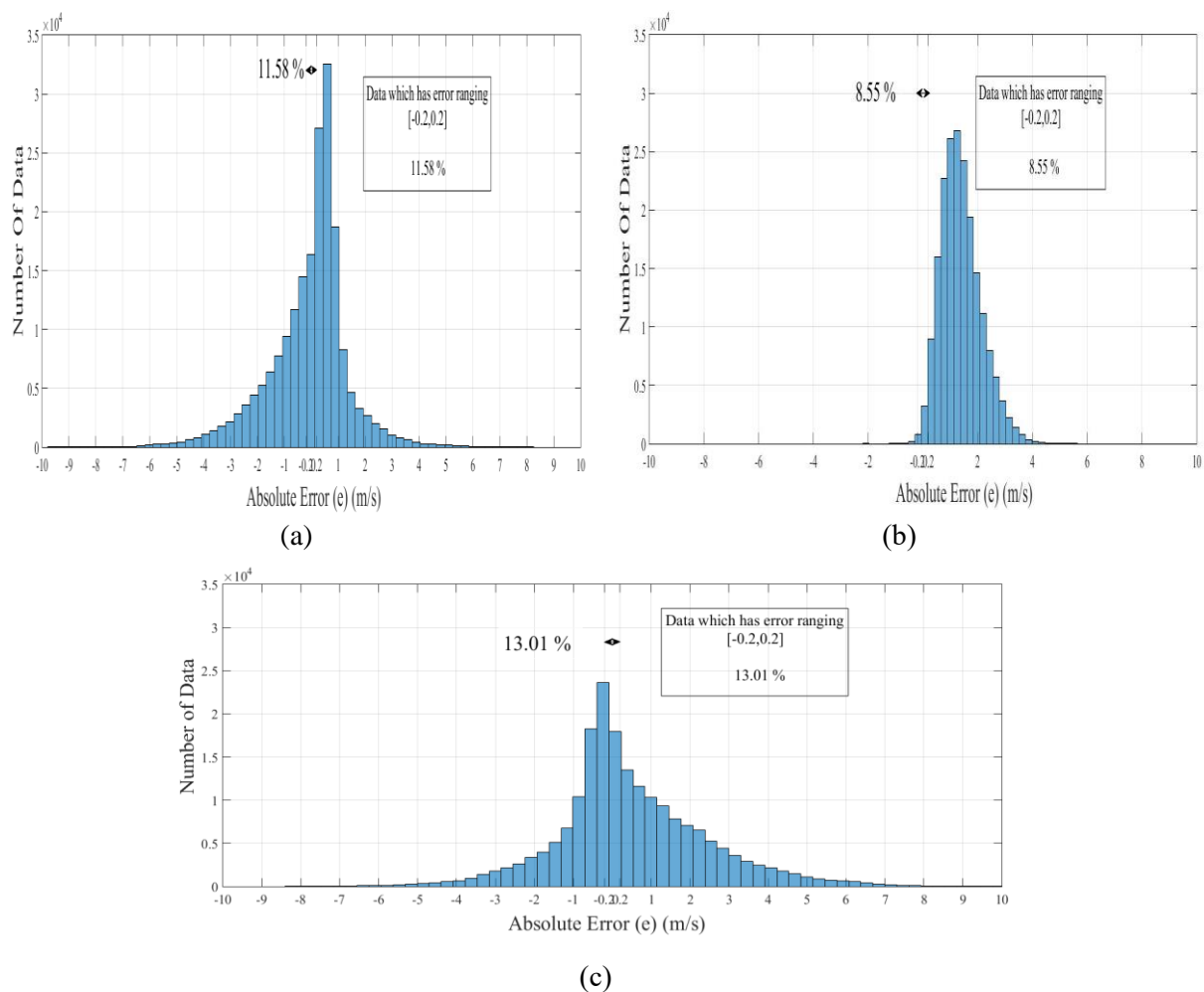


Figure 5. Absolute error histogram of Extrapolated wind speed using (a) Log Law (b) Power Law (c) Feed Forward Neural Network

Table 3. % Data whose absolute values (m/s) are between -0.2 and 0.2

Log Law	Power Law	Feed Forward Neural Network
11.58	8.55	13.01

From Figure 5(a), Figure 5(b), Figure 5(c). And Table 3. , it can be observed that percentage data with extrapolated wind speed absolute error (m/s) within $[-0.2, 0.2]$ is highest (13.01) in Developed Neural Network. And least in Power law (8.55). From all three histogram, histogram of Developed Neural Network seems more converged towards zero error.

Log law method histograms seems converged towards error in range of $[0.7, 1]$ which is slight bad than neural network approach histogram. And also it has 11.58% of data within absolute error range $[-0.2, 0.2]$. Which is better than the power law but worse than the neural network approach.

Power law histogram shows the worst result as the absolute error (m/s) within $[-0.2, 0.2]$ is least (8.55), and the histogram seems more converged towards error range $[0.7, 1.5]$.

5. Conclusion

From the study and observation of results obtained of comparisons between three extrapolation methods in terms of RMSE and the percentage number of data in the range of $[-0.2, 0.2]$ following conclusions has been drawn.

- Extrapolation of wind speed using trained feedforward neural network shows least overall RMSE over two other conventional methods.
- Extrapolation of wind speed using trained feedforward neural network gives the maximum number of data (13.01%) whose absolute error is in the range of $[-0.2, 0.2]$ compared to two other conventional methods.
- Since conventional methods does not consider changes in environmental and changes in wind parameters, they give lower performance than the ANN approach for extrapolation of wind speed at elevated height.
- Since overall results of Neural Network approach is better than the conventional methods, we can say that since Neural network approach considers changes in some parameters which directly or indirectly are related to the wind speed at different heights and different time horizons, Neural network approach gives better result than the conventional methods.
- Since in ANN approach the data used for training of network is only for one particular location, ANN approach is limited for extrapolation of wind speed at the location of Gulf of Khambhat, Gujarat only. While conventional methods are applicable to any location resulting in low extrapolation performance.

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