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Research Article

A Bayesian Regularized Artificial Neural Network for Up-Scaling Wind Speed Profile

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Abstract

Maximizing gains from wind energy potential is the principle objective of the wind power sector. Consequently, wind tower size is radically increasing. However, choosing an appropriate wind turbine for a selected site requires having an accurate estimation of vertical wind profile. This is also imperative from the cost and maintenance strategy point of view. Installing tall towers or other expensive devices such as LIDAR or SODAR raises the costs of a wind power project. In this work, we aim to investigate the ability of a Neural Network trained using the Bayesian Regularization technique to estimate wind speed profile up to a height of 100m based on knowledge of wind speed at lower heights. Results show that the proposed approach can achieve satisfactory predictions and prove the suitability of the proposed method for generating wind speed profile and probability distributions based on knowledge of wind speed at lower heights.

Keywords: *Wind energy, Wind speed profile, Neural network, Bayesian regularization.*

1. Introduction

Due to the draining of fossil fuel based energy sources and the adverse effects of this on the environment developers have been obliged to seek out other cleaner energy resources arising from the sun, such as wind, hydro, and photovoltaic power. Of these renewable energies, wind power is perceived as the most affordable due to its generated electricity capacity and its cost (Tabassum-Abbasi *et al*. 2014). The feasibility (i.e. technical and commercial) study of a wind farm project should give an accurate estimation of the average annual amount of energy that the wind turbine can provide throughout its lifetime (typically 20-30 years)(Staffell and Green 2014). The choice of turbines and their specific location requires precise determination of wind and turbulence conditions, taking into account local factors. The energy potential thus is defined taking into consideration uncertainties. For the years ahead, the expected trend is towards the construction of large wind turbines (see Figure.1), and this means developing robust and reliable tools to assess sites with suitable accuracy. In general, wind is measured below hub height because of the high cost of new measurement technologies such as LIDAR and SODAR (Holtslag *et al,*2014). Consequently, wind measurements have to be extrapolated to the target hub height from the measurements at the reference height. In wind energy engineering, the determination of vertical wind shear (i.e. the variation of wind speeds with elevation or the vertical profile of the wind speed) is a crucial issue. It is necessary to evaluate effectively available wind power at a given site, design the wind turbine components and evaluate the impact of fatigue loads caused by wind shear (Holtslag *et al,*2014)

With the advent of artificial intelligence paradigms and machine learning, behavior modeling of complex and stochastic processes like wind velocity and its conversion into energy becomes possible with reasonable accuracy. In the literature we find that artificial intelligence methods have been widely used for forecasting wind and estimating wind energy. These methods include artificial neural networks(Pinson and Kariniotakis 2003), adaptive neuro-fuzzy inference systems, support vector machines (Foley *et al.* 2012), evolutionary algorithms, neuro-fuzzy Networks (Foley *et al.* 2012), Neural Networks and Radial Basis Function (Chang 2013). Other methods are given in references (Soman *et al.* 2010)and (G. Giebel *et al,* 2014).

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Artificial Neural Networks are a promising alternative for approximating any bounded function (Sheela and Deepa 2013).They are strongly connected assemblies of computational units referred to as "formal neurons" and forming computer models capable of solving any complex problem: classification, pattern recognition, time series prediction, etc. They often constitute an ideal solution for "black box" modeling.

However, inherent problems with artificial Neural Networks are over-fitting and generalization during learning (Sheela and Deepa 2013), hence the need to combine the method with other techniques for regularization.

The purpose of this work is to investigate the ability of the Bayesian Regularized Feed-forward Artificial Neural Network to extract the relationship linking mean wind speed and wind speed distributions at different hub heights of wind turbines, then to estimate these figures at higher altitudes based on measurements at lower altitudes.

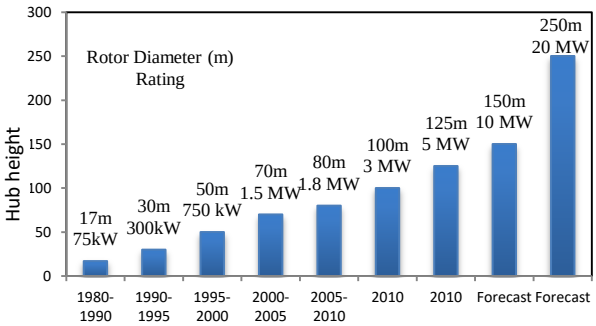

Figure.1.

Figure.2. Growth in size of commercial wind turbines (Tabassum*et al*. 2014)

2. Vertical wind profile

In the atmospheric surface layer (5%-10% of the atmospheric boundary layer, also known as planetary boundary layer), the atmosphere is directly influenced by contact with the earth's surface. The turbulent fluxes of heat, moisture and momentum are approximately considered to be constant and independent of height. The Monin-Obukhov similarity theory (i.e. dimensional analysis) assumes that Coriolis effects and thermal effects, resulting from the diurnal cycle of heating and cooling of the earth's surface, are suppressed by the frictional effect(Monin and Obukhov 1954), and the corrected neutral logarithmic wind profile including stability effects is defined a:

$$U(z)=\frac{u_*}{k}\left[\ln\left(\frac{z}{z_0}\right)-\psi(\xi)+\psi(\xi_0)\right] \quad (1)$$

where$z$ is the height above the surface (m), k is the von Karman constant ($k \approx 0.40$), u_* is the friction velocity (m.s^{-1}), and $z_0$is the roughness length (m). The Monin-Obukhov stability function ψ is given by:

$$\psi(\xi)\begin{cases} = 4.7\xi \quad for\,\xi>0 \\ = 2\ln\left[\frac{1+(1-15\xi)^{1/4}}{2}\right]-\ln\left[\frac{1+(1-15\xi)^{1/2}}{2}\right] \quad for\,\xi<0 \\ +\tan^{-1}(1+15\xi)^{/4}-\frac{\Pi}{2} \\ = 0 \quad for\,\xi=0 \end{cases} \quad (2)$$

where ξ is the non-dimensional parameter defined thus:

$$\xi=\frac{z}{L}=z\times\left(-\frac{kQ_0 g}{u_*^3\theta_0}\right). \quad (3)$$

$\zeta_0$is calculated for $z=z_0$.$g$is the gravitational acceleration (m.s^{-2}), L is the Obukhov length, Q_0 is the turbulent flux of virtual potential heat at the surface, and θ_0 is the mean virtual potential temperature. Based on equation (2), the stability correction function ψ depends on the Obukhov length L. If L is negative the atmosphere is unstable, while for positive values the atmosphere is stable. As shown in equation (3), to estimate L directly, we can use observed data for turbulent fluxes of heat and virtual temperature. Other empirical methods can be applied to wind speed and temperature measurements, such as Richardson-methods(Holtslag*et al,* 2015).

Equation (1) allows extrapolation of the vertical wind velocity. However, it has the disadvantage of necessitating measurement of surface sensible heat flux and the quantities of motions. As it is not possible to collect this data continuously, works have been conducted to assimilate increase of wind speed with altitude in the surface layer to empirical laws. In the literature, two approaches are found: the first is the extrapolation of instantaneous wind speed records, and the second approach concerns the extrapolation of the wind speed probability distribution function.

There are several theoretical and empirical models describing vertical mean wind speed in the atmospheric boundary layer. The I.E. Committee (I.E. Committee 2013)recommends using the logarithmic profile (4) or the power law profile (9)for wind speed variation with height above ground level.

2.1 Logarithmic Profile (Log Model)

Generally limited to the lowest 100m of the atmosphere, this logarithmic profile is expressed as:

$$U(z)=\frac{u_*}{k}\ln\left(\frac{z}{z_0}\right). \quad (4)$$

This is a specific form of the stability corrected logarithmic wind profile (1) for neutral conditions. Under certain conditions, such as a forest or dense urban areas, the roughness length is shifted by distance Z_0. This parameter is called zero-plane displacement, and is defined as the height above ground-level at which zero wind speed is achieved as a result of

obstacles such as trees or buildings(Gualtieri and Secci 2012).

2.2 DeavesAnd Harris Model (D–H Model)

The D-H model, known chiefly for its "logarithmic with parabolic defect" mean velocity profile, is supposed to be applicable to the entire atmospheric boundary layer and is not limited to the surface layer. The D–H model is explained as (Tieleman 2008):

$$U(z) = \frac{u_*}{k} \times \left[\ln\left(\frac{z}{z_0}\right) + 5.75\left(\frac{z}{h}\right) - 1.88\left(\frac{z}{h}\right)^2 - 1.33\left(\frac{z}{h}\right)^3 + 0.25\left(\frac{z}{h}\right)^4 \right], \quad (5)$$

h is the equilibrium boundary layer height and is determined by:

$$h = \frac{u_*}{6f} \quad (6)$$

where$f$ is Coriolis parameter (9.375×10^{-5} s^{-1}).
Under neutral conditions below 300m, the mean profile expression can be estimated from the mean wind speed at 10m (Tieleman 2008):

$$U(z) = U(10)\left[\ln\left(\frac{z}{z_0}\right) / \ln\left(\frac{10}{z_0}\right) \right] + 86.25 * f * z. \quad (7)$$

As with the log law, the D-H model has two critical parameters that must be estimated prior to application ofz_0 and u_*. In the proposed work we use the methodology proposed by Liu *et al*. (Liu, Xuan, and Park 2003)to estimate the roughness length using the empirical expression of turbulent intensity variation with height up to 100m provided by the Engineering Science Data (Liu, Xuan, and Park 2003):

$$\frac{\sigma_u}{U} = \frac{B\left(0.867 + 0.556\log_{10} z - 0.246\log^2{}_{10} z\right)}{\ln\left(\frac{z}{z_0}\right)}, \quad (8)$$

where B=1.0 for$Z_0 \leq 0.02$m,
B=0.76. $Z_0^{-0.07}$ for $0.02m \leq Z_0 \leq 1.0$m,
B=0.76for $Z_0=1.0m$.

2.3 Power Law (Pmodel)

For the assessment of wind loads on structures, the power law profile is the most widely used. Despite its simplicity, this model is based on empirical field tests without any physical theory. The formulation as proposed by Hellman is as follows:

$$U(z) = U(z_{ref})\left(\frac{z}{z_{ref}}\right)^{\alpha} \quad (9)$$

Where z_{ref} is a reference height above ground level specific to the profile, and α is Hellman's wind shear (or friction) exponent.

2.4 Justus AndMikhailel Model (J-Mmodel)

To describe the random behavior of wind speed over an extended period of time, it is often recommended to use the Weibull probability density function (10). With known values for the Weibull scale factor c_1 and the shape factor k_1 at height z_1, the values of c_2 and $k_2$can subsequently be assessed at any desired height z_2 (i.e. the turbine hub height) by means of (11) and (12) ((Gualtieri and Secci 2014),(Justus *et al,* 1976)):

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left(-\frac{v}{c}\right) \quad (10)$$

$$c_2 = c_1\left(\frac{z_2}{z_1}\right)^n \quad (11)$$

$$k_2 = k_1\left[\frac{1 - 0.088\frac{z_1}{z_{ref}}}{1 - 0.088\frac{z_2}{z_{ref}}}\right] \quad (12)$$

n is the Weibull distribution extrapolation exponent expressed by(En *et al.* 2012)

$$n = \frac{0.37 - 0.0881\ln(c_1)}{1 - 0.0881\ln(\frac{z_1}{z_{ref}})}. \quad (13)$$

Owing to its simplicity, its independence of stability conditions and the fact that it avoids overestimation of available wind energy, the Justus and Mikhailel model based on Weibull distributions proves preferable to other extrapolation wind speed probability distribution functions (Gualtieri and Secci 2014).

Recently, a number of mathematical models of the wind speed profile have become available. An extended power law for vertical wind speed extrapolation and Weibull probability distribution parameters on the basis of the perturbation theory has been developed by (En *et al.* 2012), by adding standard deviations and a cross-correlation coefficient to the calculation. Another study has been conducted by (Ghita, Andrei, and Marin 2013)based on the least squares methodology. In our work a new approach based on the Artificial Neural Network will be introduced and compared with logarithmic law and the Justus and Mikhailel model.

3. Bayesian Regularized Artificial Neural Network methodology

Artificial Neural Networks are classified in the ranks of artificial intelligence paradigms. Aswith nervous systems, Neural Networks are strongly connected assemblies of processing units named "formal neurons", forming computational models that are able to solve very complex classification problems, pattern recognition, time series prediction, etc. They often constitute an ideal solution for "black box" modeling. They constitute dynamic systems that learn from examples. The interactions between neurons are defined by the connection weights, which, in general,

change intensity during the learning period. This learning aims to modify the connection weights until stabilization of the Network is achieved, which involves training until the weights change no more than a negligible amount(Giebel *et al*. 2011).

Generally, there are two strands of training. The first one is referred to as online learning, where the Network performance is evaluated after presenting each input/output data pair. The second is referred to as offline, or batch learning; the Network performance is calculated after presenting a batch of input/target patterns $D=\{x^m,t^m\}$, where *m* is a label running over the *N* pairs. The performance function is expressed as follows(D. MacKay 1992):

$$E_D(D/w,A)=\sum_m^N \frac{1}{2}\left[y(x^m,w,A)-t^m\right], \quad (14)$$

where*w* is assigned to the connections (i.e. weights) in the Network, and *A* is the topology specification of the Network in terms of number of hidden layers, neurons and the type of activation function.

There are several training algorithms for feed-forward Networks; the most commonly used is the back-propagation algorithm. The back-propagation algorithm is a supervised learning method, which consists in the minimization of the cost function by the gradient method, i.e. by varying the weights in the direction indicated by the gradient of the square error. However, this method is not fast and can get caught up in local minima.

The Artificial Neural Networks have the disadvantage of over-fitting and poor generalization problems, during learning: the error on the training set is driven to a very small value, but when new data is presented to the Network, the error is large (Sheela and Deepa 2013), which implies the need to combine the method with other techniques for regularization.

The regularization technique aims to force the Network to converge to a set of weights with lower-value means, so that the Network response is smoother and less susceptible to over-fitting (Li and Shi 2012). This technique improves the generalization capability of the Neural Network by adding a weight decay component to the objective function(Qiu *et al*. 2011). A simple term is (D. MacKay 1992):

$$E_w(w/A)=\sum_i^M \frac{1}{2}[w_i]^2 \quad (15)$$

M denotes the number of weights in the Network.

The training algorithm, then, should calibrate the Network parameters by optimizing the combined function:

$$F=\alpha E_w+\beta E_D, \quad (16)$$

Where α and β are the decay rates, or the regularizing constants.

Applying David Mackay's approach(D. MacKay 1992), the use of weight decay does not fully avoid the problem of generalization even if the Network consists of a good many hidden units. In this situation, the optimization problem can be considered as a probabilistic inference. Based on Bayes theorem (D. J. C. MacKay 1991), minimizing the performance function(16) is identical to finding the most probable parameters w^{MP}, which then equates to maximizing the posterior likelihood of the parameters w^{ML} (17)given the data, the regularizing constants and all other assumptions *A*. Thus,

$$P(w/D,\alpha,\beta,A)=\frac{P(D/w,\beta,A)\times P(w/\alpha,A)}{P(D/\alpha,\beta,A)}. \quad (17)$$

P(w/α,A) is the prior density, which represents the knowledge about the weights before any data is collected. *P(D/w,β,A)* is the likelihood function, which is the probability of the data occurring, given the weights. *P(D/α,β,A)* is a normalization factor, which guarantees that the total probability is 1.

According to David Mackay (D. J. C. MacKay 1991), in the Neural Network learning process, training data consists of independent variables and the output of the Network is assumed to be noisy. The likelihood function is given by (18):

$$P(D/w,\beta,A)=\prod_m^N P(t_m/x_m,w,A). \quad (18)$$

Obviously if E_D is a quadratic error function, the noise included in t_m is Gaussian with variance $\sigma_v^2=1/2\beta$andmean equal to zero. The probability of the data given the weights is:

$$P(D/w,\beta,A)=\frac{\exp(-\beta E_D)}{Z_D(\beta)}. \quad (19)$$

As for the prior density of the weights which are expected to come from a Gaussian distribution with zero mean and variance $\sigma_w^2=1/2\alpha$,

$$P(w/\alpha,A)=\frac{\exp(-\alpha Ew)}{Z_w(\alpha)} \quad (20)$$

where

$$Z_D(\beta)=\left(\frac{2\Pi}{\beta}\right)^{N/2} \quad (21)$$

and

$$Z_w(\alpha)=\left(\frac{2\Pi}{\alpha}\right)^{M/2}. \quad (22)$$

If we substitute these probabilities into (17), we obtain:

$$P(w/D,\alpha,\beta,A)=\frac{\exp(-M)}{Z_F(\alpha,\beta)}. \quad (23)$$

The main problem when implementing regularization is setting the optimal values for the objective function parameters (Foresee and Hagan 1997). In fact if α is smaller than β, the weights become large and this leads to a small value for error *F*.

As for training, Bayes's rule is applied to optimize the regularization parameters (24), then maximizing the posterior probability is achieved by maximizing the likelihood function *P(D/α,β,A)*.

$$P(\alpha,\beta/D,A)=\frac{P(D/\alpha,\beta,A)P(\alpha,\beta/A)}{P(D/A)} \quad (24)$$

Resuming (19), this likelihood function will be written as:

$$P(D/w,\beta,A)=\frac{Z_F(\alpha,\beta)}{Z_w(\alpha)Z_D(\beta)}. \quad (25)$$

Since the objective function has a quadratic shape, it can be expanded in a second order Taylor series around its minimum point w^{MP}. Around this point the gradient is zero, and *F* can be written as:

$$F \approx F_{Mp}+\frac{1}{2}\left(w-w^{MP}\right)^T H^{MP}\left(w-w^{MP}\right), \quad (26)$$

Where $H^{MP}$is the Hessian evaluated at W^{MP}. Placing this formula into the expression for the posterior density (16):

$$P(w/D,\alpha,\beta,A)\approx \frac{\exp(-F^{MP})\exp\left(\frac{-1}{2}(w-w^{MP})^T H^{MP}(w-w^{MP})\right)}{Z_F(\alpha,\beta)}. \quad (27)$$

For *M* weights the standard form of the multivariate Gaussian density is

$$P(w)=\frac{1}{(\det(H^{MP}))^{-1/2}\sqrt{(2\Pi)^n}}\exp\left(\frac{-(w-w^{MP})^T(w-w^{MP})}{2H^{MP}}\right). \quad (28)$$

As a result, equating (25) with (26), we can solve for $Z_F(\alpha,\beta)$:

$$Z_F(\alpha,\beta)\approx(\det(H^{MP}))^{-1/2}\sqrt{(2\Pi)^n}\exp(-F^{MP}). \quad (29)$$

And the likelihood function (23) becomes:

$$P(D/\alpha,\beta,A)=\frac{(\det(H^{MP}))^{-1/2}\sqrt{(2\Pi)^n}\exp(-F^{MP})}{\left(\frac{\Pi}{\beta}\right)^{N/2}\left(\frac{\Pi}{\alpha}\right)^{M/2}}. \quad (30)$$

The optimal estimators α^{MP} and β^{MP} will be given by taking the derivatives of the Log-likelihood (i.e. Log*P(D/α,β,A))* and setting them to zero.

$$\frac{\partial}{\partial\alpha}Log\left[\frac{(\det(H^{MP}))^{-1/2}\sqrt{(2\Pi)^n}\exp(-F^{MP})}{\left(\frac{\Pi}{\beta}\right)^{N/2}\left(\frac{\Pi}{\alpha}\right)^{M/2}}\right]=0 \quad (31)$$

$$\frac{\partial}{\partial\beta}Log\left[\frac{(\det(H^{MP}))^{-1/2}\sqrt{(2\Pi)^n}\exp(-F^{MP})}{\left(\frac{\Pi}{\beta}\right)^{N/2}\left(\frac{\Pi}{\alpha}\right)^{M/2}}\right]=0 \quad (32)$$

By solving this system, α^{MP} and β^{MP} will be written as follows:

$$\alpha^{MP}=\frac{\gamma}{2E_w(w^{MP})} \quad (33)$$

and

$$\beta^{MP}=\frac{N-\gamma}{2E_D(w^{MP})}, \quad (34)$$

Where

$$\gamma=n-2\alpha^{MP}tr(H^{MP^{-1}}). \quad (35)$$

The practical implementation of the algorithm allowing this optimization is first addressed by F.DAN FORESEE and Martin T HAGAN in their pioneering work(Foresee and Hagan 1997) .

4. Results and discussion

In order to evaluate the ability of Neural Networks to extrapolate the probability distribution of wind speeds, wind speed measurements in theGermany city of Freisen (Longitude 7.15E Latitude: 49.33N Altitude: 516m) are used. Data, available online (http://renknownet2.iwes.fraunhofer.de/pages/wind_energy _0150.htm), is recorded every 5 minutes up to 10m and 30m and covers the period from January, 4 2003 to March, 31 2004.

The monthly average and probability distribution of wind speed are predicted using the Neural Network model described in the previous section. Learning data consists of monthly wind speed frequencies $F_z(v)$ measured at heights of 10m, 15m and 20m Above Ground Level (AGL), wind speed averages $<V_z>$ and heights *z=15m*, *z=20m*, *z=25m* AGL with corresponding monthly average wind speed and frequencies (figure2). The transfer functions in neurons are sigmoid. Generally there is no universal formula for choosing the number of neurons in the hidden layer. The choice is made by the test-error increasing (i.e. structural method) or de-creasing (i.e. pruning method) the number of neurons(Sheela and Deepa 2013). Optimizing the architecture of the model is beyond the scope of this work, where it sufficesto choose any satisfactory solution.

The Bayesian Regularized Artificial Neural Network (BRANN) is implemented with 27 inputs, 26 outputs and 8 hidden neurons. The corresponding data format can be seen in Figure2.

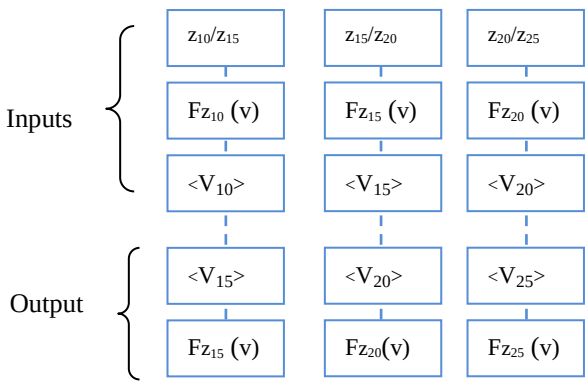

Figure.3. Data format of inputting and outputting

Having only the measurements at 10m and 30m AGL, it was useful to compare the aforementioned empirical wind speed profiles to find the best model to fit the wind distribution at the known height and then assume that the vertical wind profile follows this model.

The investigation of the model's performance was made qualitatively by determining the Bravais-Pearson correlation coefficient R^2 and root mean square error *MSE,* which were given by the following relationships:

$$R^2 = \frac{\Sigma(f_m - \overline{f_m})(f_p - \overline{f_p})}{\sqrt{\Sigma(f_m - \overline{f_m})^2 \Sigma(f_p - \overline{f_p})^2}} \quad (36)$$

And

$$MSE = \frac{1}{n}\Sigma(f_m - f_p)^2 , \quad (37)$$

Where f_m and f_p are measured and predicted values, and $\overline{f_m}$ and $\overline{f_p}$ are the average of measured values and the average of predicted values.

As shown in Figure3, wind fluctuates with time, which makes modeling it a challenge. In Figure3 it can be seen that the measured mean wind speed basically agrees with that determined by the D-H model, the Log-model and the P model. Indeed it can be seen that D-H model fits the measured data for the observed lapse of time well. However, there are obvious differences between the profile laws and the measured profile.

Based on the power law, wind shear coefficients are calculated on the basis of 5 min wind speeds measured simultaneously at 10m and 30m AGL. The results are illustrated in Figure4. It can be clearly seen that the wind shear coefficient is not stable: the results give a maximum value of 0.19 and a minimum of 0.11. The effect of wind shear coefficient on the variation of wind power becomes more marked at different distances from ground level, as demonstrated by the variations in Figure 5.

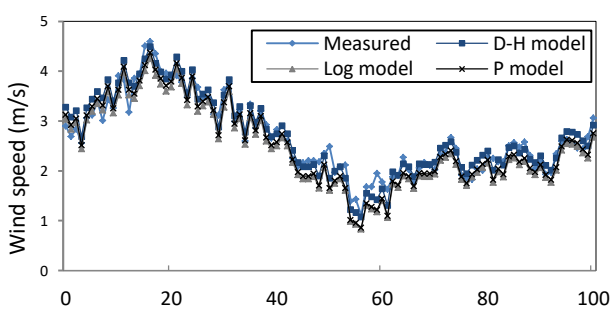

Figure.4. Comparison of 5 min average measured and modeled wind speed at 30m AGL

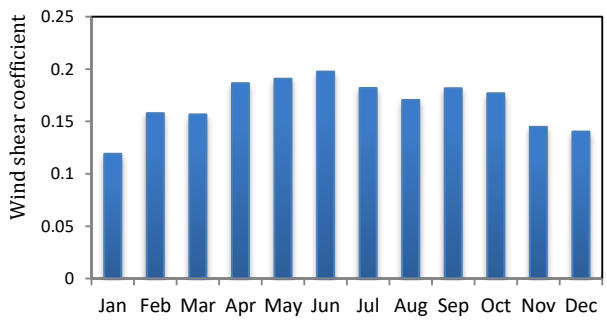

Figure.5. Monthly wind shear coefficients

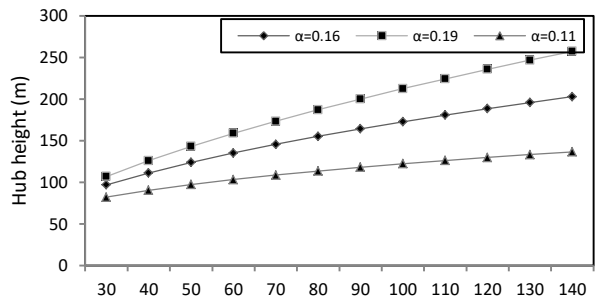

Figure.6. Wind Power Density (watts/m^2) over different heights with wind shear coefficients

For the site under study, three different profiles of wind power can be identified based on minimum, maximum and average values of wind shear coefficient from knowing wind speed at a 10m height, which illustrates the sensitivity of vertical wind profile to other factors, such as atmospheric condition, pressure, humidity (i.e. seasonality) and surface roughness.

Given data from wind measurements at 10m and30m AGL, the atmospheric turbulence intensity profile for different values of the surface roughness length is obtained from equation (8).

The surface roughness length z_0 is determined by comparing the turbulent intensity profile determined by the maximum value recorded at 30m AGL with the turbulent intensity profile given by (8).It should be noted that the surface roughness determined from the set of measured data samples taken over a long time period does not generate the corrected values given by the D-H model and Log-model as measured values at 30m AGL. Based on the methodology of (Liu, Xuan, and Park 2003), Figure6 illustrates that the experimental data that lies between +15% and -15% turbulent intensity profile corresponds to about Z_0=0.01 m.

Table I and Table II summarize the R^2 and *MSE* errors between model estimations of extrapolated wind speed time series at 30m AGL knowing wind speed time series at 10m AGL, using the estimated surface roughness length, mean wind shear exponent for Pmodel1, and monthly wind shear exponent for P-model2. P-model2 predicted values are found to be in close agreement with those measured with R^2 of 97877 and *MSE* value of 0.32.

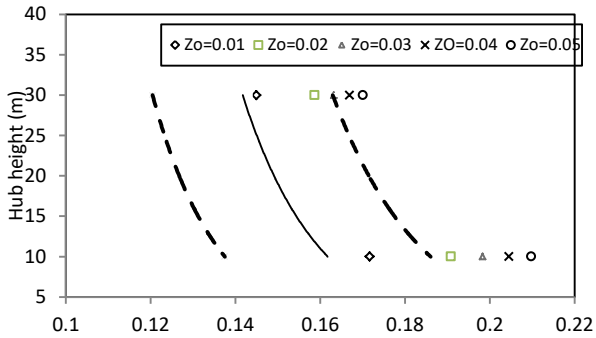

Figure.7. Variations of atmospheric turbulent intensity with height for different surface roughness lengths

For further validation, the selected J-M model for extrapolating wind speed distribution was applied. Figure7 depicts the vertical wind speed variation; extrapolated from 10m to 100m AGL using the different models and shows that the Pmodel2 and the D-H model give a good fit to real wind data, at least between 10m and 30m AGL.

Thus, we can assume that wind speed at this location follows the Power law provided that the wind shear component is monthly (Figure4).

In this example, wind speed time series were generated by means of the Power law model at 15m, 20m and 25m.

As shown in Figure 8, the scatter diagram of measured 30m AGL probability distribution of wind speed values and those predicted by the proposed BRANN model are in agreement, with an R^2 value of 97.2%.

The mean wind speeds were extrapolated from 30m AGL up to 100m AGL in 5m steps. They are then compared with those extrapolated using the P model and D-H model(Figure9).The values appear to be very close to those achieved with the P model.

Table1. R^2 obtained results.

Month	D-H model	Log model	P model 1	P model 2
Jan	98.586	97.186	98.493	98.586
Feb	99.365	96.365	99.365	99.365
Mar	95.826	96.172	98.893	98.901
Apr	95.114	97.522	97.502	97.520
May	97.626	98.398	98.375	98.394
Jun	95.081	97.01	96.976	97.007
Jul	96.147	96.101	97.058	97.088
Aug	94.758	96.014	96.685	96.691
Sep	94.207	96.586	96.662	96.614
Oct	94.703	97.161	97.086	97.135
Nov	97.135	98.249	98.249	98.248
Dec	97.228	97.96	98.949	98.974
Average	**96.315**	**97.060**	**97.858**	**97.877**

Table2. MSE obtained results.

Month	D-H model	Log model	P model 1	P model 2
Jan	0.60	0.49	0.65	0.47
Feb	0.22	0.24	0.26	0.25
Mar	0.91	0.27	0.29	0.29
Apr	0.80	0.50	0.43	0.41
May	0.27	0.32	0.26	0.26
Jun	0.45	0.35	0.30	0.29
Jul	0.36	0.31	0.28	0.28
Aug	0.40	0.27	0.26	0.27
Sep	0.52	0.35	0.33	0.34
Oct	0.86	0.52	0.46	0.45
Nov	0.46	0.28	0.30	0.28
Dec	0.78	0.29	0.36	0.30
Average	0.55	0.35	0.35	0.32

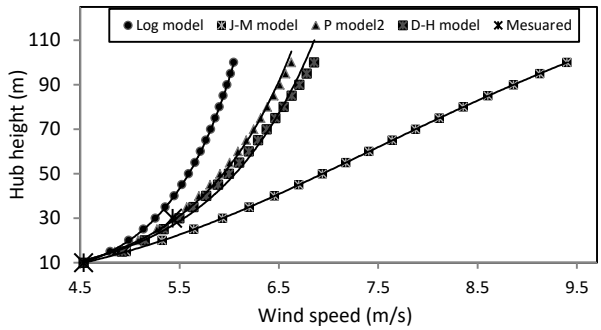

Figure.8. Wind speed profile with different selected models up to 100m AGL

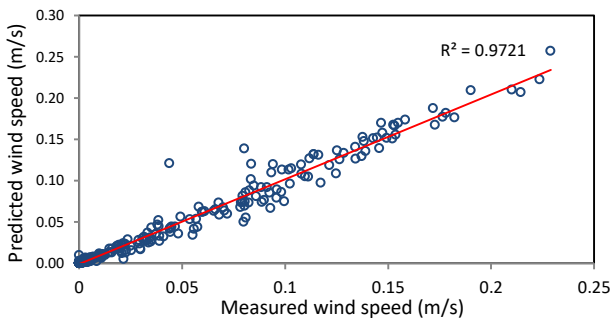

Figure.9. Scatter diagram of measured and predicted wind speed distribution values at 40m AGL with BRANN model

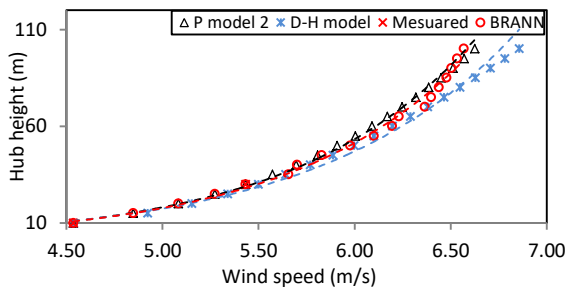

Figure.10. Performance of BRANN model versus Pmodel2 and D-H model on wind speed profile estimation up to 100m AGL

Conclusion

In this paper, we present a new framework for estimating wind speed at different heights using Artificial Neural Networks. The model used here is based on the Bayesian Regularization technique to avoid problems of over-fitting and poor generalization.

A comparative study of classical models shows that the calculated D-H model and P model with monthly wind shear component perform a better result compared with the Log-model and the J-M model. The power law was used to generate the data for training the proposed BRANN model. After training, the system was tested for measured wind speed values at 30m AGL. The system was validated by the good results achieved. To simplify the study, we conducted an empirical method leading to a satisfactory solution in terms of errors. Optimization of the study can be performed thereafter.

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