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Literature Survey on Octa-Parameter Analysis of Mined Wind Data for Effective Wind Turbine Installation

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Abstract

*Selection of site for the installation of wind turbine is a key for effective power generation, many government sectors, private power giants, small size power investors are prefers high velocity profile sites for location. Presently a binary factor is mainly used for selection of site location and they are wind velocity and sea level of the site. But the explicit factors influencing the variations to the wind velocity is not taken for analysis or predication of site location. In this thesis work, a correlation based mined data weight-age model using implicit octa parameter system which affects wind velocity is arrived***.**

1. Introduction

Green energy is the most vital need of the modern world, concerning over the increase of green house effect causes global warming which leads to many chain reaction and a major threat to human. Wind turbines are green and clean energy suppliers around the world. Wind velocity is the major player in wind turbine power production, presently the turbine installation location sites are selected using binary factors like average wind velocity and sea level of the site. But the implicit factors causing variations in the wind velocity is not explored in detail. In this work, taking all the implicit factors in the form of octa parameter system to arrive the best site location for the wind turbine using correlation analysis of mined wind data based weight-age model is proposed.

2. Literature review

Wind turbine power delivery prediction is vital for any new installation, this research work [1] models wind turbine power delivery predication (PDP) using parametric and non-parametric techniques and compared them to select best methods for PDP. Wind farm power production forecast is modeled in this paper [2] using artificial neural network. It is comparatively better than predicator and auto aggressive moving average models. Performance predication through distinct curves of power, blade pitch and rotor are modelled using historical data and multivariate outlier detection is proposed using data mining algorithms is presented in this paper [3]. A computation based two parameter virtual model is presented [4]; controllable and non-controllable virtual models are developed and tested with different data mining algorithms. Implicit wind velocity affecting factors like ambient temperature are taken for power curve modelling, this model evaluated with quad data mining approach and compared with adaptive neuro-fuzzy-interference system technique. These literatures showed binary parameters selection for their data mining analysis to predict wind turbine power performance and implicit variables which are affecting wind velocity and their influence over the same is not presented.

3. Data Mining Techniques

Data mining allows us to extract data in terms of models which may be set of laws, hypothesis, pattern, variance or trends that is useful and intelligible for the end-user. Nowadays, databases or data warehouses of significant size implicitly contain a large amount of relevant information. Their extraction presents an interest in various domains such as marketing, design, forecasting, medical research, and telecommunication networks, dynamic restructuring of websites, manufacturing sciences, and so on. Data mining models can be categorized into four types: classification, clustering, prediction, and association rules. Such approaches have been widely carried out in manufacturing areas.

4. Wind Turbine

For the past four decades, there has been an increased application of wind turbines around the world, with growth in rating from 30 KW to 5+

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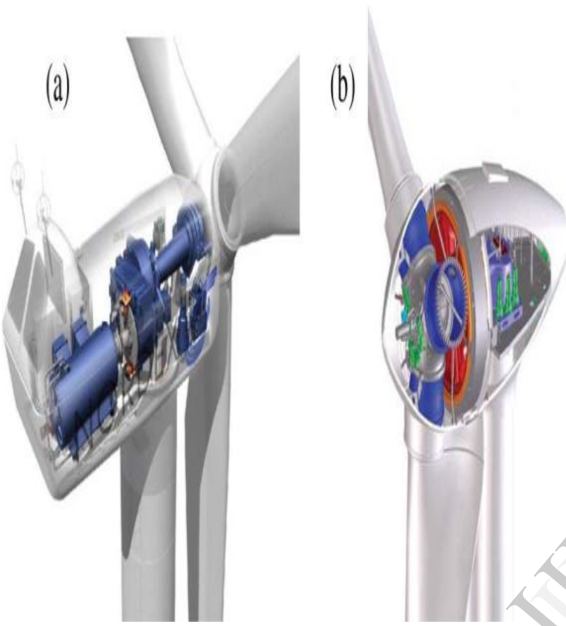
MW and, more recently, their application offshore. To reduce the cost of energy from wind turbine, there is a pressing need to improve the wind turbine availability and reduce the operational and maintenance.

Many advances increases the performance of the wind turbine like geared turbines to direct drives which reduces overall weight, increases power generation, space and less maintenance, but above all selection of site for installation needs more versatile system, the present installation method uses wind velocity as the major player for installation with sea level.



(a) Geared (b) Direct drive

Figure1. Structure of wind turbines

5. Octa Parameter System

Wind velocity and sea level are the key parameter in site selection, ultimately wind velocity decides the power output of the wind turbine majorly, the total output of the turbine cubed with the increase in the wind velocity. But the implicit parameters influences wind velocity variances are more important for site selection of wind turbine. The implicit parameters like rain fall, relative humidity, pressure, air density, temperature and wind chill are plays influencing role with wind velocity to generate power in a location, these parameters are modeled in a way called octa parameter system to perform more honed data mining analysis to predict the effectiveness of a site selection.

$$P = \int (V \int (Rf, Rh, Pr, Ad, Te, Wc)) \quad (1)$$

The octa model shows a nested function model, which is operated in a manner that is the Power is a function of wind velocity and the wind velocity is a function of other hexa parameter like rain fall, relative humidity, pressure, air density, temperature and chillness.

The octa parameter have inter depended model like the pressure is modeled in association with wind velocity and wind chillness is a modelled in association with temperature, so these parameter are tightly related to them to cause enough changes in the wind velocity and with power generation.

$$P^{[5]} = \sqrt{V/20.016} \times 25.4 \text{ mm of water} \quad (2)$$

$$Wc\ (°F)^{[6]} = 35.74 + 0.6215T - 35.75(V^{0.16}) + 0.4275(V^{0.16}) \quad (3)$$

The octa parameter system hold good bondage between them to cause effects to other variables, but the integrity of the model is decided by the data mining analysis through correlation algorithm.

6. Data Modelling

Data modelling consists of developing data sets from the mined data collected from the data authorities; here the data authorities are mostly from weather stations, reliable web data and other published data. Penta data of the octa parameter system is collected from the above mode and the remaining tri data is arrived through the penta data. Power generation is the mono priority parameter to be arrived through other Hepta data.

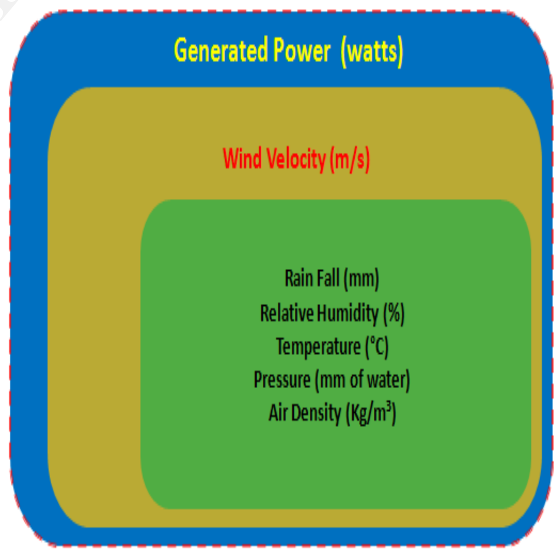


Figure 2. Nested Model of Power Generation in Octa parameter[5]

The nest shows the inter dependency of penta to wind velocity and the turn with generate power. A sample training data work out is given below to explore the influencing details

The influence relation of the each parameter is graphed and power or polynomial equation modelled is presented below. The wind velocity to rain fall relation is shown in the following chart.

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Table1. Sample Training Data Model

DATA MODELLING							
Wind Velocity (m/s)	Rainfall(mm)	Temperature(° C)	Pressure (mmow)	Rel. Humitity (%)	Wind Chill(°F)	Air Density(Kg/m^3)	Power Capacity(Kw)
3.75	12.00	20.00	0.8915	30.00	-1.4819	1.205	0.006384994
4.25	14.00	30.00	1.1451	35.00	3.7287	1.165	0.008986123
4.57	5.00	30.00	1.3241	25.00	3.1369	1.165	0.011172597
4.55	5.00	40.00	1.3125	37.00	9.3879	1.128	0.010676353
3.55	6.00	30.00	0.7990	67.00	5.1666	1.165	0.005237097
3.15	17.00	20.00	0.6291	21.00	-0.1160	1.205	0.003784411
3.56	21.00	30.00	0.8035	12.00	5.1444	1.165	0.005281479
4.75	18.00	20.00	1.4304	14.00	-3.3958	1.205	0.012976199
5.15	12.00	10.00	1.6815	15.00	-10.2822	1.247	0.01711464
5.11	4.00	10.00	1.6555	50.00	-10.2171	1.247	0.016718942
4.86	0.00	30.00	1.4974	23.00	2.6299	1.165	0.013437373
4.25	1.00	30.00	1.1451	45.00	3.7287	1.160	0.008947556

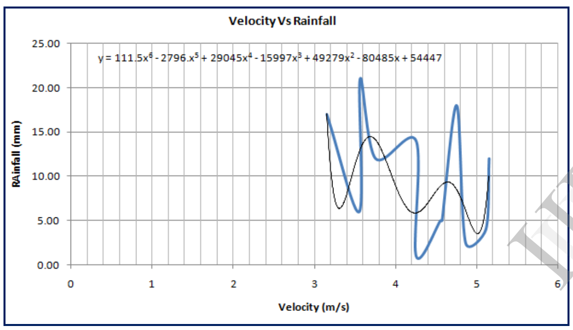

Figure 3. Velocity vs. Rainfall[6]

A fourth order polynomial approximation fit equation shows the relation between velocity and rain fall, this training data model shows high non-linearity between the each other and the rain fall bounded into a velocity region data from 3.15 m/s to 5.15 m/s.

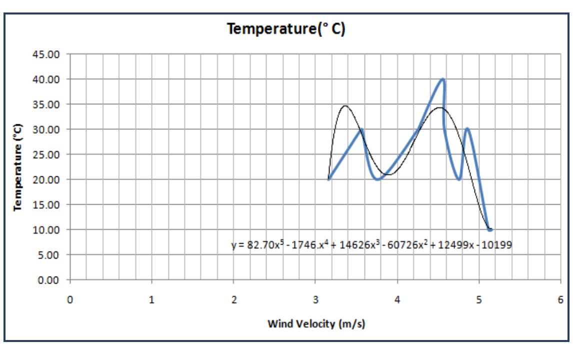

Figure 4. Velocity vs. Temperature[6]

Velocity and temperature also holds high nonlinearity and behaves an approximate 5th order polynomial fit equation.

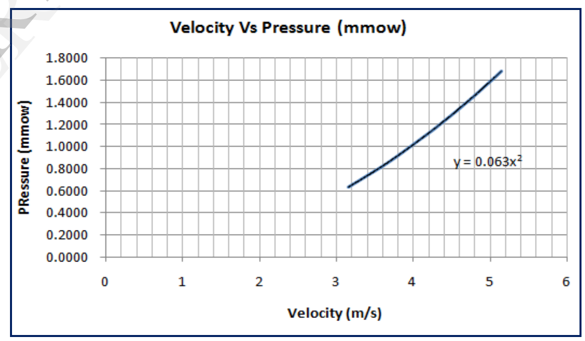

Figure 5. Velocity vs. Pressure[6]

Since the pressure is modelled with velocity is shows a perfect power law fit with the velocity and follows a $y = 0.063x^2$ equation model.

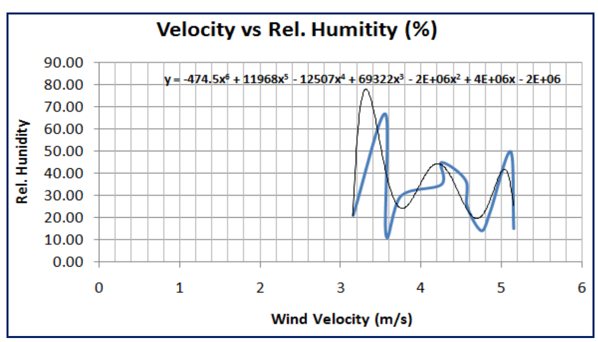

Figure 6. Velocity vs. Rel. Humidity[6]

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The rel. humidity follows high non-linear behaviour with velocity and follows an approximate 6th order fit equation model with velocity. The chillness follows 5th order poly fit with the velocity. This is also a non linear with velocity.

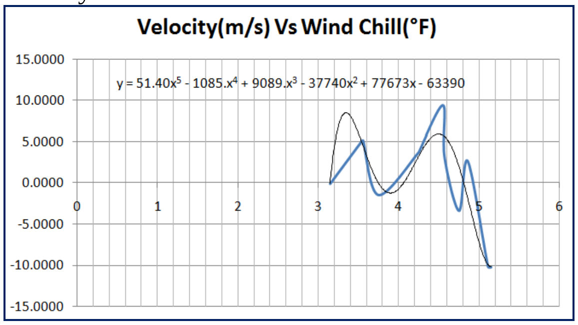

Figure 7. Velocity vs. Wind-chill[6]

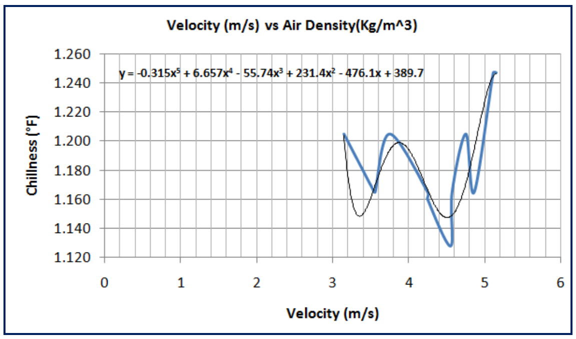

Figure 8. Velocity Vs Air Density[6]

This is also follows 5th order approximate model with velocity in a non-linear fashion.

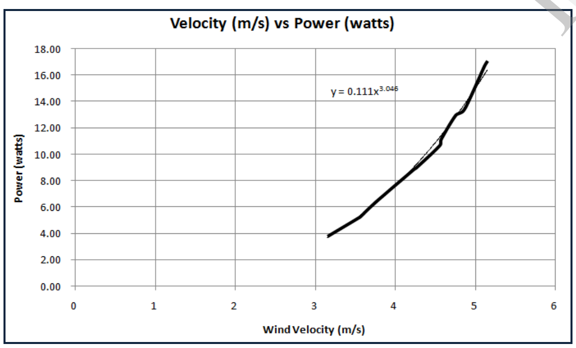

Figure 9. Velocity Vs Power[6]

Finally the power follows a near perfect power fir model with the velocity in a $y = 0.111x^{3.046}$ manner. Likewise all the parameter can be interrelated to generate power or poly fit to predict the association between them; this can be generated for every installation location octa parameter data to perform first stage predication of wind turbine installation.

7. Correlation Analysis

With data modelling one can understand the association between each parameter involved in the octa parameter system, but it requires more accurate prediction of the influencing parameter in a weight-age model. Correlation analysis is one of a powerful data mining analysis tool used to evaluate and arrives the relationship between two variables. Here, in this work, correlation analysis is used to establish degree of cohesiveness between each variable in a combination mode is arrived and weight-age of each parameter is independently taken for final overall weight-age model. The correlation swings between -1 to 1, to show that > +0.5 shows strong relation between selected set of variables, 0 shows idealism and both the variables are in mutual state without affecting each other, <- 0.5 shows no relation between the variables, based on this each parameter have 7 point credit is set for maximum and an average of all individual weight-age decides the location factor with the power curve for the same site location formed from the mined wind data.

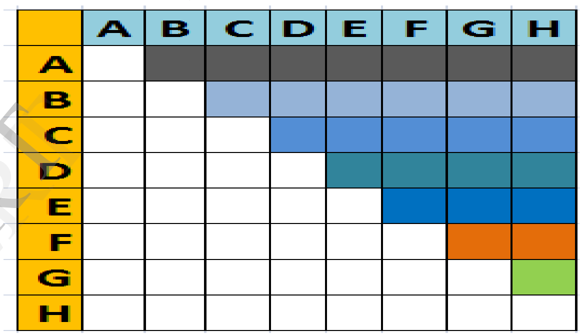

Figure 9. Correlation Combination Model for Octa Parameter System[5]

Based on the weight-age and power curve a user can effectively predict the worthiness of installation of wind turbine in that site.

8. Conclusion

The proposed octa parameter system hold many advantage over two parameter installation parameter model, even though the implicit parameters covered by the wind velocity explicitly the deeper understating of the associative parameters can give more clarity in evaluation of installation site selection and can combine with other relevant and experience based judgmental values to perform more accurate location predication.

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