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# A Deterministic Bases Piecewise Wind Power Forecasting Models

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**Abstract-** Continue emphasis in mitigating the environmental impacts of fossil generated electrical energy has fuelled interest in sustainable and renewable energy; as a result of this interest, renewable energy penetration into power utilities energy mix has increased significantly. Two major issues delaying further increase of renewable energy are supply intermittency and availability. Prediction of renewable energy availability can never be over emphasized. In this paper we propose a simple nonlinear least square piecewise model to predict output power of a small Canadian wind farm. The proposed model decomposes the wind speed sweeping the wind turbine into three major speed groups, slow, moderate and fast speed. The dynamics of the wind speed in each group defines the model and the prediction error performance. We showed that the piecewise model outperformed the manufacturer's power curve that is traditionally uses by wind farms. We present typical predictions for Fall, Winter, Spring and Summer and compared results from our proposed model to the manufacturer's power curve. The piecewise model as well as the manufacturer's power curve performances are both related to the skill of the wind speed estimator, accurate wind speed estimates will result to excellent forecast for both models.

**Keywords-** Wind power technological model building, Wind power forecasting, statistical analysis.

## 1. Introduction

Environmental concerns, increase in the depletion of non-renewable resources and security concerns continue to motivate advances in renewable energy. Wind power has attracted much attention as a promising renewable energy resource. The potential benefits of incorporating wind energy into our energy mix, include curbing emissions and reduction in non-renewable fuel consumption. Wind energy is one of the cheapest available renewable energy sources and the industry is experiencing a period of rapid growth worldwide.

While the real technology for harnessing wind energy has matured over the years, wind turbine output power continues to be intermittent - intrinsically depending on the availability and the variability in the wind speed [1]. Utility scale integration of wind power normally presents some challenges to utility system dispatchers in the form of availability and reliability [2], [5]. The electricity commodity market operates on a one or two day's ahead generating unit commitment. The commodity market requires power suppliers to commit their commodity 24 hours ahead of the time, mandating market participants including suppliers to guarantee the availability of their commodities. It is obvious that wind energy based market participants cannot guarantee their commodity due to high uncertainties and the inherent stochastic nature of wind speed.

Wind power is a complex function of the wind speed, air density and turbine sweep area. Efforts to improve wind power forecast includes [3, 6-8] and [10]. In [3] the authors discussed a short-term probabilistic wind power forecast, the key discussion is optimal bidding strategy focusing on forecast uncertainty. In [12] the authors presented a brief overview of wind power forecasting models and their various applications in the electricity market place. The authors noted the benefits of integrating wind power forecast into overall system operations from operating reserve to unit commitment and dispatch decisions. In [6] and [7] the authors discussed various statistical approaches that uses historicaldata to train forecasting models. In [8], the authors discussed a model that predicts one hour ahead wind power outputs. In [13], the authors formulated the power system unit commitment problem as probabilistic, modelling expected unserved energy as probability distribution of forecast errors of wind and loss of load. In [16], the authors proposed conditionally parametric ARX-models that uses adaptive and recursive parameter estimation techniques. Their proposed model produced superior estimates when compared with estimations based on conventional techniques. In [20], the authors described a method that accounts for both the interdependence structure of prediction errors and the distributions of wind power production. Prediction errors were converted to multivariate Gaussian random variables, using covariance matrix to summarize the interdependent structure. In [22], the authors used Gaussian Processes to predict one-day-ahead short-term wind power. The authors applied Gaussian Processes to the outputs of a Numerical Weather Prediction model. Standardizing the protocol for the evaluation of short-term wind power prediction was proposed [4], a number of reference prediction models were described including a comparison of their performance evaluation. Advanced statistical, physical and combined modeling approaches were discussed [9], methods for online uncertainty and risk assessment prediction were presented and discussed. Our analysis of the wind power function suggests a major variable with significant influence over the turbine power is simply the wind speed. The turbine sweep area is rather a constant, and the air density has no easily definable correlation with the turbine power. The air density is normally included in the manufacturer's power curve; however our statistical analysis concluded that at this time, there is no measurable correlation between the air density and the turbine output power.

## 2. Methodology

Scotia Weather Services Incorporation [SWIS] supplied the data used for this research, the data belong to a wind farm in Prince Edward Island. For the purposes of this research, we rearranged the data into seasons from January 1st 2011 up to April 30th 2013. We condensed the original ten-minute intervals data into hourly readings by simple averaging. Compiling all measurements on a season-by-season basis, the seasonal wind speed was then plotted against the output power, producing the familiar wind power curve shown Figure 1 below

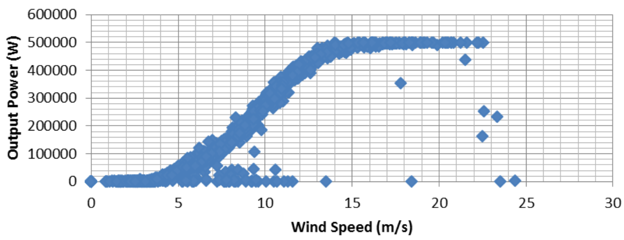


**Fig. 1.** Output Power vs Wind Speed (Turbine 1, Winter 2011-2012)

Figure 2 below plots a filtered version of Fig. 1 with recording errors removed.

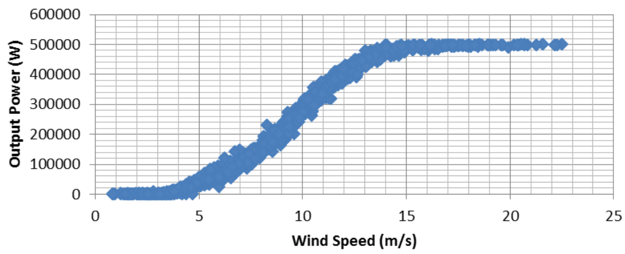


**Fig. 2.** Negatively affected data has been treated

The data appears to form a sigmoid function, with one of the possible forms being:

$$P(v) = \frac{a*v}{\sqrt{b-v^2}} + c \quad (1)$$

Where P(v) is the power output as a function of wind speed in watts, v is the average wind speed in m/s, and a, b, and c are real constants. Equation (1) is a typical symmetrical "s" curve with horizontal asymptotes at both a and c, a hypothetical mathematical model for wind turbine output power. We observed that rotating the power curve 180° about its center point, two distinct regions failed to overlap as would be expected for a sigmoid model.

Figure 3 below shows the plot of the original data in blue, and the rotated data about the center axis in red, the plot demonstrates the subtle asymmetry of the wind speed power relationship. Two distinct areas stand out where the rotated curve does not match the behavior of the original curve. In case 1, the "ramp down" time is less sharply defined than its inverse in red (ie, ramp up time). In case 2, as one might expect, there exists a higher variance in the wind-speed relationship at lower wind speeds than at higher. Hence we conclude, while a sigmoid model was certainly relevant, piecewise models based on behavior-based regions could potentially produce more accurate predictions.

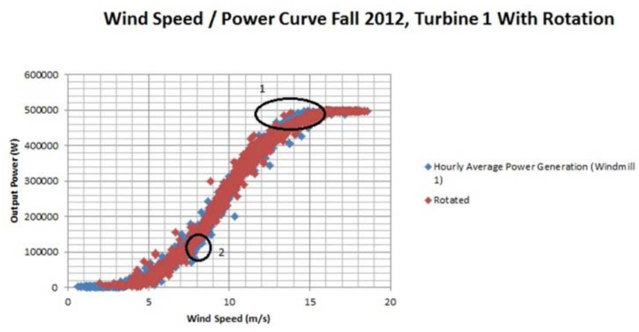


**Fig. 3.** Seasonal graph for Fall 2012 behavior.

## 3. Data Consideration

When inspected, it was found that seasonal data sets held the highest rate of similarity/correspondence for purposes of prediction. In essence, the behavior of the wind/power curve for the fall of one year had far less variance compared to the fall of the next year than for two weeks or months being compared that are a year apart. Attempts to linearized the sigmoidal relationship between the wind speed and turbine output power was not successful. None of the seasons matched a sigmoid function of any type without a slight degree of deviation, Fig. [4] below support this assertion:

In Figure [4] section 1 demonstrates the decreasing reliability for the linear regression for higher wind speeds. Section 2 describes the “lip” created by the constant or zero power value for wind speeds below 3 m/s . If we remove the outliers shown dotted around the primary curve above, these two sections accounts for the deviations noted in Figure [3].

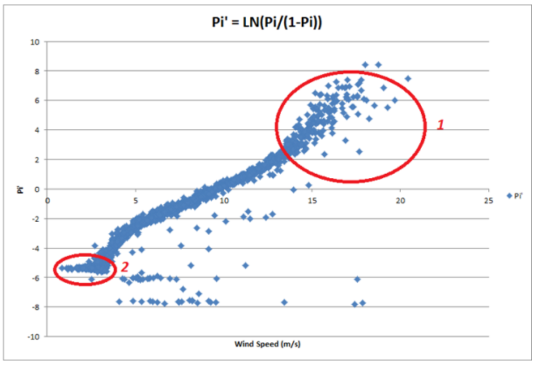


**Fig. 4.** Linearization of Output Power vs Wind speed

The nature of two primary behavioral regions which potentially vary across seasons called for a piecewise approach. For the purpose of this research, we divided the Sigmoid Function into four primary sections as shown in Fig. 5.

In Figure 5, section 1 and 4 represent the constant power regions – the asymptotes of the wind-speed to power function. Sections 2 and 3 represent the “acceleration” regions of the power curve, where the power/wind speed ratio is increasing and decreasing respectively. Since the rate of increase in section 1 and the rate of decrease in section 3 are not equal (Figure [5] is "steeper" near the maximum and more level near the minimum), we felt the need treat these sections separately to enhance model accuracy. We inspected the sigmoidal function locating the inflection point as the line separating these sections. Further analysis suggested that wind speed less than 5 m/s is very unstable and turbulent. These range of wind speeds result in undispatchable output power, hence we separated these perceived undispatchable power from dispatchable power.

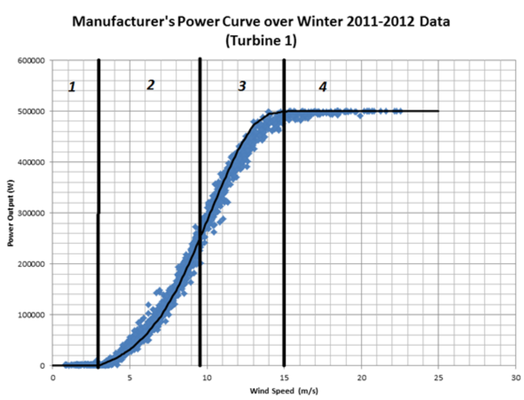


**Fig. 5.** Four Behavioral Regions of Turbine 1's Power Curve for Winter 2011-2012

## 4. Piecewise Models

Analysis of the real wind turbine power versus the wind speed indicates some consistency with the following assumptions. [1] For wind speed less than or equal to 3.5m/s the output power could be set equal to 500 watts minimum output or approximated to zero. [2] For wind speed greater than 16 m/s, the output power could be set equal to 500 kilowatts turbine maximum output power. These two observations simplified our model fitting problem allowing us to decompose the sigmoidal function into three flexible piecewise compartments.

A regression model is treated as linear model if the model is a linear combination of the parameters, i.e.,

$$f(x_i, \beta) = \sum_{j=1}^{n} \beta_j \emptyset_j(x_i) \tag{2}$$

here the parameters $\emptyset_j$ *and* $\beta_j$ are functions of $x_i$; and

$$X_{ij} = \frac{\partial f(x_i, \beta)}{\partial \beta_j} = \emptyset_j(x_i) \tag{3}$$

It is obvious in our case that the least square estimator, in the context of a random sample $\beta$ is given by

$$\hat{\beta} = (X^T X)^{-1} X^T y \tag{4}$$

## 5. Results and Analysis

We fitted deterministic linear, quadratic, and cubic models the following wind speed groups, greater than 3.5m/s and equal to 5.0 m/s, greater than 5.0 m/s and equal to 9.0 m/s, greater than 9.0 m/s and equal 16.0 m/s. We also fitted other models to these wind speed groups such as the weighted least square and the nonlinear multivariate models. These other models produced results that are comparable to the single variable models based on wind speed alone. The weighted least square model used the wind speed and the air temperature as independent variables. Heteroscedasticity observed in the relationship between the air temperature and turbine output power, encouraged us to treat the air temperature as the weighting function. The nonlinear multivariate models used a combine wind speed and the temperature, wind speed air pressure, wind speed dry-bulb temperature, and wind speed air density with little or no success. We were not that much surprised in these outcomes, since our data analysis section supports no definable correlation between the turbine output power and these other variables.

Figure 6 to Figure 11 shows typical plots of real and predicted power, and prediction errors for each of the three wind groups for Turbine #1, the combined data is plotted in Figure 14.

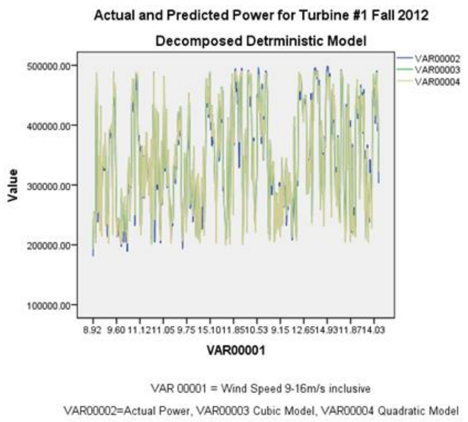


**Fig. 6.**

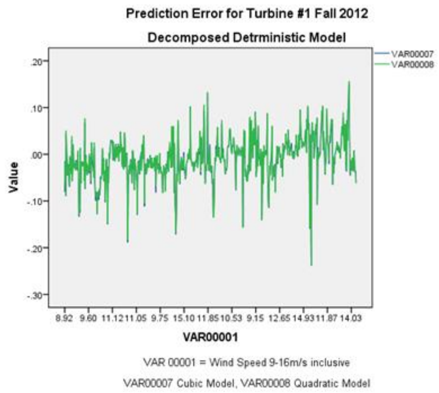


**Fig. 7.**

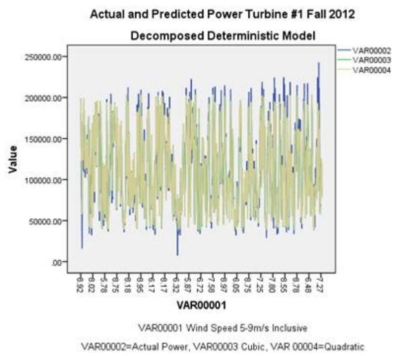


**Fig. 8.**

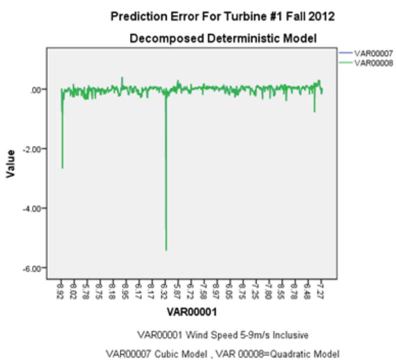


**Fig. 9.**

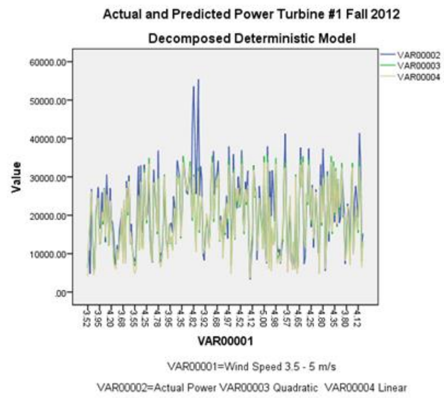


**Fig. 10.**

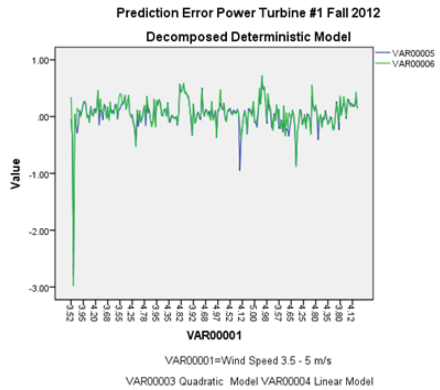


**Fig. 11.**

As mentioned earlier, we did not attempt fitting curves to sections 1 and 4 of the decomposed sigmoidal function, these sections we regarded as the cut-in and cut-out wind speeds. At wind speed less than 3.5 m/s, our analysis of the sigmoidal function suggest insufficient torque to make the turbine blades rotate hence negligible output power. At wind speed greater than 16 m/s, the turbine power reaches it maximum output capacity, thus leveling out until the cut-off wind speed.

We further observed that within the wind speed window 3.5 m/s and 16 m/s, the wind turbulence becomes very significant as the wind speed picks up from the cut-in speed of 3.5 m/s and gradually decreases as the wind speed nears the turbine peak speed of 16 m/s. This is clear from the high variability of the turbine output power in the lower wind speed regions; where the turbine output power fluctuates in synchronisms with the wind speed fluctuation.

## 6. Discussions and Error Analysis

The simulations and predictions displayed above show some interesting outcomes. We observed that wind speeds between 9-16 m/s produced very remarkable results when comparing the predicted and the observed values. Both the quadratic and cubic models fitted to this range of wind speed produced estimation and prediction errors less than 10% 97% of the time. Further analysis linked the exceptional performances of these models to the stability of the wind in this wind speed window. The dynamics of the wind sweeping the turbine becomes more stable as its speed builds up. Thus the relationship between the wind speed and the turbine output power in this wind speed window is very stable and consistent.

For wind speed greater than 5m/s but less than or equal to 9m/s we observed estimation and prediction errors less than 14% 90% of the time. We further observed that the wind dynamics in this wind speed window are somehow unstable. Thus, the wind speed turbine power relationship is somehow turbulent. This is responsible for the mild dispersion observed in the wind speed turbine power relationship for this wind speed regime.

For wind speed greater than 3.5m/s but less than or equal to 5m/s, these models produced estimation and prediction errors less than 14% 80% of the time. Again we observed that the wind dynamics for this region of the wind speed were highly unstable, and again demonstrated dispersion when charted. The error associated with the models fitted to this regime of wind speed is a testimony of this dispersion.

Figure 12 to Figure 15 compares the predicted output power from the proposed piecewise model with the predicted output power using the manufacturer's power curve for the four seasons of 2012. Figure 12 to Figure 15 below plots the predicted power using our proposed method and the method based on manufacturer's power curve four the seasons of 2012. The manufacturer's power curve is in green over the data, and the piecewise is in black.

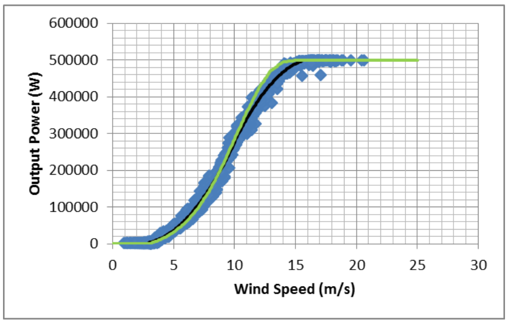


**Fig. 12.** Piecewise vs. Manufacturer's Model over Spring 2012 Data

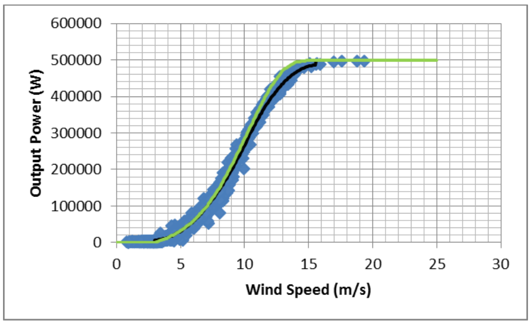


**Fig. 13.** Piecewise vs. Manufacturer's Model over Summer 2012 Data

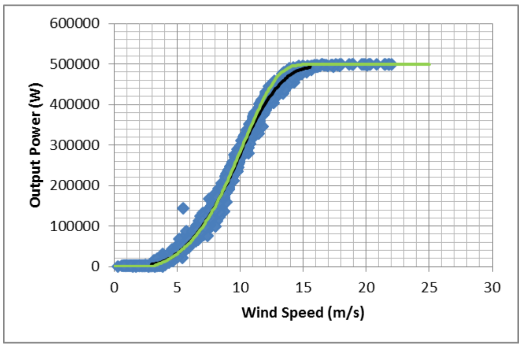


**Fig. 14.** Piecewise vs. Manufacturer's Model over Fall 2012 Data

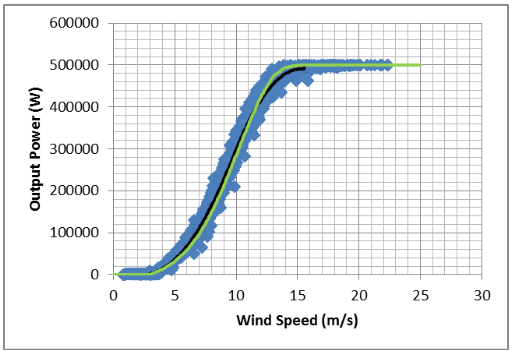


**Fig. 15.** Piecewise vs. Manufacturer's Model over Winter 2012 Data

The above Figures demonstrates that the piecewise models are able to shape themselves to the unique power curves for each season. The % improvement of the piecewise models is given by equation (5):

$$\%\ Improvement = \frac{Manufacturer's\ Curve\ Error - Piecewise\ Model\ Error}{Manufacturer's\ Curve\ Error} * 100\% \qquad (5)$$

Table 1 list the average error for both models and the percentage improvement obtained by using the piecewise model as against the manufacturer's power curve for the year 2012.

**Table 1.** Average Error for Turbine #1 2012 Data

| Year | Average Error kW | | |
|---|---|---|---|
| 2012 | Manufacturer's Curve | Piecewise Model | % Improvement |
| Spring | 10,500 | 7,190 | 31.63 |
| Summer | 12,100 | 7,160 | 40.76 |
| Fall | 11,190 | 8,390 | 25.01 |
| Winter | 12,955 | 9,720 | 24.95 |

Table 1 show the robustness of the piecewise model over the manufacturer's power curve. From Figure 12 to Figure 15, the piecewise over all better performance of the proposed model over the manufacturer's power curve stems from the regions of higher wind speed. At the wind speed window greater than 5 m/s and up to 16 m/s, the wind speed output power relationship approximate quadratic, piece-wising this window enhances its performance, however it increases computational time.

## 7. Conclusion and Recommendation

This research has demonstrated that a simple piecewise single variable least square model has the potential to predict the output power of a wind turbine within acceptable error margin. We compared the proposed model with the manufacturer's power curve and the results presented and discussed. The results indicate that the piecewise model has superior results when compared with the power curve. The results for both the proposed method and the power curve depend on the accuracy of the method used to estimate the wind speed, thus our next effort will focus on developing wind speed prediction model (s).

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