What You Don’t Know About Power Curves

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Abstract

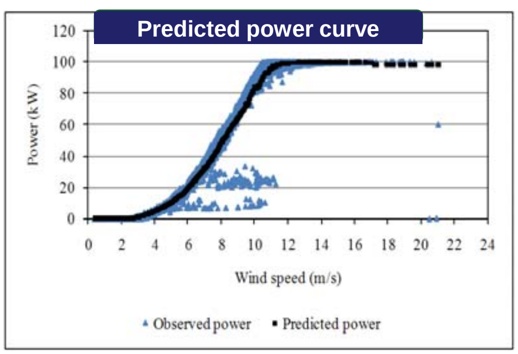
The function of a power curve in a wind turbine can be compared to that of the human heart. As a healthy heart contributes to a person’s productivity, a power curve conditions a turbine’s energy output. The manufacturer’s certified power curve is analogous to a genetic blueprint marking the beginning of the turbine’s life cycle. The moment a turbine is erected, it is exposed to uncontrollable wind (environmental conditions), marking the evolving shape of a power curve. Though these external conditions can not be modified, their impact on turbine can be certainly altered. Anticipating the adverse impact of wind conditions is the key to a turbine’s performance. Strategies for optimizing the performance of wind turbines, given the natural wind conditions, are discussed. The prevention of unexpected faults from occurring is the primary goal, followed by early detection of emerging faults, and the most effective identification for full and timely repair of faults that could not be prevented. None of the turbine’s problems can be addressed without the knowledge of the power curve over the future horizons. A computational tool for prediction of a power curve is presented. The high expectations set for a power curve are realized with computational methods using data collected by a standard SCADA system. These methods allow for an effective diagnosis and communication of turbine imperfections to the wind farm operators, which would otherwise be impossible. The new developments’ related continuous prediction, visualization, and detection of anomalies of a power curve are illustrated with a live software demonstration.

Objectives

Overall Objective

- ❖ Understanding power curves
- ❖ Optimization of turbine performance
- ❖ Fault monitoring, detection, and prevention

Predicted power curve



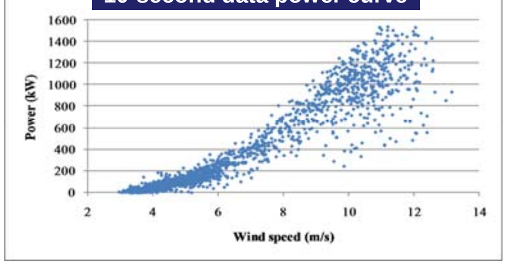
A data-driven approach to the performance analysis of wind turbines is presented. Turbine performance is captured with a power curve. The power curves are constructed using historical wind turbine data. The power curve model constructed by the least squares method outperforms the one built by the maximum likelihood approach. The third model is non-parametric and is built with a data-mining algorithm. The least squares (parametric) model and the non-parametric model are used for on-line monitoring of the power curve and their performance is analyzed.

Methods

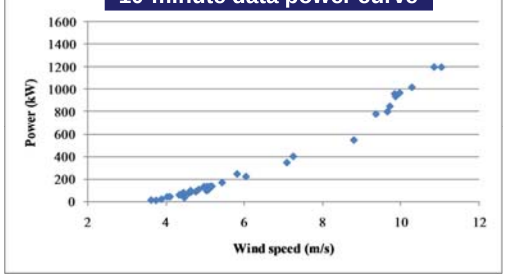
Computational intelligence models and algorithms to benefit of wind industry.

Power curves constructed from high frequency SCADA demonstrate the turbine dynamics.

10-second data power curve



10-minute data power curve



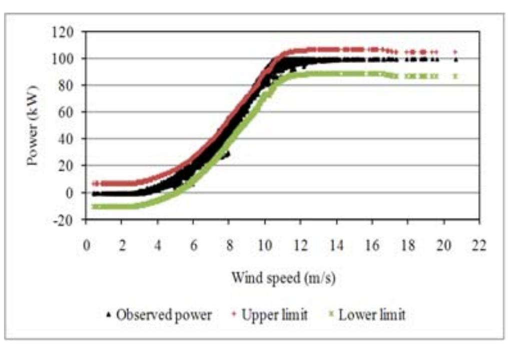
Power curve confidence limits

$$UCL_1 = \mu_{Train} + 4\frac{\sigma_{Train}}{\sqrt{n}}$$

$$CenterLine_1 = \mu_{Train}$$

$$LCL_1 = \mu_{Train} - 4\frac{\sigma_{Train}}{\sqrt{n}}$$

The above equations have been implemented to form control charts of a model constructed with a data mining algorithm. The observed power curve was constructed from the data selected from SCADA data.



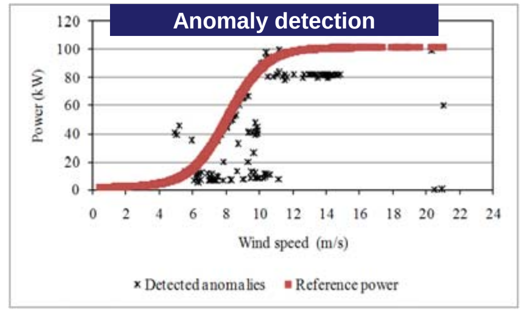
The control chart approach allows the residuals and their variations to be monitored, thus detecting the outlier and data indicating the abnormal conditions of the turbine.

Results

Benefits to wind farms:

- ❖ High accuracy prediction of power to be produced in the future in different time scales
- ❖ Generation of future wind power curves
- ❖ Maximization of the energy captured from the wind
- ❖ Prevention and early detection of emerging faults
- ❖ Reduces turbine maintenance cost
- ❖ Electric grid advantages

Anomaly detection



The anomalies in this power curve might be due to numerous reasons, such as sensor malfunctions, pitch control malfunctions, unsuitable blade pitch angle settings, blade damage fouling, control program problems, incorrect controller settings, constrained operations, environmental conditions (bug, dirt or ice on the turbine), and so on. The anomalies of the power curve detected by a data mining and a parametric model.

Conclusions

The models developed in this research were validated with three data sets sharing different characteristics, including the wind speed range, the time period, and the source of origin. The first data set included data corresponding to low wind speeds, the second data set was generated at high wind speeds, and the final data set was randomly selected from a turbine at the same wind farm. Although the test data sets share different characteristics, the parameters predicted by the models were accurate. This implies that the virtual models can be used to predict emerging faults and performance parameters of interest to a user.

The control chart approach can be used to monitor the residual between the observed and the reference power, and then anomalies in the power generation can be detected. The industrial case study demonstrated that the control chart applied to either a non-parametric or a parametric model produced satisfactory results applicable to monitoring power curves.

References

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