Short-term Wind Power Forecasting with Support Vector Regression

CS 74/174 Machine Learning Project Milestone

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1 Problem

With the growing movement towards renewable energy sources, clean fuel sources such as wind power have increased market penetration. This increase in penetration gives rise to the need for power market operators to determine the size of operating reserves to balance power generation with load [1]. Our project will use a regression algorithm to provide a point prediction for power output from wind turbines up to 48 hours in advance.

2 Dataset

The dataset for wind measurements was graciously provided to us by Dr. Brian Hirth, research professor at Texas Tech University and the National Wind Institute [2]. The dataset contains measurements dating from January 1, 2002 – present for three sites in the West Texas Mesonet. Each site recorded 5-minute averages of 3-second measurements of wind speed, wind direction, temperature, and dew-point. The wind turbine power vs. wind data was downloaded from the National Renewable Energy Laboratory (NREL) Western Wind Resources Dataset [3]. This dataset contains wind speed and rated power output at 10-minute intervals for the years 2004–2006.

3 Algorithm

We will use a Support Vector Regression (SVR) algorithm as described in [4], [5] and §7.1.4 of [6]. We will incorporate data points of wind speed, wind direction, temperature, and humidity into our model. Instead of predicting wind power directly, we will predict wind speed first, then calculate expected power output based on data from typical wind turbines located near our wind data source.

The specific algorithm we will implement is known as the ϵ-SVM, because the error function is replaced by Vapnik's *ϵ-insensitive error function*, which gives zero error if the prediction is within some tolerance ϵ of the target value $y_i \in \mathbb{R}$ [6, p. 340]. The primal optimization problem is then given by

$$\min_{\mathbf{w}} \quad C\sum_{i=1}^{m}(\xi_i+\xi_i^*)+\frac{1}{2}\mathbf{w}^{\mathrm{T}}\mathbf{w} \tag{3.1}$$

$$\text{s.t.} \quad \xi_i \geq 0 \tag{3.2}$$

$$\xi_i^* \geq 0 \tag{3.3}$$

$$y_i \leq \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}_i)+b+\epsilon+\xi_i \tag{3.4}$$

$$y_i \geq \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}_i)+b-\epsilon-\xi_i \tag{3.5}$$

where C is a regularization parameter. This optimization is more readily computed by converting to the dual formulation (*see* [6] for details)

$$\max_{\alpha,\alpha^*} \quad -\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)k(\mathbf{x}_i,\mathbf{x}_j) \tag{3.6}$$

$$-\epsilon\sum_{i=1}^{m}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{m}(\alpha_i-\alpha_i^*)y_i \tag{3.7}$$

$$\text{s.t.} \quad 0 \leq \alpha_i \leq C \tag{3.8}$$

$$0 \leq \alpha_i^* \leq C \tag{3.9}$$

$$\sum_{i=1}^{m}(\alpha_i-\alpha_i^*)=0 \tag{3.10}$$

where $k(\mathbf{x}_i,\mathbf{x}_j)=\phi(\mathbf{x}_i)^{\mathrm{T}}\phi(\mathbf{x}_j)$ is the *kernel function*. We will use the Gaussian kernel function

$$k(\mathbf{x}_i,\mathbf{x}_j)=\exp\left(-\frac{\|\mathbf{x}_i-\mathbf{x}_j\|^2}{\sigma^2}\right) \tag{3.11}$$

shown by [4] to be effective for wind speed prediction.

4 Results

4.1 Wind Speed Prediction

We will solve the support vector regression optimization problem using the Sequential Minimal Optimization (SMO) algorithm, put forth by Platt et al. [7], and refined for use with regression by Smola and Schölkopf [8]. Currently, our implementation of the algorithm does not converge appropriately, so no prediction can be made. A potential source of error is the wind speed data itself. Figure 1 shows a two month period from the Abernathy, TX site. Data points are taken every 5 minutes, as an average of 3-second measurements accumulated during those time periods. Our half-hour moving average is also shown, providing considerable improvement in the smoothness of the data. Pre-processing could lead to better convergence.

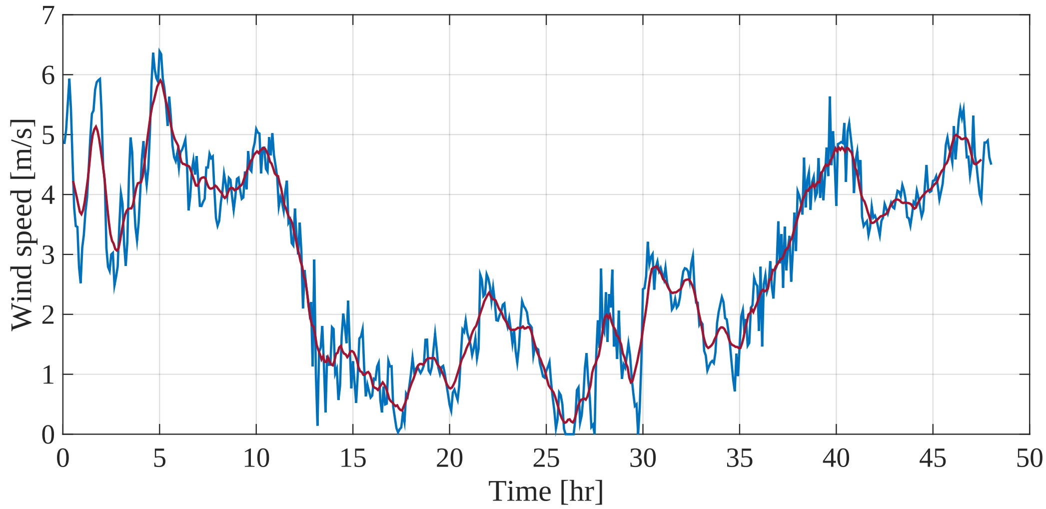

Figure 1: Wind speed data shown for 5-minute intervals, as well as a 1/2-hr moving average, which provides considerable smoothing.

4.2 Wind Power Prediction

To predict wind power from wind speed, we use logistic regression to fit a sigmoid curve to the data. It is merely a coincidence that a sigmoid curve fits the statistical data well. Because this prediction is not a time-series, we only need to perform the curve fit once, and can then use the fitted curve to predict output power from wind speed. A plot showing this fitted curve is shown in Figure 2.

Although available wind power is given by

$$P = \frac{1}{2}\rho V^3 A \tag{4.1}$$

where ρ is air density, A is wind turbine frontal area, and V is wind speed, the true power output varies significantly from this theoretical maximum. The sites from which we took the power output data were actually a aggregate of 10, 3-MW Vestas V90 turbines [9]. These turbines have nominal power limits

$$\begin{aligned} V_{\text{cut in}} &= 3.5 \text{ [m/s]} \\ V_{\text{rated}} &= 15 \text{ [m/s]} \\ V_{\text{cut out}} &= 25 \text{ [m/s]} \end{aligned}$$

The slight spread in the manufacturer's power curve represents the variability in wind farm power output due to different wind direction, turbulence, and other factors; however, Potter et al. [10] presents the Statistical Correction to Output from a Record Extension (SCORE), which accounts for data acquisition errors, and the hysteresis loop created at the top end of power output. Notably, both of these sets of data deviate from the V^3 relationship as they near V_{rated}. The sigmoid curve

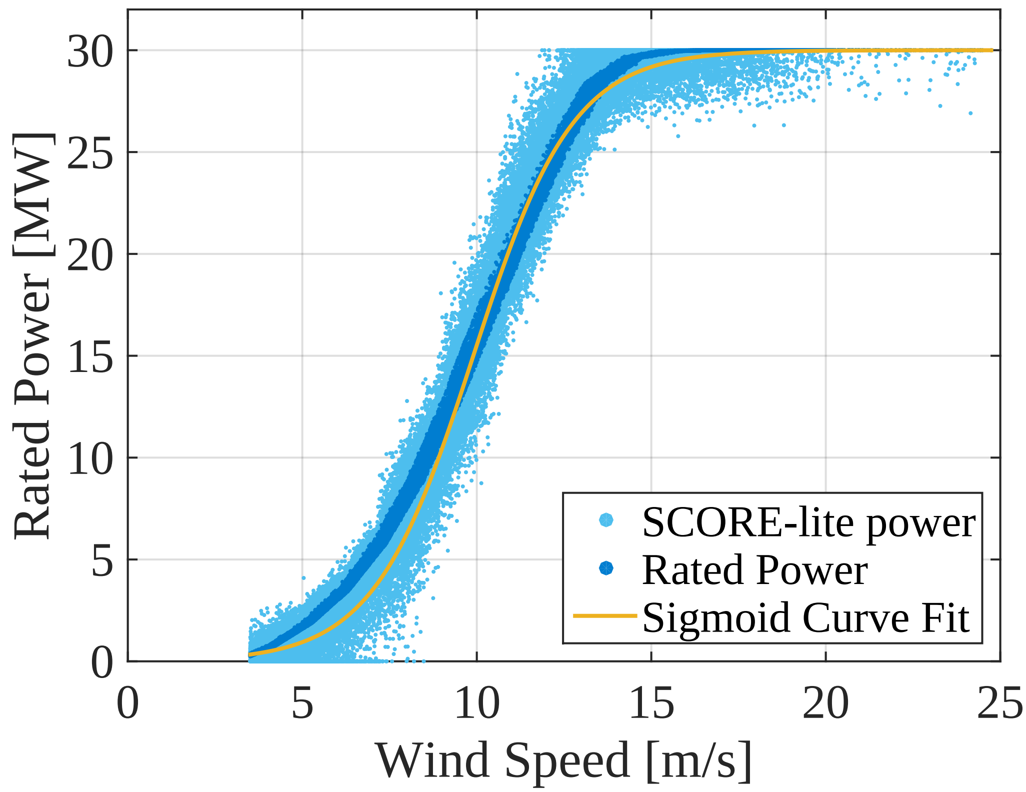

Figure 2: Wind power curve fit. Also shown is the SCORE-lite data and the manufacturer's power curve.

fits the statistical data, which better estimates real-world conditions, rather than the manufacturer-provided curve.

5 Future Work

Before the final submission, we will get the SMO algorithm running properly to fit to the wind speed data. We will implement a time-series prediction scheme to predict the wind up to 48 hrs in advance of the present time. We will also report prediction error, as well as a run-time comparison between the SMO algorithm and a typical quadratic programming solver (such as Matlab's `quadprog` routine).

References

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