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Integrated Prediction of Wind-Farm Power Output

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Introduction

As the market share of wind energy in the electricity market has been increasing significantly during the recent decade, prediction of wind-farm power output is critical to manage its production process.

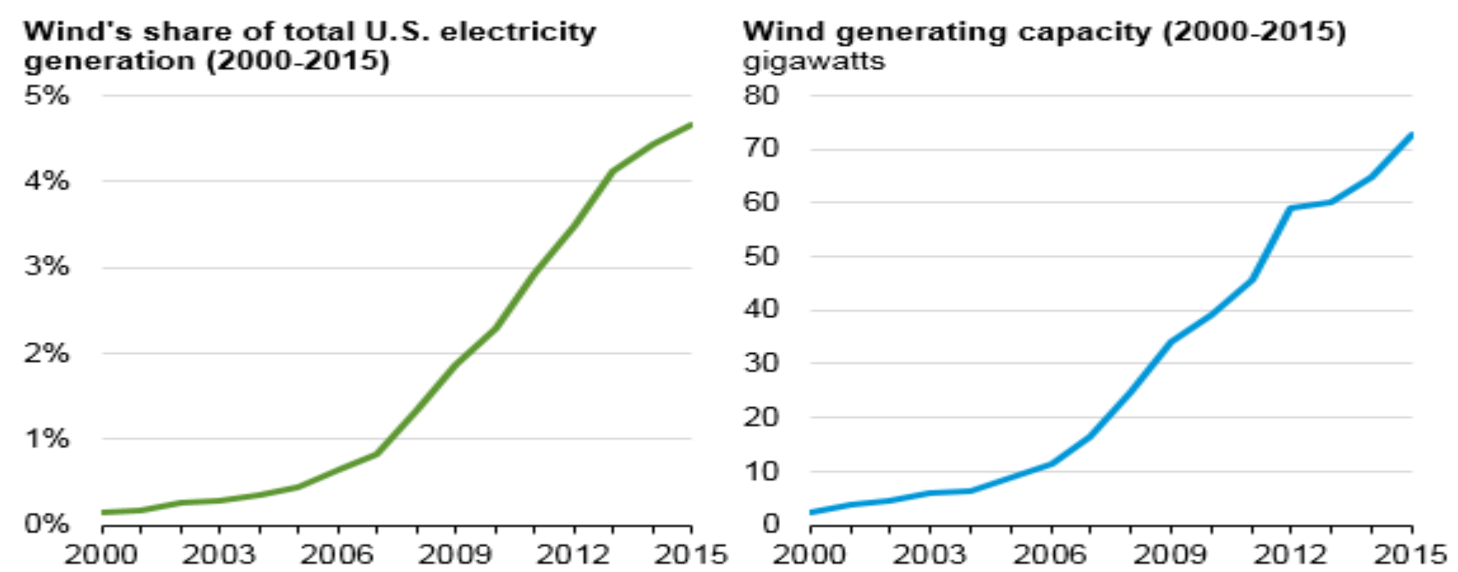


Figure 1: Wind Energy's Market Share and Generation Capacity in US (2000-2015) [1]

Objectives

Propose a wind farm power output prediction model which:

- Captures the time-dependent wind-power relations.
- Quantifies the variability by providing the distributions of both wind speed and power output.
- Achieves better prediction accuracy.

Wind Speed Model

- The wind speed S(t) follows an inhomogeneous geometric Brownian motion:

$$dS(t) = \mu_s(t)S(t)dt + \sigma_s(t)S(t)dW(t)$$

- $\mu_s(t)$ and $\sigma_s(t)$ are time-dependent parameters.
- $W(t)$ is a standard Brownian process.
- The parameters are estimated by a dual Kalman filter.
- Let $\mathrm{x}(t) = \ln(S(t))$ in Figure 2 below.

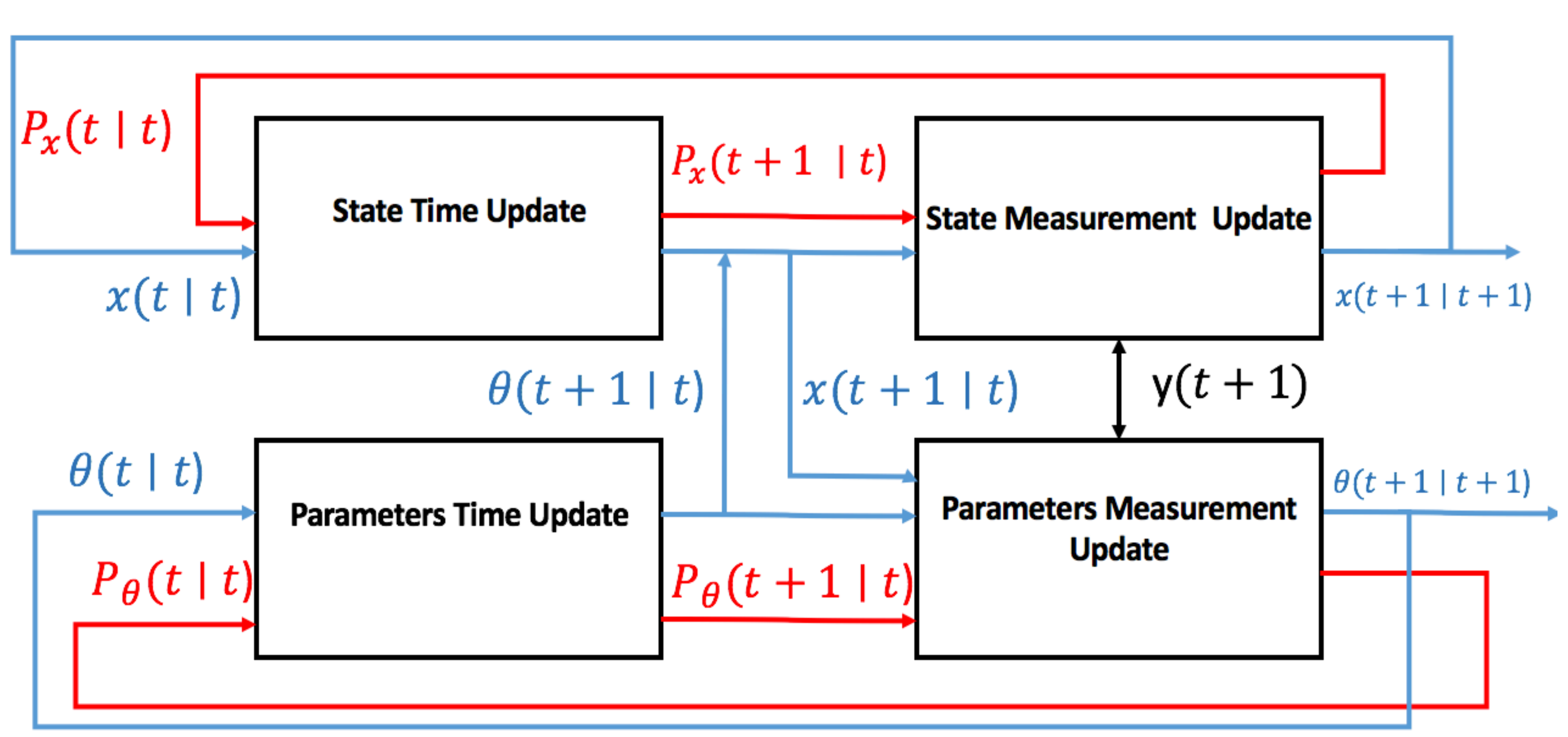


Figure 2: Dual Kalman filter [4]

Dynamic Power Curve

- Quantify the relationship between wind speed and power output, F(t, S(t)), in a dynamic manner.
- The adaptive learning method [2] is employed to capture the dynamic dependency.

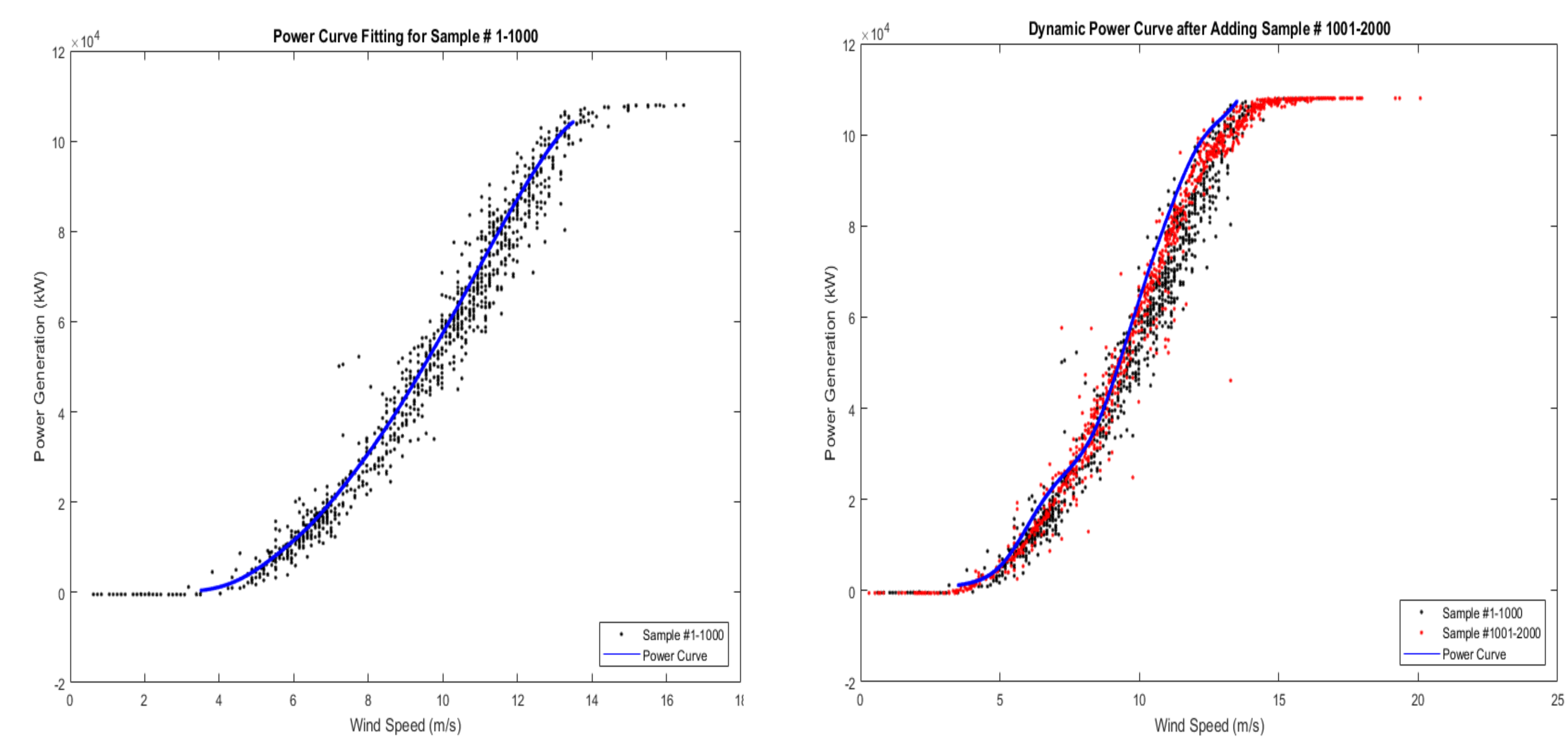


Figure 3: Dynamic Power Curves

Power Output Model

- The power output P(t) follows an inhomogeneous geometric Brownian motion:

$$dP(t) = \mu_P(t)P(t)dt + \sigma_P(t)P(t)dW(t)$$

- $W(t)$ is a standard Brownian process and

$$\mu_P = \frac{F_t + \mu_s s F_s + \frac{1}{2}\sigma_s^2 s^2 F_{ss}}{F}$$

$$\sigma_P = \frac{\mu_s s F_s}{F}$$

- The initial condition P(t)=p_0.
- The predicted power output at t+1 is K.
- The price of a real call option, c(K; t. p_0), quantifies the amount of under-estimation.
- The price of a real put option, p(K; t, p_0) quantifies the amount of under-estimation.

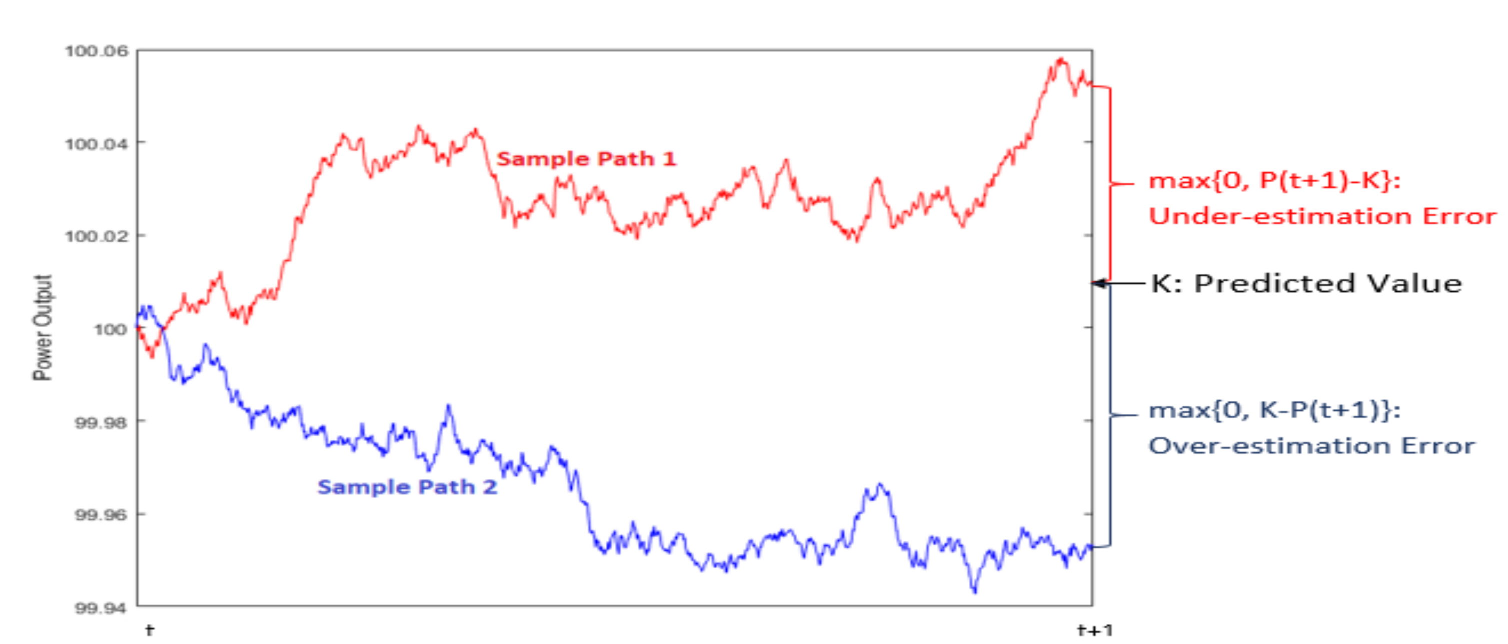


Figure 4: Explanation to real call (red) and put (blue) options and under-/over-estimation

- Calculate the prices of the real call and put options [3].
- Minimize the weighted sum of real call and put options

$$MIN_K\ w_c c(K; t, p_0) + w_p p(K; t, p_0)$$

Results and Discussion

- The algorithm is tested using data sets from two land-based commercial wind farms with $w_c = w_p$
- Less prediction error is obtained when compared to benchmark methods: persistent and ARMA.

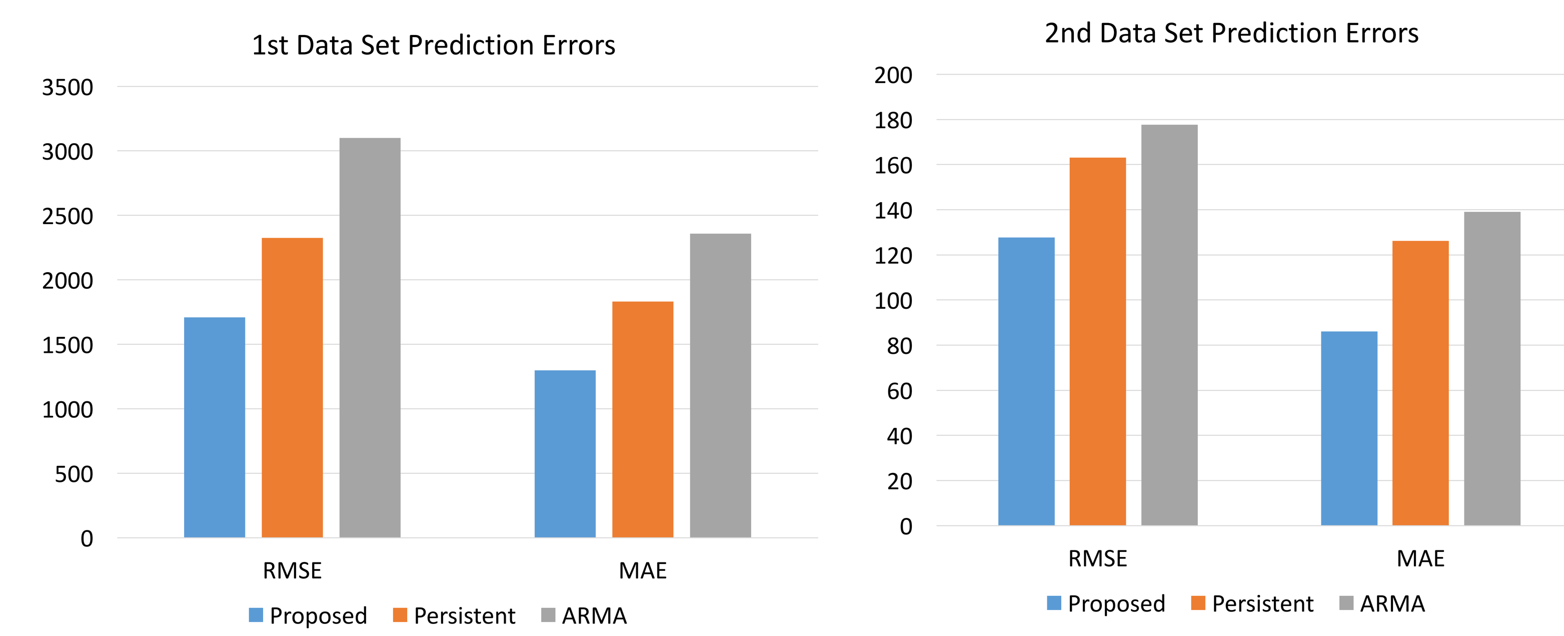
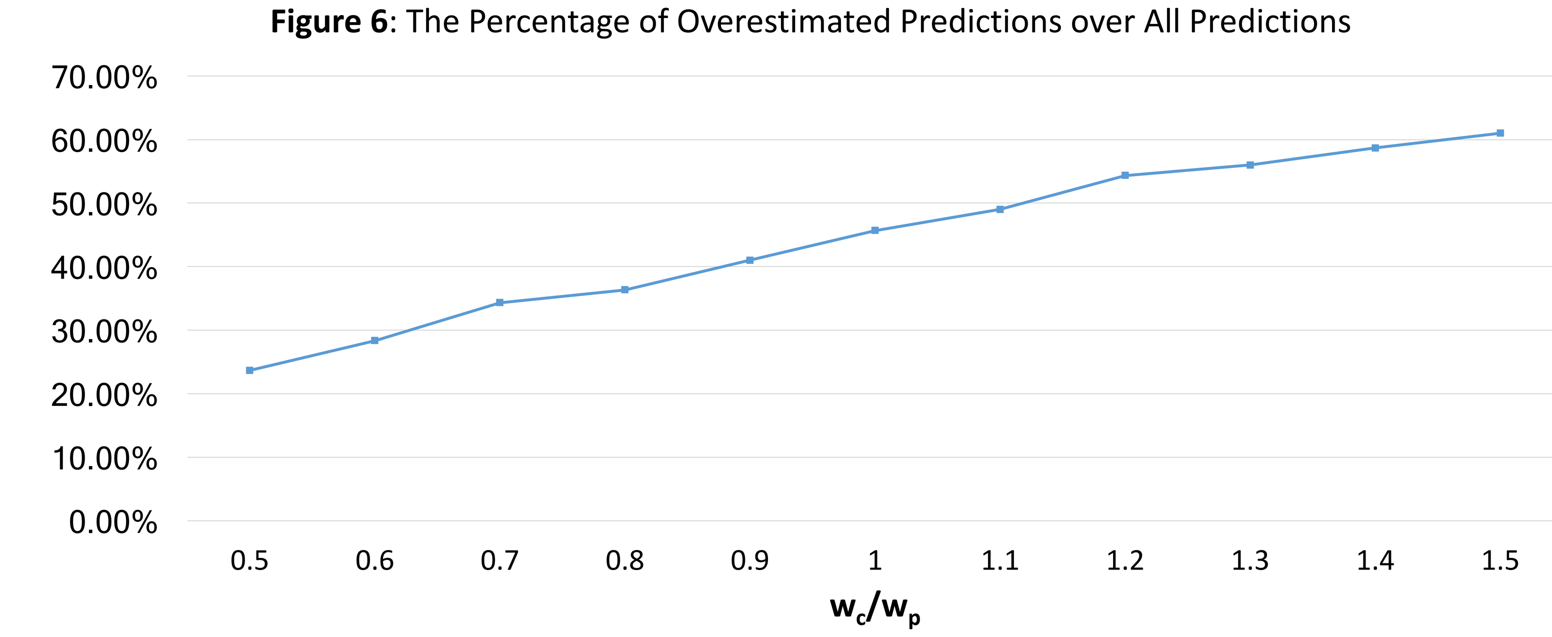


Figure 5: Prediction Errors on two data sets using the proposed algorithm and two benchmarks

- w_c/w_p is observed to affect the prediction's bias on underestimation or overestimation.
- The predicted value biases to overestimation when w_c/w_p increases.

Figure 6: The Percentage of Overestimated Predictions over All Predictions



References

[1] U.S. Energy Information Administration, Electric Power Monthly, https://www.eia.gov/todayinenergy/detail.php?id=25912
[2] E. Byon, Y. Choe, N. Yampikulsakul, "Adaptive learning in time-variant processes with application to wind power systems", IEEE Trans. Autom. Sci. Eng., vol. 13, no. 2, pp. 997-1007, Apr. 2016.
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