Probabilistic Wind Power Forecasting

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Introduction

Reliable wind power generation forecasting is crucial to:

- Meet energy demand through renewable power sources.
- Energy trading of future excess power.
- Design of investment strategies.

We propose a stochastic forecast error model to:

- Simulate forecast error and quantify its uncertainty with respect to real-world performance.
- Calibrate a short-term stochastic forecast model for optimal dispatch of electric power.

This model is based on:

- Parametric Stochastic Differential Equations.
- Approximate Maximum Likelihood based on continuous optimization.

The result is a skewed stochastic process that simulates the uncertainty of wind power forecasts accounting for maximum power production limit and other temporal effects. We apply the model to historical Uruguayan data and forecasts (2016-2017).

Model

Phenomenological Model

We propose to model and predict errors in wind power production forecasts according to their real-world performance and conditions.

Physical Constrains

The proposed model respects the full installed capacity of the wind farms. Additionally, it is unbiased with respect to the wind power forecast.

Sample Data Set

To capture real-world performance of wind power forecasts, our model incorporates historical wind power production data along with their corresponding forecasts.

We apply the model to Uruguayan wind power generation data and their corresponding numerical wind power production forecasts.

The wind power generation data set contains hourly samples of aggregated wind power production throughout the country. Each sample path contains 72 hourly observations and we have a total of 1217 sample paths spanning the year 2016 to 2017 (87,624 data points).

The numerical wind power generation forecast set contains 1217 forecasts of the wind power generation corresponding to the actual wind power generation data set mentioned above.

Forecast_data_68.pdf

Forecast_data_82.pdf

Figure 1: *Examples of wind power generation set along with the wind power generation forecast from the data set.*

Inference

Using inference techniques, we were able to obtain the optimal parameters to our model of stochastic differential equations.

Moreover, the results are confirmed by the increasing accuracy of our optimal parameters estimation as we increase the number of samples in the data set.

The proposed model is computationally efficient, providing an accurate and reliable solution.

Results

We were able to obtain the optimal parameters of the model based on the complete data sets mentioned earlier.

In Figure (2) and (3), we simulate possible paths wind power production for a given wind power forecast.

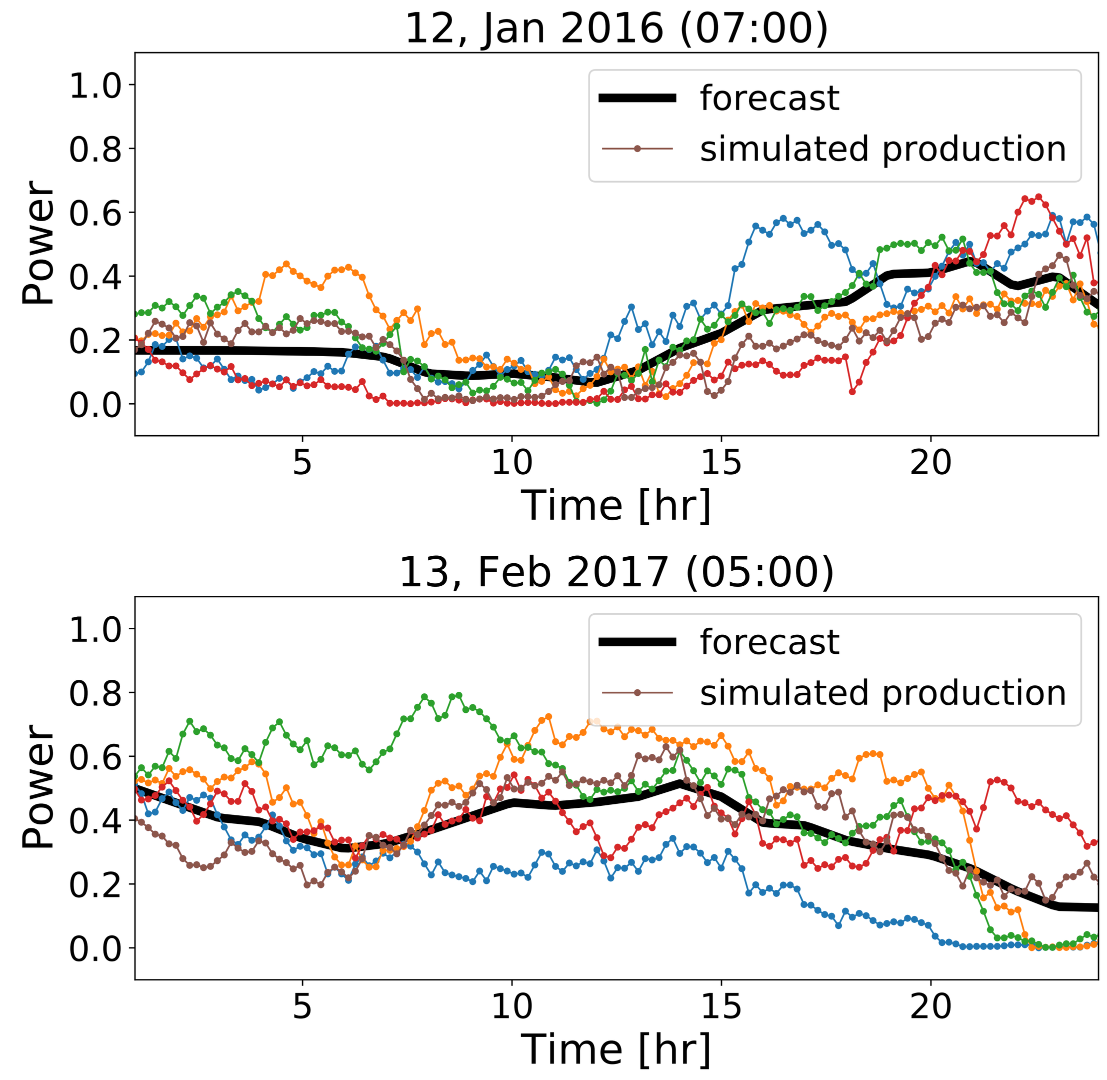

Figure 2: *Examples of simulated paths of wind power production for the next 24 hours.*

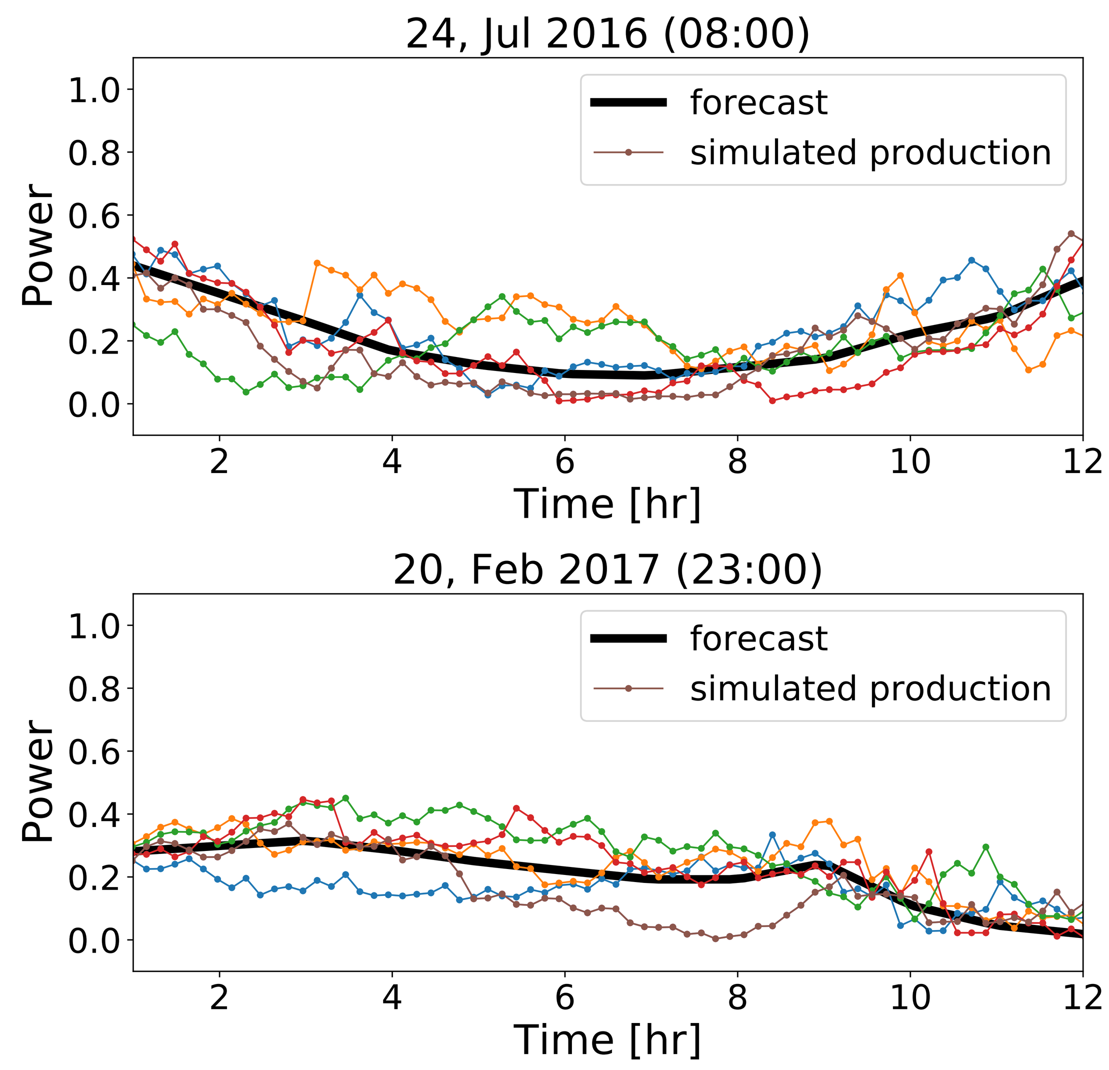

Figure 3: *Examples of simulated paths of wind power production for the next 12 hours.*

In Figure (4) and (5), we obtain empirical confidence bands using the optimal parameters.

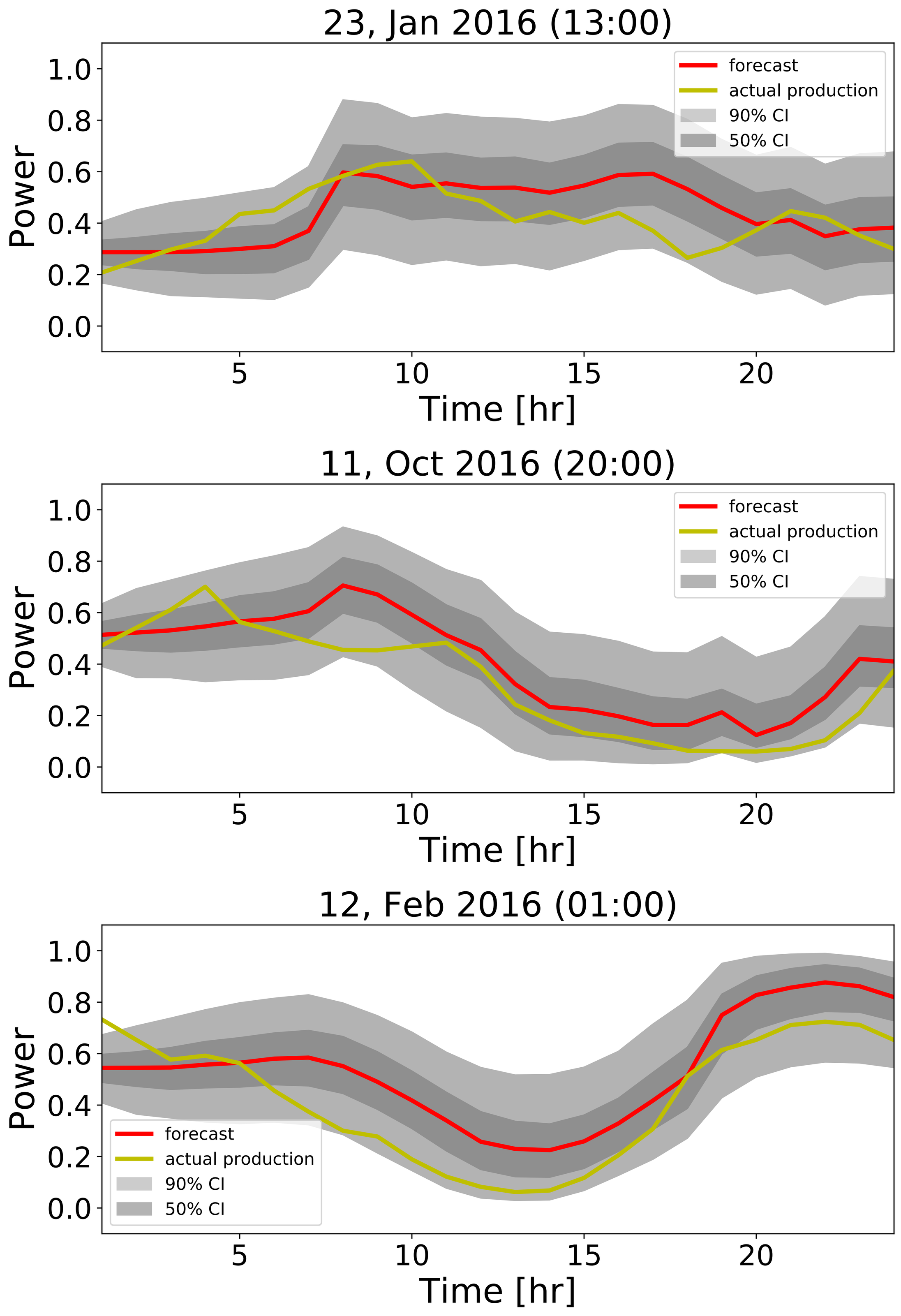

Figure 4: *Examples of confidence bands obtained for 24 hour forecasts. We can see that the model captures the fluctuations in the actual production with non-trivial and asymmetric confidence intervals.*

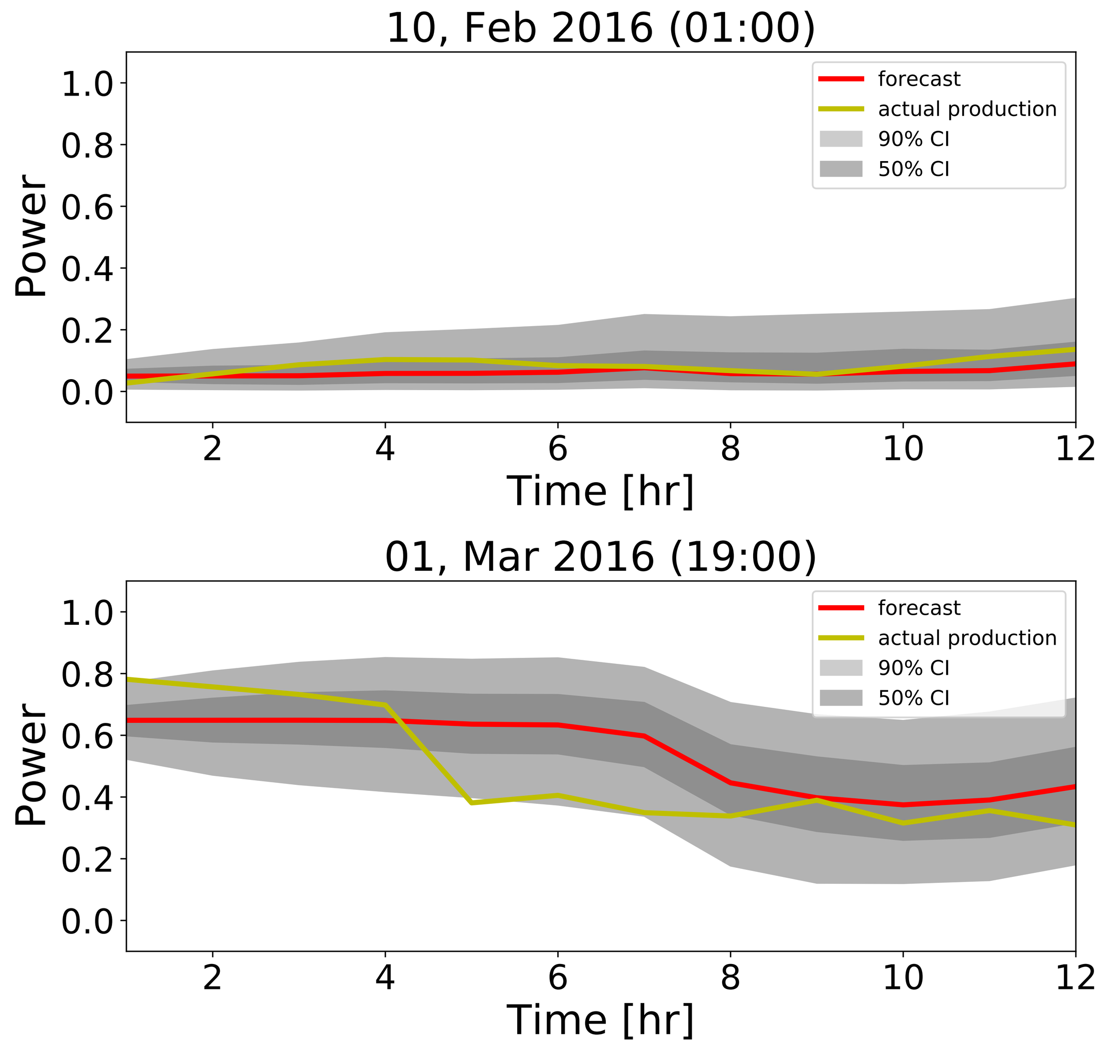

Figure 5: *Examples of confidence bands obtained for the first 12 hours of the forecasts. Note that this forecasting company computes a new forecast every 6-9 hours for reliability.*

Conclusions

In this project, we have proposed a model based on parametric Stochastic Differential Equations and advanced inference to quantify uncertainties in wind power generation forecasts. It has the following advantages:

- Represents and quantifies uncertainty in wind power forecasts accordingly to their real-world performance.
- Ability to simulate paths of wind power production.
- It is forecast technology agnostic.
- Takes into account physical constrains and the skew-symmetric nature of forecast error.
- Provides a basis for decision making in the optimal dispatch of electric power.