

Abstract

Chinese Market

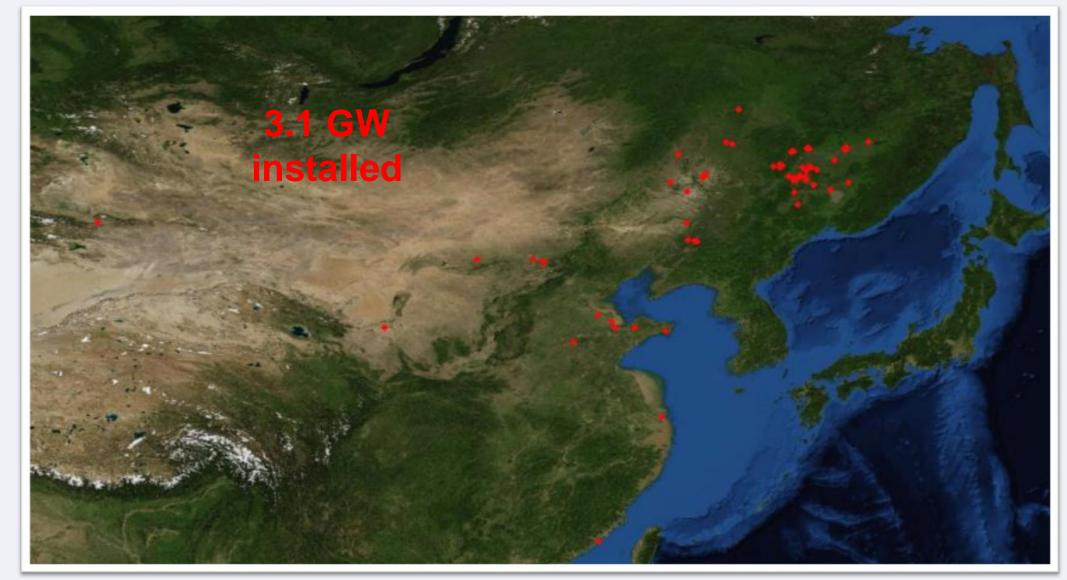
Results

Short-term wind power forecasting is applied on several wind farms in China.

Meteodyn's solution is first presented, with a specific emphasis on the Artificial Neural Network correction tool.

Then, the specific role of the Grid Operator in Chinese market is described. The consequences on forecast is exhibited.

Last, some strategies to take care of these limitations are presented. We conclude that the ANN correction Meteodyn is operating Short-term wind power forecast on more than 40 wind farms in China, with an overall power capacity exceeding 3 000 MW.



1/ Manual selection

Periods of limitation are manually detected within the data set. This strategy is human-time consuming, and not reliable. It has been tested on a single wind farm.

A first ANN is computed over the whole data, but the normalized Root Mean Square Error is calculated excluding the curtailed periods. Final nRMSE is 15.2%.

A second ANN is computed over the data with no curtailment. Final score is 15.5% nRMSE, which is

tool is able to deal with this curtailment cuts.

System description

Meteodyn Forecast system is based on both physical and statistical modeling.

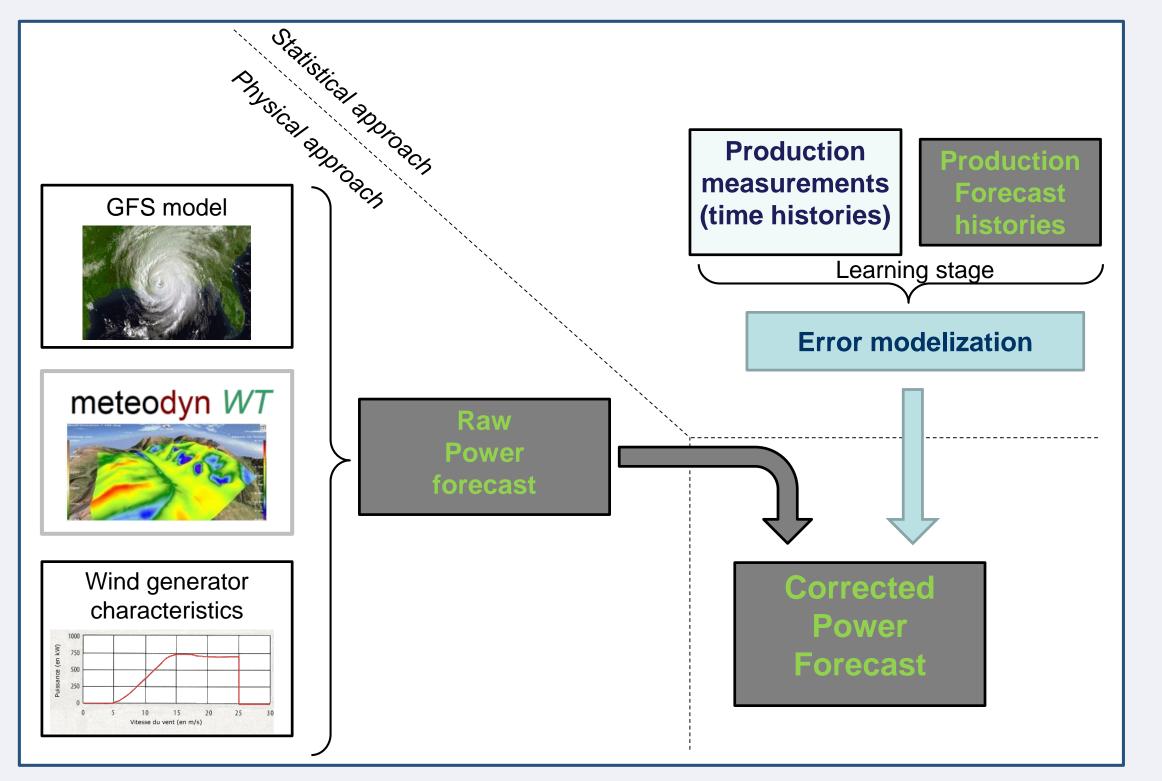


Fig. 1: Meteodyn Forecast's architecture

Fig. 2: Chinese wind farms operated with Meteodyn Forecast

In several wind farms, the measured Production Time histories exhibit strange behavior:

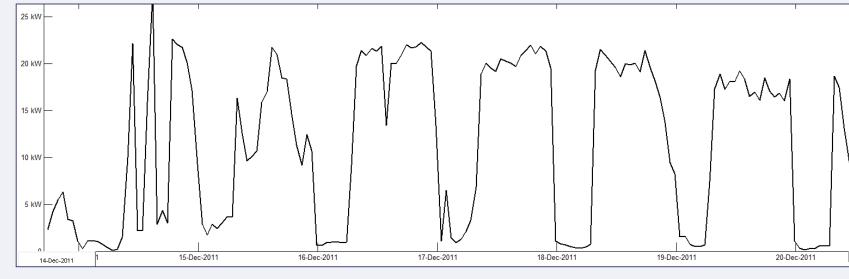


Fig. 3: Production Time series with curtailment

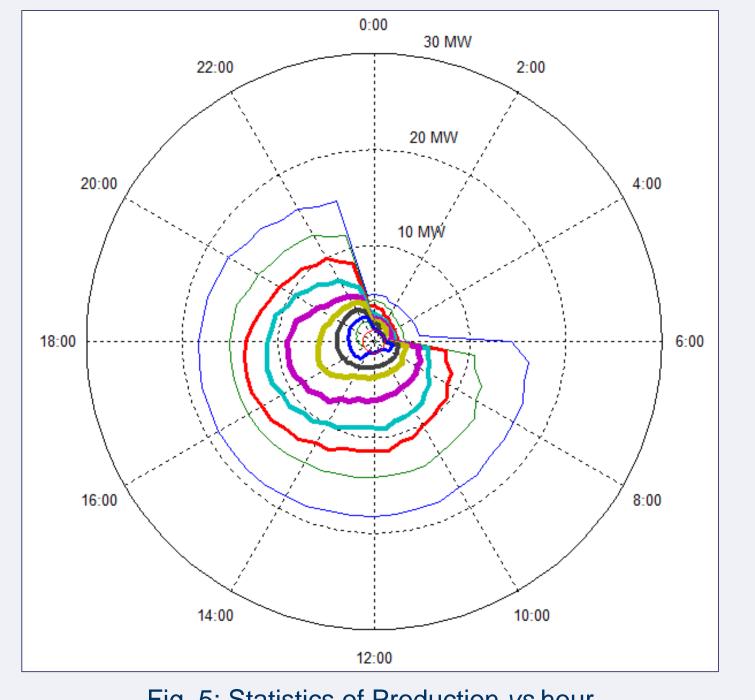
This period corresponds to a windy week, with a mesoscale forecast wind speed equal to 9m/s in average (always above 6m/s). The daily Production drop off is due to Grid curtailment: in China, when the grid is over powered (under-loaded), producers are asked to curtail their farm to a mandatory production level, limiting artificially the production. Nevertheless, the curtailment orders are not given in advance, and recording them is

similar to previous one.

This means that the curtailed data do not affect the ANN correction on un-curtailed data. The manual selection does not bring any improvement.

2/ Deterministic Power limitation

In this approach, a systematic rule is inferred from the figure 4: between 23:00 and 6:00, Forecast Production is artificially divided by 4. ANN learning is applied with this corrected input variable. Results are plotted similarly as fig.4 :



The physical approach is based on GFS meteorological forecast, coupled with a Computational Fluid Dynamics micro down scaling, in order to deal with high terrain complexity.

Statistical learning is based on past measurements compared to past power forecasts (supervised learning). Our solution is a fully-connected Artificial Neural Network. Our learning process allows to choose for the best shape of this ANN.

The ANN inputs are:

- ForecastProduction ∈ [0-Nominal Power] kW
- MesoDirection \in [0 360]° (cyclic)
- TimeOfTheDay \in [0 24]H (cyclic)
- DayOfTheYear \in [0 365] day (cyclic)
- MesoSpeed ∈ [0 20] m/s
- ForecastHorizon \in [22 46]H

The Forecast Horizon is the time lag between the NWP forecasted time and the local time. It includes the GFS time delivery, jet lag, mandatory delay, and maximum time ahead in the Chinese market.

As one can see, this is a static vision of the Power Forecasting: the correction function explains the As one can see, curtailment is not systematic: the production from a given situation. Thus, the underlying Artificial Neural Network has a fully connected feedforward architecture.

quite impossible (no curtailment time series available). Thus, the forecast system has to deal with it.

These curtailments seem to be periodic, once a day, and during the night. To check this behavior, Production Time histories are binned by the forecast hour; then, Power distribution is calculated in each bin. The deciles are plotted in a radial axis in next figure:

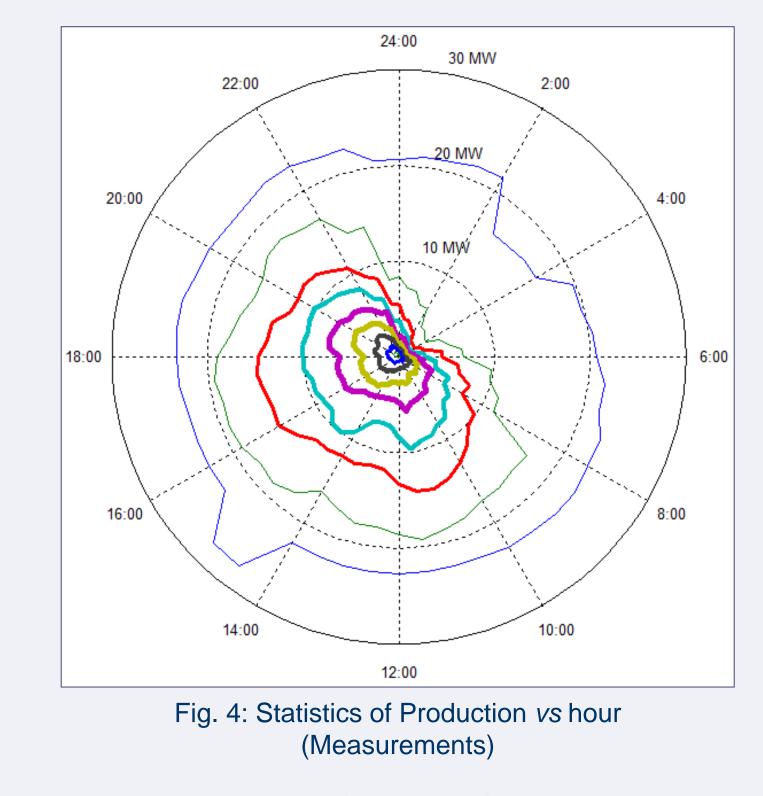
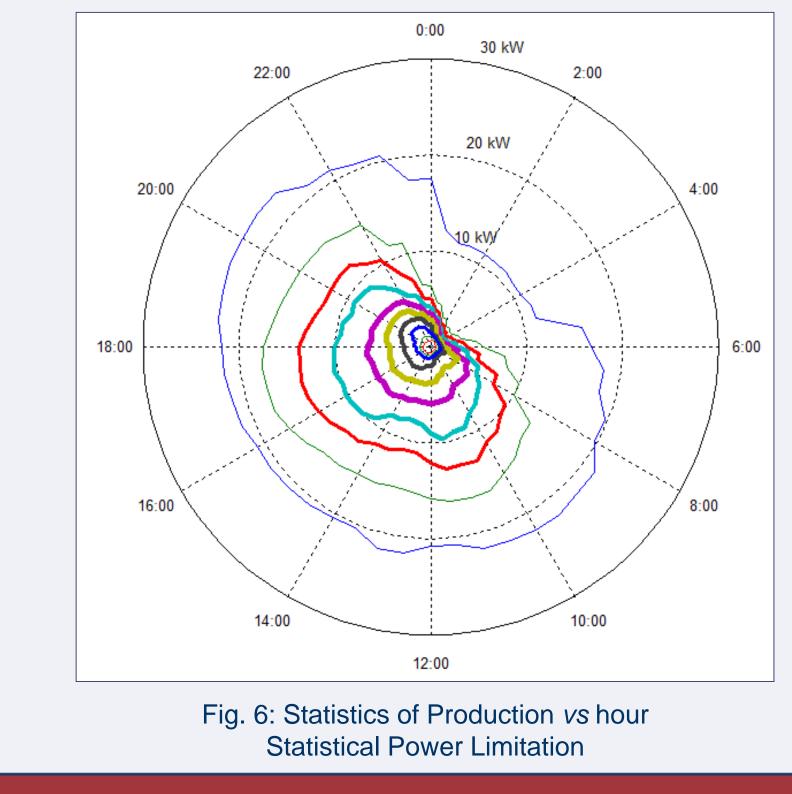




Fig. 5: Statistics of Production vs hour **Deterministic Power Limitation**

3/ **Probabilistic Power Limitation**

Here, no data manipulation is done: the ANN automatically learns from the data (note that TimeOfTheDay becomes a mandatory variable).



Note that there is some implicit variables, such as air density and atmospheric stability, throughout the ForecastProduction variable. From the statistical and machine learning points of views, this can be seen as a non linear pre-processing of input variables.

Training is made thanks to a the back-propagation algorithm, while the architecture selection is provided by a genetic algorithm (the test set is one third of the whole data set).

100% decile (blue curve) do not depend on hour. Nevertheless, even for the 90% decile (green line), production is very limited between 23:00 and 6:00.

Three strategies are investigated to deal with this daily curtailment:

- 1. Manually Ignore the curtailment periods
- 2. Deterministic Power limitation (fixed hours)
- 3. Probabilistic Power limitation (throughout ANN)

Conclusions

Three techniques, developed to deal with grid-ordered curtailment in China, have been explored. The three ones give similar results. Nevertheless, the probabilistic approach is fully automated: the ANN is able to detect and to simulate the rule of curtailment.

References

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- 3. Implementation of a Fast Artificial Neural Network Library (FANN), S. Nissen, University of Copenhagen (DIKU), 2003.



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