Optimising the use of ensemble information in forecasts of wind power

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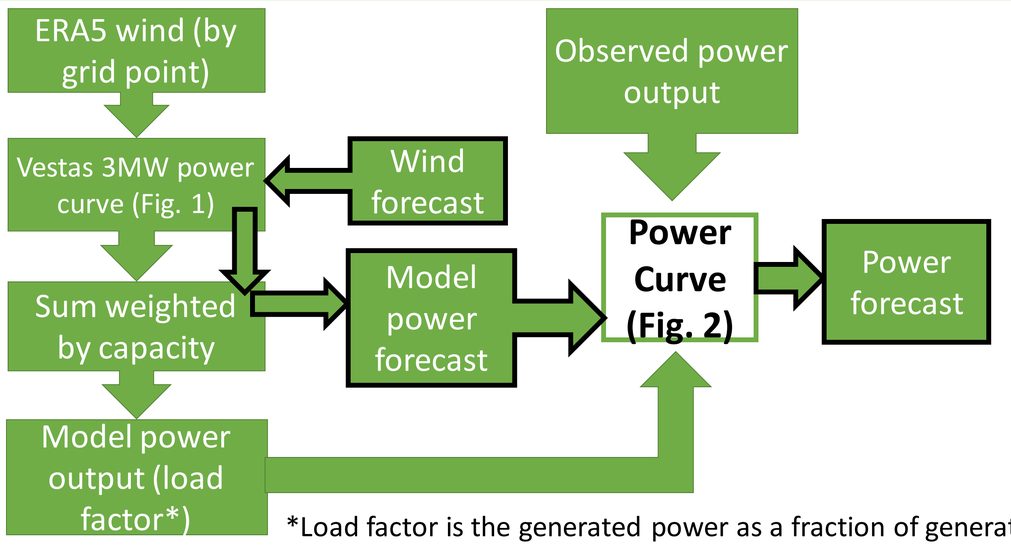
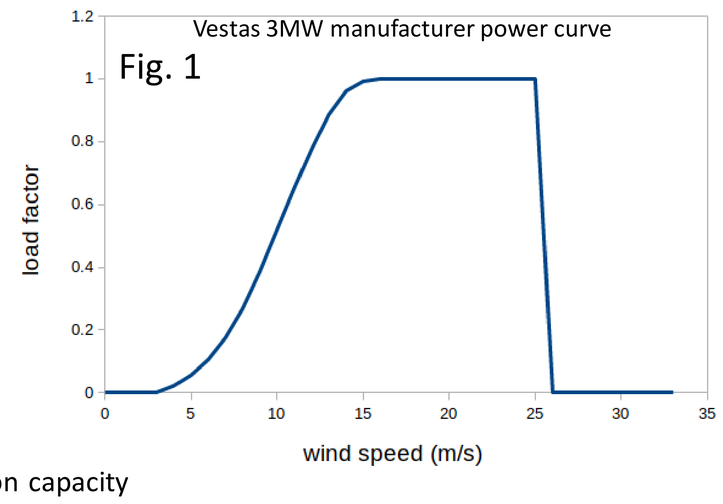
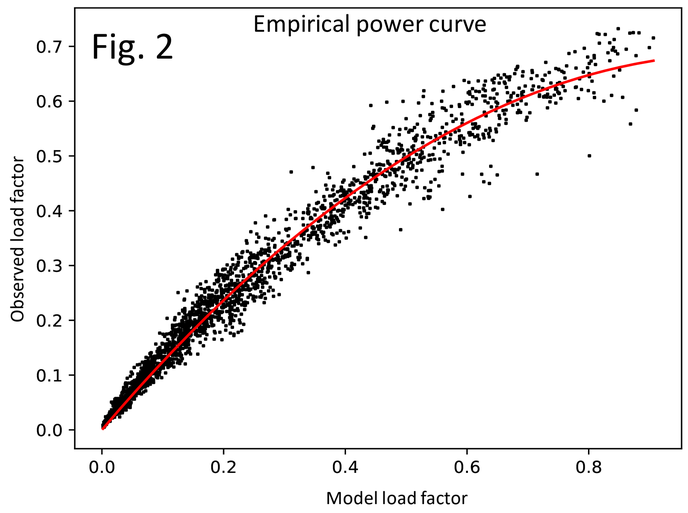
Power Curve



*Load factor is the generated power as a fraction of generation capacity

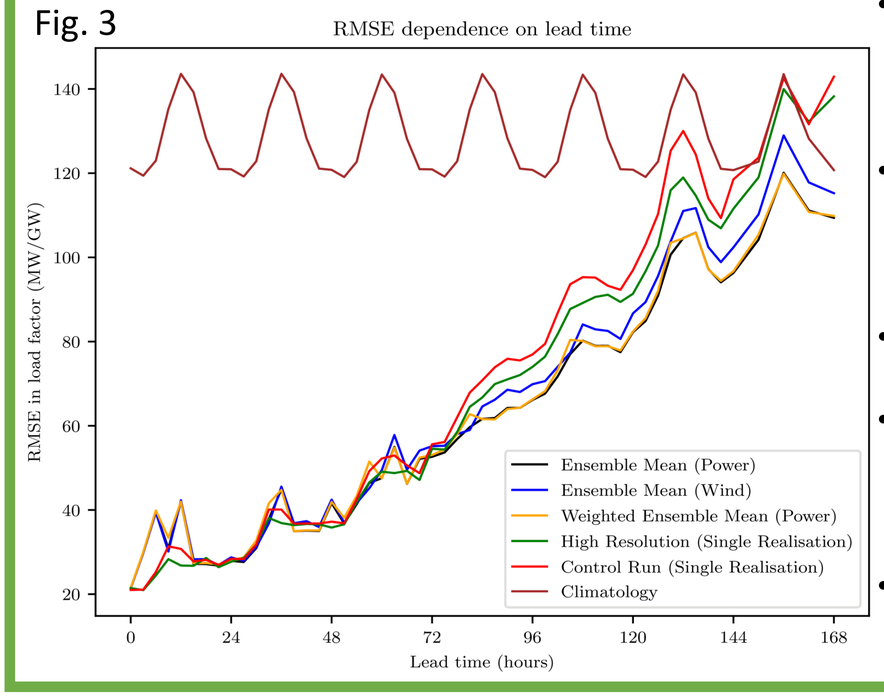




Outline

- Electricity generation output forecasts for wind farms use NWP model output such as the ECMWF's.
- Use of ensemble information is limited – most users use ensemble mean wind speed. Can we do better?
- Better forecasts can:
  - Reduce operational costs of wind farms.
  - Help to reduce carbon emissions.
  - Improve profitability of trading strategies.
- **Key questions:**
  - What is the best way to convert a wind forecast into a power forecast?
  - What is the most effective forecasting method in terms of RMSE?
  - What is the most effective forecasting method in terms of profitability of trading strategy?

Outcomes



- Ensemble mean performs the best of the methods tested in terms of RMSE, especially at longer lead times (Fig. 3), and out-performs the climatology even at 7 days.
- At early lead times – out to around 3 days - there is not much difference in performance between the forecast methods, though the deterministic forecasts seem to do better. (Figs 3, 4)
- Improvement by weighting is small, if any exists (Fig. 3).
- The ensemble mean power forecast out-performs the power produced by the ensemble mean wind forecast in terms of RMSE. This is due to the non-linearity of the power transformation (Fig 3).
- Considerable improvements can be made in trading strategy by using the ensemble spread to decide on size of trade (Fig 4).

Trading Strategy

Weighted Ensemble Mean

- Rank histograms tell us about the consistency of errors of the ensemble. If we consistently over-estimate, can we correct for it?
  - Take a **weighted ensemble mean** with weights given by frequency in rank histogram.
  - For observation outside ensemble (First and last bin), calculate a mean distance and weight this by frequency.

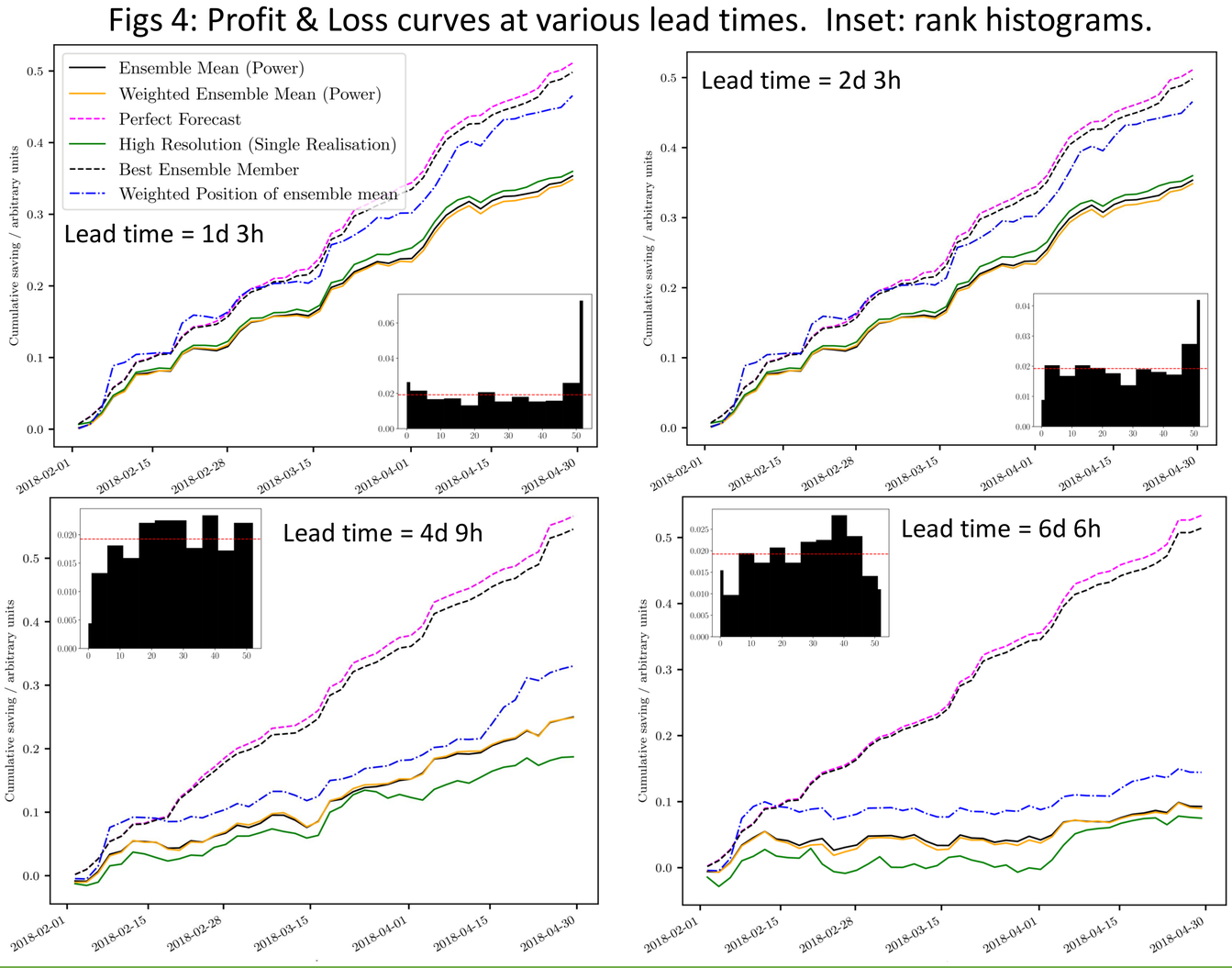
Trading strategy

- Increasing wind power reduces electricity prices.
- If trader has a better forecast than the rest of the market and it tells them electricity will be cheaper (due to higher wind power) than current market price, then the trader should sell now and buy later, and vice versa.

Variable position

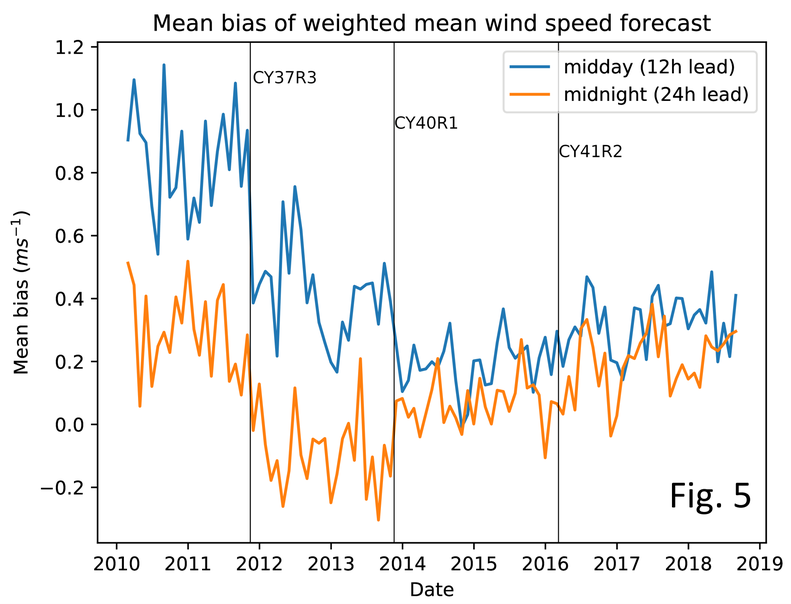
- Trading a fixed amount of energy means risk fluctuates with uncertainty in forecast.
- Keep risk constant by trading more when ensemble spread is less and vice versa.
- Calculate a **weighted position** by weighting the value of the trade by ensemble spread.
- Normalise the weighting using in-sample ensemble RMSE so the mean trade is fixed.

Figs 4: Profit & Loss curves at various lead times. Inset: rank histograms.



The Data

- Model changes meant we used limited data (See Fig 5).
- Covering Germany on a 1° grid and the time period 08/03/2016 to 30/08/2018:
  - ECMWF ensemble forecasts of wind speed at 100m, 3 hourly.
  - ERA5 reanalysis, hourly.
  - Low and high resolution operational forecasts, 3 hourly.
  - Power output observations, hourly.
  - Wind farm capacity, monthly, and percentage of capacity at each grid point,
- Wind speed was corrected for biases with respect to ERA5 winds.



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