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Highlight results

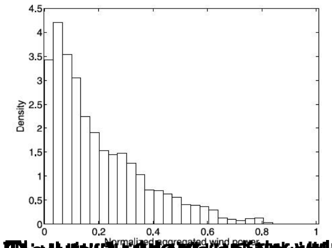
- **Production of an evaluation protocol for verifying and evaluating the quality of probabilistic forecasts**

Background:

Wind power forecasts are reequired for the efficient operation, management and planning of national power systems. Inherent uncertainly presents substantial challenges to decision-makers and only a comprehensive probabilistic forecast technology can deliver a solution that is capable of increasing efficiency and managing risk in the long run. One of the greatest challenges of modelling wind power data is the bounded non-Gaussian time series. There are now many techniques available for producing probabilistic forecasts (either for quantiles or the full density), ranging from statistical to meteorological to hybrid techniques [1-3]. Standards are required to provide a consistent approach for verifying and evaluating the quality of probabilistic forecasts.

Overview:

The unconditional empirical density of nromalised aggregated wind power data is non-Gaussian due to the bounded nature of the time series (Figure 1). It is also skewed and has a sharper peak than a Gaussian distirbution.



Models:

We employ a number of benchmarks in our forecast comparison. The hierarchy of the models from simple to complicated structures facilitates an understanding of the advantages in terms of forecast performance versus complexity (both in terms of number of parameters and computational expense). The models included climatology (empirical density) and both a constant and persistence benchmark obtained from the truncated normal (TN) approach, In addition, an exponentially weighted moving average (EWMA) conditional density forecast was produced. The TN approach was combined with exponential smoothing or error, trend and seasonality (ETS) methods. This provided a model for the level and another for both the level and variance. The logistic transform appraoch (LT) was used to estimate an ARIMA model for the level and a combined ARIMA-GARCH for the level and variance.

Evaluation study:

1 hour

6 hours

Persistence

0.019

0.077

Constant

0.159

0.159

Climatology

0.175

0.175

EWMA cconditional density

0.098

0.111

ARIMA(2,1,3)

0.017

0.065

ARIMA(4,1,3)-GARCH(1,1)

0.016

0.063

ETS(A,N,N|EC)

0.017

0.068

ETS(A,N,N|EC)-(A,N,N|EC)

0.017

0.069

Table 1: Summary of density forecast performances using CRPS.

We consider aggregated wind power generated from 64 wind farms in Ireland for approximately six months from 13-Jul-2007 to 01-Jan-2008. The data are recorded every 15 minutes, giving a total number of 16,512 observations during the period. We divided the data into a training set of about 4 months (the first 11,008 data points) for parameter estimation, and a testing set of about two months (the remaining 5504 data points) for out-of-sample forecast evaluations. We calculated the forecast performance for all horizons from 15 minutes to 24 hours ahead. Table 1 reports the CRPS values fro 1 and 6 hours.

We used the root mean squared error (RMSE) and the continuous ranked probability score (CRPS) to evaluate the point and probabilsitic forecasts respectively. The ARIMA(4, 1, 3)–GARCH(1, 1) was the best performing model both in terms of RMSE and CRPS over the 15 minute to six hour forecast horizon. However the simpler (fewer parameters) ETS models were highly competitive.

Further work:

Additional research is needed to address the modelling challenges of wind power from individual wind farms where there is greater variability and a larger numbers of zeros in the time series. Accurate descriptions of the mixture of processes underlying distribution and appropriate dynamical models for the time series are required.

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[4] Gneiting, T. & Raftery, A. (2007). Strictly proper scoring rules, prediction, and estimation. Journal of the American Statistical Association, 102:359–378.