THE APPLICABILITY OF EMPIRICAL PREDICTION INTERVALS TO ENERGY FORECASTING

Lynn Kaack, Carnegie Mellon University, Phone: +1 (919) 904-1258, E-mail: kaack@cmu.edu
Jay Apt, Carnegie Mellon University, Phone: +1 (412) 268-3003, E-mail: japt@andrew.cmu.edu
M. Granger Morgan, Carnegie Mellon University, Phone: +1 (412) 268-2672, E-mail: granger.morgan@andrew.cmu.edu
Patrick McSharry, Oxford University, Phone: +250 (786) 734866, E-mail: patrick@mcsharry.net

Overview

Energy projections, such as those contained in the Annual Energy Outlook (AEO) by the U.S. Energy Information Administration (EIA) and the World Energy Outlook by the International Energy Agency, are important because they are often used as the basis for investment and policy decisions. Retrospective analyses of past energy projections have shown that the observed evolution of the quantities can sometimes differ from the projection by several hundred percent. A thorough treatment of uncertainty is essential for good decision-making. This work evaluates a method for probabilistic forecasts - empirical prediction intervals - which is based on past projection errors. The approach is illustrated using the EIA's AEO. We present an evaluation of the out-of-sample forecasting performance of several empirical density forecasting methods. We find prediction intervals for the AEO projections that capture the true uncertainty better than the range of EIA's scenarios. We give guidance on how to evaluate and communicate uncertainty in future energy outlooks, but findings are also applicable to forecasts in other fields.

Methods

The method of empirical prediction intervals (EPIs), first published by Williams and Goodman [1], uses the distribution of past errors to create a probability density forecast around an existing point forecast. It relies on the assumption that the past deviations of forecasted values from actual values are a good estimator of the forecaster's current ability to predict the future. Stationarity of past forecasting errors is an essential requirement of the known framework [2]. We focus on analyzing the scope and limitations of EPIs for the given data set. We apply the method to the EIA Annual Energy Outlook (AEO) to obtain comprehensive probabilistic projections for twenty quantities. We estimate the forecast error distribution in a non-parametric fashion, assess the stationarity of the projection errors, and discuss bias. We then apply the developed method to the most recent AEO reference case projection to obtain a comprehensive probabilistic forecast for the quantities. We assess the calibration of the prediction intervals, and compare it to data-driven benchmark forecasts and the scenarios published in the AEO. With modifications to the method, our goal is to improve the calibration of the prediction intervals. The different density forecasting methods are evaluated and compared with the continuous ranked probability score [3]. A systematic approach to estimating and evaluating different methods considering the effect of non-stationarities on empirical prediction intervals has, to our knowledge, not been taken in similar analyses such as [4], [5], [6] and [7]. Our findings could naturally be transferred to forecasts in other fields with similar restrictions.

Results

We find that the method of empirical prediction intervals can provide approximately well-calibrated prediction intervals in energy forecasting. Choosing a density forecasting method however demands careful examination of calibration. We identify the most serious limitations of EPIs in energy forecasting as non-stationarities in the errors and small sample sizes due to short forecasting records. Especially in comparison to uncertainty based on the scenarios, EPIs can add valuable information to decision-making. We find that the EPIs generally have a better coverage than the scenario intervals. We cannot find strong evidence of consistent bias in time in the AEO data, and see that a bias correction by the EPI performs worse than the reference case projection for almost all of the analysed quantities. We therefore recommend centering a density forecast in the reference case. This approach may be outperformed by a Gaussian density forecasts with a well-chosen standard deviation, which should be informed by the standard deviation of the errors and optimized for out-of-sample performance.

Conclusions

Especially, where alternative density forecasting methods are not feasible, not available, or are too costly, EPIs and well-chosen Gaussian uncertainties can add great value to the decision-making process. In particular, when the forecast user has an interest in retaining a point forecast as the best estimate, the EPI is a quantitative solution to finding a density forecast. Our analysis showed that in comparison with probability distributions bounded by the scenarios, EPIs are broader and better capture the range of uncertainty. Ideally, the user should consider the density forecast jointly with the scenarios, as density predictions are not conditional on past observations. Scenarios are projections conditional on certain inputs (e.g. high oil price) and can provide insight in the dynamics of the system. Our evaluation analysis suggest that bounding scenarios should be wider. Considering our results and the importance of long-term energy forecasts for the private and public sector, we advise the forecasting institutions to revisit their communication of uncertainties of the projections. We found that users of long-term energy forecasts for example in academia and the electricity industry see value in probabilistic forecasts. Besides the need for refinement of the methods under non-stationarities and small sample sizes, we found that methods based on retrospective errors can deliver reasonably well-calibrated prediction intervals. The simplicity and transparency of EPIs is valuable in its own right.

References

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