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Short communication

How accurate are forecasts of costs of energy? A methodological contribution

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HIGHLIGHTS

- A methodology to assess the accuracy of forecasts of costs of energy is outlined.
- Method applied to illustrative data for four electricity generation technologies.
- Results give an objective basis for sensitivity analysis around point estimates.

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ABSTRACT

Forecasts of the cost of energy are typically presented as point estimates; however forecasts are seldom accurate, which makes it important to understand the uncertainty around these point estimates. The scale of the differences between forecasts and outturns (i.e. contemporary estimates) of costs may have important implications for government decisions on the appropriate form (and level) of support, modelling energy scenarios or industry investment appraisal. This paper proposes a methodology to assess the accuracy of cost forecasts. We apply this to levelised costs of energy for different generation technologies due to the availability of comparable forecasts and contemporary estimates, however the same methodology could be applied to the components of levelised costs, such as capital costs. The estimated "forecast errors" capture the accuracy of previous forecasts and can provide objective bounds to the range around current forecasts for such costs. The results from applying this method are illustrated using publicly available data for on- and off-shore wind, Nuclear and CCGT technologies, revealing the possible scale of "forecast errors" for these technologies.

1. Introduction

Forecasts of costs of energy technologies are often used to provide narratives for energy development, and are typically presented as a point estimate. This paper proposes a methodology to assess the accuracy of forecasts of energy costs. Our methodology considers comparable data on historic cost forecasts and matched "contemporary estimates" to generate "forecast errors".[1] In addition, quantifying these errors will provide a range around point estimates of costs, which are important inputs to policy-making as well as in empirical work (e.g. using Integrated Assessment Models (IAMs)). This would provide an objective basis for understanding the accuracy of point estimates and for guiding sensitivity analysis.

IAMs have been extensively used to develop energy scenarios for countries and regions across the world (Edenhofer et al., 2013). Such models are particularly useful as (among other factors) they include economic criteria of each technology option to form energy scenarios which are endogenous to the model (Krey and Clarke, 2011). Despite this, IAMs have some limitations which have been previously noted, for instance not capturing the heterogeneous aspect of electricity from different technologies (Edenhofer et al., 2013). A number of detailed elements affecting the future supply of energy are included in these models, including (but not limited to) future values of costs for different

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[1] We use the term contemporary estimate throughout this paper to refer to the known cost for a generation technology in a specific year. Our use of this terminology is consistent with e.g. Gross et al. (2013). Where there is more than one unit of a generation technology developed in a year, publicly available data are likely to represent the average for that technology in that country, see Grubler (2010), although this would not necessarily be the case for the use of these methods with proprietary data. We thank an anonymous referee for requesting this clarification.

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technologies. IAMs typically focus on long term scenarios e.g. greater than 25 years, and make use of a given set of assumptions, including point estimates for costs of different technologies.

Comparisons across energy costs, such as levelised cost of energy (LCOE),[2] are often used to inform a government's stance on particular technologies, such as the level of financial support a technology may require to be "competitive" with other technologies (Allan et al., 2011). Some recent work has attempted to refine the costs for technologies which might be used in IAMs by, for example, estimating "system-level" costs for variable technologies (Gross et al., 2007), while others assess the marginal economic value of changes in generation technologies (Borenstein, 2012). Each of these approaches however, produce "point estimates" for the costs of each technology, and do not capture the possible range within which the future costs will lie, i.e. they ignore the issue of forecast errors.

Section 2 introduces the method, which has its origins in the assessment of economic forecasts (Granger, 1996), discusses the alternative measures of costs to which the methodology could be applied and the data used for the empirical application in this paper. Our methodology could be applied to any energy cost, including capital or fuel costs, however due to data availability the empirical example we use in this paper uses the LCOE for four technologies. The empirical results from the illustrative example give an indication of the accuracy of previous forecasts and objective bounds to the range of uncertainty around current forecasts of LCOE. The results from this illustrative application using LCOEs are set out briefly in Section 3, before a discussion of the results and method in Section 4. Section 5 sets out conclusions and directions for future research, including applying the proposed methodology against other measures of costs.

2. Methods

2.1. Measures of forecast accuracy

There is a substantial literature on techniques for assessing the accuracy of economic forecasts. This literature, for example, has shown the accuracy of forecasts made by private organisations compared to public organisations, the accuracy of forecasts produced by different multinational organisations (e.g. Granger, 1996; Pons, 2000; Loungani, 2001) and the accuracy of forecasts over different horizons, i.e. the duration between when the forecast is made and the point of time to which the forecast relates (e.g. Ashiya, 2006; Allan, 2011). This literature has developed a number of empirical measures that can be used to gauge the accuracy of a forecast, including the mean absolute error (MAE), root mean square error (RMSE), root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE).

In our application, the MAE for each generation type g can be calculated as the absolute mean of all "forecast errors", i.e. the distance between the forecast and the "contemporary estimate" of the cost. In Eq. (1), y^f_{p-h} is the forecasted cost relating to year p made at a forecast horizon of h years, e.g. the cost for onshore wind in 2010 made in 2005, where h=5. y^a_{gp} is the contemporary estimate of the cost for technology g in period p, and N the total number of paired cost forecasts and contemporary estimates for technology g. The further from the date of the forecast that the forecast is evaluated, one might expect errors in the forecast to be larger. Therefore we might want to produce evaluations for each forecast horizon, h, e.g. 5, 6, 7,…, k years. This being the case, for each h, we would calculate[3]

$$MAE_g = \frac{1}{N}\sum_{n=1}^{N}|y^f_{p-h} - y^a_p| \tag{1}$$

The root mean square error (RMSE), when compared to the MAE, places slightly more emphasis on larger errors due to the squaring process, as seen in Eq. (2). This can be useful for forecasters or analysts who are concerned about larger errors:

$$RMSE_g = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y^f_{p-h} - y^a_p)^2} \tag{2}$$

Percentage (or proportional) errors are an alternative measure of the accuracy of forecasts. These take into account the scale of errors relative to the contemporary estimates and the Root Mean Squared Proportional Error (RMSPE) and Mean Absolute Proportional Error (MAPE) are shown in the following equations:

$$RMSPE_g = \sqrt{\frac{1}{N}\sum_{n=1}^{T}\frac{(y^f_{p-h} - y^a_p)^2}{y^a_p}} \times 100\% \tag{3}$$

$$MAPE_g = \frac{1}{N}\sum_{n=1}^{N}\frac{|y^f_{p-h} - y^a_p|}{y^a_p} \times 100\% \tag{4}$$

2.2. What cost measure is appropriate?

In principle, the methods outlined above can be used to calculate and analyse forecast errors for any energy costs for which there are forecasts and contemporary estimates, i.e. a contemporary estimate for a given year of a forecasted cost for a specific technology, made in a year prior to which the forecast relates. The precise cost figure to which the method can be applied is likely to depend upon the availability of comparable data. For example, capital costs (i.e. including development, construction and installation) would appear to be a useful measure. For many technologies, these will be a significant portion of total project costs. However, forecast and contemporary estimates of capital costs can be difficult to find in the public domain, with both typically known only to the developers of that technology. We return to this point in Section 4.

In the absence of such proprietary data, an alternative cost figure – and what we use in the empirical example which follows – is the LCOE. As described above, these are widely reported, and so easier to access the matched forecast and contemporary estimates that our methodology requires. There are some issues however in using LCOEs; specifically they are based on an aggregation of individual cost elements, such as capital and fuel costs, as well as production data. If there were forecast and outturn values for each element, the analyst could decompose the LCOE "forecast errors" in terms of the contribution of its individual components. This may be insightful, as elements within the LCOE could differ between their forecast and outturn values in ways which offset, or exaggerate their individual errors. For example, Harris et al. (2013, p. 440) noted that observed increases in construction cost estimates can have a "dramatic" effect on the estimated future LCOE. However, in the absence of comparable forecast and outturn data either for all components of the LCOE or just capital costs, in the empirical illustration of the methodologies which follows, we use LCOE as our measure of costs.[4]

[2] This is the "the discounted life-time fixed and variable cost of a generation technology in euro/MWh" (Edenhofer et al., 2013, p. S17)

[3] An alternative approach, although notationally messier, would be to introduce a new subscript in Equation (1) denoting the forecast horizon being evaluated.

[4] We thank a referee for drawing our attention to this empirical challenge by using the LCOE measure.