Probabilistic uncertainty forecasting with electricity system models in 31 European countries

Xin Wen, University of Geneva, +41 (0) 22 379 09 10, xin.wen@unige.ch
Marc Jaxa-Rozen, University of Geneva, +41 (0) 22 379 04 09, marc.jaxa-rozen@unige.ch
Nik Zielonka, University of Geneva, +41 (0) 22 379 08 26, nik.zielonka@unige.ch
Evelina Trutnevyte, University of Geneva, +41 (0) 22 379 06 62, evelina.trutnevyte@unige.ch

Overview

Technology-rich, optimization-based electricity system models are commonly used to generate electricity projections for policy support, especially at a national level [1]. Looking retrospectively, while there are good reasons why modelled projections are consistently different from historical transitions [2–4], there are many examples where these projections were systematically overconfident and underestimated future uncertainties [4]. Novel probabilistic uncertainty forecasting methods have been pioneered for the case of the US energy projections [5], but it remains unclear to what extent these methods can be applied to other countries and can be integrated in energy system models rather than applied post-hoc on the past projections. In this study, using a cost-optimization modeling framework D-EXPANSE for the electricity sectors of 31 European countries, we demonstrate and evaluate empirical density forecasting methods in order to find the most suitable method to generate probabilistic projections for each model output in national electricity system modeling.

Methods

In this study, we conduct probabilistic uncertainty forecasting with empirical prediction intervals for electricity sector transitions in 31 European countries, using a cost-optimization modeling framework D-EXPANSE [2,3]. First, we use D-EXPANSE to retrospectively model national electricity sectors in 31 European countries over the 1990 – 2019 period. D-EXPANSE is a national-level model with a bottom-up, perfect foresight, and cost-optimization structure. By comparing the modeled cost-optimal pathway and the historical pathway in the real world, we quantify the empirical projection errors of different types.

Second, we build out-of-sample probabilistic density forecasting model [5]. Different empirical density forecasting methods are implemented to obtain the prediction intervals, considering various error types and error distribution assumptions. The error types include mean error (ME), mean logarithmic error (MLE), symmetric mean percentage error (sMPE). The error distribution assumptions include non-parametric distribution [6], parametric (Gaussian) distribution, and Chebyshev inequality-based distribution.

Third, we evaluate various probabilistic density forecasting methods for each model output and use the best one to obtain the future uncertainty forecasting results. We evaluate the performance of the uncertainty density forecasting model in multiple countries, using the weighted interval score (WIS) [7]. Once identifying the best probabilistic density forecast method for each model output, we apply these methods for estimating uncertainties around each modelled projection for the future until 2050.

Results

With D-EXPANSE retrospective modeling of electricity system transitions in each country, the different model projections are generated under each model run with different starting years. The results show that the projection errors and their standard deviation at each horizon differ in projection horizon from 1 to 20. Also, the projection errors behave differently regarding the values and their distribution. The performances of different density forecasting methods are evaluated with the calculation of weighted interval scores (WIS). Overall, the Chebyshev's inequality-based ME has the most accurate empirical prediction interval forecast with the narrowest WIS variation bounds and a relatively high normalized WIS value for multiple renewable technologies, such as the installed capacity and annual generation of solar PV, onshore wind, offshore wind, hydro dam, hydro run-of-river, biomass and biogas. However, for the fossil fuel-based technologies and nuclear power plants, many other methods outperform Chebyshev's inequality-based ME.

Finally, using the best probabilistic density forecasting method for each model output, we estimate the uncertainties around each modelled projection for the future. For example, for onshore wind power generation (Fig. 1), we use Chebyshev's inequality-based ME method to estimate the uncertainty around the model projection until 2050. The results show that in different countries, the projections are different in terms of both the modeled projection and the probabilistic density intervals for onshore wind power generation. The increasing trend is less drastic in Italy, Germany and France compared to Austria, while the uncertainty interval is much broader.

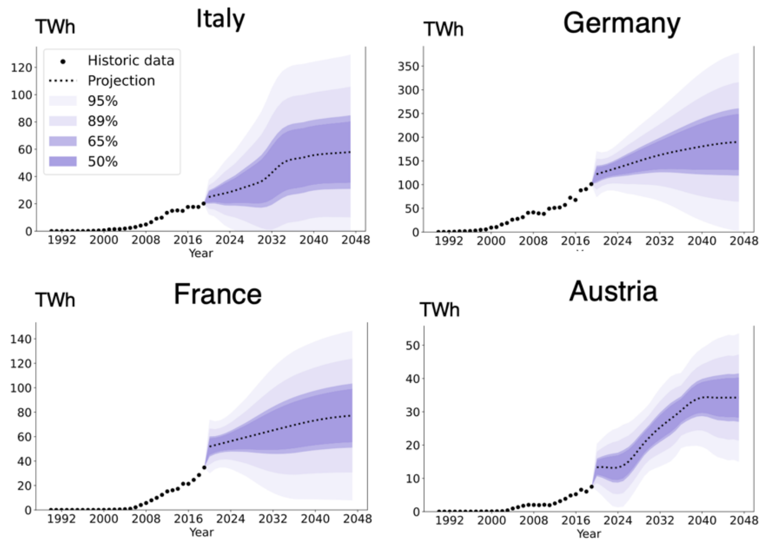

Fig. 1 Probabilistic density forecast for onshore wind power generation in Italy, Germany, France and Austria, using Chebyshev's inequality-based ME method. The black dots indicate the historic data and the dotted line is the model projection. The shaded area indicates the probabilistic density of 50%, 65%, 89% and 95%.

Conclusions

In this study, we present an uncertainty forecasting approach with empirical prediction intervals using retrospective modeling exercise with D-EXPANSE model for national electricity sectors in 31 European countries over the 1990–2019 period. We develop multiple empirical density forecasting methods with different projection errors and error distributions, using retrospective modeling for the out-of-sample accuracy testing of these model output projections. The results show that for each model output, there may be different preferred empirical density forecasting methods that should be chosen to obtain the most accurate uncertainty interval forecasts. In this way, we gather first-of-the-kind evidence to inform how and to what extent the probabilistic uncertainty projections can be applied for forward-looking analysis in bottom-up models.

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