INCORPORATING WEATHER AND CLIMATE FEATURES INTO A LONG-RANGE ELECTRICITY DEMAND FORECASTING FRAMEWORK FROM INTRADAY POWER MARKET DATA

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Overview

Having a careful understanding of power markets is essential in the process of achieving an energy transition. It is often an understated component of energy system planning, where much attention is given to long-range planning, the introduction of new technologies and/or retirement of fossil fuels for cleaner alternatives such as renewable. These are undoubtedly pivotal considerations, yet at the same time the operational edge of energy markets also has important market implications.

The objective of this paper is to jointly understand drivers of intraday energy consumption in a framework conducive to generating long-term energy-demand projections, with sensitivity bounds and potential for assessing counterfactual future climate change scenarios. Similar attributes have been explored for example in the case of Australia (Hyndman and Fan, 2015) using a fairly involved modelling framework to develop the 'Monash Electricity Forecasting Model' documented on the Australian Energy Market Operator (AEMO) website. The approach may not have yet seen an expansive uptake in the academic literature, but has a number of appealing attributes ranging from the data demands and scalability to different market contexts, together with the flexibility of themodelling framework to allow for counterfactual analysis e.g. of future climate conditions, as well as the ability to describe long-range demand dynamics whilst maintaining a description of key power market indicators such as the estimated di-urnal demand system pressures and how they might evolve.

Methods

The modelling procedure is based closely on Hyndman and Fan (2015), adapted to a different geographic context, and expanded to incorporate a broader suite of weather variables (beyond temperature) as well as introducing additional high-resolution climate variables which allow to test whether enduring climate change effects are giving rise to changes to di-urnal energy system requirements. It is assumed that the demand for energy, q in period t is decomposed into two parts, reflecting seasonal (quarterly) demand variation and within-season demand:

$$\log(y_{t,p}) = \log(y^*_{t,p}) + \log(\bar{y}_i) \tag{1}$$

Where p denotes the {1,…,24} hourly periods in the day. The intraday component of demand is assumed further to be governed by seasonal, weekly and daily patterns, as well as public holidays captured as determinstic features in $h_p(t)$, coupled with weather and climate related variables which are linked with demand via a non-parametric identty in $f(w_{1,t},w_{2,t})$. Allowing for idiosyncratic noise we have the following estimable relationship:

$$\log(y^*_{t,p}) = h_p(t) + f(w_{1,t}, w_{2,t}) + e_t \tag{2}$$

Long term demand is governed by a more conventional set of variables including for example GDP, population, energy prices and other factors. These are evaluated using per-capita demand for variables in z, estimating the coefficient c using dynamic ordinary least squares:

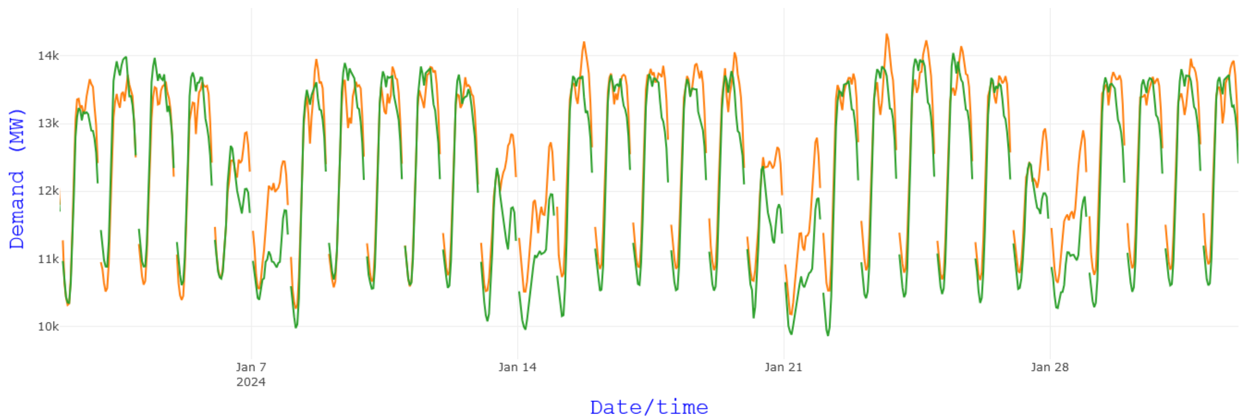
$$\bar{y}_i^{pc} = \sum_{j=1}^{J} c_j z_{j,i} + \varepsilon_i \tag{3}$$

The model is designed for forecasting based on the ability to derive long-range stable per-capita seasonal demand from (3), and utilise the regularity of climate related variables--using a double seasonal bootstrap—in (2) together with block estimation to maintain informative/plausible intra-day demand patterns as a basis for simulating future intraday demand patterns.

In-sample estimation of (2) is done via regression boosting, which following Hyndman and Fan (2015), includes all variables in a linear manner at the first level of the regression, and enters climate variables non-parametrically in higher levels of boosting, limiting the 'strong model' to the intial regression plus three boosting stages with a 50% shrinkage factor. Further, the specific set of variables at each stage of the boosting framework are selected on the basis of out of sample forecasting performance.

Results

The results of the analysis are too involved to describe in any depth within this abstract, however the figure below gives a visual comparison of the actual demand (orange line) versus the model predictions (green line). From this it can be seen that the model provides for a generally close fit for the true data at a high-resolution time frequency e.g. intraday, and with clear day of week effect discernible. The long run model performance is equally strong across the full sample ranging from 2003 to 2025, and is even able to capture well the vaiable demand dynamics observed in the grobal financial crisis period (2008/2009) and Covid pandemic (2020/2021).



In terms of the role of weather and in particular climate related variables. The evidence points towards a complex balance of weather related effects. The importance of this may seem obvious and intuitive, but in the context of Singapore it is not to be understated, since more conventioal econometric approaches to regional demand modeling based for example on error correction models or other time-series based approaches to monthly data, generally fail to reveal significant weather effects. It is however well understood that weather effects are important to the operational dynamics of the power sector, and subsequent policy design that might need to address what is generally a quite volatile wholesale power market i.e. the underlying electricity price dynamics which may influence long-range strategic energy system planning.

Conclusions

The work presented in this study reflects the development of an econometric framework which permits for the simultaneous description of intraday demand patterns as well as medium-range system demand growth. The model, despite requiring some effort in both data processing and estimation, has relatively low-intensity data requirements, with many variables being freely available for different country contexts.

References

Hyndman, R. J., & Fan, S. (2015). Monash electricity forecasting model. Monash University.