# Scalable Additive Models for Energy Forecasting


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## Overview

Reliable electricity demand forecasts are an essential input for electricity production planning and power grid management. The UK has historically relied heavily on fossil fuel power plants, whose high ramp-up rates made adjusting for forecasting errors easy. As such stations are replaced with less flexible nuclear plants and renewables, the network will become much more reliant on accurate forecasts. The project described below focusses on developing cutting-edge non-parametric regression methods aimed at tackling new challenges in the electricity industry.

The project will start in September 2024 and will be funded for 3.5 years. Applications should be submitted via:

https://bristol.ac.uk/maths/postgraduate/phd/mathematics/apply/

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## Project: Additive Model Aggregation Methods

Future grid management systems will coordinate distributed production and storage resources to manage, in a cost effective fashion, the increased load and variability brought by the electrification of transportation and by a higher share of weather dependent production. Electricity demand forecasts at a low level of aggregation will be key inputs for such systems. However, forecasting electricity demand at the individual household level is very challenging, due to the low signal-to-noise ratio and to the heterogeneity of consumption patterns across households (see the figure below).

Capezza et al. (2020) propose a new ensemble method for probabilistic forecasting, which borrows strength across the households while accommodating their individual idiosyncrasies. In particular, they develop a set of models or 'experts' which capture different demand dynamics and they fit each of them to the data from each household. Then they construct an aggregation of experts where the ensemble weights are estimated on the whole data set, the main innovation being that they let the weights vary with the covariates by adopting an additive model structure. In particular, their aggregation method is an extension of regression stacking (Breiman, 1996) where the mixture weights are modelled using linear combinations of parametric, smooth or random effects.

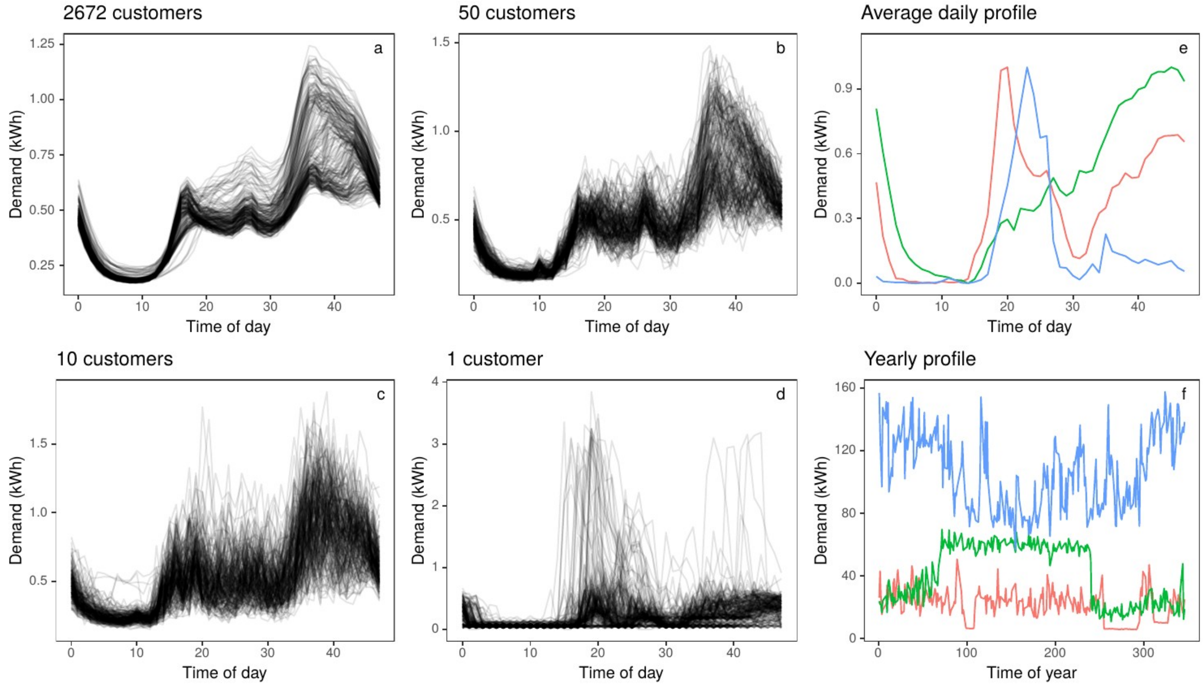


*Illustration 1: Plots a-d show the daily profiles of the demand averaged over increasingly smallgroups of customers from the CER trial (Commission for Energy Regulation, 2012). Plots e and f show the average daily and yearly demand profiles ofthree customers. The blue profile in plot f has been vertically shifted for visibility.*

The aim of this project is extending existing model aggregation methods to provide aggregation strategies that are tailored to specific problems. In particular, the additive stacking framework of Capezza et al. (2020) could be adapted to better tackle:

1. bottom-up forecasting of aggregate demand by aggregating experts at different levels of aggregation (household → feeder → substation → regional electricity system);
2. adaptive forecasting by aggregating experts that capture different temporal resolutions (intra-day → daily → weekly → monthly). The most direct application would be developing methods that are able to handle atypical demand periods, such as those induced by socio-economical events (e.g., the COVID-19 epidemic) but also network reconfigurations and other grid events.

To tackle these applications, current additive stacking methods would need deep modifications aimed at exploiting the spatial, temporal or hierarchical structure of the experts (which is completely ignored by current additive stacking methods).

## References


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