Rescaling of Historic Electricity Demand Series for Forward-Looking Risk Calculations

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***Abstract*—This paper presents a forecasting approach for national annual peak electricity demand. Forecasting is performed by rescaling observed historic demand. The rescaled peaks are then used to produce probabilistic forecasts of peak demand for a target year. Both the rescaling approach and the probabilistic forecasting methodology are carefully validated and shown to provide a good fit to the data. Comparisons are made with the National Grid's Average Cold Spell (ACS) Methodology which aims to estimate the level of electricity demand in Great Britain for which there is a 50 percent probability of exceedance in a given year.**

***Index Terms*—Demand Forecasting, Power Demand, Risk Analysis, Uncertainty**

I. Introduction

An important role of national energy planners is to maintain an appropriately low risk that electricity demand exceeds available supply, in particular in the peak months for demand. Key to this is typically the production of future projections for peak demand. In Great Britain (GB), a winter-peaking system, this process is undertaken by National Grid Electricity System Operator (NGESO) using its Average Cold Spell (ACS) methodology [1]. In particular, every August, NGESO provides an estimate for the level of demand for which there is a 50 percent probability of exceedance in the coming winter (the 'ACS peak demand'). Projections are also made further into the future to support longer term energy planning decisions, and the process is carried out retrospectively to track the historical trend of the peak demand level.

Electricity demand is typically made up of two elements: that which is weather-dependent, resulting mostly from heating, and that which is not. Both of these elements are highly dependent on societal changes such as technological and economic development, and population growth. As a consequence, it is unreasonable to expect weather conditions to have the same impact on demand in different years. For example, if society increasingly depends heavily on electric heating, the effect of temperature on demand is likely to increase. Societal changes represent a considerable challenge for forecasting since one cannot simply go back in time and assume historic demand patterns will persist. To deal with this, historic demand is typically rescaled to attempt to estimate the effect of historic weather patterns were they to occur in the year of interest. The aim of this paper is to present an approach to rescaling historic demand to a particular target year. We then demonstrate how the rescaled demand can be used as part of a risk assessment, though we stress that it is not within the scope of this paper to estimate the effects of societal changes; rather the methodology is suitable for use alongside the type of intelligence about the future likely to be available from national and regional operators.

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Under the methodology presented in this paper, rescaling is performed by considering changes in both weather dependent and non weather-dependent demand. Rescaled demand can then be used to produce a risk assessment for a given year, which might be in terms either of a probabilistic forecast of outcome peak demand or a summary statistic which considers underlying demand growth or shrinkage but strips out the variation between years arising from the weather; the latter is helpful in tracking trends in demand levels as per the ACS peak. A key application is rescaling electricity demand data from historic years to estimate a demand series for the combination of a future scenario of connected demand and the weather from that historic year.

We treat peak demand forecasting as a process consisting of three steps: firstly, a statistical model is fitted to relate temporal and weather effects to historic demand. Secondly, the model is used to provide a time series of demand based on historic weather and scaled to the time period of interest. Thirdly, this time series is used to provide a risk estimate for annual peak demand in a given year.

This paper is organised as follows. In section II, NGESO's ACS methodology is described. In section III, other approaches to demand forecasting are discussed. In section IV, we present a linear model for relating weather and temporal effects to demand, along with an approach to rescaling historic demand. Section V is used for discussion.

II. National Grid's Average Cold Spell Methodology

NGESO's ACS statistic is defined as the level of peak demand for which there is a 50 percent probability of exceedance in a given winter. This is estimated using data from past winters (including weather data), and, where ACS is estimated for a future winter, intelligence regarding interannual economic and technological developments is also used. According to the public documentation [1], the basis for estimating ACS peak is a linear model in the following form for constructing a demand series for the past or future year of interest, based on a scenario of what is connected to the system for that year, and on weather data from a historic year:

$$\begin{aligned}\text{Demand} &= \text{basic demand} + \text{temporal effect} \\ &+ \text{weather effect} - \text{unmetered generation} + \text{residual}\end{aligned} \tag{1}$$

where the terms in the equation are the following:

- basic demand - underlying demand independent of temporal effects over the course of a winter.
- temporal effect - temporal effects such as day of the year and day of the week.
- weather effect - demand that is dependent on weather
- unmetered generation - unmetered wind generation.
- residual - demand that cannot be explained by the model.

For an historic winter, this model would be based at least partly on regression (e.g. least squares), and, for a future winter, the coefficients would need to be estimated either through economic modelling or by some form of expert judgment.

The estimation process then involves simulating 20,000 synthetic weather winters, each constructed from week-long blocks of temperature data sampled from around 30 historic winters; a similar process is followed for unmetered generation based on a smaller number of historic winters. This is mapped to a demand series using the above formula including randomly sampled residuals. The ACS peak demand is then the median winter peak demand outcome across these 20,000 synthetic peak seasons.

The ACS methodology accounts for the most important factors that determine demand, and is the incumbent approach of the System Operator for tracking underlying changes in the peak demand level considering what is connected to the system but discounting weather effects. There are, however, reasons why alternatives might be considered. The Monte-Carlo simulation approach is at the complex end of possible options, which limits transparency. It also removes key temporal correlations affecting the distribution of peak demand that result from weather systems (a synthetic weather year that is assembled out of weeks from different real warmer/cooler or windier/calmer years might be deeply unrealistic) and there are question marks over the validity of drawing weather from different portions of the winter (for example, it may be unrealistic to treat, say, November and January, as interchangeable).

We also note that other statistics can be estimated using this same approach, such as the '1 in 20 year' peak demand statistic also produced by NGESO. It is important to note that this, or any other assessment of the form of the tails of the distribution of outcome peak demand, is necessarily tentative due to the limited number of historic years of data available.

III. Demand Series for Risk Calculations

It is widely recognised in demand modelling that historic demand is valuable in terms of forward-looking calculations (such as risk analysis), but cannot be used in its raw form due to underlying changes in what is connected to the system and how customers behave. Generally one of two approaches is taken to deal with this: (i) rescaling of a historic demand series, or (ii) simulation of winters using a model that estimates demand from covariates such as weather. NGESO's approach is a hybrid, in that it uses approach (ii) to estimate the ACS peak statistic, then uses the ACS statistic as the basis for approach (i).

A. Rescaling Historic Demand

This is perhaps the most common approach in practical resource adequacy calculations, and is used in calculations underpinning the GB Capacity Assessment Study [2] and in related research [3]. In these works, the demand series from a historic year is rescaled through multiplying all values by the ratio of the projected ACS peak in the year under study to the ACS peak for the historic year. [4] takes essentially the same approach using ACS peak – the authors confirm [private communication] that this is what they refer to by 'peak demand' in their rescaling. By contrast [5] rescales historic demand from each year to give the same estimated Loss of Load Expectation (LOLE), conditional on data from each historic year. This approach is seriously flawed, in that it removes information on variability of risk level between years due to differing weather conditions.

B. Generating Synthetic Demand Series

Use of synthetic demand series in practical risk calculations is less common, perhaps because of the complications involved in making this sufficiently realistic given the range of different human behavioural effects to be considered. One example of the use of synthetic/simulated demand is the California Independent System Operator (CAISO), which collects ratios between demand in each hour of the target year and its corresponding hour in each historic year [6]. These are then resampled to drive a stochastic simulation model. A related approach is suggested by [7], which uses 'blocks' of weather, each consisting of nine days of observations taken from the historic record, to create simulated winters. The aim is thus to maintain most of the temporal correlation in the record but produce a larger number of simulations than would be possible if historic winters were simply rescaled.

IV. An approach to rescaling demand

We present a rescaling approach in which, for a given target year, historic demand is rescaled to attempt to reflect the level of demand that would have resulted had the weather conditions from the historic year occurred with a chosen scenario of what is connected to the system. A probability distribution of annual peak demand can then be estimated, from which the median (the NGESO ACS peak) can be calculated.

A. Data

We make use of estimated hourly demand data for GB from [8] and MERRA1 reanalysis temperature data averaged over GB, weighted by population [9]. In particular, we estimate gross demand, i.e. adding back on an estimate of the demand met by renewables that are distribution-connected. The data set includes observations of gross demand between the 1st of January 1991 and and the 31st December 2015, and we make use of the data over this entire period. A time series of the daily peak in GB demand is shown in Fig. 1 both for the entire data set and zoomed in on the winter of 2014/15, the most recent available full winter. The annual sustained drop in demand is caused by the Christmas period where many businesses close and demand for electricity falls.

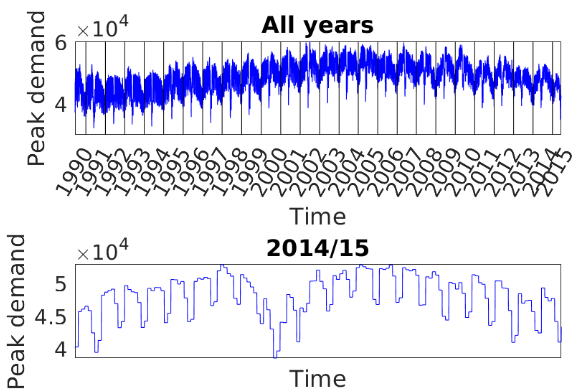

Fig. 1: Peak GB daily demand in the winter months for (i) all years in the data set (top), and (ii) the winter of 2014/15.

B. A linear model for demand

We present a Linear Regression model which relates important temporal and weather factors to daily peak electricity demand. Temperature is a key factor in electricity demand since low temperatures increase demand for heating. We therefore use a temperature variable specialised to reflect electricity demand. In general, due to insulation and behavioural aspects such as a lag in customers updating their heating settings, heat demand in GB depends on the temperature both at the current time and over the preceding hours or days. To deal with this, we use the 'effective temperature' approach taken by the National Grid in which a variable TE_t is defined that considers both the most recent observation and lagged observations from the previous 24 hours (see discussion starting at 11:07 in [10]). Let TA_t be the observed air temperature at hour t. Define the average air temperature over the last 4 observations to be

$$\mathrm{TO}_t = \frac{\mathrm{TA}_t + \mathrm{TA}_{t-1} + \mathrm{TA}_{t-2} + \mathrm{TA}_{t-3}}{4}. \tag{2}$$

The variable TE_t is then defined as

$$\mathrm{TE}_t = \frac{\mathrm{TO}_t + \mathrm{TE}_{t-24}}{2}. \tag{3}$$

Since we aim to estimate the daily peak demand, we take TE_t at 6pm on each day.

We consider the following predictor variables for the linear regression model:

- W_i - An indicator variable for each winter from 1991 to 2015 (here, for example, by 2005, we refer to the 2005/06 winter). The variable is set to one if the observation occurred in that winter and zero otherwise. The winter of 1990/91 is included in the analysis but is not assigned an indicator variable and, instead, is used as a reference dummy variable.
- Indicator variable $\mathrm{DOW_j}$ for the jth day of the week where DOW_1 corresponds to Sunday, DOW_2 to Monday etc. Saturday is excluded and therefore used as a reference indicator variable.
- Days since November 1st (DSN).
- Days since November 1st squared (DSN^2).
- For each winter i, a variable defined by TE_tW_i for all t, therefore consisting of TE_t if in year i and zero otherwise. This allows the dependence of demand on the variable TE_t to be different in each year.

The regression model is defined by

$$D_t = \alpha + \sum_{i=1990}^{N} (\beta_i W_{i,t} + \gamma_i TE_t W_{i,t}) + \sum_{j=1}^{6} \omega_j \mathrm{DOW_j} + \delta_1 \mathrm{DSN} + \delta_2 \mathrm{DSN}^2 + \epsilon \tag{4}$$

where N is the most recent available year, and α, $\beta_{1990}, ..., \beta_N, \gamma_{1990}, ..., \gamma_N, \omega_1, ..., \omega_4$, δ_1 and δ_2 are regression parameters, estimated via least squares.

It is useful to note that, whilst each of the TE_tW_i variables is non-Gaussian due to the existence of a large number of zeros, the effect of this is that the variable is essentially disregarded when W_i is zero. Therefore, this does not cause any problems with the normality assumption.

C. Assessing the fit of the model

We fit the regression model described above to all of the available data and obtain the parameters shown in Table I. All of the parameters are strongly significant ($p < 0.01$) other than β_{1994} and an adjusted R^2 value of 0.970 is achieved. There is a clear pattern in the β parameters in that the non weather-dependent year effect roughly follows the behaviour of the raw data (see Fig. 1), that is it starts off relatively low, peaks in the mid 2000's and subsequently declines. The γ parameters have a much higher degree of variability and there is a less clear trend over time. This large degree of variability is likely caused by confounding between the constant year effect and the weather-dependent year effect. The true underlying trend is likely to be far smoother. Applying a t-test on Pearson's Product Moment Correlation Coefficient yields a negative linear relationship with $p < 0.001$, suggesting that temperature-dependence increased over this period. This may be a result of increased demand for electric heating, which is expected to increase the sensitivity of demand to weather in the coming decades [4], [11]. Increases in the population are also likely to have an impact [12]. The day of the week parameters ($\omega_1, ..., \omega_4$) reflect that demand tends to

TABLE I: Regression parameters for the linear model when fitted to daily peak demand between January 1st 1990 and December 31st 2015.

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	43255.4	γ_{1990}	-445.3	D_{Sun}	-711.3
β_{1991}	-664.6	γ_{1991}	-382.8	D_{Mon}	6707.9
β_{1992}	-1113.1	γ_{1992}	-330.6	D_{Tue}	6734.3
β_{1993}	-583.9	γ_{1993}	-338.3	D_{Wed}	6632.4
β_{1994}	92.5	γ_{1994}	-320.3	D_{Thu}	6437.5
β_{1995}	1742.7	γ_{1995}	-437.3	D_{Fri}	4919.9
β_{1996}	2253.1	γ_{1996}	-391.7	δ_1	57.9
β_{1997}	2630.6	γ_{1997}	-358.3	δ_2	-0.6
β_{1998}	3390.5	γ_{1998}	-382.1		
β_{1999}	4146.6	γ_{1999}	-351.6		
β_{2000}	5648.0	γ_{2000}	-390.8		
β_{2001}	6487.2	γ_{2001}	-395.5		
β_{2002}	7861.1	γ_{2002}	-459.3		
β_{2003}	8487.0	γ_{2003}	-463.1		
β_{2004}	8975.7	γ_{2004}	-500.7		
β_{2005}	8846.0	γ_{2005}	-512.5		
β_{2006}	6947.7	γ_{2006}	-376.3		
β_{2007}	7969.5	γ_{2007}	-446.5		
β_{2008}	6518.3	γ_{2008}	-517.2		
β_{2009}	6475.2	γ_{2009}	-559.1		
β_{2010}	6528.2	γ_{2010}	-558.5		
β_{2011}	4879.7	γ_{2011}	-466.7		
β_{2012}	5079.0	γ_{2012}	-588.4		
β_{2013}	3434.3	γ_{2013}	-470.7		
β_{2014}	3501.1	γ_{2014}	-506.6		
β_{2015}	1636.0	γ_{2015}	-415.0		

be lower at weekends and δ_1 and δ_2 reflect a concave quadratic relationship between the number of days since November and the level of demand.

It is important to check that the model provides a good fit to the data and is not subject to major biases. To check whether this is the case, we carry out a number of diagnostic checks. The first check considers the mean and variance of the residuals over time. These are shown in Fig. 2, where the blue dots show the residual of the model on each day and the black line the moving mean, averaged over 150 observations (roughly one winter) at a time. Here, the mean of the residuals appears to stay roughly constant, whilst the variance appears to be higher at the beginning and end of the data set. We therefore have evidence of heteroscedasticity. To attempt to understand this, it is worth considering the variability of the demand over the time. Generally, demand is more variable towards the beginning of the data set and declines with time. This may explain the relatively high residuals at the beginning of the data set. Towards the end of the data set, variability in demand is relatively low and a likely explanation is a reduction in the predictability of weather-dependent and non weather-dependent demand.

Another important diagnostic considers the effect of the size of the demand on the residuals. Since we are interested in yearly peaks, when demand is particularly high, it is important that the model is able to reproduce these accurately. Observed and fitted daily peak demand are plotted against each other in Fig. 3. The larger green points represent yearly peaks. Here, there is no clear evidence that the model is impacted by the level of demand since the observed values appear to be scattered around the $x = y$ line in a constant fashion. This suggests that the model is fit for the purpose of reconstructing demand when it is high. It is perhaps notable that the yearly peaks tend to lie above the $x = y$ line. This, however, is due to the fact that the yearly peak in demand is more likely to

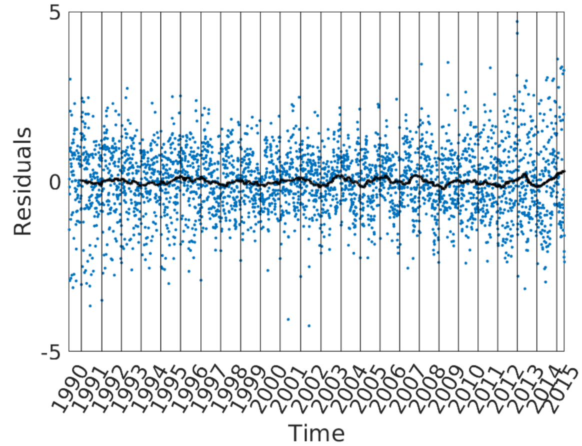

Fig. 2: Residuals of the regression model as a function of time. The black line is a moving average over 150 observations (roughly a winter's worth).

occur when the residual is positive (i.e. when there are other positive effects modelled as random).

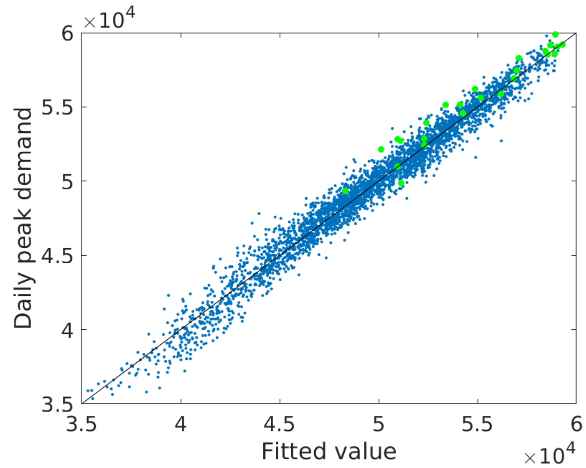

Fig. 3: Scatterplot showing fitted vs observed daily peak demand. The large green points highlight the yearly peaks and the diagonal line shows where the two would be equal.

D. Rescaling demand

We present a simple approach to rescaling historic demand using the model defined in section IV-B. The model breaks down demand into a number of components, some of which are year-specific and others which are not. In our model, we have two modelled year specific effects for an observation in year i: a non-weather dependent effect represented by β_i, and a weather dependent effect represented by γ_i. In addition, since the variance of the residuals varies by year, we treat this as an additional year effect. The approach to rescaling is to remove the year specific effects of the year in which the demand was observed and to replace them with those of the target year. To rescale the residuals, we define R_i to be the mean absolute error of the residuals in year i. For a given level of demand

D_t at time t, which falls in winter i, the demand rescaled to winter j is given by

$$\tilde{D}_t = D_t - \beta_i + \beta_j - (\gamma_i - \gamma_j)TE_t + (R_j - R_i)\epsilon_t, \quad (5)$$

where ϵ_t is the residual of the model at time t. Effectively, this process replaces the year effects of the year in which the demand was observed and replaces it with that of the target year, whilst rescaling the residuals to reflect differences in the size of random effects at different points in time. Observed demand over the entire data set, rescaled to three different years, is shown in Fig. 4. Here, the largest effect is typically to shift the entire demand profile upwards or downwards, but there is also a change in the variability of the demand caused largely by different sensitivities to temperature in different years.

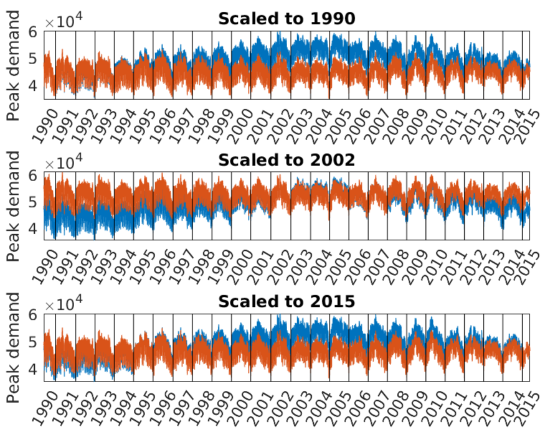

Fig. 4: Original (blue) and rescaled (red) demand for three different target years.

E. Probabilistic forecasting

We now demonstrate the use of the demand rescaling methodology to provide a basis with which to produce probabilistic forecasts for the annual peak in electricity demand. The approach taken is to rescale demand from historic years, record the annual peaks in each year, and use them to fit a Gaussian probabilistic forecast distribution. The median of that distribution is then analogous to NG's ACS statistic. In order to rescale historic demand to a target year j, estimated values of the regression parameters β_j and γ_j are required. In addition, we require an estimate of the mean absolute error of the residuals R_j. These three values cannot be estimated from the data and therefore must be selected in advance.

A probabilistic forecast is produced as follows:

1) For the target year j, select the values of β_j and γ_j, and R_j. We refer to these as the Target Year Parameters (TYP).
2) Use the demand rescaling approach to rescale demand in historic winters to the target year and record the maximum value for each one.
3) Fit a Gaussian distribution to the peak rescaled demand over historic years. This distribution is then used as a probabilistic forecast.

The requirement to estimate the TYPs in advance is similar in nature to the NG's requirement for an estimate of baseline demand under their ACS methodology. Under that methodology, technological and economic intelligence is typically used, though NG does not provide further details of this [1]. We consider the methodology used to select the TYPs to be beyond the scope of this paper but note that similar approaches to those used by NG are likely to be appropriate. Instead, we demonstrate the probabilistic forecasting approach under an idealised setting in which the TYPs are taken to be the fitted values from the regression mode for a given historic year. This approach, which we call the *Idealised* case, is not, of course, how the method would be applied in forward-looking calculations for future years, but it suffices for demonstration of the estimation process. Additionally, we consider a second, alternative, approach to the Idealised case, in which the TYPs are set to $\beta_j = \beta_{j-1}$, $\gamma_j = \gamma_{j-1}$, and $R_j = R_{j-1}$, that is to the regression parameters and mean absolute error of the residuals from the previous winter. We refer to this as the *Persistence* approach and note that this approach can be carried out in practice, though may miss important interannual changes in underlying demand and weather sensitivity.

The forecasts and outcomes for the Idealised and Persistence cases are visualised in Fig. 5 where the blue lines correspond to the mean (solid blue line) and quantiles (dashed: 2.5% - 97.5%, dotted: 0.56% - 99.5%) of the forecast distribution and the red starred line the outcomes. The green line shows the National Grid's ACS statistic for the years in which it is available. Notably, the median in the Idealised case is similar to the ACS statistic. Here, the outcomes appear to be fairly consistent with the forecasts, typically falling within the quantiles of the forecasts.

It is useful to formally assess the probabilistic skill of the forecasts formed under the rescaling approach. To do this, we compare the skill of the forecasts with a benchmark model produced in the same way but without rescaling the demand first. To assess the skill of the forecasts, we make use of the Ignorance score (often known as the Logarithmic Score) [13], [14] which is defined as

$$S(p(Y)) = -\log_2(p(Y)) \quad (6)$$

where p is the forecast distribution and Y is the outcome. The score rewards forecasts that place more probability on the outcome and is *proper*, meaning that, on average, a perfect probabilistic forecast (i.e. one that coincides with the true probability) is always favoured over any other [15].

The relative Ignorance between our forecasts and the benchmark model is given by

$$\mathrm{IGN}_{\mathrm{rel}} = S(p(Y)) - S(p_b(Y)), \quad (7)$$

where p and p_b are the forecasts from our rescaling approach and the benchmark model, respectively. If the relative ignorance is negative, the rescaling approach places more probability on the outcome than the benchmark model, on average. The mean relative ignorance of the model under the Idealised and Persistence approaches are shown in table II

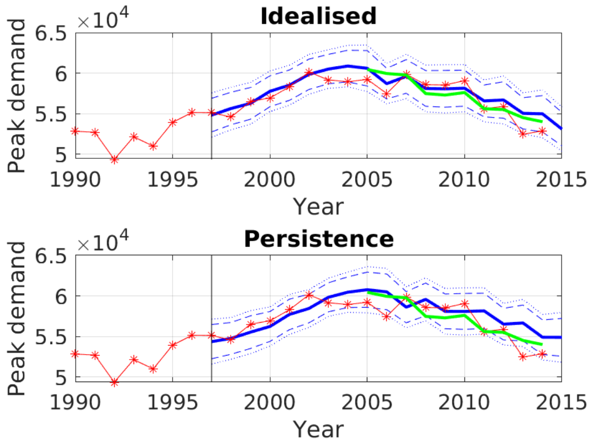

Fig. 5: Probabilistic forecasts and outcomes as a function of time under the Idealised approach (top) and the Persistence approach (bottom). The blue solid line is the mean of the forecast distribution, whilst the blue dashed and dotted lines contain the middle 95% and 99% of the distribution, respectively. The red starred line corresponds to the outcomes and the green line shows the National Grid's ACS statistic where available. Note that no forecast is produced for the years prior to 1997 since we deem that not enough previous data are available at this point.

TABLE II: Mean Ignorance for the Idealised and Persistence cases.

Idealised	Persistence
-1.50(-2.31,-0.62)	-0.40(-1.58,1.66)

along with 95 percent bootstrap resampling intervals. Here, in both cases, the rescaling approach outperforms the benchmark model, although, for the persistence approach, the difference is not significant since zero lies within the confidence interval. In practice, however, we believe that it should be possible to set the Target Year Parameters such that the forecast performance falls somewhere between that of the Idealised approach and the Persistence approach.

V. Discussion

In this paper, we have proposed a rescaling approach to historic electricity demand and a framework for producing probabilistic forecasts of peak annual demand. As noted in the introduction, there are multiple specific applications of different parts of our rescaling and forecasting approach, including performing forward-looking risk calculations, making probabilistic forecasts of peak demand in future seasons, and estimating statistics such as ACS peak. It is important to recognise that the approach consists of multiple components that can be used independently, or replaced by analogous components from another source. For instance, one could replace our regression model for daily peak demand with NGESO's – this would provide a route, for instance, to estimating ACS peak using NGESO's demand reconstruction formula by direct means based on entire historic winters rather than by MC simulation of synthetic winters.

One advantage of the work presented here is that it uses data that are widely available for GB (and we would anticipate analogous data being available for other systems). However, it could be developed further to make more efficient use of data or reduce concerns about confounding between variables. We hope that this will contribute to increased discussion in the community and literature of methods for constructing demand series for forward-looking risk calculations – this is clearly a vital input to such models, and is a statistically subtle matter, but has received limited attention from the relevant communities of research and practice.

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