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CIGRE US National Committee
2018 Grid of the Future Symposium

Weather-Normalized Demand Analytics

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SUMMARY

Traditional electricity systems are designed to provide unidirectional power flow from generators to consumers via the transmission and distribution networks. However, with the increased use of weather-sensitive renewables, energy storage, and demand side response, electricity networks are becoming increasingly complex. Understanding the changing behavior of electricity consumers requires new analytical solutions that account for this complexity, including the increased sensitivity of transmission and distribution systems to weather events.

Established long-term demand forecasts rely on a combination of historical records of demand and socio-economic models broadly describing changes in population, consumer behavior, and the adoption of new technologies (e.g. rooftop PV installations, or electric cars). Underpinning these future scenarios is a baseline extrapolation of current weather-corrected demand trends. Traditionally this analysis is conducted on a network wide level, which does not allow for geographical variations in the weather, nor the varied behavior of consumers at different network connection points. This makes it difficult to determine the long-term baseline demand at a local level, and thus the level of investment required in different parts of the network.

We present here the results of an original study led by Digital Engineering (DE), in which the effect of weather patterns and consumer behavior on peak electricity demand were analysed at the level of individual substations. The described method was applied to a distribution network managed by SP Energy Networks (SPEN), based in the UK. The results of this study are being used by SPEN to accurately determine weather-normalized long-term trends in the local demand observed at approximately 400 primary (MV) substations within their network. The corrected trends showed significant geographical variation, as well as differences between substations serving residential or commercial/industrial consumers. This was due to varying local weather conditions as well as the wide range of response characteristics of different consumer types.

KEYWORDS

Demand modelling; peak load; consumer behavior; long-term trends; embedded wind and solar generation; renewables; climate sensitivity; clustering; classification algorithms;

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DATA

Weather Data

Digital Engineering (DE)'s weather modelling suite was used to generate high-resolution regional weather data for SP Energy Networks (SPEN)'s Scottish licence area, utilizing the WRF-ARW numerical weather prediction model [1]. This model reconstructs the historical state of the atmosphere, capturing the evolving dynamics of weather systems as well as the impact of complex physical processes such as clouds, precipitation, turbulence, solar radiation, and surface-atmosphere interactions. NCEP Climate Forecast System data [2] was used to provide boundary conditions for the regional weather simulations. Time-series of all required weather variables were extracted at the location of each substation at high temporal and spatial resolution over a ten-year period, to coincide with data supplied by SPEN.

Transformer Flow Data

Transformer flow data was provided by SPEN for approximately 400 primary (MV) substations on their network, serving a total of nearly 2 million electricity consumers. This data consisted of various data streams recorded at each substation for a 10-year period between the UK financial year beginning in April 2007 to that ending in March 2017. The measured values of real power (expressed in MW) and reactive power (expressed in MVAr) flowing through the transformer breakers at each substation were used to calculate the apparent power flow (expressed in MVA) through the site.

Embedded Generation Data

Embedded generation data was provided by SPEN on a half-hourly basis and factored into the apparent power flow. Figure 1 shows a year of transformer flow and embedded generation data for one example substation.

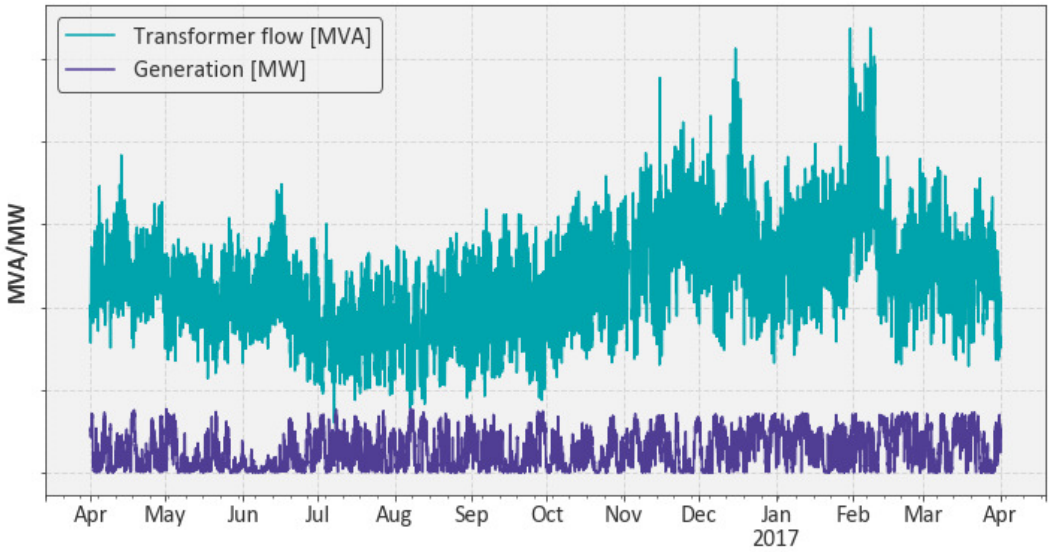

Figure 1: Embedded generation and transformer flow data for one example substation

METHODOLOGY

Data Pre-Processing

To convert load and generation data to electricity demand at each substation, the data were pre-processed and filtered. This included data coverage and quality checks, as well as correcting for negative load polarity (negative readings not due to embedded generation). The load and embedded generation data were then combined to determine the demand at each substation. Following this, the demand data were filtered using a set of adaptive moving filters tuned to the data under examination.

As very different demand behaviors can be found from substation to substation, two stages of outlier data filtering were applied independently:

1. A global outlier rejection filter removed extreme demand values at any time of day or year that were far outside usual bounds.

2. A local outlier rejection filter removed demand values that were considered "anomalous" relative to a reference profile constructed using the observed diurnal, weekly, monthly and annual cycles.

In general, both filtering approaches were conservative, to avoid the removal of moderately unusual periods of demand variability that may nevertheless be a consequence of real underlying changes in consumer behavior.

The two processes are shown in Figure 2 for an example site. The area highlighted in red contains global outliers (greater than four standard deviations from the mean). Areas highlighted in purple contain local outliers, identified according to the time of day, day of week and month of year.

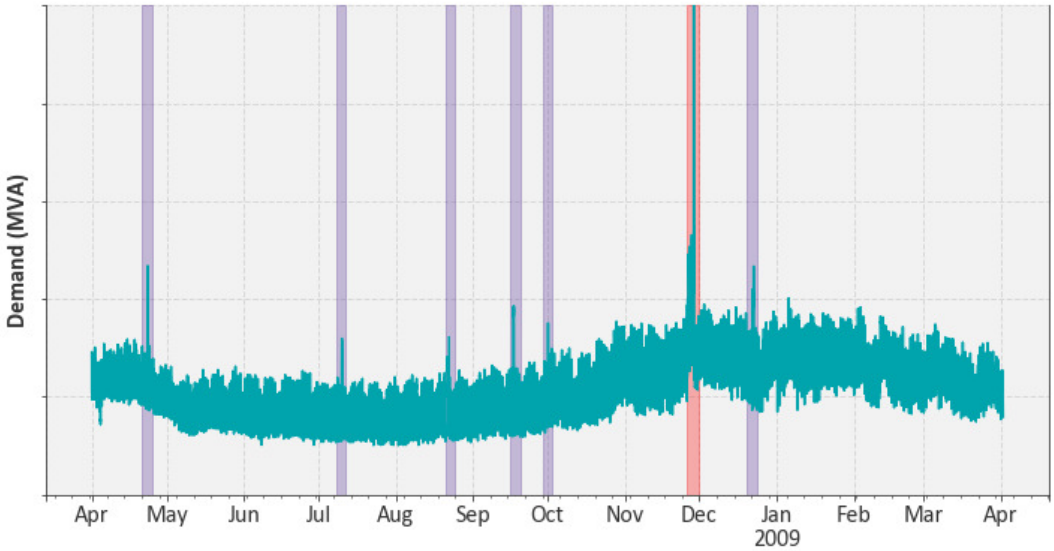

Figure 2: Global (red) and local (purple) outlier rejection for an example substation

DEMAND MODELLING

The demand model developed by DE applies an advanced non-linear, multi-variate regression analysis to construct a model of demand based on both weather and non-weather variables. To avoid over-fitting, the functions used to train the model are constrained to be smoothly varying over the range of the dependent variables. In addition, the model results at each substation were calculated using data from all other substations. The model is thus never trained using the same data as is used to evaluate the model performance.

In this study, the daily-mean demand was simulated using the following variables:

Effective Temperature (TE): Atmospheric temperature is a major driver of electricity demand variability. The demand response however tends to lag behind atmospheric temperature changes due to delays in the response of appliances within buildings [3] [4]. To account for this lag, an *effective temperature* based on the daily mean temperature and the effective temperature from the previous day was defined. This uses the functional form adopted by the UK's National Grid [3][4].

Cooling Power of Wind (CPW): Wind speed has a smaller but still significant effect on electricity demand by introducing cooling draughts when the temperature is low. Again, the approach of the UK's National Grid is followed, where the *cooling power of the wind* is defined based on the square root of wind speed and the atmospheric temperature deficit below a given threshold, above which wind gusts no longer have a cooling effect [3][4].

Clear-Sky Global Horizontal Irradiance (GHI): Another major influence on electricity demand is the availability of sunlight. On dark days more lighting is used and thus more electricity. This effect is represented by the *clear-sky global horizontal irradiance*, which provides a reliable proxy for the daylight expected on each calendar day. This does not depend on the local weather conditions (e.g. cloud cover) and is therefore entirely predictable.

Day of the Week (DAY): Consumer behavior can vary significantly depending on the day of the week, particularly from weekdays to weekends.

Additional weather-derived variables representing the effect of cloud cover (including the surface downward irradiance deficit, relative humidity and precipitation rate) were also considered, but did not lead to significantly improved model skill at the level of individual substations. Figure 3 shows a comparison between the modeled and observed demand data for an example site.

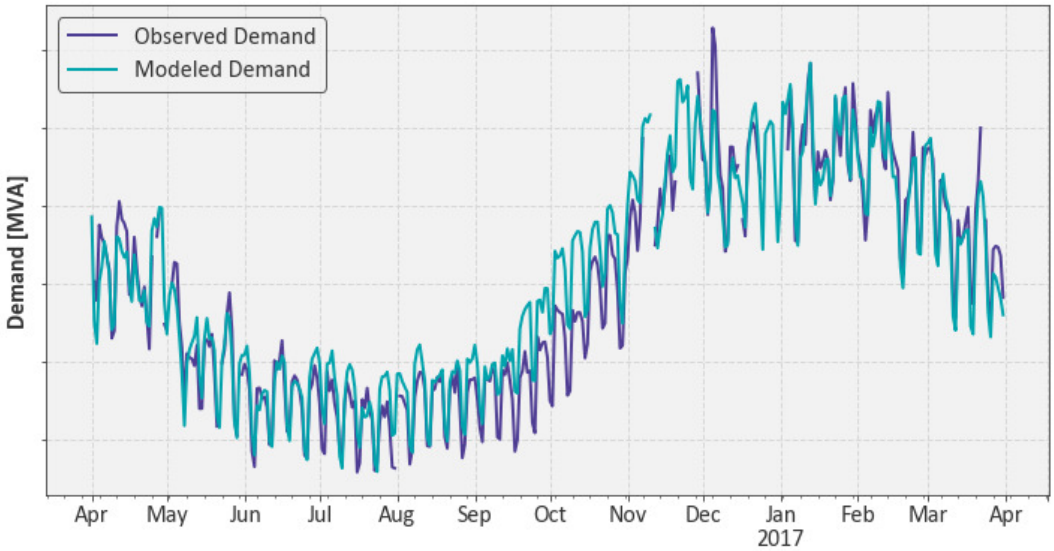

Figure 3: Observed and modeled daily-mean demand data for an example substation

Consumer-Type Clustering

Considerable differences were observed in the patterns of demand at different substations. To account for this range of observed consumer behaviors, DE's demand model was fitted separately to different sub-groups of substation data. This reduced the influence of noisy data on the results while permitting the model flexibility to distinguish between different consumer behaviours. These groups were determined using a clustering algorithm, trained using parameters describing the sensitivity of demand to the four training variables defined above. These differences may be driven by the proportion of different types of connected consumer from substation to substation. For example, rural substations supplying a high proportion of residential consumers typically show high sensitivity to the ambient environmental conditions; whereas those supplying a high proportion of industrial or commercial consumers typically exhibit greatly reduced demand at weekends.

Weather Correction Factors

Weather Correction Factors (WCFs) quantify the degree to which the annual peak demand for a given substation and year is influenced by the ambient environmental conditions. The WCF is equal to the percentage change required to convert the annual peak demand to a baseline value. This baseline value is calculated as the average annual peak demand modelled using all 10 years of weather data.

For each available year and substation, a simulated peak demand value as well as a baseline value and corresponding WCF is calculated. Re-training the model using each year of data independently allows the demand response characteristics of each cluster of substations to evolve over time. For example, increased uptake of efficient lighting and better insulation may reduce the sensitivity of demand to environmental factors, as could the connection of non-residential consumers. New consumer connections lead to step changes in demand as well as a change in the sensitivity of demand to the weather. In addition, the quality and coverage of the metered data has improved noticeably over time, and so re-training also allows for more accurate model results in later years.

RESULTS

WCF values were calculated for all primaries and years for which adequate demand data was available. As shown in Figure 4, these values were found to vary significantly from year to year and from substation to substation. Positive WCF values usually correspond to warm winters, where peak demand is lower than usual and needs to be corrected upwards. Negative WCF values usually correspond to cold winters, where peak demand is higher than usual and needs to be corrected downwards. Substations that show little sensitivity to the weather show consistently small WCF values for all years, whereas those with a large sensitivity fluctuate between large positive and large negative correction factors.

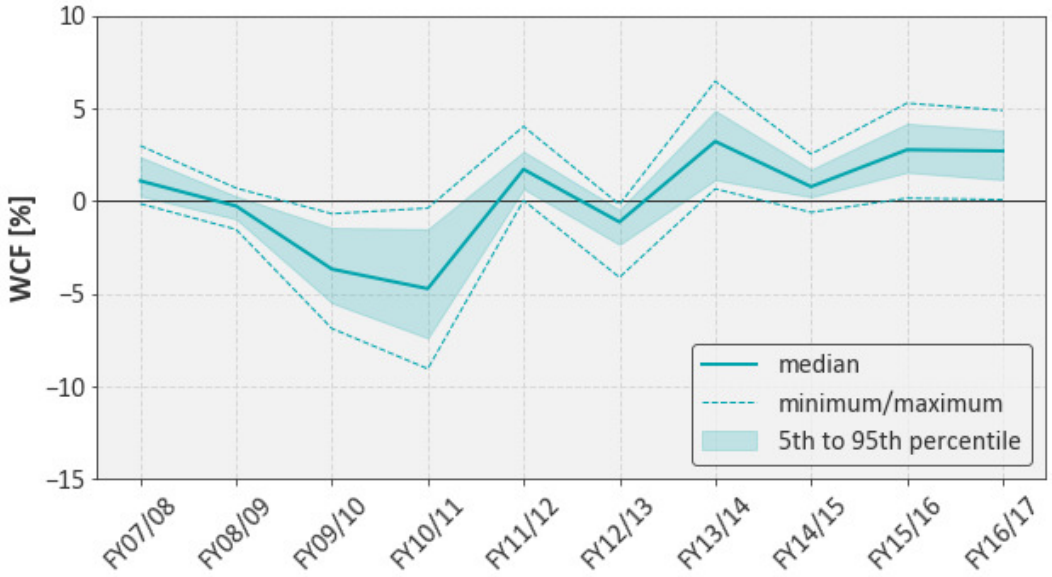

Figure 4: Median and distribution of WCFs for all substations, shown for each financial year.

The financial year 2010/11 saw a prolonged winter cold spell in the UK and the coldest December in 100 years. As shown by the median line in Figure 4, half of the substations considered showed a peak demand at least 4.7% higher than usual (and so need to be corrected *down* by 4.7%). However, individual substations show very different sensitivity to the weather (minimum/maximum lines in Figure 4), and so while the most sensitive substation requires a -9.0% correction to peak demand, the least sensitive substation requires only a -0.4% correction.

To make optimal planning decisions, distribution network operators like SPEN need to assess the rate at which the weather-corrected peak demand is changing at individual substations, accounting for the way in which consumer behavior is evolving. Figure 5 demonstrates the application of DE's model to an example substation. The weather-corrected peak demand for each year is shown relative to the observed (metered) demand. Cold years (such as financial years 2009/10 and 2010/11) are corrected down and warm years (such as 2013/14 onwards) are corrected upwards. Applying these corrections reduces the weather-driven variability in observed annual peak demand, revealing more accurately the underlying trend.

The shaded area in Figure 5 (and Figure 6) represents the uncertainty on the weather-corrected prediction. Although a wide range of weather conditions were observed over the 10-year period considered, it is possible that future weather events could fall outside of this range, and so additional safety margins should be assumed in practice.

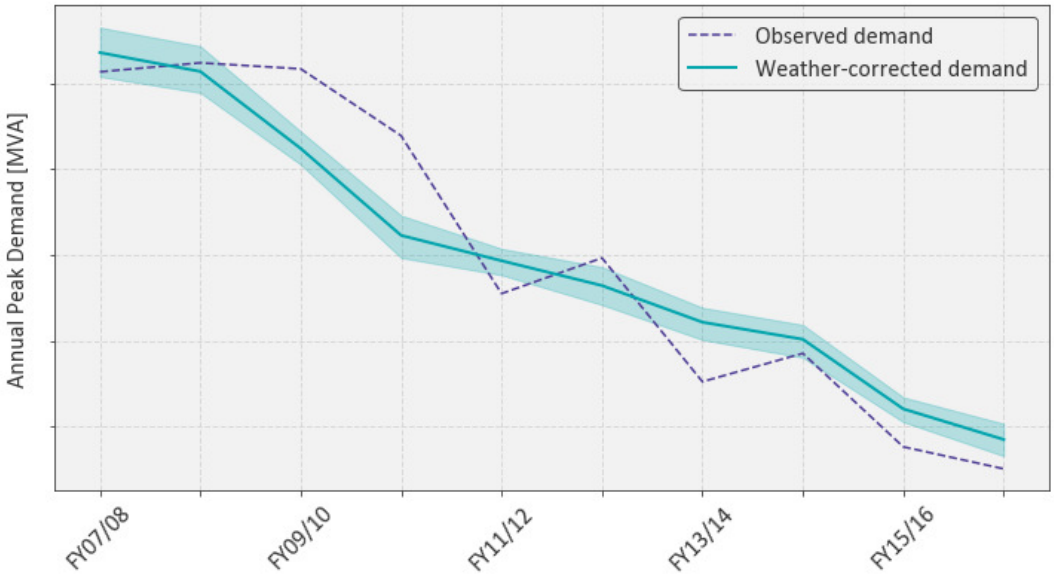

Figure 5 Observed and weather-corrected annual peak demand at an example substation.

The substation-specific weather correction factors are being used by SPEN to determine baseline future projections of demand at the level of individual substations. To illustrate the importance of this analysis at a substation-specific level, Figure 6 shows another example of observed and weather-corrected peak demand. In contrast to that shown in Figure 5, the weather-corrected demand at this substation dropped initially, only to rise steadily since financial year 2011/12. This trend would be lost in the year-to-year weather-driven variability if the substation-specific WCF was not applied.

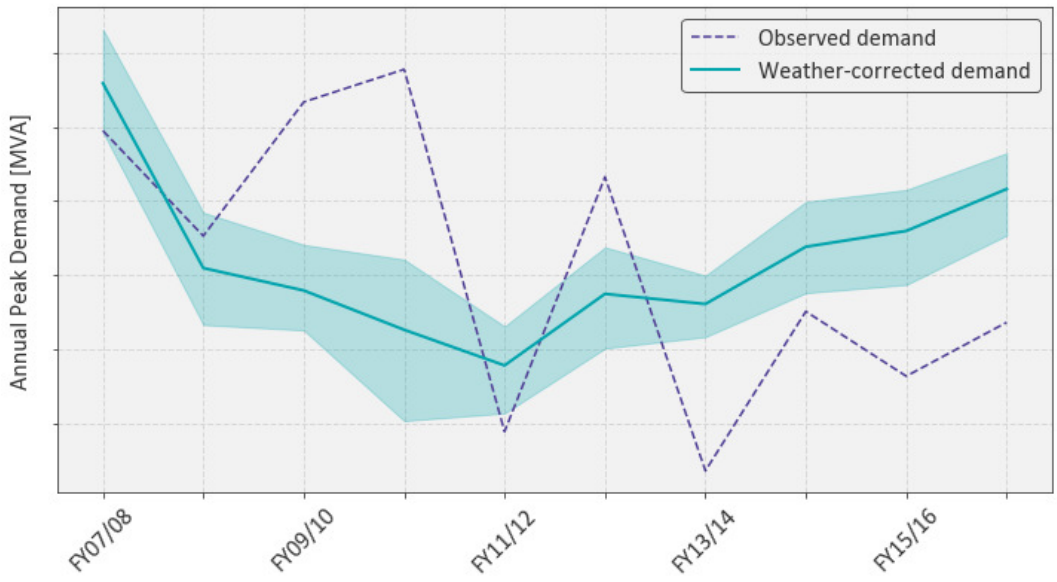

Figure 6: Observed and weather-corrected annual peak demand at a substation with increasing demand.

The weather-corrected trends at a substation level show wide variability, and this is true even within residential and non-residential sub-groups. This is perhaps not surprising, as it is quite possible for two commercial areas to experience opposite long-term trends, should businesses in one area be expanding and in the other contracting. Likewise, a burgeoning new-build residential area may experience growth in demand as new households are connected, while an established residential area experiences a reduction in demand due to increased energy efficiency. More research is required to fully assess the many drivers of consumer demand and accurately quantify their impacts at a local level.

CONCLUSIONS

This paper has presented results of a novel application combining data from advanced numerical weather simulations with power system data from SP Energy Networks (SPEN), a UK electricity distribution network operator. This work was commissioned to help SPEN understand changing consumer behavior trends at the level of individual MV substations on their network.

By extrapolating the trends of peak demand forward in time, SPEN are using these localized weather-corrected trends as a baseline from which the impact of new technologies such as electric vehicles and battery storage, as well as future economic and policy scenarios, can be added. Localized estimates of demand trends will help SPEN target investments in their network more efficiently, and to avoid or defer unnecessary network upgrades.

Further research will focus on improved understanding of the demographic and socio-economic drivers of demand variability, and their impact on long-term peak demand trends. This will allow for more advanced classification algorithms and thus a greater understanding of future changes in demand associated with specific consumer groups.

ACKNOWLEDGEMENTS

This work was conducted in partnership with SPEN, funded through the UK's Office of Gas and Electricity Market's Network Innovation Allowance. NIA__SPEN0022: *Weather Normalised Demand Analytics (WaNDA)*.

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