ANALYSIS OF LOCAL DEMAND TRENDS AND FORECASTING THROUGH WEATHER CORRECTION AND BENEFIT TO DSO TRANSISTION AND MICROGRIDS

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ABSTRACT

This paper presents the methodology for separating the effect of weather patterns and customer behaviour on peak demand at a local, primary substation level. It uses real data from SP Energy Networks (SPEN), a UK Distribution Network Operator (DNO), and a demand model developed by Digital Engineering Limited.

The innovation presented in this paper is the use of Numerical Weather Prediction Models and Machine Learning techniques to undertake weather correction at a local level. This has benefits for network planning, flexibility in distribution networks and the development of microgrids.

INTRODUCTION

Traditionally, distribution networks have been passive, designed around centralized power generation with the unique direction of electricity flow from the transmission system to the customers. However, transitioning to low carbon future changes the way electricity is being produced and consumed. Traditional power stations, such as large coal power plants are being replaced with the low carbon technologies (LCT), such as wind and solar, as well as electric storage, connected to lower distribution levels. Hence, distribution networks have become active and complexity has started to appear due to reverse power flows, voltage rise and constraints, which introduced significant network issues.

Moreover, in order to meet the climate change and energy targets, the electrification of heat and transport has become essential and has been emphasized by the recent announcement by the UK Government to ban on the sale of new petrol and diesel vehicles from 2040, which will introduce an increasing reliance on the electricity networks.

In order to facilitate the variable nature of distributed generation output and unpredictable loads and the transition to a low carbon future in a cost effective way, the potential of the existing electrical infrastructure should be maximized. This could only be achievable if Distribution Network Operator's (DNOs) have a more active role in the network operation by extending the current role of DNOs to that of Distribution System Operators (DSOs) [1].

Distribution systems with DERs which can operate in an islanded mode can be considered as microgrids [2]. The islanded mode for a particular Grid Supply Point (GSP) can occur during a grid outage or if there is no available interconnection and there is a loss of infeed from the upstream system. This is particularly beneficial in the areas rich in terms of wind yield and land but with low population density and therefore low electrical demand.

In order to operate the future DSO model and future microgrids and to accurately determine the volume, type and location of the future network investments, accurate forecasting of local demand has become one of the main challenges for future networks.

Load Forecasting

To plan the network efficiently and effectively, greater understanding of local demand trends is required. Load forecasts at local substations are based upon substations flows adjusted for embedded generation on the network. However, there is no regular adjustment made for the effect of local weather upon demand at each individual substation. If a weather adjustment is made, it is generally based upon a simplistic, high level model using temperature over a wide area [3].

Therefore, it is extremely difficult to separate out the effect of weather and other customer behaviour upon demand such as increased number of electric cars being charged, energy efficiency schemes, closure of industrial premises, etc. This results in planning and investment uncertainty.

Annual peak demand is used in network planning as it is a measure of the maximum loading that the network has to cope with. Year-on-year peak demand variability is a function of the following variables:

f(weather, underlying trends, generation)
where: underlying trend consists of efficiency, growth and churn.

Given that generation output levels are known, quantifying weather driven demand can expose underlying trends. This then enables the creation of scenarios using a range of weather and generation inputs and provides a methodology to measure the demand sensitivity of customers at individual substations to each variable.

This paper presents the methodology for separating the effect of weather patterns and customer behaviour on peak demand for distribution networks. Weather Correction Factors (WCFs) are used to describe the effect of weather upon demand and therefore measure the annual percentage change between the observed peak demand and the weather-normalised peak demand at a substation level. Substations show correction factors of +/-5 % up to +/-10 % dependent on weather experienced and local customer sensitivity to weather.

DESCRIPTION OF THE NETWORK AND DATA

In the proof of concept phase of the project, thirteen 33/11 kV primary substations were analysed. They were selected based on their variation in location, type of customers and level of embedded generation connected. The substations were grouped by the GSPs that they were connected to. Fig 1 shows the spread of the proof of concept primary substations across central Scotland.

Fig. 1: Map with assessed primary substations represented as purple dots

In the production phase of the project, the analysis was expanded to cover almost 400 primary substations across Scotland.

Network Data

Transformer flow data was provided by SPEN at primary substation level for each of the primary substations studied. This data consisted of power and current flows recorded at the primary over 10 years.

To accurately capture the load at each primary substation, the embedded generation feeding into the primary substation had to be netted off. Embedded generation was aggregated for each primary substation and added to the transformer flow data which is shown in Fig. 2.

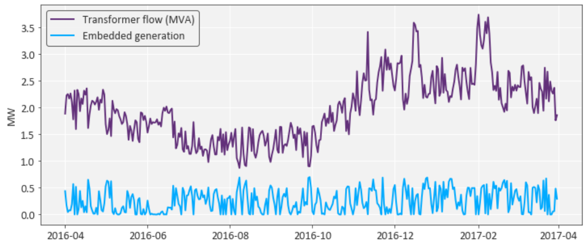

Fig. 2: Example of embedded generation with transformer flow

This data was then filtered to remove erroneous values and, in the production phase of the project, substations with similar characteristics were clustered to improve the quality of the data available to the model, reduce data gaps and prevent the overfitting of the demand model.

Weather Data

Weather data was generated by using a Numerical Weather Prediction (NWP) model. 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.

The modelled data was run at 30 minute intervals over 10 years and was broken into 1 km squares prior to being mapped to substations.

METHODOLOGY & RESULTS

Overview of Stages

There are 7 key stages in the methodology:

- Simulate historical weather conditions across Scotland using Numerical Weather Prediction.
- Break into 1 km squares and determine values of key weather variables.
- Map local weather to substations, weighted by customer density.
- Filter and standardise the data. Use clustering techniques to group similar data.
- Train machine learning algorithms against measured demand, creating weather vs. demand model.
- Run historic weather data through model to create ‘what if’ scenarios.
- Calculate Weather Correction Factors (WCFs) per substation.

Hypotheses

Given that it is a more intensive task than a simple system level correction, four hypotheses were set out which, if proven, would provide a positive benefits case for the use of the methodology in network planning and microgrid development.

- Weather is masking demand trends.
- There is a clear relationship between demand and multiple weather variables.
- The effect of weather conditions at local substations will be different.
- The variability of weather driven demand at a local level is significant.

These are explored in detail below.

Weather is masking demand trends

A chart which shows the raw power flows (blue, thin) and weather corrected power flows (green, thick) at an example substation is shown in Fig. 3.

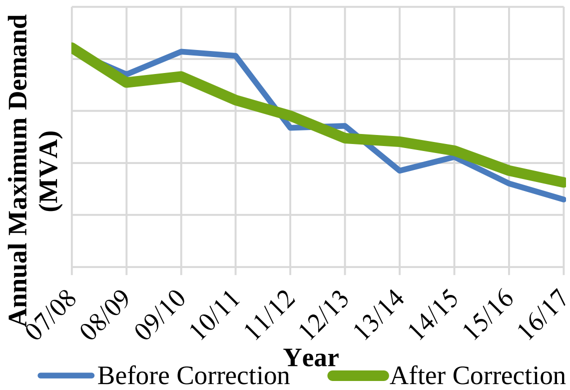

Fig. 3: Corrected demand trend at example substation

Taking the years 07/08 till 10/11, the raw power flows indicate that demand is steady but it can be seen from the weather corrected flows that the underlying trend is falling. This could lead to suboptimal planning decisions. Conversely, from 13/14 till 16/17 (a period of mild winters) the underlying trend is higher than expected from the raw power flows and, for certain substations, could result in the overloading of assets should a cold winter hit. This clearly shows that the masking effect of weather and potential consequences at local substations.

This is relevant to microgrid development when considering the potential balancing issues between load and generation and the asset ratings required to achieve this.

There is a clear relationship between demand and multiple weather variables

Existing correction techniques tend to rely upon temperature as an explanatory variable [4]. It is possible to easily extract many other variables from the NWP model and factor them into the demand model.

Each of weather variables was analysed to understand their explanatory power in the model. The variables that explained the most variation were effective temperature (TE), global horizontal irradiance (GHI) and the cooling power of the wind (CPW). Relative humidity (RH) was tested as a simply proxy for precipitation but was found to have no significant explanatory power.

The effect of weather conditions at local substations will be different

It was found that, for the 13 sites in the proof of concept phase, the sensitivity of customer's demand to weather conditions was variable at a local level. When considering the variability of weather across multiple substations, effective temperature can be shown to be close to linear over a small range of temperatures for a given substation. When looking at effective temperature only, it was found that customer sensitivity ranged from 1.4 % to 4.8 % change in demand per degree Celsius. This is due to different types of customers reacting differently to the same set of weather conditions e.g. industrial customers tend to have a demand profile that is more independent of demand than domestic customers. The range of sensitivities for substations in the proof of concept phase is given in Fig. 4.

Substation Group	Number of customers	Sensitivity (%/C)
East Coast (Rural)	2,500	-2.9 %
	6,000	-2.2 %
	2,000	-3.4 %
	1,500	-4.8 %
	1,000	-3.0 %
Glasgow (Urban)	9,000	-2.5 %
	6,500	-3.4 %
	7,000	-3.4 %
	15,000	-2.4 %
West Coast (Mixed)	8,500	-2.5 %
	4,500	-1.4 %
	11,000	-2.9 %
	8,000	-2.6 %

Fig. 4: Customer sensitivity to changes in effective temperature

In the production phase of the project where all 400 primaries were analysed, clustering was used to categorise customer type and bundle similar substations together. There were two key variables that appeared to describe the majority of the variation: strength of the weekly cycle (i.e. ratio of weekday peak demand to weekend peak demand) and the sensitivity of customers to effective temperature. The clusters are shown in Fig. 5.

Furthermore, it can be seen that different substations in the Scottish network are subjected to different weather conditions when they experience their peak demand (in part due to the fact that not every substation sees its peak demand on the same day and in part due to geographic location). This introduces further variability which is captured by the model that is not considered by traditional techniques. By analysing the effective temperatures at the 10 highest demand peaks in a year, it was found that average temperature variations seen at substations on each of Scotland's coasts at peak demand could be as great as 1 °C.

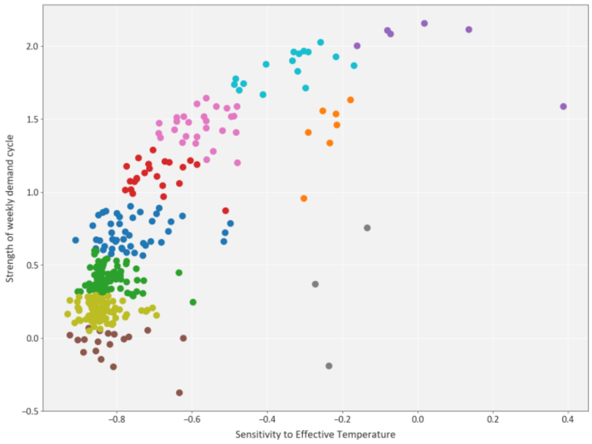

Fig. 5: Customer type clustering

The variability of weather driven demand at a local level is significant

To understand the variability of weather driven demand and to create practical outputs, Weather Correction Factors (WCFs) focussing upon calculating WCFs for annual peak demand. However, it was shown that correction for daily averages - a figure that is useful for microgrid development - is equally feasible.

Peak weather correction factors for individual substations were calculated by:

- Running the previous 10 years of weather data from the NWP simulation through the trained demand model. This creates 10 'what if' scenarios which represent the expected demand profile if historical weather conditions had occurred in the year under analysis.
- The Weather Correction Factor is calculated to be the percentage difference between the average peak demand in each of these 10 scenarios and the demand in the current year of analysis.

The comparison between average modelled demand and in year peak demand is charted in Fig. 6.

The variability seen from customer's sensitivity to weather and the variability in weather across Scotland come together to create WCFs that show both a) clear variation between geographical groups of substations and variation within these groups. This level of variation backs up the benefits case for local correction.

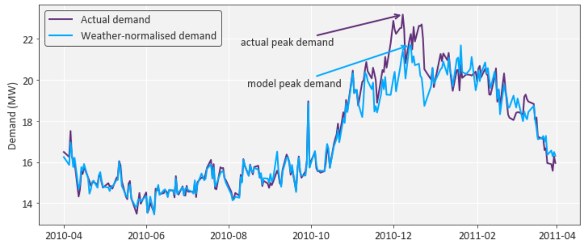

Fig. 6: Annual peak demand from actual demand and weather-normalised demand

CONCLUSION

The work presented in this paper demonstrates that the weather has a strong influence on electricity demand. It investigated the historical trends in customer behaviour for distribution network by correcting the varying annual peak demand to account for the effect of variable weather conditions. Key findings of the paper are as follows:

- There is a clear relationship between demand and multiple weather variables.
- The effect of weather conditions at local substations will be different.
- The variability of weather driven demand at a local level is significant.

Understanding demand at this level of granularity is a key enabler for DSO and microgrids. It provides tools to improve the targeting of investment, provides earlier warning of shifts in demand and provides a platform to run scenarios upon.

Future work will expand the presented analysis to entire SPEN's distribution network in order to determine long term trends, identify patterns and create forecasts. Further uncertainty analysis will be undertaken to further refine the forecasts.

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