A COMPOSITE MODEL FOR LONG-TERM FORECASTING OF DISTRIBUTION PEAK DEMANDS

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ABSTRACT

This paper presents a model for forecasting peak power demands on distribution networks, using two forecasting components. The baseline component is based on a top-down approach and combines energy, load factor and historic peak forecasts, integrated into a single forecast using an interactive procedure. The incremental component is a bottom-up approach that adjusts the baseline using information supplied by local planning authorities. The proposed methodology is being developed to forecast peak demand at all bulk supply substations within the Electricity North West area.

INTRODUCTION

This paper presents the latest developments of a methodology for forecasting distribution peak demands. A spatially disaggregated forecasting approach has been selected to enable more accurate predictions and efficient network investments. A previous paper [1] described a software project linking half-hourly SCADA readings with the tools for outage, connections and development planning. The initial project phase, which has now been completed, focused on extensive data cleansing and extraction of historic annual extremes and their projections.

However, further development was required because there could be high volatility in historic annual peaks which made trending less reliable, and other exogenous and local influences were not incorporated. As a result, a new composite model for peak demand forecasting has been developed, currently in spreadsheet form with VBA macros. This paper presents its essential components and features. Figure 1 overleaf shows a simplified flowchart of the proposed composite forecasting model. The baseline forecast (left branch) combines spatial, econometric and trending methods. The incremental forecast (right branch) adjusts the baseline with the aid of a spatial approach using knowledge of local circumstances.

This paper describes the baseline and incremental components first, then results and conclusions.

BASELINE COMPONENT

The building blocks of the composite baseline forecast are 1) energy forecast models, 2) peak demand forecasting using energy and load factor forecasts, and 3) historic peak demand forecasting. All three forecasts are finally fed into the composite forecast block which generates a single forecast data-series of peak demands. This block contains a set of pre-specified algorithmic steps and rules, and it is partly interactive.

Energy Forecasting Model

A spatial, econometric model is used for long-term forecasting of energy demands at pre-specified network points. It was envisaged that such a model would best reflect the changing nature/profile of electricity demand in response to future uncertainties such as pricing, energy polices and technology changes. A normalised energy consumption forecast is calculated by combining annual energy forecasts per economic sector with the mix of economic sectors within each local planning authority (LPA) area. The main stages are:

1. Develop national and regional econometric electrical energy forecast by economic sector. Figure 2 overleaf gives an example of these forecasts.
2. Find mix of economic sectors by LPA.
3. Get normalised electrical energy forecast by LPA.
4. Map LPA to primary substation (33/11or 33/6.6 kV)
5. Map primary to bulk supply point (BSP) (132/33 kV)
6. Find normalised electrical energy forecast by BSPs.

Econometric Electrical Energy Forecasts

The regional forecast is derived from our own annual updates to a commissioned model [2]. The model uses inputs on trends in dwellings and household members, income, gross value added, energy intensity, price elasticity, wholesale prices and supplier obligations to derive future forecasts. Outputs are forecast GWh of electrical energy for the domestic, commercial and industrial sectors connected at the low-voltage (LV) and high-voltage (HV). All forecasts are produced for three price scenarios (High, Base and Low) and the Base is used in our approach. The regional model is applied in the medium-term and switching to the national forecast is based on assessment of the validity of assumptions.

In the longer term, we use the output from a national government econometric forecast of energy and electricity consumption [3]. This forecast covers seven economic sectors (domestic, commercial, public administration, agriculture, iron & steel, other industry and transport), five demand categories and four pricing scenarios – the Central scenario is used. It is envisaged that the forecast will need to be adjusted to reflect long-term electricity demand from electric vehicles**.**

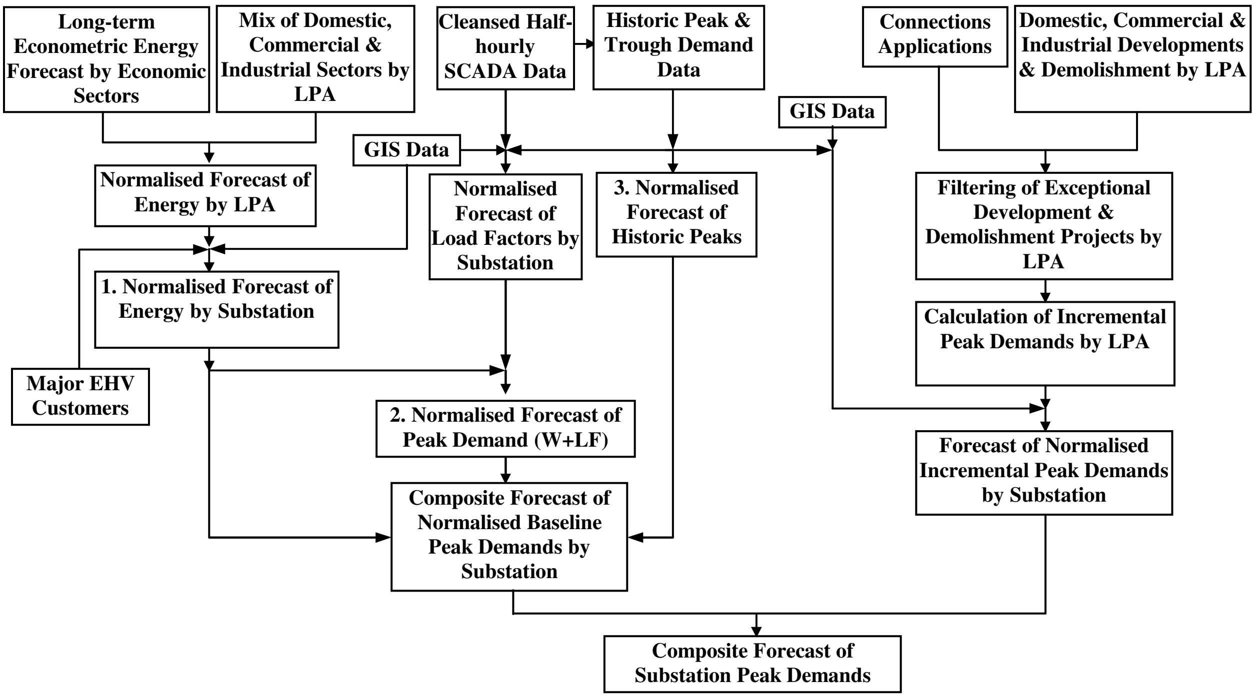

Figure 1 – Flowchart of the forecasting methodology

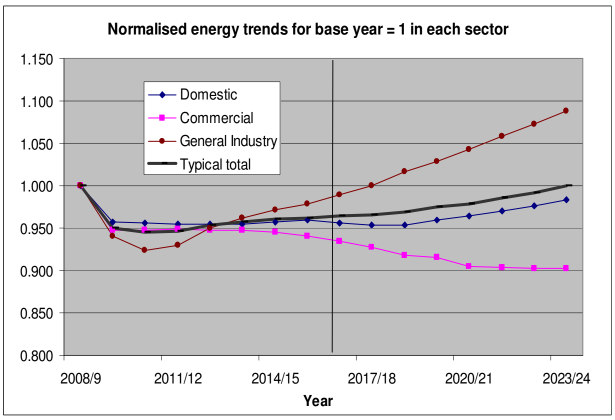

Figure 2 – Electricity trends in largest sectors

Mix of Economic Sectors

Historic GWh electricity usage by LPA [4] gives a split between domestic and non-domestic usage. Non-domestic is further divided into six classes using information on major connected customers and statistical inputs such as [3]. Typical values for LPAs in our distribution area are domestic 40%, commercial 21%, public administration 6%, agriculture 1%, transport 2%, and other industry 30%.

Normalised Electricity Forecast by Substation

The econometric forecast and the mix of sectors are combined to give normalised electricity forecasts by LPA, which are then associated with the primary substations in each LPA. The normalised electricity forecast for each BSP is an average (weighted by peak demands) and connected primaries EHV customers.

Load Factor Forecasting Model

Load factor forecasts are used in conjunction with the energy forecast to obtain predicted peak demands:

Normal_Peak=Normal_Energy/Normal_Load_Factor (1)

The main stages of the load factor forecasting are:

1. Calculate historic load factors from cleansed half-hourly SCADA data.
2. Forecast load factors using two approaches, with the user deciding on the preferred solution. This approach was taken because forecasting of load factors is notoriously difficult and any change needs to be analysed and fully understood [5].
3. Normalise load factor predictions.

The first forecasting approach is iterative linear weighted least squares (WLS). The second approach uses nonlinear regression analysis against pre-specified saturation curves.

Iterative Linear WLS Method

Analysis of historic load factor data series has revealed not only regular variations over a time period (e.g. small increases or decays), but also sudden changes which were hard to explain. For this reason, the weights associated with historic data were generated automatically based on the Tukey BiWeight method [6]. The iterative linear regression procedure can be summarised as follows:

1. Initialise model, i.e. find a LS solution to unknowns.
2. Calculate the weights using the BiWeight method.
3. Solve for parameters using the linear WLS method.
4. If the change in parameters is less then threshold, exit. Otherwise, return to step No. 2.

The essential idea of the Tukey BiWeight method is to eliminate outliers and calculate weights using absolute value of residuals. Historic data with small residuals are given more weight, while data with large residuals are considered less reliable. The algorithm is as follows:

1. Determine absolute value of residuals.
2. Find median of the absolute value of residuals = M.
3. Calculate cut-off value C=6*M and set weight equal to zero for all data where |residual|>C (i.e. outliers).
4. Set weights of all other data to weight = $(1-(R/C)^2)^2$, where R is residual.

Forecast load factors can be capped with the aid of a user-defined parameter. If this option is selected, the user has to input maximum allowed percentage change in future.

Nonlinear WLS Method

Forecasting of load factors is also done using saturation curves which limit future increases (or decreases). The following types of saturation curve were applied, with nonlinear regression analysis combined with the Tukey BiWeight method to calculate the unknowns A, B and C:

$$Y = C + \frac{A}{1+10^{B-X}} \quad \text{(positive slope)} \qquad (2)$$

$$Y = C + \frac{A}{1+10^{X-B}} \quad \text{(negative slope)} \qquad (3)$$

The algorithm is similar to iterative linear WLS, the only difference is that iterations refer to steps of the iterative solution procedure. Optimisation of weighted squared residuals is done with the aid of the steepest descent method and quadratic interpolation approach [7]. The number of iterations was less than 10. Selection of saturation curve (2) or (3) is based on the sign of the slope of the first forecast solution. However, there were a few cases where optimisation diverged, so that convergence was achieved by (automatic) switching to the other curve. An illustrative example of both load factor forecasts (from 2010 onward) is shown in Fig. 3.

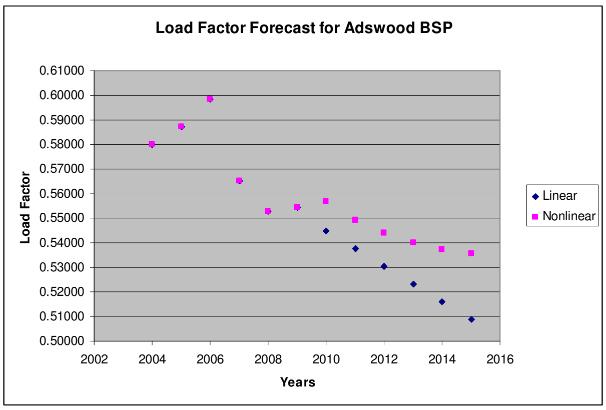

Fig 3– Forecasts of load factor by two methods

Historic Peak Forecasting Model

Historic peaks are extracted from the half-hourly SCADA readings after having applied a suite of data cleansing algorithms [1]. The current approach is to forecast annual peaks using the linear WLS method, where several weighting scenarios are offered to the user. It was found that the quadratic regression was not acceptable due to large year-on-year changes. Quality of the forecast is assessed by calculating the R^2 and confidence intervals [8].

Inherent problems linked with forecasting of annual peaks are the small number of historic data and their variability. A preferred solution would be development of a forecasting model based on weekly peaks (i.e. 52 points per year) where both the trend and seasonal component are modelled and separately forecast [9].

Composite Baseline Model

Aggregation of several forecasts into a single prediction can be done with the aid of weights that can be generated either automatically or interactively. Several combination techniques for automatic calculation are presented in [5]. The interactive approach used here is based on a set of pre-defined rules and constraints for selecting weights e.g.

- Weighting factors can change between years.
- Annual change is limited by user-defined factors. Different factors can be specified in short-term (0-5yr), medium-term (5-10 yr) and long-term (10-15 yr).
- The overall upward or downward change can be limited by another user-defined factor.
- Historic peak and load factor forecasts were classified as reliable, partly-reliable and unreliable based on the volatility and quality of the input data. Reliable historic peak forecasts are given the highest weights, particularly in the short-term. Where an unreliable load factor forecast is encountered, the normalised energy forecast is preferred to the peak prediction.
- Where the historic and load factor forecasts are considered reliable, highest weights are associated with the historic peak forecast in the short-term, with the peak model (energy and load factor) in the medium-term and energy forecast in the longer-term. This approach could be developed further using fuzzy algebra to determine these weights.

INCREMENTAL COMPONENT

The incremental demand component is based on local information supplied by LPAs and in applications for connection to the distribution network. It is assumed that changes in consumption of existing customers and 'standard' development and/or demolishment projects are already modelled within the baseline. Only 'exceptional' projects are incorporated in the incremental forecast, with smaller projects filtered out based on the project size (eg number of dwellings, total floor-space, total nominal kW for industry, etc.), to avoid double-counting.

LPAs are sent questionnaires with data columns to provide information on development and demolishment projects. These data, in conjunction with connections applications, are then used to calculate an additive component that is superimposed on the baseline forecast (Fig. 1). Approaches used for different sectors are given below. In each case, the

LPA needs to indicate the probability of the connection project going ahead in a specific timeframe.

Residential Sector

This forecasting model belongs to the class of 'appliance saturation' models [10]. Dwelling types are classified as a) Mansions; b) Farmhouses; c) Detached; d) Semi-detached; e) Terraced; f) Apartments-low rise and g) Apartments-high rise. End-use categories are electric space heating, air-conditioning, electric water heating, and electric cooking. LPAs are asked for project type and status, number of dwellings, nominal kW and penetration rates by end-use categories. Percentage contributions of end-use categories towards peaks are then determined from past data.

Commercial/Service/Municipal Sector

Forecasting model is based on the floor-space model [10]. Commercial sector buildings are classified as shopping malls, supermarkets, convenience shops, retail warehouses, factory outlets and rural shops. Service categories include offices-low rise, offices-high rise, leisure and entertainment, while municipal sector is split into education, health, government, utilities, waste treatment and worship places. The end-use categories are similar to the residential sector, and an LPA provides information on project type, status, total floor-space, percentage of total floor-space per end-use category, penetration rates etc. This component is calculated using W/m^2 factors and contribution towards peaks for each end-use category.

Industry, Agriculture and Transport Sectors

Floor-space and demand-use models [10] are used for industry and agriculture, and a demand-use model for electric transport sector. Industry is split into mining, construction, manufacturing-heavy, manufacturing-durable goods, manufacturing-consumer goods and other, with further classification of all three manufacturing sectors. The end-use categories for the floor-space model are space and water heating and lighting, while thermal processes, motor driven processes and other processes are used for demand-use models. Data on specific W/m^2 for floor-space categories and nominal kW for different processes are combined with contributions towards peaks to find this incremental component.

ILLUSTRATIVE RESULTS

An illustrative example applying the composite forecasting model to predict peak at one BSP is shown in Fig. 4. For this BSP, historic peak data-series was considered reliable and load factor series partly reliable, so the historic peak forecast was given the largest weight in the short-term. In the medium-term, the historic peak and the 'energy and load forecast' model were aggregated with similar weights. The energy forecast was given the highest weight in the longer-term. Confidence intervals are not shown in Fig. 4 – so far these have been calculated based on the variability of historic peak data, but future development will reflect high and low energy scenarios.

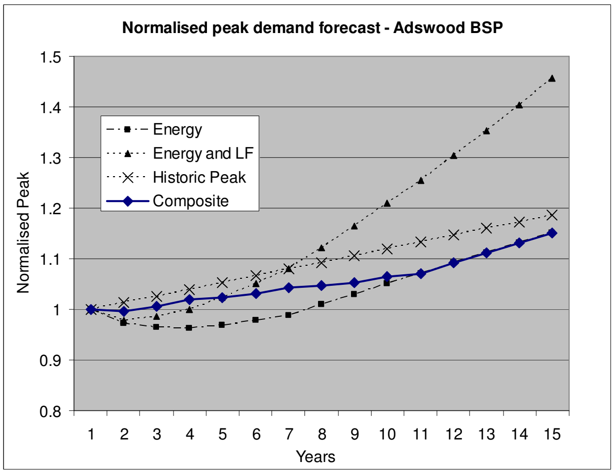

Fig 4 –Baseline components and composite forecast

CONCLUSIONS

A composite model for forecasting distribution peak demands has been developed to overcome difficulties experienced with prediction of historic annual peaks. The model combines three top-down forecasting approaches to get the baseline forecast, and adjusts this based on local knowledge of approved and planned projects. Possible improvements include replacing annual historic peak forecast with weekly historic peaks to reflect seasonal and annual trends.

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