MEASUREMENT AND PREDICTION OF NETWORK DEMAND IN THE PRESENCE OF RENEWABLE DISTRIBUTED GENERATION

Peter BOAIT
De Montfort University – UK
p.boait@dmu.ac.uk

Mary GILLIE
EA Technology Ltd – UK
mary.gillie@eatechnology.com

Suyeon KIM
Exergy Devices Ltd-UK
Suyeon.kim@exergydevices.co.uk

ABSTRACT
As the amount of renewable generation on the LV and 11kV distribution networks rises, it becomes difficult for distribution network operators to track the underlying demand for electricity. This paper describes a system under development to deduce renewable generator capacity, generation and consumer demand on individual feeders from current measurement data collected at the primary or distribution transformer. This provides DNOs with a low cost system to understand the true impact of generation on their network, better plan for outages and manage fault conditions. It gives them knowledge of the actual demand on their system, the generation connected and prediction of these values for the hours or days ahead using data already available.

INTRODUCTION
The established method for distribution operators to determine and record local electricity load is by measurement of current flow at the start of each feeder from a transformer using a current transformer (CT). However if distributed generation (DG) is present on the feeder this measurement will not indicate the actual demand. When a fault occurs or a network reconfiguration is necessary it is important to know the likely power flows. Records of current measurements will not include the current supplied by the generator and therefore will not provide accurate information of the maximum power flow that could be expected under planned or unplanned outage conditions. The estimate of the cold load pick-up will also not be accurate.

With the introduction of feed-in tariffs and regulatory changes to facilitate connection of renewable generation, installations of wind and photovoltaic DG are proliferating rapidly at LV and 11kV on the distribution network. Although distribution system operators should be aware of connections, they do not usually have up to date metering data on the actual output of these generators. They therefore have difficulty in interpreting feeder load measurements to obtain the actual underlying demand. Furthermore, generation at these voltage levels is designed to trip off under fault conditions.

In this paper we define actual demand or load as the power that would be fed from the transformer if there was no generation connected to the feeder. We define measured load as the power flow detected at the transformer by a CT combined with an assumed or measured voltage. The paper describes methods under development by the authors for analysis of the data from current measurements to detect the presence of renewable generation on the feeder, calculate its capacity, and find the underlying actual load. These methods only use CT measurements and weather data from which it is possible to characterise the renewable generators and the actual load present using a range of mathematical techniques. They exploit the weather dependent nature of renewable generation and its inherent physical properties such as the dependency of photovoltaic (PV) generators on the solar cycle. Once the type and capacity of DG on a feeder is known, it is possible to predict its future output given a weather forecast, while prediction of actual consumer demand is possible once records of actual demand are available. By combining predictions of DG output and actual demand the net measured load can also be predicted.

SYSTEM CONCEPT
The system conceived in this work will take as inputs real-time streams of CT measurements from a set of transformer feeders and weather data (present and forecast) from a service such as Weatheronline.co.uk. Having run for a month or more, it will identify any significant renewable generation present on any of the feeders and estimate its capacity. It will calculate the underlying actual consumer demand taking account of power factor. It will predict actual demand, generator output, and net measured transformer load over the next 24 hours or any further period for which a weather forecast is available, with an indication of the confidence in the forecast. The rest of the paper describes progress in meeting these requirements.

DETECTION AND CHARACTERISATION OF RENEWABLE DG

Wind Generators
For initial detection of the presence of renewable DG on a feeder a frequency domain analysis is useful as discussed in our CIRED 2009 paper [1]. An idealised spectrum of wind from Van Der Hoven [2] is shown in Figure 1

[2] Suyeon.Kim@exergydevices.co.uk
In practice the spectrum is quite noisy but it provides a means of diagnosing the type of DG present. To obtain an initial estimate of the capacity of wind DG it is necessary to correlate a data set from the feeder CT, preferably of several months duration, with wind speed records over the same period. Because of the non-linear nature of the relationship between wind speed and generator output, a generic model of a wind generator is required to transform the wind speed records into the expected generator output for each day, normalised with respect to the unknown capacity.

Figure 2 shows the generalised wind generator operating function adopted. To reflect the short term variability in wind speed visible in Figure 1, the average wind speed from weather records was converted into a Rayleigh distribution with the same mean. Each wind speed interval in the distribution could then be converted to a corresponding generator output using the Figure 2 function. Integrating the resulting output distribution gave an expected normalised generator output for the day.

Regression of the expected generator output for each day against the average load for the day measured with the CT then gives an estimate of the generator capacity from the slope of the line of best fit. An example regression using a single month’s data is given in Figure 3. The slope of 40A on an 11kV feeder leads to an estimated generator capacity of 40*11*√3 = 762kVA. In this case the plated capacity was 890kVA.

The sources of inaccuracy in this simple technique include:

- Discrepancies between the generic operating function and the actual generators.
- Wind chill effects, where consumer demand increases with wind speed so affects the regression.
- Interaction of the real and reactive power components of the generation and demand which tends to cause the generator output be underestimated.

Methods have been developed to address these limitations. For example, the wind chill effect can be modelled using data from a feeder with similar consumer demographics to the feeder under test but no wind generation. With corrections for wind chill and power factor the estimated capacity from the Figure 3 data was 815 kVA.

Regression of the expected generator output for each day against the average load for the day measured with the CT then gives an estimate of the generator capacity from the slope of the line of best fit. An example regression using a single month’s data is given in Figure 3. The slope of 40A on an 11kV feeder leads to an estimated generator capacity of 40*11*√3 = 762kVA. In this case the plated capacity was 890kVA.

The sources of inaccuracy in this simple technique include:

- Discrepancies between the generic operating function and the actual generators.
- Wind chill effects, where consumer demand increases with wind speed so affects the regression.
- Interaction of the real and reactive power components of the generation and demand which tends to cause the generator output be underestimated.

Methods have been developed to address these limitations. For example, the wind chill effect can be modelled using data from a feeder with similar consumer demographics to the feeder under test but no wind generation. With corrections for wind chill and power factor the estimated capacity from the Figure 3 data was 815 kVA.
daily peaks are distinct from the single diurnal peak of wind generation in Figure 1.

A generic operating function is also needed for PV relating weather records, in this case sunshine hours per day, to output. This is somewhat dependent on location, as the local climate affects the distribution of sunshine over the day. Figure 5 shows a set of curves relating sunshine hours to normalised average PV output for July. These were obtained from a single PV installation leading to the visible artifacts such as the 2 peaks. Building this function from a wider range of PV data is one of the tasks for further work.

![Figure 5. Operating curves for PV generation at a UK location.](image)

The remaining process for determining PV generator capacity is similar to that for wind but takes advantage of the diurnal pattern of PV output, as illustrated in Figure 6. This compares average load on days with high sunshine hours (blue line) with days with low sunshine hours (black line). The difference comprises the sum of PV output and extra demand on low sun days due to lighting etc. By finding the best fit to this gap from our models of both components we can estimate the PV element.

![Figure 6. Estimation of PV generator output.](image)

**Other types of generator and appliance**

Some initial tests have been performed on models of micro CHP output. These indicate that it will be possible to detect the relationship between generator output and weather-dependent demand for space heating, as long as the increasing output as temperatures fall is not wholly masked by electrical space heating on the same feeder. Generators with relatively constant output such as micro hydro and landfill gas are less amenable to weather correlation, but there is some evidence they may be identified and characterised from their effect on voltage and power factor.

It is also possible that these techniques can be extended to identify particular types of consumer appliance that present particular issues to distribution networks. An example is heat pumps, whose compressor motors when connected in large numbers are a potential problem under black start conditions in cold weather. In [3] we describe the load characteristics of these devices.

**PREDICTION OF DEMAND**

Once underlying actual demand on a feeder has been obtained by phasor addition of the calculated generator output to the measured load, it is possible to model and predict actual demand using neural network techniques. This is a well recognised method for performing electricity demand prediction [4],[5],[6] that is able to capture the cyclic patterns of demand dependent on time of day, day of the week, and time of year. It can also take account of the more limited effects of weather on demand given that the conflicting effect of weather dependent generation has been removed.

![Figure 7. Comparison of neural network prediction with actual demand.](image)

Figure 7 shows the prediction for an 11kV feeder provided by a neural network compared with actual demand for the first day of the month for 5 months, showing good tracking both within the day and across seasons. It uses a single hidden layer and the Levenberg–Marquardt algorithm for training. Figure 8 provides an analysis of the error
performance resulting in a Mean Absolute Error (MAE) of 3.5 Amps and Mean Absolute Percentage Error of 10.4%. With development we expect to be able to improve on this performance.

**Figure 8.** Error analysis for the neural network prediction sampled in Figure 7.

**Compatibility with smart metering**

The smart meter networks being rolled out in many countries have the potential to augment this system but cannot provide the same capability, for two reasons. Firstly metering at the network connection point for domestic and SME consumers will only record net import and export, not local generation so presents the same issue as a transformer CT measurement but on a more localised basis. Secondly metering data of itself will not provide the weather-dependent prediction required by network managers. So we envisage smart meter data as a feed into this system which can improve its accuracy and detail of analysis but will not replace it.

**CONCLUSIONS**

The results achieved so from analysis of CT data give confidence that a system can be constructed that will give distribution network operators a valuable tool giving insight at a feeder level on the renewable generation present and the underlying actual demand from consumers, using simple and low cost data collection techniques that do not depend on metering and are already widely available.

Further development will allow DNOs to integrate the algorithms into their network management systems to have increased visibility and predictions at 11kV and LV of actual consumer load, generation types connected and their output. The work to date has illustrated the significant information can be derived using existing data and acquisition methods resulting a very cost effective system.

**ACKNOWLEDGMENT**

The authors would like to acknowledge the support of Scottish and Southern Electricity plc including provision of data for this analysis.

**REFERENCES**


