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Forecasting low voltage distribution network demand profiles using a pattern recognition based expert system

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ABSTRACT

The advent of distributed renewable energy supply sources and storage systems has placed a greater degree of focus on the operations of the LV (low voltage) electricity distribution network. However, LV networks are characterised by having much higher variability in time series demand meaning that modelling techniques solely relying on iterative forecasts to produce a next day demand profile forecast are insufficient. To cater for the complexity of LV network demand, a novel hybrid expert system comprised of three modules, namely, correlation clustering, discrete classification neural network, and a post-processing procedure was developed. The system operates by classifying a set of key variables associated with a future day and refining a recalled historical demand profile as the forecast. The expert system exhibited high hindcast accuracy when trained with a residential LV transformer's demand data with R^2 values ranging from 0.86 to 0.87 and MAPE (mean absolute percentage error) ranging from 11% to 12% across the three phases of the network. Under simulated real world conditions the R^2 statistic reduced slightly to 0.81–0.84 and the MAPE increased to 12.5–13.5%. Future work will involve integrating the developed expert system for forecasting next day demand in an LV network into a comprehensive distributed energy resource management algorithm.

1. Introduction

As the region-wide electricity generation and supply system steps down to the LV (low voltage) distribution network, the number of customers serviced by a transformer decreases, which in-turn, correlates with an increase in variability of time series electricity demand. Over short time periods (intraday to intra-week), demand is observed to have a greater degree of randomness, increased frequency of '*shocks*' and less continuity between daily demand profiles of sequential days. The increase in variability can be attributed to the greater relative weighting of the behaviours of individual customers and influences of local phenomena e.g. weather, special events, etc.

The increase in demand variability poses a resource management problem for the operation of microgrids and DER (distributed energy resources). As an example, a time based heuristic energy management control system for an energy storage system would not be able to adequately meet its objectives due the times at which the system should optimally charge and discharge would be changing on a daily basis. Similar to the operation of the conventional electricity generation and supply system, to overcome this resource management problem, control systems will need to rely on demand forecasts. Demand forecasts will enable the derivation of information such as how much power is required, the scheduling of charging and discharging of energy storage systems, and whether or not remedial measures are required to be employed.

This current research focusses on the development of a forecasting component for an energy management control algorithm for the purposes of scheduling DER in residential LV distribution networks. For the energy management control algorithm to achieve the optimal scheduling of DER, it is necessary for the demand profile for the next and subsequent days to be forecast as well as its key features, such as the time(s) of day when peak demand occurs and associated values.

ARIMA (autoregressive integrated moving average) modelling techniques have been shown to provide adequate forecasts when applied to systems with greater customer aggregation or longer forecast time intervals [1–6]. However, conventional modelling techniques such as ARIMA are sensitive to LV network prevalent uncharacteristic daily profiles and random shocks which will increase these models' propensity to produce naïve predictions. Applying iterative forecasting alone, the residuals of the random shocks would bias subsequent forecasts. To overcome some of the

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deficiencies of traditional time series forecasting techniques, forecasting researchers have begun to explore the application of Artificial NN (Neural Networks) to forecast demand and demand profiles [7–10]. The main benefits of the use of NNs include their ability to generalize, identify non-linear relationships and applicability to a wide range of applications [7].

To achieve the research goal to forecast demand profiles for high variance LV residential distribution networks, an expert system based on pattern recognition which incorporates a clustering algorithm and NN was developed. This paper describes the development and validation process for the expert system when applied to three phases of an LV transformer supplying power to 128 residential customers located in Brisbane, Australia.

2. Research background

Griffith University, Elevare, Ergon Energy and Energex are working on a joint project to assess the feasibility of the installation of STATCOM (static synchronous compensators) with BESS (battery energy storage systems) in the LV distribution network. Funding for this project has been provided by the Queensland State Government 2012–2014 Research Partnership Grant. STATCOMs are four quadrant synchronous inverters with the ability to correct frequency distortions and dampen harmonics. The combination of STATCOMs and BESS will enable the reduction of peak demand on network infrastructure and the active maintenance of power quality. The installation of this technology has the potential to reduce network expenditures through the replacement or deferral of other expenditures such as replacing transformers and/or upgrading lines.

The assessment of the feasibility involves the design and quantification of the effectiveness of STATCOMs with BESS. A number of subprojects were initiated to achieve the project's goals including determining the technical parameters, developing a STATCOM with BESS energy management control algorithm and performing economic analysis. The research reported in this paper denotes the completion of the demand forecasting component of the energy management control algorithm. Information generated from the determination of technical parameters, simulation of the STATCOM with BESS in the LV distribution network and physical trialling will be used as input variables in the economic analysis.

3. Literature review

3.1. Short-term electricity demand modelling

The most notable publications apply conventional modelling techniques including ARIMA, multivariate regression and machine learning techniques (e.g. support vector machines, fuzzy inference systems, NN, etc.). ARIMA(p,d,q) is the general model of the Box Jenkins set of time series modelling techniques. The 'p' represents that number of lagged parameters (autoregressive parameters); the 'd' represents the number of discrete differences; and the 'q' represents the number of lagged forecast error parameters in the model to account for a moving average in the time series. Regression models in the electricity demand space involve the addition of deterministic parameters to the use of the lagged forecast parameters. Additional parameters may include weather, economic, behavioural and time dependent variables. Many regression models can be considered ARIMAX (Auto Regressive Integrated Moving Average with Exogeneous Input) models due to the combination of the ARIMA model with exogenous variables. NNs mimic how biological neural networks model systems. NNs are composed of two or more layers of artificial neurons with synapse (weights) linking each neuron of the previous lay to the next. Signals (inputs) are multiplied by weights connected to the neuron, summated, inputted into the neuron's activation function and the output is sent to the neurons of the next layer. A training algorithm adjusts the weights throughout the network in order to model the desired system.

Engle et al. [1], Taylor [4], Mirasgedis et al. [5] and Taylor [6] developed network demand time series models based on the ARIMA or regression modelling techniques. Taylor [4] and Taylor [6] developed ARIMA models using the exponential smoothing, double seasonable exponential smoothing and triple seasonal algorithms. Taylor [4] used 30 min demand data from England and Wales. Taylor [6] used demand data from Britain and France. The research showed that the developed models were accurate and that accuracy increases as more seasonalities are included in the models. Engle et al. [1] and Mirasgedis et al. [5] developed time series models with autoregressive parameters and additional variables including heating and cooling days, RH (relative humidity) and day of the week dummy variables. It was noted that models performed well and models with weather variables performed better than models without.

Kassaei et al. [11], Darbellay and Slama [2], Abraham and Nath [12], Ringwood et al. [3] and Cavallaro [13] developed short-term electricity demand forecast models using NN. Darbellay and Slama [2] used Czech Republic demand data and Ringwood et al. [3] used Ireland's Electricity Supply Board's data to construct univariate NN models. The autocorrelation function was used to identify cyclical components in the demand time series and to structure the models accordingly. The models achieved a high level of accuracy and performed better than univariate ARIMA models. Cavallaro [13] constructed a multivariate NN with variables such as day of the week and average temperature and noted a high accuracy. Kassaei et al. [11] and Abraham and Nath [12] combined NN with fuzzy logic. Kassaei [11] used a univariate NN to model normal loads and fuzzy logic model to model weather dependent loads. The forecast is generated by the output of the NN and fuzzy logic model. It was found that the NN and fuzzy logic model performed better than the singular NN model. Abraham and Nath [12] applied an ARIMA, EFuNN (evolving fuzzy NN) and a NN to Victoria's demand data. The EFuNN approach differs from a conventional NN since the neurons in the network are performing functions such as '*fuzzification*' of inputs, rule based transformations and defuzzification. The weights in the network are altered by a training algorithm. The EFuNN performed the best out of the set of developed models.

The above mentioned models were all short-term electricity demand models applied to networks with a large number of consumers. All achieved high levels of accuracy and there were not any clear distinctions regarding which modelling method yields the best results. The work conducted by Taylor [6] provided evidence that the greater number of seasonality variables included in the model accounted for increases in model accuracy. Engle et al. [1], Darbellay and Slama [2] and Mirasgedis et al. [5] indicated that the inclusion of deterministic variables such as weather variables improves model accuracy. An inference may be drawn from these studies that the inclusion of both ARIMA variables and deterministic variables would derive higher model accuracy. However, this inference becomes less applicable as the forecast period shortens due to the relationship between demand and deterministic variables not being apparent [4]. Forecast windows such as a day ahead or greater are more responsive to deterministic variables.

3.2. Demand profile forecasting

For the case of short-term demand forecasting models (i.e. 30 min ahead, an hour head, etc.) iterative forecasting techniques are essential. Iterative forecasting is where the forecast at time t is used as an input variable in the model to forecast at time $t+1$. This process repeats itself until the desired number of forecasts has been made. A shortcoming of this technique to forecast demand profiles is that the