DISAGGREGATED ACTIVE AND REACTIVE DEMAND FORECASTING USING FIRST DIFFERENCE MEASURED DATA AND NEURAL NETWORKS

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ABSTRACT

This work presents a complete methodology for disaggregated substation peak active and non-compensated reactive power forecasting. The method requires measured active and reactive power from substation transformers, billing data divided by consumer type and global energy forecasting by consumer type. The peak active power forecasting is based on the cointegration between this variable and the energy associated with the substation. The non-compensated peak reactive power is based on artificial neural networks and uses the first difference from the measured data to filter atypical events such as capacitor banks switching. The forecast of peak power of substations permits to support the planning of new investments on grid expansion, reactive support and energy purchasing.

INTRODUCTION

With the liberalization of the Brazilian electric sector, power forecasts started to play a key role with regard to investments in distribution, planning and energy management strategies at regional and national systems. Inaccurate results may increase operating costs, since the overestimation in future demand results in an unnecessary spinning reserve. Also reactive power management has become important for Distribution System Operators (DSO), who need to keep voltage limits, providing power quality and system reliability. Additionally, Brazilian DSOs must make active and reactive power forecasts to provide necessary information for national transmission and generation planning studies according to regulatory legislation.

There are several load forecasting methodologies using techniques such as the naive forecast, autoregressive methods, econometric methods and methods involving intelligent algorithms such as genetic algorithms and neural networks [1-5]. As an example the reference [6] presents a methodology for probabilistic forecasting active load, based on measurements of load, historic temperatures and the country's GDP, which seeks to take advantage of the large amount of data available in modern electrical systems. Reference [7] presents a methodology to forecast hourly reactive power in the short term through statistical models. The study showed that reactive power cannot be modelled by a simple regression of active power, the adoption of other measures being necessary. Reference [8] describes a system based on artificial neural networks for prediction of active and reactive power in the short term for substation transformers, using measured data from feeders.

It is proposed in this paper a complete methodology for peak active and peak non-compensated reactive power forecasting for long-term perspective. The active power forecast is based on cointegrated series theory. The non-compensated reactive power forecast is based on the use of artificial neural networks with the use of first differences of historical active and reactive power measurements to evidence atypical events like capacitor bank switching. To do so it is used measurements from active and reactive power from substations transformers, billing data and energy forecasting.

This methodology can be used as a tool to several planning decisions such as reactive support and energy purchasing.

ACTIVE POWER FORECASTING

The active power forecasting methodology is based on the cointegrated series theory to obtain a regression function that allows mapping energy associated with the substation with its monthly peak active power.

The first step is the computation of vegetative growth per substation by the disaggregation of global energy projections by consumer type. It is known that different substations, depending on the location region, have different behaviours regarding load growth. And these differences can be captured by historical consumption growth analysis observed in the substation for each consumer type. The energy disaggregation is analysed considering breakdown into classes of consumption, large consumers, energy losses, energy generation and changes in network configuration. Therefore the total energy associated with the substation can be estimated.

Energy values per substation, when aggregated under the conditions set by punctual adjustments, shall provide an overall value harmonized with the overall value projected by market team (unless of uncertainties, confidence

intervals and the data source designed considering information beyond those related to billed consumption). To obtain such compliance, the growths per class per substation are elected susceptible to changed.
The total monthly load of a substation, determined via disaggregation and validated by comparing with the measured value, is used as input in determining the monthly peak demand. This determination is based on the concept of cointegration and is applied from the knowledge of the time series of monthly measured data and power for energy substation.
The global energy disaggregation per class in all substations was treated as a mathematical optimization problem whose results were growth rates by consumer type in each considered substation.
Figure 1 illustrates the behaviour of two sets of data: the monthly consumed energy and the measured peak active power. The series have a strong correlation. This high degree of correlation indicates an equilibrium relationship between the quantities being measured. That is, Figure 1 shows that a variation in the amount of monthly energy is accompanied by a similar variation to the monthly peak power.

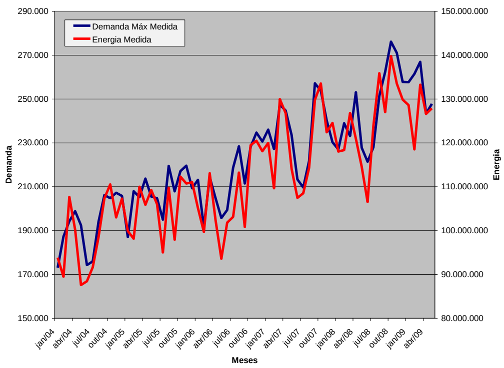

Figure 1: Energy (red) and peak active power (blue) series

These two variables have a linear relation as shown in Figure 2. The cointegration method permits to model the mathematical relation between the variables. Through this linear model it is possible to forecast the peak active power with only billing data and global energy forecasting.
A flowchart that summarizes the methodology is presented in Figure 3. First, using the billing data for each substation, the annual growth rate per consumer type is obtained. Then the disaggregation method uses the global forecast in order to estimate the energy consumption by consumer type for all substations. An energy balance is made by adding energy losses, distributed generation and other data. With the total energy computation, i.e. the total amount of energy associated with each substation, energy series are cointegrated with peak active power of the respective substation in order to create a liner model between these two variables. The validation of the model is done by comparing actual data of peak active power with the forecasted for the same period.

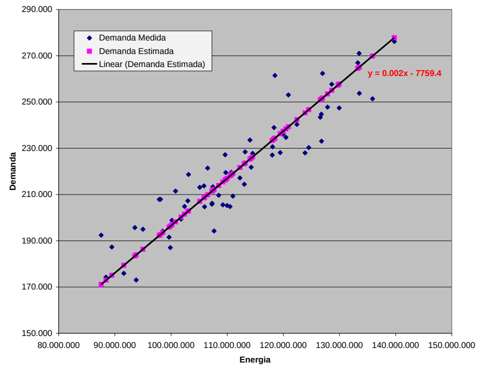

Figure 2: Linear relation between monthly energy and peak active power

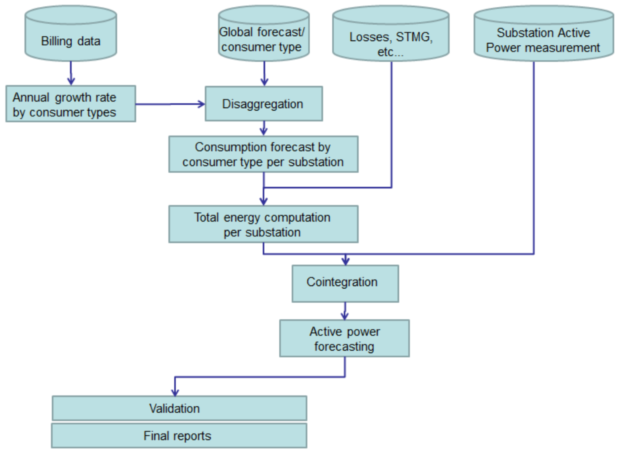

Figure 3: Active power forecast methodology flowchart.

REACTIVE POWER FORECASTING

The reactive power forecasting methodology aims to make a prediction that is free from influences of events that would induce errors in the result, such as capacitor banks or large consumer's switching. The goal is to forecast the peak demand of reactive power without the presence of reactive support.
The starting point for the methodology development was based on the active and reactive power measurements on substations transformers (Figure 4). This analysis shows grouped clouds of data that depends on the number of capacitor banks on the substation feeders. For example, the substation shown in Figure 4 (a) has one capacitor bank, and in Figure 4 (b) the substation has two capacitor banks. Each cloud of data can be modelled by a linear curve that will have approximately the same slope.

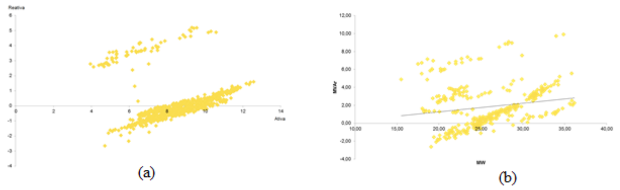

Figure 4: Active and reactive power measurements – (a) Substation with one capacitor bank. (b) Substation with two capacitor banks.

This analysis exemplifies the difficulty already evidenced in the literature to perform a reactive power forecast using measuring data. To solve this problem it was considered the analysis of the differences between sequential measurements of active and reactive power, i.e. the first difference of the series. By analysing the scatter plot of these series it was noted that the point clouds tend to focus on a single cloud with a linear relation and only a few outliers. The outliers represent momentary load variations (active power on the x-axis and reactive power on y-axis). In the case of reactive power, this happens with the switching of reactive support equipment on the grid, such as bank capacitors, and the strong variation of active power is related to the switching of large consumers. A linear regression is made between the two first difference series with an outlier removal method.

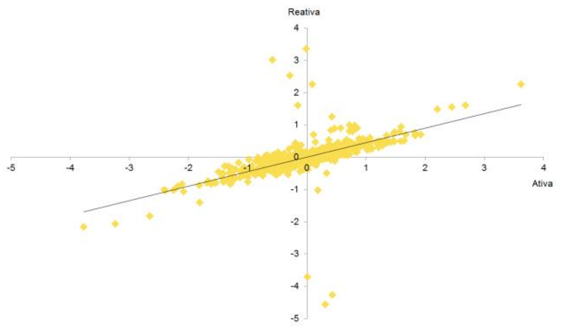

Figure 5: Scatter diagram between first difference series of active and reactive power

The difference scatter will give the relation between variations of active and reactive power. The proposed methodology assumes the angular coefficient as a function of consumer types participation on the total energy consumption per substation. A model is created with a neural network to recognize standards, using historical measurement, associating the monthly market share with the angular coefficients that relates the variations between active and reactive power. This model will assess the influence of each consumer type in the angle variations.

In this approach, the billing data were normalized by the total month consumption, seeking the relationship between the angles of the variations in the share of each consumer type relative to the total monthly consumption.

With the obtained relationship between the variation angle and billing data by consumer type, the angles of future changes can be estimated through the disaggregated consumption forecasts by consumer class.

In addition to the angular coefficient between variations of active and reactive power, more data is needed in order to forecast the non-compensated peak reactive power. The power factor relates instantaneous active and reactive power, and also should relate the monthly peak active and reactive power, since the peak demand of reactive power should occur simultaneously with the peak demand of active power, when there is no reactive support equipment on the grid.

Therefore in order to forecast the non-compensated peak reactive power, a neural network is developed with power factor, peak active power and the angular coefficients as inputs. To develop the model it is necessary data of non-compensated reactive power. To do so, instantaneous measurements of reactive power from capacitor banks and substations transformers should be added.

This refinement uses the actual non-compensated power factor of the substation, as well as the values of maximum active and reactive power of a set of circuits with different market share in order to represent the different possible circuits in the network.

Figure 6 shows a representative neural network models development flow chart for the angular variations, as well as for reactive power forecast.

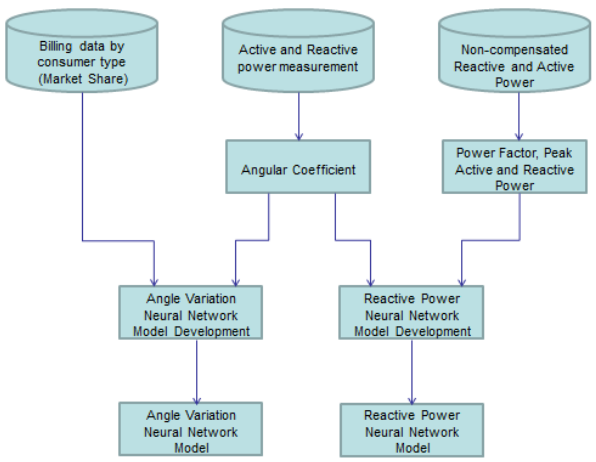

Figure 6: Angular coefficient and peak reactive power forecast models development.

The both neural network models, together with a power factor estimation technique, are the tools to the non-compensated peak reactive power forecasting. The models use only the market-share of the substation and the peak active power factor to forecast the non-compensated peak reactive power.

The power factor estimation technique uses the clustering of the substation being studied with several other known substations, using as decision variable the market-share, i.e. the percentage of each type of consumer, in order to identify the type of this studied substation, and the power factor estimated is the standard power factor of that substation group.

The use of the methodology is explained in Figure 7. This flowchart shows how the neural networks models are used in order to forecast the non-compensated peak reactive power of the substation.

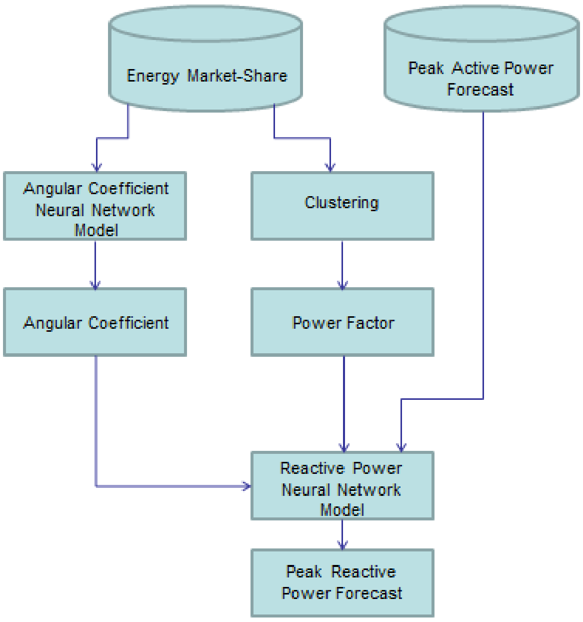

Figure 7: Peak reactive power forecast calculation.

FORECASTING RESULTS

In order to evaluate the methodology, historical measurements of active and reactive power in several DSO substations were used. In addition to these data, there are the historical billings of all consumers of these substations. It was found that there are no generators installed in these feeders and large consumers billing data are included in the historical data. Historical data comprise a total of thirty-six months from January 2011 to December 2013. As the billing calendar readings are held on specific dates for different groups of consumers, monthly billings do not coincide with days of the month, which required a pre-treatment for performing cointegration analysis.

The two first years are used to develop the models and the last year of data is used to validate the method, by comparing the forecasting with actual historical data.

For the peak active power forecasting, the result shown in Figure 8 was obtained, where the measured and forecasted points for one substation are shown. The average relative error found for this analysis was of 8%.

The methodology for the non-compensated peak reactive power forecast was developed using measurements from 16 different substations with different types of consumers, one group predominantly industrial, another group predominantly residential and one group with mixed types of consumers. The historical data from these substations were used to acquire the neural network of the angular coefficient between first difference of active and reactive power, to create a database of average power factors from different types of substations and to acquire the neural network of the peak reactive power.

In Figure 9 it is presented the monthly non-compensated peak reactive power forecast for a typical residential region. The average relative error found for this analysis was of 6.5%. The data used as input to the forecasting was only the peak active power and the market-share, as the neural network models, developed with several measurements and analysis of different substations, permits to estimate data of this substation

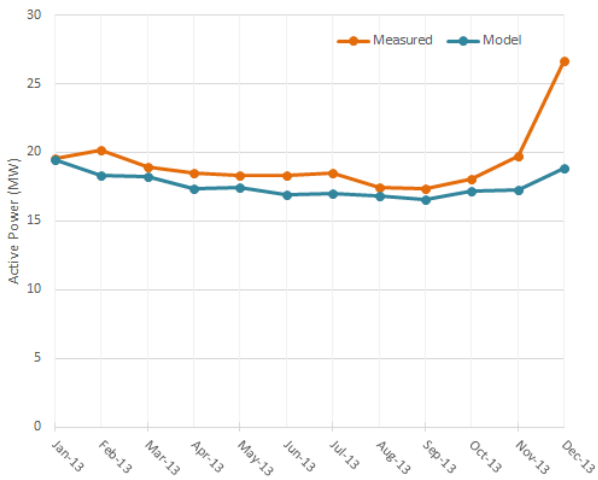

Figure 8: Peak active power forecast and measured data for predominantly residential substation

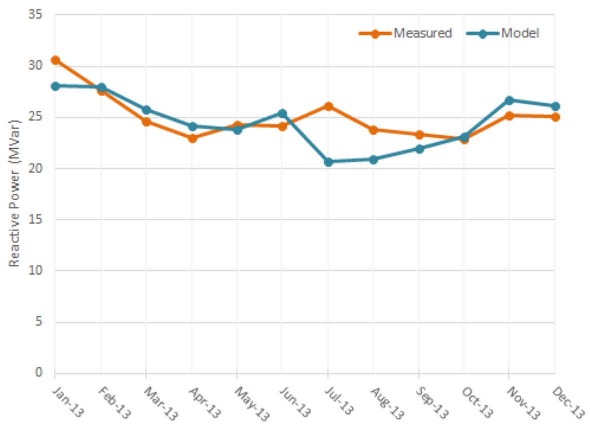

Figure 9: Peak reactive power forecast and measured data for predominantly residential substation

The method was also applied to a predominantly industrial substation, where the peak active power and non-compensated peak reactive power have a more complex behaviour. In Figure 10, the measurements of the historical data and the forecasted series for both active and non-compensated peak reactive power to the same substation are shown. This figure shows how the peak active power and non-compensated peak reactive power are strongly related when the reactive support is removed. The average relative errors for the active and reactive cases are respectively 12% and 8%.

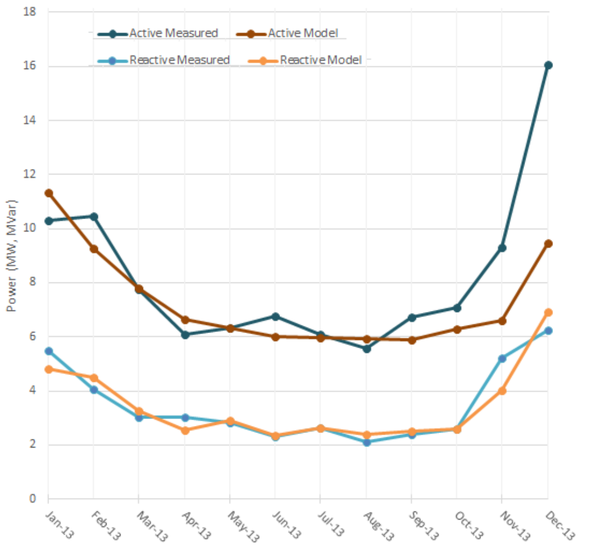

Figure 10: Peak active and reactive power for predominantly industrial substation

CONCLUSIONS

This paper proposed a complete methodology to peak active and non-compensated reactive power forecasting using data that is commonly available for DSOs:

- Billing data;
- Global energy forecast by consumer type;
- Substations active and reactive power measurements.

The peak active power forecasting method uses these data to develop a cointegration model to relate total substation energy with peak active power. The results show that these two variables are strongly related. The method was validated comparing real measurements with forecasted data.

In the case of non-compensated peak reactive forecasting, the first difference of active and reactive power series is used to filter atypical events such as bank capacitors switching.

An artificial neural network uses the relation between these first difference series, the peak active power and the non-compensated power factor as inputs to estimate the non-compensated peak reactive power.

The results show that both methods can successfully forecast the peak active power and non-compensated peak reactive power with average errors about 10%, which is adequate to long-term planning studies.

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