Very short-term load forecast for demand side management in absence of historical data

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Abstract: Load forecasting plays an important role in today's electricity grid, due to the presence of distributed generation. In this paper, various methods for short-term load forecasting are presented with the purpose to serve as tool to operate within a demand side management system. The need for large amount of historical data is avoided, opening the possibility for immediate use by customers without recorded load history. Widely distributed, such system can increase the reliability of the modern grid. The results showed that the Holt-Winters forecasting procedure give better results in comparison to neural networks with gradient descent, principally if the load rises fast in the early morning hours.

Keywords:

Demand side management, load forecasting, time series analysis, artificial neural networks, easy use.

1. Introduction

Today's electricity grid is walking in fast steps toward a grid with fully integrated distributed generation. The new distributed energy sources are almost based on renewable energy sources, mainly wind and solar, which have small power rating. Located near the consumers, they inject their intermittent power in a historical underscored grid, mostly operating on its limits. There is immediate need to integrate all those distributed renewable energy sources, without bringing down the grid. To avoid supply bottlenecks, the instantaneous demand must be adjusted to the power availability at the same moment. That means that there must be a system anticipation of the needs from the consumers before they arrive, and capable to take action, insight of a generation/load mismatch. Therefore, a modern demand management system has to achieve three main goals:

- Demand shedding – the old demand response solution. The new focus is only to shed as the last resort, when other measures miss the desired results;

- Demand shifting – being aware of the future status of the system, load can be shifted forwards (most and easy cases) or backwards;
- Load curve shaping – real time demand fine tuning, also known as “flexible load curve”;

Such a system, described above, needs a core algorithm to forecast the demand. Much research has been done, and a relative wide range of approaches has been proposed. Most of them based on neural networks [1][2][3], or time series analysis such as ARIMA or SARIMA models [4]. Interesting work was the fading-memory Kalman filter algorithm [5]. A comparison of different methods, including the Holt-Winters exponential smoothing is found in [6]. However, most of the above-cited approaches have a main problem: the need of large amounts of historical data, as minimum and maximum daily temperatures and load curves from the past. No practical use of such system can be expected on “normal” consumers, that means, where only a simple kWh meter is installed today (no demand history available).

This paper presents the early results for a more comprehensive system that is under development by the CEEMA (Centro de Estudos em Energia e Meio Ambiente) from the Universidade Federal de Santa Maria, Brazil. Research is underway for a complete real-time distributed demand side management system, planned for medium to large sized educational, government or business buildings.

2. Problem identification and objectives

Although a modernization of the electrical system is underway in great parts of the world, including Brazil, the majority of the consumers still have old kWh meters installed. The only historical data available are the monthly energy consumption. So, to include a forecast capability in a demand management system, to be installed for such a customer, a special approach is

needed. In the present case, load forecast means estimate the future load a few steps ahead in time. The system proposed must be capable to start immediately, and adapt automatically from the ingoing data, independently from the consumers nature and behavior.

To obtain a real data set for research, an intelligent energy meter (smart meter) was installed on the substation from the Technology Center engineering laboratories, on the campus from the University of Santa Maria, to register the energy load in 15-minute intervals. As result, we obtain the typical load curve, for this site, for workdays, shown in figure 1.

Figure 1: Typical daily load curve, Technology Center Engineering Laboratories substation

The load's typical behavior is a fast rise in the morning, a mid-day valley, and a most slowly decay on the end of the day. The smart meter is providing data to trains and validate the forecast algorithm (over 4000 measures, 96 per day, in 15-minute intervals).

3. The Holt-Winters forecasting procedure

The Holt-Winters forecasting procedure [7], is an exponential smoothing method for univariate time series containing trend and seasonal variation. In the present case, the seasonal variation is on daily basis, because the load rise and fall occurs every workday approximately at the same time. Meteorological variations or long term seasonal trends are reflected directly by the demand series itself, due its slow changing nature.

The value of the Holt-Winters forecasting procedure has already been shown by Taylor and McSharry [8].

The great advantage of this method is the need of, at last, only one day of past data.

The future load (one-step ahead) is given by:

$$y_t = R_{t-1} + G_{t-1} + S_{t-L} \quad (1)$$

Where:

y_t is the load estimated for the present time slot – initialized with the most recent load measure, obtained at $t-1$ (15 minutes ago).

R_{t-1} is the estimate of the deseasonalized level from the past time slot. Is this case the time slot is 24 hours, and

initialized with the mean load from the past 24 hours (mean on 96 fifteen minute interval values);

G_{t-1} is the estimate of the trend from the past time slot – initialized with zero, because no trend observed.

S_{t-L} is the estimate of the seasonal component, from the past season (in this case the past day). The initial value is given by the difference between the load from the same moment on the past day and the mean load from the last 24 hours;

The estimates are updated as follows:

$$R_t = \alpha(y_t - S_{t-L}) + (1 - \alpha)(R_{t-1} + G_{t-1}) \quad (2)$$

$$G_t = \beta(S_t - S_{t-1}) + (1 - \beta)G_{t-1} \quad (3)$$

$$S_t = \gamma(y_t - R_{t-1}) + (1 - \gamma)S_{t-L} \quad (4)$$

The value of S_{t-1} in (3) is initialized with the same value of S_{t-L} .

In the above formulas (2), (3) and (4), α , β and γ are smoothing constants.

Using the available data set (over 4,000 samples), each constant was varied between 0 and 1, and the MAPE (Mean Absolute Percentage Error) was observed.

Figure 2 shows the comparison between the real load, estimated load and percentage error based on data measured on June 28, 2011.

The best results were obtained with the smoothing constants $\alpha=0,7$ $\beta=0$ (no trend) and $\gamma=0,35$, resulting in a MAPE (Mean Absolute Percentage Error) equal to 4.93%.

Figure 2: Comparison between the real load, estimated load by exponential smoothing and percentage error

4. Artificial Neural Networks forecasting method

Another approach to “track” time series is the use of a focused time lagged feedforward network (TLFN). The difference to the normal multilayered perceptrons is the incorporation of time, represented implicitly by a short-term memory structure. Haykin [9], refers to the TLFN as a temporal pattern recognition method that “*process patterns that evolve over time, with the response at a particular instant of time depending not only on the present value of the input but also on its past values*”. Figure 3 represents such network.

Every neuron has an associated transfer function applied to the sum of the product of the entries and the respective weights.

Always when a new load value appears on the timeline, the previous output from the network is compared with the new value, and the weights are updated backwards in a process called back propagation learning.

Figure 3: Focused time lagged feed forward network

For the presented case, experiences were made on two layered neural networks: one output layer, with a single neuron, and one hidden layer with variable number of neurons. The number of neurons in the hidden layer were successively increased, and the type and number of entries too.

The transfer function for the output layer was chosen to be linear, as shown in equation (5) below:

$$y_k = \alpha \left(\sum_{j=1}^m w_{kj} y_j \right) + b_k \quad (5)$$

In addition, the transfer functions in the hidden layer were chosen to be sigmoid (6):

$$y_j = \frac{1}{1 + e^{-v_j}} \quad (6)$$

Where:

$$v_j = \sum_{i=1}^m w_{ij} x_i + b_j \quad (7)$$

The initial random weights between 0 and 1, are backwards updated depending on the output error:

$$e_k = L - y_k \quad (8)$$

Where L in (8) is the real measured load.

$$w_{kj}(t+1) = w_{kj}(t) + \eta(e_k y_j(t)) \quad (9)$$

$$w_{ij}(t+1) = w_{ij}(t) + \eta[e_k w_{kj} y_j(t)(1 - y_j(t))] \quad (10)$$

The equations (9) and (10) shows how the weights are update in a method called method of steepest descent.

Based on the above rapidly explained network formulas, simulations were made, whose results are in the table 1, below. It is interesting to observe that the number of entries and hidden neurons has no influence over the MAPE. It appears that the MAPE is only influenced by the “quality” of the entries (where they are located in time).

Figure 4 shows the comparison between the real load, estimated load by the focused time lagged feedforward network and percentage error, based on data measured on June 28, 2011. The method resulting in this graph was the last of table 1 (Three previous loads + four loads of four previous days).

Figure 4: Comparison between the real load, estimated load by neural network and percentage error

Table 1: Summary of simulations made and the resulting MAPE

Type of entries	Nr. hidden neurons	MAPE
Four previous loads	4	5.1%
Five previous loads	5	5.1%
Six previous loads	6	5.1%
Ten previous loads	10	5.1%
Twenty previous loads	10	5.0%
Ten previous loads + ten previous loads one day before	10	5.0%
Three previous loads + three loads of three previous days	4	4.7%
Three previous loads + four loads of four previous days	5	4.6%

5. Conclusions:

In this paper, preliminary results in the search of a robust, fast and easy to use algorithm for load forecast are presented. The surprise was that the number of hidden neurons in a focused time lagged feed forward network had only limited impact on the MAPE. Networks that include data from a few previous days have lightly better results. However, compared to the Holt-Winters forecasting procedure, there are only a very small error improvement.

Keeping a closer eye on the data, it reveals that the Holt-Winters method is better, because when the load rises fast in the early morning hours, it returns lower errors in comparison to the similar neural network. On the other hand, the fact that the Holt-Winters method look back only one day, can introduce large errors if the previous day was abnormal (for example a cold day followed by a day with higher temperatures).

The above-mentioned facts must be seen in light of the methods used: focused time lagged feedforward network with steepest descent learning algorithm or Holt-Winters exponential smoothing, with no trend. There were chosen to keep the processing fast and simple, to match the goal for a real-time load management.

However, as advantages of such algorithms can be cited:

- No need of load data, more than a week ago;
- No need of long computational time, for training;
- The need of only a few logic and calculus steps, to make a forecast;

More work must be done to fine-tuning the Holt-Winters method. In addition, for the neural networks, more days backwards must be included. Of course, not too much days, otherwise the goals are missed. Eventually other faster optimization algorithms must be tested.

To achieve the proposed goals, the need of historical data must be limited, perhaps to a maximum 5 workdays. This means that, once installed on a consumer, the system can operate fully within a week.

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