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Load Forecasting dealing with Medium Voltage Network Reconfiguration

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Abstract. Planing the operation in modern power systems requires suitable anticipation of load evolution at different levels of distribution network. Under this perspective, load forecasting performs an important task, allowing the optimization of investments and the adequate exploitation of existing distribution networks. This paper describes the models developed for current intensity forecasting at primary substation feeders. The main goal consists on defining a regression process characterized by good quality estimates of those future intensity values, based on historical database. Anticipation interval shall include from the next hour to one week in advance. The forecasting method shall also be adaptable to power network reconfiguration, whenever planned or not. In this work, artificial neural networks (ANN) were used as the basic regression tool. This paper describes used ANN as well as the premises that led to the implementation of selected forecasting models. At last, some illustrative results attained so far are presented, supporting the adequacy of adopted approach.

1 Introduction

Especially on last decade, one has been witnessing not only the growing of power transmission and distribution networks but also its increasing complexity. At the same time, it has been also growing the demands on environment preservation as well as the need of energy efficiency. Load forecasting constitutes an important tool for efficient planning and exploration of power systems, and its significance has been intensifying particularly because of movement towards open energy markets and the need to assure high standards on reliability.

Prediction of future values of temporal series is a rather common problem and it is largely amply divulged on scientific literature. Economists aim to predict economic tendencies, meteorologists the weather conditions, stockholders (everybody?) would like to predict future prices of stock market. Interest fields on forecasting are so vast that justifies the huge quantity of prediction methods, since long, well established. However, ANN has been replacing traditional methods in many applications offering, besides a better performance, a handful of advantages: need no system model, tolerate bizarre patterns, notable adaptive capability and so on. Load forecasting is one of the most successful applications of ANN to power systems [1,2,3,4]. Different strategies have been applied on the development of forecasting procedures. In this area, each case is a case. Forecasting goals, variables to predict historical data e analysis tools available are issues that contribute for each implementation being so particular.
Sometimes, one aim to predict the total consumption of a given region, or the power

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delivered by a given substation, or the load at a given level of power distribution network. Historical data available also coerce the prediction methodology. Data type (active power, current intensities, etc), data quantity (allowing or not to implicitly characterize the all universe of variable behaviors to emulate) and, finally, data quality (record bugs, SCADA failures, anomalous situations, etc) contribute decisively on the definition of the approach of the specific forecasting problem.

The present paper describes part of the forecasting work so far developed to be integrated in a commercial software for helping to manage electric distribution networks. The forecasting tool is expected to provide: a) active and reactive power at primary substation's transformers and b) current intensity at primary substation's feeders. In this article only includes descriptions of issues related to the b) case. An innovative issue is related to adopted approach to deal with programmed power network reconfiguration. In fact, most commons forecasting techniques can't perform reasonably when facing any kind of load transfer. This article presents a description of the adopted approach to overcome this question as well as some illustrative results.

2 Neural Networks

It is not a major goal of the present article to present a exhaustive description of the basic principles about ANN [5,6,7]. It's a well-known tool, widely divulged on academic and scientific literature. However, for completeness we will refer a few generic details related with ANN type and training. All implemented ANN are feedforward. ANN training algorithm was the Adaptive Backpropagation Algorithm (APA)[8]. This algorithm is based on the traditional Backpropagation [5], but instead of a single fixed learning rate, uses an individual learning rate for each weight. Each learning rate adapts itself to error surface, being incremented or decremented if the error surface on that particular weight direction is monotonous or not. With this strategy the authors experienced, for some complex mappings, a reduction of 1/1000 in the number of training epochs needed by BP. The stop training criterion was based on the well known cross validation principle, in order to fight against overtraining.

3 Training data

Historical data available characterizes current intensity evolution on about 800 substation feeders, in a hourly base, over 8 months. This (huge) amount of information allowed, in one hand, some latitude on building models and architectures (sometimes, a small amount of data imposes some reduction to the minimum of free ANN parameters). Besides, the utilization of a large amount of training patterns is a effective antidote to fight against overfitting. On the other hand, the whole process is slower and morose, due to the computation time required.

Half of the total patterns where used for training, while the other half is used for testing and evaluation of generalization performance. Results presented in this paper always refer to patterns never used in the process of defining ANN parameters.

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4 Results

4.1 Current intensity forecasting for the following hour

In this case, the ANN output is naturally the intensity (I) to predict. Feature selection was based on the following criteria: a) analysis of correlation between the value to be forecasted and preceding time series values; b) ANN performance results; c) the good old engineering judgement. The ANN architecture that produced the best results so far is presented on Figure 1.

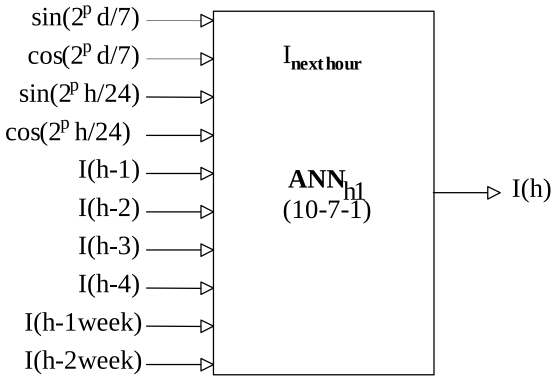

Figure 1 – ANN architecture for $I_{next\ hour}$ prediction

Variable h represents the hour of the day (0, …, 23) while d represents the weekday (Sunday=1, Monday=2,…, Saturday=7). Input variables are: I on the previous 4 hours, I one week ago at the prediction hour (i.e. I_{h-168}) and also I two weeks ago at the same hour (i.e. I_{h-336}). Furthermore, there are two inputs to characterize the weekday and two more for the hour of the day. Being h a cyclic variable with period 24, it is convenient to pass that information to the ANN. This can be achieved by defining 2 inputs based in sine and cosine functions, as shown on Figure 1. So the hour of the day is interpreted by a periodic measure, being each hour univocally specified. For similar reasons there are also two inputs for representation of the weekday. Figure 2 shows some forecasting examples for a given feeder.

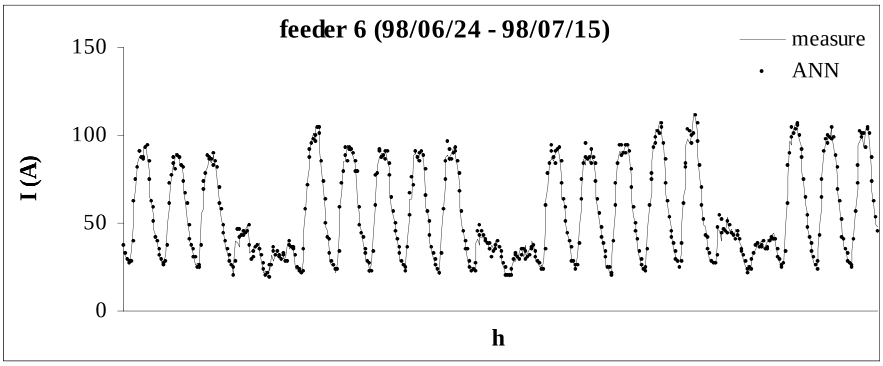

Figure 2 – Predicting I for the next hour – example

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Table 1 – ANN_{h1} performance

mean absolute error	4.31
mean rms error	6.34
mean absolute deviation	0.057
mean rms deviation	0.085

4.2 Forecasting I diagram for the next day

In this case, output variables are current intensities in each hour of following day I(h),..,I(h+23). Inputs are: the weekday, previous day diagram I(h-48),..,I(h+23-48), the diagram one week before I(h-1week),..,I(h+23-1week), and the diagram two weeks before I(h-2week),..,I(h+23-2week). The architecture that produces the best performance results is shown in Figure 3. Table 2 shows the performance errors attained with ANN_{d1} and Figure 4 shows two forecasting examples.

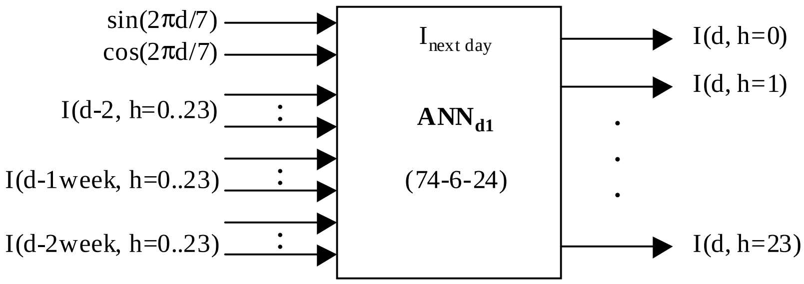

Figure 3 – ANN_{d1} for forecasting intensity diagram in the following day

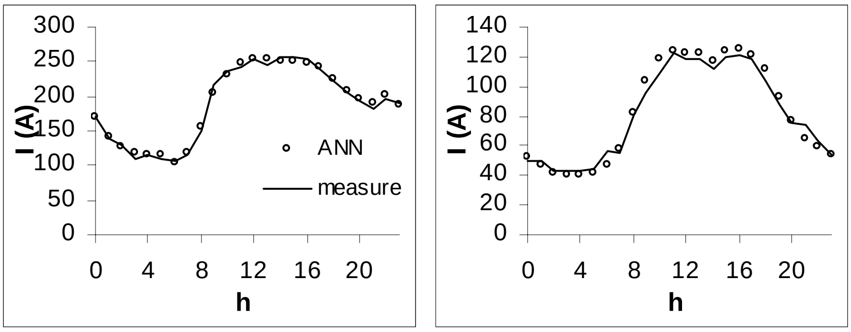

Figure 4 – Two examples of diagrams forecasted with ANN_{d1}

Table 2 – ANN_{d1} performance

mean absolute error	6.55
mean rms error	8.83
mean absolute deviation	0.09
mean rms deviation	0.12

4.3 Dealing with power network reconfiguration

Switching operations changes power systems configuration and, in consequence, the current intensities at feeders is redistributed. If intensity changes abnormally, ANN could not perform as well as usually. However, as long as the new intensity measures are presented at ANN inputs, ANN output will tend to adapt to the new curve evolution.

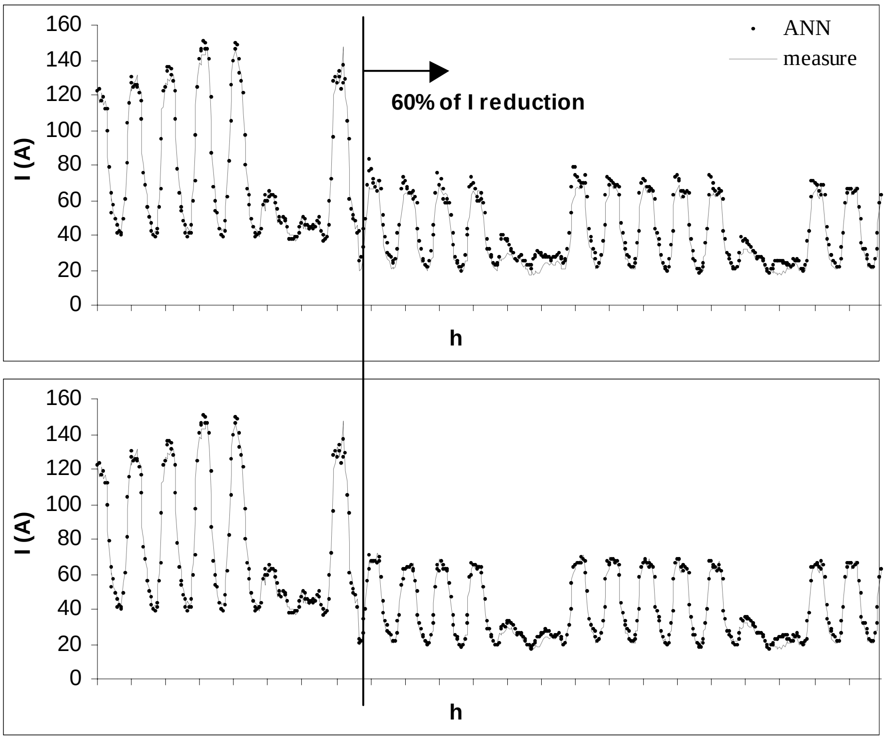

Figure 5 – Simulation of a transfer of 60% of I (after the dotted line).On top, ANN_{h1} "normal" output. Below, ANN_{h1} when I type inputs are reduced 60%.

Figure 5 illustrates this fact. On top, it shows a simulation of a reduction of 60% on I values after the dotted line. Forecasts just after this line are poor quality but the difference between targets and forecasts tend to be smaller as long as ANN inputs will go on absorbing the new values. It seems that if we could fool ANN by presenting at its inputs the I values affected by the transferring factor, then the ANN would perform better even for those values just after the switching. Whenever the maneuver is programmed, for instance, by equipment maintenance needs, system operators may estimate the changes on predicted intensities by using the following strategy:

1. Perform a forecast at instant t^- (before maneuver), obtaining estimates of I in all feeders;
2. Switching operations;
   a) Perform load allocation using data at t^- and obtaining estimates of (P, Q);
   b) Perform load Flow t^+ (new system state – transferred I);
3. New forecasting, using information about I transferred at t. I type ANN inputs are

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changed accordingly to estimated transfer for the periods under analysis. Note that I transferred is estimated for a single instant t but can be used for prediction on several periods (from the next hour to one week in advance).

An application example of this strategy is shown on bottom of Figure 5. Here, ANN answer is much closer the target values, even for those points close to the switching.

5 Conclusions

Performance results obtained so far support the validity of adopted approach, especially if random nature of predicting variables is taken into account.

The strategy adopted for dealing with programmed switching operations has also produced very interesting results.

There are many other interesting features of the present work data were not referred in this paper and some others that are still in development. Among then, we would like to mention:

- ANN models for the other forecasting intervals (remember that one wants to predict from the next hour to one week in advance);
- ANN models for active and reactive power;
- Weather effects;
- Estimation of confidence intervals using ANN [9].

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