PREDIELEC
A SHORT-TERM ELECTRIC LOAD FORECASTING SYSTEM USING AN ARTIFICIAL NEURAL NETWORK

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SUMMARY

We present in this paper a short-term (24 hours) electric load forecasting approach based on Artificial Neural Network (ANN). The forecasting is made for each node of a distribution network taking into account the factors with most significative impact on the network load behaviour, namely type of day and temperature besides the energy consumption of selected previous time periods (i.e., hours). We report some results for real problems drawn from the Spanish electrical distribution network.

INTRODUCTION

In order to supply high quality electric energy to the customer in a secure and economic way and also in an open market environment to optimise the energy bilateral sales contract and the strategy for the bidding to the pool in a competitive market, an electric company faces many economical and technical problems in operation, planning, and control of an electric energy system. For the purpose of optimal planning, operation and energy sales in this large scale system, modern system theory and optimization techniques are being applied with the expectation of considerable cost savings. In achieving this goal, the knowledge of future power system load is the first prerequisite; therefore, long and short term load predictions are very important subjects.
The load prediction periods may range from months to years for the long- and medium-term forecasts, and weeks, days or hours for the short-term forecast. The long- and the medium-term forecasts are used to determine capacity needs for the energy generation, transmission and distribution systems, to obtain energy generators and transmission and distribution equipment maintenance scheduling (probably in a yearly basis), etc. The short-term forecast is needed for control and scheduling of power system, and also as inputs to load flow study or contingency analysis and has a great importance in the real-time operating strategies for the power system.
Short-term load forecasting (STLF) plays a key role in the formulation of economic, reliable, and secure operating strategies for the power system as in the bidding strategy to the pool. The principal objective of the STLF function is to drive the scheduling functions that determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies, and physical, environmental, and equipment limitations.
A second application of STLF is for predictive assessment of the power system security. The system load forecast is an essential data requirement of the off-line network analysis function for the detection of future conditions under which the power system may be vulnerable. This information permits the dispatchers to prepare the necessary corrective actions to operate the power system securely.
The third application of STLF is to provide system dispatchers with timely information, i.e., the most recent load forecast, with the latest weather prediction and random behavior taken into account. The dispatchers need this information to operate the system economically and reliably.
The timeliness and accuracy of STLF have significant effects on power system operations and production costs. System dispatchers must anticipate the system load patterns so as to have sufficient generation to satisfy the demand. At the same time, sufficient levels of spinning and standby reserves are required to mitigate the impacts of the uncertainty inherent to forecasting and the availability of generating units. The cost of reserves is high since the units that make up the reserves are not fully loaded and consequently may be operating at less than their maximum efficiencies. The spinning and standby reserve capacities are set at levels dictated by the desired measure of security and reliability for the power system operation. Thus by reducing the forecast inaccuracy, reserve levels may be reduced without affecting the reliability and security of the system. In this way, the operating costs are reduced.
In addition, forecast error in load predictions results in increased operating costs. Load underprediction, results in a failure to provide the necessary reserves which, in turn, translates to higher costs due to the use of expensive peaking units. Load overprediction, on the other hand, involves the start-up of too many units resulting in an unnecessary increase in reserves and hence operating costs.

SYSTEM DESCRIPTION

The PREDIELEC system goal is to provide the best hourly electrical forecasting demand for every consuming node of a distribution network. This system uses one of the technologies which, according to reliable studies, ratified by several tests described in the literature, offers the best

results as for the error minimization. This technology is known as Artificial Neural Network (ANN).
ANN is a term, adopted from the brain physiology through the actual models are not much in relation with.
An ANN includes a set of information exchanging elements. Each one of them executes a very simple information process and communicates it to its neighbours.
However, all them together, are able to achieve an elaborated computation and learn behavior patterns. An ANN incharged of a task achieving, as the hourly load forecasting must be trained for its correct operation with some particular examples for which the model entries are associated to the right corresponding answer. This training process allows the model parameters fitting.
Although the forecasting model elaboration can be very complicated due to the inherent complexity of the problem to forecast and is time consuming, once the model is built and is really operated, its processing time is very short.
Overmore these kind of models present these others advantages :

- Operation capacity with uncompleted or mistaken data; this situation is very frequent in a real operation environment.
- Behavior generalization facing changing inputs; even in situations which were not considered in the model fitting, the system is able to generalize the observed behavior.
- Error minimization in particular days. Some days and in some nodes of the distribution network, the load usage pattern varies for example during local holidays. Other technologies give very high errors for these kind of situations.
- Its use is non-dependent on an expert and they can be updated by the user himself. The only requirement for the model update is a significative set data availability.

The first major aspect in the model building is the input variables selection. The load behavior is influenced by a number of factors. In particular, the hourly load demand is mainly affected by two factors, time and weather.
In this first release of PREDIELEC a 24 hours forecasting network has been introduced in the application. As the model used in the system is for the hourly load forecasting demand, the selected input variables included out of their accessibility and influence are :

1. Day type which includes the day of the week and holiday type.

The day type is perhaps the most important key factor in hourly load forecasting since different day types suppose qualitatively different load behaviors.

2. Temperature.

One of the variables with most influence on the load behavior is the temperature. In order to increase the forecast accuracy it is necessary to take into account the forecasted temperature of the forecasted day and the temperature of previous day since the importance of the thermic inertia in the consumption behavior has been verified.
So the input variables introduced in the system in relation with temperature are the maximum and minimum temperature of previous day and the forecasted maximum and minimum temperature of the forecasted day.

3. Historical load data

Furthermore the explicative variables of the load behavior, the real load itself in the previous hours is important to set the load variation rank. Day type and temperature determine the load qualitative aspect meanwhile the previous periods load determine the load quantitative aspect. In this case the load of the 5 last hours of the day before was used.

4. Another important factor related with historical data is also the increase of the demand in the last months that could be higher than the model could explain. So another input variable considered by PREDIELEC is the sum of the consumption in the last twelve months at the hour for which the forecasted demand is calculated.

In addition to these three key factors there exist other ones not considered in this application due to the data unavailability for the model building or to their random disturbances on the hourly load that cannot be explained in terms of the previously discussed factors.
Sure enough in addition to a large number of very small disturbances, there are large loads whose operation can cause large variations in electricity usage. Since the operation hours of these large devices are usually unknown to utility dispatchers, they represent large unpredictable disturbances. There are also certain events such as wide spread strikes, shutdown of industrial facilities, etc..., whose occurrence is known a priori, but whose effect on the load is uncertain.

MODEL UPDATE

The ANN offers the possibility to update the initially designed model very easily without users specific knowledge on the technology.
The application is equipped with an alarm system which is activated when the forecast mean error among all the nodes during the previous month exceed the user defined threshold. In this case, making some very easy steps, the system is able to self-update the model to the new behaviors, so that, if they tend to generalize themselves they are adopted as new consumption guidelines.
For the model update achievement is necessary to execute an error analysis process. Divided in days and nodes, this process allows to identify the need of the update and the possible reasons of the errors, for example if the forecast error is due to a specific day, to a special kind of nodes, etc. This analysis is carried out graphically on the display.

RESULTS

The forecasting results for the 24 hours of the day forecasted, for each selected node of the distribution network, could be graphically represented on the display

or archived in an ASCII file to be consulted afterwards or used in the study error which allows to identify the need of a model update.
The results getted by the model introduced in the system could be different according to the selected node.
Here are some results getted with data from IBERDROLA Sales Department for some hours in different months of the year 1997 and 1998, where the problem was to obtain the hourly global forecasted demand.

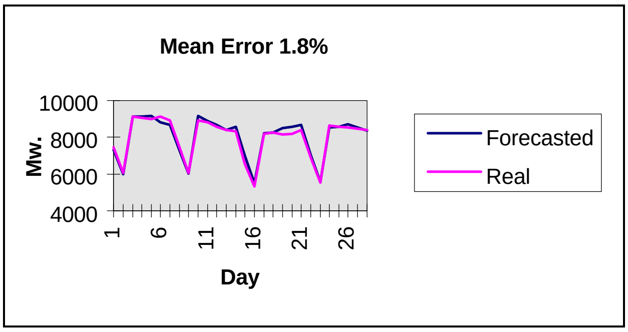

Figure 1. Forecasted Load versus Real Data. Hour 13 (February 1997)

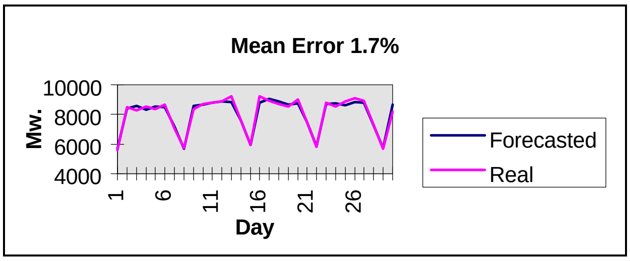

Figure 2. Forecasted Load versus Real Data. Hour 13 (June 1997)

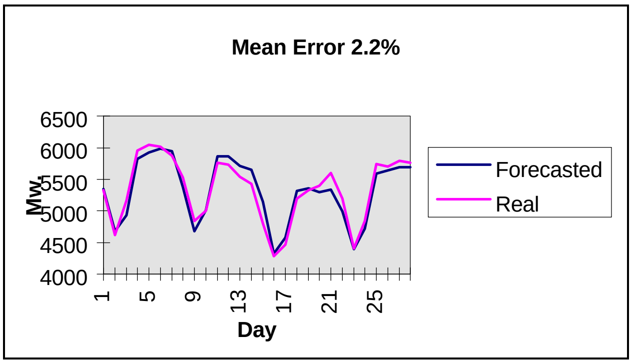

Figure 3. Forecasted Load versus Real Data. Hour 6 (February 1997)

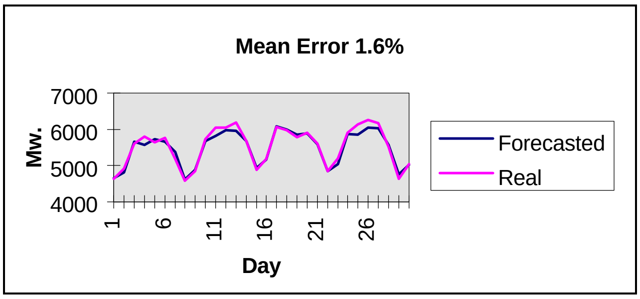

Figure 4. Forecasted Load versus Real Data. Hora 6 (June 1997)

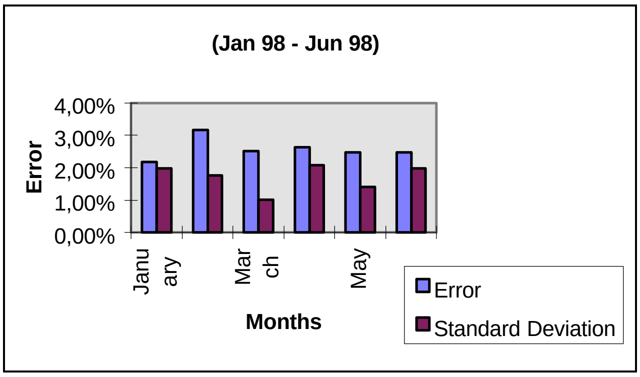

Figure 5. Mean Error and Standard Deviation for the hour 13

SYSTEM CHARACTERISTICS

PREDIELEC has been implemented in a PC 486 under Windows environment and uses the following tools :

- Visual Basic for the user's interface
- C for the model implementation

The specific neural network libraries for hourly electric demand forecasting and for model updating are property of IBERDROLA Ingeniería y Consultoría.

CONCLUSIONS

This paper has presented PREDIELEC, a short-term load forecasting system based in Artificial Neural Networks.
These are the most remarkable aspects of PREDIELEC :

- PC platform system
- Load forecasts depending on weather conditions and day type.
- Providement of accurate hourly demand forecast.
- Operation in real system environments, with data lacking or acquisition disturbances.
- Easy way for the model to react to new operational conditions.
- Error minimisation in abnormal situations (i.e., days).
- Non-dependent on the user's specific knowledge of the technology.
- Model self-update as new data are introduced in the system.
- Error analysis to determine the need of the model update.
- Alarm system for the forecast mean error.

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