A NEW NEURAL SYSTEM FOR LOAD FORECAST IN ELECTRICAL POWER SYSTEMS

A Topological Level Integration of Two Horizon Model Forecasting

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Abstract: This work presents a new integrated neural model approach for two horizons of load forecasting. First of all is presented a justification about the design of a computational neural forecasting model, explaining the importance of the load forecast for the electrical power systems. Here is presented the design of the two neural models, one for short and other for long term forecasting. Also is showed how these models are integrated in the topological level. A neural model that could integrate two forecasting horizons is very useful for electrical system enterprises. The computational system, here presented, was tested in three different scenarios, where each scenario has specific electrical load behaviour. At last the results is commented and explained.

1 INTRODUCTION

Actually the load forecasting is an important tool for energy enterprises. The forecast for electrical power systems is subject to internal variables in addition of external variables, stochastics variables, like meteorological and macroeconomic variables. The first one has an imply in residential loads and the second one has a strong imply in industrial loads (Ardil et al, 2007). The modern way to develop a forecaster is by the using of ANN, Artificial Neural Network, models.

In the literature, there are many papers about the use of neural modeling for only one forecasting horizon, examples are the work of Botha (Botha, 1998), Drezga (Drezga, 1999), Saad (Saad, 1999), Charytoniuk (Charytoniuk, 2000), Fukuyama (Fukuyama, 2002), Funabashi (Funabashi, 2002) and Abdel-Aal (Abdel-Aal, 2004). But neural modeling for two or more forecasting horizons is scare, one of the few exmples is the work of Shirvany (Shirvany, 2007).

The present paper propouses a new neural model for load forecasting by the using of two integrated models, one for short term and other for long term load forecasting. The resulting model has the ability for short and long term load forecasting at the same time, with better performance, both in response quality and computational performance.

The electrical power system focused in this forecast system is located in a large area in the south of Brazil. All the tests and results showed in this paper are referred to this system. This area is divided in seven nodes and each node has one type of the three electrical consuption behaviour, residential, industrial or a mixed type. After this introduction, follows the description of the proposed system, the tests performed and the results obtained and, finaly, our conclusions.

2 THE COMPUTATIONAL FORECASTING SYSTEM

The forecasting system consists in two neural models, one for short term and other for long term forecasting. These neural models are given by the artificial neural network application. The models were individually designed and validated to later be integrated. The data base of variables available to be used to design the models are given by meteorological, macroeconomic and electrical variables.

The variable space for an electrical system is too large, even when it is reduced for the three types showed above. For a better model response this

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space must be reduced. Variable selection methods are the best way to reduce the variable space removing from model most of redundant and irrelevant variables.

2.1 Variable Selection

The variables were selected by the using of forward selection. In this method the neural model is constructed by its interaction, where in each interacttion one variable is included in model. The criteria used to the model construction are the minor response error for a validation (Seeger, 2003). This algorithm runs until a stop criteria, in this paper case an error level minor than fifteen percent. For the two models, short and long term, this method is applied by individually manner. In the variable selection in addition to the inclusion of new variables were also varied the number of neurons in the hidden layer of ANNs, seeking for the best system performance.

2.2 Long Term Model

The main objective of this model is to provide the behaviour information of the electrical system to short term model, through the topological integration. In this model the forecasting horizon chosen was the monthly horizon, because that information is very important for the business of the electrical energy sector utilities (Quintanilha et al, 2005).

After the forward selection application the variables were selected, resulting in the neural model for long term forecasting. The monthly information of temperature and residential, commercial and industrial electrical load as input, with six neurons in hidden layer and one as output, indicating the long term total load forecast. This model uses as input the monthly information of one year and one day ago. That information give to the long term model the monthly tendency of each month of the year with all seasonal influences. This fact makes the model more robust.

2.3 Short Term Model

This model try, as main objective, mimetizes the electrical power system load behaviour. As like long term model, this model uses the forward selection to choose its variables. In this model case faster variables behaviour is relevant to it, like meteorological and electrical variables.

After the use of forward selection the neural model was constructed with the variables selected. This uses the daily information, about one day ago, of temperature, humidity and total electrical load as input, with six neurons in the hidden layer and one as output, representing the total load for the shot term forecast.

2.4 Model Integration

The integration of the short and long term forecast models is the main step of the computational system design. Is important keep in mind that this integration is given in the topological level. With this type of integration only the tendencies of each model are passed to the other. In other types of integration the error also is integrated.

The neurons sharing guarantee the tendencies exchange between long and short term models without polluting yours responses. But this is not a total share, only a parcel of these neurons is shared.

Using the neural models for short and long term forecasting with six neuron in hidden layer, a new neural model are created with merging these models. There were made tests to verify the number of shared neurons in hidden layer is needed to bettering the model response. In this test the number of shared neurons was varied in one to all (twelve).

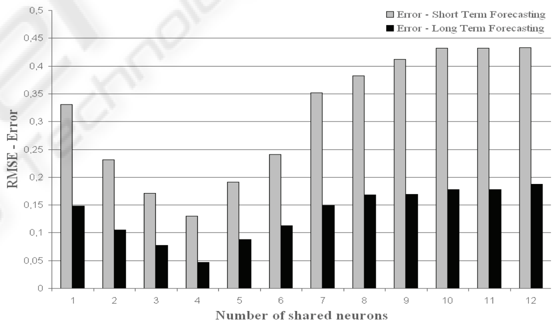

Figure 1: Trial with neurons sharing.

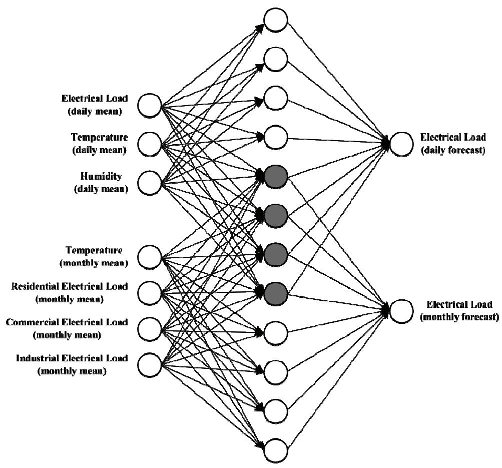

Figure 2: Neural model integration.

The Figure 1 shows that four is the best number of shared neurons to this application. The Figure 2 shows the final arrange of neural model, in highlighting the shared neurons in dark color. Also are showed the inputs and the outputs of final model.

The final model uses twelve neurons in hidden layer, with four exclusively used by short term model, four for the long term model and four neurons being shared by the two models, unifying these models in only one.

2.5 System Architecture

The architecture of the computational system is given by three main parts, or modules. This architect-ture is showed in Figure 3.

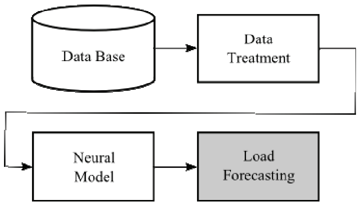

Figure 3: Computational system architecture.

Database contains all information about the electrical power system. For forecasting models is very important a large database as possible (Swinder et al, 2007). In the data treatment module the data is synchronized, normalized and separated per type. This learning occurs throughout the artificial neural network (ANN) training. The data set is delivered to the neural model aligned like is showed in Figure 4.

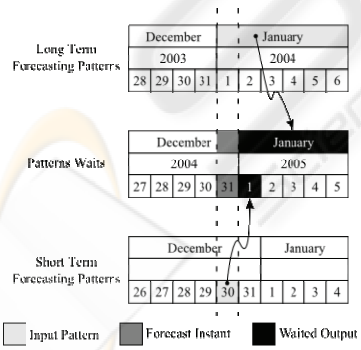

Figure 4: Data set temporal aligning.

In Figure 4 the forecast instant represents the moment when the computational forecasting system is executed. This data alignment avoids the need for not available data. That case occur when two forecast-ting horizons are used in the same model and one horizon is overridden by the other.

3 TESTS AND RESULTS

The system proposed was subjected to three different scenarios of load consumption being that, Industrial Load Region, Residential Load Region and Mixed Load Region. The tests outcomes of the integrated system are compared with the outcomes of the separated models for short and long term forecasting. In the tests was used the same number of sample for each region data set, and the same data set to individually forecaster (short and long term) and the integrated proposed system. There are performed the Ten-Fold Cross Validation method to prove the benefit of the models integration. As quantitative metric was used was the Root Mean Squared Error (RMSE), and all the results presented in this section were obtained with this metric.

3.1 Industrial Load Region Test

Industrial load has a seasonal behaviour with strong dependence of macroeconomic factors, that indicates the production behaviour of the industry and per consequence it is your electrical power consumption. The proposed system and individually models, developed to create the proposed system, results for this scenario are showed in Table 1.

Table 1: Industrial region test results.

Forecast Horizon	Propose Integrated System	Individually Models
Long Term	4,6%	21,4%
Short Term	13,2%	23,7%

3.2 Residential Load Region Test

The residential load presents a different behaviour, it is not seasonal. This type of consumer has a behaviour closely liked to the meteorological conditions. In cold days the residential consumer uses their heaters, and in the hot days they use their air conditioners. The system outcome to this type of load consumption is given in Table 2.

Table 2: Industrial region test results.

Forecast Horizon	Propose Integrated System	Individually Models
Long Term	6,7%	22,9%
Short Term	13,0%	24,8%

3.3 Mixed Load Region Test

Mixed load consumer regions are areas where there is a balance between residential and industrial consumers. In those areas there is no definition about the load behaviour, because it follows the trend given by the industrial and residential load. The system outcome to the mixed type of load consumption is given in Table 3.

Table 3: Industrial region test results.

Forecast Horizon	Propose Integrated System	Individually Models
Long Term	5,5%	22,1%
Short Term	11,7%	24,6%

In Figure 5 is ploted the results for short term forecast, comparing the pattern wait with outcomes of conventional forecasting system and the new neural system proposed in this paper. Note that the proposed system (represented by solid black line) fits perfectly with the pattern waited (grey line), the conventional neural system, represented by the short term model (dashed line) before developed has a worst behaviour.

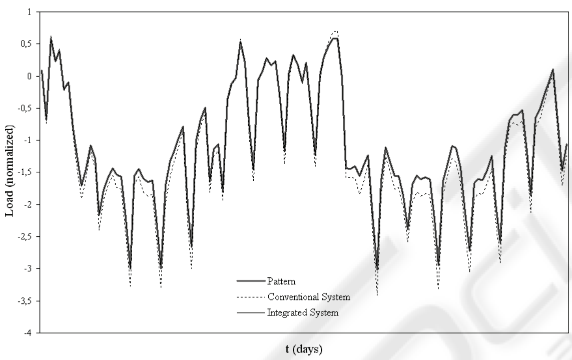

Figure 5: Short term load forecasting for mixed region.

4 CONCLUSIONS

The results show that integration of long and short term model is beneficial to the response of the integrated system. This integration improve the system accuracy for both forecast horizon and also turns the resulting model generic. That affirmation can be proved by the close results for the tree types of load consumption. A generic forecasting system has a important advantage for commercial usage, because they could forecast many instances with only one model.

Finally, the main contribution of this work is a new neural model for load forecasting, by the topological level integration usage. With this integration, the computational system has proved flexible and capable to generating excellent results. Some other aspects of the load forecast in electric systems, like the expansion of the time horizon, will be published in future works.

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