Comparison of serial and parallel approaches using artificial neural networks for Algerian short-term load forecasting

Kheir Eddine Farfar, Mohamed Tarek Khadir, Oussama Laib

Abstract—Knowing that electrical load is a non storable resource; short term electric load forecasting becomes an important tool to optimise dispatching of electrical load in regular system planning. Several techniques have been used to accomplish this task, from traditional linear regression and Box-Jenkins to artificial intelligence approaches such as Artificial Neural Networks (ANN). This work presents a comparative study of serial and parallel ANN approaches for forecasting 168 hours ahead using a multiple linear regression model as a benchmark for comparison. The results obtained by the latter method, are compared with the ANN serial and parallel developed approaches. These models were trained solely on past load consumption data, given by the Algerian national electricity company. This results in Nonlinear Autoregressive Models (NAR), however once the approach validity is proven, the addition of exogenous inputs can only improve model results.

Keywords—neural network, time series, short term forecasting, multiple linear regressions

I. Introduction

Power system reliability is the one of the main concerns for Electricity producers where electricity cannot be stored; making the major constraint, being balancing supply and demand permanently in real time. In order to control any technological or economical risks, the dispatching operators use load forecasting previsions to take decision that ensures good load balance and prepares the system in advance to answer future demands [1].

Electricity load may be considered as a chronological time series. Load series are, therefore, complex, exhibiting nonlinear patterns and depend on many random-like factors especially weather changes for short term and economic variations for medium and long terms, making the forecasting task difficult [2]. Load forecasting later can be categorised in three terms: short term, medium term and long term. Each category has specific objectives in its application and they had been largely discussed in recent decades [3].

The present study concentrates on short-term load forecasting which is an important tool for regular system planning and where several techniques can be found and applied on data from different countries. These approaches can be grouped into two parts. On one hand, some variation of traditional time series techniques such as ARIMA (Auto regressive integrated moving average) [4] and regression methods [5].

Where on the other hand, artificial intelligence approaches such as Artificial Neural Networks [6] and Support Vector Machine [7] may be applied. Other researches tried hybrid approaches to increase model efficiency [8].

Indeed, [9] used the connexionist approach to model their forecast problem, and in particular Artificial Neural Networks, and in [10,11,12] fuzzy approach was investigated, with a combination of two paradigms in [12]. Rajurkar and Newill, have developed a multi model approach dependant on the data, i.e, of the types of classes given by the electric load [13]. A system expert approach applied to Algerian data is also given in [14].

In this work, three techniques are compared for short term forecasting of 168 Hours ahead for Algerian power system, for instance: Multiple linear regression, serial ANN and parallel ANN architectures.

The remaining sections of this paper are organized as follows: Section 2 shows the features of Algerian electricity load. Our proposed models are described in details in section 3 and experimental results are presented in section 4. Finally, section 5 is a summary of our conclusions.

II. Algerian electricity load and Data

The Algerian national electric load energy from 1/1/2000 to 12/31/2004 is schematized in “Fig 1”. We can notice an increasing tendency reflecting a notable economic activity which rose during this period.

The electric load can be divided into groups, called day types, each group having common characteristics. A clear difference between a work day and a week end in the electric load diagram “Fig. 2”. This is due to a reduction in the economic activity and the weekly prayer of Fridays. Algeria knew a weekend shift in 2009 from Thursday and Friday to

Kheir Eddine Farfar, Mohamed Tarek Khadir, Oussama Laib
LabGED Laboratory, Badji Mokhtar University, Annaba
ALGERIA

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Friday and Saturday, this shift had an impact on electricity consumption as visualized in “Fig. 4”.

Available load data, concern years between 2000 and 2012 on an hourly base. However, the increased economic development in Algeria made the old data less appropriate to track recent trends, as can be seen in “Fig. 3” where the load tendencies in summer 2004 and summer 2010 are different.

We therefore decided to focus on the last 3 years for a total of 26304 data point.

III. Electricity load modeling

A. Linear Model

In order to validate and evaluate the enhancement in performance given by ANN models in this comparison, a traditional technique of time series analysis was introduced in the form of a multiple linear regression, in which the series is explained by three past values: \( t-1 \), \( t-24 \) and \( t-168 \) respectively the previous hour load, the last day load at the same time and last week load at the same time of the day, as detailed in equation (1):

\[
L_t = \theta_0 + \theta_1 L_{t-1} + \theta_2 L_{t-24} + \theta_p L_{t-168} + \varepsilon(t) \tag{1}
\]

Where: \( \theta_0 \ldots \theta_p \) are the model parameters and \( \varepsilon(t) \) is white noise.

B. Serial Model

In this approach, only a unique ANN model predicts the load of next hours, we will thus have 168 steps ahead to get one week predicted load. The training set consists of an output vector contains the load of hour \( (t) \) and an input vector contains the loads in the precedent hour \( (t-1) \), same hour in the previous day \( (t-24) \) and same hour in the previous week \( (t-168) \) similarly to the linear model and presented equation (2). This was found to better explain future load as the model will always contain a real value, instead of using predicted values.

\[
L_t = f_{ANN-s}(L_{t-1}, L_{t-24}, L_{t-168}) \tag{2}
\]
Indeed, multi step ahead prediction suffers from including only, at a certain point in prediction, estimated values, which will significantly, deteriorates prediction results.

Including a real regressive value that will be taken into account until the last prediction, i.e., (t+168), will anchor the model to reality and avoid using only biased estimated values.

To test the model, after every forecasting step we take the predicted load and use it as an input to predict the next hour. The same situation will be when forecasting t+25, so we start injecting the 24th previous predicted load as an input until (t+168), as shown in “Fig. 5”.

C. Parallel Model

This approach, explores the way of considering every hour (or a group of similar hours) of the day as a single time series.

Every model will predict a single one step ahead load value. Then, combining 24 one step ahead predictions will constitute the daily forecast, see “Fig 6”.

Subsequently, to forecast a week ahead, 7 step ahead predictions of each model will suffice, when compared to the 168 steps ahead needed for the parallel approach. Each model takes focus on forecasting a number similar daily hours, reducing the number of models needed from 24, to a lesser number to be determined.

The model for hour h, will include past load values for hour h, and h-1, respectively $L_{t-h}$ and $L_{t-h-1}$ as well as last week load value of the same hour: $L_{t-7}$, as given in equation (3).

$$L^h_t = f^h_{ANN-p}(L^h_{t-1}, L^h_{t-2}, L^h_{t-7})$$

(3)

In order to determine the similar daily hours, the load correlation between each hour of the day is calculated. The result is represented in “Fig. 7” where a high correlation is given by a darker shade, whereas a lighter shade of grey will indicates poor correlation.

Through the observation of the correlation between daily hours, five groups of similar hours are defined. Five ANN models for the parallel method are therefore trained with the data hours detailed in “Table. I”. Regrouping similar daily hours, implies reducing the number of nonlinear functions in equation (3) from 24 to only 5. Therefore $f^h_{ANN-p}$ will be equal to $f^1_{ANN-p}$ for h=0 to 6, $f^2_{ANN-p}$ for h=7 to 9... $f^5_{ANN-p}$ for h=21 to 23.
iv. Results

To evaluate each developed model and approach, the Mean Absolute Percentage Error (MAPE) is used as a metric on the test data, which is calculated by the following equation where \( m \) is the data size:

\[
MAPE = \frac{100}{m} \sum_{i=1}^{m} \left( \frac{|Reaload_{i} - ForecastedLoad_{i}|}{Reaload_{i}} \right)
\]

(3)

The parameters of multiple linear regression model was fitted on the same database used in the two methods of neural networks. The result is given in equation (4):

\[
L_t = \theta_0 + 0.3522 \, L_{t-1} + 0.4935 \, L_{t-24} + 0.1642 \, L_{t-168} + \varepsilon(t)
\]

(4)

For the multiple linear regression model, we obtained a MAPE = 7.21% on prediction of next 168 hour, which can be considered as a benchmark for neural network models and “Fig. 8” presents the results 168 steps ahead prediction. It can be seen that the linear model fits well the overall load daily shape, with a weakness predicting peaks and valleys. This is understandable due to the high nonlinear nature of these phenomenon.

During experiments, several architectures of multilayer perceptrons have been tested to choose the appropriate serial model, using a single hidden layer then two hidden layers, as well as modifying the number of neurons in each layer. The resulting architecture with their corresponding error percentage are detailed in “Table. II”.

<table>
<thead>
<tr>
<th>Model Number</th>
<th>Time interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>00 AM - 06 AM</td>
</tr>
<tr>
<td>Model 2</td>
<td>07 AM - 09 AM</td>
</tr>
<tr>
<td>Model 3</td>
<td>10 AM - 17 PM</td>
</tr>
<tr>
<td>Model 4</td>
<td>18 PM - 20 PM</td>
</tr>
<tr>
<td>Model 5</td>
<td>21 PM - 23 PM</td>
</tr>
</tbody>
</table>

The same approach was conducted when developing the parallel approach. Several architectures were developed for every model until an appropriate error was found for every five models. It was found that the learning and validation error converges to the same value, this is principally due to the relative small size of the ANN developed. “Table. III” show the smallest MAPE of each ANN model of the parallel approach.

<table>
<thead>
<tr>
<th>Architecture</th>
<th>MAPE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8-0</td>
<td>3.05</td>
</tr>
<tr>
<td>20-0</td>
<td>2.96</td>
</tr>
<tr>
<td>8-8</td>
<td>3.08</td>
</tr>
<tr>
<td>5-3</td>
<td>3.29</td>
</tr>
<tr>
<td>10-10</td>
<td>3.19</td>
</tr>
</tbody>
</table>

The network topology with 20 neurons and one hidden layer gives the smallest MAPE when compared to other tested ones. Therefore this topology was chosen for model development of 168 steps ahead and giving a MAPE = 6.79%.

<table>
<thead>
<tr>
<th>Model</th>
<th>MAPE 168 steps ahead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>7.21%</td>
</tr>
<tr>
<td>ANN (Serial)</td>
<td>6.79%</td>
</tr>
<tr>
<td>ANN (parallel)</td>
<td>6.50%</td>
</tr>
</tbody>
</table>

The results as showed in “Table. IV” are encouraging, by observing the error results, it is clear that the Artificial Neural Networks have better results than those obtained by the multiple linear regression. In addition, the parallel method gives interesting result compared to serial method as can be seen in “Fig. 9”. The relative complexity of using five smaller networks of MLP compared to one medium size network of the serial approach is compensated by the small prediction horizon needed, as explained in Section III.
v. Conclusion

In this work, a time series prediction problem with specific application on Algerian electric load was depicted. A multiple linear regression model is used as a benchmark for comparison. The Experiments aim to compare on forecasting 168 hours ahead, and the results have shown that the prediction using an ANN parallel method surpasses performance results obtained using the series ANN approach or multiple Linear Regression. Indeed, this is explained by the lower prediction step (1 step for the prediction of a day and 7 for the weekly prediction).

Many suggestions are possible to improve and develop the present work. One can cite the inclusion of exogenous inputs from atmospheric parameters such as temperature to type of day as weekends. This will only consolidates the results obtained with NAR models.

References
