

A Short-Term Bus Load Forecasting System

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Abstract: This paper proposes a methodology for short-term bus load forecasting. This approach calculates the short-term bus load forecast using few aggregate models. The idea is to cluster the buses in groups with similar daily load profiles and for each cluster an aggregate forecasting model is built based on the analysis of individual bus load data. The solution obtained through aggregate approach is similar to the solution obtained by individual bus load forecasting model, but with lower computational effort. This proposed methodology was implemented in a user friendly computational forecasting support system. The use of the computational prediction was essential to provide ease and speed in finding the solutions.

Keywords: Bus Load Forecasting, Forecasting Model, Clustering Algorithm, Forecasting Support System.

I. Introduction

The electrical energy is produced at power plants and transported to the consumption centers through transmission systems. A transmission system is composed mainly by transmission lines, transformers and control devices and can be mathematically modeled as graph flow system, in which the arcs represent transmission lines and transformers and the nodes, called bus, represent the connection point of these components. The electrical energy consumptions are connected to these buses and the sum of all consumers of a bus gives its bus load demand to be supplied. The electrical energy company must operate the system safely and in this sense it is important to assess the operation of the transmission system, that is based on load forecast on each bus [1].

The assessment of transmission system operation is executed at the short-term operational planning step, in which operation schedule of the power system for the next day is determined. This short-term planning must specify in hourly or half-hour basis the start-up and shut-down of generation units and the dispatch of these online units. This solution must satisfy all power generation and transmission systems requirements. To assure transmission secure operation, it is important to evaluate the impact of the dispatch at a given time interval, considering the transmission network and bus load expected to that interval [2]. Thus, to assess the

short-term transmission operation planning, a short-term bus load forecast is necessary [3].

The short-term bus load forecasting can be treated as conventional global load forecasting problem [4], [5]. In this case, for each bus would be necessary to adjust a specific forecasting model and to execute it every day. However, in power system with thousands of buses, this individual bus load forecasting will be a time consuming activity and inadequate to short-term decision process [6]. In this sense, this paper presents a short-term bus load forecasting methodology that aim to find accurate forecasts with reduced computational time. Thus, the main idea is to cluster the buses in groups with similar daily bus load profiles and for each group to built only one forecasting model that calculate all bus load forecast of the group [4], [6].

Since 1970's, a new computer science area called Decision Support System (DSS) was emerged with the main concern about computer program applications [7]. The main focus was on the facility to use the computer program [8]. In that time, the Windows based application was not available, and the majority of computer program were very difficult to be used. From these studies, it was proposed a computer system that integrated a data base system, a models basis and a user friendly interface system [9]. These DSS aim to facilitate user data handling, input data organization, program execution, and finally, to the program output presentation (results) [9].

In many decision making process, initially it needs to treat data that represent system information. In this step, it is necessary to verify the data consistence, to organize the data structure, and finally, the data storage and its visualization [10]. The next step is to organize the data input to computer programs. The last step is the computer program execution and presentation of program output [11]. To obtain a forecasting is necessary to perform each steps, and this process becomes complex when working with a lot of data. The short-term bus load forecasting problem has these features, because in Brazil there are more than 4000 buses, thus without a friendly computer system is difficult to make the forecasting studies rapidly and reliably. To solve this problem this paper presents a bus load forecasting support

system, that includes a data basis, a models basis, a user friendly interfaces, with facilities for data analysis, visualization and update to new models.

This approach was tested on bus load data from the Brazilian North/Northeast system; the proposed model was efficient in providing an adequate level of errors, a smaller number of forecasts, and faster results.

The remaining sections of this paper are organized as follows. Section II shown details the electrical power operation planning. Section III discusses about the short-term bus load forecasting problem. In Section IV present the proposed bus load forecasting model and outlines the steps involved. Section V shown the overview of the Forecasting Support System. The discussion of the case study and the numerical results obtained was presented in section VI. Section VII concludes the paper and outline issues for further investigation.

II. The Electric Power Operation Planning

The Brazilian electric power system is composed predominantly of the hydroelectric power generation, generally located very far from consumption centers. Due its continental extension, the Brazilian electric power transmission system is composed of long distance high voltage transmission lines, as can see in Figure 3. The transmission system has approximately four thousands nodes and five thousands transmission lines, and the generation system has approximately two hundred hydroelectric and fifty thermoelectric power plants.

The Brazilian electric power operation planning is decomposed in two steps [14]. Initially, a mid/long term planning is executed, in which a time horizon of 2 to 5 years ahead is considered. This step aims to optimize the annual river inflows, storing water at the reservoir during rainy periods to be used during dry periods [12], [13]. The main output of this planning is the short-term generation targets for each power generation plant [15]. This planning does not consider transmission system and load demand is usually represented by the monthly average demand. The last step is the definition of short-term operation schedule. This short-term operation planning must consider the system operation in detail, such as the hourly load demand (Figure 1), the start-up/shutdown generation schedule and the transmission systems operation constraints at each time interval [1].

To evaluate the impact of a given generation dispatch, it is necessary to have an estimative of the load demand at each bus node [3], [2]. The knowledge about bus load demand is also important for decision-making such as reliability analysis [3], congestion analysis, system operation, commercial strategies, tariffs definition [16], [17] and energy prices in the electricity markets [18].

In general short-term bus load forecasting can be viewed as a traditional short-term global load forecasting, in which for each bus can be developed a specific forecasting model. However, due to the great number of buses, the execution of all these individual models requires considerable computational time and it can be inadequate to short-term decisions.

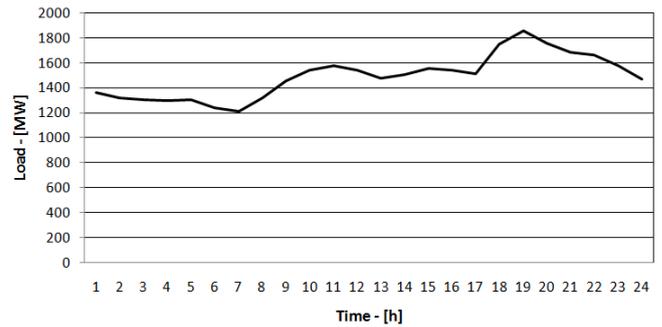


Figure 1. Typical Brazilian Daily Load Curve.

Figure 2 shows an electrical network example corresponding to time interval t , where there is a decision problem related to power system dispatch. In this case, the buses 1 and 2 are connected to power plants that inject $G_1(t)$ and $G_2(t)$ (MW), and the buses 3 and 4 are load buses with load of $P_3(t)$ and $P_4(t)$ MW, respectively.

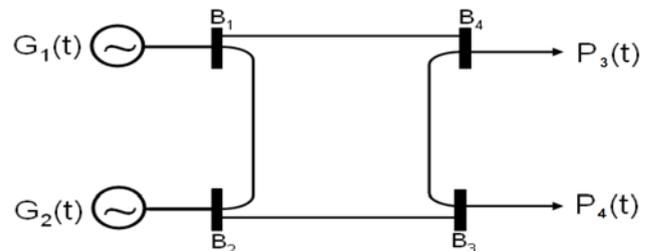


Figure 2. Simple Electrical Network Diagram.

III. The Short-Term Bus Load Forecasting Problem

The bus load forecasting process can be defined as the conventional time series forecasting in which for each bus can be developed a specific forecasting model.

In general way, the prediction of bus loads usually may be more complex than the forecasting of global system demand, because the bus loads are more variable than global demand. Generally the bus load data has more outlier's data, nonlinearity, and high frequency components than the system global demand. In many cases, the historical load demand data of a given bus may have significant distortion due to change on network configuration. Another relevant factor is the diversity of the profiles that increase the complexity of problem [5].

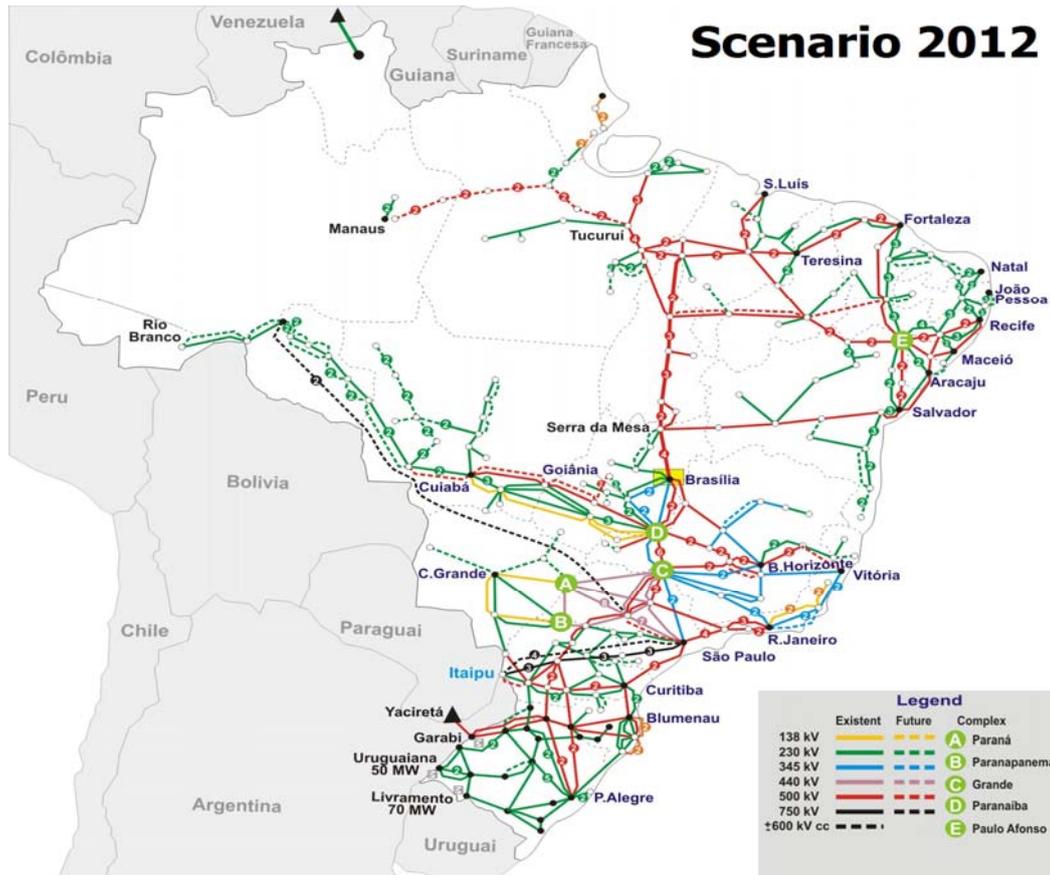


Figure 3. Brazilian Electric Power System (Source: National Operator of the Brazilian Electric System – ONS/2011).

The daily load demand of a bus depends on its consumers consumption pattern, and it may be much different from one bus to another, either in terms of consumption level (average demand) or in terms of daily load profiles, as can be noted in the first two load curves of Figure 4, in which the bus #59 presents a typical residential daily load profile, and the bus #53 represents industrial consumers. In terms of daily average demand, the difference between them is also important, with the first bus load about one hundred times higher than the second bus. Furthermore, during real time operation, there are changes on the transmission network that may transfer the load demand of some bus to another bus. This alters significantly the load demand profile of some buses and it must be considered in the bus load forecasting. Bus #47 in Figure 4 illustrates an example of bus load demand change that presents a drastic daily profile change in consecutive days.

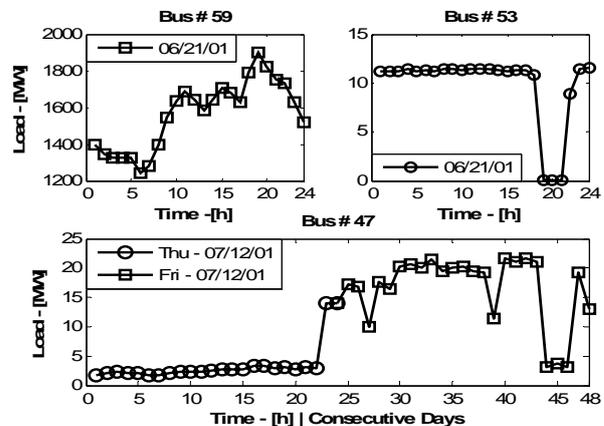


Figure 4. Daily Profiles and Pattern Change.

IV. The Bus Load Forecasting Methodology

The proposed bus load forecasting methodology calculates the short-term bus load demand forecast using few models. The main idea is to cluster the buses in groups with similar daily load profile and to adjust one load forecasting model for each cluster. The entire process is executed in two phases. In the first phase the bus clustering process is executed. In the second phase a forecasting model is adjusted for each cluster.

A. Clustering Phase

There are several clustering techniques, such as Kohonen ANN [19], Fuzzy c-Means (FCM) [20], Subtractive Clustering algorithm (SC), originally proposed in [21],

K-Means [22] and other statistical models. In this paper was used the Subtractive Clustering algorithm, because it determines automatically the number of groups. The goal of this phase is to cluster the buses with similar daily load profiles. In order to capture this load profile, independent of load demand level, it is necessary to normalize the load curve, as shown in Figure 5. The original curves are in Figure 5(a), which they are very different in terms the load demand levels, but when they are normalized as in Figure 5(b) they are very similar in terms of daily load profiles [23].

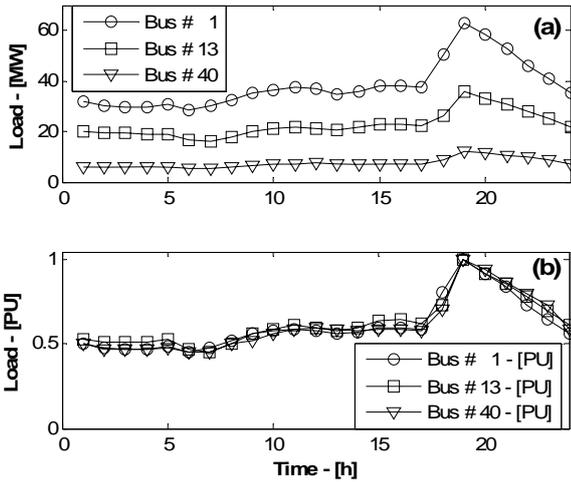


Figure 5. Buses Normalization Motivation.

B. Bus Load Forecasting Model

In this phase a predictive model is adjusted for each cluster. The proposed forecasting model was based on a nonlinear multi-layer perceptron (MLP) neural network [24], [27]. As each bus of the group uses the same model for its load forecast, it is important that the cluster ANN model incorporate the information all bus. In this sense, the methodology aggregates the information of individual bus in a unique model, and so it is called aggregate model. Other techniques, such as linear regression [26], neurofuzzy system [25] can be used in the aggregate model. To define the aggregate model it is necessary initially to determine what are the input variables. These inputs are defined based on the analysis of individual bus load time series. The model has only one output, the bus load prediction for time interval t .

1) Definition of Input Variables

A simple example illustrates how the aggregate model is formed. Suppose a cluster with two buses #1 and #33. In this paper, the inputs related to a given bus are determined through a partial autocorrelation analysis. Thus, suppose in the case of the bus #1 that it was selected as inputs the loads $D_1(t-1)$ and $D_1(t-24)$, and the input $D_{33}(t-1)$ and $D_{33}(t-2)$ for bus #33.

2) ANN Model Architecture

The aggregated forecasting model for this cluster is formed using the inputs selected by autocorrelation analysis as in Figure 6. The first two inputs are the same inputs selected for the bus #1 and the last two are the inputs for the bus #33. Thus, the aggregated model preserves the same inputs of individual models for each bus of the cluster.

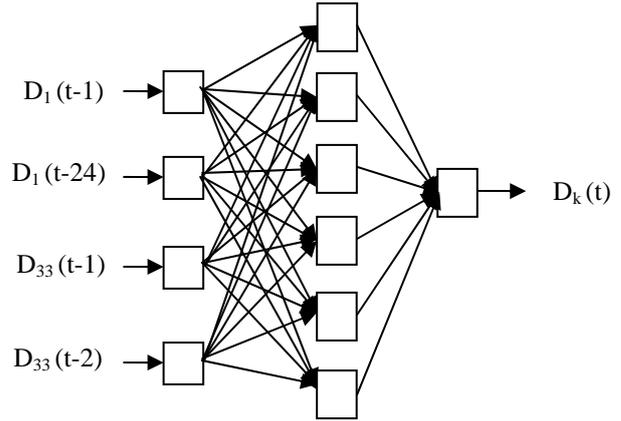


Figure 6. Aggregate Diagram.

C. ANN Training Step

The ANN model presented above has a specific training process. Usually, a set of all input values is presented to the model at the same time in order to adjust the weights. But, in the training process of the proposed model the data of each bus is presented separately from the data of others buses. Figure 7 shows the presentation of data of the bus #1; here the inputs related to bus #33 are null, and the output is the desired load of the bus #1. Figure 8 shows the presentation of data of the bus #33; here the inputs related to bus #1 are null and the output is the desired load of the bus #33. This training procedure preserves, in some sense, the individual training. In this paper, the learning algorithm employed is the well-known error backpropagation method [24].

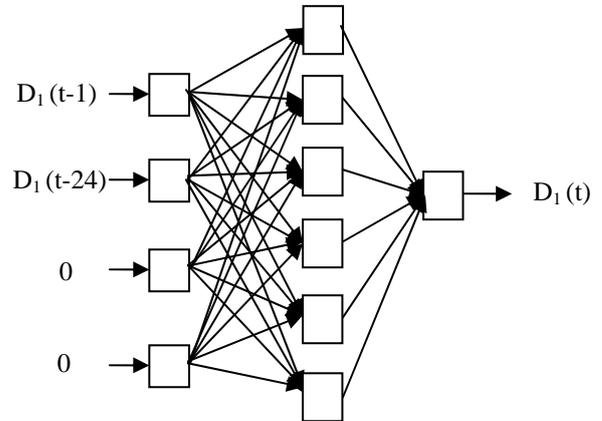


Figure 7. Bus #1 Data Presentation (Training step).

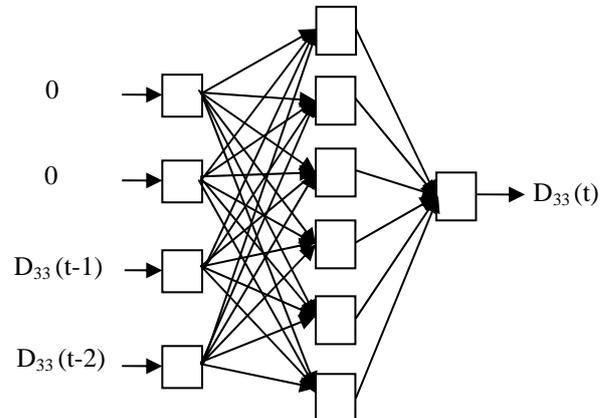


Figure 8. Bus #33 Data Presentation (Training step).

V. The Forecasting Support System

The daily load forecasting process must be easy and fast. In this sense, the proposed methodology was implemented computationally as a forecasting support system. As the load forecasting requires data, models and handling of data and

model solutions, the developed forecasting support system is composed of a data basis, a models basis and an interface system. Figure 9 shows the idea used in the development of the computation system.

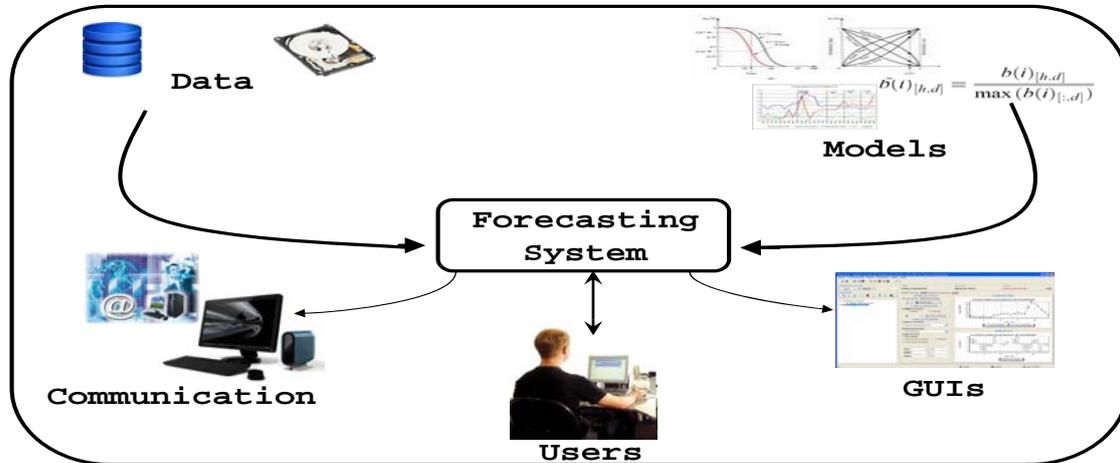


Figure 9. Forecasting Support System – Idea and Modeling.

A. Database Administrator

The forecasting support system has a storage structure and data management of bus loads, calendars, climatic information and others relevant information's. This module provides access to any required information, concatenating and generating visualizations of data, enabling the loading and import sources from other repositories and performs the recording results for later analysis. These bases uses a SQL based system that facilitate the data query, handling, data management and security.

B. Package of Mathematical Models

The package of models, implemented in the system, manages the whole structure of predictive tools, models of data mining and statistical tools. This module supports the simultaneous execution of several tools that can be used to solve different forecasting problems in parallel.

This package has a set of tools developed to aid the tasks of analysis and data consolidation. For example, in the proposed forecasting methodology are used normalization, clustering, partial autocorrelation analysis and ANN load forecasting model. These functions may have several alternatives, such as normalization by the maximum value, normalization by the average value. In terms of clustering models, there are Kohonen based system [19], Fuzzy C-Means [20] and Subtractive Clustering [21], K-Means [22] and others. In terms of forecasting models, there are many other options such as Auto-Regressive [26], Artificial Neural Networks [24], [27], Neurofuzzy models [25], models based on SVMs [29], Ensemble Techniques [28] and others.

C. Graphical User Interface Package

The interaction between the user and computational system is executed through the interface system. The interfaces facilitate the selection of data, visualization of data and model solutions, and selection of models and its configurations.

Figures 10 and 11 shows the configuration interface to the models ANN/MLP and Kohonen Self Organized Maps. Figures 15, 16, 17 and 18 show examples of GUIs (Graphical User Interface) that were developed in the system to assist the user in a bus load forecasting study.

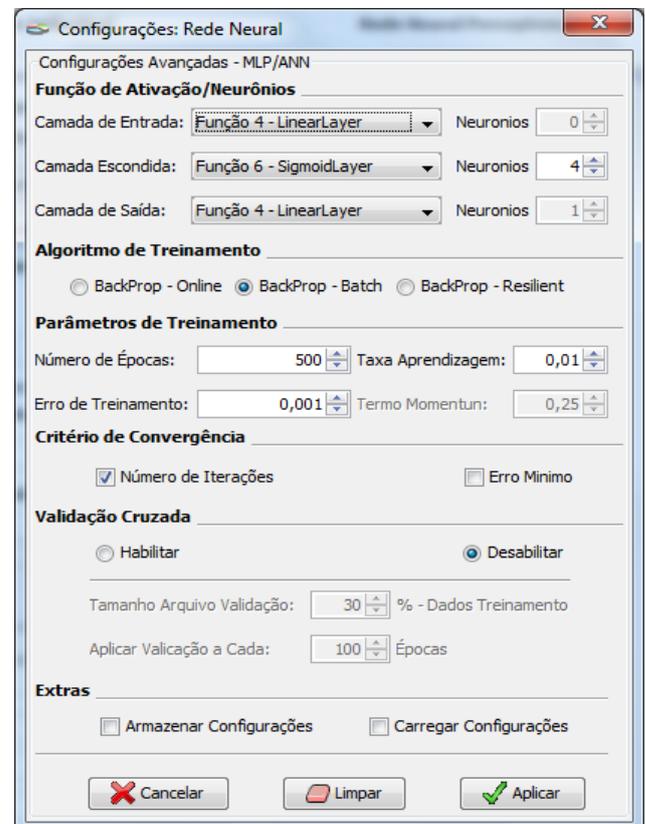


Figure 10. GUI – ANN/MLP Configuration.

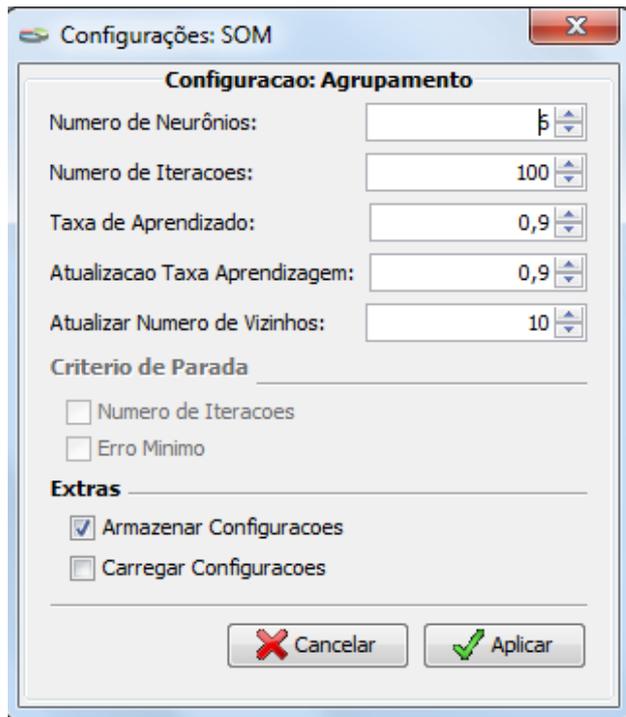


Figure 11. GUI – SOM/Kohonen Configuration.

The forecasting support systems are very useful for research, because they facilitate, for example, the test of different forecasting techniques applied to a given problem. It can be performed more rapidly on a user friendly computational system. Another important aspect is the visualization facilities of data and model solution; this provided insight to the users about the problem and its solutions.

VI. Case Study

Each day, a bus load forecasting for next day is determined. The forecasting using the proposed methodology must initially to determine the cluster, and then to execute the bus load forecasting for each group. In the following a case study is presented, starting with clustering step and then the bus load forecast is determined. The proposed methodology was applied on a test system with 73 buses, from Brazilian Northeast system.

A. Clustering

The SC algorithm divided the 73 buses load curves of 09/24/2001 in 34 clusters, in which 14 groups have 2 or more buses. The total of electrical load in all buses was 9024.14MW. The clusters with two or more buses represent 88.3% of the total load. For the buses with specific daily load profile (group with one bus), it is recommended individualized forecasting models. Table 1 shows the clusters with two or more buses, their respective cluster total load and standard deviation. Figure 12 shows four examples of clusters obtained by SC algorithm.

Cluster	N. of Buses	Load (MW)	Load (%)	Std (PU)
1	2	3.75	0,04%	0.0041

2	2	218.76	2,42%	0.0074
3	2	170.37	1,89%	0.0064
4	2	31.80	0,35%	0.0055
5	2	82.89	0,92%	0.0063
6	2	221.93	2,46%	0.0091
7	3	68.46	0,76%	0.0059
8	3	54.29	0,60%	0.0088
9	3	431.87	4,79%	0.0088
10	4	278.82	3,09%	0.0070
11	5	399.39	4,43%	0.0061
12	5	145.66	1,61%	0.0058
13	7	877.80	9,73%	0.0077
14	11	4983.44	55,22%	0.0043

Table 1. Bus Clustering.

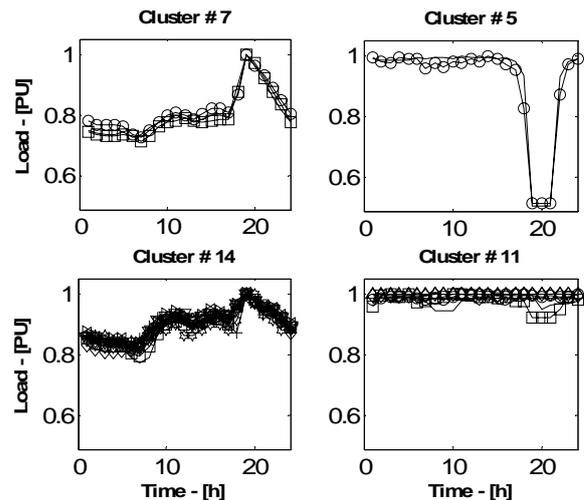


Figure 12. Clusters with 2 or more Buses.

1) Bus Cluster Analysis.

To analyze the stability of clusters, 15 of the 73 buses previously presented were selected and clustered for 44 consecutive days. Table 2 shows the distribution of buses over the 44 days. In most cases, it was observed stability in clusters, where similar buses remained in the same group on most days. For example, the buses #1, #10, #12 and #13 are always at the same cluster.

Of course, there are some variations between groups of elements due to little changes in the profile of some buses. However, in general this analysis shows that there is stability in the behavior of buses in terms of consumption profile. This fact can be explained because during short time (44 days) there are no major changes in terms of the electrical connection (of insertion/removal of consumers from the bus) that means that the buses has essentially the same profile, consequently the clusters tend to be the same.

B. Bus load forecasting

The training data set was composed by load from 01 June to 24 September of 2001 and the test data set was composed by loads measured on September 25 of 2001.

The ANN used in this paper (individual and aggregate way) is a well-know multilayer perceptron trained with backpropagation method. The number of the neurons in a hidden layer and the moment term was found by an exhausting search in the domain [1, 15] and [0, 0.99] respectively, the neurons limits values are found using Baum-Haussler metric [30]. The initial learning rate was 0.9, and in each iteration a unidimensional line-search to found the next value of the learning rate was used [31] and [32].

The forecasting performance was evaluated by the indexes *MAPE*(%) (Mean Absolute Percentage Error) and *E*(MW) (Standard Error) between the observed and forecasted loads. These are well-known statistical indexes for evaluation of forecast methods, defined by equations (1) and (2).

$$MAPE(\%) = \frac{100}{24} \sum_{i=1}^{24} \frac{|x_i - \hat{x}_i|}{x_i} \quad (1)$$

$$E(MW) = \sum_{i=1}^{24} (x_i - \hat{x}_i) \quad (2)$$

To measure the performance of the aggregate model, we executed a forecast for each bus using an individual forecasting model. These results will be used to evaluate the performance of the proposed model. To facilitate the identification of the forecasting approaches used in this paper were named: 1-Ind_ANN- individual approach with Artificial Neural Network; 2-Agg_ANN- aggregate approach with Artificial Neural Network.

Bus	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15
#1	0	21	0	0	3	4	5	11	0	44	0	44	44	0	0
#2		0	3	10	26	27	27	34	2	21	1	21	21	0	0
#3			0	34	13	12	13	7	42	0	21	0	0	1	0
#4				0	23	22	23	16	32	0	16	0	0	0	0
#5					0	39	37	34	11	3	2	3	3	1	0
#6						0	38	37	10	4	2	4	4	1	0
#7							0	35	12	5	2	5	5	0	0
#8								0	5	11	1	11	11	0	0
#9									0	0	23	0	0	2	0
#10										0	0	44	44	0	0
#11											0	0	0	18	5
#12												0	44	0	0
#13													0	0	0
#14														0	31
#15															0

Table 2. 44 Consecutive Days Clustering.

1) One Day Forecasting.

The aggregate model was configured to foresee one single day ahead. To determine the load demand curve of the next day (24 hours ahead) an adjustment of the models is accomplished to deal with every hour of the day. Thus, there is a specific forecasting model adjusted for each time interval. Table 3 shows the forecast results obtained through the two methodologies. Observing these results it is possible to note that the models Ind_ANN and Agg_ANN had very similar performances, with low variations in their errors.

Cluster	Ind_ANN	Agg_ANN
#1	3.67	3.83
#2	3.30	3.50
#3	3.67	3.77
#4	7.13	7.32
#5	1.87	1.90
#6	2.94	2.83
#7	3.96	3.70
#8	2.59	2.48
#9	1.97	1.89
#10	2.36	2.34
#11	3.42	3.91
#12	3.59	3.68
#13	4.59	2.96
#14	3.26	3.45

Table 3. Average Percentual Error.

Figure 13 presents the MAPE for the buses of the clusters 8 and 14. These results show that the models Ind_ANN and Agg_ANN had a similar performance for 11 buses of the groups. Figure 14 presents the hourly load of bus #59 obtained by the two approaches. Here also the performances of the two models are very similar. It is possible to note that the aggregate and individual ANN models were able to forecast the curve in an efficient way. In terms of the error both models are compatible where IM_ANN has error level of

the 2.21% and the aggregate model of the 1.94% in all day.

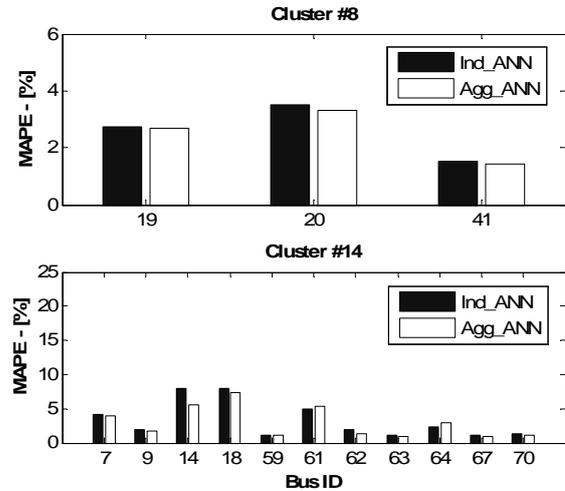


Figure 13. Average MAPE - Cluster #8 and #14.

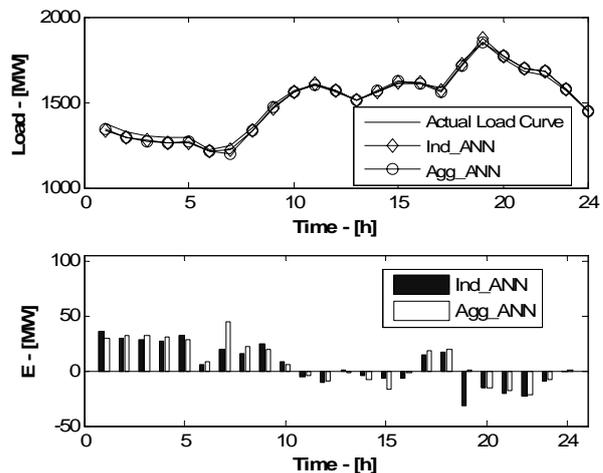


Figure 14. Actual x Forecasted Curve and Hourly Error - Bus # 59 09/25/2001.

Table 4 shows the computational time to foresee the bus load in all the models. To provide equality in the tests all models were running in the unique hardware system using same operational system, software and mathematical library. The tests were made on a PC with AMD Opteron 175 Dual Core 2.2GHz; 4GB DDR-400 Memory, with Linux Kernel 2.6.26. Observing the numerical results we can see that aggregate model was about 14 times faster than Ind_ANN model. Using the aggregate model the results are so good or better than the individual model with lower computational effort.

	Ind_ANN	Agg_ANN
Time execution (min)	20.52	1.47

Table 4. Computational Time - Forecasting Models.

Another advantage present in proposed model is the possibility of choose any forecasting model to predict the bus load forecasting. We chose an ANN/MLP as the main model to forecast the bus load because this model is a classic method in electric load forecast, but without loss of generality it is possible to use any other predictors, liner or nonlinear, (like as PAR or fuzzy predictors).

We know that there are other important variables that can improve the quality of the load forecasts (climatic information and others exogenous variables). This work did not use these information because do not have available climatic or exogenous data for the bus area used in this paper.

VII. Conclusion

In this paper an aggregate bus forecast model was proposed to solve the short-term bus daily load forecasting problem. The aggregate model presented robustness with good generalization capability. The model was effective in the solution of the problem with low errors in the most buses.

Even with efficient results the proposed model can be improved to present forecasts more efficiently. We can add climatic-related variables and other exogenous information that tends to improve the bus load forecasting. Thus, this technique emerges as a promising alternative to deal with short-term bus load forecasting problems.

The forecasting supports system provided easily in the obtaining solutions in a user friendly and intuitive graphical environment. We can say that a support system provides a better understanding of the data easier to obtain results quickly and conveniently.

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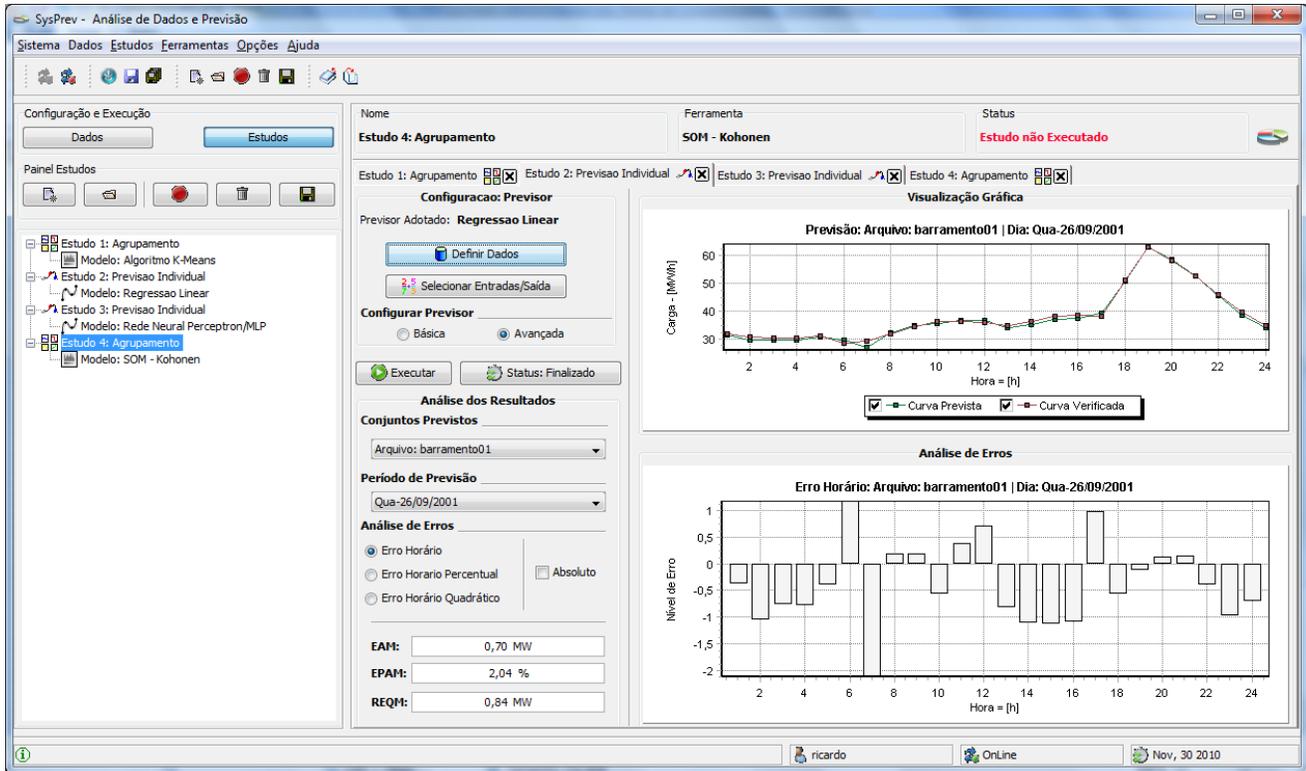


Figure 15. Main GUI – Forecasting Support System.

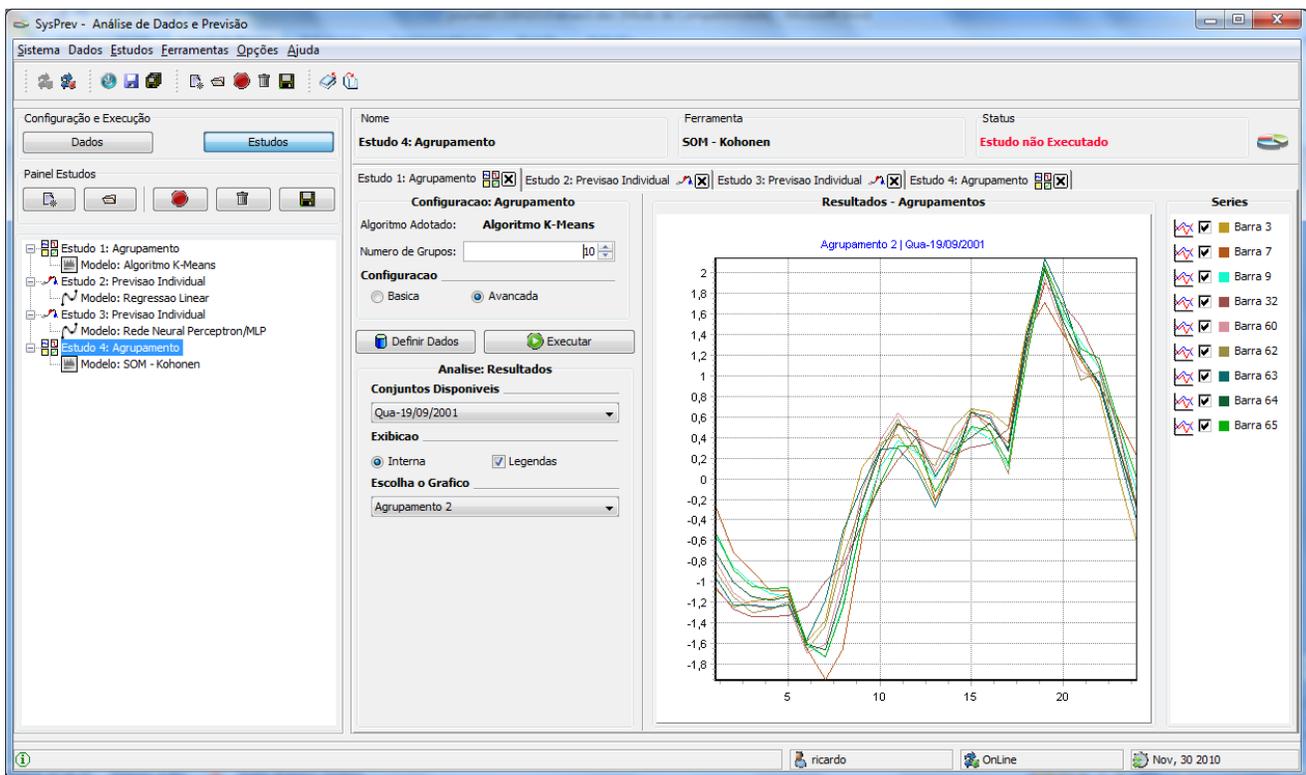


Figure 16. Example 01/GUI's – Forecasting Support System.

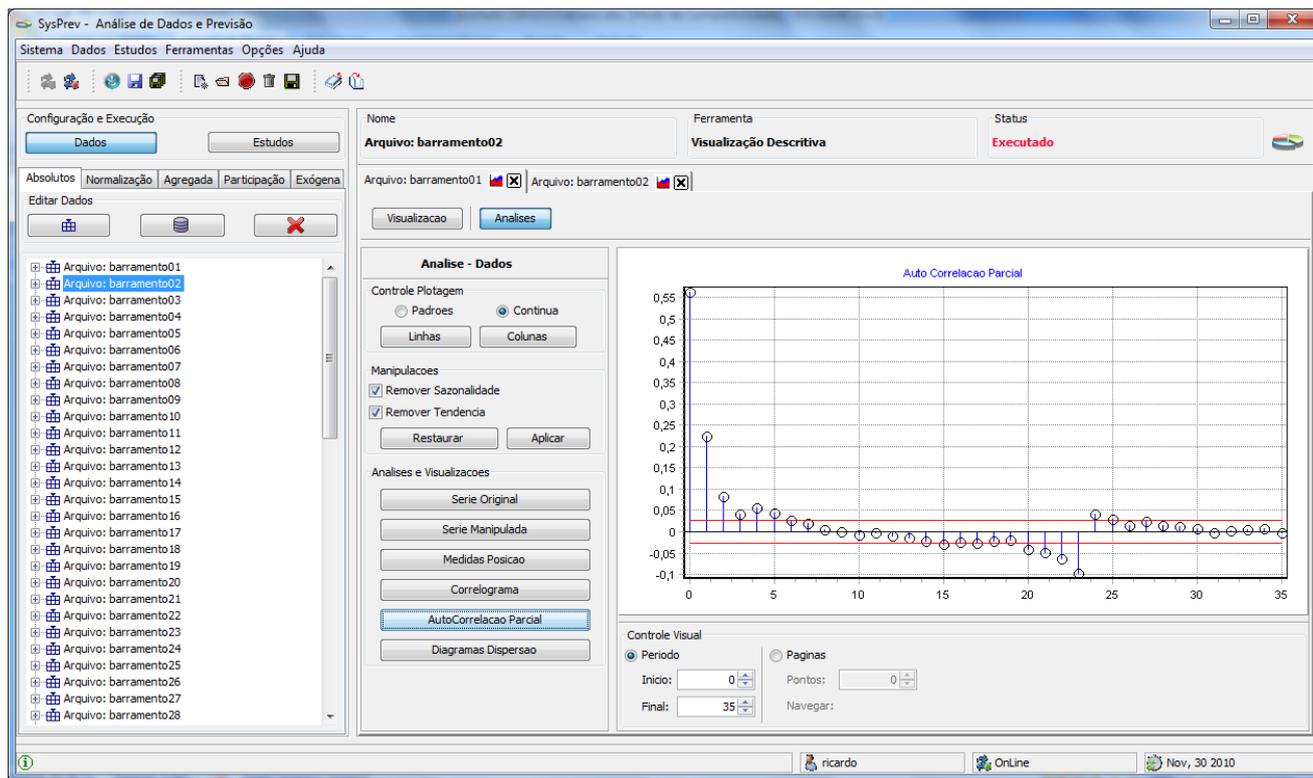


Figure 17. Example 02/GUI's – Forecasting Support System.

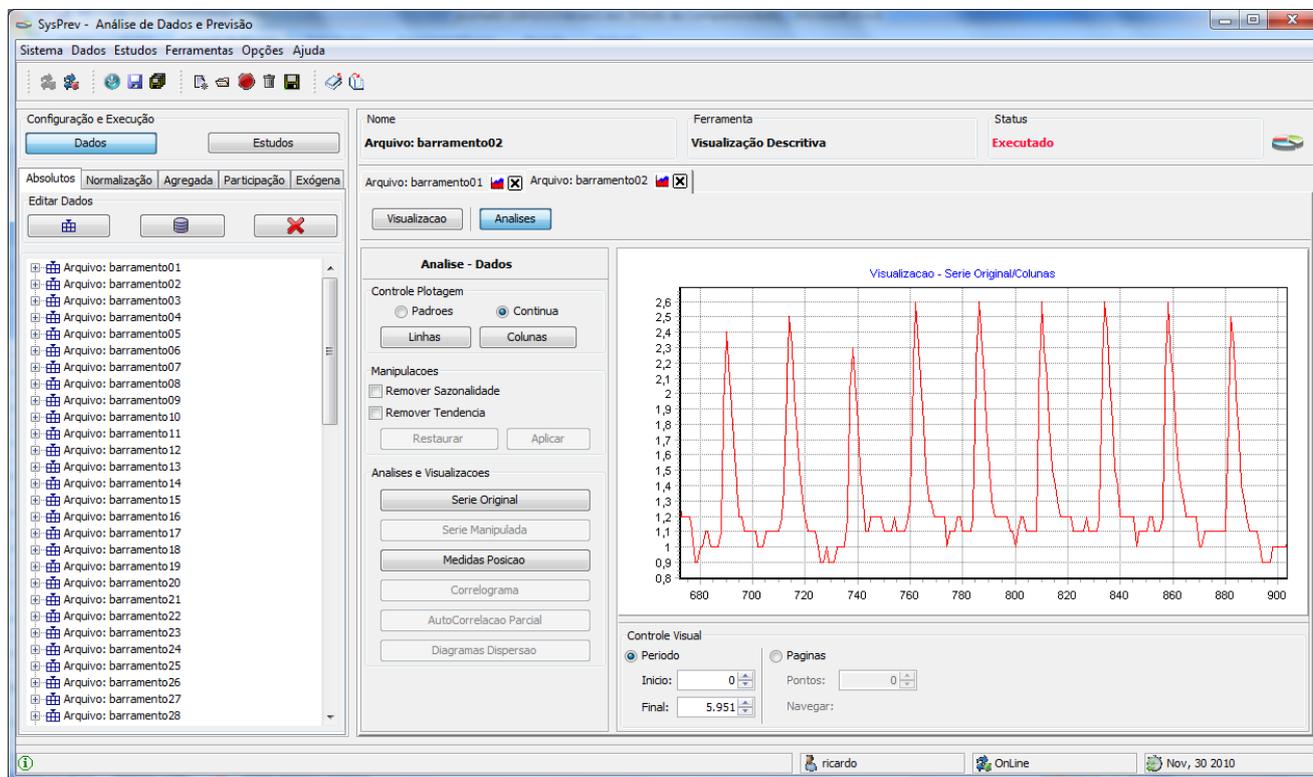


Figure 18. Example 02/GUI's – Forecasting Support System.