Abstract- This work presents a new methodology for short term loading forecasting whereas the influence of climatic variables (temperature, relative humidity of the air and wind speed) in the consumption behavior of an electrical power distribution system. The proposed methodology involves creating a discrete probability model (Markov chain) from the classification of historical data in a Self-Organizing Map (SOM). It is therefore possible to estimate the probability of a certain demand level to happen given a current climatic condition, as well as the number of time intervals (hours) until this happens. In addition, the Self-Organizing Maps allows the knowledge extraction, i.e. the search for relationships between the variables involved in the problem.

Index Terms-- Load Forecasting, Markov Models, Self-Organizing Maps.

I. INTRODUCTION

There are several methodologies to achieve the loading forecasting by varying the range of projection [1], but most of these are aimed at quantifying the energy for medium and large power systems over longer time intervals (days, weeks, etc.). It is clear that climatic variables have significant interference in the projection of demand for electricity in very short term, as well in the generation capacity of solar and wind generators, therefore they should be incorporated into the projection model.

A projection model that includes very short-term climatic variables may be a discrete probability model (Markov chain), but it is necessary to define the states and calculate the transition rate between them. Accordingly, the application of a classification method to historical data of demand and weather variables can group similar characteristics in the same state.

Since the measurements are observed at a set interval of time, you can check the transition from one state to another every interval. The Self-Organizing Map (SOM) is a very efficient and robust classification method that provides the creation of the desired Markov model.

The presented methodology is applied to MUX Energy Company, a distributor of electric power to the cities of Tapejara and Ibiaçá in the brazilian’s southern state. This company has the generation of a Small Hydroelectric Plant (SHP), whose scheme of operation is limited to the small storage capacity of water reservoir. Typically, there is constraint generation in the dry season (summer), since there isn’t enough water for the plant to generate continuously, being necessary to define time slots for the generation. It is interest of the utility that the SHP is in operation at times when there is prediction that energy demand will exceed the contracted one, to avoid paying fines. Thus, a method of load forecasting, very short-term horizon, it is of great value to the company, therefore knowledge of the electricity demand serves also as a marker for the best times to order the SHP dispatch.

II. PROJECTION OF ELECTRICITY DEMAND

The various approaches to achieving the forecast of electricity demand have been developed and applied in various fields of knowledge. As regards the planning of the operation and expansion of electrical systems, the demand projection is performed in very short horizons, short, medium and long term, according to the objective of the study under review. Thus, short-term projections are those with intervals of minutes to hours ahead. Already short-term projections are made for days and weeks ahead. In the same context, the medium-term projections covering time intervals of one to several months ahead. Finally, the long-term projections are made for intervals longer than one year ahead.

A. Methods for projecting short and very short term

A large amount of statistical analysis and artificial intelligence has been successfully used for estimating loads in a short period of time. Methods based on linear regression and time series used for the projection of energy demand were proposed by [2]. Different models to project short-term loads were developed using Artificial Neural Networks (ANN) in its various types of topologies, including Multilayer Perceptron (MLP) and Radial Basis Neural Networks (RBF) as shown in [3]. Aiming to improve the performance of models based on ANN hybrid systems using Neural Networks and Fuzzy Logic (Neuro-Fuzzy) were developed combining the potential of these methods [4].

Regardless of the methodology and the forecast period of the study, some factors that have significant influence should be incorporated into the model to improve the accuracy of the projection. Climatic factors are of particular interest, because environment’s air conditioning and lighting are directly influenced by temperature, humidity and wind, reflecting the behavior of electricity demand.

Knowing the load pattern in a very short-term horizon can be considered as a prediction of real-time and is used to detect dangerous conditions of operation, and help in
developing strategies for the dispatch of alternative energy sources [5].

The shorter the forecast horizon, the greater the need for precision and detail. Another requirement in this horizon, is the robustness of the model adopted for the projection, since the model must rapidly adjust to unusual situations.

B. Influence of Climate Variables About Standard Electric Energy Demand

The climatic variables have great relevance in terms of their effects on electricity demand in the very short term. Accordingly, a study data set of electricity demand and weather considering the actual values of electric charge, temperature and humidity obtained from the database of the company for approximately two consecutive years (2008-2009).

After the consolidation of the database, it is important to obtain and evaluate the daily demand profiles. This analysis helps to understand the behavior of electricity demand over time. Fig. 1 illustrates the electrical power demanded in a full week, where there was no holiday.

![Daily and weekly demand patterns.](image)

Observe that on weekdays (Monday to Friday) the demand profile is somewhat similar, and that on weekends this demand decreases significantly. One can also observe that the demand exceeded the 7.8 MW at peak times on Monday, Tuesday and Wednesday, but only approaches it on Thursday and Friday. Even knowing the typical behaviour of the load, it is difficult to predict whether the demand will reach a certain value. However, it is remarkable influence of climatic variables, since the air conditioning of environments is a significant burden on practically all branches of consumption.

To check the influence of climatic variables studied (temperature, humidity and wind) and electric power demand the correlation between them were calculated on the database, as can be seen in Table I.

![Component maps for the classification of 3290 hourly measurements of demand, temperature, humidity and wind speed on a network with 36 neurons (6x6). The black color indicates the highest values, while white minors. The scale on the side of the map indicates the average value of the variable demand in MW, temperature in °C, humidity in % and wind speed in m/s.](image)

It appears that the temperature is the variable with greatest influence on variations in demand. Also, using the same table, it is remarkable inverse relationship between wind speed and power consumption, explained by the negative sign.

III. SELF-ORGANIZING MAPS (SOM)

The Self-Organizing Map (SOM) is a type of neural network developed for pattern recognition. The SOM algorithm is defined as a non-linear transformation \( \Phi \) which maps a continuous input space whose topology is defined by the metric ratio of the data vector \( D \in E \) to a discrete output space \( S \), whose topology is defined by a set of models \( M \) arranged in a two-dimensional grid, as shown in Fig. 2 [6]. Normally this network of neurons has hexagonal synaptic connections (weights).

![Fig. 2. A transformation \( \Phi: E \rightarrow S \) in a 4x4 map with hexagonal connections.](image)

The algorithm performs a process of sorting that takes place in three stages to find the model that best represents a given network entry (winner). The links are used to adjust models of neurons close to the winner (neighbours) to the standard input. Thus, at the end of several iterations the map displays the data associated with each neuron, so that similar patterns are found in adjacent neurons, with a topological organization. Thus it is possible to extract abstract relations between the variables of vector data through their position on the components maps, using a color scale to show the amount of a specific variable in each neuron of the map.

Each component map is a representation of the trained map with reference to only one of the variables involved, so the position of neurons is the same in all components maps, which allows the identification of correlations between variables. Similar components maps indicate variables with strong correlation [7].

Small maps, with less than a neuron for every ten input data, have little room to reveal topological relations. However they form well defined groups, despite the distance between the data contained in each neuron can be somewhat significant. Fig. 3 shows the component maps for the classification of 3290 hourly measurements of demand, temperature, humidity and wind speed on a network with 36 neurons (6x6). The black color indicates the highest values, while white minors. The scale on the side of the map indicates the average value of the variable demand in MW, temperature in °C, humidity in % and wind speed in m/s.
In the figure above it is possible to identify some relationships between variables, e.g., in the upper left corner, there is high demand, high temperature, high humidity and intermediary wind. In the bottom left corner, where greater wind speeds are predominant there is a low demand. In the case of larger maps, with a higher ratio of neurons to the input data, one obtains a greater topological dispersion capable of revealing relationships between variables that do not appear in smaller dimensions. See the example in Fig. 4, with a 20x20 map trained with the same database of Fig. 3.

In Fig. 4 it is possible to see new relationships that were not evident in the maps of Fig. 3, for example, in the central region of the map, where demand is medium-high, the temperature is low and humidity and wind are intermediaries, featuring winter days in the southern Brazil, in which the population should have resorted to electric heaters. This shows an inverse trend between temperature and demand as well, which makes a linear prediction model unsuccessful under these conditions.

Thus, the study used the Self-Organizing Maps in the process of load forecasting to build groups of similar measures. Table II shows the four variables of the seven samples that were grouped into one of the neurons in this region previously mentioned, where you can observe the homogeneity of the classified data.

<table>
<thead>
<tr>
<th>Sample Number</th>
<th>Demand (MW)</th>
<th>Temperat. (°C)</th>
<th>Humid. (%)</th>
<th>Wind (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>83</td>
<td>7,111</td>
<td>5,76</td>
<td>54,40</td>
<td>14,26</td>
</tr>
<tr>
<td>90</td>
<td>7,025</td>
<td>5,74</td>
<td>59,50</td>
<td>12,12</td>
</tr>
<tr>
<td>91</td>
<td>7,365</td>
<td>5,95</td>
<td>60,67</td>
<td>12,52</td>
</tr>
<tr>
<td>2814</td>
<td>7,053</td>
<td>8,29</td>
<td>59,50</td>
<td>14,12</td>
</tr>
<tr>
<td>2969</td>
<td>7,628</td>
<td>6,69</td>
<td>66,50</td>
<td>14,41</td>
</tr>
<tr>
<td>2972</td>
<td>7,557</td>
<td>6,80</td>
<td>65,58</td>
<td>14,15</td>
</tr>
<tr>
<td>2979</td>
<td>7,919</td>
<td>5,81</td>
<td>56,78</td>
<td>13,63</td>
</tr>
</tbody>
</table>

Therefore, the samples, including the new ones, are always assigned to the most similar neuron considering the measures of demand, temperature, humidity and wind speed.

IV. MARKOV MODEL

A Markov model represents a stochastic process, usually with discrete states and continuous time in which the system is modeled on observable parameters. The proposal then is that this model can be used to perform analysis of the evolution of states over time. There is a principle that earlier states are irrelevant for predicting the following states, since the current state is known [8].

A Markov chain is a sequence $X_1, X_2, X_3, \ldots$ of random variables. The scope of these variables, i.e., the set of values they may take, is called the state space, where $X_n$ denotes the process state at time $n$. If the conditional probability distribution of $X_{n+1}$ on past states is a function only of $X_n$, then:

$$P(X_{n+1} = x | X_0, X_1, \ldots, X_n) = P(X_{n+1} = x | X_n)$$  \hspace{1cm} (1)

If the model is in a state $y$ at time $n$, then the probability that it moves to the state $x$ at time $n+1$ is independent of $n$ and only depends on the current state $y$ where it is. So at any time $n$, a finite Markov chain can be characterized by a matrix of probabilities whose element $(x, y)$ is given by (2) and is independent of time $n$.

$$P(X_{n+1} = x | X_n = y)$$  \hspace{1cm} (2)

A state space is representable by a matrix of transition in the $(i, j)$-th element equal to (3).

$$P_{ij} = P(X_{n+1} = j | X_n = i)$$  \hspace{1cm} (3)

For a space of discrete states, the integrations in the transition probability of $k$ steps are summations, and can be calculated as the $k$-th power of the transition matrix. That is, if $P$ is the transition matrix for one step, then $P^k$ is the transition matrix for the transition of $k$ steps.

Insofar as time progresses, the values of probability of finding each of the states tend to a constant limit value. Therefore, these probability values are independent of the time limit, and results in a sum.
Example of a model of demand forecast

In a simple example, observed that the demand is low at a given time, the probability that it will be high in the next hour is 0.5. If demand is high, otherwise the likelihood of it being low on time following is equal to 0.25.

The transitions between high and low demand can be modeled as a homogeneous Markov chain, and the transition probability matrix is given in Table III.

<table>
<thead>
<tr>
<th>Load</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>High</td>
<td>0.25</td>
<td>0.75</td>
</tr>
</tbody>
</table>

When the number of states is small, it is convenient to represent a transition diagram like Fig. 5.

Fig. 5. State diagram of a Markov chain with transition matrix in Table III.

Defined the model and the matrix of transitions $P$, one can then calculate the probability that the system is in a state after a certain number of time intervals with the following equation:

$$ P(n) = P(0). P^n $$

where:
- $P(n)$ = vector with the probabilities of each state;
- $P(0)$ = vector with the probabilities of initial state;
- $P$ = matrix of transition;
- $n$ = num. time intervals after the initial state.

Thus, for example, knowing the current state of demand as low, the odds of the system being in each state after four time intervals are 33.4% to low demand and 66.6% to being high.

States assignment using the SOM

It is necessary to establish discrete states to create a Markov model from measurements of climate variables and demand. One way to define these states is with a clustering method, and as presented in the previous section, the Self-Organizing Map (SOM) is a good tool [9]. In this case, each neuron in the SOM represents a state of the Markov model, allowing for the transition probability of states (neurons) each time.

The proposal is to train a SOM with a history of measurements of the variables you want, and then define each neuron as a condition for a Markov model. The transition matrix $P$ is constructed by tracking the change of neurons at each time step (hourly intervals), i.e. the path followed by the measured samples trough the map.

With the map trained, and considering each neuron as a state for the Markov model, the next step is to check the distribution of the sequence of samples by neurons, computing the transitions from one neuron to another in order to form the matrix of transitions $P$. Thus, there is the sequence of hourly samples, such as the map of Fig. 6, where the sample of the sixth hour is allocated in neuron number 1 (top left), since the next sample (7h), moved to the second neuron, and sample 8 was allocated to the middle.

Fig. 6. 4x4 map with sample data.

The rate of transition from a state $i$ to another $j$ is equal to the number of exits to state $j$ divided by the total number of visits to state $i$. Fig. 7 illustrates the transitions between neurons.

Fig. 7. Transitions between neurons as a result of sampled data.

The diagram in Fig. 7, representing the transitions of the data between neurons, can be redesigned as a state diagram of a Markov model, as shown in Fig. 8.

Fig. 8. Example of a Markov model created from the map of Fig. 6.

The model of Fig. 8 is just an illustration, for a demand forecasting model built in this way have a good assertiveness is necessary to train the SOM with a history of measurements from at least one year, so it is possible to construct a representative space state. Because the model is constructed from states already visited by the system, their behaviour tends to reproduce the history. However, we can improve the model by increasing the size of the map to be trained, and considering the nonactivated neurons (empty) with a small transition probability.
Thus, for example, if we had as its starting point the same measures of the 6 h, the model would make the load forecasting respecting the state transitions (neurons) of Fig. 8, i.e., replicate the order of states in their schedules. However, considering a larger historical database of measurements, that order would not necessarily be respected, since each neuron would have a probability of transition to several other neurons in the history function, the first neuron, which contains the measures of hour 6 could have a history of moving to the states "E", "F" and "G".

V. SIMULATIONS AND RESULTS

A history with 3290 measures of hourly demand, temperature, humidity and wind speed was used to train a network with 900 neurons (30x30). The transition matrix, and the resulting Markov model was constructed considering each neuron as a state, and then the transition of neurons was calculated in sequence.

In possession of the trained map and the transition matrix, it can be seen in what state (neuron) is a particular demand condition and weather, along the shortest Euclidean distance between the sample and the model neurons. So, from this initial state P(0), one can calculate the probabilities of demand will be carried over to other states as well as the probability of reaching a certain level within a stipulated period.

A simulation was made with the following sample = [4.475 12.29 69.00 18.84], which represents a measurement taken at 0 h and was out of the database used for training the map. This sample was allocated in the neuron number 208. From this state P(0) = 208, the system can go in the next hour to the states of number 178, 208, 238 and 267, with probabilities P(1) = [0.1667 0.5000 0.1667 0.1667 ], i.e. a 50% chance of having a demand of around 4.91 MW. The other mean levels would be 5.31, 4.86 and 5.18 MW for the states 178, 238 and 267, respectively.

After four hours, the system can undergo a great change, and can stop in 44 different states, highlighting the state 900, with a probability of 14.02%.

Aiming to determine the probability of exceeding the contracted demand, it was used a sample off the database, obtained at 17 h. The chance of this happening in the next hour was 12.71%, to two hours ahead increased to 22.86% and 17.58% for the third hour. Past five hours, there is no more chance of exceeding the contracted demand.

Thus, the system signals the power plant's operator of the chance of the contracted demand being exceeded, aiding in the decision of whether or not to use the water, as usually there is not enough to sustain the generation for long.

VI. CONCLUSION

The Self-Organizing Map allows the creation of a Markov model based on the analysis of a database with sequential measurements. In this case, we developed a decision support tool for the operator of a Small Hydroelectric Plant (SHP), given the likelihood that demand exceeds a certain level in the next few hours in function of climatic variables measurements. Thus, the utility avoids the payment of fines to its supplier by dispatching the SHP at critical times, since the reservoir is not sufficient to sustain the generation for a long time, and in drought periods it may have to accumulate water during several hours.

ACKNOWLEDGEMENTS

The authors acknowledge the technical and financial support of the electric utility MuxEnergia, through R & D project entitled "Development of Algorithms and Software for Load Forecasting in the Concession Area of MuxEnergia – Very short-term horizon."

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