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A FORECAST CLOUD-TO-GROUND LIGHTNING SYSTEM BASED ON A NEURAL NETWORK – PRELIMINARY RESULTS

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1. INTRODUCTION

Brazil is the largest tropical country in the world and, in consequence, one of the countries with highest lightning activity. Based on meteorological satellite data, it is known that most thunderstorms are associated with local convection conditions, fronts and large systems like mesoscale convective complexes (Pinto and Pinto Jr., 2003). In order to study the lightning physics and support engineering applications, lightning location networks (LLN) consisting basically of several sensors, which determine the angle and/or the time to the lightning stroke at the sensor location, and a processing unit, which calculates stroke characteristics like the strike point location and time, peak current, and others, are being operating over many decades to detect and locate all type of flashes (Pinto Jr. et al., 2006). LLN have collected a large number of data, which have been used in many applications by power utilities, weather services, aviation and geophysical research.

The most obvious impact of lightning on electric utility operations is power outages as a result of some severe phenomena. Severe weather can be classified as weather events that are life threatening. In the utility industry severe weather is classified as a weather event that directly causes widespread outages to a utility's distribution system or, in a worst case, causes extensive damage to a utility's transmission system. Therefore it is important to improve the knowledge about the development of lightning forecast systems since utilities can use severe weather forecasts to plan and mobilize resources to meet the anticipated challenges of storm restoration. Lightning and wind damage associated with severe thunderstorm activity can disrupt electrical service throughout the year. Then forecasts of storms with high probability of intense electrical activity with just a few hours lead time would reduce customer outage time.

The proposal of the present work is to show preliminary results of an initial study to develop a cloud-to-ground (CG) lightning forecast system using neural networks (NN) for *Companhia Paulista de Força e Luz* – CPFL Energy area. The basis of this study consists of correlations between CG lightning data and analysis fields of meteorological parameters obtained with the ETA model. Next it is proposed and tested a lightning forecast system based on NN. At the moment, only a few forecast lightning systems using artificial intelligence as basic tool are available.

Figure 1 shows a sketch to illustrate the objective of this work. The real dynamics of the atmosphere that relates the chosen input variables with the output is sufficiently complex and, evidently, not well known. The effort consists exactly in making the NN to learn this dynamics, foreseeing the behavior of the atmosphere a few hours later in terms of a severity index defined according to the lightning activity as: low, medium and high lightning activity.

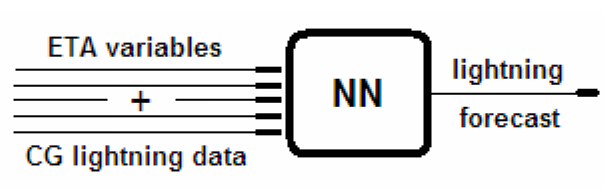

Figure 1. Basic diagram of the forecast lightning system.

2. DATA AND METHODS

Neural network is a technique that artificially simulates the way human brain which basically consists of a large number of units called neuron connected each other by synapse performing intelligent operations. The benefit to use NN in conjunction with an engineering issue is that it is only necessary to focus on input and output, and a problem can be solved without aware of exact principle of cause and effect. Bibliographical references about NN can easily be found in literature. This is a subject that has deserved great attention by the scientific community. Several applications of artificial neural networks have been proposed in wide technological domains (Jung and Hsia, 1998; Nagae et al., 2000; Miller III et al., 1995; Zepka et al., 2007).

To impose the NN to have a forecast character with real practical applicability it seems reasonable to assume that the simulator is trustworthy or at least it confers numerical results with errors inside acceptable limits and different numerical values for a set of input variables induce different outputs. Other important condition is that the chosen input variables to the neural forecast system should be really representative of the phenomenon.

The NN proposed architecture to the lightning forecast is a backpropagation, multilayer, feedforward and fully connected network. It was used a backpropagation with momentum as training rule and an axon as activation function with genetic algorithm (Beale and Jackson, 1990; Fausett, 1994). Figure 2 presents a generic topology of a multi-layer perceptron (MLP) adopted in this study.

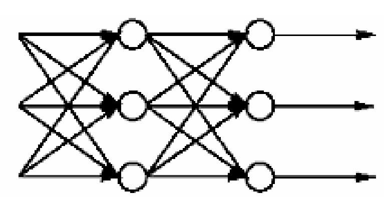

Figure 2. Generic topology of a MLP composed by input, intermediate and output layers and its respectively fully connected neurons.

The NN input variables set is composed by hourly number of lightning flashes and analysis fields of meteorological parameters from ETA model both picked and chosen for CPFL area.

CG lightning data from December 2005 and January 2006 were provided by the Brazilian Lightning Detection Network (BrasilDat) for the CPFL area which extends from 21° to 24° S latitude and 50.5° to 45.5° W longitude across the state of São Paulo (Figure 3). Figure 4 shows the BrasilDat sensor configuration. More details about the BrasilDat can be obtained in Pinto Jr. et al. (2006, 2007).

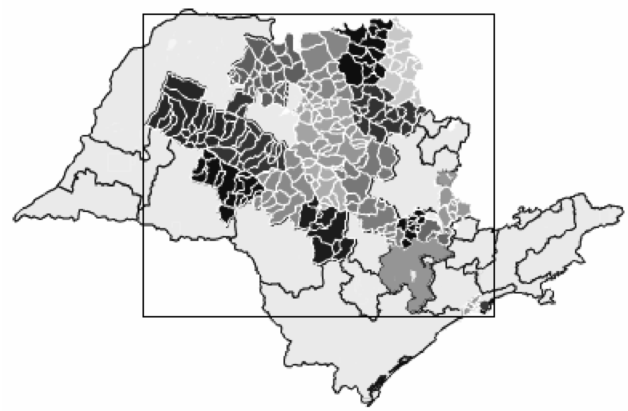

Figure 3. Map of the state of São Paulo (in the Southeast region of Brazil). Inside the black rectangle is located the CPFL area.

Figure 4. Map of the location of the sensors of the BrasilDat network.

It was chosen the convective available potential energy (CAPE) index and the best lifted index (BLI) as meteorological inputs in the NN. These variables were studied from ETA model analysis fields covering CPFL area with horizontal resolution of 20 km. The initial condition to 12 UT was taken from the analysis of the National Centers for Environmental Prediction (NCEP) and the lateral boundary conditions were taken from the Center for Weather Forecasting and Climate Studies

(CPTEC)/ Center for Ocean-Land-Atmosphere Studies (COLA) Global Model forecasts and updated every 6 hours. Model details are given in Black (1994).

3. PRELIMINARY RESULTS

Some preliminary results of the study to develop a lightning forecast system applied to CPFL area will be shown next. All process has involved six steps: selection and collection input data, choice of NN training and testing sets, NN topology and configuration, NN training, NN testing, lightning forecasting in terms of severity electrical activity index.

Many different data sets were tested as input until the NN to achieve the best performance in the output: hourly and diurnal totals of CG lightning, including at the utmost accumulated of five days before the forecast date, and meteorological variables as instability indexes, equivalent potential temperature, air temperature, specific humidity and omega for different atmospheric levels. Different spatial areas in the CPFL domain were also considered as calculating the input data sets. In addition different configurations of NN were tested with others activation functions and varying the number of neurons in the intermediate layer.

Therefore two NN inputs were chosen: CG lightning accumulated from 00 to 09 local time (LT) and maximum CAPE and minimum BLI values of ETA model analysis at 12 UT (09 LT). For the first a saturation point was defined and for both lightning data and meteorological variables a running average was applied. December 2005 was elected as training month. The NN has trained in a dynamic form which means that the January predicted days were replacing the December trained days so as to maintain always 31 days in training. All data involving quantities of CG lightning were converted in an index for the purpose of unifying and comparing inputs and output. The trained NN has foreseed how would be the CG lightning behavior at 15-18 LT according to a scale provided by the index cited above. This index indicates the following possibilities: 0 to low, 1 to medium and 2 to high CG lightning activity.

The best forecast preliminary result is presented below in Figure 5. Analyzing the three answer levels and comparing both curves in the Figure 5, it can be observed that the CG lightning forecast has 67% perchance and none quadratic error that is the real output was not overestimated or underestimate by the NN forecast system in two levels.

As it was put in evidence in this study, results with the NN indicate that there is a promising approach to deal with lightning forecast.

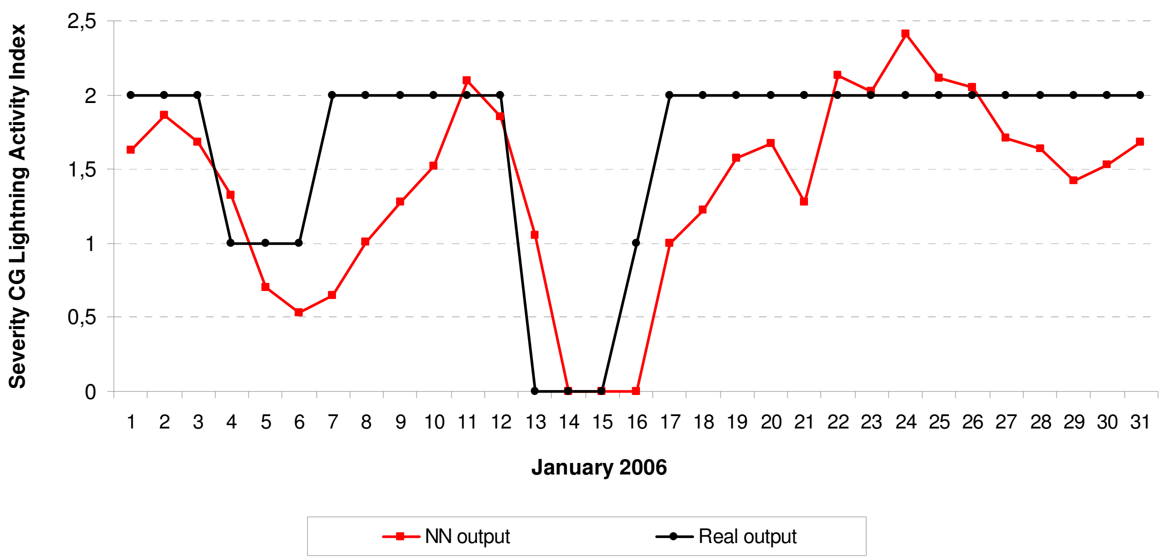

Figure 5. Forecast in terms of a severity CG lightning activity index with NN.

4. CONCLUSION

The study presented in this work allows one to conclude that the use of artificial neural network can be an important tool for the construction of an efficient lightning forecast system applied on electric utilities operations. It was verified that the chosen NN input variables well represent the phenomenon, or either, they are correlated with the electric storm. It is important to say that the good performance of the forecast system depends on the precision and resolution of the mesoscale model and the lightning detection system for the considered area.

In future works new tests of NN input data sets will be investigated exploring others atmospheric variables simulated in a different meteorological model. The proposal is evaluate the Weather Research and Forecasting (WRF) Model a next-generation mesoscale numerical weather prediction system designed to serve both operational forecasting and atmospheric research needs.

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