NEURAL NETWORK FOR SEASONAL CLIMATE PRECIPITATION PREDICTION ON THE BRAZIL

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Resumo

Precipitação é o campo meteorológico mais difícil de ser predito. Uma abordagem baseada em rede neural ótima é aplicada para previsão de precipitação para o Brasil. Uma rede neural perceptron de múltiplas camadas (RN-PMC) auto-configurada é usada como ferramenta predição. A topologia da MLP-NN é encontrada resolvendo um problema de otimização pelo algoritmo de colisão de múltiplas partíiculas (MPCA). Previsões para estações de inverno e verão são mostradas. A previsão neural é avaliada usando dados de reanálise do NCEP/NCAR e dados do satélite GPCP (Global Precipitation Climatology Project – monthly precipitation dataset).

Palavras-chave: Precipitação, previsão climática sazonal, redes neurais auto-configuradas.

Abstract

Precipitation is the hardest meteorological field to be predicted. An approach based on and optimal neural netework is applied for climate precipitation prediction for the Brazil. A self-configured multi-layer perceptron neural network (MLP-NN) is used as a predictor tool. The MLP-NN topology is found by solving an optimization problem by the Multi-Particle Collision Algorithm (MPCA). Prediction for Summer and Winter seasons are shown. The neural forecasting is evaluated by using the reanalysis data from the NCEP/NCAR and data from satellite GPCP (Global Precipitation Climatology Project – monthly precipitation dataset).

Keywords: Precipitation, seasonal climate prediction, self-configured neural network.

1. Introduction

The climate forecast is a key factor for many social and economic sectors, such as civil defense for disasters, energy production, agricultural, transportion systems, insurance price. Brazil is a country with a great territorial extension, with different precipitation and temperature regimes. The CPTEC-INPE (CPTEC: Center for Weather Prediction and Climate Studies, INPE: National Institute for Space Research) has global and regional models to perform the weather and climate predictions based on numerical integration of partial differential equations. These are complex and sophisticated computer models executed by a supercomputer.

Models for carrying out prediction and climate monitoring using artificial intelligence are already employed in research related to climate precipitation by Anochi et al. (ANOCHI; CAMPOS VELHO, 2014), hydrology by Sousa et al. (SOUSA; SOUSA, 2010), severe weather by Ruivo et al. (RUIVO et al., 2015), Baboo et al. (BABOO; SHEREEF, 2010), among others.

Brazil presents a strong climate variability, having equatorial, tropical, and sub-tropical climate regions. In the North, there is a rainy equatorial climate, practically without dry season. In the Northeast, the rainy season, with low rainfall rates, is restricted to a few months, characterizing a

semi-arid climate and presents higher climatic predictability. The Southeast and Center-West regions are influenced by both tropical and mid-latitude systems, with a well defined dry season in winter and a rainy season in summer with convective rain-fall. Both regions have low predictability due to less dependence on ocean conditions and the wide variety of meteorological systems that affect them. Finally, the Southern region of Brazil, as well as the North region, do not have a rainy or dry seasons well defined. In the South of Brazil, there is approximately an uniform rainfall distribution during all year. But this region is characterised by medium predictability, and due to its latitudinal location, it is more influenced by medium latitude systems, where frontal systems are the main cause of rainfall during the year.

Several climatic regimes motivated Anochi et al. (ANOCHI; SILVA, 2009) to develop a climate prediction model for the precipitation field by Neural Networks (NN). The neural model was adapted to the precipitation field for monthly and seasonal forecasting.

Different from our previous studies, where the NN were designed for climate prediction associated at each Brazilian regions, here the NN forecaster is applied for the entire country.

The paper is structured as follows: Section 2 describes the methodology employed: the optimal neural network designed by the metaheuristic MPCA (Multi-Particle Collision Algorithm); the data used to configure the NN, for the NN training and for evaluation, is reported in Section 3; the results are shown in Section 4, and Section 5 brings the conclusion and final remarks.

2. Theoretical foundations
2.1 Neural networks

Artificial neural networks are computational methods in which the operating principle is conducted by a mathematical model inspired by the functioning of the basic elements that form the neural structure of intelligent organisms, that acquire knowledge through experience. Their behavior results from the interactions between the processing units, from their environment, through a learning process.

Neural networks are distributed parallel systems, composed of neurons or processing units, which compute certain mathematical functions, usually non-linear. Processing neurons can be distributed in one or more layers and interconnected by a large number of connections (synaptic weights), which store the knowledge represented in the model.

Mathematically, we can describe a neuron k by writing the following pair of equations (HAYKIN, 1994):

$$input : v_k = \sum_{j=1}^{n} w_{kj} x_j, \tag{1}$$

$$output : y_k = \varphi(v_k + b_k), \tag{2}$$

where x_n are the inputs; w_{kj} are the connection weights; b_k is the bias; φ is the activation function; and y_k is the output.

The different architectures of neural networks can be formed by the combination of artificial neurons and are defined by the type of connection between networks. Each neuron transfers its signal to the neurons that are in one of the subsequent layers.

In this work, the Multiple Layer Perceptron (MLP) network was used. The MLP has emerged as an alternative solution for non-linearly separable problems and has been successfully applied to solve complex problems through its supervised training using the error backpropagation algorithm based on the learning rule for correction of error (HAYKIN, 1994).

The architecture of the MLP network consists of the topological arrangement of the processing units of the neurons with the respective values of weights associated with the connections. The synaptic weights are adjusted by delta rule. The MLP network has an input layer, at least one intermediate layer, and an output layer.

Although a NN model has great potential, its performance depends on the definition of its parameters, since the definition of the topology can significantly influence the phase of the training process.

2.2 MPCA to identify the best topology NN

In practice, the NN topology is usually selected by using empirical or statistical methods that are used to find the best parameters. Here, we use the Multiple Particle Collision Algorithm (MPCA) metaheuristic for configuration the topology of the MLP network. The strategy applied by Anochi et al. (ANOCHI et al., 2013) can be considered as an optimization problem, where each point in the search space represents a NN with different topologies.

The MPCA metaheuristic was introduced by Luz et al. (LUZ; BECCENERI; CAMPOS VELHO, 2008), and it is an extension of the canonical Particle Collision Algorithm (PCA) (SACCO; OLIVEIRA, 2005). The proposed structure for the MPCA algorithm uses a set of n particles, independently exploring but collaboratively, the same search space. The introduction of n particles leads to the need to implement an indirect communication mechanism between particles.

The MPCA starts with a selection of an initial solution, it is modified by a stochastic perturbation conducing to the construction of a new solution. The new solution is compared and this solution can or cannot be accepted. If the new solution is not accepted, the particle can be send to a different location of the search space. If a new solution is better than the new solution is absorbed. The figure 1 shows the pseudo-code of the MPCA metaheuristics (LUZ; BECCENERI; CAMPOS VELHO, 2008).

```
Generate an initial solution: Old-Config
Best-Fitness = Fitness{Old-Config}
Update Blackboard
For n = 0 to # of particles
        For n = 0 to # iterations
        Update Blackboard
        Perturbation{.}
                If Fitness{New-Config} > Fitness{Old-Config}
                        If Fitness{New-Config} > Best-Fitness
                                Best-Fitness = Fitness{New-Config}
                        End If
                        Old-Config = New-Config
                        Exploration{.}
                Else
                        Scattering{.}
                End If
        End For
End For
```

Figure 1 – Pseudo-code for MPCA. Adaptada de Luz, Becceneri e CAMPOS VELHO (2008).

The MPCA has been used successfully in several optimization problems, such as: diagnosis of failures (ECHEVARRÍA; SANTIAGO; NETO, 2014), identification of atmospheric temperature profile (SAMBATTI et al., 2012), climate prediction (ANOCHI; CAMPOS VELHO, 2014), solution of a radiative inverse problem (TORRES; LUZ; CAMPOS VELHO, 2015), and the other applications.

3. Methodology

The proposal is focused on the application of neural networks in meteorology. The methodological novelty consists in the definition of an optimal neural network. The optimal network identification is formulated as an optimization problem, solved by the meta-heuristic MPCA — this methodology is called the self-configuring network. The methodology can be applied without the support from an expert on neural network. For applying the methodology, the user provides a data set, and the system defines the best neural network type multilayer perceptron type for the application.

3.1 Meteorological data

For the climatic forecasting of precipitation using neural networks, different data sets were collected, from reanalysis data from the National Centers for Environmental Prediction (NCEP/NCAR) to Global Precipitation Climatology Project monthly precipitation dataset (GPCP).

The NCEP/NCAR provides historical series of meteorological data obtained through the assimilation and analysis of data observed for the entire planet from 1948 up to the present. These data come from radiosondes, land surface meteorological stations, oceanic buoys, ship, airplanes, satellites, GNSS (General Navigation Satellite Systems) stations, and data from model (control) and analysis (assimilation process). For the constitution of these data, global atmospheric and surface flow fields derived from numerical forecasting and data assimilation systems are used (KALNAY et al., 1996).

The input variables to the neural network were selected from the NCEP Reanalysis data from the NOAA/OAR/ESRL PSD, Boulder (CO), USA, by the website: `https://www.esrl.noaa.gov/psd/`. The input variables are: zonal and meridional winds at three levels (300 hPa, 500 hPa, 850 hPa), air temperature at 850 hPA, and specific humidity at 850 hPa.

The GPCP Monthly product provides a consistent analysis of global precipitation from an integration of various satellite data sets over land and ocean, and a analysis calibration over land. Data from rain gauge stations, satellites, and sounding observations have been merged to estimate monthly rainfall on a 2.5-degree global grid from 1979 to the present (ADLER et al., 2003).

The variable used as output to the NN was selected from the monthly precipitation dataset – GPCP provided by the NOAA/OAR/ESRL PSD, Colorado, USA.

3.2 Experimental settings

The strategy for optimizing the NN architecture is considered as a mono-objective optimization problem. Four search space parameters will be optimized: two continuous variables (the learning rate parameter (η), and the momentum constant (α)), and two discrete variables (the number of neurons in the hidden layer, and the type of activation function).

For the neural network learning phase, a well known procedure is the delta rule, where a correction $\Delta w_{ji}(n)$ is applied to the synaptic weight, for minimizing the square difference between the network output and the target values $\varepsilon(n)$. Following the rule delta, the synaptic weight are found by (HAYKIN, 1994):

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) - \eta \frac{\partial \varepsilon(n)}{\partial w_{ji}}, \tag{3}$$

where $\Delta w_{ji}(n) \equiv w_{ji}(n) - w_{ji}(n-1)$.

In this experiment, several realizations are executed to find representative solutions. The configuration of the NN topology for the climatic prediction experiment is described below – the NN is applied for each grid point:

- Nine inputs (meteorological variables).

- One output node for the results: the precipitation at the grid point. In the training algorithm, the MLP computes the output y_s and does a comparison with the target data y_k (observed precipitation).

- One hidden layer with 12 neurons.

- The hyperbolic tangent is the activation function.

- Learning rate η and momentum value α produce the best fitness (MLP-MPCA) for the following numerical values: η = 0.57 and α = 0.65.

- The iteration the training phase stops when the error reaches the value 10^{-6}.

- For determining the NN configuration by the MPCA, 25 experiments are performed to find the best fitness to NN.

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4. Results

The results presented in this section show the behavior of the neural network as a predictor model of the precipitation variable.

The numerical experiments carried out in this study show a good performance of using the MPCA tool. The procedure identifies the best parameters for the NN application, finding its topology by minimizing the a cost functional. The mentioned approach does not require a specialist to the task for NN configuration. The neural model can be implemented for both applications, for operational use or/and in research activities.

Figure 2(a) is the observed precipitation by GPCP in the Summer at 2015 in Brazil. Figure 2(b) is the forecast of precipitation obtained by the Artificial Neural Network (ANN) at same period (Summer 2015). The NN presented a good performance for describing the precipitation patterns for the Brazilian regions: North, Northeast, Midwest, and Southeast. In the states of São Paulo and Mato Grosso do Sul, the NN underestimated the precipitation. For the Santa Catarina state, the NN model overestimated the precipitation. However, in general, the results obtained with the neural model showed a good behavior when compared with the observed data (GPCP).
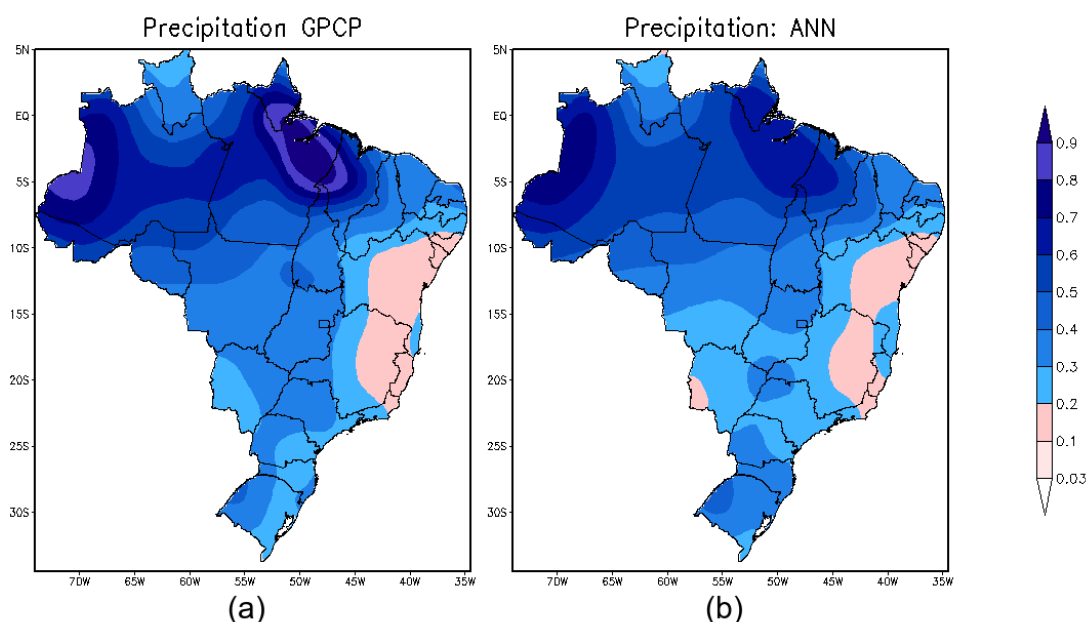

Figure 2 – Climate precipitation prediction in Brazil for Summer 2015.

Figure 3(a) is the precipitation observed by GPCP in the Autumn at 2015 in Brazil. Figure 3(b) is the prediction of precipitation predicted by ANN in the Fall 2015. For the cited season, the neural network did a good prediction for the rainfall behavior for the regions: in the east of the northeast (period of the rainy season); the extreme north of Brazil, and in the South Region of Brazil, composed by the states of Paraná, Santa Catarina, and Rio Grande do Sul – these three states form the *South (Brazilian) region*, presenting a subtropical climate regime, and the precipitation is well distributed throughout the year in this region.

5. Conclusions

Brazil is a country with different climatic conditions: equatorial, tropical, and subtropical climatic zones. The variable precipitation has a high variability implying in difficulties to be predicted. Precipitation has a strong impact for the society (natural disasters) and for several economical sectors.

It is a hard task to develop models to predict the precipitation. There are many reasons for such difficulties: local and synoptic patterns has different influences, and different variables and/or conditions are associated with the rain-fall depending on the season of the year. In addition, the
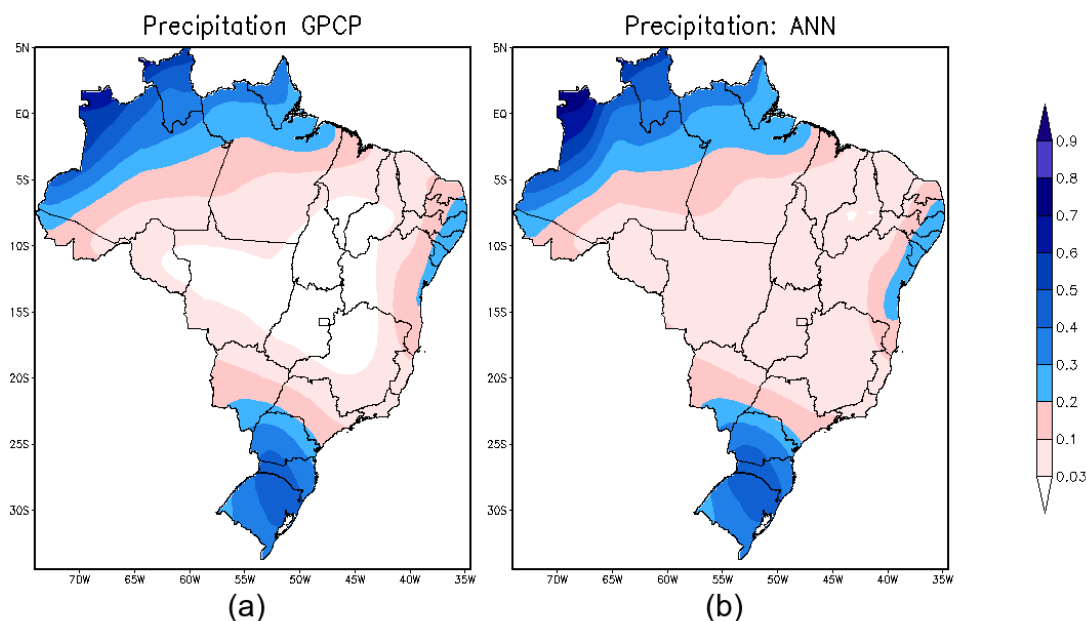
Figure 3 – Climate precipitation prediction in Brazil for Autumn 2015.

precipitation has high variability in space and time. All these factors has strongly influence in the behavior of the precipitation.

Neural network is a prestigious area of Artificial Intelligence and has shown their efficiency in various application areas, being meteorology one of them. Predictive models based on NNs are easy to use, and do not require very powerful computers.

The results present in this paper are consistent with observation data (GPCP), becoming a good tool to support seasonal climate prediction.

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