# Automatic Configuration of an Artificial Neural Network for Fire Risk Analysis

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**Abstract**

Artificial Neural Networks (ANN) have been used as a methodology for develop fire risk models, achieving good results. This methodology tries to imitate the human brain, due to your capacity of acquired knowledge on artificial neurons connections. One of issues related with the use of ANN is its configuration parameters: number of hidden layers, number of neurons in each layer, type of activation function, among others. One standard approach is to do some experimental tests by the expert until find to get a good performance. Here, an automatic formulation for configuring the ANN is adotped, where the problem is addressed as an optimization problem. The optimal solution is computed by using the MPCA-NN (Multiple Particle Collision Algorithm Neural Networks), finding the best architecture for a supervised ANN. This tool uses the back-propagation algorithm; and calculates the learning rate, the momentum rate, the activation function, the number of hidden layers and neurons for each hidden layer. Such computed ANN parameters are employed in the experiment. The MPCA-NN is a metaheuristic to optimize a cost function, where the training and the generalization errors are considered including a penalty term associated to the ANN complexity. So the aim of this work is to develop a neural fire risk model, using the MPCA-NN for self-configurated ANN. The neural model is applied in the Metropolitan region of Belo Horizonte, Minas Gerais state, Brazil. Environmental data are used in the input layer, as meteorological data, land use, NDVI, slope and terrain aspect. For target output, the data is the Active Fire satellite products, where each cells of fire and no-fire events were associated with the input data to do the patterns for training and validation phases of the network. In the generalization phase, the neural network must do the prediction of most propitious fire areas, seeking to minimize possible damages caused by fires.

**Keywords**: MPCA-NN, Artificial Neural Networks, Fire Risk, computer science

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## 1. Introduction

Forest Fires are one of the major concerns related with the environmental, since they devastated great portions of forests, fields and agricultural regions. Among your main impacts there are: the fauna and flora destruction, erosion, soil degradation, trees weakness, habitats destruction, human health damages and landscape reduction (ROY, 2004). In addition of causing the increase of gases in the atmosphere, such as: $CO_2$ (dioxide of carbon), $CH_4$ (methane gas) and $NO_x$ (nitrous gases), that are responsible for increasing the greenhouse effect and causing respiratory problems (ICHOKU; KAUFMAN, 2005).

The fire risk calculation consists in verify the probability of fire occurring in determined place, that is, the chance of ignition (HARDY, 2005). So it is possible to do a critical evaluation of fire occurrence, and do the correct monitoring and prevention of burned areas, using objective tools (CHUVIECO et al., 2010).

The importance of determining areas with higher risk of fires is related with activities planning for your prevention. So, it is possible to know the seasons that most occur the forest fires, allowing controlled burns, combat and prevention of it, notify the population about the risks and do environmental education programs and, in extreme cases, limited the access in this areas.

Artificial Neural Networks (ANN) have been used as a methodology for developing fire risk models, achieving good results (ALONSO-BETANZOS, 2003; GOLDARAG et al, 2016; SATIR et al., 2016). This methodology tries to imitate the human brain, due to your capacity of acquired knowledge on artificial neurons connections.

One of issues related with the use of ANN is its configuration parameters: number of hidden layers, number of neurons in each layer, type of activation function, among others. One standard approach is to do some experimental tests by the expert until find to get a good performance. The MPCA-NN (Multiple Particle Collision Algorithm  Neural Networks), developed by Luz, Becceneri e Campos Velho (2008) it is a optimization algorithm used to find the best ANN architecture, where the problem is addressed as an optimization problem. Optimization algorithms has the aim to find best solutions maximizing or minimizing an objective function (ANOCHI; CAMPOS VELHO, 2014).

So, the aim of this article is to mapping fire risk areas in the Metropolitan region of Belo Horizonte, located in the Minas Gerais State, in the Southeast Region of Brazi using ANN. The proposed modeling is to create an artificial neural network with supervised training, using the MPCA-NN for automatic configuration. This estimate will provide the outline of priority areas for prevention activities and allocation of brigade teams, seeking to minimize possible damages caused by fires.

## 2. Study area

The Metropolitan Region of Belo Horizonte state is geographically located in the latitude $19^o00$' e $20^o30$' south and longitude $43^o15$' e $44^o45$', in the central area of Minas Gerais, state of Brazil, with 450 km of distance of Atlantic Ocean. The region is composed with 34 cities, with a 9460 $Km^2$ extension (AGENCIA RMBH, 2016) It is inserted in the third biggest metropolitan region of Brazil, named (VELOSO et al.1991) as a Ecological Tension Area. It is a transition area between two important Brazilian biomes: the Cerrado and the Mata Atlntica, both of them considerate biodiversity hotspots that demanding concrete measures of protecting. The weather in the region is defined by subtropical semi-humid with a defined dry season with duration of 4 to 5 months, between April and September. Approximately 80% of annual precipitation occurs in the rainy season. The region presents seasons of low humidity, especially in the winter, due the presence of the anticyclones that brings dry air mass and decrease the temperature and humidity. This low humidity became the region propitious to forest fires. See figure 1.

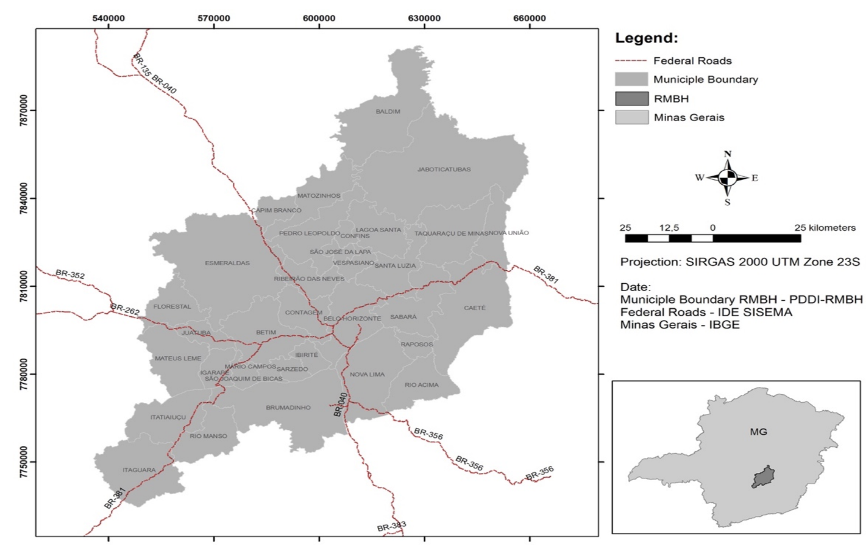


Figure 1: Metropolitan Region of Belo Horizonte

## 3. Materials and Methods

### 3.1 Input and Output Variables

The data used as input of the ANN is explain in Table 1.

Table 1: Input data presented to ANN.

| Data | Source | Method | Date | Input |
|---|---|---|---|---|
| SRTM (Shuttle Radar Topography Mission) | (USGS, 2014) | Function *terrain* in R | 2000 | Slope and Aspect |
| Land Cover | (MAPBIOMAS, 2017) | | Years of 2014 to 2016 | Land Cover |
| Meteorological Data | (INMET, 2017) | Thin Plate Spline function, from rgdal package in R. | January from December of 2014 to 2016 | Average Temperature, Air pressure, Air Relative Humidity, Wind Speed and Radiation |
| Roads | (UFMG, 2015) | Euclidean Distance | 2010 | Distance from Roads |
| Urban Area | (UFMG, 2015) | Euclidean Distance | 2010 | Distance from Urban Area |
| B4 and B5 LANDSAT-8 bands | (USGS, 2017) | NDVI | January from December of 2014 to 2016 | NDVI |
| Precipitation Data | (ANA, 2018) | Thin Plate Spline function, from rgdal package in R. | January from December of 2014 to 2016 | Monthly Total Precipitation |

All the data were set in the same projection, with geographic coordinates, datum WGS84, in the same extent and resolution, using **R** *rgdal* package.

Resulted in a regular grid $30x30$ m resolution, with 5144 rows and 4240 columns. For each pixel of the fire map were related each of 12 parameters, generating the samples to input to present the ANN. As the non-occurrence samples (background pixels) were much larger than the occurrence samples, the area were partitioned in squares of 10km2 and background samples were selected randomly.

The samples presented to MPCA input files were divided in: train (60%), validate (20%) and test (20%).

### 3.2. The Artificial Neural Network

An Artificial Neural Network (ANN) consists in simple process units that works in parallel, storing experimental knowledge and becoming available to use in modeling of acquired knowledge. This technique seeks to reproduce the human brain behavior in two aspects: the acquired knowledge for the network, done from a learn process and the connection strength between neurons, known as synaptic weight, that stores the knowledge (Haykin, 2001). Between the ANN benefits are the possibility of non-linearity, the fact of mapping inputs and outputs, from supervised training, that also allows the ANN to be adaptable, modifying your synaptic weights according to changes in the environment.

There are many architectures for ANN, from that the Multilayer feed-forward Perceptron, is one of the most used, as can be seen in the figure (Fig. 2), that has two hidden layers, where each input (x) is multiplied by an appropriate weight (w) and the sum of these weighted (Eq.1) inputs and the bias (b) results in the input transfer function f(x) (Eq.2), becomes the input of following layer. The input layer is the source node, that provide the initial signal and the output layer is the response for the input (HAYKIN, 2001).

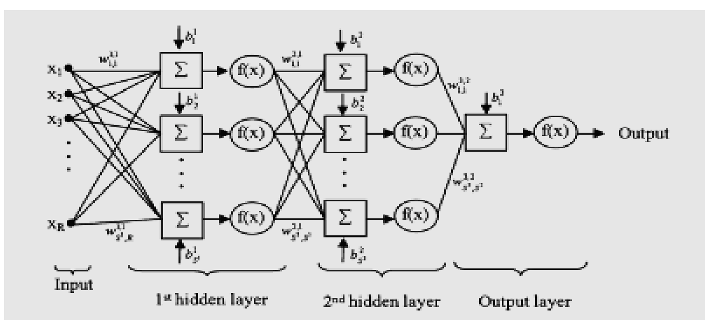


Figure 2: Multilayer feed-forward Perceptron(GOLDARAG et al., 2016)

$$u_i = \sum\nolimits_{j=1}^{m} w_{ij} x_j \tag{1}$$
$$y_i = (u_i + b_i) \tag{2}$$

The transfer function is important because restricts the amplitude of the signal at the output of the neuron as a function of the arguments and can define the linearity or not of the network output. The used in this article are the hyperbolic-tangent (Eq.3).

$$(v) = \frac{1 - exp\left(-\beta v\right)}{1 + exp\left(-\beta v\right)} \tag{3}$$

The training is very important to the network learning and improve your performance. It is used an interactive process to adjust weights and bias. Generally the data are divided in 3 subsets. The first one, training subset, consists in the knowing patterns to adjust the network parameters, the validation has the aim of verify the capacity of generalization of the network and the third, the test, tests the behavior of the ANN with new data (ANOCHI; CAMPOS VELHO, 2014). The supervised learning is the training where is given a desired output and the parameters are adjusted based on that (GOULART et al., 2006).

To training the multilayer perceptron the most used algorithm is the back-propagation, which is based in the Delta rule. This rule has the aim of minimizing the cost function of error (Eq. 5), where a delta (Eq. 6) based in the error computed is used to update the weights.

$$\varepsilon\left(n\right) = \frac{1}{2}e_k^2\left(n\right)\Delta w_{kj} = \eta e_k\left(n\right)x_j\left(n\right) \tag{4}$$

The back-propagation algorithm consists of two steps: the step forward and the step backward, where the error is back-propagated from the output layer to the input layer. And the delta is given by the gradient from the transfer function.

$$\Delta w_{jk}\left(n\right) = -\eta\frac{\partial\varepsilon\left(n\right)}{\partial w_{jk}\left(n\right)} \tag{5}$$

### 3.3. ANN self-configured: Multi-Particle Collision Algorithm (MPCA)

The MPCA were inspired by the Particle Collision Algorithm (PCA) (SACCO; DE OLIVEIRA, 2005), the differences are that the first use several particles moving in a searching space. These algorithms are inspired in a nuclear reactor principle of absorption and scattering (ANOCHI; CAMPOS VELHO, 2014).

The algorithm first selects an initial solution to initialize, the is changed by a stochastic perturbation, that came with a new solution. This is compared with the previous solution and can be accepted or not. If this is a better solution its absorbed, instead it is scattered in the space. Perturbation operators are used to explore nearly positions. The best fit solution is shared with all particles of the process. This algorithm is implemented in *Message Passing Interface* (MPI) (ANOCHI; CAMPOS VELHO, 2014). The pseudo code is show in the Figure 3.

```
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 3: Algorithm Pseudo code MPCA (ANOCHI; DE CAMPOS VELHO, 2014)

In the ANN application has the aim to find the optimal value that best represents the architecture, which is achieved minimizing the cost function giving by the eq. , proposed from Carvalho, Ramos e Chaves (2011). Where $\rho\,1 = 1$ e $\rho\,2 = 0{,}1$, that adjusts the train ($E_{train}$) and generalization ($E_{gen}$) error. The train error reflects the capacity of network memory and the generalization error reflects the ability to identify the patterns of validation set. The penalty is applied to find the best architecture with the minor complexity, as given in the eq. 8 (ANOCHI; CAMPOS VELHO, 2014).

$$penalidade = C_1 \left(\varepsilon^{neurons}\right)^2 C_1 \left(epochs\right) + 1 \tag{6}$$

where $C_1 = 1$, $C_2 = 0,1$ e $\varepsilon^{neurons}$ is the number of neurons.

So the MPCA gives: the number of hidden layers, number of neurons in each layer, the learn rate, the momentum rate and the best activation function. The limits values are showed in the table 2 (ANOCHI; CAMPOS VELHO, 2014).

### 3.4. ANN evaluation

For the model evaluation was used the overall accuracy and the Positive Predicted Value. The first one reflects the accuracy of the model accounting the fire and background points. The second evaluates if the model is capable to find the fire points (WEISS; KULIKOWSKI, 1991) .The calculation is based on the number of true positives (TP), number of fires classified

Table 2: adapted from ANOCHI; CAMPOS VELHO, 2014)

| **Parameter** | **Value** |
|---|---|
| Neurons in the hidden layer | \| 1,0\| ...\| 32\| |
| Learn rate () | \| 0,0\| ...\| 1,0\| |
| Momentum rate () | \| 0,1\| ...\| 0,9\| |
| Activation Function | \| Tanh\| Logistic \| Gauss\| |

corrected, the number of true negatives (TN), number of no-fires classified corrected, false positives (FP), number of fires classified uncorrected and false negatives (FN), number of no-fires classified uncorrected. As in the equations 7 and 8.

$$Accuracy(A) = (TP + TP)/(TP + FN + FP + TN) \tag{7}$$

$$PositivePredictedValue(PPV) = TP/(TP + FP) \tag{8}$$

## 4. Results and Discussion

The MPCA-NN was executed and the results are are shown in the Table 3. After that the parameters were used to train the ANN. The minimum error encountered was 0.067, with 1000 epochs.

Table 3: adapted from ANOCHI; CAMPOS VELHO, 2014)

| **Parameter** | **Value** |
|---|---|
| Neurons in the hidden layer | 6 |
| Learn rate () | 0.0118 |
| Momentum rate () | 0.5961 |
| Activation Function | \| Tanh\| |

The results of generalization/MLP model of MPCA-NN results are shown in the Table **4**. From the results it can be seen that the ANN performance was good. Since almost all of your fire points was classified as a probability higher than 50% (High or Very High Risk). And just a few were classified as low risk (probability less than 25% ).

The model accuracy was good as find in other research (ALONSO-BETANZOS et al., 2003; GOLDARAG; MOHAMMADZADEH; ARDAKANI, 2016; SATIR; BERBEROGLU; DONMEZ, 2016), where was find accuracies from 75% to 95% . The PPV was also high, this is important because shows that the ANN was capable to find the fire points, along with the accuracy that also was high shows that the ANN can found the points of high and low risk very well.

Table 4: adapted from ANOCHI; CAMPOS VELHO, 2014)

| Data Set | Fire Probab. | Fire Points | | Accuracy | PPV |
|---|---|---|---|---|---|
| | | Quantity | Percentage | | |
| Training set | 0.75-1 | 1164 | 55,65% | 77.5 % | 84.8% |
| | 0.5-0.75 | 609 | 29,11 % | | |
| | 0.25-0.5 | 319 | 15,24 % | | |
| | 0-0.25 | 0 | 0 % | | |
| Test set | 0.75-1 | 157 | 28,5 % | 78,9 % | 69,3 % |
| | 0.5-0.75 | 224 | 40,7% | | |
| | 0.25-0.5 | 168 | 30,5 % | | |
| | 0-0.25 | 1 | 0,02 % | | |
| Generalization set | 0.75-1 | 232 | 44,1 % | 78,8 % | 74,53 % |
| | 0.5-0.75 | 160 | 30,4 % | | |
| | 0.25-0.5 | 131 | 24,9% | | |
| | 0-0.25 | 3 | 0,06% | | |

## 6. Conclusion

The MPCA-NN it is a improvement in studies that applied Artificial Neural Network, filling the gap in the use of these methodology. As it gives the best parameters to be used to perform a ANN, using that as a optimization problem.

The use of ANN to calculate the Fire Risk also have showed as a good methodology, as it could recognize well the fire points and also the background points. Having a trained and tested ANN it is useful to do predicted models of forest fire risk and give the priority areas of risk dependent of the meteorological conditions.

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