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# Predicting the flame characteristics and rate of spread in fires propagating in a bed of *Pinus pinaster* using Artificial Neural Networks

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ABSTRACT

Physical and geometrical characteristics of flame propagation are very important to better understand the forest fire spread behaviour and to improve risk management tools. Having a tool to predict these characteristics is of practical and theoretical interest for a better understanding of the complex chemical and physical mechanisms which occur during forest fire phenomena. A metamodel is presented based on Artificial Neural Networks (ANNs) for estimating physical and geometrical parameters of the forest fire front, namely the rate of spread (ROS), flame height ($H_f$) and flame tilt angle ($\alpha_f$). The ANN was developed using literature data obtained from experiments of fire propagation in beds of *Pinus pinaster* needles. The optimal feedforward ANN architecture with error backpropagation (BPNN) was determined by the cross validation method. The ANN architecture having 5 hidden neurons proved to be the best choice. Comparing the modelled values by the ANN with the experimental data indicates that neural network model provide accurate results. The performance of the ANN model was compared with a metamodelling method using a multilinear regression approximation.


## 1. Introduction

Forest fires have always existed and nowadays, due to climate changes, they are becoming a growing threat for human life and ecosystems in the world. Every year, the average areas of forest destroyed by fire in the world and in Europe are about 28 and 1.6 million hectares, respectively. Moreover, in Europe the burnt area increases annually, a trend likely to continue as the World Health Organization identified fire as a growing threat for the coming years because of global warming. Despite the dramatic rise of forest fires all around the world, currently, 11 ha/s burn in the whole world, it is noticeable that forest managers have always tried to increase their efforts towards fighting forest fires, but in many cases the main problem comes from determining the current state of the fire front. This valuable information can be described by the geometrical characteristics of the flame (position, height and tilt angle) and rate of spread.

Some authors have measured these physical and geometrical characteristics of the flame using thermal and/or image processing techniques (Zhou et al., 2005; Pastor et al., 2006; Ononye et al., 2007; Chetehouna et al., 2008; Martinez-de Dios et al., 2008; Rudz et al., 2011). In addition, it was shown that these parameters depend on wind velocity, fuel moisture content and slope of ground surface (Viegas, 2004; Boboulos and Purvis, 2009). Studies of the effects of these factors are

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carried out in laboratory conditions (Anderson, 1968; Nelson and Adkins, 1986; Bradstock and Gill, 1993; Dupuy, 1995; Morandini et al., 2001, 2013; Santoni et al., 2002; Dupuy et al., 2003; Mendes-Lopes et al., 2003; Bartoli et al., 2011; Fuentes and Consalvi, 2013) or under controlled fires in real vegetation beds (Marsdden-Smedley and Catchpole, 1995; Burrows, 1999; Butler et al., 2004). One of the largest database found in the literature about flame characteristics and rate of spread is presented by Mendes-Lopes et al. (2003). Their experiments were performed in a dedicated burning tray, where wind velocity, fuel moisture content and slope were varied to study fire propagation in beds of *Pinus pinaster* needles. However, the main drawback is that their experimental tests are costly and they do not cover the entire range of test conditions. Therefore, it is extremely difficult and sometimes impossible to predict the flame characteristics and the rate of spread for new cases which are not included in the database. Thus, having a tool for generalization of new cases is of practical interest for saving time and money.

Other literature sources have focused on the determination of these flame characteristics using physics-based computational fire models (Morvan and Dupuy, 2001; Morvan and Larini, 2001; Simeoni et al., 2001, 2003; Balbi and Rossi, 2007; Morvan et al., 2009; Balbi et al., 2010; Menage et al., 2012). These valuable approaches are useful to improve the understanding of the mechanisms that are responsible for fire behaviour. On the other hand they need a large amount of computational resources (Nmira et al., 2010) and several input parameters (e.g. heat transfer coefficient, characteristics of thermal degradation, turbulent kinetic energy and its dissipation rate) which are hard to measure or not available in many cases. It is also not possible to integrate observed data directly at desired locations to improve model results. Simplified or reduced propagation models have therefore been developed (Margerit and Séro-Guillaume, 2002; Koo et al., 2005). These models generally require input parameters, which depend on the fire itself, such as flame length and tilt angle (Nmira et al., 2010). Empirical models based on experimental results have been also developed to create relationships between variations in fire behaviour factors and characteristics (Pastor et al., 2003). For the ability to simulate quickly and accurately, the geometrical characteristics of the flame and rate of spread are of crucial importance in fire forecasting operations.

Here an approach is proposed based on artificial neural networks (ANNs) for simulating the rate of spread (ROS), flame height ($H_f$) and flame angle ($\alpha_f$). The ANN provides a quick and flexible approach for data integration and model development. Over the last two decades, ANNs have been successfully used by many researchers for a wide range of engineering applications (El Tabach et al., 2007). An ANN is based on the substitution of the complex simulation model by an approximation of the input–output relationship. The ANN has the advantage over regression that the form of the model needs not to be pre-determined (Kleijnen, 2009). In addition, the ANN can theoretically approximate any function to any level of accuracy, which is very interesting when the governing physical mechanisms are non-linear like in forest fire propagation behaviour research. The experimental results found in the literature (Mendes-Lopes et al., 2003) are used to construct, to optimize and to validate the ANN model. The performance of the proposed ANN model is compared with a multilinear regression approximation method.

## 2. Construction of ANN models

### 2.1. Artificial neural networks

In this study, an artificial neural network (ANN) was used to predict the flame height ($H_f$), flame angle ($\alpha_f$) and rate of spread (ROS) of a bed of *P. pinaster* needles. An ANN is a powerful mathematical tool used to model non-linear relationships between inputs and outputs without any a priori knowledge of the model. ANN models learn the relationship between the input and the output parameters as a result of training with previously recorded data.

### 2.2. Construction of the database

The database was built using experimental data which were collected from the literature (Mendes-Lopes et al., 2003) with input parameters: slope (S), fuel moisture content (FMC) and wind velocity (W) varying in a range of representative values: $-15°$, $-10°$, $-5°$, $0°$, $5°$, $10°$ and $15°$ for S; $(10 \pm 1)\%$ and $(18 \pm 1)\%$ for FMC and −3, −2, −1, 0, 1, 2 and 3 m/s for W. The fuel bed used in the experiments (Mendes-Lopes et al., 2003) is composed of *P. pinaster* needles with a depth of 4 cm and a load of 0.5 kg/m$^2$. It should be noted that the negative values of W refer to backing fires and the negative value for S corresponds to down-slope orientation. More information about the experimental procedure can be found in Mendes-Lopes et al. (2003). Totally, the database contains an appreciable size of 64 experimental test points.

The present database was subdivided in three subsets. A first subset (30 experimental tests) was used to train the network. A second one (16 experimental tests) was used to test the ANN models to determine when to stop the training stage. The third subset (18 experimental tests) was used to validate the performance of the selected model on unseen cases.

Each input or output parameter was normalized relative to its minimum and maximum values observed in the data (according to Eq. (1)) to make the training procedure more efficient.

$$X_{norm} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

where X is an arbitrary parameter, $X_{norm}$ is the normalized value, and $X_{max}$ and $X_{min}$ are the maximum and minimum values of X, respectively.

### 2.3. Architecture and learning process of ANN models

An artificial neural network model is composed of interconnected groups of artificial neurons or nodes. The most frequently utilized network is the multilayer backpropagation neural network (BPNN) which is used in the present study. The BPNN structure consists of three layers, an input layer which receives data; an output layer which sends computed information; and one or more hidden layers to link the input and output layer. All the neurons (nodes) in a layer are connected with all the neurons of the previous and the next layer. In general, the number of the nodes in the input and output layer are determined by the nature of the problem. The architecture of a typical 3-layer backpropagation neural network is shown in Fig. 1.