Aceh International Journal of Science and Technology

ISSN: p-2088-9860; e-2503-2398

Journal homepage: http://jurnal.unsyiah.ac.id/aijst

Atmospheric Pollutant Flow and Precipitation: Modeling Effects on the Vegetation Ecosystem

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Abstract – Because of their fixed life and wide distribution, plants are the first victims of air pollution. The atmosphere is considered polluted when the increase of the rate of certain components causes harmful effects on the different constituents of the ecosystems. The study of the flow of air near a polluting source (cement plant in our case), allows to predict its impact on the surrounding plant ecosystem. Different factors are to be considered. The chemical composition of the air, the climatic conditions, and the impacted plant species are complex parameters to be analyzed using conventional mathematical methods. In this study, we propose a system based on artificial neural networks. Since artificial neural networks have the capacity to treat different complex parameters, their application in this domain is adequate. The proposed system makes it possible to match the input and output spaces. The variables that constitute the input space are the chemical composition, the concentration of the latter in the rainwater, their duration of deposition on the leaves and stems, the climatic conditions characterizing the environment, as well as the species of plant studied. The proposed model supports the complexity of the factors that influence plant vulnerability and susceptibility to pollutants. The chemical composition of pollutants affects each plant species in a different way. Also, at the level of the same plant, the effect differs between its different parts from the stem to the leaves. The accumulation effect is regulated by climatic conditions such as winds and precipitation. Considering several factors as input variables in correspondence with the impact on a given plant species, the proposed artificial neural network allows this complexity to be taken care of. Prevention of the ecosystem around a source of pollution will then be possible.

Keywords: atmospheric pollutants, modeling, ecosystem, vegetation, artificial neural networks.

Introduction

It is essential to predict the impact of a pollution source on their environment. This makes it possible to take the necessary measures before the establishment of a polluting industry or even to provide techniques for limiting this pollution. For this, it should be noted that the polluted water that affects the vegetation comes from two different sources. The first source is from the soil that feeds the vegetation from the bottom up and is characterized by its specific chemical composition including pollutants. This water usually comes from rainwater with all it contains as constituents of the atmospheric layer mixed with the chemical composition of the soil. The other affects directly the plant on the surface of leaves and stems. The whole can be analyzed using the biogeochemical cycle that characterizes the soil-atmosphere interaction (Parker, 1990). The first category of water is affected by exchange reactions that occur between surface water and rainfall. For this, stochastic models are proposed (Calder, 1986). Precipitation water is affected by the removal rate of leaf area particles. This depends on the size of the particles, the size of the droplets, the acidity of the rains, its frequency, its duration, intensity and the duration of its arrangement on the leaves (McCune, 1986). Since rainwater is a means of trapping pollutants from the atmosphere, the composition of the atmosphere reflects the composition of the atmosphere through which it falls (Marco,

2014). This air pollution determines the acidity or alkalinity of rainwater (Ham, 2010). This can cover a distance of a hundred kilometers (Nasiruddin, 2014). Thus, the study of the chemical composition of precipitation is necessary to characterize the atmospheric pollution of a region (Ham, 2010). In this area, several studies are reported in the literature relating to this topic. (Alastuey, 1999; Al-Momani, 2003; Hontoria, 2003; Compos, 1998; de Mello, 2001; Lara, 2001; Flues, 2002; Migliavacca, 2004).

All this atmospheric pollution carried by rainwater directly affects the vegetation. This vegetation is damaged through various stages of degradation that are identified (Pompéia, 1998). For example, the fluoride emitted by the industry that has been identified as a pollutant that significantly affects the vegetation mainly by its accumulation on the leaves with sulphates and induces metabolic variations typical of growth (Klumpp, 1993; Leitão, 1993).

The state of vegetation degradation depends on the nature of the water pollution in terms of composition, concentration, duration, climatic conditions as well as the nature of the plant species itself, whose sensitivity is variable. This study proposes to analyze the impact of atmospheric pollutants carried by precipitation waters on plant species. However, these factors are very complex to analyze those using conventional mathematical models. An intelligent analysis based on artificial neural networks is proposed. As artificial neural networks have the capacity to handle a wide variety of complex factors, its application in this area is adequate (Allag, 2018). The proposed system has five input variables (chemical composition, concentration, duration, climatic conditions, and plant species) and an output variable that expresses the rate of degradation of the plant species considered. The impact of these input factors on the vulnerability of the plant species is expressed by the output variable of the system. Once several input-output combinations have been introduced, the mapping function between the two spaces is adjusted to the minimum of error. It will then be possible to predict the impact of atmospheric pollutants on a plant species from the random introduction of the input variables to automatically read the result in terms of impact on the vegetation at the output.

Materials and Methods

The different plant species surrounding the study area (cement plant) are listed. In our study these species are mainly cereals (soft wheat and barley). Vegetations are collected at different stages of growth and at different distances and orientation from the source of pollution. Each plant is divided into three parts (leaves, stems, roots). The chemical composition of the ejections in the atmosphere of the cement plant is known at the source. The climatic conditions of the study area are obtained from the services of the Setif meteorological station at different times of the year. The next step is to match these different factors. As the system is very complex, because other factors can intervene in the process and they are ignored. Also, the weight of each factor is poorly understood. The proposed artificial neural network system can handle all this complexity.

Neural networks are designed to mimic the performance of the human brain. There is inputs level, output level, and a variable number of internal (or hidden) layers. The inputs are connected to hidden layer and they are in turn connected to output. Figure1. As the neural network learns from a data set, the connection weights are adjusted. Data are fed into the input nodes, processed through the hidden layer(s), and the connection weights to the output nodes are adjusted (Bouharati, 2018).

Artificial neural networks possess the ability to model complex systems. Their application is well adapted to these problems. A learning phase of the network is carried out on half the analyzed variables. The other half is used for network testing. The system makes it possible to match the input variables with the output variable. By assigning values to the input and output, the system provides a transfer function between the two spaces. When other variables are affected, the system adjusts the function by changing the weights that are mathematical coefficients. Note that this method allows adjusting the function without changing the entire system. The database that the system refers to must include all possible combinations. This called the learning phase. Once the function has been adjusted with the minimum of error, it allows input variables to be introduced in any real case (chemical composition, concentration, duration, climatic conditions, and plant species) to read automatically and instantly the predicted rate of degradation on the plant species considered.

Factors involved

A system is constructed with input variables (chemical composition, concentration, duration, climatic conditions, and plant species) and an output variable that expresses the offending species.

Climatic conditions include a set of variables such as temperature, precipitation, wind speeds, and atmospheric pressures.

Each variable is numerically coded in three levels (1,2,3). The chemical composition as a variable is expressed in three levels according to its impact on the vegetation. In the same way the other variables are coded in three levels according to their effects on the plant species which is also codified in three levels according to its sensitivity to pollution.

Results and Discussion

The proposed network consists of three layers (input layer, hidden layer and output layer). By introducing values to the input variables in correspondence with the output variable and processing several combinations, the transfer function is constructed.
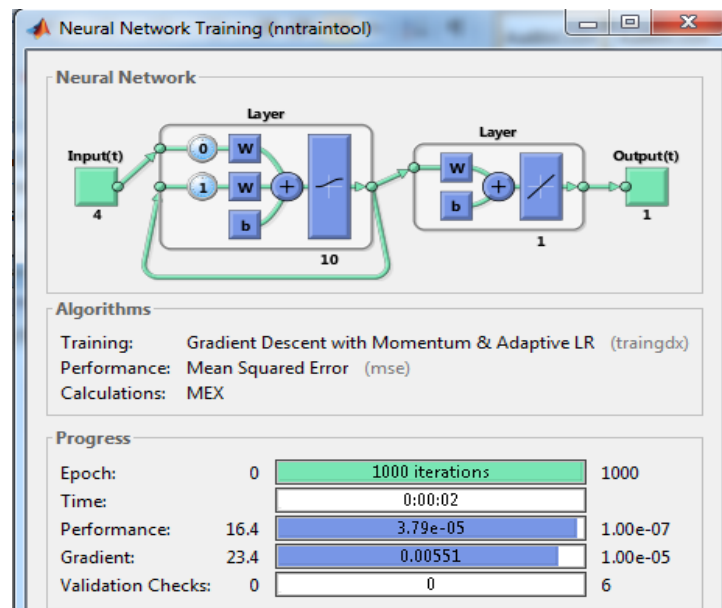

Figure 1. Block diagram of the system

$$\text{Let } y = p1 * z^2 + p2 * z + p3 \tag{1}$$

where z is centered and scaled:

$$\tag{2}$$

$$z = (z - mu)/sigma$$

$mu = 500$ and $sigma = 289.11$

coefficients:

$$p1 = 0.16421, \ p2 = -0.11792, \ p3 = -0.094637 \tag{3}$$

The best training is:

$$y = p1 * x^2 + p2 * x + p3$$

coefficients:

$$p1 = -0.0061666, \ p2 = 6.1666, \ p3 = 3.7912e - 05 \tag{4}$$

Norm of residuals= 77.782

The goal training is:

$$y = p1 * x^2 + p2 * x + p3$$

coefficients:

$$p1 = -0, \ p2 = 0, \ p3 = 1e - 07$$

Norm of residuals= 0

At each input-output, the function is adjusted via weights (mathematical coefficients). This phase is the phase of learning the network. This continues up to the optimum of the desired function. The optimum of the learning is reached at 991 iterations with a performance of 3.7.10-5 with a gradient 5.5.10-3.

The collection of system input variable values from actual cases is mapped to the recorded rate of degradation of the plant species. These real values are coded in three levels as an Excel table. The system uses the coded values to establish the learning function. It should be noted that more than the variables are numerous, more than the accuracy is great.

After the learning phase of the network, it becomes possible to predict the result at the output of the system from the input of the variables at the input. As the effect of each parameter is supported as weight (mathematical coefficient) when adjusting the function, the result will be as accurate as possible. The proposed system will then make it possible to predict the nature of the species that survive under the conditions of the parameters fixed at the input of the system.
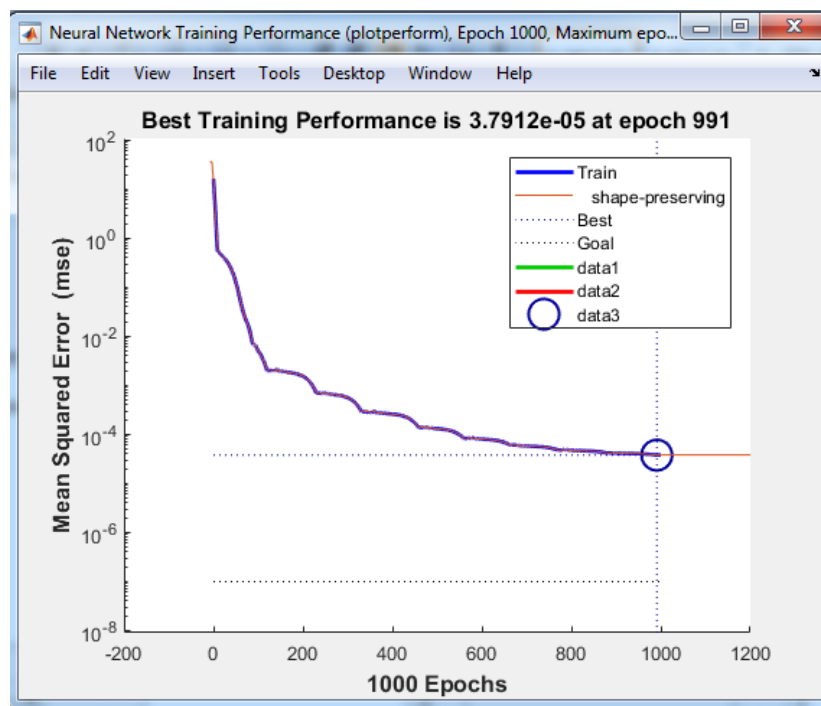

Figure 2. Optimum at 991 epocs

Conclusions

Vulnerability to atmospheric pollutants varies from one plant species to another. The chemical composition of these pollutants is also a determining factor in their use of plants. Soil composition and climatic conditions are also factors to consider. The system is very complex. The analysis system proposed using artificial neural networks allows taking care of all this complexity. With the factors influencing the plant species studied as input variables to the system, the output variable expressing the impact of these on the plant is the result of the contribution of all the input factors. This is obtained after learning the system from the actual values. After several combinations entered at the input and output of the system, the adjustment of the transfer function reaches the minimum of error. This study can be a tool to help prevention in the protection of ecosystems in the vicinity of industrial pollution sources.

Conflict of interest

The author declares that there is no conflict of interests regarding the publication of this manuscript.

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