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Artificial Neural Networks: A Non-Linear Tool for Air Quality Modeling and Monitoring

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Abstract

Environmental problems including air pollution have increased in recent years. Due to the complexity and nonlinear nature of these phenomena and problems, this paper was prepared to explore the application of Artificial Neural Networks as a nonlinear model effective to tackle these problems. This paper applied main neural networks to atmospheric science, creation process, examples, limitations and advantages. Advantages of the model are its effective capacity to relate underlying relations between input and output variables and high tolerance to errors of input variables. Some disadvantages are that the model's success is dependent on both the quality and quantity of data.

Keywords: Artificial neural networks, air quality, predict, unique approach

1. Introduction

Artificial neural networks, as a branch of artificial intelligence, can model highly non-linear functions. Neural networks have been shown to be an effective alternative to more traditional techniques of statistical analysis when the complexity of a problem increases and theoretical understanding decreases. Neural networks approximate highly non-linear functions between input features and output features and require no prior knowledge of the nature of that relationship [1]. The basic element of a neural network is the neuron; several neurons are organized into layers; input, hidden and output. Each neuron has a simple structure that mimics the functionality of neurons found in a human brain. All connections between neurons are weighted and these interconnections are the basic parameters of a model and due to the difference between the target and the model output, they are adjusted during the learning or training process. Artificial neural networks can be divided into several groups according to their topology. Multilayer perceptron artificial Neural Network (MPNN) and Kohonen neural network (KNN) are the main artificial

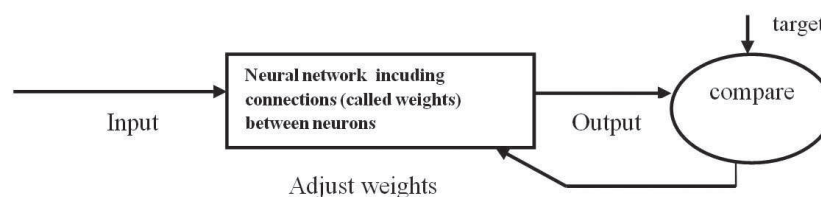


Figure 1. Typical ANN structure

neural networks that can cover a huge variety of air pollution and meteorological modeling applications [8].

2. Multilayer perceptron And Kohonen neural networks

A multilayer perceptron consists of a system of simple interconnected neurons. A multilayer perceptron is able to learn during the training process. Training requires a set of training data, which consists of a series of input and associated output features. There are many algorithms that can be used to train a multilayer perceptron. The back propagation algorithm is the most computationally straightforward algorithm for training this network. When a network is trained with suitably representative training data, the multilayer perceptron can generalize to new, unseen input data. Therefore it has three main applications in atmospheric and meteorological sciences; prediction, function approximation and pattern classification.

- **Prediction:** as respects the relationship between meteorology and pollution is complex and potentially multiscale in nature, the multilayer perceptron can be applied to quality prediction.
- **Function approximation:** unlike prediction, function approximation aims to use multilayer perceptron to better and more fully model relationships between data.
- **Pattern classification:** multilayer perceptron can be used to work in pattern classification in order to better distinguish data [1,3].

Kohonen neural network (KNN) significantly differs from multilayer perceptron and the main purpose of KNN is to sort multivariable patterns into groups of similar patterns. It is important that the grouping criteria need not be known, therefore this is unsupervised learning. So the Kohonen neural network is a very practical and effective tool to establish groups of similar patterns in data sets [8].

3. Model creation process

The first stage is feature determination in order to define a model's domain. It is done to enable incorporation of all the important information; to simplify multilayer perceptron and therefore achieve more effective learning and to reduce the number of learning patterns needed. Then, the database of measurements is divided into several sets for construction of the model. The model includes a training set that is used to adjust the interconnection weights of the multilayer perceptron neural networks: a testing set that is used to periodically during the learning process to test a model's generalizing capacity and its is optimization during learning; a production set that is used for model verification to determine expected error, when the model has been trained; it can be used on patterns with unknown output values. This set of patterns is the on line set. In the next step, pattern selection can be used to sort patterns into groups to show which ones are the more important. These patterns contain all the information about the studied phenomenon. Network topology determination is another step; whereby numbers of neurons in the input, hidden, and output layers are determined and it is from the number of features and number of patterns that

better performance of the model is achieved. Then the training and testing process is carried out periodically on the testing set and the training algorithm is used to determine the model's interconnection weights for the best results on the optimization and testing set. Finally when the model is trained it is validated by the production set to determine the expected error in further on line use. Feature determination and pattern selection are therefore the most crucial steps in a model's construction and usually determine a model's ability [8].

4. Examples of studies by artificial neural networks in the field of atmospheric science

4.1. Application of backpropagation neural network in predicting emissions from a palm oil mill

In Malaysia, the palm oil industry is one of the major main industries and it occupies a large sector of the country's economy. The industry produces air pollution from emissions that can contribute to health problems in nearby communities especially when fuels are mixed disproportionately. It is therefore necessary to reduce air polluting emissions either by using air pollutant removing devices or by improving the combustion efficiency of boilers used in the industry by detecting effective parameters to emission pollutants. Input variables were fiber flow, shell flow, steam capacity, feed water, steam pressure, power output, main pressure, flue gas temperature and output variables were carbon monoxide, nitrogen oxide, sulphur dioxide and particulate matters. Finally the trained data by NN agrees well with the measured data almost within 8 % error for emission pollutants [4].

4.2. Forecasting extreme PM_{10} concentrations using artificial neural networks

Particulate matter has a major effect on public health because of air pollution, this has been a major concern in Tehran for recent years and the city has been suffering from PM_{10} . an artificial neural network was used to forecast estimates for maximum PM_{10} concentrations 24 hour ahead in Tehran from meteorological and gaseous pollutants. Input features were date, day of week, month of year, mean of solar radiation, mean and max temperatures, mean wind direction and speed, mean CO, mean NO and mean and max of PM_{10} from the day before and mean solar radiation, mean temperature, mean wind direction, and mean of wind speed for the next day. Results showed that forecasting PM_{10} was promising with an index of agreement of up to 83%[5] .

4.3. Measurement and prediction of ozone levels around a heavy industrialized area: a neural network approach

It is well known that ozone is formed from the complex chemical interaction of primary pollutants and a presence of solar radiation. Therefore a neural network was applied to forecast ozone levels near an industrial area in Kuwait. The inputs to the network were wind speed and direction, relative humidity, temperature, solar intensity and concentrations of methane, carbon monoxide, carbon dioxide, nitrogen oxide, nitrogen dioxide, sulfur dioxide, non-methane hydrocarbons and dust. It was found that those precursors having the most effect on predicted ozone concentrations and temperature played an important role. In addition neural networks

were compared against linear and non-linear regression models and it was found that the neural network model provided superior predictions [6].

4.4. An online air pollution forecasting system using artificial neural networks

Urban air quality management and information systems are required to predict the next days air pollution levels to implement the appropriate action and control strategy, therefore neural networking was applied to develop an online air pollution forecasting system for the greater Istanbul area. The system predicts three air pollution indicator levels for the next three days. The inputs were general condition, wind direction, pressure, day temperature, night temperature, relative humidity and wind speed. Output parameters were sulfur dioxide, particulate matter and carbon monoxide. The results showed that quite accurate predictions of air pollutant indicators are possible with a simple neural network and further optimization of the model can be achieved using different input parameters and better forecasts are observed using day of week as an input parameter [7].

5. Limitations and vantage of neural networks

5.1. Limitations

One of the limits of artificial neural networks in practice is that they are difficult to implement and interpret. The success of an artificial neural network depends on both the quality and quantity of data. Deciding on a network structure or architecture, determining a number of layers and neurons is another problem and there are no rules to help in this process. The lack of physical attributes and relations is another limitation. The inability to explain in a comprehensible form the process through which a given decision was made by the neural networks. Neural networks are not a miracle to all real world problems; therefore other traditional techniques are powerful in their own way [1,2].

5.2. Advantages

The ability of artificial neural networks is to gain an understanding of underlying relations between input variables and output variables and to solve complex and non linear problems and high tolerance to data containing noise and measurement errors due to distributed processing within a network [2].

6. Summary and conclusion

This paper has briefly reviewed techniques of artificial neural networks. According to performance of the networks in this study the results demonstrate that artificial neural networks can be useful a tool to model hidden phenomenon, particularly in atmospheric science and there are many freely available software packages to implement neural networks easily. Therefore the current approach can be extended by further research to model environmental and air pollution problems.

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