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Atmospheric Pollutant Dispersion and Congenital Malformation: Artificial Neural Networks Modelling

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Abstract

The quality of air we breathe every day is essential to a healthy lifestyle. Maternal during pregnancy and anthropometric measures at birth in an Ain El-Kebira area in Algeria exposure to air pollution has been related to fetal growth in a number of recent scientific studies. The objective of this study was to assess the association between exposure to air pollution (36°36' N and 5°5' E). The accumulated evidence indicates that children's health is adversely affected by air pollution levels currently. Outcome variables were birth weight, length, and head circumference, along with being small for gestational age. The association between exposure to residential outdoor NO_2 and outcomes was assessed controlling for potential confounders and examining the shape of the relationship. In view of the fact that data sets of atmospheric pollution are very complex and uncertain, we propose that a form of artificial neural networks needs to be adopted. This will help to create a reasoned approach to determine an air pollution effect. That will permit regulatory bodies to set effect of air pollution and assist authorities of manufacturers like a pollution sources in developing a prevent regulation of atmospheric pollutants. The initial data used are measured variables (birth weight, birth length and head circumference of newborns at different distances and different directions from pollution sources cement Manufacturing, wind speed, and months during last decade). The number of cases is considered as an output. The air pollution effect on newborns system is based on artificial neural network. It is designed for measurement of different parameters like weight, height and head circumference of newborns in different area in front of pollution source and in its opposite at different period before and after installing the filter at the plant as a source of pollution.

Keywords

Wind Dispersion, Air Pollution, Newborns, ANN, Artificial Intelligence

1. Introduction

In recent years a growing body of epidemiological research has focused on the potential impact of prenatal exposure to air pollution on birth outcomes. Several outcomes have been related to exposure to air pollution during pregnancy, including low birth weight, reduced birth size, and intrauterine growth retardation [1-4].

The relation between NO_2 exposure during the first trimester and birth weight and length and between NO_2 exposure during the second trimester and head circumference suggested a change in slope [5]. Results of the analysis indicated that NO_2 exposure during the first trimester was associated with a reduction in birth length. Birth weight was just marginally associated with NO_2 exposure. Also a significant reduction in head circumference was found for exposures throughout the entire pregnancy, more often born with lower birth weight and smaller head circumference [6, 7, 8]. Effect of mothers' exposure to high concentration of

particulate matter (above the median 36.3 μg/m^3) of fine particles was reflected in significantly lower mean weight (128.3 g) and length (0.9 cm) and lower mean head circumference (0.3) of newborns [9]. The researchers in the USA found that mothers who lived in areas with the highest levels of particulate matter 2.5 during their pregnancy delivered slightly smaller babies than their counterparts who lived in areas with lower levels of particulate matter 2.5 exposure. They also observed association between number of traffic-related pollutants and small for gestational birth weight as well as preterm births (before 37 weeks) [10, 11]. Outcome variables were birth weight, birth length and head circumference. Birth weight was measured by the midwife that attended the birth, whereas birth length and head circumference were measured by a nurse when the newborn arrived in the hospital ward within the first twelve hours of life. The three measures were standardized for gestational age and sex using the residuals method [12].

As the numerical measured values are characterized by their complexity, process and analyze them using conventional mathematical methods is very difficult if not even some times impossible, it becomes necessary to analyze such data with the tools of artificial intelligence especially artificial neural networks. The nonlinear systems difficult to model mathematically are usually monitored by ANN. Given the specificity of the environment and its complexity, we give an overview on the fundamentals of the technical analysis data that are used (Artificial Neural Networks). Artificial neural networks are a methodology for problem solving or in other words "problem solving control system methodology". Its implementation can be performed in hardware or software or by combining both.

2. Materials and Methods

As materials, the data are collected from the newborns at University Hospital Campus issues from 4 areas (*Ain Touilla, El-Khareba, Ouled Adouene*) in the wind direction, and (Ain Arnat) in the opposite of the direction during the last decade. The number of newborns listed by regions is listed in Table 1

2.1. ANN Principles

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. 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. Neural nets are categorized based on their learning paradigm. Neural networks can reveal unexpected and otherwise undetectable patterns in large data sets. The major weakness in neural network solutions is the fact that the methods by which a relationship is discovered are hidden and therefore not readily understood or explained [13]. In the simplest way, a cooperative model [14, 15], can be considered as a preprocessor wherein artificial neural network (ANN) learning mechanism determines the training data [16].

Expression of the problem

Mapping of the space of parameters involved in the pollution effect on new born, we consider inputs:

i. Area (that represents different direction from pollution source)
ii. Morphological characteristics (weight, height, head circumference)
iii. Period (during the decade 2000-2010)

The number of new born recorded to be given according different cases is considerate as output of system.

Figure 1, describes the topology with three inputs extensible, two hidden layers, and an output (3-2-1) in the terminology of models of artificial neural networks. W_{ij} and W_{jk} are weights, which represents the connection between the inputs and the output of the system. Weights contain all the information about the network. The objective is the training of the network to reach the minimum value of the reading error at the output observed.

Table 1. *Number of newborns according areas with anatomic parameters.*

Area	Morphological characteristics		2000-2003	2004-2006	2008-2010
AinTouilla	weight (kg)	<3	56	35	24
		>3	117	38	104
	height (Cm)	<50	73	42	21
		>50	88	50	102
	head circumference (Cm)	<35	82	51	72
		>35	72	41	51
El-Kharba	weight (kg)	<3	41	27	25
		>3	89	141	69
	height (Cm)	<50	59	57	36
		>50	70	94	56
	head circumference (Cm)	<35	45	76	36
		>35	75	77	56
OuledAdouane	weight (kg)	<3	3	12	4
		>3	17	25	9
	height (Cm)	<50	12	13	2
		>50	8	17	9

Area	Morphological characteristics		2000-2003	2004-2006	2008-2010
AinArnat	head circumference (Cm)	<35	11	14	4
		>35	9	16	7
	weight (kg)	<3	11	9	8
		>3	91	87	96
	height (Cm)	<50	54	9	65
		>50	41	43	39
	head circumference (Cm)	<35	31	32	35
		>35	73	70	71

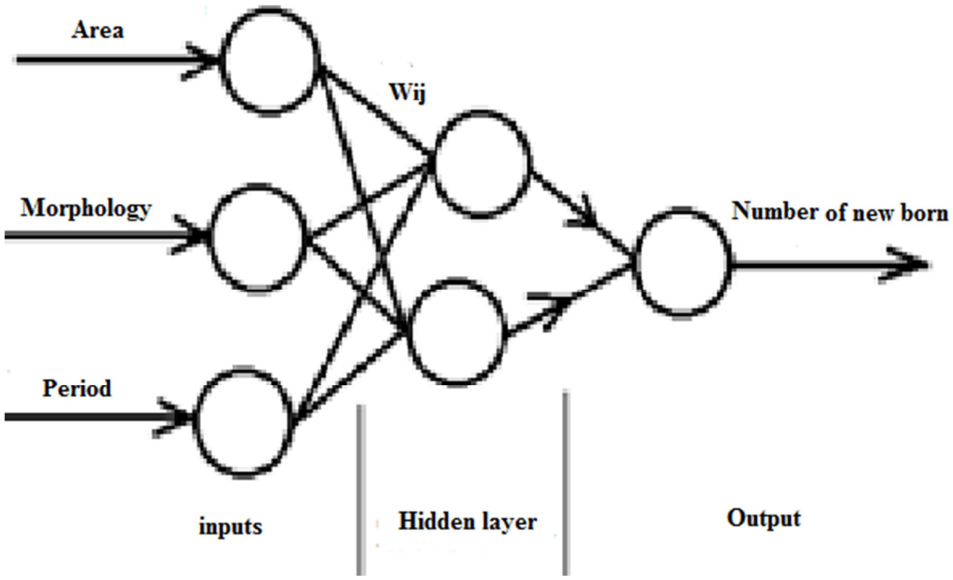

Figure 1. *Network structure.*

Structure of the artificial neural network: Artificial neural networks can be defined as highly connected arrays of neurons. The activity of a single neuron computes the weighted sum of the inputs $e_i(net)$ and passes this sum through a non linear function according to:

$$net = \sum_{i=1}^{n} W_i e_i + W_b$$

Another term called the bias term W_b is associated with this sum. The function (W_b used as a non linear function *f*. In our case is a sigmoid function:

$$f(net) = \frac{1}{1 + e^{-gs}}$$

2.2. Model

24 line number of newborn measured (Table 1) as matrix in area, morphological characteristics, and period. We choose to keep 12 tests (50%) while 25 tests, (50%) are used for learning. A priori, the relationship between these two spaces is complex (in particular non-linear) which justifies the use of a multilayer network.

Consequently, the output layer produces an output signal. The calculation of weights is performed with the learning algorithm.

Learning of the neural network

It is in this case to introduce different data to the input in correspondence with the degree of neural weight variations. To achieve this, the method is a kind of imitation of the brain: if the answer is correct, it is, but if there is an error, we must modify the network so as not to repeat the mistake. Is repeated several hundred times the operation, until the system has the smallest error value as possible.

Note: To change the system, just work on the weights *W* which are in the form of real numbers linking neurons. As these weights involved in the sum made by each neuron (the sum is weighted), it is possible to modify the network by changing their values without changing the network itself. That said, it is not clear how much weight we need to modify these.

3. Results and Discussion

Since there are several factors involved in the process and each has a combined effect with others, in our study we are limited only to the main factors interconnected. To get a result with minimal errors, the weight of each factor is adjusted in correspondence with the result set to the output of real recorded values.

This is done by readjustment of weight. The goal is to achieve convergence towards a minimum error. In our case, a validation check at 200 epochs corresponds to 0 errors. The learning rate is largely achieved for a value of 1.0097 at 200

epochs. Figure 2.

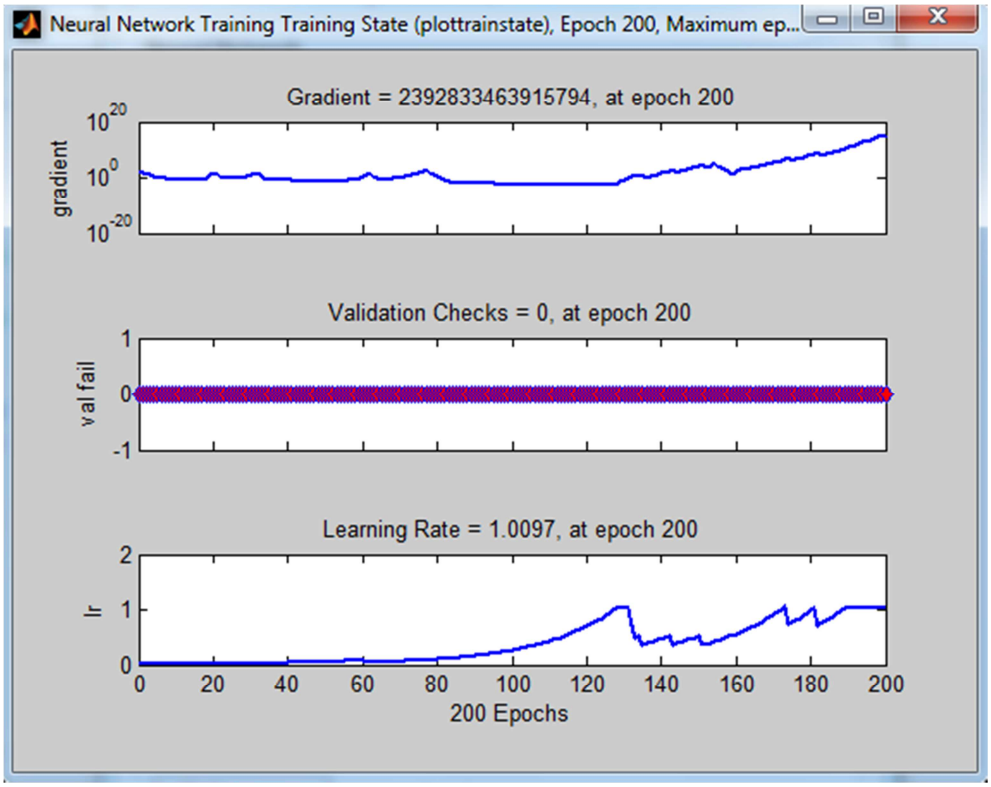

Figure 2. *Error correction functions.*

The result after training is shown in Figure 2. The proposed program predicts the changes in number of newborn according congenital malformation under the effect of the atmospheric pollutant based on the input parameters. Test values are fully consistent with the recorded values just after 20 iterations. Figure 3.

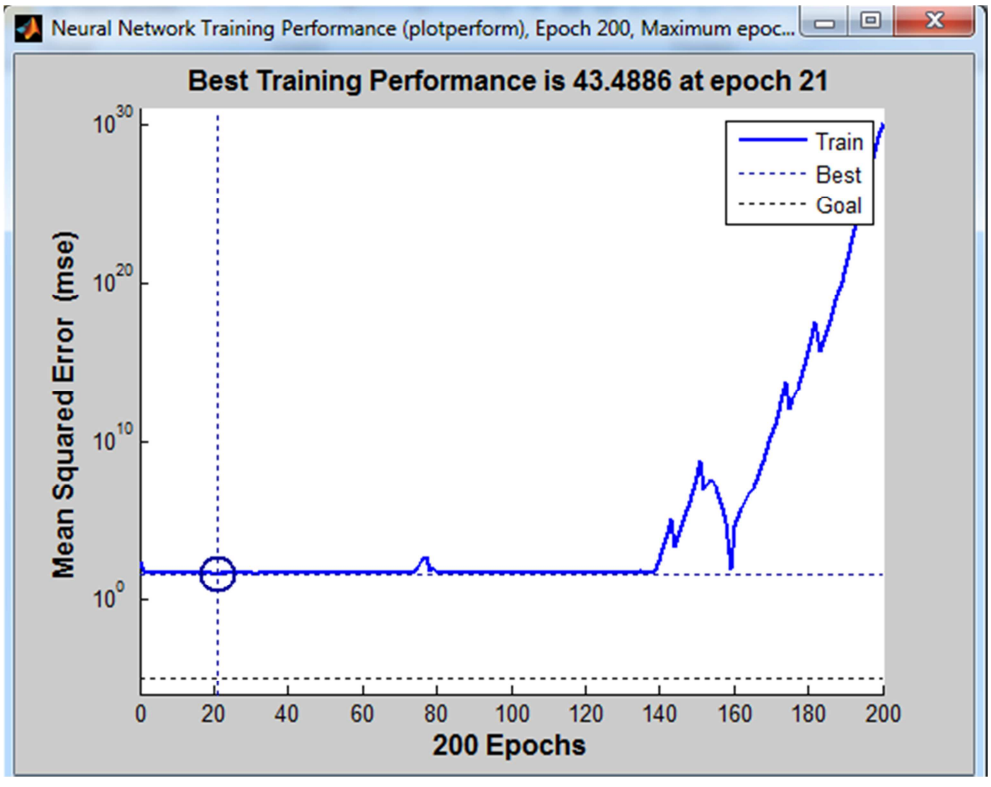

Figure 3. *Error correction functions.*

The air pollution effect on newborns system is based on artificial neural network. It is designed for measurement of different parameters like weight, height and head circumference of newborns in different area in front of pollution source and in its opposite at different period before and after installing the filter at the plant as a source of pollution. This system consists of three input variables. The rule base of this system is used to determine the output parameter values at different inputs variables. MATLAB 10 simulation is used by applying rules. One plot at a time shows the relation between inputs with one output. The output number of newborn affected shows the dependences on inputs. The designed system can be extended for any other factors can influence the result in inputs. We can define this system for any number of inputs. The design work is being carried out to design state of the art artificial neural network congenital malformation of newborn prediction system in future using hybrid ANFIS System.

4. Conclusion

One of the problems in air pollution quality modeling is the vagueness in the values of pollutants sources, arising either form natural randomness in time and space. In this study, we used different areas at different directions from the pollution source. The data were analyzed by ANN modeling technique in an attempt to predict level of pollution effect on newborns. With the ANN modeling, we can represent imprecise and complexes data and produce a precise output in the numeric form. As the inputs are the areas, periods, weights, heights and head circumferences of newborns as inputs, similarly we can define this system more than other inputs to get more efficient pollution effect on newborns around pollution source. From the results obtained by this study, appear to be useful tool for future air pollution effect-testing on chemical pollution risk identification, quantification and development of early warning systems for air quality. The result of the ANN algorithm so far is a numeric terms of air pollution effect.

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