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RESEARCH ARTICLE

Prediction of O_3 in the respiratory system of children using the artificial neural network model and with selection of input based on gamma test, Ahvaz, Iran

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Abstract

In recent years, concerns over the issue of air pollution have increased as one of the significant environmental and health problems. Air pollutants can be toxic or harmful to the life of plants, animals, and humans. Contrast to primary pollutants, ozone is a secondary pollutant that is produced by the reaction between primary precursors in the atmosphere. The average of air pollutant data was compiled for the purpose of analyzing their correlation with the pulmonary function of students and the FENO biomarker from the air pollutants of the Environmental Protection Agency. According to the average of 3 days, the concentration of ozone in the (S_3) region was higher than the other regions, and this level was significantly different from the ANOVA test ($p < 0.05$). The results of artificial neural network modeling for three particular combinations in the cold season, two hidden layers with 9 and 12 neurons, with $R^2 = 0.859$ and in the warm season, layer with 13 neurons, with $R^2 = 0.74$, showed the best performance.

Keywords O_3 · Gamma test · ANN model · Respiratory system · Children · Ahvaz

Introduction

In recent years, concerns over the issue of air pollution have increased as one of the significant environmental and health problems (Daryanoosh et al. 2017). Air pollutants can be toxic or harmful to the life of plants, animals, and humans (Hashemzadeh et al. 2016). Exposure to air pollutants can cause acute (short-term) and chronic (long-term) effects on human health (Goudarzi et al. 2015; Neisi et al. 2017b). Most of these pollutants are subsidiary products that are emitted through the several industries such as transportation and energy generation (Naimabadi et al. 2016; Neisi et al. 2017a). In the early decades, the amount of ground level of ozone has universally increased. Contrast to primary pollutants, ozone is a secondary pollutant that is produced by the reaction between primary precursors in the atmosphere. Formation of ozone depends on photochemical reactions between primary precursors such as NO_x and volatile organic compounds (VOCs), containing aromatic hydrocarbons, alkanes, alkenes, carbonyl compounds, alcohols, and organic peroxides (Sartor et al. 1995). Meteorological parameter, including sunlight, has significant impact on the formation of ozone in the troposphere. Some researchers reported that carbon monoxide and methane may be other precursors for ozone-forming. For this reason, the prediction of ozone concentration in the atmosphere is difficult as well as the parameters affecting it (Pope III 2007). People in normal daily activities are exposed to ground level ozone both indoors and outdoors they participate. Ozone has strong oxidant properties, which may cause damage to humans, animals, vegetation, and materials. Short-term exposure to outdoor ozone has several adverse health effects,

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including high rates of mortality, high rates of respiratory disease, hospital admissions, and low lung function (Epton et al. 2008; Gauderman et al. 2004; Jansen et al. 2005). Some studies in several cities also found a linear relationship between ozone and mortality (Goudarzi et al. 2015; Neisi et al. 2017b). Two types of statistical and definitive models can be used to predict ozone concentrations. With developing the petroleum industries, rapid industrialization and urbanization have been increased in Ahvaz City. In recent decades, Ahvaz has converted to one of the cities with the highest air pollutants concentrations in the world due to the emission of pollutants from industries and dust storms. Ahvaz metropolitan is located in central of Khuzestan Province (Fig. 1), and it is surrounded by several industries. Ahvaz has a desert climate and involves hot summers and short, mild winters. Ahvaz is one of the hottest cities in Iran with summer temperatures reaching 45 to sometimes 50° centigrade. Fractional exhaled nitric oxide (FeNO) has been known as a suitable marker for predicting the responses to inhaled corticosteroids as well as to monitor its anti-inflammatory effects (Marletta et al. 1988; Sheffield et al. 2006). In the respiratory system, NO is an essential mediator of the inflammatory response and is involved in the regulation of vasodilation, neurotransmission, and cell-mediated immunity. It can be prompted by specific inflammatory cytokines, and this activation is seemed to be responsible for an increased production of NO in the exhaled air (FeNO) of subjects with asthma, rhinitis, and atopy, particularly those with airway inflammation condition (Lane et al. 2004; Neisi et al. 2017a; Ricciardolo et al. 2006; Sheffield et al. 2006). Therefore, FeNO is considered as a reliable non-invasive marker of airway inflammation. A neural network is defined as a system of simple processing elements called neurons, which are connected by a set of weights to the network. The neural cell is a processing element, it receives input data, adds weight, summarizes it, adds a bias, and uses the result as an argument for a function (the transfer function), which result is a neuron output (Emad and Malay 2011). Artificial neural networks (ANN) can significantly exploit the results of complex data and can be used to extract patterns and identify processes that are too complicated to be used by humans or other computer techniques (Al-Gburi et al. 2015). Therefore, due to the proper accuracy of the ANN method, this study also uses this method to determine the concentration of ozone contaminant in the respiratory air of the elementary students of Ahwaz in three regions. However, the use of all data in the training of the neural network is not essential. In many cases, the application of some parameters leads to the inferiority of the neural network. On the other hand, the use of all input data is costly and time-consuming. For this reason, it is best to select the optimal input parameters for training the neural network. One of the effective methods in this field is the use of gamma test. In this method, using gamma statistics and *V*-ratio, the model's response can be determined to deletion or addition of each parameter. This method has the high capacity for organization and processing, which allows solving various problems of high complexity. In this context, multi-layer integration is a type of artificial neural network, which is an invaluable tool for predicting, approximating performance, and

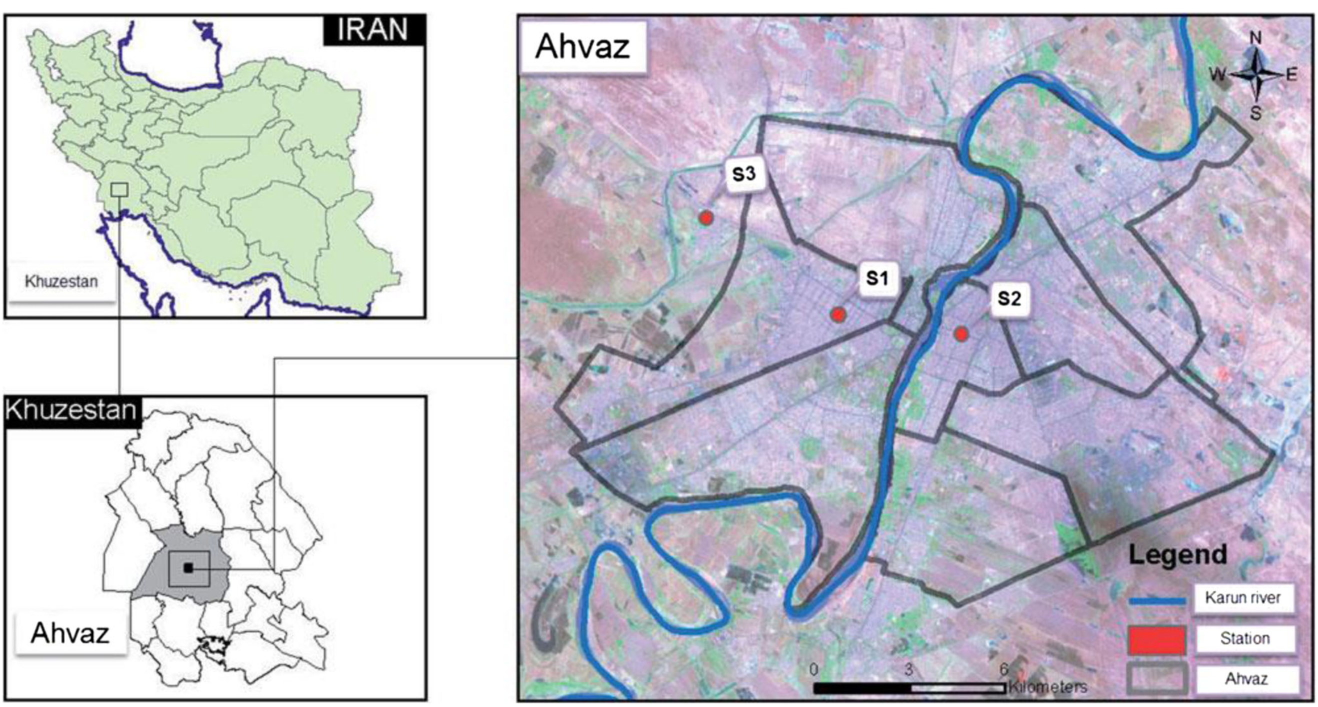


Fig. 1 Location of the study area and sampling stations in Khuzestan Province (Ahvaz City), in the southwest of Iran (Camplow: S1, Naderi: S2, and Ein2: S3)

classification. The benefits of multilayer perceptron are obvious, especially in applications where the complete theoretical model cannot be done, and especially in dealing with non-linear systems (Luna et al. 2014). Models based on ANN have the potential to describe non-linear relationships such as the concentration of O_3 in the respiratory system of students. In addition, this method has been successfully used to predict ozone concentrations (Biancofiore et al. 2015; Faris et al. 2014; Luna et al. 2014; Souza et al. 2015; Tamas et al. 2014). This study was aimed to survey the FENO in children in exposure to ozone in Ahvaz with ANN model.

Materials and methods

Study area

Ahwaz is one of the eight polluted metropolises in Iran, where the rate of air pollution in this city is increasing and intensifying. Ahvaz City due to abundant resources of oil and gas, as well as petrochemical industries, large metal and non-metallic industries, cellulose and electricity, geographic location and topography, and also hot and humid weather conditions in most seasons of the year with contamination air is a type of event of dust. The areas in which the stations in Ahwaz were located were selected so that we can use the environmental data from air pollutants. One of these areas (region 1 studied in Ahvaz City S2), which was high due to high transport and traffic, and another region (region 2 studied in the west of Ahwaz) and was moderate in terms of transport and traffic and the amount of air pollution was reported to be moderate. The study area 3 was the same for S3 outside Ahwaz, where air pollution was lower than the previous two. The distance between the students was less than 5 km from their place of residence and their primary school.

Data collection

The average of air pollutant data was compiled for the purpose of analyzed their correlation with the pulmonary function of students and the FENO biomarker from the air pollutants of the Environmental Protection Agency. In the region 2, due to the lack of measurement of air pollutants by the Environmental Protection Agency, ozone was measured with O_3 EST-1015. Also, due to environmental deficiencies data at some hours (due to power outages or technical problems), statistical integration was used to replace lost data. The measurements were carried out in two cold and hot seasons. In these seasons, we tried to measure the sample of students on different days to make changes in the air pollutants, and based on these changes, we examined the changes in pulmonary and biomarker activity. The devices were used in region 3 of the air pollutants were measured and compared with the values measured by the environmental sensing station, which did not differ significantly between them, which required no correction factor. On the day of the experiment, the air pollutant data was measured from 9 am to 12 pm. The correction factor was not corrected due to the insignificant differences in our readings and data from the Ahwaz Environmental Protection Agency.

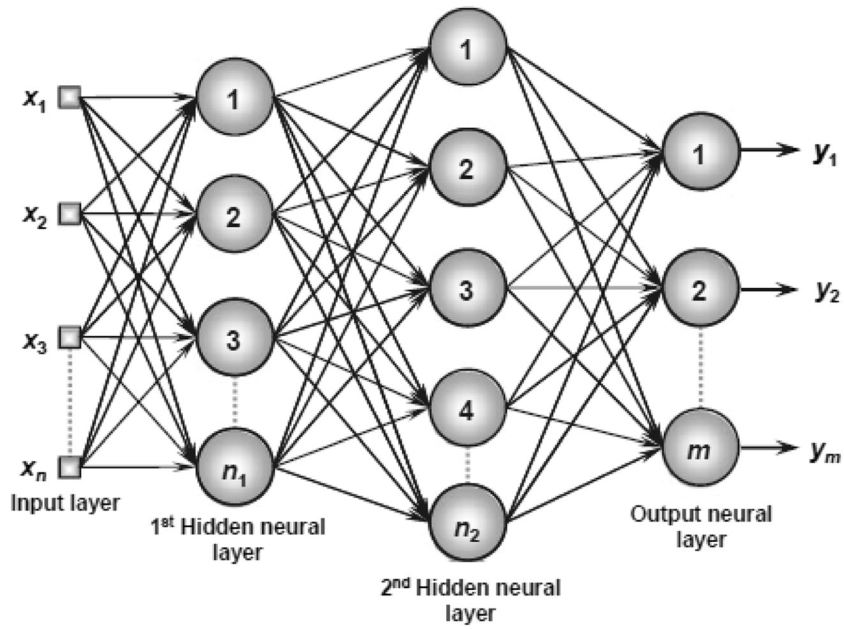
ANN modeling

ANNs or connectionist systems are computing systems vaguely inspired by the biological neural networks that constitute the animal brain. Such systems "learn" (i.e., progressively improve performance on) tasks by considering examples, generally without task-specific programming. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any a priori knowledge about cats, e.g., that they have fur, tails, whiskers, and cat-like faces. Instead, they evolve their own set of relevant characteristics from the learning material that they process. An ANN is based on a collection of connected units or nodes called artificial neurons (a simplified version of biological neurons in an animal brain). Each connection (a simplified version of a synapse) between artificial neurons can transmit a signal from one to another. The artificial neuron that receives the signal can process it and then signal artificial neurons connected to it. In common ANN implementations, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is calculated by a non-linear function of the sum of its inputs. Artificial neurons and connections typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that only if the aggregate signal crosses that threshold is the signal sent. Typically, artificial neurons are organized in layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first (input) to the last (output) layer possibly after traversing the layers multiple times (Evans and Jones 2008; Jones et al. 2002).

Differently, from networks belonging to the previous architecture, feedforward networks with multiple layers are composed of one or more hidden neural layers (Fig. 1). They are employed in the solution of diverse problems, like those related to function approximation, pattern classification, system identification, process control, optimization, and robotics.

Figure 2 shows a feedforward network with multiple layers composed of one input layer with sample signals; two hidden neural layers consisting of n1 and n2 neurons, respectively; and finally, one output neural layer composed of m neurons representing the respective output values of the problem being analyzed. Among the

Fig. 2 Example of a feedforward network with multiple layers



main networks using multiple-layer feedforward architectures are the multilayer perceptron (MLP) and the radial basis function (RBF), whose learning algorithms used in their training processes are, respectively, based on the generalized delta rule and the competitive/delta rule (da Silva et al. 2017). The mathematical equation of a neuron with n input is a function of the following type (Tamas et al. 2014):

$$y = f\left(\sum_{i=1}^{N} wi.xi + b\right) \tag{1}$$

The mathematical equation of MLP trained is a simple non-linear regression of input for a network with one hidden layer shown in Eq. 2 (Eq. (3)):

$$\mathrm{y} = g\left(\sum_{j=1}^{nh} \mathrm{wjo}.\left(\mathrm{f}\sum_{i=1}^{Ni} wij.xi + bj\right) + \mathrm{bo}\right) \tag{2}$$

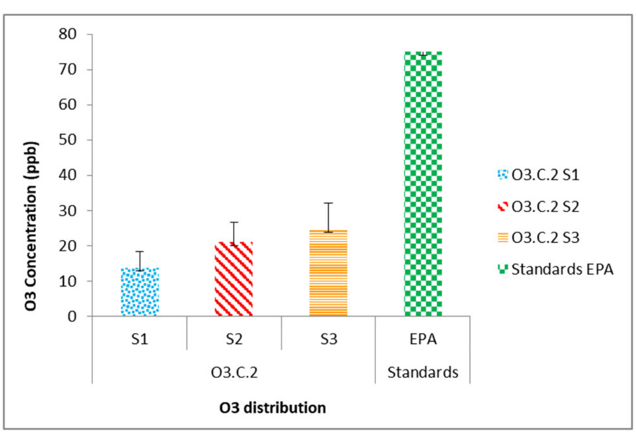


Fig. 3 Average O_3 concentration in three areas in the cold season 2 days before pulmonary test

The gamma test

The gamma test is a non-linear modeling analysis tool that allows us to quantify the extent to which a numerical input/output data set can be expressed as a smooth relationship. In essence, it allows us to efficiently calculate that part of the variance of the output that cannot be accounted for by the existence of any smooth model based on the inputs, even though this model is unknown. A vital aspect of this tool is its speed: the gamma test has time complexity O (Mlog$M$), where M is the number of data points. For data sets consisting of a few thousand points and a reasonable number of attributes, a single run of the gamma test typically takes a few seconds. The gamma test computes the second moment of the noise distribution. Developments in 2002 (Evans and Jones 2008) include new algorithms to compute as many higher moments of the noise distribution as is justified by the amount of available data.

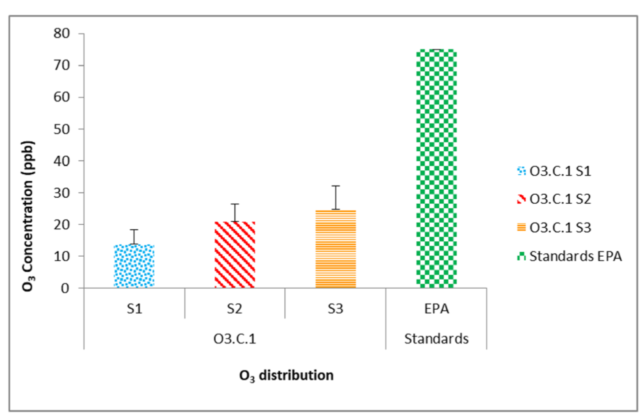


Fig. 4 Average O_3 concentration in three areas in the cold season 1 day before pulmonary tests

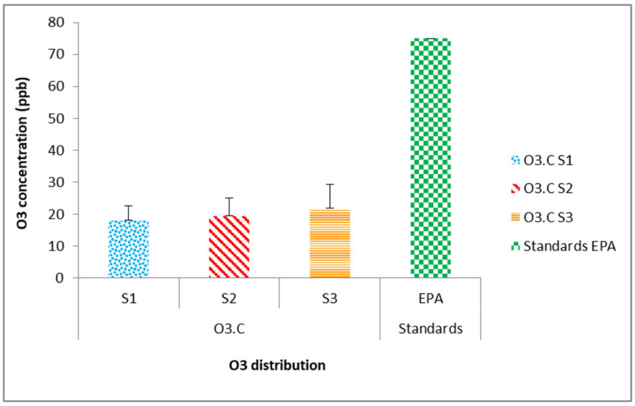


Fig. 5 Average O_3 concentration in three areas in the cold season at pulmonary test day

Let x and $x0$ be any two points in the input space C and r, $r0$ the associated noise on the corresponding outputs. By Eq. (3):

$$y = f(x_1; ::::; x_m) + r \tag{3}$$

we have $y = f(x) + r$ and $y0 = f(\times 0) + r0$, and therefore,

$$\frac{1}{2}(y-y')^2 = ((r-r') + (f(x)-f(x')))^2 \tag{4}$$

The continuity of f implies that

$$|f(x)-f\left(x'\right)|\to 0 \quad \text{as} \quad |x-x'|\to 0 \tag{5}$$

There for, by Eq. (3), we obtain

$$\frac{1}{2}(y-y)^2 \to \left(r-r'\right)^2 \quad \text{as} \quad |x-x|\to 0 \tag{6}$$

Since the expectation of r is zero and r and $r0$ are assumed to be independent and identically distributed, we have

$$\varepsilon\left(\frac{1}{2}\,(r-r')^2\right) = \sigma 2 \tag{7}$$

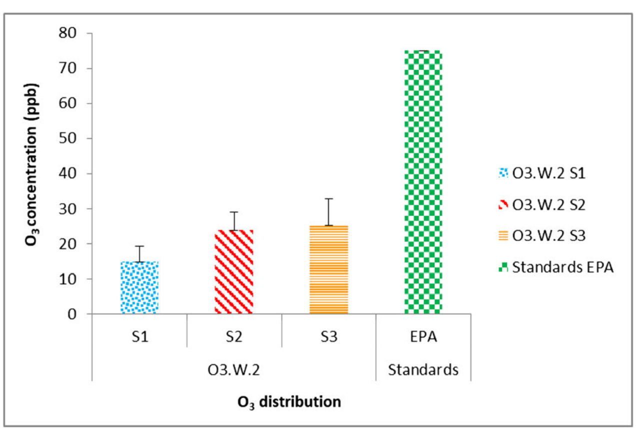


Fig. 6 Average O_3 concentration in three areas in the warm season 2 days before pulmonary test

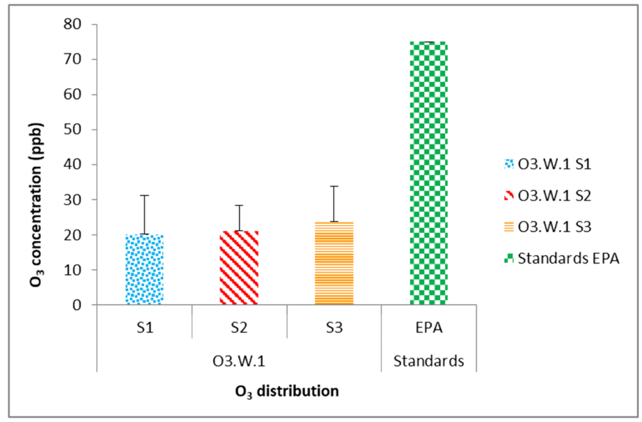


Fig. 7 Average O_3 concentration in three areas in the warm season 1 day before pulmonary tests

Hence, taking expectations of both sides in Eq. (6), it follows that

$$\varepsilon\left(\frac{1}{2}(y-y)^2\right) \to \sigma^2 \quad \text{as} \quad |x-x|\to 0$$

In the limit, if $x = x_0$, then Eq. (7) implies $\varepsilon\left(\frac{1}{2}\,(r-r')^2\right) = \sigma 2$, so we look for points x_0 close to x and use the associated ys in order to estimate (Friedman 1977).

Result and discussion

The concentration of O_3 in cold season

Ozone (O_3) is one of the pollutants for determining air pollution indicators. Figures 3, 4, and 5 show the concentration of O_3 in the 2 days before, 1 day before and at the pulmonary test day in the cold season, respectively. According to the Fig. 1, the ozone concentration in the (S_3) region was higher than the other areas. The amount of ozone in the (S_1) region has been lower than the (S_3) region. According to the average of 3 days,

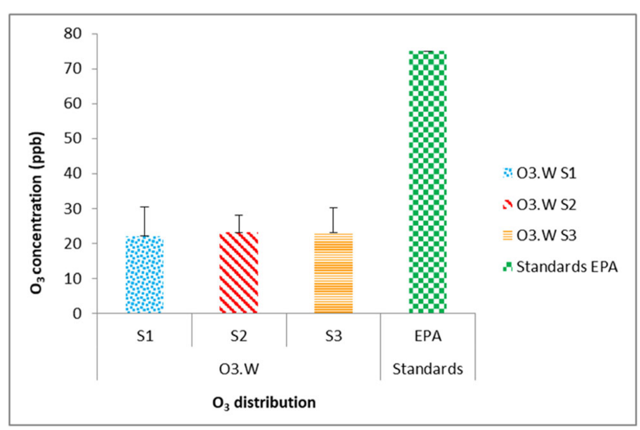


Fig. 8 Average O_3 concentration in three areas in the warm season at pulmonary test day

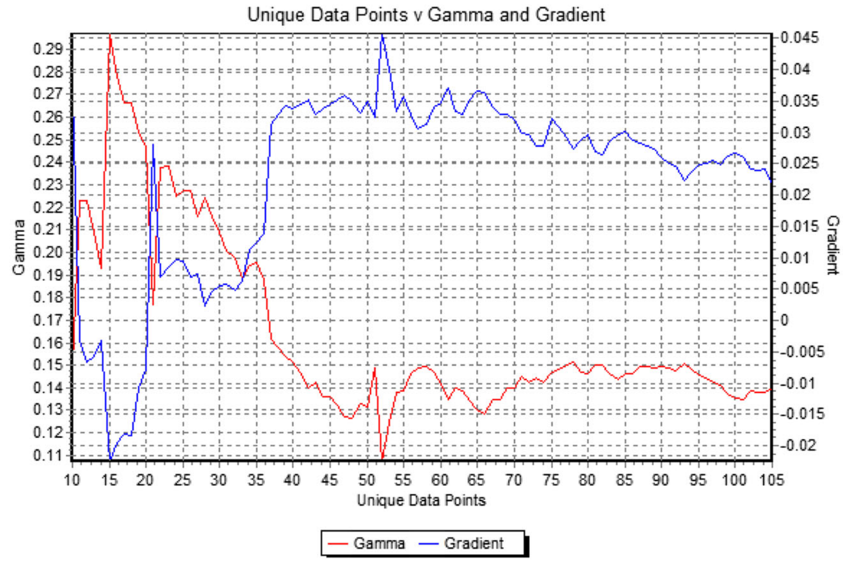


Fig. 9 The *M* test charts of the gamma values and standard error tests for the selected combination in the cold season

the concentration of ozone in the (S_3) region was higher than the other regions, and this level was significantly different from the ANOVA test ($p < 0.05$).

The concentration of O_3 in the warm season

Figures 6, 7, and 8 show the concentration of O_3 in the 2 days before, 1 day before and the pulmonary test day in the warm season. According to 3 days, the concentration of O_3 in the (S_3) region was higher than other areas and the concentration of O_3 in (S_1) region also less than (S_2) region. Regarding the average of 3 days, the concentration of O_3 in the (S_3) region was lower than the other two regions, and this level was significantly different with the ANOVA test ($p < 0.05$). There was no significant difference between the two other regions in terms of O_3 concentration.

Gamma test analysis results

The GT is able to provide the best mean square error that can be achieved using any non-linear smooth models (Remesan et al. 2008). Using the gamma test method for pre-processing parameters, the order of importance of the input parameters can be obtained by the best combination of possible combinations and the data needed to create a smooth model for entering the artificial neural network. In this study, various input data were tested to measure the effect of each parameter on the rate of pulmonary function. To determine the order of the importance of the input parameters, first the combined GT test, which involves all the input parameters, was performed. In the next step, one of the parameters was eliminated from the initial set of parameters, and this time the step by step in this study with the parameters, the remainder will be computed. In the next step add the deleted variable to the main parameter set and delete the other parameter. This process was performed for all variables in the order, and each step of the atomic step statistic was calculated. In this process, the amount of GT statistics increases by removing the effective parameter. By deleting the less important parameter, the number of this statistic was declined. The results of this test for the effect of each parameter on the rate of pulmonary function were presented in Table 1. Over the past years, research has been conducted on gamma test (Asagha et al. 2012; Durrant 2001; Remesan et al. 2008). The gamma test (GT) has been used for the first time in modeling of solar radiation (Remesan et al. 2008). Nkoro et al. have reported the implementation of a new perspective in the

Table 1 Results of gamma values for combining of different input parameters

Cold season		Warm season	
Gamma values	Combining input parameters	Gamma values	Combining input parameters
0.0625	Height, weight, age, temperature, humidity, O_3.a1, and O_3a	0.12507	Weight, BMI, temperature, humidity, O_3.b2, and O_3.b1
0.0664	Weight, age, temperature, humidity, O3.a1, and O_3.a	0.1267	BMI, age, humidity, O_3.b2, and O_3.b1
0.0675	Height, weight, BMI, age, temperature, humidity, and O_3.a	0.1293	Weight, temperature, humidity, O_3b2, and O_3.b1

Table 2 Results of gamma value, gradient, standard error, and *V*-ratio for input parameters

Parameter	All-height	All-weight	All-BMI	All-age	All-temperature	All-humidity	All-O_3.2	All-O_3.1	All-O_3
Gamma	0.1845	0.1936	0.2163	0.1803	0.25	0.2204	0.1897	0.2483	0.2258
Gradient	0.0177	0.0157	− 0.0167	0.186	− 0.048	− 0.0125	0.0203	− 0.0341	0.0028
SE	0.016	0.0183	0.0218	0.0146	0.0105	0..0201	0.0149	0.0237	0.0104
V-ratio	0.738	0.7745	0.8653	0.7209	1	0.8819	0.7588	0.9933	0.9035

non-linear modeling, resulting in the development of data models for prediction of global solar radiation (G_{sr}) in Bauchi (10.19°N, 9.51°E) Nigeria (Asagha et al. 2012).

Choose the best combination

In this study, taking into account nine input parameters, more than 200 different combinations are created for modeling using ANN model; testing each combination to find the best combination is time-consuming and frustrating. Therefore, using this test gamma value of input parameters were given in Table 2.

According to the results of the gamma test, three combinations for the cold season and three combinations for the warm season were selected. Among these combinations, the combination with the lowest gamma values was selected as the best combination. Among the input parameters in the best combination of cold season, BMI and O_3 for 2 days before the pulmonary function test and in the warm season, height, weight, and O_3 that were measured on the test day have the lowest effects. Based on the results of the effective parameters obtained from the gamma test, the best combination was determined from the input parameters for entering the neural network.

M test analysis

One of the main challenges in modeling data is the evaluation of existing information and the adequacy of data. In other words, how many patterns of input pattern sets should be used? Although by adding more information, the model performance improves at the calibration stage. It should be noted that adding more information can improve the performance of the model. The number of data can be tested by using *M* test graph to create a smooth model for predicting O_3 levels in the respiratory system of children, and how the standard error and gamma statistics were measured by increasing the number of data (Figs. 9 and 10).

ANN model results

According to the results of the pre-processing of input parameters, based on the gamma test method, for training using the artificial neural network, the input layer used a combination of different input parameters. The hidden layer, with a number of different neurons, was used and their optimal number was determined to minimize the error. The process of working with the number of small neurons and adding additional overlays continued until the increase of the neurons was not effect

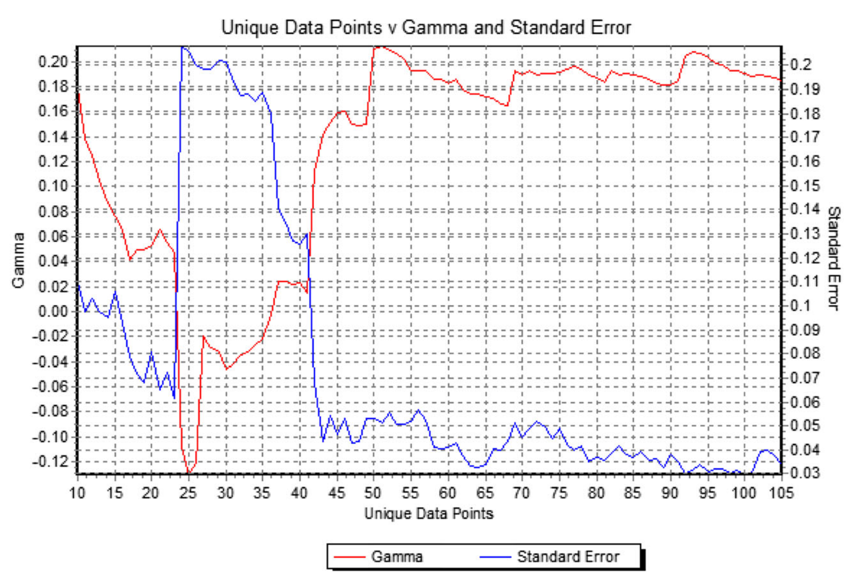


Fig. 10 The *M* test charts of the gamma values and standard error tests for the selected combination in the warm season

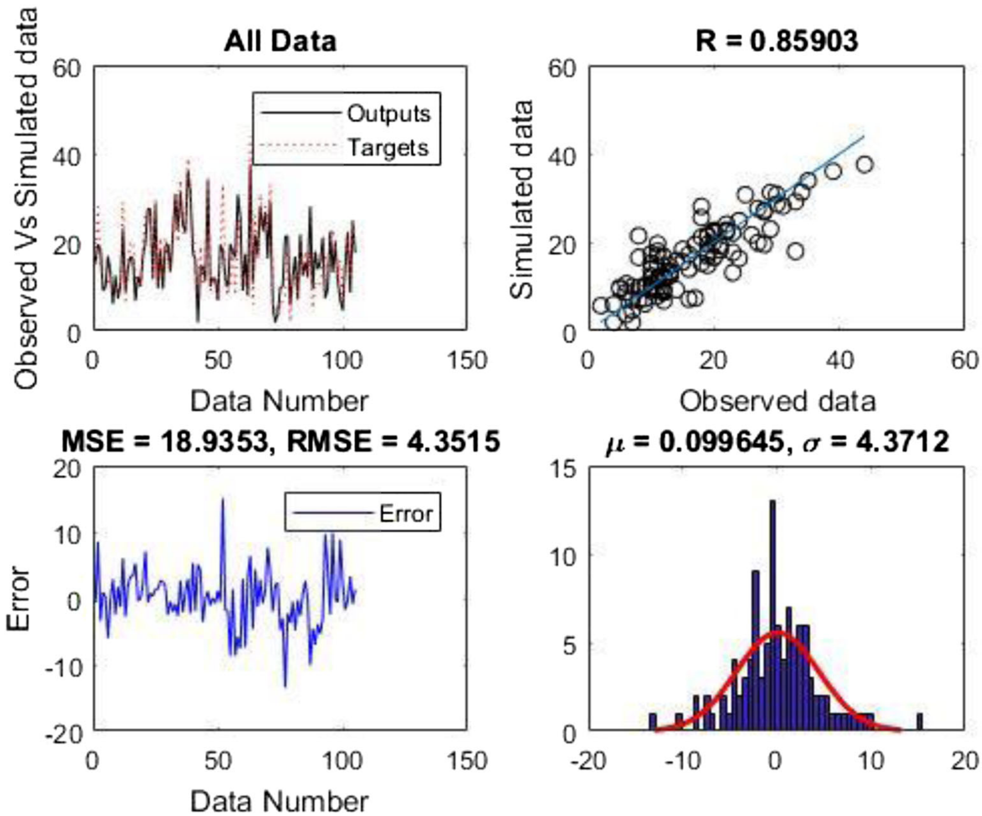


Fig. 11 Comparison of the experimental results with those calculated via neural network modeling for the train and test sets in the cold season

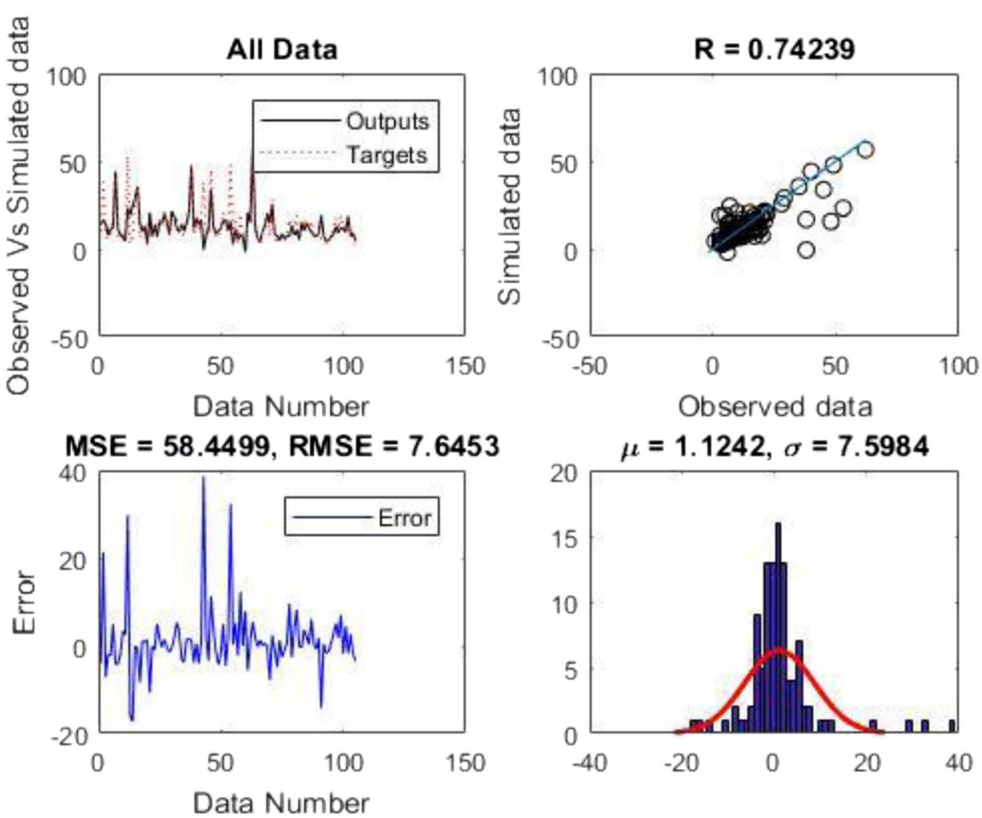
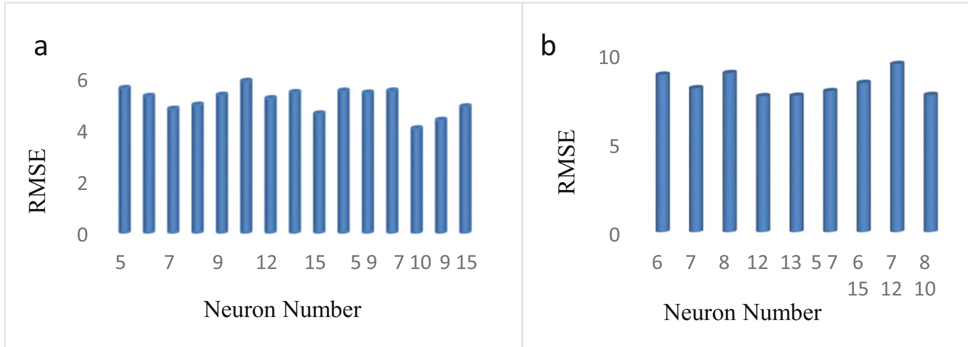


Fig. 12 Comparison of the experimental results with those calculated via neural network modeling for the train and test sets in the warm season

Fig. 13 The results of test and train the network with different number of neurons. **a** Cold season and **b** warm season



on the improvement of the error. For this purpose, 5 to 15 neurons were used. Each experiment with MLP (network training + test) was run seven times, and we gave the average values of error indices, to study the relationship, between predictors and performance. The results of artificial neural network modeling for three particular combinations in the cold season (Fig. 11), two hidden layers, with 9 and 12 neurons with $R^2 = 0.859$ and in the warm season (Fig. 12), layer with 13 neurons with $R^2 = 0.74$, showed the best performance.

The results of the test and train of the network for different number of neurons were shown in Fig. 13a (the cold season) and Fig. 13b (the warm season). In the cool season, the two hidden layers with the number of 9 and 12 neurons showed the best performance and had the highest $R^2 > 0.859$. In the warm season, one hidden layer with the number of 13 neurons had the highest $R^2 > 0.742$, and no change in performance was observed by increasing the hidden layers.

Conclusion

Ozone (O_3) is one of the pollutants for determining air pollution indicators. Figures 3, 4, and 5 show the concentration of O_3 in the 2 days before, 1 day before and at the pulmonary test day in the cold season, respectively. The amount of ozone in the (S_1) region has been lower than the (S_3) region. According to the average of 3 days, the concentration of ozone in the (S_3) region was higher than the other regions, and this level was significantly different from the ANOVA test ($p < 0.05$). Using the gamma test method for pre-processing parameters, the order of importance of the input parameters can be obtained by the best combination of possible combinations and the data needed to create a smooth model for entering the artificial neural network. In this study, various input data were tested to measure the effect of each parameter on the rate of pulmonary function. Based on the results of the effective parameters obtained from the gamma test, the best combination was determined from the input parameters for entering the neural network. The number of data can be tested by using *M* test graph to create a smooth model for predicting O_3 levels in the respiratory system of children, and how the standard error and gamma statistics were measured by increasing the number of data (Figs. 9 and 10). The results of artificial neural network modeling for three particular combinations in the cold season (Fig. 11), two hidden layers, with 9 and 12 neurons with $R^2 = 0.859$ and in the warm season (Fig. 12), layer with 13 neurons with $R^2 = 0.74$ showed the best performance. In the cold season, the two hidden layers, with the number of 9 and 12 neurons, showed the best performance and had the highest $R^2 > 0.859$. In the warm season, one hidden layer, with the number of 13 neurons, had the highest $R^2 > 0.742$, and no change in performance was observed by increasing the hidden layers.

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