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Research Article

Prediction of Dust Storm Frequency in Iraq by Artificial Neural Networks

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Abstract: Dust storms in deserts, arid, and semi-arid regions are considered a more costly and destructive atmospheric event that can cause massive damage to natural environments and human lives. This study uses an intelligent artificial neural network consisting of three layers (input, hidden, output) to predict the frequency of dust storm events. The neural network Back Propagation Artificial Neural Network (PBANN) algorithms employed; this network is divided into three algorithms training for predicted monthly dust storm frequency events for the first year, second monthly annual events, and third annual frequency events for a period extended to 47 years from 1971-2017. This year's taken as a data basis in three stations (Baghdad, Basra, Rutba, and Mosul) that represent regions middle, south, west, and north respectively for Iraq country. To estimate the difference between the observed (O) and predicted (P), dust storm number events, many statistical indices were applied such as correlation coefficient R, Route Mean Square Error, Normal mean square error, and difference bias, these four indices were calculated to the performance of the optimum PBANN scheme. It was found that the optimum performance model according to these indices for the algorithmic function to predict monthly annual and annual frequency data events, but the situation difference for predicted one-year 2017 is because frequency observed data is few and sporadic it's not continuous specifically in stations Rutba and Mosul.

Keywords: Dust storm frequency; Back propagation artificial networks; BPANN; Statistical indices.

1. Introduction

Dust storms are seasonal meteorological phenomena. Usually, dust storms occur in arid and semiarid regions and can travel long distances. The dust storm may have a negative effect in our planet and human life in different ways; such as cloud formation, respiratory illness, and aerial and terrestrial transportation. This phenomenon can also damage crops and may cause fertile soil erosion [1, 2]. One of the major problems is a reduction of visibility that limits various activities, increases traffic accidents, and may increase the occurrence of vertigo in aircraft pilots [3]. a reduction of solar radiation and in a consequence the efficiency of solar devices, [4] damage to telecommunications and mechanical systems, dirt, air pollution, an increase of respiratory diseases, and so on [5]. Iraq, Saudi Arabia and the Persian Gulf, are the regions that reported the greatest occurrence of dust storms, specifically in summer [6]. There are many projects to predicted happening these phenomena by many models such as Weather Research and Forecasting model (WRF), and artificial neural network (ANN) and fuzzy inference systems [7-9].

Many Types of ANNs, all depend on enhance forecasting accuracy relative to previously used statistical procedures, these include the back-propagation neural network (BPNN), multilayer perceptron (MLP), radial basis function (RBF) [10]. Many of these projects used artificial intelligent to predicted dust storm, one by Almurayziq Tariq. That used in its Ph.D. Thesis historical data to prediction dust events, depend on Bayesian network (BN) with a case-based reasoning (CBR) approach and rule-based system (RBS), the results reveal similarty between dust and some atmospheric attributes such as wind speed, which consider as optimal weight in this prediction [11]. Kaboodvandpour, Shahram, et al. 2015, used Adaptive Neuro-Fuzzy Inference System (ANFIS) model in simulating dust storm occurrences in the Sanandaj area, western region of Iran, during spring and summer, the simulation results, among the other three models, have highest Pearson correlation coefficient between the observed and the estimated dust storm occurrences [12]. Huang, Mei, et al. used ANN approach to model and predict the occurrence of dust storms in Northwest China, by using a combination of daily mean meteorological measurements and dust storm occurrence [13]. In Iraq although there are some projects to predicted some atmospheric elements such as rainfall and temperature by used ANN [14], but there are few studies consider dust storm events by used some AI, this study is an attempt to predicted frequency of dust storms in some station in Iraq by ANN, depend on last events and on different period time. The efficiency of ANN values predicted tested by some statistical procedures such as fractional bias, root Mean Square Error, Normalized Mean Square Error.

2. Materials and Methods

Iraq located in western-Southey part of Asia, and the north east of Arab home land between latitudes 37.22o-29.5o, three lines east of the Grinch Line, the nature and characteristic of the regional climate determine from this location, see Figure 1. The monthly dust storm evens observed by Iraqi Meteorological Organization and Seismology, through the years (1971-2017). Selected at Certain stations (Baghdad, Mosul, Basra, Rutba) and used as data basic in this project, where it’s making as input data in ANN. Many stations excluded because of incomplete histories or large amounts of missing data. Mosul station represents the north zone of Iraq as shown figure 1, while Basra represents south zone, Baghdad represents east and middle area. Rutba represents the west zone, table 1, show the latitude and longitude and the heights of stations locations. It’s necessary to examination data of dust storm in order to obtain the best picture about the behavior of dust frequency, thus these data will be used as training data in Artificial Neural Network, ANN, to predict the dust storm event frequency later. as shown in figure 2 (a, b, c, d), show the assumed monthly frequency events to the four stations (Basra, Baghdad, Mosul, Rutba), At the period from 1971 to 2017. Y-axis in figure 2 refer to the number of days of monthly dust storm at every station through the period study, the highest monthly frequency is recorded at Basra station at July month, its reach to 78day, at Baghdad about 75 days in May month, while Rutba about 49 days at May month.

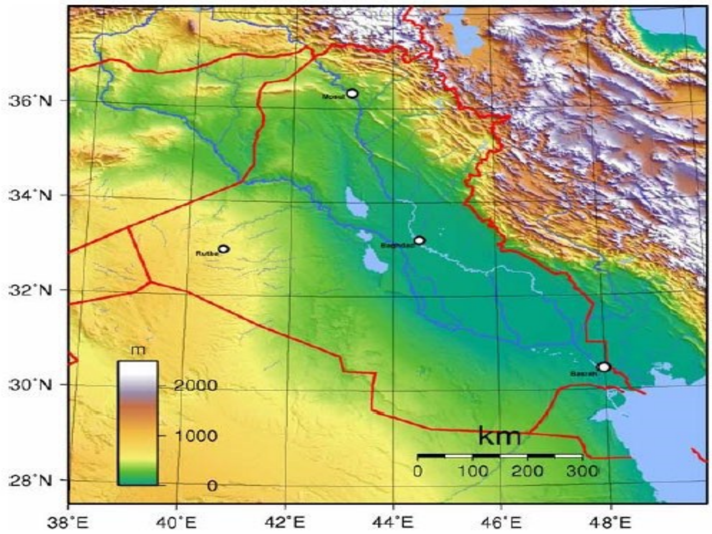

Figure 1. Stations of study in Iraq.

Dust storm can happen or occur at any month from the year but concentrated at months (April, May, June, and July), because the increase in wind speed, air temperature, updraft wind current and scarcity of rain fall. The lowest a summed monthly value recorded for the number of dust storm, Ascending from Mosul station in January (1 day), and Rutba station in December (3 days), while in Basra at March (5 days), Baghdad station in November (7 days).

Table 1. Information about stations used.

Station name	Latitude	Longitude	Station number	Height (m)	Location in Iraq map
Mosul	36.19	43.09	608	223	North
Basra	33.18	47.47	689	2	South
Rutba	33.02	40.17	642	630.8	West
Baghdad	33.18	44.24	650	31.7	East and Middle

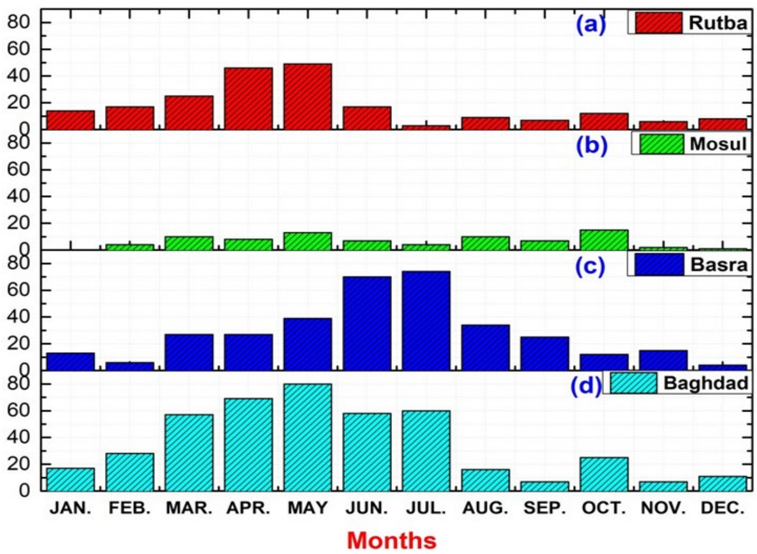

Figure 2. Monthly frequency of dust storm for years (1971-2017), at stations (a) Rutba, (b) Mosul (c)Basra, (d)Baghdad.

Annual analysis of dust storm reported from figure 3 (a, b, c, d), by summed the number of days for dust storm in study stations every year, where every station exposed to dust storm but every station has high and low in frequent of dust storm differ from other, this resulted because the atmospheric elements effected in that station and atmospheric element domain. In figure 3b the summed annual variation for the number of days for Mosul station at period from 1971-2017. Figure 3d show the annual summed for number of the dust storm in Baghdad station, where the most years have large frequency is 2008, with freq. reach to 32. In Rutba station annual variation frequency dust storm can be note through the figure 3a, large frequency of dust storm is 18. In Basra station annual variation for dust storm can be note from the figure 3c, large frequency in 1972, and frequency is reach to 27 per year.

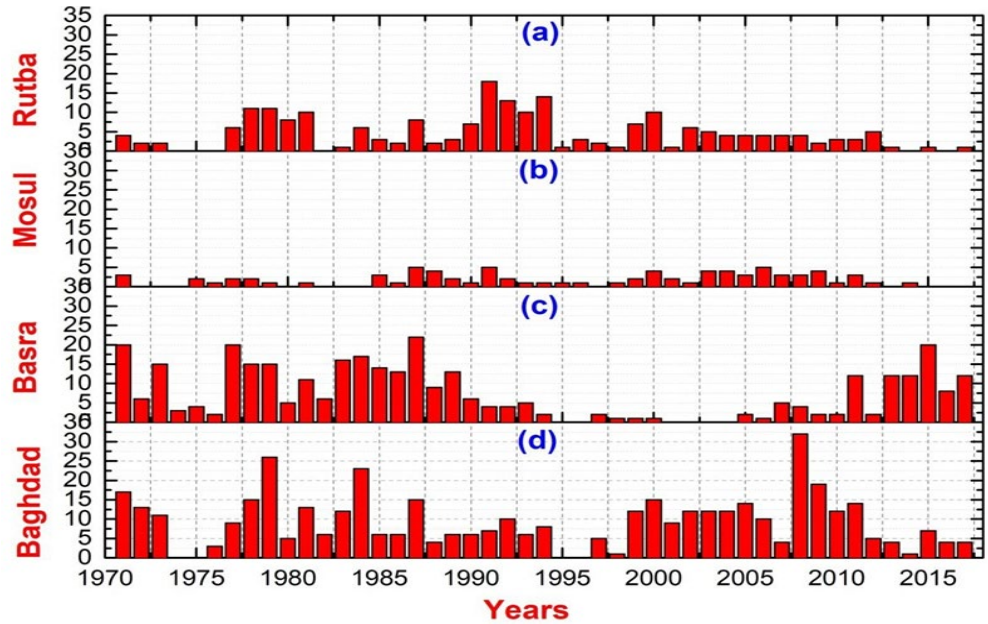

Figure 3. Annually frequency for stations (a) Rutba, (b) Mosul (c) Basra, (d) Baghdad.

3. Methodology

3.1. Artificial Neural Network Technique

The ANNs are parallel distributed systems, which are composed of simple processing units that calculate some mathematical functions. Such units are arranged into one or more layers and interlinked by a high number of connections. In most models, these connections are associated to weights that store the knowledge represented in the model after the learning process. The behavior of these networks is based on a biological structure conceived by nature: the human brain [15]. Brain is made of cells called neurons. Interconnection of such cells (neurons) makes up the neural network or the brain. There are about 1011 neurons in the human brain and about 10000 connections with each other [16]. ANN is an imitation of the natural neural network where the artificial neurons are connected in a similar fashion as the brain network [17]. An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron, the inputs are weighted what means that every input value is multiplied with individual weigh, see figure 4. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron, the sum of previously weighted inputs and bias is passing through activation function that is also called transfer function as shown in figure 4 [18].

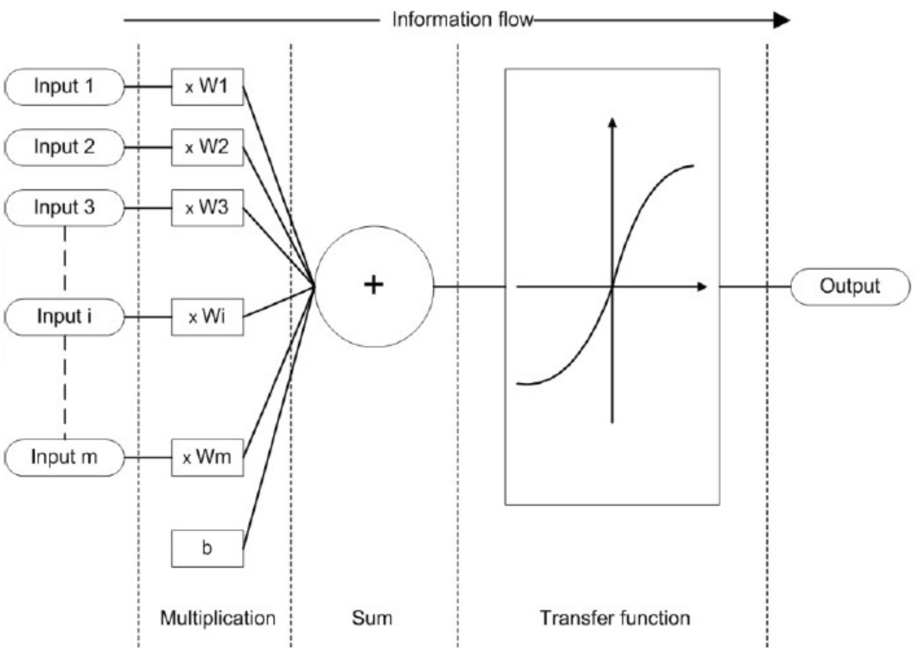

Figure 4. Working principle of an artificial neuron [19].

The selection of an appropriate architecture for an ANN will depend upon the problem to be solved and the type of learning algorithm to be applied. In particular, the use of Kohonen networks for unsupervised classification of patterns and the use of Hopfield networks for recalling previously learned patterns are two approaches commonly used in pattern recognition. For the more general approach to systems identification, one wishes to train an ANN to provide a correct output response to a given input stimulus.

3.2. Backpropagation Artificial Neural Network (BPANN)

One of the effective methods for algorithms is Backpropagation Artificial Neural Network (BPANN), which approximates a huge function class. A backpropagation network comprises at least 3 layers: input, output, and at least one hidden layer. In a BPANN the connection weights are in one way different from the Hopfield networks. In the backpropagation algorithm, it indicates the errors and it consequently the learning propagates backward coming from the output nodes to the internal nodes. Thus, backpropagation is actually utilized to compute the gradient of the error of ANN regard to the network's modifiable weights. This gradient is constantly used in a basic stochastic gradient inclination algorithm to locate weights that reduce the errors. Typically, the term "backpropagation" is used in a most overall sense to describe the whole entire operation including both the calculation of the gradient and its usage in stochastic gradient descent. Backpropagation generally makes it possible for fast convergence on satisfying local minimum error in the type of networks to which that is satisfied [20]. In this research BPANN technique is utilized for forecasting dust storm frequency. The proposed system results are compared with real work from meteorological organization (IMOS). This proposed system assists the meteorologist in forecasting the future weather accurately and easily.

3.3. Statistical Procedures

The root mean square error (RMSE) has been used generally as a standard statistical metric to measure model performance in meteorology, air quality, and climate research studies. RMSE estimates the deviation of the actual y-values from the regression line [21]. RMSE is computed as:

$$RMSE = \frac{\sqrt{\sum(O-P)^2}}{n} \tag{1}$$

Correlation coefficient (R), its measures the strength and direction of a linear relationship between two variables on a scatterplot. The value of r is always between +1 and –1, given as:

$$R = \frac{\sum(O-\bar{O})(P-\bar{P})}{\sum\sqrt{(O-\bar{O})^2(P-\bar{P})^2}} \tag{2}$$

On other hand, highlights the scatter in the entire data set acknowledged as Normalized Mean Square Error (NMSE). Smaller values of NMSE indicate better model performance. The expression for the NMSE is given by:

$$NMSE = \frac{\overline{(O-P)^2}}{\bar{O}*\bar{P}} \tag{3}$$

The verification of resulted data can be tested also by the bias its normalized value and nondimensionalizes. This fractional bias (FB) varies between +2 and -2 and has an ideal value of zero for an ideal scheme. It is written in symbolic form as [22-24].

$$FB = 2\left(\frac{\bar{O}-\bar{P}}{\bar{O}+\bar{P}}\right) \tag{4}$$

Where: $\bar{O}$ = Observed value, $\bar{P}$ = Predicted value, n = number of observed or predicted values.

4. Results

4.1. Model implemented

Overall, the process started from input observed data (dust storm frequency) to network, at this status it's necessary to reach to zero values for the error in network and rate of learning coefficient for input data. The training input data pass to hidden layer neurons, where the construction of hidden layer and generated weights of network build at this case. The hidden layer is pass to the output layer neurons, where the activities is computed for the neuron's outputs, at this situation errors of the output neurons compute and there is a change in the output-hidden, and also change in weights in hidden – input layer. The processing ended by make a new weight computed through adding change in the old weights, after that there is steps and stages of the forward and backward and modification of the weighted calculated the rate if real to end process or recycled as input data step, according to the progresses of ANN and results of predicted data, as shown in figure 5. Overall, this cycle called the back propagation ANN (BPANN), the model consists of two stages the first one is the feed forward and the second stage is backward. In Feedforward there is a generated weight between zero and one. While in second stage the weighted is consider as real number between 15, -15, this represents frequency.

4.2. Predicted Dust Storm Frequency for One Year

PBANN applied to test its suitability to predict dust storm frequency in one year, 2017, last year in data observed selected in range extend from 1971 to 2017. BPANN used input layer consist from 12 node, it represents months in input layer, while the hidden layer consists of about 47node, represent all year's number from 1971 to 2017. Through hidden layer weights for results constructed for the neurons, and the output layer produces in similar node to the input one. Figure 6, show the frequency dust storm predicted from applied BPANN model and compared with observed.

Unfortunately, there is few records of dust storm events at this year, this can be reflected on the method of processes of the predicted dust storm events, and consequently from used statistical indices in equations 1,2,3,4 some Statistical Indices values not represent the real case.

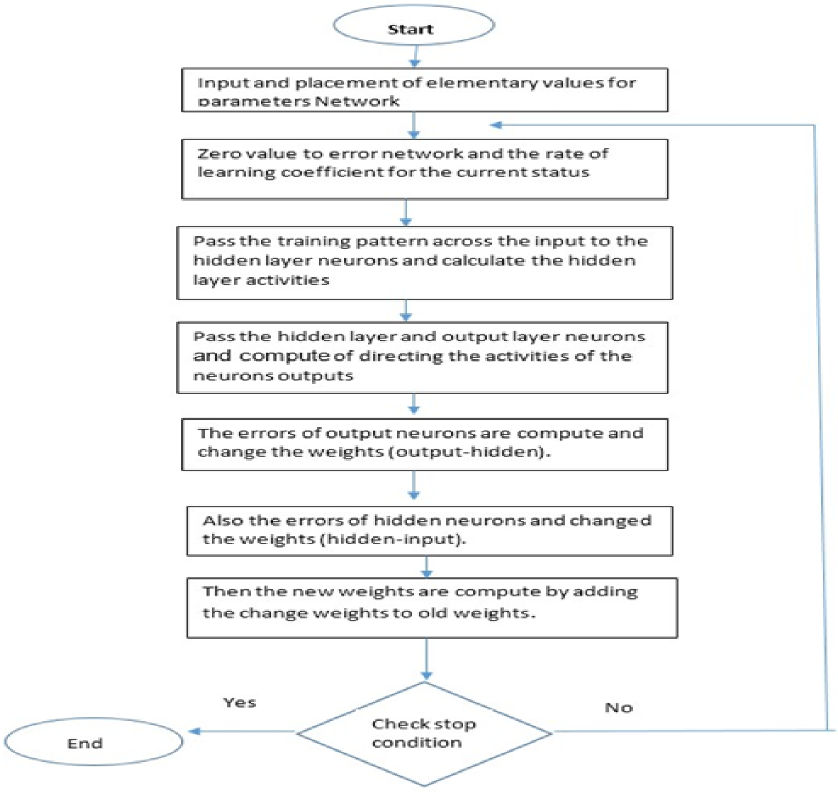

Figure 5. Steps of back propagation ANN implemented model.

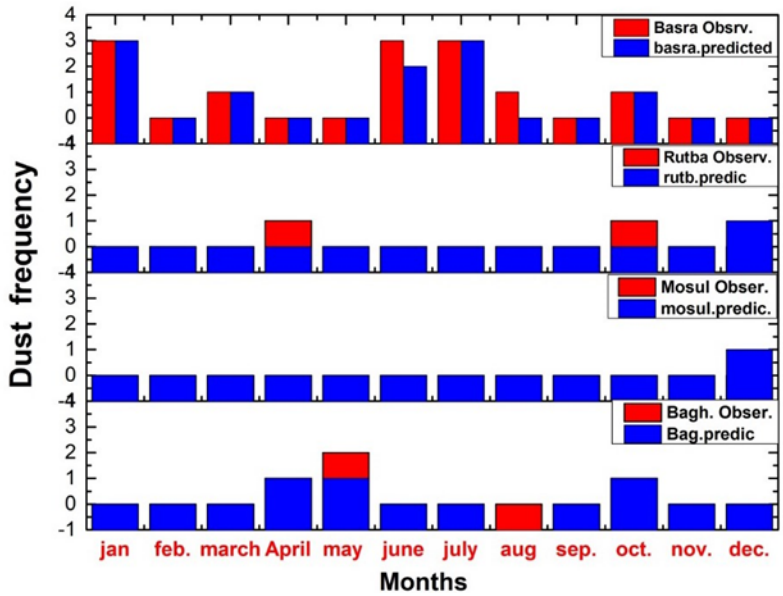

Figure 6. Observed and predicated dust storm frequency for stations Baghdad, Basra, Mosul, Rutba through 2017 by (BPANN).

Because there is no data or very few data to make decision to compare between observed and predicted. Overall Baghdad and Basra given very good relation but Mosul and Rutba not given this due to decrease in cases recorded, as shown in table 2.

Table 2. statistical indices to compare between observed and predicted dust storm frequency for stations Baghdad, Basra, Mosul, Rutba through 2017 by (BPANN).

Stations	Statistical Indices			
	R	RMSE	NMSE	FB
Baghdad	1	0.0833	1	0.1428
Basra	0.9818	0.11785	0.2	0.091
Mosul	no data	0.08333	----	-1
Rutba	0.52	0.14434	18	0.333

4.3. Annual Monthly Predicted Dust Storm Frequency

The model implemented in this study tested on the data observed through every month through the years from 1971 to 2017. BPANN used to predicted dust frequency events and compared with observed, as shown in figure 7. Highest frequency in stations Baghdad, Mosul, Rutba concentration on May month while Basra concentrated on June and July. There are small frequency events in July for stations Rutba and Mosul, as shown in figure 3. Statistical indices between observed and predicted according to BPANN and annul monthly data refer to strong relationship. Correlation coefficient in fist column table, have value 1 (strong linear relation), RMSE have range between 0.1863 to 0.236 it refers to very small deviation for predicted dust events data from the observed one. In other hand NMSE almost have very small value 0.000821 to 0.00163 this refer to very small scatter in the predicted data from observed, this case is present in FB indices where its reach to zero (in range 0.01-0.015), these consider as ideal value to description suitability relation between observed and predicted.

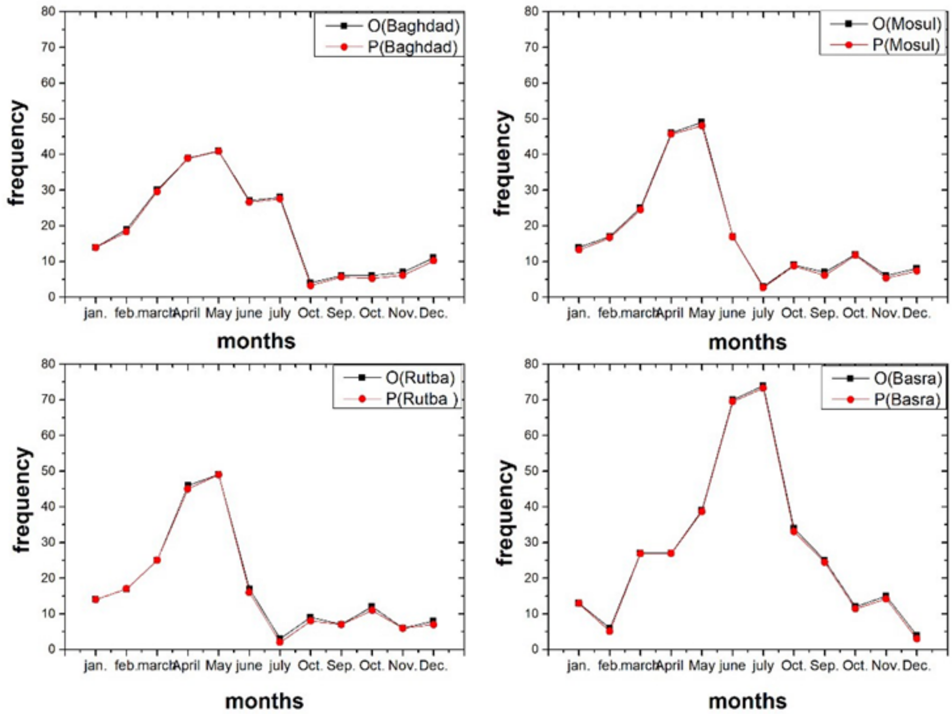

Figure 7. Annual monthly Observed and predicated dust storm frequency for stations Baghdad, Basra, Mosul, Rutba through (1971-2017) by (BPANN).

Table 3. Annual monthly Observed and predicated dust storm frequency.

Station	Statistical indices			
	R	RMSE	NMSE	FB
Baghdad	1	0.18633	0.0011393	0.0109
Basra	1	0.236	0.000821	0.012
Mosul	1	0.204124	0.0016329	0.0143
Rutba	1	0.2041	0.001633	0.0143

4.4. Annual Predicted Dust Storm Frequency

Every year consist of 12 months, the yearly events from these months and at about 47 years consider as observed dust storm events and inter to the neutral network in BPANN model. Input layer in model constructed from about 47 node it represents number of years, while the hidden is about 95 nodes, a according to rule of weighted function (2n+1) where n=47, the backward and forward propagation for this weights processes will result in about 47 node that represent the output layer. The highest yearly frequency events in stations Baghdad and Basra concentrated in year 2008 about 32 frequent events, figure 3d, 3c, while in Mosul and Rutba about 18 at year 1991. Figure 3 (a, b), these cases founded in figure 8. Figure 8 show the plotted annually data for the observed and predicted dust storm events, through 1971- 2017. From applied statistical indices between the observed and predicted event of dust storm it has strong relationship, table 4. In this indices correlation coefficient have range from 0.9999 to 1, RMSE have range from 0.08081 to 0.08898, while NMSE in range from 8.539 *10-5 to 0.8156, FB for all stations very small escape Rutba station about 0.32416, table 4.

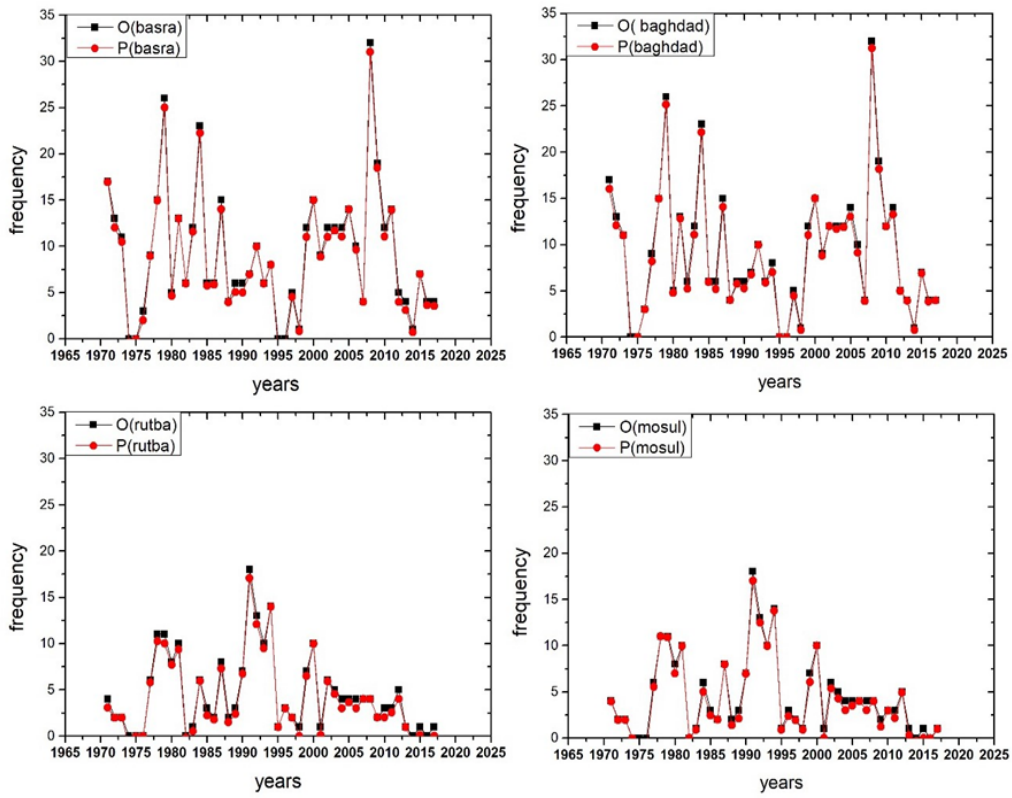

Figure 8. Annual Observed and predicated dust storm frequency for stations Baghdad, Basra, Mosul, Rutba through (1971-2017) by (BPANN).

Table 4. Annual Summation between Observed and predicated dust storm frequency.

Stations	Statistical Indices			
	R	RMSE	NMSE	FB
Baghdad	1	0.0808124	8.5393*10^-5	0.0404228
Basra	0.9998	0.087407	0.1520923	0.0182433
Mosul	1	0.081829	0.6054235	0.04675
Rutba	0.9994	0.088988	0.81565248	0.324162

5. Conclusions

Most blowing sand and dust occurs over open desert, where there are few weather stations to observed, in other hand forecast of these phenomena difficult. The modern tool to forecast dust storm depend on satellite imagery but this is expensive and have disadvantage. There are other tools to forecast dust storm events such as simulation and modelling by use Artificial neural networks where human brain is followed as a pattern for producing ANN. ANN have many algorithms one of it is back propagation Artificial neural network PBANN. In this study BPANN used to predict frequency of dust storm event in some selected locations in Iraq. Method implemented model divided to three ways, first one predicts happening dust event for one year, second method predict monthly annual through 47-year, third method is summed annual frequency dust events also test results of predicted data. These methods prove that PBANN model can be develop to produce reliable predicted frequent dust events and with high accuracy can dependence to determine number of dust storm at specified period and at any location over Iraq. The IA tool by BPANN can develop more to management the risk of dust storm in particular region in Iraq to forecast dust storm happened depend on historical archives for last period. Thus, can be concluded that BPANN method applied seem a powerful tool in predicted dust event in different period short or long depending on the input data in neural network layer.

Supplementary Materials:

Author Contributions: Ahmed Fattah Hassoon put the research idea and analysis frequency dust storm data, Hind Saleem Ibrahim Harba write MATLAB program to treat neural network, Hind Kamil Kareem Salem printed and edit paper paragraphs.

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Data Availability Statement: We declare that the submitted manuscript is our work, which has not been published before and is not currently being considered for publication elsewhere.

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Conflicts of Interest: no interest

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