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Utilizing an Artificial Neural Network with Limited Meteorological Data in AL-Fallujah City to Estimate AOD550 with MODIS AODs

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Abstract

The amount of solar radiation that is absorbed by particles in the atmosphere is measured by the Aerosol Optical Depth (AOD550). Determining the precise role of aerosols requires an understanding of the fluctuations in worldwide AOD550. A neural network (ANN) model was created in AL-Fallujah, Iraq, with the purpose of training and estimating daily (AOD550). The statistical parameters Root Mean Square Error (RMSE), which are dependent on the correlation coefficient (R), and standard division (SD) were established to assess the produced ANN-models. For both the hidden and output layers, the activation functions (Segmiont, Gaussean, Hyperbolic Tangent, Hyperbolic Secant), hidden layers (1, 2, 3, and 4), and changes ranging from 10000 to 60000 with a 10000 interval were used. The created artificial neural network models were examined based on statistical criteria that were computed. ANN model (25) is found to be the best among all the models that were studied. Their corresponding (R) and (RMSE) values for the estimate phases were 0.939, 0.962, and 0.055, 4.3. These results show the generalization ability and full efficacy of the ANN model in pollution assessments.

Keywords: AOD550; Aerosols; Particulate Matter; ANN; AL-Fallujah; Iraq

1. Introduction

Aerosols are essential to most atmospheric processes, including the formation of the atmospheric thermal structure, as evidenced by the Arctic's current warming, which, in comparison to the rest of Earth, is happening two to three times quicker. Incoming and outgoing radiation are both absorbed and scattered by aerosols, hastening the process of climate change [1]. The suspended particles are made up of both liquid and solid particles, and they all represented atmospheric aerosols, which have radii ranging from a few nanometers to 10 micrometers. The atmospheric aerosols can originate directly from natural sources like dust, volcanic ash, and marine aerosol, or they can be produced artificially by precursor gases similar to organic secondary aerosol[1]. Regarding environmental problems such as stratospheric ozone depletion and photochemical haze, global warming, and poor air quality, atmospheric aerosols are thought to have the most impact [2]. Therefore, precise measurements of aerosols' characteristics are necessary to determine their exact influence and how they interact with other elements of the climate system. Aerosol characteristics exhibit significant spatial variability due to a multitude of variables. Chemical composition, size distribution, form, wind direction and speed, topographical characteristics, relative humidity, and many other factors are the main culprits. There is a great deal of uncertainty surrounding aerosol measurement, which in turn raises questions about how aerosols may affect the climate (Report on the 2007–2013 IPCC). This is a fascinating area of study because of the uncertainties in aerosol measurements and their impact on the climate. Quantifying aerosol impacts and associated uncertainty is more difficult due to high geographical and temporal variability in aerosol dispersion (Srivastava et al. 2016). Researchers have investigated the properties and role of aerosol in the climate system using a range of methodologies in an effort to reduce uncertainty (Wilcox et al. 2006). In order to study aerosol properties, a variety of techniques are often employed (Chin et al. 2009; Lu et al. 2011; Yang et al. 2017; Li et al. 2019). Applications of ANN

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may also be found in the many specialized fields of atmospheric science, such as air pollution and aerosol research. After training their neural network with worldwide data from the MODIS satellite. Their results demonstrated that as compared to the operational retrieval approach, neural networks operate more efficiently. Neural networks are employed by Ali et al. (2013) in the data assimilation sector. They created the three-dimensional aerosol patterns over Europe using a chemical transport model. They put out a neural network-based approach to calculate the AOD data that is missing from satellites. ANN, air mass trajectories, and AOD data from other stations have all been used by Luis et al. (2015) to infer missing AOD values at a station using neural networks. Cloudy days make it difficult to keep an eye on the AOD. Therefore, for calculating AOD and other optical parameters on foggy days, the proposed technique is useful. In a different study, García et al. (2016) employed artificial neural networks (ANN) in conjunction with observational data to rebuild a time series for AOD over a 73-year period for a location in Spain during the summer months due to increased aerosol loading during this season. A neural network model in Santiago, Chile [20] performed well when compared to a multi-linear model. In China, a lot of work has gone into estimating ARF and AOD. Zhang et al. [64] used the KM-Elterman approach to investigate the temporal and geographical fluctuations of AOD values from 1973 to 2014. The outcomes demonstrated that there was a strong correlation (R = 0.942) between the calculated AOD values and the AOD values obtained from MODIS products. The regions with fast growing AOD values were the areas with significantly declining AOD values were determined to be southwest China. Using a broadband extinction model, Xu et al. [65] rebuilt the AOD values for the years 1993–2012 over China. In the meanwhile, several regional-scale investigations have been carried out in China with the use of satellite observations and meteorological data [67–71]. China is a large nation with high anthropogenic aerosol emissions, which has raised serious concerns about climate change worldwide. In China, a great deal of research has been done on the aerosol radiative effect's temporal and geographic fluctuations. The regions with dense populations and high levels of air pollution, such as Central-East China [72], were the primary focus of these investigations.

In this work, we examine three years of ongoing observations of The daily.mean of air temperat., maxim., minim., solar.radiation, solar.radiation daily.sum, atmospheric.pressure, and AOD550 concentration are among the meteorological characteristics used as inputs and outputs in the data set. To estimate AOD550 concentrations, a neural network-based artificial intelligence technique has been used. using various activation algorithms, hidden layers, and modifications, together with climatic data as input parameters.

2. Methodology, MODIS AOD_{550}, Meteorological parameters

Neural networks are large, highly parallel computer systems composed of discrete processing units that collect and deliver experience data. Within artificial intelligence technology, an artificial neural network is a branch that simulates how the human brain functions. [9, 10]. An artificial neural network (ANN) mimics the morphology and functionality of real neurons. Neural networks are often composed of several computer components. Neuronal alliances are formed, and the presence of a relation determines how the network is structured. It can be characterized by the neural network strictures. Equations (1) and (2) can be used to assess the inclusive performance of artificial neural networks [23].

$$y_i^m = f(v_i^m) \text{ ....} (1)$$

$$v_i^m = \sum_{j=1}^{i} w_{ji}^{m-1}\, y_i^{m-1} + \, b_i^m \text{ ....} (2)$$

Activation function (f) is the place where the source and result of the i-th neuron in the m-th hidden layer are located. The weight and bias are represented by the number L, which is connections to previously hidden data. The Qnet 2000 program has created a wide range of ANN.activation functions (sigmiont, Gaussian, Hyperbolic.Tangent, Hyperbolic.Secant), hidden layers, and modifications that are available where neural network models are used in the current work. AOD, or aerosol optical depth, is a satellite metric that measures how much suspended particulate matter affects light transmission, scattering, or absorption [24]. Consequently, it is a measurement of the indirect particles present in the air column at a certain moment. In contrast to MODIS standard products, NASA has developed MAIAC, a multi-angle version of the method, This offers 1 km^2 of excellent quality AOD correction spatial resolution data. [12]. The 20 reflected solar bands (RSB) and 16 thermal emissive bands (TEB) of the Moderate Resolution Imaging Spectroradiometer (MODIS) have wavelengths between 0,41 and 2,2 µm and 3,75 to 14,24 µm, respectively. Three nadir spatial resolutions are included in the MODIS observations: 1 km for 8.36 observations for 8.36, and 2500 meters for 1-2.500 meters for 3.7. The MODIS instrument's enhanced capability to provide reliable on-orbit calibration and feature over legacy sensors is a significant improvement [13].

2.1. Region study

In 2018, Fallujah's population, which had previously been tiny, had increased to over 250,900. The Euphrates River forms Fallujah's western border. The Euphrates originates in the west (Ramadi), runs via Fallujah, and into the Baghdad region. The river forms the "peninsula" region, so named because it turns fast north and then south when it reaches the western border of Fallujah. Fallujah has two bridges that span the Euphrates. Fallujah has below-freezing temperatures in January and February and around 38 degrees Celsius (100.4 degrees Fahrenheit) in July and August on average. The majority of the rainy season falls between December and April, with an average of 340 to 512 mm falling per year. The months of November through April, and particularly December through March, account for about 90% of the yearly rainfall. For the remaining months, rain is uncommon, particularly during hot months like June, July, and August.

3. Results and Discussion

An ANN must be trained with correct and adequate data, which is a critical issue. The primary data influences ANNs' ability to react to novel situations in certain ways. Approximately 10220 data points (1460 days) were used to train multiple artificial neural network (ANN) algorithms in the current study Table 1 shows the average input data that was calculated . The air quality parameters included in the analysis are AOD550, and the meteorological parameters included in the analysis are the day of the.year, daily.mean air.temperature, maximum, minimum, daily.mean solar radiation, daily sum solar.radiation, and atmospheric pressure. The current study includes 260 training stage experiments employing 7 inputs with various activation functions (Hyperbolic.Secant, Segmiont, Gaussian, and Hyperbolic.Tangent), hidden layers (1, 2, 3, and 4), and modifications ranging from 10000 to 60000 with intervals of 10000.

Any neural network's performance is determined by the activation function, hyperparameters, and network properties, all of which have a substantial impact on the outcomes that the network produces. Since hyperparameters regulate the ANN's learning process, they are an integral component of an ANN. In order to estimate the aerosol parameters using various hyperparameters, we have therefore assessed the performance of ANN in this study. The evaluation of ANN performance involves changing the hyperparameters of the model (count of concealed layers) and the optimizer (rate of learning and quantity of iterations). The following is a quick summary of the work's parameters:

- Hidden layer: Two and three hidden layer simulations are conducted to observe the differences in the performance of an ANN.
- Iterations: After that, we altered the assessment process's iteration count to 150, 250, 500, and 750.
- The evaluation of ANN performance is conducted using varying learning rates. At intervals of 0.5, the learning rate fluctuated between 0.5 and 2.5.
- Activation function: For each layer in the current study, the sigmoid activation function was employed.
- The neurons within the hidden layer: We employed five neurons per hidden layer, resulting in a range of neurons from 10 to 15.

AOD550 statistical summary and the parameters that were considered and used to get the AOD550 estimate in the present study. There were no prior studies conducted in the study area, so we turned to comparable research conducted in other nations. There, the fluctuating behavior of atmospheric parameters helped identify developed models that were able to estimate the concentration of AOD550 in extreme cases. The statistics tabulated in Table (1) shows the clear range of measured AOD550 fluctuations as well as the atmospheric parameters, which are individual in the area in which the study was undertaken (Fallujah city). For instance, variations in AOD550 values received by satellite from a MODIS sensor.

Table 1 The average input data that was calculated

parameters	AOD_{550}	T_{mean} C^o	T_{max} C^o	T_{min} C^o	S_{mean} Watt/m^2	S_{sum} Watt/m^2	P Mb
Mean	0.347	33.01	18.68	25.58	156.56	16.6756	1012.1
SDEV	0.2216	11.01	8.7715	9.8378	100.31	6.0933	66.538
Min	0.072	7.51	0.14	5.385	3.6589	3.0689	991.2
Max	1.079	49.6	35.86	39.81	365.2	30.503	1175.1

3.1. ANN Estimation of AOD_{550}

The efficacy of the recommended ANN models throughout the preparation and estimating process was assessed using the evaluation standards using statistics of RMSE, R, and SD, as indicated in Tables 1. Because it has the fewest mistakes among the other ANN models, ANN model 25 is recommended. For the phases of estimation and training, respectively, the ANN model 25 results show an accurate daily AOD550 estimation in Fallujah city with an RMSE of 0.059208, a correlation coefficient (R) of 0.914407, and a standard division (SD) of 0.08687. The dispersion chart of the estimated vs measured AOD550 and the comparison of the measured value and the estimated AOD550 using ANN models were shown in Figure 1. The results show that the points typically follow the diagonal line and seldom deviate from it. indicating that ANN model 25 is better than the other ANN models.

Table 2 Top ten Daily AOD550 Mean of ANN Models for Estimated Stage Validation according to Statistical Criteria

Model No.	ANN Structure	Activation Function	Alterations	RMSE	R	S.D.
25	788881	Gaussian	30000	0.059208	0.914407	0.08687
2	777771	secant	60000	0.067656	0.886595	0.09926
3	77771	Gaussian	50000	0.069111	0.881332	0.1014
4	766661	Gaussian	60000	0.069533	0.87978	0.10201
5	77771	Gaussian	60000	0.069876	0.878507	0.10252
6	78881	Gaussian	30000	0.070165	0.877434	0.10294
7	77771	Gaussian	30000	0.070632	0.875677	0.10363
8	766661	Gaussian	40000	0.071382	0.872831	0.10473
9	78881	Gaussian	40000	0.071393	0.87279	0.10474
10	788881	Tangent	40000	0.072794	0.867361	0.1068

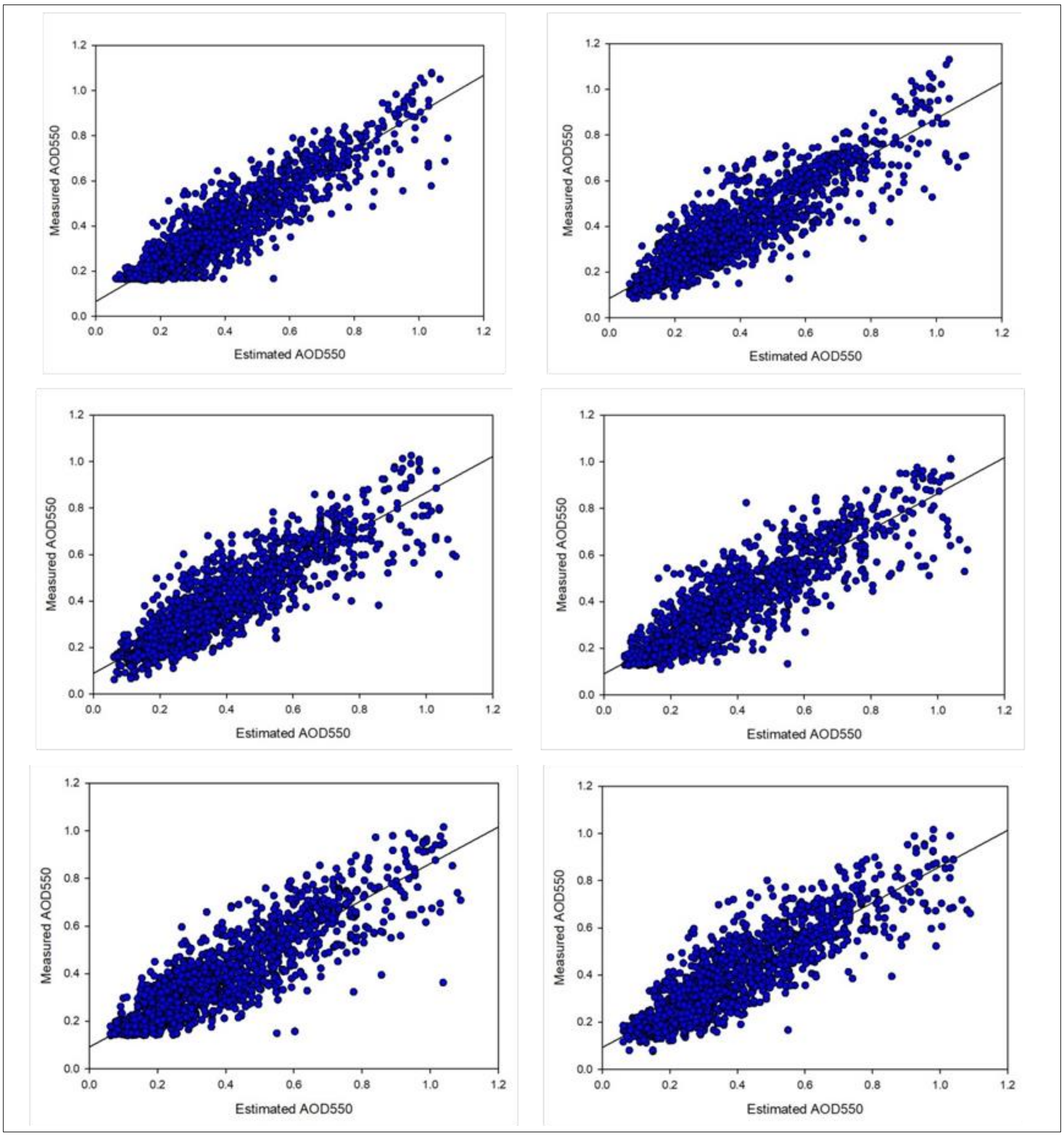

Figure 1 Plot showing the difference between the estimated and measured AOD550

From Table 2, it is clear that the ideal artificial neural network that will be used to estimate the AOD550 is one that consists of four hidden layers and seven inputs with eight neurons, and the Gaussian function was used in each of the hidden layers with iteration 30000.

4. Conclusion

A number of ANN models that make use of meteorological data were put out in an effort to improve their ability to estimate AOD550 levels. Together with MODIS and AOD550 data, meteorological characteristics were also used in the construction of the ANN models. The models that were produced were examined for AL-Anbar in Fallujah, Iraq. Up to now, no study of this kind has been conducted in this city, despite the relevance of airborne particle impacts and difficulties and the necessity of investigating novel measuring methodologies. The feasibility of creating models for AOD550 estimates was investigated, and the outcomes were contrasted with those of the other models that were put forward.

An artificial neural network was created, which included four hidden layers, where each layer included a Gaussian function with a repetition factor of 30000. The results of this ANN were an RMSE of 0.059208, a correlation coefficient (R) of 0.914407, and a standard division (SD) of 0.08687. would be appropriate for predicting AOD550 using little meteorological data in various parts of Iraq.

It is possible to use the proposed artificial neural network in Table2 in order to apply it to estimate other parameters and apply it in other specialties.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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