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FEED-FORWARD AND CASCADE BACK PROPAGATION ARTIFICIAL NEURAL NETWORK MODELS FOR PREDICTING AEROSOL OPTICAL DEPTH IN ILORIN-NIGERIA

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ABSTRACT
This study presents feed forward and cascade back propagation Artificial Neural Networks (ANNs) approach to predict daily Aerosol Optical Depth (AOD) in Ilorin-Nigeria using Bayesian regularization (trainbr) and Levenberg– Marquardt (trainlm)) algorithms. The daily AOD data for ten years (2007-2017) was collected from Aerosol Robotic Network (AERONET) and was modelled as a function of meteorological data (visibility and relative humidity) downloaded from NOAA-NCDC (National Oceanic Atmospheric Administration-National Climate Data Centre). The data linearity was checked, and the network was trained and tested using 70% and 30%. The numbers of neurons in the hidden layer were varied 3-3, 6-6, 7-7, 15-15, and 20-20 using tansigmoidal transfer function. In each adjustment, the networks were trained 15 times and the results that represent the best output were recorded. The combination which has the highest coefficient of determination R^2 and the lowest errors were finally chosen. Results indicate that visibility and relative humidity in all the two networks and algorithms using both the overall and seasonal data can be used to explain at least 71% of the variation in AOD. The ANN has shown high accuracy on the overall (January-December) compared to the Harmattan and summer seasons data. The result also showed that, the feed forward network performed better than the cascade network. It further revealed that both feed forward and cascade provide lowest error (lower RMSE) and faster convergent speed (lower epoch) when train with Levenberg–Marquardt algorithm (trainlm) than the Bayesian regularizations algorithm.

Keywords: Aerosol Optical depth; ANN; Ilorin; Relative humidity; Visibility

INTRODUCTION

Atmospheric aerosols are those aerosol particles suspended in the atmospheric column (Balarabe *et al.,* 2015). The term is mainly associated with particulate matter and is generally found in the lower layers of the atmosphere (troposphere and stratosphere) (Balarabe and Koko, 2018). They aremainly categorized based on size, ranging from a few nanometres up to a hundred micrometers (Balarabe *et al* 2015) and exhibit range of chemical properties. Atmospheric aerosol may come from natural or anthropogenic sources. Their concentrations are functions of location, anthropogenic activities, and climate change.

Nigeria is located in Sub-Sahara West Africa (Anuforom *et al*. 2007; Ogunjobi *et al*. 2012; Balarabe *et al.* 2015&2016a) where dust aerosol are being transported from Sahara to AtlanticOcean across Nigeria. The intensity and the period of dust transport is revealed in the work of Odekunle, (2004); Anuforom *et al.,* 2007 and Adelekan, (2013) who opined that the Nigerian climate is influenced by interaction of Tropical continental air mass and Tropical maritime air mass system during the periods of November-March (Harmattan) and April-October (Summer). The entire country experiences large quantities of dust and smoke from biomass burning during the Harmattan season. The weather conditions during Harmattan contribute to more dust emission and distribution in the atmosphere, coupled with anthropogenic activities arising from high energy demands and increase pressure on land for infrastructure and agricultural purposes.

Similar to greenhouse gasses, atmospheric aerosols affects the radiation pattern of the earth (Ogunjobi *et al.,* 2012). They affect the quantity of solar radiation reaching the Earth's surface, as well as the behavioural pattern of cloud conditions. Anthropogenic aerosols can also reduce the quality of air in the atmosphere, thereby increasing the health problems (Tan *et al*., 2015a). It can also directly leads to visibility reduction (Balarabe *et al*., 2015; Ogunjobi *et al.,* 2012) which in turn affect the economy of a particular region. Thus, even though, Nigeria is regarded as one of the most heavily aerosol-laden regions of West Africa, where aerosol studies are of great concern, quantification of the influence of artificial and natural aerosols in the region is quite challenging. The inconsistency in the physical, chemical, and optical composition of the aerosol makes it difficult to assess their impact on both humans and the global climate (Balarabe *et al.*, 2018).

Aerosol optical depth (AOD) plays significant role for assessing air quality, air condition, aerosol characterizations and aerosol studies in general (Tan *et al* 2015a; Balarabe *et al.*, 2015). Several studies on aerosol optical properties have been carried out (Tan *et al*., 2015b; Balarabe *et al*., 2016b; Toledano *et al.*, 2009; Salinas *et al.*, 2007) in different regions of the world using aerosol measurements generated from the ground-based stations AERONET (Holben *et al.*, 1998). Measurement from Aeronet (upper case) are some of the most trusted results, however, AERONET stations are limited in spatial density. Recently, extracting the properties of aerosols using space-based observations (Satellite), presents a more explicit method of enabling measurements of aerosol at the global level (Tan *et al.*, 2015b). However, aerosol observations using both the AERONET and satellite sensors are being affected by the presence of cloud in the atmosphere. Aerosol data due to cloud-contamination leave gaps in our remote sensing data record, and makes it difficult for scientists studying aerosols. Therefore, it is found necessary to develop a regional/local model which has not yet being applied over the region to enable detail aerosol studies.

Some research effort has been made to estimate AOD values by using different meteorology data (Tan *et al.*, 2014; Qin *et al.*, 2010; Lin *et al.*, 2014; Balarabe and Koko 2018; Balarabe and Koko 2019) in different regions of the world. Tan *et al* (2015b) and Cordero *et al* (2014) established that AOD is directly proportional to particulate matter (PM) but inversely proportional to visibility (Vis) (Tan *et al* 2015a; Balarabe and Koko 2018 and Balarabe and Koko 2018) assuming the distribution of aerosol in the atmospheric column to be uniform (Balarabe and Koko 2018; Balarabe and Koko 2019). Balarabe and Koko (2019) also obtained a significant correlation between relative humidity and AOD.

ANN allows an efficient approach of forming an empirical and possibly nonlinear relationship between one or more outputs variables and a number of inputs variables. ANN has been useful for modelling in many branches of science such as rainfall (Chiapello *et al.*, 1999; Khidir *et al*., 2013), solar radiation (Azadeh *et al.*, 2009; Benghanem *et al* 2010), green house strawberry yield (Keshavarzi *et al*., 2015; Moosavi *et al.*, 2014), soil phosphorous (De Vos and Rientjes, 2005), air quality (Khoshnevisan *et al*., 2014) and many more. However, the use of ANN in aerosol studies particularly AOD based on daily, monthly, or even decade has been neglected by many researchers. To appreciate and fulfil the potential of ANN approach in modelling, its application aerosol studies particularly AOD needs to be researched more extensively. In this work, a multi-layer feed forward and cascade ANNs for AERONET AOD prediction on daily basis in Ilorin-Nigeria using daily visibility and relative humidity as an input data were developed and tested.

DATA AND METHODOLOGY

Aeronet and Meteorological Data

The AERONET observation site is located in Ilorin-Nigeria (latitude 8°32' N and longitude 4°34' E). Aerosol data from this site has been used by many authors for aerosol related studies in West Africa (Pinker *et al.* 2001; Ogunjobi *et al.*, 2008). The description of the study site is provided in detail by Nwafor et al (2007) and Ogunjobi *et al* (2008) while the the instrument was fully described by Holben*et al* (1998). The daily AERONET AOD data from level 2 (cloud screen and quality assured) (Smirnov *et al*., 2000) for ten years period (2007-2017) was dowloaded and used in this study. The meteorological data (relative humidity and visibility) for the corresponding ten years period (2007-2017) of study were downloaded from the National Oceanic and Atmospheric Administration-National Climatic Data Centre (NOAA-NCDC) (htt://gis.ncdc.noaa.gov/). Ilorin meteorological station was found to keep at least 75% data for the ten years period as suggested by Engelstaedter *et al.* (2003). The data was arranged in series of January to December and then separated into Hamattan (Nov.-Mar.) and summer (Apr.-Oct.) in line with Anuforom *et al* (2007).

Methodology (ANN)

In order to predict AOD and allow comparison with multiple linear regressions (MLR) in future study, the meteorological variables (relative humidity and visibility) used in the MLR model in the earlier study of Balarabe *et al* (2019) are adopted here as the input variables. In the present study, the AOD is chosen as the required outputs parameter while visibility and relative humidity are the input parameters.

To ensure sufficient representation for all the maximum and minimum data values in the training and testing of the network, the data points were selected randomly. This will enable the network to reproduce the existing relations between input and output variables. The 70% of the data used for the MLR model in the earlier study of Balarabe *et al* (2019) are adopted here for training and the remaining 30% for testing the networks. Data points were normalized for equalization which prevents excessive shrinking weights using the relationship (Equation 1).

$$\mathrm{Y}_{\mathrm{normal}} = \frac{y_{o-\bar{y}_i}}{y_{\max}-y_{\min}} \qquad (1)$$

where, y_{max} is the maximum data, y_{min} is theminimum data, $\bar{y}_i$ is the mean value of measured values, and y_o presents observed values.

In order to determine the best network in the prediction of AOD, this study, chooses feed-forward and cascade neural network with two hidden layers due to their efficiency and simplicity (Keshavarzi *et al.*, 2015). The details of the feed forward and cascade network structure are provided in the work of Badde *et al.* (2013). The numbers of neurons were varied from three to twenty in each hidden layer. The error back propagation learning rule was used for the learning of the networks (Azadeh *et al.*, 2009). To reach the optimized status, the tan-sigmoid (tansig) transfer function in the hidden layers and linear transfer function (purelin) in the output layer was used as the activation function. The Bayesian regularization (trainbr) and Levenberg–Marquardt (trainlm) training algorithm were used in order to identify which of the chosen algorithm trains the selected networks more efficiently.

The learning rate per layer and the training tolerance of maximum epoch size was set at 0.001, and 1000. The Matrix Laboratory (MATLAB) software version 7.1 (R2012a) were used for designing and testing of the ANN model with topology of 4-2-1, (4 inputs, 2 hidden layers and 1 output layer). Many authors believe that, a single hidden layer could be sufficient for neural network to approximate any complex non-linear function, even though the learning may be slow (Noori *et al.*, 2009 &2010). For these reasons, two hidden layers are adopted and applied to train and test the overall, Harmattan and summer data sets. In each case, the network was trained 15 times out of which the best outputs were selected. The assigned weights during the training process of the neurons are kept in the memory of the neural network (Goh 1995). The result of the training and testing displayed. In each case, the coefficient of determination (R^2), for both training and testing, training RMSE, and epoch size are tabulated. These parameters ($R^{2,}$ and RMSE) were used for the evaluation of model performance (Wosten *et al.*, 2001) and the number of epoch gives an indication of the convergent speed of the algorithm.

RESULTS AND DISCUSSION

Table 1 revealed the best model performance from the training and testing of feed forward ANN using trainbr (left) and trainlm (right) varying the numbers of neurons in the hidden layer (3-3, 6-6, 7-7, 15-15, and 20-20) for 15 times each and for the overall, Harmattan and Summer Seasons data. The parameters used for the performance evaluation includes, the R^2 for the data used in training (T_rR^2), the RMSE, the R^2 for the data used in Testing (T_sR^2) and convergent speed (Epoch).

Table 1: Evaluations Bayesian regularization algorithm (trainbr) and Levenberg– Marquardt algorithm (trainlm) for Feed forward network in predicting the overall, Harmattan and Summer AOD in Ilorin-Nigeria

Season	Bayesian regularization algorithm (trainbr)				Levenberg– Marquardt algorithm (trainlm)			
	T_rR^2	RMSE	T_SR^2	Epoch	T_rR^2	RMSE	T_SR^2	Epoch
Overall	0.95	0.003	0.80	231	0.80	0.002	0.76	11
Harmattan	0.78	0.006	0.74	995	0.71	0.005	0.66	13
Summer	0.80	0.004	0.77	240	0.75	0.003	0.74	12

From the table it is obvious that, the proposed ANN (feed forward) train and tested with both Bayesian regularization (trainbr) and Levenberg– Marquardt (trainlm) algorithms indicate a good performance and can adequately be used to predict AOD due to reasonable training and testing R^2 and lower RMSE which revealed high levels of accuracy for prediction. Even though, it is observed that the prediction ability of both depends on season (more in the overall, then summer and lowest during Harmattan).

The range of T_rR^2 (0.71-0.95) and T_sR^2 (0.66-0.80) for both train br (Bayesian regularization) and lm (Levenberg–Marquardt) showed that the models are capable of explaining at least 71% of the training and 66% of the testing phase which further support the application of ANN in AOD modeling. It is obvious that the T_rR^2 for the two algorithms are relatively similar even though high in br then lm. This is Similar to what is observed in the T_sR^2 which revealed that the networks efficiently and consistently produce results with sufficient precision and reliability. In addition, the network train and tested with Levenberg– Marquardt algorithm provide minimum errors compared to the one train with Bayesian regularization algorithm.

Table 2 also revealed the best model performance from training of cascade network using trainbr (left) and trainlm (right) after equal adjustment of the numbers of neurons in the hidden layer for equal number of times and data set. The results show that cascade network showed excellent performance where the RMSE show less error with very good R^2.It also revealed similar pattern as in the case of feed forward network where the network train with br outperformed lm.

Table 2: Evaluations of Bayesian regularization algorithm (trainbr) and Levenberg– Marquardt algorithm (trainlm) for Cascade network in predicting the overall, Harmattan and Summer AOD in Ilorin-Nigeria

Season	Bayesian regularization algorithm Levenberg– Marquardt algorithm (trainbr)(trainlm)							
	T_rR^2	RMSE	T_SR^2	Epoch	T_rR^2	RMSE	T_SR^2	Epoch
Overall	0.85	0.09	0.78	233	078	0.008	0.74	10
Harmattan	0.67	0.014	0.65	1000	0.62	0.010	0.63	13
Summer	0.75	0.012	0.74	334	0.73	0.006	0.70	12

From Table 1 and 2, it is obvious that, feed forward network performed better than the cascade in terms of fitting (highest R^2) for both training and testing, error minimization (lowest RMSE), and faster convergent speed (as indicated by the number of epoch). This result is in contrast with the results obtained by Badde *et al* (2013), who found that Cascade outperformed feed forward in predicting the compressive strength of ready mix concrete.
The results also revealed that both feed forward and cascade provide RMSE lower epoch when train with Levenberg–Marquardt algorithm (trainlm) than the Bayesian regularization algorithm (trainbr). For that reason, since ANN is all about error minimization, feed forward with lm as training algorithm will be the best for AOD modelling. It is observed that if different training algorithms, data set and number of training are varied, the accuracy of the ANN model in predicting AOD can be improved.

CONCLUSION

The study for the prediction of AOD using feed forward and cascade algorithms were carried out. Daily meteorological data of visibility and relative humidity were used as input variables. Bayesian regularization algorithm (trainbr) and Levenberg–Marquardt algorithm (trainlm) having equal adjustments of neurons were used as training algorithms. The study revealed that, both feed forward and cascade network showed excellent performance where the RMSE show less error with very good R^2. It further revealed that feed forward network performed better than the cascade network, using both Bayesian regularization algorithm (trainbr) and Levenberg– Marquardt algorithm (trainlm) for instance, for the overall data and for br R^2= 0.95, 0.85; RMSE = 0.003, 0.09 Training R^2= 0.80, 0.78 and epoch = 231, 233 for feed forward and cascade. It is also obvious that both feed forward and cascade provide lowest RMSE and lower epoch when train with Levenberg– Marquardt algorithm (trainlm) than the Bayesian regularization algorithm (trainbr). For this reason, since ANN is all about error minimization, feed forward with lm as training algorithm will be the best for AOD modelling in the study area.

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