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Evaluating Different Functions of Artificial Neural Networks for Predicting the Hourly Variations of Horizontal Visibility under Dry and Humid Conditions (Case Study: Zabol City)

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Abstract

The present research was conducted to compare different functions of two artificial neural networks (ANNs) including the multilayer perceptron (MLP) and radial basis function (RBF) in order to forecast the Horizontal Visibility (HV<1km) in Zabol city under dry and humid weather conditions. For this purpose, hourly data of horizontal visibility (HV), wind speed, relative humidity, temperature, and atmospheric pressure were used. Before importing these data to the ANNs, they were normalized and multicollinearity impact between the climatic variables was calculated using the variance inflation factor. In this study, 70% of data were used for data training and 30% for data testing. Accuracy of the models was estimated using the mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and the correlation coefficient (R) between observed and predicted values of HV. The sensitivity of the output data was determined based on the most accurate model. The results showed that according to function MLP4, the prediction accuracy of HV was more than the accuracy of other functions of neural networks (ANNs) for both dry and humid climates. The mentioned error values were estimated at less than 0.5. Pearson correlation between observed and predicted values was estimated according to training data and testing data as 0.66 and 0.7, respectively. These coefficients were calculated 0.9 and 0.99 for humid and dry weather, respectively. Moreover, the wind speed and air temperature for dry and humid climate were identified as the most important factors effective on HV at the time of dust storm occurrence.

Keywords: Climatic Parameters, Short-term Prediction, Evaluating Model Accuracy, Intelligent Systems, Arid Region.

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1. Introduction

Horizontal visibility (HV) as one of the important properties of atmosphere is taken into consideration with respect to different aspects such as air pollution, air traffic, flights safety, road traffic, cruise safety. HV is defined as the maximum distance at which a black object of suitable dimensions (located on the background) can be recognized (WMO, 1992). This important meteorological criterion, which is recorded by observers of the synoptic station during 8 times observing at 3-hour intervals once a day, represents the concentration of dust particles in the atmosphere and the relative intensity of dust storms (Baddock et al., 2017). Large HV values show the good air quality of a region and vice versa (Tang et al., 2018).

In order to predict the HV changes, choosing a practical and quick method is of the highest importance issues in sand-dust storms. Choosing such a method is significantly taken into account in terms of management, planning, and policy-making for economic and environmental developments, especially in arid regions of Iran, wherein frequency and severity of sand and dust storms have been increased within recent years (Khaefi et al., 2017; Modarres and Sadeghi, 2018). There are varieties of statistical methods for predicting different variables such as meteorological variables; however, using intelligent models and particularly artificial neural networks (ANNs) have been the subject of intense research for ages. One of the important reasons for the widespread use of these models can be their high speed and accuracy in processing and predicting different variables because of simultaneous structure, using the concept of learning, creating nonlinear mapping, storing information in an extended memory that does not interfere the network function, generalization ability, detecting and classifying patterns, and optimization and self-regulatory ability (Moatamednia et al., 2015). In recent years, by a massive expansion of computer techniques, ANN-based implicit methods have been widely used for forecasting different parameters of meteorology, and high accuracy of this method has been proved by Iranian and foreign researchers in different research aspects, especially those associated with wind erosion and dust. In this regard, Jamalizadeh et al. (2011) used the ANN method to forecast dust storms of Zabol city according to the variables such as rainfall, temperature, evapotranspiration, wind speed, and relative humidity for the time period of 1985-2005. They showed that the accuracy of the ANN in short-term predictions was more than long-term predictions. In a research conducted by Shekari et al. (2014), the priority of multilayer perceptron (MLP) ANN was proved compared with radial basis function (RBF) in estimating the wind deposits volume of Darab Plain, Iran. Yousefi and Ekhtesasi (2015) utilized ANN and decision tree in order to detect the factors effective on dust phenomenon in Yazd Province, Iran. The results demonstrated that the ANN with correlation coefficient (R) of 0.87 and root mean squared error (RMSE) of 0.04 had high accuracy than the decision tree with R = 0.86 and RMSE = 0.06. The prevailing wind speed, wind continuity, and the mean of monthly wind speed were detected as the most important factors affecting the occurrence of dust storms. Firouzi et al. (2016) used the ANN in order to forecast the number of dusty days of Ahvaz city. To this end, the average monthly wind speed, relative humidity, rainfall, and dew point temperature was used during 2005-2010. They demonstrated that 41% of changes in dusty days is explained and justified by using climatic parameters. Chaudhuri et al. (2015) examined the performance of different functions of the ANNs in predicting HV arisen from haze phenomenon occurrence according to the meteorological parameters in three synoptic stations located in Delhi, Kolkata, and Bengaluru airports in India. They reported that that the MLP has priority over the RFB for predicting HV. García et al. (2016) utilized the ANN to investigate the association between aerosols optical depth and earth observation of dust for the summer months of 1941 to 2013. The results of their investigation proved the high efficiency of this method, such that they reported an R = 0.8 between observed and predicted values. Vakili et al. (2017) examined the impact of pollution arising from particulate matter along with relative humidity, wind speed, and daily minimum and maximum temperatures on daily sunlight level affecting the HV range. To this end, they used the ANN and estimated the R as 0.99 and error mean less than 0.05 for the dependent variable (i.e., particulate matter). Aldababseh and Temimi (2017) examined the reduction cause of HV arising from two phenomena, namely haze, and dust, in dry and humid climates in the United Arab Emirates and proved that climatic factors play a different role in different regions of this country. They reported that high relative humidity and the presence of haze are the leading causes of poor visibility in humid condition. Despite predicting its changes, the investigation shows that detecting effective factors on HV by various techniques and methods has a long history. Particularly, it has been reported that the low wind speed and high relative humidity are the causes of remarkable reduction of surface visibility in 279 synoptic stations in India during 1961-2008 (Jaswal et al., 2013). In addition, relative humidity can give rise to poor visibility as a result of an increase in particle sizes by absorbing water vapor existing in the air (Singh et al., 2017). The direct relationship between surface wind speed and HV has been proved in China (Sun et al., 2018). The impact of high temperature between the Mediterranean Sea and Syrian deserts is another leading cause of dust occurrence in this region (Eskandari et al., 2016). In another study, Kaskaoutis et al. (2017a) examined the effects of winter atmospheric dynamics on sand and dust storms in southwest Asia using the Caspian Sea-Hindu Kush Index (CasHKI). According to their results, the reduction of air temperature and the increase in relative humidity in this season are among the main causes of dust concentration increase and air quality decline.

In general, the change in air quality due to various factors, such as the introduction of dust particles into the atmosphere, has led to biological instability and irreparable economic, social, and health damages in the southwest of Asia, especially in Zabol city. The main cause for air quality changes in this area is that it is located near one of the most important sources of dust production, namely dried Hamoun wetlands. In this regard, it has been reported that the intensity and frequency of sand and dust storms have been growing in these regions (Rashki et al., 2017; Rezaei et al., 2018). Therefore, the development of prediction methods and warning systems in terms of air quality or criteria indicating air quality status are among the demanding requirements of citizens in this region of the country. However, different factors affect this phenomenon, making them difficult to analyze. Although statistical and regression models are the most common analytical methods providing results associated with errors for the linear solution of this phenomenon, they cannot model the time changes of the considered phenomenon with acceptable accuracy. Currently, regarding their outstanding efficiency and ability, intelligent systems have extensive uses for predicting different variables, especially HV (Chen et al., 2018; Stafoggia et al., 2017; Vakili et al., 2017). Consequently, in the present research, ANNs were used for predicting the HV arising from the occurrence of sand and dust storms in the southeast of Iran. To our knowledge, the climatic factors affecting HV changes are different in the dry (RH<50%) and humid weather conditions (RH>50%) (Lawrence, 2005) and previous studies have mainly focused on predicting HV changes. Therefore, the innovation of the current research is proposing HV predictive models suitable for different climatic conditions in a given region. For this purpose, the following objectives are pursued:

(1) Frequency analysis of dusty h under dry and humid conditions

(2) Introducing a precise and appropriate model to predict the hourly HV under both conditions using different functions of ANN

(3) Determining the relative importance of the effective variables on HV changes less than 1 km under dry and humid air conditions

2. Materials and Methods

2.1. Study Region

The study area is Zabol city in Sistan and Baluchestan Province that is located in Southeast of Iran at a distance of 15 km from

Hamoun Lake (Fig 1). The average rainfall, temperature, annual relative humidity, and average wind speed are 54.3 mm, 22.66℃, 28%, and 20 m/s, respectively (Alizadeh-Choobari et al., 2014). The hyper-arid climate is dominant in this region resulting from poor rainfall, high-speed winds, and severe evaporation (Whitney, 2006). The most permanent and strongest winds prevailing in the southeast of Iran are called Levar winds or 120-days winds blowing from northwest to the northeast (Alizadeh Choobari et al., 2013; Miri et al., 2007). These winds blow with 70 to 90 km/hr speed from late in May to late in September consistently (Middleton, 1986). Zabol city has been known as one of the dustiest cities of southwest Asia and northeast Iran (Middleton, 1986; Rashki et al., 2013; Rashki et al., 2018). The main reason for this phenomenon in this area is its vicinity to the most important sources of dust in the southeastern part of Iran, namely the dried lakes of Hamoun-e Hirmand, Hamoun-e Saberi, and Hamoun-e Puzak. These lakes are fed with Hirmand River. However, in recent years, a major area of these lakes has dried up and turned to as an important source of dust production due to human interference and climatic factors such as prolonged drought (Mehrizi et al., 2017). Fig. 1 shows the geographical location of the study area.

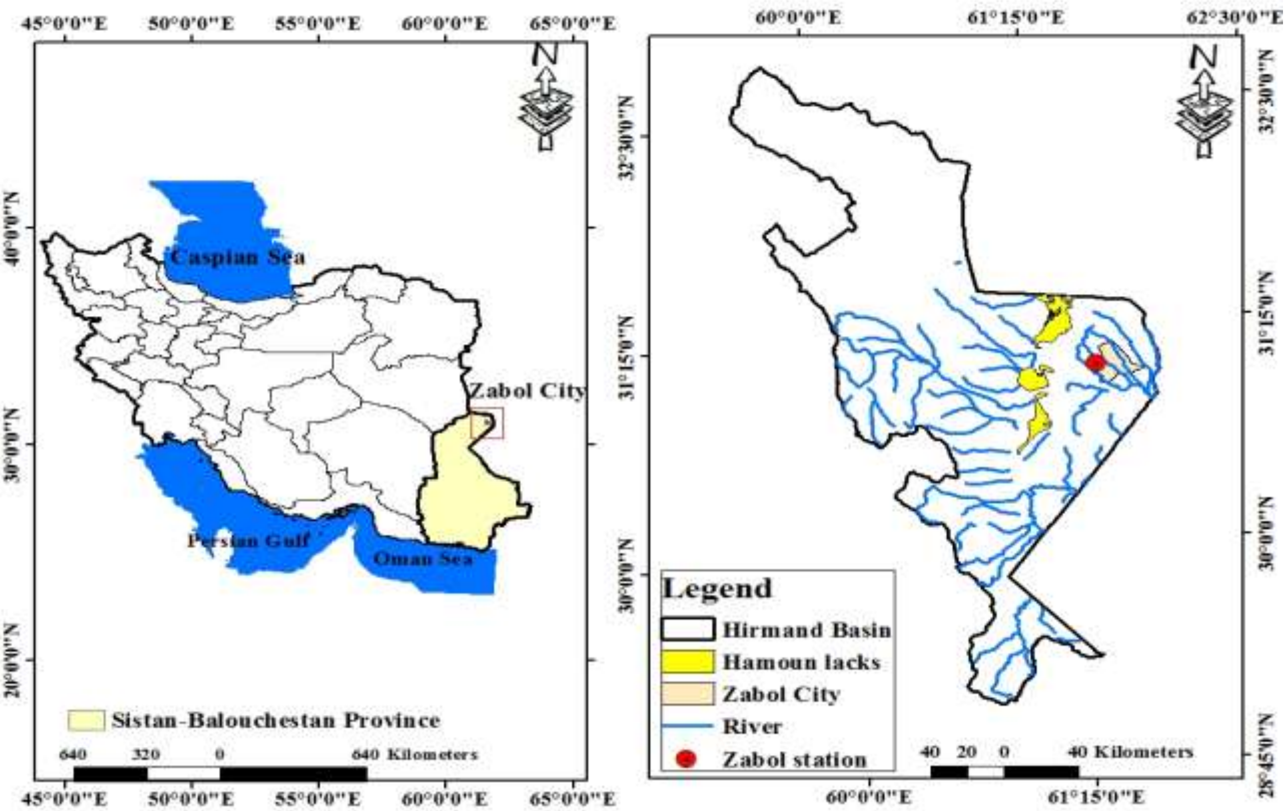

Figure 1: The Geographical Location of Study Area in Iran and Sistan and Baluchestan Province

2.2. Methodology

The general steps of this research are presented in Fig. 2.

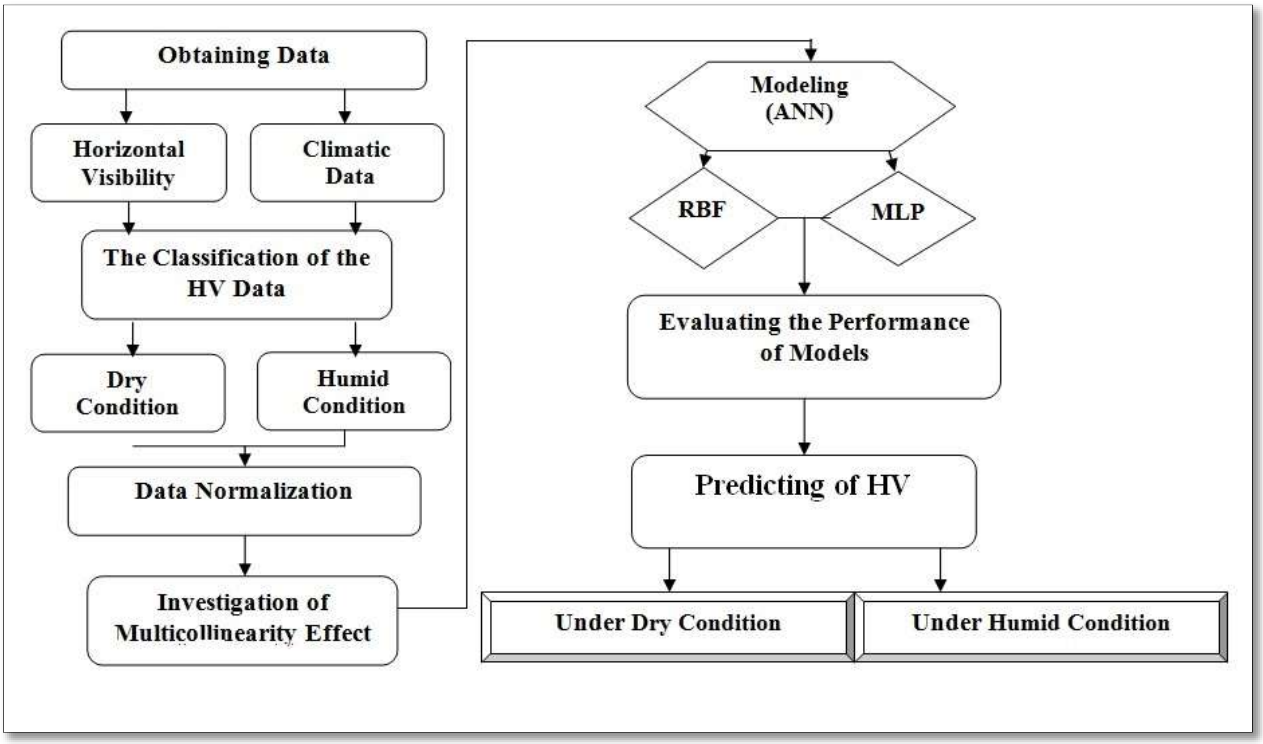

Figure 2: Flowchart of present research methodology

2.2.1. Obtaining Climatic Data

In the present study, the hourly data regarding HV and type of phenomena occurred at that hour in Zabol's synoptic station was obtained from Iran Meteorological Organization for a 5-years statistical period (2013-2017). In addition to the HV data, the hourly data associated with meteorological parameters such as temperature, relative humidity, wind speed, and atmospheric pressure were obtained from this organization. Zabol station was selected in this study because it is close to dry-bed of Hamoun wetlands. These wetlands are presently fed through the Hirmand River, but in recent years, due to human intervention and the effects of climate and droughts, the vast majority of these lakes have dried up and become major sources of dust production (Mehrizi et al., 2017; Rashki et al., 2017; Rashki et al., 2013; Rashki et al., 2018).

2.2.2. The Classification of HV Data

In this step, the dust events associated with dry and humid climate were separated from each other according to the threshold of 50% relative humidity. To better understand the frequency status of dusty h under dry and humid climate, the HV criterion was utilized. According to this criterion, the frequency of dusty h was investigated for three classes less than 1, 1-2.5, and 2.5-5, in which the poor HV indicated the high dustiness of the regional air. Hence, in the present study, to predict the hourly changes of visibility under dry and humid climates, the hourly data of dusty events with HV less than 1 km were selected. The main reason for selecting these data is that the storms, which decrease the HV to this range, have a more destructive effect than other dust events. To predict the HV less than 1 km, the recorded hourly data of four parameters were used at occurrence time of sand and dust storms. These parameters are air temperature, surface wind speed, relative humidity, and atmospheric pressure.

2.2.3 Data Normalization

The data were normalized using Eq. (1) before importing them to SPSS20.

Eq. (1) $$XN = \frac{X_{\max} - X_i}{X_{\max} - X_{\min}}$$

Where

X_i: values of the variable under consideration

XN: Normalized value of the variable under consideration

X_{Max}: The maximum data recorded among the examined data

X_{Min}: Minimum data recorded among the examined data

2.2.4. The Investigation of Multi-colinearity effect

Regarding that using variance inflation factors (VIFs) do not involve complex statistical calculations and their efficiency has been proved in most studies, they were employed for the rapid detection of appropriate independent variables in this study. To this end, Stata 12 was used.

The VIF coefficient for K=1,…, P is calculated as follows:

Eq. (2) $$VIF_K = (1 - R_K^2)^{-1}$$

where R_K^2 is the coefficient of multiple determination between variables when XK is returned over other variables (Thompson et al., 2017).

2.2.5. Modeling

The supervised ANN was selected to predict HV based on the climatic parameters under study. As mentioned earlier, the efficiency of this method has been proved in a wide range of functions such as classification, pattern identification, interpolation, prediction, and modeling (Chen et al., 2018; Vakili et al., 2017). In the present research, four climatic parameters, namely wind speed, relative humidity, atmospheric pressure, and temperature are considered as network inputs and HV variable as network output. The ANN toolbox of the SPSS20 was used for designing and performing an ANN. Here, 70% of data was imported to the ANN as training data and 30% as test data. Furthermore, the sensitivity of output data compared with each independent variable was examined by SPSS20 software. Given that there is no training algorithm for determining the number of hidden layers and the number of neurons in each specific layer, the training algorithms, the number of hidden layers, and the number of neurons of each layer were determined by trial and error. This process was continued until the error between data and observations reached a minimum level.

2.2.6. Evaluating the Performance of Models

The prediction accuracy of different functions was compared based on four criteria: the mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), and the correlation coefficient (R) between observed and predicted values of HV (Chai and Draxler, 2014) (Eqs. 3-6).

Eq(3) $$MSE = \frac{\sum_{i=1}^{N}(Q_O - Q_e)^2}{N}$$

Eq.(4) $$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_O - Q_e)^2}{N}}$$

Eq.(5) $$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Q_O - Q_e\right|$$

Eq.(6) $$R = \frac{\sum_{i}^{n}(Q_O - \overline{Q_O})(Q_e - \overline{Q_e})}{\sqrt{\sum_{i}^{n}(Q_O - \overline{Q_o})^2 \sum_{i=1}^{n}(Q_e - \overline{Q_e})^2}}$$

Where N is the number of observation, Q_O is the observation amount of HV, Q_e is the estimated amount of HV, $\overline{Q_e}$ is the mean of estimated amounts of HV, and $\overline{Q_o}$ is the mean of the observation amount of HV**.**

2.2.7. Predicting

After selecting the most accurate forecasting model for both dry and wet conditions, the diagram of predicted and observed HV changes based on the most suitable model for training and testing data was drawn. Next, the importance of each climatic parameter affecting the hourly changes of HV was determined according to estimated weight and the most accurate function. The importance value of a dependent variable indicates that to what extent a predicted data changes by a network with different amount of the independent variable. In other words, a variable that has the most impact gains an importance level of 100%. The importance normalization of other variables is obtained by dividing the relative importance involved with that variable on the importance value of the most important variable (Cao et al., 2017).

3. Results and Discussion

3.1. Analysis of Raw Data

Figyre 3 and 4 present the results of investigating the monthly frequency of recorded dust events in the synoptic station of Zabol for all three classes in a statistical period being examined (2013-2017) under dry and humid weather conditions.

Figure 3: The frequency of dusty hours of Zabol city during the studied period (2013-2017) under dry condition

Figure 4: The frequency of dusty hours of Zabol city during the studied period (2013-2017) under humid condition

Generally, the results of dusty h' frequency of Zabol city in dry weather (Fig. 3) indicate that the total frequency of dusty h associated with each three defined classes is for HV of January (26 h). Nevertheless, the most frequency of dusty h for these classes has occurred in July (585 h during 5 years), June (284 h), and August (276 h). This result points out that dust emission, which causes poor visibility in spring and summer, has been more than other seasons of the year. In previous studies, it has been proved that sand and dust storms occurrence increase in spring and summer in Sistan province, particularly in Zabol city (Rashki et al., 2017; Sanjerehei and Rundel, 2017), confirming the results of this research.

In contrast, investigating the obtained results of dusty hours' frequency in a humid climate (Fig. 4) showed that the frequency of dust events in this condition was 10% of the recorded events in a dry climate at examined intervals. The more detailed investigation of humid weather (Fig. 4) demonstrated that the most frequency of the dusty hours has occurred in March and November and the lowest dust events in May and September. Among the months that had the dustiest events (i.e., November, March, and February), February has allocated the most severe dust storms causing the poor visibility less than 1 km. In comparison, November and March had the dusty hours' frequency reaching less than 1 km HV. Although the occurrence of storms increases the visibility of more than 1 km, the storms that decrease visibility less than 1 km in humid weather condition are important as well. In other words, the occurrence of such storms in humid weather suggests the crisis of severe desertification and the multiple roles of factors effective on the occurrence of this destructive environmental phenomenon in Zabol city, which needs to be investigated in more detail. Consequently, the analysis result of horizontal visibilities less than 1 km, which are the most severe dust events in dry and humid climates, was presented.

3.2. Selecting the optimum model to predict the hourly HV under dry condition

The result of examining the number of dusty h with a HV less than 1 km at the studied intervals (2013-2017) demonstrated that the sum of dusty hours with a visibility less than 1 km under dry climate was 463 h, of which 325 h of the beginning of the study were used as the training data and 138 dusty hours of the ending of the period were considered as the test data. The multicollinearity effect between the variables was investigated using VIF before importing the training data into the ANN. The results indicated that VIF was less than 10 for all variables (Table 1), showing the insignificant effect of multicollinearity between climatic parameters. Then, it was possible to transfer all the variables into the modeling process. Table 2 illustrates the results of the different structures analysis of MLP and RBF by using four important climatic parameters for HV less than 1 km under dry climate.

Table 1: The Result of Multicollinearity Examination of Recorded Climatic Variables for HV<1km in dry weather

Variable	VIF	1/VIF
T	4.97	0.20
RH	3.82	0.26
WS	1.1	0.9
P0	2.81	0.35

Table 2: The Evaluation of Different Structures of Multilayer Perceptron (MLP) and Radial Basis Function (RBF) for Estimating the HV Using Training and Test Data (in dry weather)

Model	Activation Function		Training				Testing			
number	In the hidden layer	In the output layer	MSE	RMSE	MAE	R	MSE	RMSE	MAE	R
MLP1	Hyperbolic tangent	identity	0.10	0.32	0.23	0.48**	0.09	0.30	0.24	0.63**
MLP2	Hyperbolic tangent	identity	0.08	0.28	0.20	0.52**	0.06	0.24	0.20	0.66**
MLP3	Hyperbolic tangent	tangent	0.08	0.29	0.22	0.51**	0.09	0.3	0.24	0.61**
MLP4	Hyperbolic tangent	Sigmoid	0.06	0.24	0.18	0.66**	0.07	0.27	0.21	0.7**
MLP5	Sigmoid	identity	0.07	0.26	0.20	0.57**	0.08	0.28	0.22	0.73**
MLP6	Sigmoid	Hyperbolic tangent	0.1	0.32	0.23	0.52**	0.09	0.30	0.24	0.62**
MLP7	Sigmoid	Sigmoid	0.07	0.27	0.21	0.48**	0.08	0.29	0.24	0.69**
RBF1	Softmax	identity	0.06	0.25	0.20	0.38**	0.09	0.30	0.25	0.59**
RBF2	Exponential	identity	0.07	0.26	0.21	0.42**	0.1	0.32	0.26	0.54**

Based on the statistical analysis results, to predict the hourly changes of HV less than 1 km for Zabol station (Table 2), the structure of MLP network in the fourth condition with sigmoid and hyperbolic tangent activation functions from input to hidden and hidden to output, respectively, had the best performance. Therefore, this model is recommended for predicting the hourly changes of HV less than 1 km. The high R between training data and estimated data of HV (R=0.6), and low MSE, RMSE, and MAE had the highest accuracy compared to other models of the network. Then, this model is selected for predicting the hourly changes of HV less than 1 km.

Although R values between the measured and estimated amounts for MLP5 model were equal to estimated R in MLP4, the model has less accuracy due to its high MSE, RMSE, and MAE; then, it was not considered as the best model. The optimization of MLP4 function for predicting the dust events was proved by Chaudhuri et al. (2015), who reported results consistent with the results of the present research. Figs. 5 and 6 present the fitting diagram between measured and estimated values of HV based on the MLP4 for training and testing data, respectively. Also, the relative importance of each climatic variable is shown in Fig. 5.

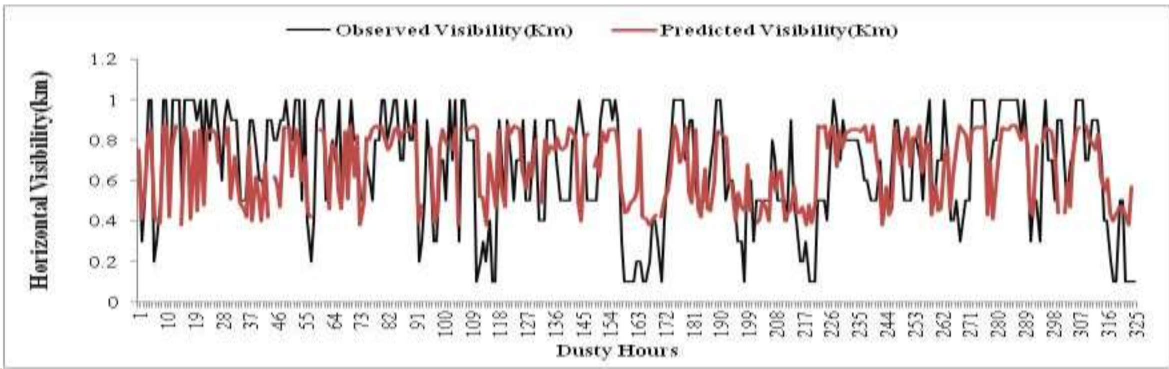

Figure 5: The Diagram of Predicted and Observed HV Changes based on the MLP4 Model in Zabol Station for Training Data

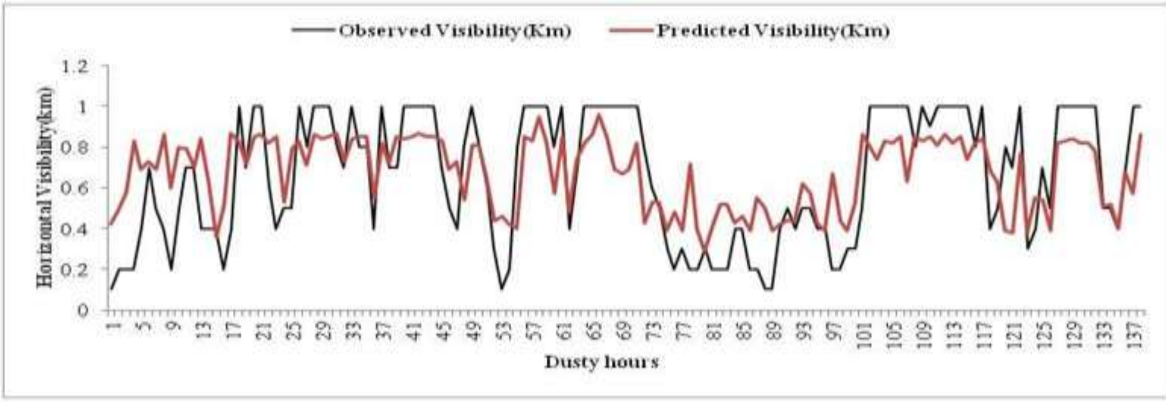

Figure 6: The Diagram of Predicted and Observed HV Changes Less than 1 km based on MLP4 Model in Zabol Station for Testing Data

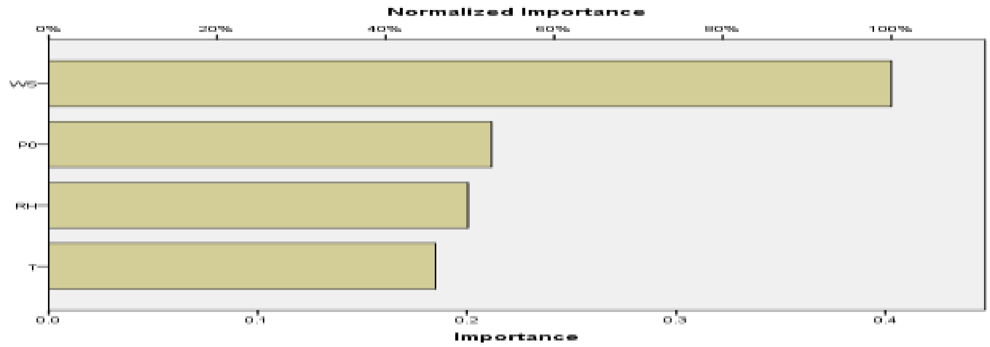

Figure 7: The Importance of the effective variables on HV changes less than 1 km under dry condition

The analysis results of the effective role of climatic factors on hourly changes of HV less than 1 km based on the MLP4 model in Zabol station (Fig. 7) indicate that the most effective factors on these changes are the average wind speed, atmospheric pressure, relative humidity, and temperature change, in the order of their appearance. The impact of each of these parameters was 41%, 21%, 20%, and 18%, respectively. Although all climatic variables affected the HV, the role of wind speed was significantly more than other variables in this region. In addition, as can be seen in Fig. 2, the highest frequency of dusty h with the HV less than 1 km occurred in June, July, and August. In these months, the speed of 120-days winds, dominating from late May to late September in southeast Iran, is high. The dominant direction of the wind is mostly from westward and northwestward to Zabol city. As previously mentioned, the main part of Hamoun wetlands has dried and turned into a major source of dust production. In fact, a considerable share of dust particles of the dried bed of these wetlands along with 120-days winds is transformed to Zabol city, causing high dustiness and poor visibility in the southeast of Iran, especially in this city (Rashki et al., 2013). Aldababseh and Temimi (2017) have pointed out the important role of wind speed changes on a high concentration of particulate matters and poor visibility when dry weather dominates in the region. This result supports the result of the present research.

3.3 Selecting the optimum model to predict the hourly HV under humid condition

The result of multicollinearity effect examination between recorded climatic variables for HV less than 1 km under humid condition showed that VIF was lower than 10 (Table 3). Therefore, to predict the hourly HV changes (< 1km) in humid weather, likewise dry weather condition, four climatic parameters were used: namely wind speed, temperature, relative humidity, and atmospheric pressure.

Table 3: The Result of Multicollinearity Examination of Recorded Climatic Variables for HV<1km in humid weather

Variable	VIF	1/VIF
T	1.5	**0.66**
RH	1.14	**0.87**
WS	1.63	**0.61**
P0	1.62	**0.61**

Previously, the results of investigating dusty hours with the HV less than 1 km in dry weather at the studied intervals (2013-2017) demonstrated that the total dusty hours was 24 h (Fig. 3), of which the beginning 16 h data were used as training batch and the end 8 h data as testing batch. Although the number of dusty hours with HV less than 1 km under humid condition was not significant than dry climate, ANN was used for predicting the causes of HV changes in this condition. The explanation for using ANN is that scarce data do not pose a serious problem in this method. The results of this analysis are summarized in Table 4.

Table 4: Evaluating the Different Structures of MLP Network and RBF for Estimation the HV Using Training and Testing Data (in humid weather)

Model	Activation Function		Training				Testing			
	In the hidden layer	In the output layer	MSE	RMSE	MAE	R	MSE	RMSE	MAE	**R**
MLP1	Hyperbolic tangent	identity	0.15	0.39	0.26	0.96	0.007	0.08	0.06	**0.98****
MLP2	Hyperbolic tangent	identity	0.21	0.51	0.45	0.63	0.14	0.35	0.5	**0.56***
MLP3	Hyperbolic tangent	Hyperbolic tangent	0.11	0.33	0.21	0.95	0.26	0.5	0.3	**0.99****
MLP4	Hyperbolic tangent	Sigmoid	0.04	0.21	0.1	0.97	0.006	0.08	0.05	**0.99****
MLP5	Sigmoid	identity	0.15	0.4	0.31	0.54	0.3	0.41	0.38	**0.49***
MLP6	Sigmoid	Hyperbolic tangent	0.22	0.49	0.43	0.58	0.12	0.36	0.43	**0.55***
MLP7	Sigmoid	Sigmoid	0.11	0.4	0.19	0.8	0.15	0.4	0.17	**0.7***
RBF1	Softmax	identity	0.22	0.47	0.3	0.72	0.32	0.6	0.44	**0.4***
RBF2	Exponential	identity	0.09	0.3	0.17	0.95	0.13	0.36	0.15	**0.9****

The result of examining different functions of ANN for predicting hourly changes of HV less than 1 km for Zabol station in dry weather (Table 4) indicated that the highest accuracy of visibility estimation was related to MLP4 model; because calculated errors by using this function for training and testing data were less than 0.5 and R was estimated more than 0.9 between observed and predicted data in both training and testing states. Then, according to this function, the diagrams of fitting between measured and predicted values of HV using training and testing data were drawn and presented in Figs. 8 and 9, respectively. Finally, the impact level of each variable was computed according to MLP4 function, which its results are shown in Fig. 10.

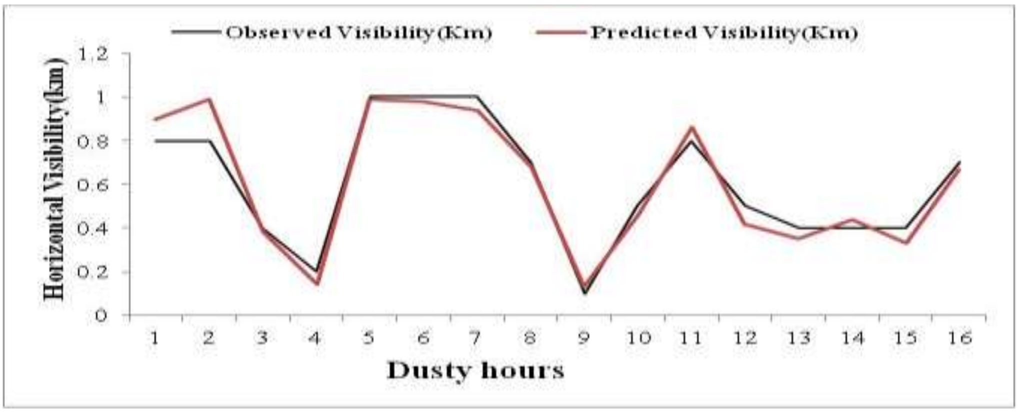

Fig. 8. The diagram of observed and predicted HV changes based on the MLP4 function in Zabol Station for training data (under humid condition)

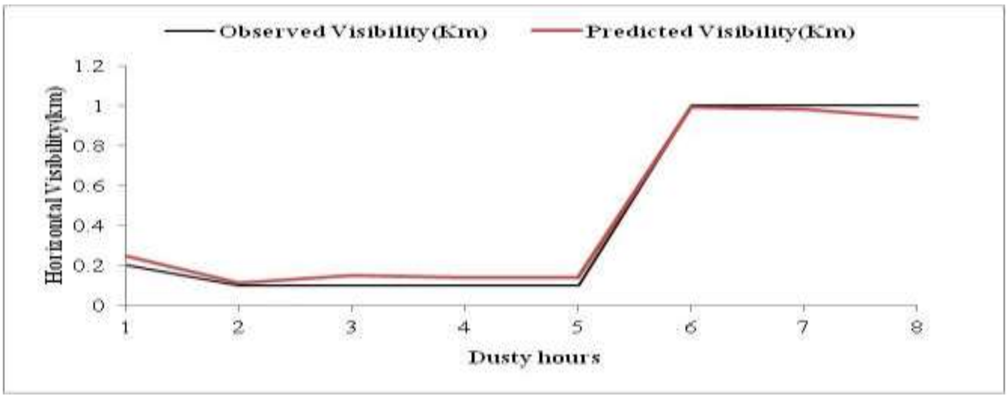

Fig. 9. The diagram of observed and predicted HV changes based on the MLP4 function in Zabol Station for testing data (under humid condition)

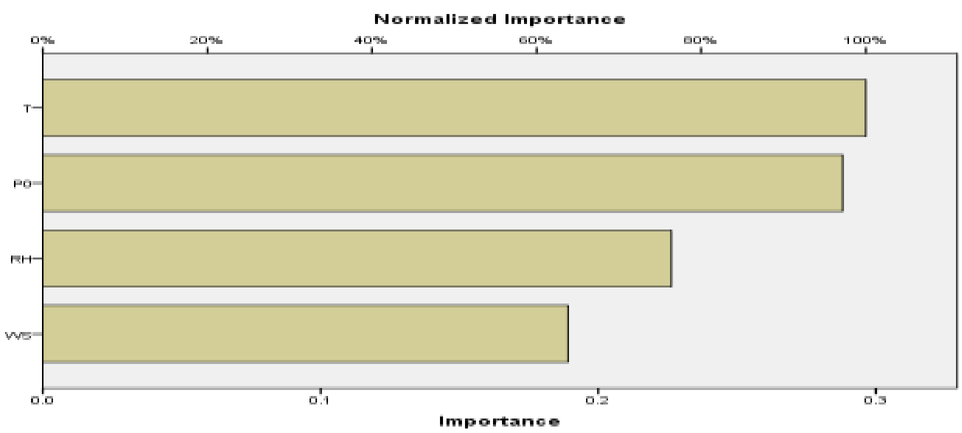

Fig. 10. The Importance of the effective variables on HV changes less than 1 km under humid condition

As presented in Table 2, the changes in temperature, atmospheric pressure, relative humidity, and surface wind speed had the most effect on the occurrence of dust and sand storms in the humid climate of the region. The relative importance effect of each of these parameters was estimated by MLP4 as 30%, 29%, 22%, and 19%, respectively. Comparing the results of the climatic conditions at the time of the occurrence of dust events indicates that the relative importance of each of the climatic variables was different under dry and humid weather conditions. In particular, the impact of wind speed changes on HV changes was significantly more than other factors in a dry climate; nevertheless, temperature and atmospheric pressure were among the most effective factors on the dust and sand storms occurrence and HV changes in humid climate at dusty hours of Zabol city. Although this the first study that surveyed separately the detection of effective climatic factors on HV changes arising from dust event in a humid climate in Iran, the results of the current research cannot be compared to the previous results. In this regard, the role of climatic changes arising from the global warming on the severity of dust events has been proved in most studies such as the one conducted by Eskandari et al. (2016), which can confirm the results of this stage of the present research.

Generally, the results of this study showed that MLP neural networks, and particularly using MLP4 function, outperforms other ANNs in predicting the hourly changes of HV based on the meteorology parameters. This result also is consistent with the results of the study conducted by Chaudhuri et al. (2015). One of the main reasons for this congruency is the flexible potential of these functions for solving the complex problems associated with natural resources. Therefore, based on the findings of this study, the use of the MLP4 function to predict horizontal hourly variations under both humid and dry weather conditions is recommended for other regions with a climate similar to the study area.

4. Conclusion

The current research was conducted to analyze the different functions of the neural network to predict the hourly changes of horizontal visibility (HV) under dry and humid weather during 5 years (2013-2017). For this purpose, four climatic parameters (i.e., temperature, relative humidity, wind speed, and atmospheric pressure) were selected as the effective independent variables at the time of dust events less than 1 km. After ensuring that there is no co-linearity effect of these variables by using the variance inflation factor (VIF), all independent variables were transferred into ANNs in order to predict the dependent variable (i.e., HV). The results analyzing the ANNs with different functions in both dry and humid conditions using statistical criteria (R, MSE, MAE, and RMSE) indicated that MLP outperforms RBF. Furthermore, among the conducted MLPs, MLP4 with the hyperbolic tangent function from input to hidden layer and sigmoid activation function from hidden to output layer was determined as the most appropriate function for predicting the hourly changes of HV less than 1 km. Pearson's coefficient of correlation (R) was estimated at 65% between the observed and estimated HV under dry condition. This result indicates that 65% of dependent variable changes (HV) depended on the changes of climatic parameters, of which, the impact of wind speed was more than the other three parameters. Pearson correlation coefficient was estimated at 90% to establish the relationship between observed and predicted amounts in humid weather. This coefficient showed the significant effect of climatic parameters on HV changes in this weather, which among 4 studied parameters in this research, the impact of temperature and atmospheric pressure changes on dust events occurrence was more than other parameters, and also, creating a condition to reach a HV less than 1 km was more than two other parameters. Generally, these results demonstrate that the changes of climatic parameters play an important role in changing dust events or HV under both dry and humid climates, and particularly in humid weather condition. In other words, only 35% of the variations in dry air and 10% of the variations in wet weather have been influenced by other climatic parameters or changes in the physical properties of the land surface, which is suggested to be investigated in future research.

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