Research Note

Prediction of monthly rainfall using artificial neural network mixture approach, Case Study: Torbat-e Heydariyeh

Zabbah, I.[1], Roshani, A. R.[2*] and Khafage, A.[3]

1. Lecturer, Department of Computer, Torbat-e Heydariyeh branch, Islamic Azad University, Torbat-e Heydariyeh, Iran
2. Assistant Professor, Department of Water Engineering, Torbat-e Heydariyeh branch, Islamic Azad University, Torbat-e Heydariyeh, Iran
3. M.Sc. Graduated, Department of Computer, Torbat-e Heydariyeh branch, Islamic Azad University, Torbat-e Heydariyeh, Iran

Abstract

Rainfall is one of the most important elements of water cycle used in evaluating climate conditions of each region. Long-term forecast of rainfall for arid and semi-arid regions is very important for managing and planning of water resources. To forecast appropriately, accurate data regarding humidity, temperature, pressure, wind speed etc. is required.This article is analytical and its database includes 7336 records situated in 11 features from daily brainstorm data within a twenty year period. The samples were selected based on a case study in Torbat-e Heydariyeh. 70% were chosen for learning and 30% were chosen for taking tests. From 7181 available data, 75% and 25% were used for training and evaluating, respectively. This research studied the performance of different neural networks in order to predict precipitation and then presented an algorithm for combining neural networks with linear and nonlinear methods. After modeling and comparing their results using neural networks, the root mean square error was recorded for each method. In the first modeling, the artificial neural network error was 0.05, in the second modeling, linear combination of neural networks error was 0.07, and in the third model, nonlinear combination neural networks error was 0.001. Reducing the error of forecasting precipitation has always been one of the goals of the researchers. This study, with the forecast of precipitation by neural networks, suggested that the use of a more robust method called a nonlinear combination neural network can lead to improve men is in for cast diagnostic accuracy.

Keywords: Monthly rainfall, artificial neural networks, experts' mixture, Torbat-e Heydariyeh Precipitation.

1. Introduction

Precipitation is one of the most important research factor in natural resources, and because of its fluctuations and irregularities, predictability and recognition of influential factors in the process are important. Precipitation forecast is important for investigation of groundwater, flooding, sedimentation and water balance. It depends on various factors including humidity, temperature, wind speed, pressure, etc. Rainfall is a non-linear phenomenon, which is difficult to forecast. Over the past few years, artificial intelligence techniques have been frequently used to predict the nonlinear time series such as for rainfall and achieved good results (Kisi, 2008; Nourani et al., 2011). A neural network model that use multi-scale input data can present more suitable prediction performance rather than a single input. (Alizdeh et al., 2015; Nourani, et al., 2009; Okkan, 2012; Rajaee et al.,

2010). Generally, using soft computing techniques such as Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Wavelet Neural Network (WNN) has the potential to reduce the computation time and effort and the possibility of errors in the calculation. Gazzaz et al. (2012) developed an ANN model for the prediction of water quality index for Kinta River. Some other research for rainfall predictions, done by different intelligence method include:
Nasseri (2011) forecasted rainfall in Fars, Iran and Australia using neural networks and PACF, and compared the results with genetic algorithm. He compared cumulative discrete network and self-made modeling and concluded that self-made cumulative modeling showed more efficiency to forecast. He also claimed that by reducing types of input, network training would be accelerated

*Corresponding author: ar.roshani3380@gmail.com

and more varied networks would be tested. Halabiyan (2011) forecasted rainfall in Isfahan using artificial neural networks. Their results showed that because of the decrease in data swing range, it would be better to use logarithmic functions for normalization, and the most appropriate kind of artificial neural network to forecast the rainfall for the next month was a network with a hidden layer. Khalili et al. (2016) used artificial neural networks to forecast rainfall accurately. Shafei et al., Aksory and Dashmeh (2009) forecasted one-month rainfall in three stations (A, B, C) with different regional conditions, and compared the results with MLR regression. They concluded that for stations with humid and arid conditions, FFBP and MLR were more appropriate models respectively. In another study, Bustami et al. (2007) forecasted rainfall and water level using artificial neural network technique in Boudap, Malaysia. Their results showed that artificial neural networks could forecast rainfall over a lake with 96.4% accuracy. Using neural networks, Fallah Ghalhery et al. (2010) forecasted spring rainfall in Khorasan Razavi, Iran, in a 37-year period (1970-2007). The results showed that neural networks could forecast rainfall accurately through all the period. Nastos et al. (2011) estimated the rainfall intensity in terms of (mm / day) in Athens, Greece. Chen et al. (2010) used SVM to scale daily precipitation and compared them with multivariate analysis. He indicated that the SVM results were more accurate than SVM forecasts. In order to forecast seasonal precipitation, Fallahi Ghaloery (2011), determined the meteorological signals affecting the precipitation of Khorasan province by Pearson correlation method. ANN has been used as an alternative tool to traditional deterministic rainfall-runoff modeling (Sirhan and Koch, 2013) and in forecasting groundwater levels fluctuation. Using the M5 tree model, Sattari and Nashin (2013) estimated the daily reference evapotranspiration in Bonab region and compared the results with the artificial neural network. Tryland et al. (2014) investigated the impact of rainfall on the hygienic quality of blue mussels and water in urban areas in the Inner Oslofjord, Norway. Sharma et al. (2014) examined the function of neural network models, fuzzy networks and fuzzy logic (ANFIS) simulation of rainfall-runoff processes in the Kohlar watershed of India. The results showed that the neo-fuzzy method was significantly better than the other two models in simulating the runoff rainfall process. It also functioned better than other models in forecasting minimum and maximum values. The traditional methods that are based on linear relationships are not good enough for solving these types of problems (Alizadeh and Kavianpour, 2015).

The purpose of this paper is to investigate the performance of mixture of neural network (mixture of experts) in a linear combination neural networks (LCANN) and nonlinear combination neural networks model (Gating network) for monthly rainfall forecasting to compare their performances with that of ANN Neural Networks models. The presented study is the first application for forecasting precipitation using ANN, and combination of them. The paper is organized as it follows: The second section analyses the data characteristics. The third section introduces methodologies, including artificial neural network, designing the neural networks as an expert. Combination of neural network in linear and nonlinear is discussed in the fourth section. The fifth section gets through with applications discussion of results. Conclusions are presented in the last section of the paper.

2.Materials and Methods
2-1. Geographical location of Torbat-e Heydariyeh

The city is located within 13.59-degree longitude and 16.35-degree latitude, Torbat-e Heydariyeh is 1333 meters above sea level. It is located in north-east of Iran. The city reaches from east to Taybad and Torbat-e Jam, from west to Kashmar, from north to Mashhad, Neyshabour and Fariman and from south to Mahvelat. Its area is 9945 Km^2. Shah Jahan and Jam mountains from north, and Kouh Sorkh and Kouh Mish mountains from south are surrounding it. In north and northwestern, it has a mountainous climate with a cold winter and a mild summer while in south it has a semi-desert climate with a hot and dry summer. Its average annual rainfall is 200 mm mostly in winter and spring and maximum and minimum

temperatures are 41 and 22 degrees Celsius, respectively. Maximum and minimum atmospheric moistures are 100% and 6%, respectively. Figure 1 shows the location of Torbat-e Heydariyeh.

3. Data

The data was collected for a 20-year statistical period from 1996 to 2016. The data contained 7336 samples with 11 parameters. The parameters included year, months, days, minimum temperatures, maximum temperature, average temperatures, minimum humidity, maximum humidity, average humidity, sun hours and wind speed. At the beginning of

the analysis, the data was analyzed using SPSS software. Then, the relationships between temperature, humidity, day, month, sunny hours and rainfall parameters (monthly) were investigated. The most common method for evaluating the relationship between precipitation and synoptic indices is to investigate the correlation between them. Therefore, using correlation coefficient and regression method, this relationship was investigated. Table 1 shows descriptive statistics of the data. Based on the stepwise regression test results, in the first stage, the average temperature and humidity are the most important of these parameters.

Figure 1. Situation of Torbat-e Heydariyeh.

Table 1. Descriptive statistics of data (1996 to 2016).

Feature	Pearson Correlation	Minimum	Maximum	Mean	Std. Deviation
Wind direction (degree)	0.034	0	360	171.53	111.30
Wind speed (m/s)	0.017	0	30	6.57	2.80
Sunny hours (hr)	-0.038	0	13.80	8.9	3.58
Rainfall (mm)	1	0	54.8	0.6	2.88
Moisture (%)	0.357	9.0	100.0	45.6	19.10
Temperature (C^0)	-0.162	-14	40	14.25	9.44

Figure 2 and 3 show mean moisture and mean temperature against the rainfall in 20 years.

4. Research Method
4-1. Monthly precipitation forecast using multi-layer perceptron neural networks
Multilayer Perceptron Model (MLP) is one of the simplest and most efficient proposed structures for using in real nerve modeling, which is formed by an input layer, one or more hidden layers and an output layer. In this structure, all neurons of a layer are connected to all subsequent neurons. This arrangement forms a network with full connections. Two types of signals are used in this network that vary with each other. The first type of signals are calculated based on the inputs of each neuron and the weight parameters and its corresponding stimulus function, and the second types are error signals that are calculated by returning from the output layer and splitting into the other hidden layers. The number of hidden layer neurons depends on the network designer's view and is obtained with trial and error. In the absence of sufficient neurons, the network will not be able to make accurate mapping between input and output vectors. At the output of each neuron of the MLP network, there is a linear function and the learning process takes place in all neurons and layers. All weights and biases that are on the network can change during the learning process (24). Figure 4 shows the structure of the neural network used in this study, which is of the 3-layered type.
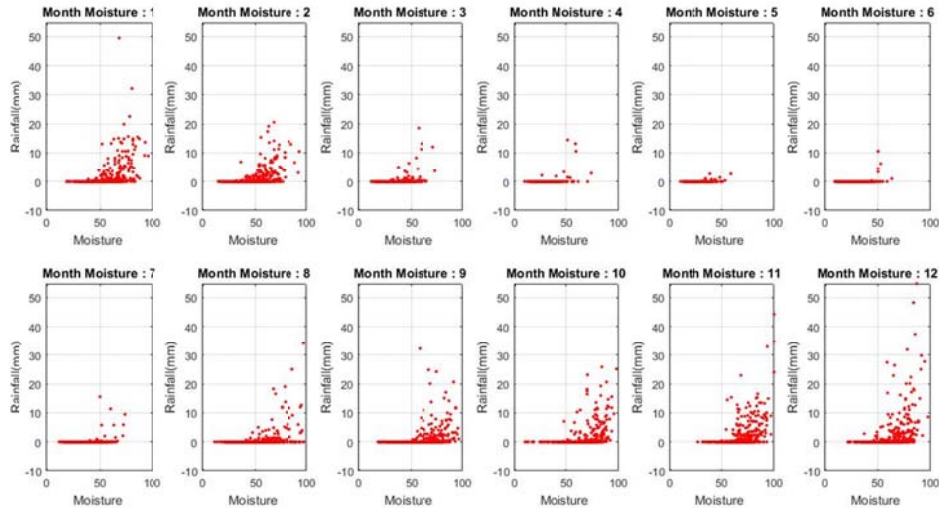

Figure 2. Monthly rainfall in terms of mean moisture in the 20-year period.
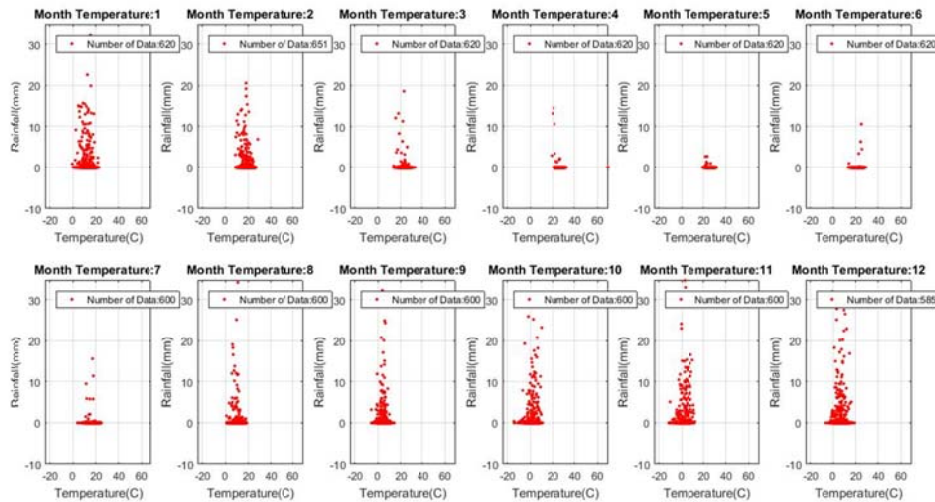

Figure 3. Monthly rainfall in terms of mean temperature in the 20-year period.

Table 2. Neural network parameters considering all input parameters. i is the variable between 10 and 100 neurons.

Neural network architecture	Training algorithm	Training parameters	Minimum error (RMSE)
1-i-10-11	Levenberg-Marquardt Back propagation	Learning Rate:0.05	0.0051

$$a_3 = f^3 (LW_{3,2} f^2 (LW_{2,1} f^1 (IW_{1,1} p + b_1) + b_2) + b_3 = y$$

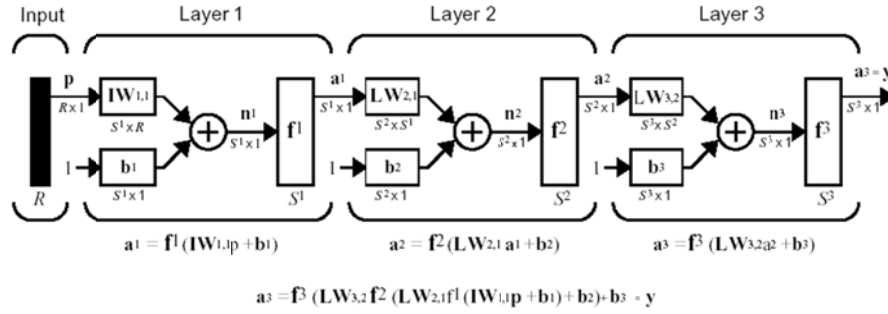**Figure 4.** 3-layered perceptron neural network architecture.

Equation (1) also illustrates the network output in the last layer.

$$O_i = sgm\left(\sum_m sgm\left(\sum_l x_i w_{lm}^h\right) w_{mi}^o\right) \qquad (1)$$

where h and o represent the hidden layer and the output layer respectively, and w is the weight of the layers. Sgm is also a sigmoid function defined as follows:

$$sgm(x) = \frac{1}{1+e^{-x}} \qquad (2)$$

In the present study, an artificial neural network with multilayer perceptron structure was used, and all parameters of sinentromium including month, day, minimum and maximum temperature, average temperature, minimum humidity, maximum humidity, humidity, sun clock, and wind speed were applied as input parameters to the network. In this research, 10 three-layered neural networks (one output and two hidden layers) with different architectures were designed to forecast precipitation with the specifications contained in Table 2. This network architecture was tested for the assumed database. The hidden layer neuron variations ranges are selected between 10 and 100 to provide the best network architecture. The result for the error of the variations of the neurons is shown in Figure 5. In order to select the best predictive model, three-layered artificial neural network models (approximately 50 structures) were investigated. In all of the above networks, 70% and 30% of the data were used in the training and the test stages respectively.
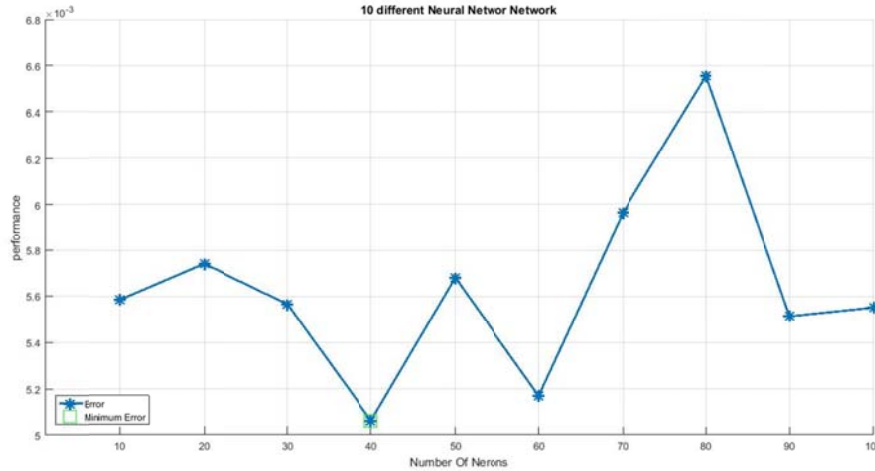

Figure 5. Error related to different architectures of multi-layer perceptron neural network in precipitation forecast.

4-2. Designing and training multiple neural networks as expert

If the number of neural networks increases, we can combine them with higher precision. Each of these neural networks is referred to as a basic expert. This variation causes some kind of variance in system performance; thus, if there are different experts and their results are used, the probability of error distribution is concentrated around the target and better results will be acquired. In order to get proper results from the combination of experts, each of the neural networks must have the following conditions:

Each expert should solely be at an acceptable level (not complete).

Each expert should complement the other; they should not be the same and produce the same result.

Considering the above conditions, several neural networks were designed. To achieve this goal based on the statistical analysis in Table 1, conducted with the SPSS software, the importance of features was investigated in the monthly precipitation forecasting. Then, five neural networks were designed and implemented. The data from this Table show that the "humidity" and "temperature" characteristics have the most effect on evaluating the precipitation. Therefore, these characteristics were used as the most important input parameters of the neural network in designing various experts. After designing five neural networks (N1, N2, N3, N4, N5) as the experts, the best neural network architecture must be investigated for each of them. The number of neural network layers and the number of neurons in the hidden layers are the parameters that regulate the neural network which can be effective in improving the accuracy of the neural network. Thus, for each of these neural networks, approximately 50 architectures were evaluated. Five neural networks which have been designed as experts, are shown in Figures (6-a) to (6-e). The sixth neural network in Figure (6-f) is in fact the gating neural network which considered the output

of each of the experts as the input with the structure of the best architecture referred to in the first sections of this article.

4-3. Combining neural networks (mixture of experts)

There are several methods to combine the experts, but in general, we can divide them into two linear and nonlinear categories. The most commonly used linear method is Majority Voting in which we summarize the views of each of the experts. One of the most well-known non-linear methods is Gating Network, in which the output of each expert is connected to the final network input. In this research, both linear and nonlinear methods of expert are used to forecast precipitation.

4-3-1. Linear mixture of experts in forecasting precipitation

One of the most common methods of linear combination methods is collecting expert opinions. The main motive for this is that in designing an expert system there are many choices, such as the display method, expert parameters, educational data, etc., and the results of several classifiers are as follows:

$$f_{com} = vote(f_1, f_2, f_3, f_4 f_5) \qquad (3)$$

The f1 to f5 are the five designed experts. In order to get a good result of the combination of experts, each one should solely be accurate enough; however, there is no need for high accuracy. Table 3 indicates that experts 1 and 2 have the best architecture because they have the lowest average error. The first one is related to the time, once five input parameters i.e., day, month, average temperature, average humidity and sun hour were involved in the network decision-making. The second network included input parameters of day, month, minimum temperature, minimum humidity and sun hour. Figure 7 illustrates the designed network error for each of the architectures listed in Table 3.
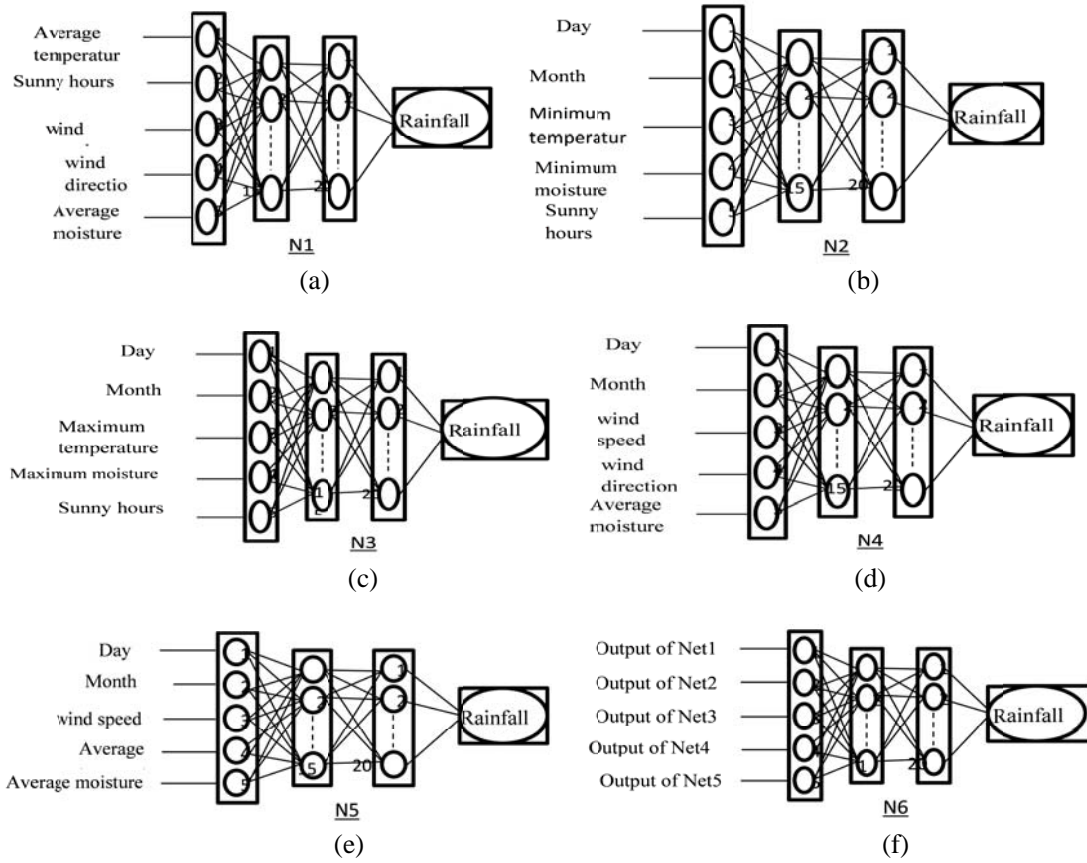
(a)   (b)

(c)   (d)

(e)   (f)

Figure 6. Designing five neural networks, as five experts with different inputs, **(a)** Designing a N1 network with inputs of average temperature - sun clock - wind speed - wind direction minimum humidity, (b) Designing N2 neural network with inputs of day-month- average humidity – minimum temperature – sun clock, (c) Designing N3 Neural Network with inputs of day - month - maximum temperature - maximum humidity – sun clock, (d) Designing N4 Neural Network with inputs of day- month - wind speed - wind direction - average humidity, (e) Designing the N5 neural network with inputs of day - month - wind speed - average temperature - average humidity, (f) Designing a gating neural network with inputs of six n1 to n6 networks.
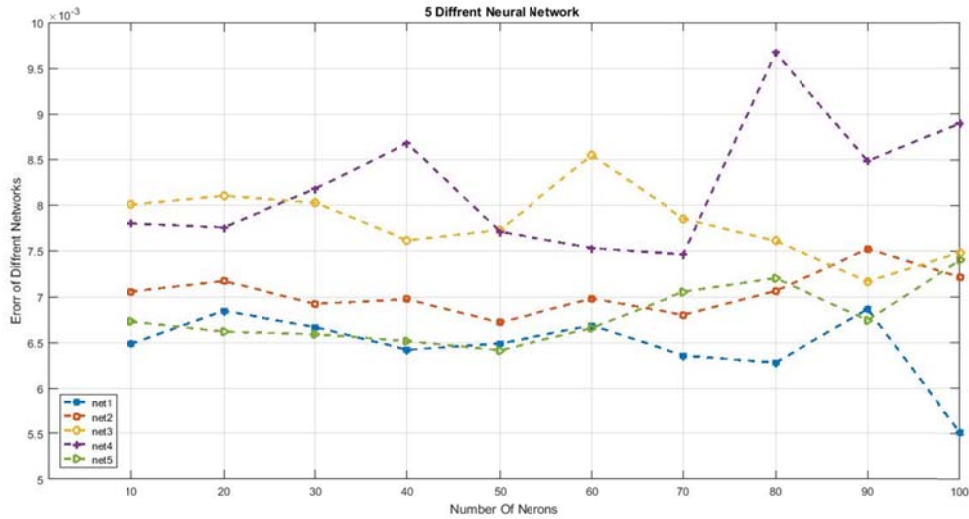

**Figure 7.** The error of networks from N1 to N5 (see text).

Table 3. The accuracy of each network alone and the average views of the experts.

Architecture (number of neurons in each layer)	network1	network2	network3	network4	network5	Average
5-10-10-1	0.0065	0.0071	0.0080	0.0078	0.0067	0.0072
5-10-20-1	0.0068	0.0072	0.0081	0.0078	0.0066	0.0073
5-10-30-1	0.0067	0.0069	0.0080	0.0082	0.0066	0.0073
5-10-40-1	0.0064	0.0070	0.0076	0.0087	0.0065	0.0072
5-10-50-1	0.0065	0.0067	0.0077	0.0077	0.0064	0.0070
5-10-60-1	0.0067	0.0070	0.0085	0.0075	0.0067	0.0073
5-10-70-1	0.0064	0.0068	0.0078	0.0075	0.0071	0.0071
5-10-80-1	0.0063	0.0071	0.0076	0.0097	0.0072	0.0076
5-10-90-1	0.0069	0.0075	0.0072	0.0085	0.0067	0.0074
5-10-100-1	0.0055	0.0072	0.0075	0.0089	0.0074	0.0073

4-3-2. Non-linear combination of experts in forecasting precipitation

One of the nonlinear combining techniques is using the Mixture of Expert method. The application of this technique is for situations where the issue is of a high complexity or when we want to improve the accuracy of the result. In this method, several MLP networks can be considered as classifiers, and depending on the input data, a mediating network may decide to learn which one of the experts or input data is more suitable for the network. In this method, the weights used for voting are based on inputs and are not constant. The output of the experts will be combined in a nonlinear final network. At the same time, each expert as well as gating network learn that how much weight is assigned to each expert to reduce the error. This will analyze the input space among the experts. It usually uses the Softmax method in the Gating network, so that the total weights become 1. Figure 8 illustrates how to combine artificial neural networks with the Gating method. In this stage, the outputs of the five networks are considered as the final input of the network. Figure 6.6 shows the designed pattern of this neural network. After designing the above network and applying the five network outputs to the network gateway input, 10 networks with different architectures were examined, and the error rate of each is shown in Figure 9.

$$E(x) = \frac{1}{2}(\sum_{i} g_i(x)f_i(x) - t)^2$$
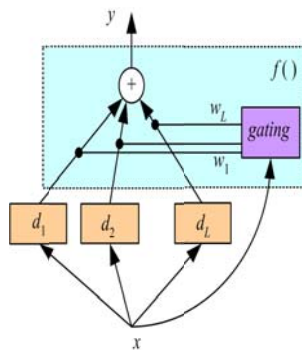
$$y = \sum_{j=1}^{L} w_j d_j$$

Figure 8. The combination of experts in the non-linear Gating method.
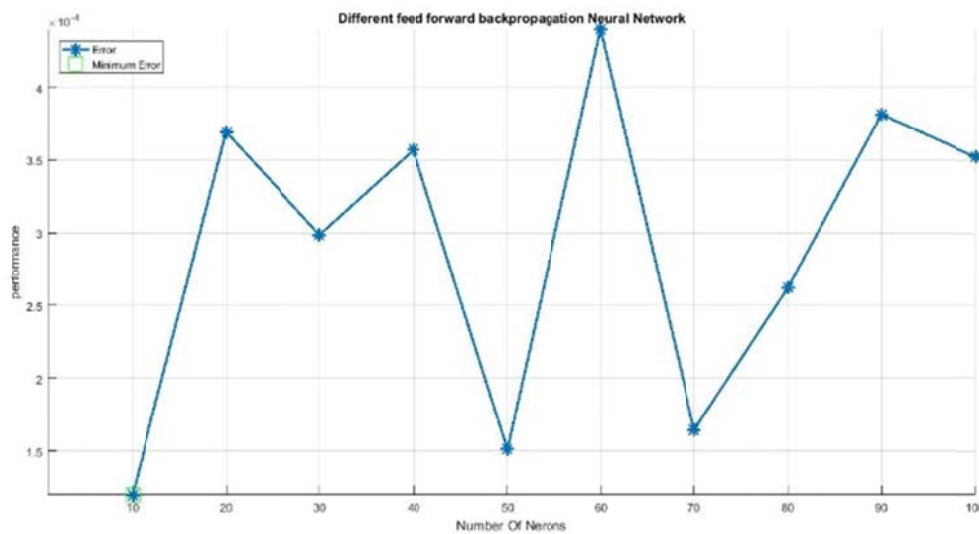
Figure 9. Designing 10 gating networks and calculating the error of each network.

As can be seen, the error of all networks is significantly reduced compared to the state where only one network was designed.

5. Conclusion

The ultimate goal of a pattern recognition system is to reach the highest possible classification rate for the desired problem. Since there is no classification algorithm perfectly suited to all issues, a mixture of experts is suggested as a solution to increase the efficiency of the classifiers. It has been proved that the combination of more independent classifiers leads to an increase in the recognition rate. Therefore, we generally try to increase the variety of the basic classifiers (Nasseri, 2008; Gholam Abbas, 2010). There are many ways to combine experts, including ECOC (Khalili et al., 2007) and Mixture of Experts (Bustami et al., 2007), Boosting (Barzay, 2006), each acts in a different way. For each basic classifier, the distribution of Boosting input samples is shifted to the direction for training in which the classifiers focus on harder samples. During the training of the experts, attempts are made to make them expert in a part of the entrance space and for a special action (Sattari and Nashin, 2013; Salajegheh

et al., 2008).

If we assume that "a" input parameter is effective on the occurrence of the phenomena, then the number of 2^n-1 significant combination of input parameters will be created. In order to model this phenomenon using ANN, investigating the technique of the created combinations to find the best combination would be quite time-consuming and boring. Therefore, once the factors affecting phenomena are high, using different methods, one can obtain the significance degree of the input parameters and the best combination among all possible combinations. To analyze the effective parameters, statistical analyzes were used and the significance of the features was measured by calculating the Pearson correlation coefficient. In the present study, a multi-layered perceptron neural network was used with a post-propagation algorithm, and all the input parameters into the precipitation forecasting system were also imposed. In the second stage, the focus of the nerve networks on the inputs was increased, i.e. instead of using one expert, several experts were designed and the number of input parameters was decreased. The results are shown in Table 4.

Table 4. Average of 10- fold modeling on five neural network to forecast –precipitation.

Model Number	Entrance parameters	Best network architecture	Data assessment based on RMSE
1	Average temperature - Average humidity - Wind speed - Wind direction - Sun clock	5-10-80-1	**0.0063**
2	Day - month - minimum temperature - minimum humidity - sun clock	5-10-50-1	**0.0067**
3	Day - month - maximum temperature - maximum humidity - maximum temperature - sun clock	5-10-90-1	**0.0072**
4	Day - month - wind speed - Wind direction - average humidity	5-10-70-1	**0.0077**
5	Day - month - wind speed - average temperature - average humidity	5- 10-50-1	**0.0064**
6	All 11 recorded parameters	11- 10-40-1	**0.0051**

In the second section of the study, one of the most common methods of linear combination, i.e. the averaging method was used. In the third section, a nonlinear method called the gating neural network was used. The main motive for this was that in designing an expert system there are many choices, such as the display method, expert parameters, educational data, etc. This variation causes some kind of variance in the performance of the system. Consequently, if there are different systems and their results are used, it is possible that the distribution of the error is centered near the goal and the better results is achieved by increasing the sampling of this distribution. Table 5 indicates the results of precipitation in Torbat-e Heydarieh using only one neural network with all 11 input factors and when the combination of neural networks was used with linear Majority Voting and nonlinear gating network.

Table 6 also indicates an example of the results obtained by the models presented in this study.

Since forecasting precipitation is a rather important issue, especially in a dry country like Iran, there are a large number of researches on precipitation forecast. In many articles, monthly data are used as input one, based on which precipitation is forecasted. In some cases, the forecast is based on an annual basis. However, in most cases, a common method is used to forecast precipitation. In this research, three different methods were used and their results are represented in Table 6, indicating that the method of combining the experts has been more accurate in forecasting monthly precipitation compared to nonlinear method.

Table 5. Precipitation estimation error of Torbat-e Heydarieh using the combination of neural networks in different methods.

no combination	combination averaging method	Combination with the gating neural network method
0.051	**0.0071**	**0.0015**

Table 6. Examples of forecasts by the presented models.

	April 2015	November 2009	March2006
Actual precipitation (Cm)	0.76	0.55	1.94
Using an expert	0.82	1.07	0.44
The combination of experts with the linear method	1.41	1.64	0.29
The combination of experts with the nonlinear method	0.85	0.36	1.89

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