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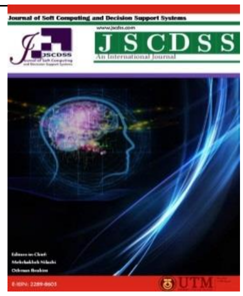

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The Precipitation Modeling through the CPSO-based Artificial Neural Networks

Hadi Bidokhti [a,*], Kazem Shokoohi-Mehr [b,*]

[a] Islamic Azad University of Gonabad, Department of Electrical Engineering, Gonabad, Iran
[b] Department of Electronics, Operational Aviation Branch, Birjand International Airport, South Khorassan Airport General Administration, Birjand, Iran

*** Corresponding author e-mail address:** hadi.bidokhti@gmail.com; k.shokoohi-mehr@airport.ir

Abstract

Precipitation has a random chaotic nature, which is hard to model and predict due to various involved parameters. Such affecting parameters include temperature, relative humidity, pressure, radiation, the average sunny hours, the humidity of ground surface and cloudiness. Given the importance of modeling and precipitation estimate in various areas, the current study deals with an effective model using three parameters; humidity, temperature and radiation. The simulation was conducted using real data for the Multi-Layered Perceptron Networks (MLP), the Radial Basis Functions (RBF) and the Compound Neural Networks based on the Particle Swarm Optimization algorithm (CPSO-ANN). From among the advantages this method has is the separate and concurrent examination of the impact of every three entry on the network and the display of the correlations. According to the simulations, the concurrent application of all of the three entries in the network along with the CPSO-ANN leads to an effective model with the minimum of Mean Squared Error (MSE) and appropriate extension capability.

Keywords: Precipitation Modeling, RBF, MLP, CPSO-ANN, MSE.

1. Introduction

The precipitation, because of it non-linear, complex nature, plays an important role in various subjects such as aerology, agriculture and watershed management so that the accurate prediction and modeling of it paves the way for the optimal storage of runoffs and floods. Considering the value of precipitation modeling and prediction, several studies were conducted using statistical techniques, classical and intelligent methods as well as Artificial Neural Networks in the recent years. Thus, the increasing use of Artificial Neural Networks in various areas, as a non-linear method to model and predict precipitation, caught the researcher's attention. To this end, Hung et al. predicted the precipitation in Bangkok using the Artificial Neural Network based on the tangent hyperbolic transitional function and some of the four-year-old parameters related to precipitation including wet bulb temperature, pressure, relative humidity and cloudiness (Hung et al., 2009).

The analysis of the accuracy obtained from the simulations showed that the most important parameter affecting the precipitation is the wet bulb temperature. Moreover, the Artificial Neural Network of Feed Forward Back-Propagation type and the Gradient Descent training algorithm were introduced to model the precipitation in Nigeria in which the best model selected on the grounds of Mean Square Error was obtained through the same number of knots in the entry and hidden layers (Onwukwe & Ikpang, 2015). The precipitation predictive system was also offered based on Data Core Based Fuzzy Min Max Neural Network (DCFMNN) with high accuracy (Palange et al., 2015). Devi et al. (2016) examined and analyzed a model for the prediction of daily precipitation using Nonlinear Autoregressive Exogenous Network (NARX). The results indicate the high capacity of this network based on Levenberg Marquardt algorithm (in order to update the weights). While estimating the monthly precipitation using two different structures, it was revealed that less variation in the rainfall leads to a better model with fewer errors (Purnomo et al., 2016). The estimate of the monthly rainfall was made through various assessment criteria including Mean Squared Error, Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) using accurate seasonal neural networks (Karthik & Arumugam, 2017). Moreover, a Neural Network in which the linear regression analysis had been used to examine the relationship between the vegetation index shown by the satellite and the rainfall data was offered to model the annual rainfall (Chanklan et al., 2017).

Through finding an effective model of precipitation, the local rainfall in any region could be accurately predicted so that an appropriate management and water storage is performed accordingly. Furthermore, the prediction of rainfall is of particular importance for preventing drought from happening without which specifying the extent and time of the drought is almost impossible requiring various complex management tools. Since precipitation is dynamic and non-linear, its modeling involves dealing with algorithms, data processing and non-linear equations with the help of computers. The non-linearity and uncertainty of precipitation prevent classical statistical methods from obtaining an accurate estimation of the affecting factors. Thus, the current study seeks to make use of an effective artificial network towards modeling such a complicated system. Several factors such as Humidity, Pressure, Temperature, Cloudiness and Seasonal or Climatic factors impact on the rainfall among which the most important ones have been used in the study to predict and model the precipitation.

This paper is organized as follows. The second section poses an introduction to neural and Multi-Layered Perceptron Networks as well as Radial Basis functions (RBF). The third section presents a brief explanation on the training of Neural Networks based on Levenberg Marquardt and CPSO, which have been used to model precipitation in the current study too. In the fourth section, in the form of three scenarios, the three networks are simulated using separate and concurrent inputs. Next, the results obtained from the three scenarios are compared. Finally, the fifth section concludes the discussion.

2. Neural Networks, MLP and RBF

The creation of an artificial intelligent system which is capable of learning, creativity, flexibility and generalization is an ultimate goal in the scientific research on the artificial intelligence (Ahani, Nilashi, Ibrahim, Sanzogni, & Weaven, 2019; Nilashi, Ahmadi, Shahmoradi, Ibrahim, & Akbari, 2019; Nilashi, Ibrahim, Ahmadi, & Shahmoradi, 2017). In this regard, Artificial Neural Networks find the hidden knowledge or rules and transfer them to the network system (Nilashi, Ahani, et al., 2019).

Such systems, which are based on computational intelligence, seek to model the neurosynaptic structure of the human brain according to the biological model it possesses. The human brain contains around 1010 neurons which themselves include inputs (dendrites), cell bodies and outputs (axons). Neurons become connected by weights or synopses. The cycling performed in an Artificial Neural Network consists of two important stages of training and testing. In the training stage, some sample data are added to the network as training models and the weights are modified so that the output of the model is closest to the real output. The extent of success in the training stage is measured by an error function. During the training stage, the weights are modified towards minimizing the error. In the testing stage, the input model is applied to the network, and the output is measured based on the model obtained from the network. Any Neural Network has features such as the way of connection between the neurons, the form of training in the network, the way of determining the values of the weights or type of the neuron stimulating function which make it distinct from the other ones.

2.1. The MLP Network

The Multi-Layer Perceptron Neural Network is one of the most common Neural Networks. It is considered as a feed-forward neural network which is capable of selecting an appropriate number of layers and neurons, creating a non-linear mapping out of the under-test system. The modifiable parameters in the networks (at the training process) involve the determination of appropriate values for the connection weights among the neurons. The most common algorithm for training these networks is the Error Back-Propagation algorithm.

The MLP network consists of an input layer, one or several hidden layers and one output layer. Through determining the appropriate number of the hidden layers and the number of neurons in each hidden layer, a model with the minimum of errors is achievable. Among the neurons of various layers are some connections with specific weights. During the process of training, the weights and fixed values (biases) are added and change continuously so that the minimum estimated error of the system and the real values are obtained. In order to transfer the output of each layer to the next layers, some transitional functions such as Logsig, Tansig and Purelin are used (Oludolapo et al., 2012).

2.2. The RBF Network

The networks of Radial Basis Function are extensively used for the nonparametric estimation of multidimensional functions using a complex of training data. The radial neural networks, due to fast and comprehensive training they offer, are considered very practical. These are in the form of feed forward ones with a middle layer the transitional functions of which are Gaussian and linear functions in the middle and output layers respectively.

The major difference between this type of network with the back-propagation error networks is that the former contains a middle layer and the neuron transitional functions are radial ones with specific center and width. Furthermore, unlike the back-propagation error network wherein the total weight of the neurons reached to the middle layer is measured as the input of the stimulating function, in these networks, the distance between each model and the vector of neuron center in the middle layer is measured to be as the input of stimulating radial function. The transitional function in the hidden layer of the RBF network is also shown in Eq. (1).

$$f(x) = \sum_{j=1}^{p} w_j . e^{-\frac{\|x-u_j\|}{\sigma_j}} \tag{1}$$

The equation shows that to approximate function f, p radial functions with the center of gravity u_j are used. The function used in Eq. (1), is a Gaussian or exponential one and σ_j is the i^{th} Kernel width factor (Oludolapo et al.,

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2012). In case the RBF network is used for the approximation of the function, the output will sound like a line, but if the classification of models is required, functions such as Sigmoid will be used for the output.

3. Training Neural Network

In order to get familiar with an Artificial Neural Network, a process of training is required, and what is important in this regard is that the network be capable of presenting respective outputs for each input vector which has not been taught. Generally, the goal of training in a neural network is to locate the best spots for all the training data. The current study first utilizes the optimization technique of Levenberg Marquardt, due to its quick convergence towards the final response, to teach the network. This method, as Eq. (2) shows, considers an approximation for the Hessian matrix while modifying the weights just as Newton method does.

$$X_{K+1} = X_k - [J^T J + \mu I]^{-1} J^T + e \qquad (2)$$

where X is the weight of the neural network, J is the Jacobian Matrix, a criterion for the performance of the network, which should be minimized. μ is the training-controlling number and e is the remaining error vector. When μ equals zero, the above equation is the same Newton method which utilizes the Hessian method, but when μ is a large value, the equation turns into an equation where Gradiant decreases as time passes. The Newton method is fast and the result it offers contains the minimum of errors.

In the recent years, various intelligent optimization techniques such as the Genetic algorithm, group optimization of particles, ant colony and gravitational search have been used for the process of training in the neural networks by the researchers. This paper also utilizes the PSO as a method of training the network. This algorithm, as an optimization technique based on group intelligence, is inspired by the social behavior and active movement of birds and fish. In this method, the search is for finding the model of group movements of the fish which look for a spot of bait. In this model, each fish sounds like a particle among many others. Among the particles, a fitness function, evaluates the appropriateness of a particle according to its location compared to the target. It is obvious that any particle in the search area which is closer to the target is more appropriate. Any particle bears a velocity and follows the other best particles in the search area. In the PSO, the movement of the particles scattered in the search area is made through the experience and knowledge the particles along with their neighbors gain. Therefore, the location and appropriateness of other particles affect the process of searching for a specific particle. The result of modeling such social behavior is a search process wherein the particles are directed towards some better spots in terms of fitness. The particles learn from one another, and based on the knowledge gained, they move towards their best neighbors. Therefore, the basis underlying this algorithm is the fact that anytime, each particle modifies its location in the search area based on the best spot where it has been and the best spot existing in its neighborhood.

After introducing the initial version of the PSO algorithm, in order to improve the capability of search in the search area, provide better responses and control the convergence velocity of the algorithm, Clerk and Kennedy developed the standard PSO algorithm by utilizing the constriction coefficient as a result of the theoretical analysis of congestion dynamics, and offered the CPSO algorithm where the velocity and place of each particle is updated through Eq. (3) and Eq. (4) (Mohammadi-Ivatloo et al., 2012).

$$V_{k+1}^i = x[V_k^i + C_1 r_1 (p_k^i - x_k^i) + C_2 r_2 (p_k^g - x_k^i)] \qquad (3)$$
$$x_{k+1}^i = V_{k+1}^i + x_k^i \qquad (4)$$

where $i = 1,2, \dots, N$ shows the particles of the population, V_k^i is the velocity of the particle and p_k^i and p_k^g are respectively the best experienced and obtained spots from among all the particles. In order to change the velocity of the particle to $Pbest$ and $gbest$, the permanent positive accelerations C_1 and C_2 are used, which are considered as self-learning and group-learning coefficients respectively. r_1 and r_2 are random ones (independent) with values between 0 and 1. Moreover, χ or the constriction coefficient is considered as a coefficient affected by C_1 and C_2 which is defined as follows (Sahu et al., 2012; Bharat et al., 2012).

$$\begin{cases} x = \frac{2}{\phi - 2 + \sqrt{\phi^2 - 4\phi}} & , \quad \phi = C_1 + C_2 \ ; \ \phi > 4 \\ C_1 = C_2 \approx 2.05 & , \quad x = 0.7298 \end{cases} \qquad (5)$$

4. The simulation of the Precipitation System Using Neural Networks

The meteorology data are basic at modeling the precipitation so that without collecting and processing such data, the prediction of the rainfall would be a hard task. In the current study, the monthly precipitation data in Birjand (Iran) through the years 1991-2017 have been modeled and simulated using three various neural networks. The input data consist of temperature, humidity and radiation while the output data are the monthly amount of rainfall the simulation of which was performed using Matlab software. Fig. 3 shows the general training and testing algorithm used to model the precipitation. In this regard, the MSE and the convergence of the three MLP networks, the RBF and the neural network have been respectively assessed based on Levenberg Marquardt training, the Error Back Propagation and group-based optimization of particles, and a network with appropriate extendibility and minimum MSE is selected as the best network for the precipitation system. At the stage of network training, various criteria such as calculations, the extent of errors and the number of datum application stages could be considered for the network. In this paper, according to Eq. (6), the achievement of zero MSE (Nilashi et al., 2018) is a point where the process of training stops.

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$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{actual_i} - y_{forecast_i}) \qquad (6)$$

where n, y_{actual_i} and $y_{forecast_i}$ are respectively the number of patterns, the real value of the variable and the predicted amount of the variable.

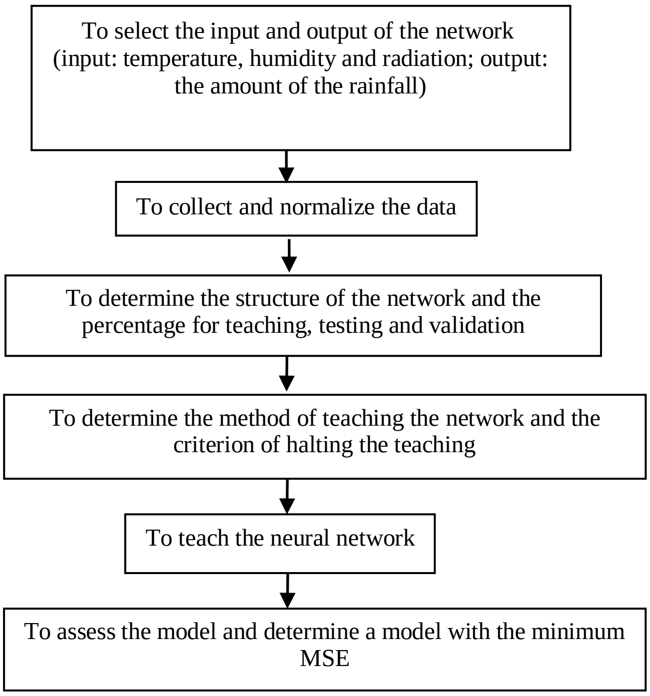

Fig. 1. The general stages of training and testing the network to model precipitation

As could be seen in the general algorithm of Fig. 1, the division of data is a basis in simulating neural networks so that if it is not done properly, the results obtained from the neural network would not be scientific. One of the most important features of neural networks is their extendibility. The training data are used during the training process and have specific values. The test data are not known and could be used after the training process. The validation data are used to determine the result of the training. The validation data do not halt anything and are simply used to specify the extent of success in the training process. It should be noted that these data are used during the training process, and so are similar to the training data. On the other hand, they could be called as unknown, which is similar to the test data. So, it could be stated that the validation data are some data between training and testing. For all of the three networks, the rate of training, testing and validation and number of the neurons in the hidden layer respectively equal 70 and 15 percent and 5. The transitional functions of the output in all of the three networks are also linear. The transitional function of the hidden layer of the RBF is a Gaussian type while the other two networks are of Hyperbolic Tangent type. The neural networks under study are assessed by applying three types of input data separately and jointly in the form of three scenarios.

4.1. Scenario One

In this scenario, upon applying three inputs of humidity, pressure and radiation to the MLP network, the results are studied after the simulation. These three inputs were separately and jointly applied to the MLP neural network for which the mean error of training and testing in 10 iterations of the network is shown in Table 1.

Table 1
The comparison of results obtained from the application of inputs to the MLP network

Data	MSE train Mean for 10 run	MSE test Mean for 10 run
Temperature	0.03261	0.04463
Humidity	0.02	0.03268
Radiation	0.02469	0.02164
Humidity + temperature	0.02054	0.04862
Humidity + radiation	0.02351	0.03345
Radiation + humidity	0.02119	0.0227
Temperature + humidity + radiation	0.0121	0.0137

In Fig. 2, the difference between the real values and the estimated ones at the MLP is shown. The error of the network upon applying the test data is also shown in Fig. 3.

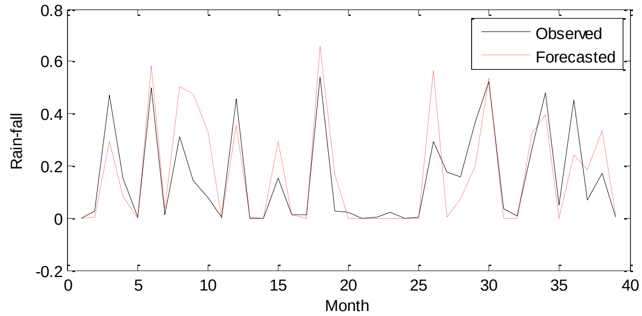

Fig. 2. The comparison of the real data of the monthly rainfall with the estimated ones by the MLP

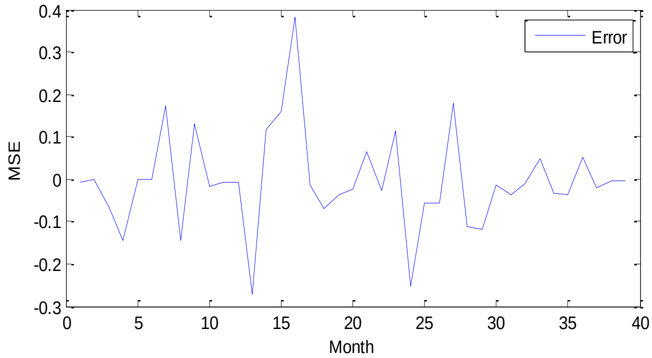

Fig. 3. The error of the MLP network upon applying the test data

Since in the neural network, not only the MSE is the criterion for assessing the appropriate performance of the network but the extendibility power of the network is important too, by running the MLP, the efficiency diagram of the network (training, validation and testing) could be shown for the precipitation data of Birjand as shown in Fig. 4. As is obvious from the efficiency curve of the validation data, this curve did not have any decrease at first and then increase after some epochs, which shows the inappropriate

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extendibility in the network. This problem is caused when the network suitably follows the models given to it, but any small change in the models cannot be answered by the network. Yet, as Fig. 6 reveals, since the validation curve has not risen after several epochs, and has been fixed in its position, the performance of the network and its extendibility could be trusted. Moreover, the validation error curve and the test error curve are so similar, and so there would not be a major problem in terms of training. As seen in the figure, the best performance belongs to the 30^{th} epoch, which shows the best neural network could be established in this position. It should be noted that given the enough data presented (several years of precipitation in Birjand), the validation is reliable.

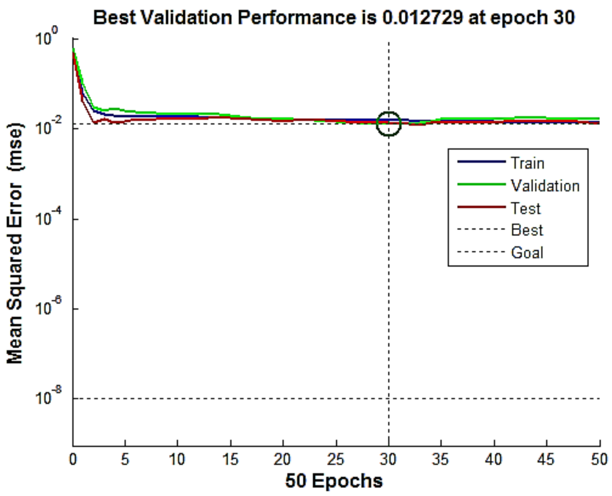

Fig. 4. A picture of efficiency curve for the precipitation data

4.2. Scenario Two

Like what was performed for Scenario One, various inputs were separately and jointly were applied to the RBF neural network the results of which are presented in Table 2.

Table 2
The comparison of the results obtained from applying the inputs to the RBF network

Data	MSE train Mean for 10 run	MSE test Mean for 10 run
Temperature	0.03216	0.04695
Humidity	0.02295	0.02312
Radiation	0.02678	0.01082
Humidity + temperature	0.02292	0.0269
Humidity + radiation	0.02535	0.02873
Radiation + humidity	0.0239	0.0269
Temperature + humidity + radiation	0.01574	0.01684

The comparison of monthly precipitation data with the estimated amount by the RBF network is shown in Fig. 5. The extent of error in the network based on test data is shown in Fig. 6.

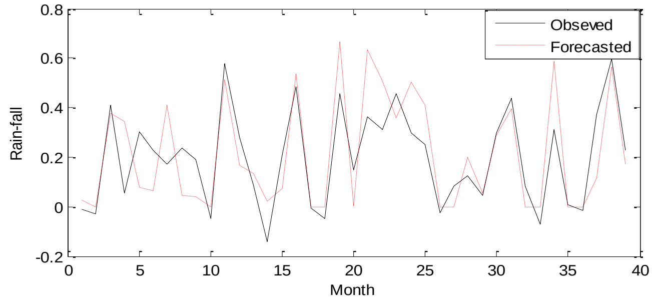

Fig. 5. The comparison of real values of monthly precipitation with the estimated amounts by the RBF network

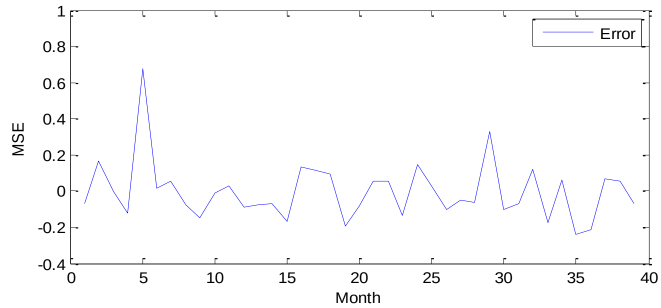

Fig. 6. The Figure of Error for the RBF Network

As could be seen in the results of the two networks, the application of the three inputs to the network improves its performance and shows the correlation among the three data. The MLP network also shows a better performance compared to the RBF.

4.3. Scenario Three

At this scenario, the intelligent algorithm of CPSO has been used to teach the network. In order to simulate and perform the network using this algorithm, the organization of the parameters is very important. Thus, in the CPSO algorithm, the initial population (number of particles) equals 40, the C_1 and C_2 indexes are 205 and the maximum of the algorithm iterations equals 200. Table 3 shows the results obtained from studying the network using various data like the previous two stages.

Table 3
The comparison of the results obtained from the application of the inputs to the ANN-CPSO network

Data	MSE train Mean for 10 run	MSE test Mean for 10 run
Temperature	0.03	0.0305
Humidity	0.0197	0.0206
Radiation	0.0201	0.0213
Humidity + temperature	0.0202	0.0251
Humidity + radiation	0.0239	0.0228
Radiation + humidity	0.02	0.0219
Temperature + humidity + radiation	0.0018	0.0023

Fig. 7 also compares the real and estimated data at the network.

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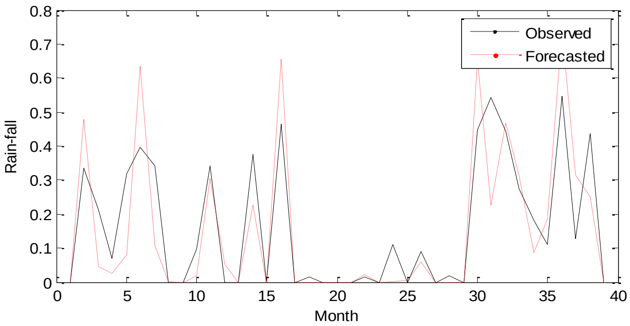

Fig. 8. The real and estimated data using the ANN-CPSO

Fig. 10 presents a sample of the MSE process decrease during the network training process using the CPSO algorithm and for 200 iterations.

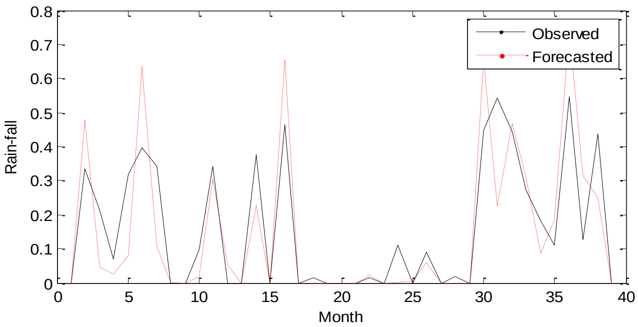

Fig. 8. A sample of the mse decrease using the ann-CPSO

4.4. The Comparison of the Results Obtained from the Three Networks

Given the mean values obtained from ten iterations of the three networks according to Table 4, it was revealed that the application of all the three inputs of temperature, humidity and radiation at the CPSO network can, at the same time of leading to efficiency and extendibility, decrease the MSE. Furthermore, using an MLP network compared to the RBF leads to better results. Therefore, by using a neural network based on particle group optimization algorithm, an approximate effective model for Birjand's precipitation is achievable.

Table 4
The comparison of the results obtained from training at the three presented networks

Method	MSE train	MSE test
MLP	0.0121	0.0137
RBF	0.01574	0.01684
ANN-CPSO	0.0018	0.0023

5. Conclusion

Various methods are used to predict hydrologic events such as precipitation. Since precipitation has a random, nonlinear and chaotic nature, using linear prediction methods, the achievement of an appropriate model for the system is not possible. Moreover, the uses of linear regression and Polly nominal models, as semi-linear methods, are not considered appropriate either. Here, the solution is to use non-linear methods one of which is neural networks which have been used in the current study because of the prediction capability of non-linear trends in order to model precipitation. The simulations using temperature, humidity and radiation were separately and jointly applied to the three neural networks, namely MLP, RBF and ANN-CPSO with the same number of neurons in the hidden layer. The results showed that firstly, given the good correlation of the three input data, the application of all the three ones to the network at the same time improves the estimation model of precipitation. Secondly, when the neural network is based on the CPSO algorithm, the accuracy of the process increases and due to fewer MSE and more extendibility, this network can lead to a better model compared to the other two in terms of monthly precipitation prediction.

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