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Prediction of Climate Change Induced Temperature Rise in Regional Scale Using Neural Network

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ABSTRACT: The objective of this paper is to develop an artificial neural network (ANN) model which can be used to predict temperature rise due to climate change in regional scale. In the present work data recorded over years 1985-2008 have been used at training and testing steps for ANN model. The multilayer perceptron (MLP) network architecture is used for this purpose. Three applied optimization methods are backpropagation (BP) (in both input selection and weight optimization), genetic algorithm (GA) (in both input selection and weight optimization) and combined GA-particle swarm optimization (PSO) (input selection by GA and weight optimization by PSO). In this framework, natural and anthropogenic parameters which affect the incoming solar radiation are considered in order to predict the climate change induced temperature rise in regional scale. Inputs of ANN model are mean temperature, dew point temperature, relative humidity, wind speed, solar radiation, cloudiness, rainfall, station-level pressure (QFE) and greenhouse gases. For predicting monthly mean temperature, input data include one month, six months, 12 months and 24 months before recorded data. In this work, nine stations namely Tehran, Mashhad, Ramsar, Orumiyeh, Sanandaj, Yazd, Ahwaz, Bandar Abbas and Chabahar in nine different climatic region of Iran are chosen to determine the temperature rise over Iran. Results show that the averaged minimum square errors (MSE) are 0.0196, 0.0224 and 0.0228 for ANN-BP, ANN-GA and ANN-GA-PSO methods, respectively. The ANN model associated with BP optimization method predict annual mean temperature rise as 0.44, 0.49, 0.20, 0.12, 0.17, 0.46, 0.41, 0.06 and $0.01\,°C$ after 10 years for mentioned stations, respectively. These values show the average temperature rise of $0.26\,°C$ after 10 years (the base year is 2008) for Iran.

Key words: Climate change, Temperature rise, Neural network, Back propagation, Genetic algorithm, Particle swarm optimization

INTRODUCTION

Since the start of the industrial era production of greenhouse gases due to human activity has caused most of the warming observed and it cannot be satisfactorily explained by natural causes alone (Cui *et al.*, 2011; Quesada-Rubio *et al.*, 2011; Montero Lorenzo *et al.*, 2011; Zou *et al.*, 2011). For the most recent 50 years most of the increase in greenhouse gas concentration took place (Kiehl 1997). The latest International Panel on Climate Change (IPCC) report shows that global surface temperature will likely rise a further 1.1 to $6.4\,°C$ during the twenty-first century (Solomon 2007). Scientists around the world have studied the effect of greenhouse gases on temperature rise (Nava-Martinez *et al.*, 2011; Wang *et al.*, 2011) , but in regional scale there is not enough research in this area. In recent years, the results and application of artificial neural networks (ANNs) have been published in many papers, and ANN models are useful tools in solving many problems in many fields such as classification in industry, engineering, prediction, control, environmental sciences, and meteorology (e.g., McCann 1992; Boznar *et al.*, 1993; Jin *et al.*, 1994; Aussem *et al.*, 1995; Bankert and Aha 1996; Eckert et al. 1996; Marzban and Stumpf 1996; Shao 1997; Noori et al. 2009; Nejadkoorki and Baroutian, 2012). Mpelasoka et al. (2001) applied multivariate statistical and ANN and multivariate statistics (MST) for climate change modeling in New Zealand. They presented that Climate change impact assessment requires data at the spatial and the temporal resolution at which impacts occur. Also, they adopted ANN and MST models to obtain changes of site precipitation and temperature characteristics in a comparative study of their potential in downscaling general circulation model (GCM) outputs. Smith et al. (2005) developed an

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enhanced ANN for short term temperature prediction. In this model 24 hours of prior weather data have been used as input data and short time prediction of temperature has been computed as output. Pasini et al. (2005) designed an ANN model for analysis of forcings and temperatures relationships at different scales in the climate system. A fully non-linear analysis of forcing influences on temperatures was performed in the climate system by means of ANN modeling. Two case studies were investigated, in order to establish the main factors that drove the temperature behavior at both global and regional scales in the last 140 years. Dombayc and Golcu (2008) published a paper about daily mean ambient temperature prediction using ANN method. The results show that the ANN approach is a reliable model for short term ambient temperature prediction.

In the present work, the area of Iran has been divided into 9 different climatic regions. Selected stations are Tehran, Mashhad, Ramsar, Orumiyeh, Yazd, Ahwaz, Bandar Abbas and Chabahar. The position of selected stations are shown in Fig.1. Here 10 monthly mean variables are considered as input data. Input data are considered in four delay time series including one month, six months, 12 months and 24 months past data. Three ANN model have been designed associated with three different optimization methods, i.e. backpropagation (BP), genetic algorithm (GA) and GA-particle swarm optimization (PSO) algorithms. Output of the designed models is monthly mean temperature data.

The remainder of paper is organized as follows. In section 2, the material and method presented. Results of applying ANN to predict the temperature rise are discussed in section 3 and in section 4, the paper is concluded with some key notes.

MATERIAL & METHODS

An ANN method is a new approach of statistical projection. In spite of the traditional statistical methods, ANN techniques are able to successfully generalize patterns that have not been previously captured, and to learn and simulate unanticipated and nonlinear characteristics of a time series without needing an insight into the underlying mechanisms (Shao 1998). The multi layer perceptron (MLP) is the

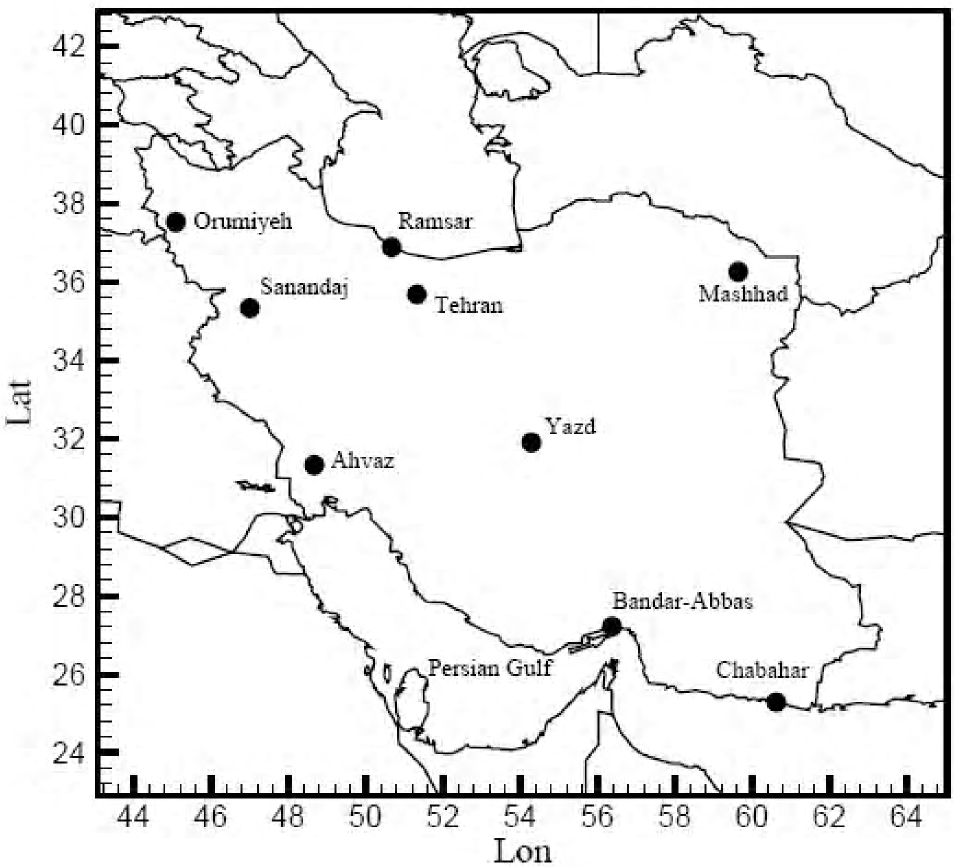

Fig. 1. Location of selected stations in region of Iran

most widely known and applied ANN algorithm (Nelles 2001). The restrictions and difficulties of perceptrons introduced by Minsky and Papert in 1969 have been significantly solved by the MLP architecture. The ANN consists of neurons that they only perform summation over weighted input data (independent variables) and pass them a nonlinear transfer function (tangents, sigmoid, etc.) to obtain a neuron output value i.e. dependent variable. (Oliviera *et al.*, 2006).

$$g(x) = \text{logistic}(x) = \frac{1}{1+\exp(-x)} \quad (1)$$

where $g(x)$ is the nonlinear transfer function that transforms the mapping results and x is an input variable (Nelles 2001).

In fact, An ANN model is a distributed computational system that combine number of individual processing elements operating largely in parallel, interconnect according to some specific architecture, and have the ability to self-modify connection strengths during the processing of element parameters (learning) (Haykin 1994). As an example the three-layer perceptron ANN with nonlinear transfer function is shown in Fig.2. It, in principle, is a universal approximator (Hornik *et al.*, 1989) and can be assumed as a set of nonlinear equations used to obtain the output variables from the input data. In the first layer, each input variable has its own neuron. The second layer is a hidden layer and it is expressed by several neurons. All the output of first layer passed to each neuron in the second layer (Fig.2). In the third layer this fully interconnected procedure is repeated again. Thus, the third layer has one neuron for each output variable (Oliviera et al. 2006). If several perceptron neurons are applied in parallel and are linked to an output neuron the MLP-ANN with one hidden layer is achieved. In basis function formulation the mathematical representation of MLP can be written as (Nelles 2001).

$$\hat{y} = \Sigma_{i=0}^{M} w_i \varphi_i (\Sigma_{j=0}^{p} w_{ij} u_j) \quad \text{with} \quad \varphi_0(.) = 1 \ \text{and} \ u_0 = 1 \quad (2)$$

where $\hat{y}$ is the output, w_i is output weight, w_{ij} is hidden layer weight, M is the number of hidden layer neurons, p is the number of inputs and u_j is input. Therefore based on above discussion, the MLP-ANN algorithm with three layers (one hidden layer) is used in this research.

The BP technique is an approach to calculate the gradients of output of an MLP network output with respect to its weights. In fact, the BP algorithm is equal to the using of the well-known chain rule for derivative calculation. However it is expensive in view of computational cost but it was found out within the ANN community how simply weights of hidden layer can be optimized. In order to optimize the hidden layer weights the BP algorithm answers to the credit assignment problem that its question is which fraction of the overall model error should be assigned to each

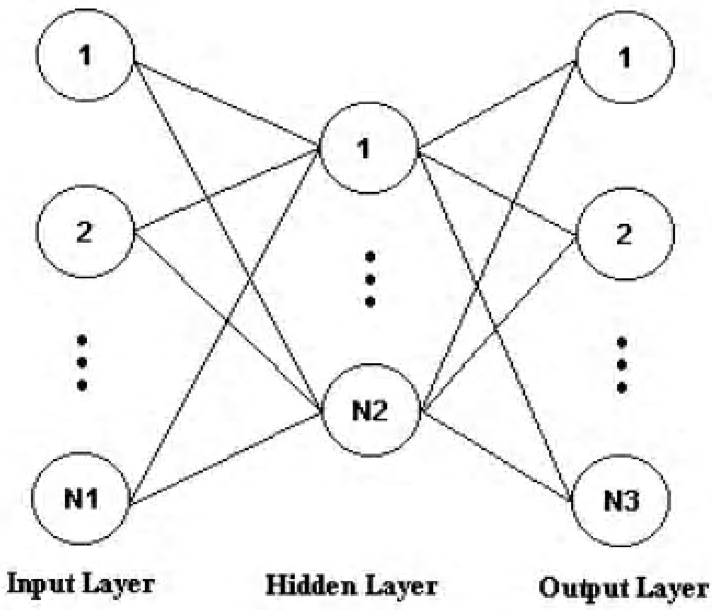

Fig. 2. A three layer neural network

of the hidden layer neurons (Nelles 2001). This work uses a standard, fully-connected ANN-BP with a single hidden layer as one of the three models and the BP algorithm is used in both input selection and weights optimization steps.

The GA techniques are global optimization methods based on idea of natural selection (Hernandez et al. 1995). The GA approaches have their origins in the 1970s (Holland 1975) and have been known to work better than the gradient descent methods, as well as simulated anealing, in numerous applications of numerical optimazion (Barth 1992). The GA approaches differ from many other optimization techniques in that rather than considering only the present value (and perhaps some past values) of the function to be optimized, they evaluate a population of values corresponding to different sets of variable of the objective function. This feature of the GA techniques permit the minimization to consider several possible global solutions at the same time. It maintain many solution points that may have the potential of being close to minima (local or global) in the pool during the coverage process. This is a manner of not getting stuck permaturately to a local minimum during the search process (Hernandez *et al.*, 1995).

A GA approach permits a population composed of many individuals to evolve under specified selection rules to a state that maximize the "fitness" i.e., minimizes the cost function. (Haupt 2004). A typical GA does its tuning in stages called generations. Usually, during the process of natural selection the average fitness of individuals will increase with each generation. In each successive generation, individuals with bad genes are eliminated while those with good genes reproduce their genetic code. The genetic code that determines the fitness of an individual is termed, logically enough, the chromosome of that individual. Given a chromosome, the GA approach should be able to approve its fitness (Lakshmanan 2000).The GA technique consists of two methods namely binary or discreet amounts and continuous amounts methods (Haupt 2004). Both of these GA techniques are used in this work, Binary GA for input selection and continuos GA for determining the weights of ANN model.

The initial ideas on particle swarms optimization (PSO) belong to Kennedy (a social psychologist) and Eberhart (an electrical engineer). This idea were essentially attempted at producing computational intelligence by employing simple analogues of social interaction, rather than purely individual cognitive abilities (Petalas *et al.*, 2007). Like to GAs, the PSO method is based on the population (i.e. the particle swarm) and fitness. An individual of the particle swarm (i.e. the particle) presents a solution. Two characters namely position and velocity are defined for each particle. The target function value corresponding to the particle position can be its fitness. In the algorithm, the fitness manifests the particle's performance. At the start time with a set of particles are considered as initial condition and then the optimum position is searched by iteration processes. During each iteration time, the particle is updated through searching two extrema including the best the best position found by the particle and the best position in the swarm at that time (Zhen-su *et al.*, 2006). All particles chose a direction to move and after that one step of the algorithm ends. This process is repeated several times until the desired answer is obtained. Actually the action of the mass of particles that searches for minimum of a function is similar to a group of birds that search for the food. PSO technique is something more than a collection of particles so that an individual particle have no power to solve any problem, but the problem can be solved when they communicate and interact with each other (Poli *et al.*, 2007).

Main input parameters of present ANN models are meteorological and environmental parameters. Meteorological parameters include mean temperature, dew point temperature, relative humidity, wind speed, solar radiation, cloudiness (clear and cloudy days), rainfall and station-level pressure (QFE) (1965-2008). Environmental parameters include the amount of greenhouse gases emission data. Data of greenhouse gases carbon dioxide, methane and nitrous oxide have been provided by National Climate Change Office that works for United Nations. Data are in the form of monthly mean values from 1965 to 2008. Trend of average temperature during this period is shown in Fig 3. As shown in Figure.3 in all stations temperature have risen during 1965-2008. For this, the modern statistical approaches like ANN model can be used to predict the temperature rise more preciously.

According to the number of delays considered for the 10 entries (4 delays for each input) number of neural network inputs is equal to 40. Considering the problem conditions and limited number of ANN data, the network is susceptible to overtraining. One of the factors is unwanted and unrelated input among specified 40 entries. In this phase of work we use BP and GA algorithm to select which inputs have the most effect on output. Thus, the input selection problem is an optimization problem that optimized answer is a chromosome among 40 pieces of 0 and 1 numbers leads to the lowest test error. Cost function of BP and GA algorithm gives 40 pieces chromosome and returns a test error. Each chromosome causes minimum test error leads to optimized ANN. We have 240 state of input selection that is a large number and because of this we use genetic algorithm.

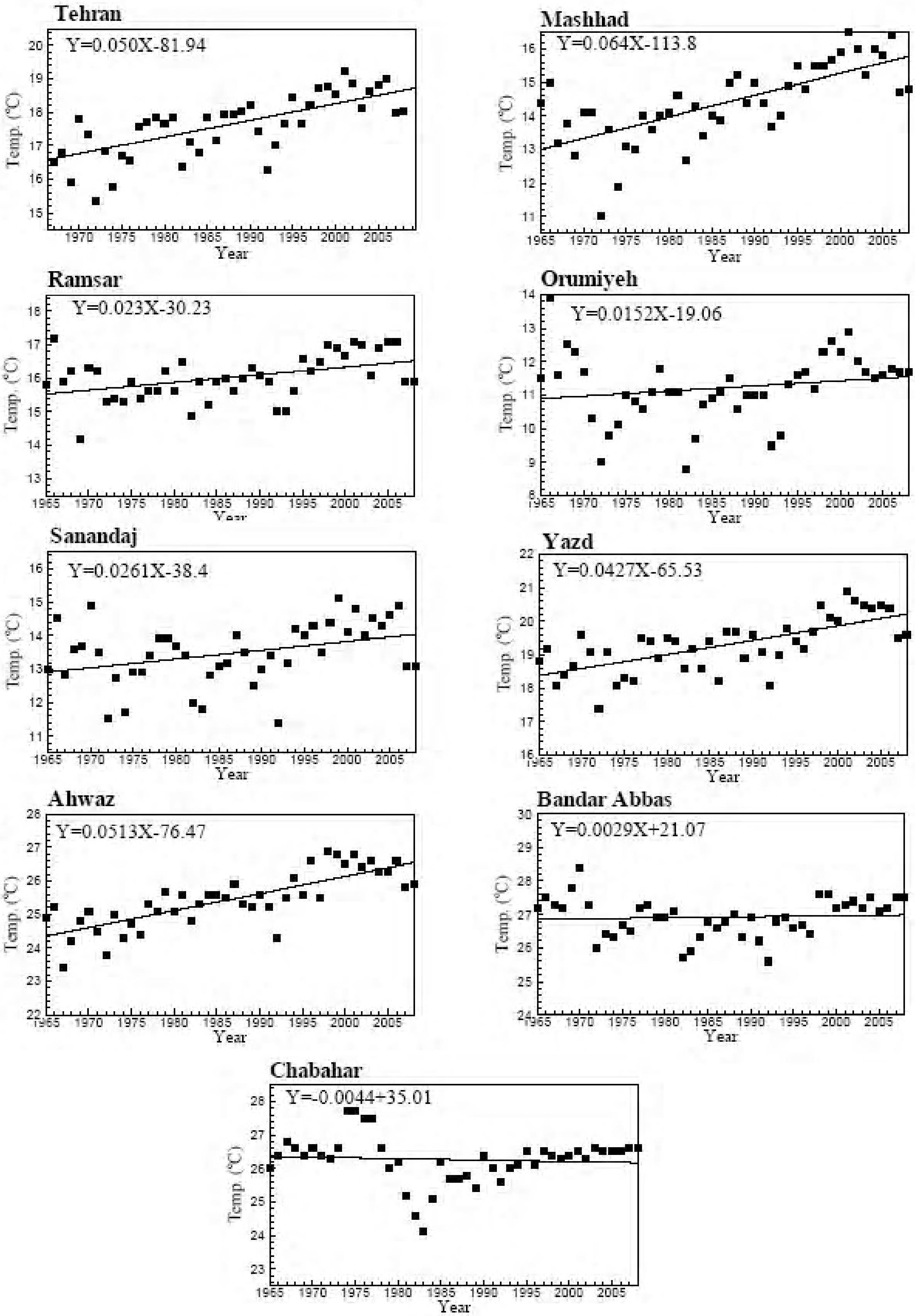

Fig. 3. Trend of mean annual temperature in nine selected stations during 1965-2008

Subsequently, we use the selected inputs and forecast the output for some steps in future. Network is trained using MATLAB ANN toolbox and BP optimization method. It should be mentioned that 80 percent of data is used as training data and 20 percent is used as testing data.

Learning problem of ANN is an optimization problem. Next to the gradient-based methods, evolutionary optimization methods are used for ANN learning. In this step we use BP, GA and PSO to determine the neural network weights. In this case chromosome string is ANN weights.

RESULTS & DISCUSSION

After introducing data to the ANN, air temperature for the next 10 years is predicted monthly. Input data are devided into two parts, 80 percent for training and 20 percent for testing steps. As mentioned in section 1 and 2, three different approaches for optimization are applied as

1. ANN-BP,
2. ANN-GA and
3. ANN-GA-PSO.

As an example Figs. 4 shows the correlation between normalized modeled temperature and normalized observed temperature ($x_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times 2 - 1$) for Tehran station for training and testing steps by ANN-BP (Figs. 4a), ANN-GA (Figs. 4b) and ANN-GA-PSO (Figs. 4c). Comparing Figs. 4a with Figs. 4b and 4c indicates that the ANN-BP approach works better than two others methods especially in testing step, but this comparison does not represent any quantified results. For this reason the minimum square error (MSE) is represented here. For all selected stations averaged MSE in training and testing steps are given in Table 1 for all selected stations. Table 1 indicats that the ANN-BP algorithm in comparision with ANN-GA and ANN-GA-PSO approach has less error in training and testing steps. Another comparision between these three approaches is shown in Fig.5. This figure compares the monthly mean temperature predicted by three metioned methods in the end of prediction time (2018). Also, in this figure the monthly mean temperature of year 2008 is shown as initial condition. As shown in Fig.5 the ANN-BP method in comparision with ANN-GA and ANN-GA-PSO methods predicts the monthly trend of temperature more correctly. This point is obviously seen in Fig.5 for Yazd and Ahwaz stations.

The predicted monthly temperatures using ANN-BP for each year are averaged and plotted in Fig.6. This figure shows the fluctuation of annual mean temperature during 2008-2018 that cannot be predicted by simple linear regression using climatological recorded data. Also, in Fig. 6 the best fitted line to these data is obtained. As shown in Fig 6, the annual mean temperature in all station increase. Using figure 6 one can obtain the increase of temperature compared to base year 2008. The temperature difference between the year 2018 and 2008 (based on obtained line) are given in table 2 for all selected stations using three different ANN methods. The predicted mean temperature rise for Iran region using ANN-BP method (preferred model) equals to $0.26\ ^{\circ}C$ and the temperature rise for Tehran station is $0.44\ ^{\circ}C$ after 10 years integration (2008-2018). Table 2 shows a distribution of temperature rise over regional scale of Iran. For visualizing the distribution of obtained data the predicted temperature rise over Iran are interpolated on grid points using inverse distance method. The contour plot of temperature rise is shown in Fig.7. However, this figure is not proper to obtain detail information because the number of stations is not sufficient for interpolation so that different interpolation technique result into the different detail data, but it can be used for general information that is the south-west to north-west belt of Iran is more sensitive to climate change and global warming.

CONCLUSION

In this paper three different ANN method including ANN-BP, ANN-GA and ANN-GA-PSO approach have been applied to predict temperature rise over regional scale. In this region (Iran) nine station s indicating different climate are chosen for test. Input data have been classified to two categories, namely meteorological and environmental data. One of the important results of this study is that the local search methods such as BP method show better results compared to global search method such as GA. Also, ANN-BP results obviously show the cyclic trend of temperature during a year better than two other methods and the local search method (BP) needs less computational time. Based on modeling of ANN-BP, it is predicted that the average temperature rise over Iran equals to $0.26\,^{\circ}C$ in 10 years. This value predicted by ANN-GA and ANN-GA-PSO equals to $0.41\,^{\circ}C$ and $0.35\,^{\circ}C$ in 10 years, respectively.

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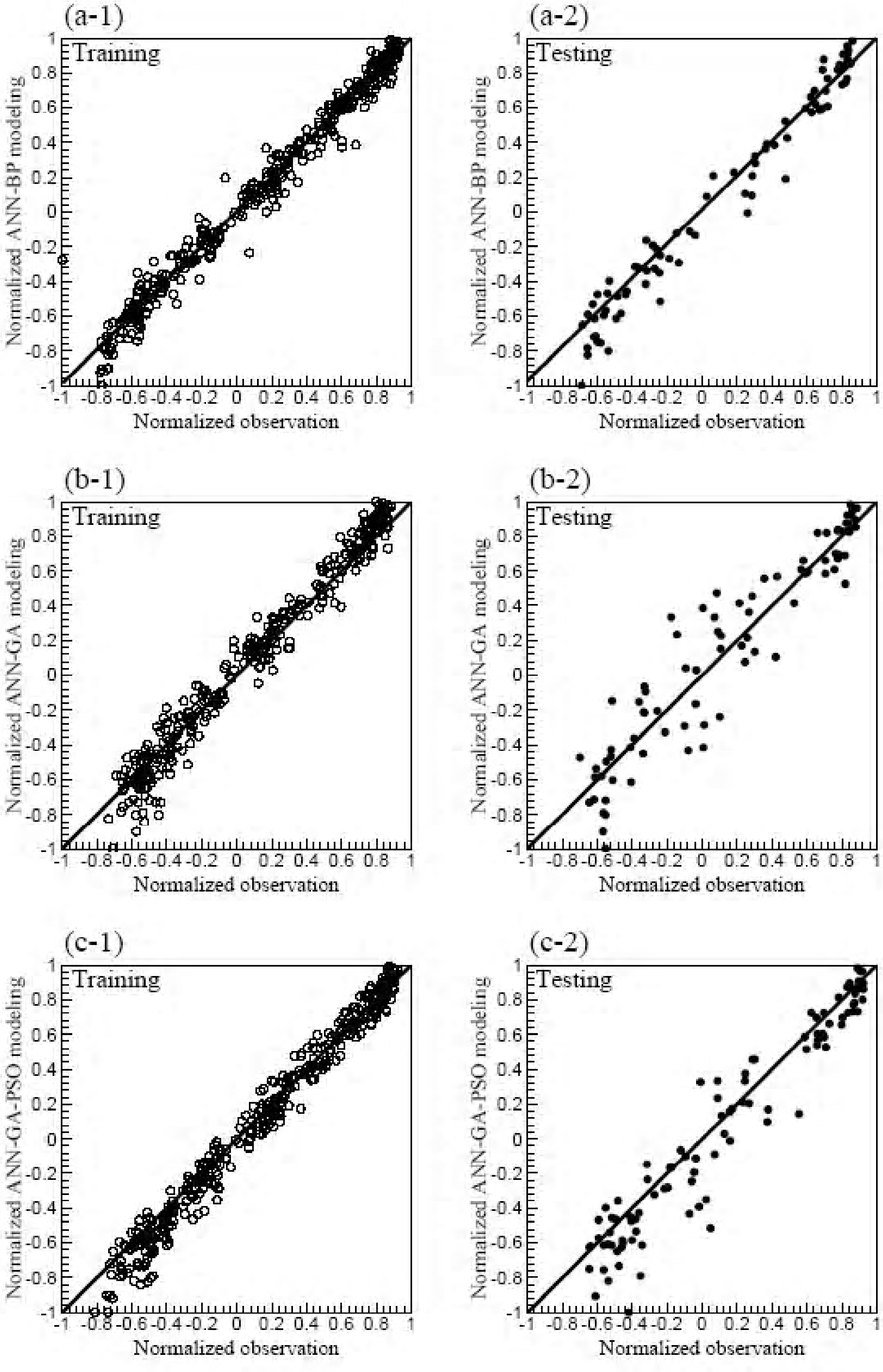

Fig. 4. Results of model for training and testing data using (a) ANN-BP method, (b) ANN-GA method and (c) ANN-GA-PSO for Tehran station. Left figures for training step and right figures for testing step

Table 1. Average MSE of training and testing steps for three different ANN model

Station	ANN-BP		ANN-GA		ANN-GA-PSO	
	Average of MSE (training)	Average of MSE (testing)	Average of MSE (training)	Average of MSE (testing)	Average of MSE (training)	Average of MSE (testing)
Tehran	0.0057	0.022	0.0193	0.0210	0.0187	0.0189
Mashhad	0.0064	0.025	0.0301	0.0369	0.0288	0.0285
Ramsar	0.0074	0.0313	0.0433	0.0403	0.0418	0.0437
Orumiyeh	0.0048	0.0271	0.0326	0.0357	0.0355	0.0361
Sanandaj	0.0082	0.0307	0.0228	0.0256	0.0179	0.0201
Yazd	0.0056	0.0214	0.0377	0.0360	0.0278	0.0265
Ahwaz	0.0082	0.0133	0.0188	0.0201	0.0377	0.0369
Bandarabbas	0.0077	0.0365	0.0290	0.0311	0.0258	0.0267
Chabahar	0.0084	0.028	0.0207	0.0218	0.0348	0.0368
Mean	0.0052	0.0196	0.0212	0.0224	0.0224	0.0228

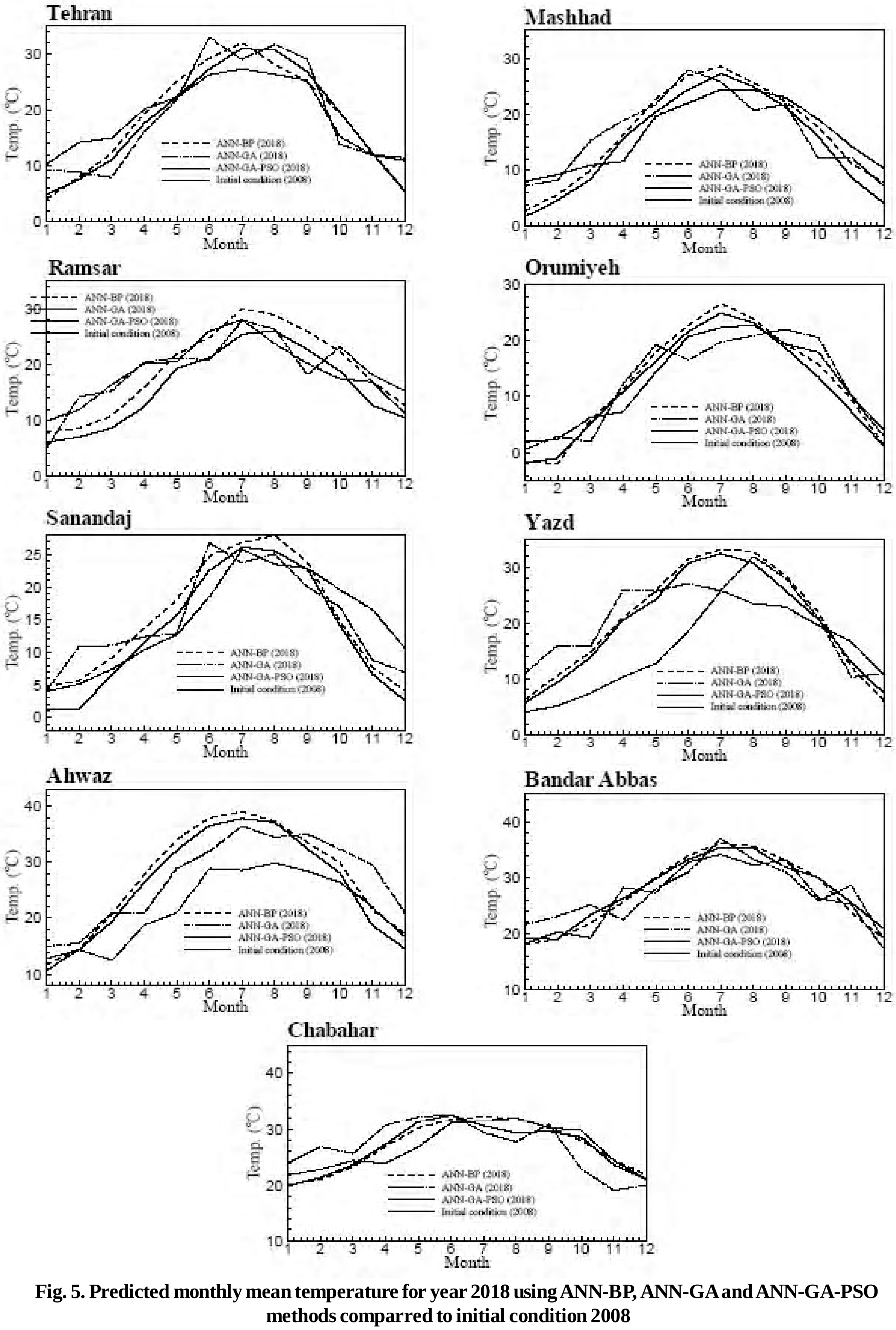

Fig. 5. Predicted monthly mean temperature for year 2018 using ANN-BP, ANN-GA and ANN-GA-PSO methods comparred to initial condition 2008

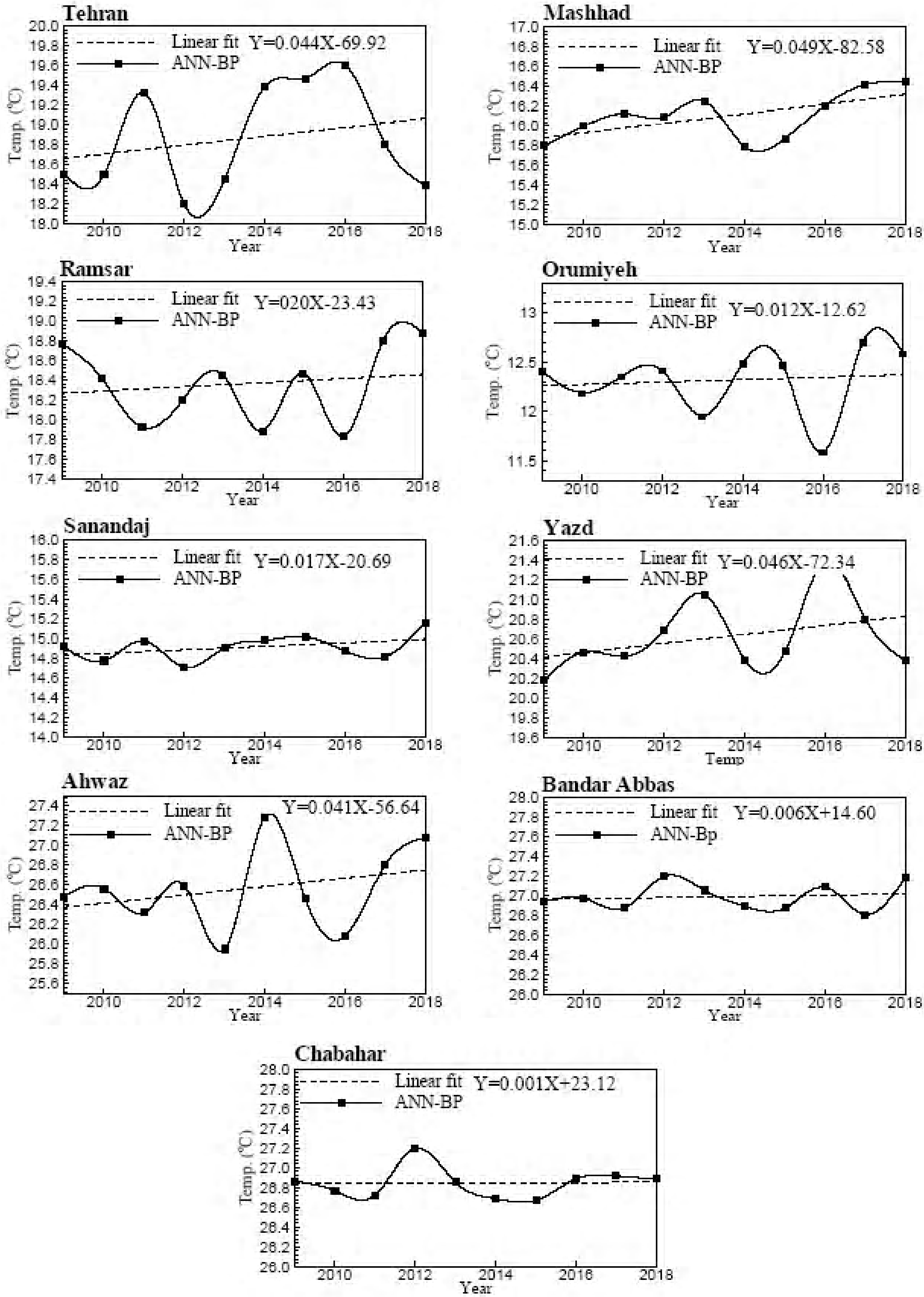

Fig. 6. Predicted annual temperature of selected stations using ANN-BP method

Table 2. Results of temperature rise for selected stations using three different ANN methods for year 2018

Station (City)	ANN-BP (℃)	ANN-GA (°C)	ANN-GA-PSO (°C)	Linear regression (℃) (Fig. 3)
Tehran	0.44	0.58	0.50	0.5
Mashhad	0.49	0.6	0.48	0.64
Ramsar	0.20	0.41	0.36	0.23
Orumiyeh	0.12	0.33	0.34	0.152
Sanandaj	0.17	0.30	0.28	0.261
Yazd	0.46	0.54	0.46	0.427
Ahwaz	0.41	0.59	0.49	0.513
Bandarabbas	0.06	0.21	0.15	0.29
Chabahar	0.01	0.16	0.11	0.044
Mean	0.26	0.41	0.35	0.34

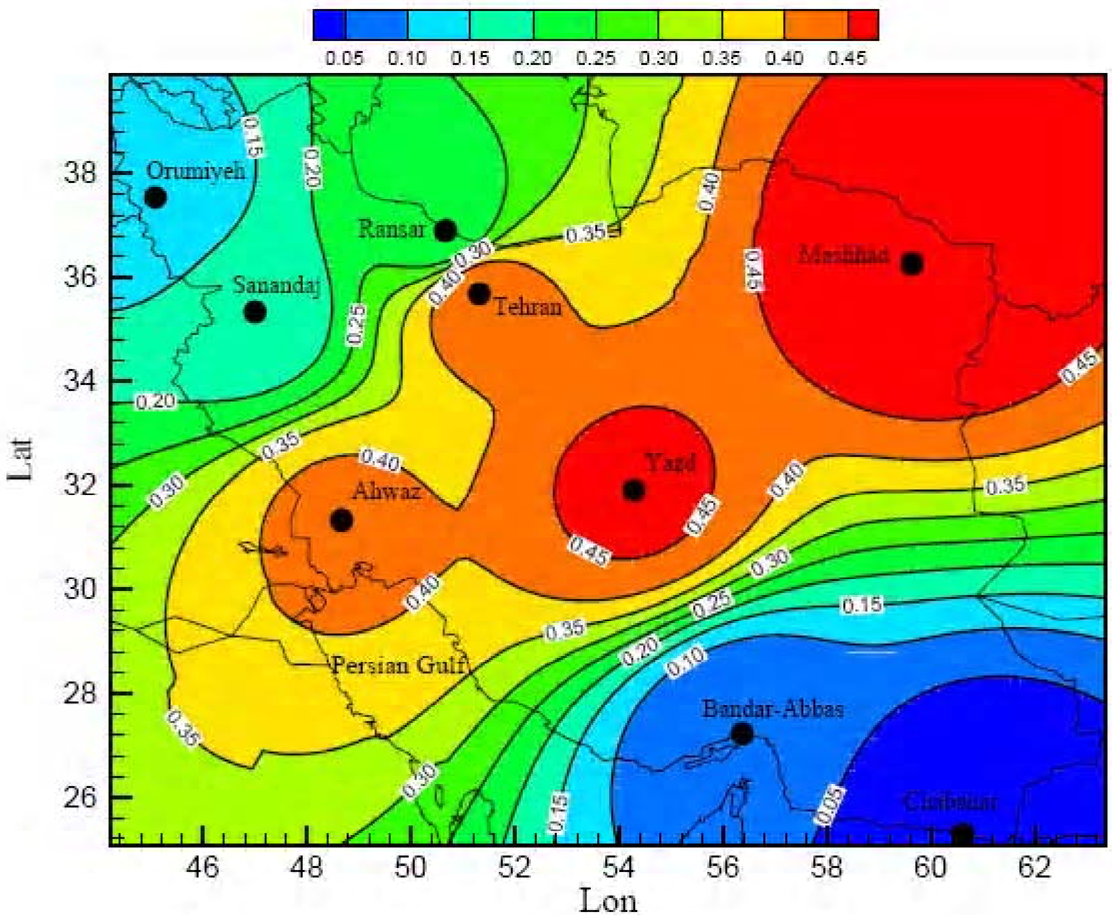

Fig. 7. Distribution of predicted temperature rise in °C over Iran for 10 years integration (2008-2018) using ANN-BP method

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