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FULL LENGTH ARTICLE

Modeling minimum temperature using adaptive neuro-fuzzy inference system based on spectral analysis of climate indices: A case study in Iran

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Abstract Nowadays, a lot of attention is paid to the application of intelligent systems in predicting natural phenomena. Artificial neural network systems, fuzzy logic, and adaptive neuro-fuzzy inference are used in this field. Daily minimum temperature of the meteorology station of the city of Mashhad, in northeast of Iran, in a 42-year statistical period, 1966-2008, has been received from the Iranian meteorological organization. Adaptive neuro-fuzzy inference system is used for modeling and forecasting the monthly minimum temperature. To find appropriate inputs, three approaches, i.e. spectral analysis, correlation coefficient, and the knowledge of experts,are used. By applying fast Fourier transform to the parameter of monthly minimum temperature and climate indices, and by using correlation coefficient and the knowledge of experts, 3 indices, Nino 1 + 2, NP, and PNA, are selected as model inputs. A hybrid training algorithm is used to train the system. According to simulation results, a correlation coefficient of 0.987 between the observed values and the predicted values, as well as amean absolute percentage deviations of 27.6% indicate an acceptable estimation of the model.

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1. Introduction

human beings have invariably been closely in touch with weather events. Owing to this fact, identification of the factors affecting long-term and short-term weather changes and also climate fluctuations is of particular importance. Since temperature is one of the most fundamental elements of climate formation and its changes may transform the weather patterns in any region, a large segment of climatology researches has been earmarked to the investigation of the temperature behavior in different time and location scales (Rosenberg et al., 1983; Smith et al., 2006; Majnooni-Heris et al., 2011). Temperature

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is one of the essential parameters of the weather and one of the few measurable thermodynamic variables. Modeling and prediction of temperature and particularly minimum temperature are of special importance in the fields of agricultural climatology, glaciation and frost management, water resources planning and management, irrigation networks, tourism and everyday life issues. Weather transformations are extremely volatile. These changes lead to the emergence of weather patterns and forms of weather flows which occur in different time scales. Large-scale transformations and synoptic factors have a great effect on temperature and the minimum temperature event is more related to transformation factors. Teleconnection patterns may be used in order to study and identify minimum temperature variations in short-term and long-term periods. The reason is the fact that teleconnection patterns can be in a way indicative of these large-scale transformations. Understanding the causes and the identity of climate changes is one of the most significant purposes of gathering climatology data and monitoring climatological phenomena. In this regard, climatological fluctuations caused by teleconnection patterns have taken on tremendous importance. Teleconnection is one of the climatic characteristics in the global scale. By means of this mechanism, the changes that occurred in the temperature or pressure pattern in a region of the Earth are transferred to other regions using large-scale systems and they affect weather conditions in different ways (Osborn, 2006, 2011). Teleconnection patterns typically possess fluctuating low-frequency behavior and they are used in order to forecast the average weather conditions during several-month or annual time periods. Figures indicating teleconnection patterns are called climate indices. Hence, it is crucial to study minimum temperatures according to these indices which represent the interaction of weather and environmental patterns and can play an important role in identifying short-term and long-term behaviors of monthly minimum temperature and the modeling thereof.

One of the important aspects of the analysis of time series is spectral analysis which deals with the analysis and decomposition of time series to components with different frequencies. Alternation and hidden cycles in the behavior of the climatic parameters are revealed in this method. Taghavi et al. (2011) presented a climatological regionalization for 65 synoptic stations of the Iranian Meteorological Organization using the spectral analysis method and clusterization. The spectral analysis method was used to investigate average temperature in northwestern Iran. According to the research findings, the temperature of the region contained a two-and-a-half-year period (Asakereh, 2010). The entire physical processes of the soil are directly or indirectly dependent on temperature. The daily and annual estimations of the soil temperature were carried out in different depths in six stations located in western Iran using the Fourier series analysis. In this research, the air temperature (2 m high) was merely used.

A review of different references indicates the existence of numerous models for the prediction of minimum air temperature which are used in order to investigate the solutions to combat the threat of frost and glaciation (Allen, 1957). Prediction of average daily temperature was carried out in Turkey using artificial neural networks (Dombayci and Gölcü, 2009). The adaptive neuro-fuzzy inference system is used as a new method for prediction (Jang, 1993). Air temperature forecast in northwestern Iran was carried out using a neuro-fuzzy inference system (Darbandi and Arvanaghi, 2009). Nayak et al. (2004, 2005) used intelligent systems in order to model precipitation-runoff. The results demonstrated that the non-linear model of precipitation-runoff is much more efficient in the adaptive neural-network-based fuzzy inference system, compared to independent neural and fuzzy systems. Rojas et al. (2008), Zounemat-Kermani and Teshnelab (2008), Wang et al. (2009), and Firat et al. (2009) separately compared the capability of ANFIS in predicting time series with that of other intelligent systems. The results indicated much better efficiency of this system compared to other intelligent systems. The adaptive neuro-fuzzy inference system was used to estimate daily evaporation in eastern Iran (Moghaddamnia et al., 2009a,b). In another research, meteorological parameters effective in the solar radiation level were determined using gamma test. The forecast of solar radiation level was then carried out using artificial neural networks and the adaptive neuro-fuzzy inference system (Moghaddamnia et al., 2009a,b). Ustaoglu et al. (2008) used three different intelligent system methods in order to predict minimum, maximum and daily average temperature. Kisi and Ozturk (2007) estimated the water requirement of the reference plant using the ANFIS system. Forecasting autumn droughts in eastern Iran was carried out using different input variables. Climatic indices, precipitation and the drought index were used as the input variables of the ANFIS system. The input variables were introduced to the model with zero-, one-, two-, and three-month delays. The results showed that appropriate inputs are different for different delays and using a certain input will not lead to optimum modeling (Hosseinpour Niknam et al., 2011). Among other researches in this context, the studies by Coulibaly et al. (2005) and Drake (2000) may be pointed out. Since temperature is one of the fundamental factors in climate formation and its changes can transform the weather patterns in any region, researchers have always paid attention to its prediction and estimation. To this end, numerous methods including intelligent systems such as the ANFIS system have been developed. This research aims at predicting the monthly minimum temperature of the region under study in order to combat frost and glaciation and the incidents caused by this environmental hazard. The appropriate inputs for the model were initially selected and then, the ANFIS system was used to forecast the monthly minimum temperature.

2. Material and methods

In this research, the statistical data pertaining to the monthly minimum temperature of the meteorology station of the region under study was used for modeling. The daily minimum temperature of the station was received from the Iranian Meteorology Organization for the 42-year statistical period since 1966–2008. Afterward, the monthly minimum temperature was extracted (1). The monthly values for 13 teleconnection indices were also extracted from the website of the National Oceanic and Atmospheric Administration in the same statistical period. The specifications of the station of the region under study are demonstrated in Table 1. In the subsequent step, the

Table 1 Specifications of the station under study.

Latitude	Longitude	Elevation
36 16 N	59 38 E	999.2 M

spectral analysis of the monthly minimum temperature and 13 teleconnection patterns was conducted using fast Fourier transform.

2.1. Fast Fourier transform

A proper mathematical transformation can be used for spectral analysis. From a general point of view, the purpose of applying a mathematical transformation to a series is to obtain extra data which are initially unavailable in the series. In most of the processing approaches, what is meant by the initial raw series is the respective series in the time domain. Most of the series, which are used, are practically in the time domain. In other words, the observations of the series are time-dependent, aside from what the respective series measures. It is obvious that this sort of representation is not the best for the description of a series. In many cases, the useful information of the series is hidden in its frequency contents, which is called the series spectrum. The spectrum of a series demonstrates the frequencies existing in that series. Fourier transforms are proper tools to measure the frequency contents of a series. In the 19th century, a French mathematician called Joseph Fourier demonstrated that every periodic function may be written in terms of an infinite summation of basic sine and cosine functions or a complex exponential function (Cartwright, 1961). This idea was generalized to other functions under the title of Fourier transform. Discrete Fourier transform should be used for discrete data. Due to lengthy calculations in the discrete Fourier transform method, a new algorithm called fast Fourier transform (FFT) may be used. This transformation is much faster than the discrete Fourier transform method in terms of calculation. The Fourier transform of the time series $x(t)$ is obtained via the following relation:

$$\mathrm{X}(\upsilon) = \sum_n x(t)\, e^{-j2\pi n\upsilon t} \tag{1}$$

where t represents time and υ is frequency. The reverse of the Fourier transform is expressed as follows:

$$x(t) = \sum_n \mathrm{X}(\upsilon)\, e^{j2\pi n\upsilon t} \tag{2}$$

The exponential term is written as follows:

$$e^{j2\pi n\upsilon t} = \cos(2\pi n\upsilon t) + j\sin(2\pi n\upsilon t) \tag{3}$$

Thus, what actually happens in a Fourier transform is multiplying the time series by a complex exponential function or a combination of two periodic functions with the frequency υ. In the next step, all of these products are added to one another. Finally, if this finite addition leads to a large number, it is said that $x(t)$ has a prominent frequency component in the frequency υ. If the summation is a small number, it is said that the υ frequency component is not dominant in this series. If the addition equals zero, it suggests that this frequency does not exist in the series. The spectral analysis of the monthly minimum temperature and patterns was conducted using fast Fourier transform. The teleconnection patterns used in modeling are demonstrated in Table 2.

Using the expert's knowledge and mathematical methods are two general methods of choosing appropriate inputs for a model. In this research, the most important criterion for selecting patterns is having a prominent frequency component with a period equal to that of the monthly minimum temperature. The four indices Nino1 + 2, NP, PNA, and EAWR were selected from among thirteen indices by applying fast Fourier transform.

Table 2 Variables used in modeling.

The pattern of boundary values of the temperature of the region Nino	Nino1 + 2
Mild pattern/North America	PNA
Western mild pattern	NP

2.2. Fuzzy inference system

Fuzzy logic theory is a powerful and flexible tool for modeling the uncertainties and the implicitness in the real world. It is a very difficult task to gather precise information and data in order to describe the behavior of natural systems. Therefore, as the complexity of systems increases, precise mathematical modeling appears to be impossible. As system complexity increases, the precision of the mathematical model decreases and it reaches a point where no acceptable comment may be made with respect to the dynamicity of the system. Fuzzy calculation is an answer to such complicated problems. Fuzzy systems may be considered as non-linear dynamic systems which are able to estimate real systems using empirical data and are based on numerical calculations with particular precision, no matter how complex the systems are. On the whole, this new theory simulates an expert by formulating uncertainties and intuitive issues which are extracted from the expression of skills and the method of learning. The ability to implement human knowledge using linguistic concepts and labels and fuzzy rules, non-linearity, the ability to compromise, and better accuracy compared to other methods when there is a limitation of data among the most important features of fuzzy systems. On the other hand, artificial neural networks have the ability to learn and to receive instructions using different patterns. These networks may be used in interpolation, forecasting, classification, etc. As a matter of fact, the application domain of artificial neural networks is very extensive. Perhaps the most significant advantage of these networks is their enormous power. Neural networks are of different types, but all of them are comprised of two components:

1. A set of nodes. Each node is in fact a calculation unit of the network which receives the inputs and processes them to produce outputs.
2. Connections among the nodes: These connections determine the way in which information is transferred among the nodes.

The interaction among the nodes through these connections causes the network to demonstrate a general behavior not observed in any individual element of the network. If the node is considered as an artificial neuron in a network, this network is called an artificial neural network, in short ANN. Thus, if fuzzy logic operators are introduced into neural networks and training and classification of neural networks are used in fuzzy systems, then the defects present in neural networks and fuzzy systems may be remedied. These systems are known as adaptive neuro-fuzzy inference systems (ANFIS). The adaptive neuro-fuzzy inference system is among the methods used in analyzing natural phenomena and investigating input–output relationships in multi-parameter systems. Developed by Jang in 1993, neuro-fuzzy models combine fuzzy systems with artificial neural networks in order to facilitate learning and adaptation. It should be noted that the main problem upon designing and using fuzzy systems is to obtain fuzzy rules or ‘‘if-then’’ sentences, which are expressed by experts. Using the learning ability of artificial neural networks effectively in order to generate these rules automatically and optimize the parameters, resolves the major problem in designing fuzzy systems. Hence, the adaptive neuro-fuzzy inference system is a hybrid model composed of fuzzy and artificial neural models. Adaptive networks are feed forward neural networks with the capability of supervised learning. An adaptive network is a network structure comprising nodes connected to each other and directional connections. Moreover, a part or all of these nodes is adaptive. In other words, the output of each node depends on the parameters pertaining to the nodes and the learning rule determines how much these parameters will be changed in order for the model error to be at a minimum. The adaptive neuro-fuzzy inference system enjoys the advantage of being able to receive fuzzy rules from the expert's knowledge and build a rule base adaptively. This system makes use of neural networks and fuzzy logic in order to design a non-linear mapping between the input and output space. In summary, it can be stated that the adaptive neuro-fuzzy inference system is considered as a powerful, appropriate, and flexible tool for modeling uncertainties and implicitness present in the real world and expressing linguistic terms adopted from human experience and knowledge in the form of mathematical relations.

The architecture of the ANFIS is shown in Fig. 1. The ANFIS consists of five layers including, the fuzzy layer, product layer, normalized layer, de-fuzzy layer and total output layer.

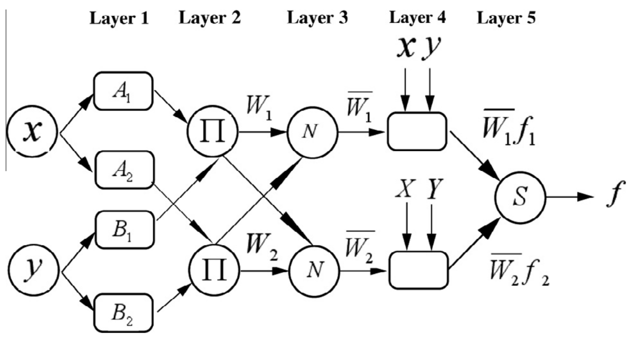

Figure 1 ANFIS architecture.

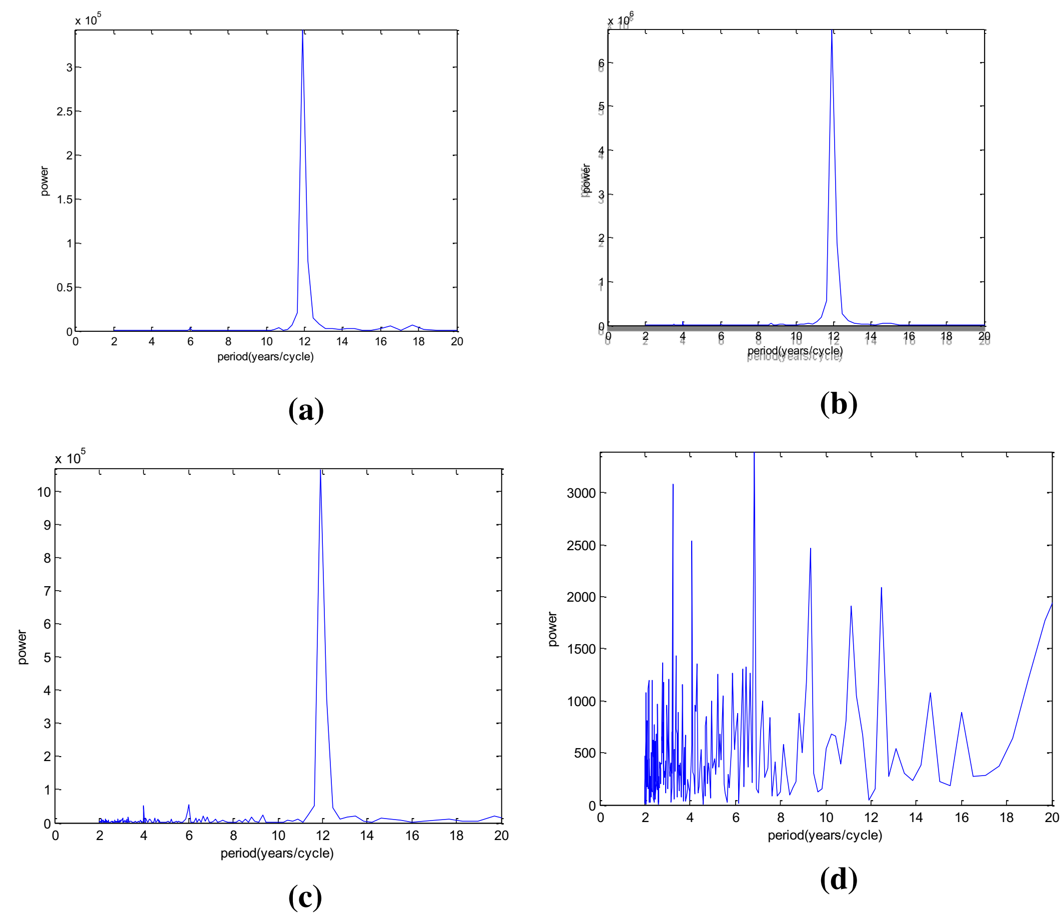

Figure 2 Diagram of spectrum power in terms of period, (a) minimum temperature, (b) Nino1 + 2 index, (c) NP index, and (d) PNA index.

Table 3 Correlation coefficient for the PNA index and the seven climate indices used in the spectral analysis.

Indices	AO	Nino3,4	Nino3	Nino4	NOI	NP	PDO
PNA	−0.190	0.145	0.099	−0.127	−0.208	−0.352	0.305

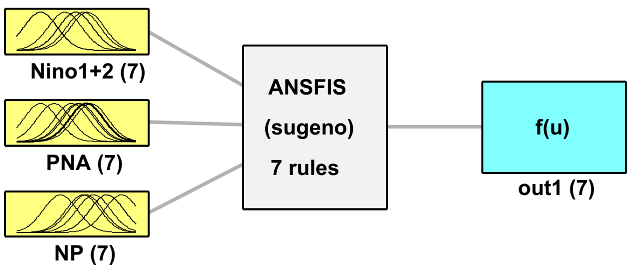

Figure 3 Simple structure of adaptive neuro-fuzzy inference model.

In the first layer (fuzzy layer), x and y are the inputs of adaptive nodes A_i and B_i, respectively. A_i and B_i are the linguistic labels used in the fuzzy theory for describing the membership functions. The outputs of layer 1 are the fuzzy membership degree of the inputs which can be expressed as given below:

$$O_i^1 = \mu_{A_i}(x), \quad i = 1, 2, \ldots, n \tag{4}$$

$$O_i^1 = \mu_{B_i}(y), \quad i = 1, 2, \ldots, n \tag{5}$$

where $\mu_{A_i}(x)$ and$\mu_{B_i}(y)$ denote the membership functions degree.

Second layer is the product layer that consists of two fixed nodes labeled with Π. The output w_1 and w_2 are the weight functions of the next layer. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2, \ldots, n \tag{6}$$

where O_i^2 is the output of layer 2.

The third layer is the normalized layer, whose nodes are also fixed and labeled with N. The outputs of this layer can be represented as:

$$O_i^3 = \bar{w}_i = w_i / \sum_{i=1}^{n} w_i, \quad i = 1, 2, \ldots, n \tag{7}$$

where O_i^3 is the output of Layer 3.

The fourth layer is the defuzzification layer. In this layer, the nodes are adaptive nodes. The relationship between the inputs and output of this layer can be expressed as given below:

$$O_i^4 = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, 2, \ldots, n \tag{8}$$

where O_i^4 is the output of Layer 4 and p_i, q_i and r_i are the constant parameters of the node.

The fifth layer is the output layer, whose node is labeled with S. This node performs the summation of all incoming signals, which represents the results of cleaning rates. The overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{n} \overline{w_i} f_i \quad i = 1, 2, \ldots, n \tag{9}$$

where O_i^5 is the output of layer 5 and the output of the system.

Table 4 Specifications of the fuzzy inference system.

Type	Sugeno
Decision method for fuzzy logic operators AND (intersection)	Product
Decision method for fuzzy logic operators OR (union)	Probabilistic or
Output combination method (Defuzzification)	Weighted average
Number of membership functions for input #1	7
Number of membership functions for input #2	7
Number of membership functions for input #3	7
Type of membership functions	Gaussian
Number of rules	7
Output function	Linear
Number of training epochs	100

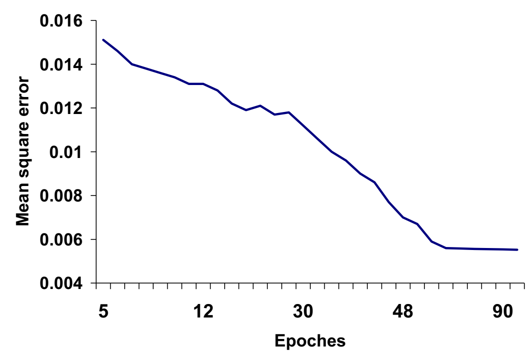

Figure 4 The curve of network error convergence of ANFIS.

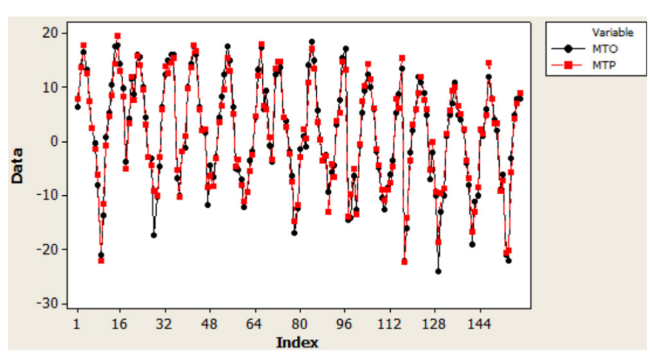

Figure 5 Diagram of minimum temperature observed values (MTO) and those predicted (MTP) by model.

Different methods may be employed in order to predict and estimate monthly minimum temperature. The existence of numerous parameters affecting climatic components and the lack of a straightforward definition of the climate phenomena denote uncertainty and implicitness in the real world.

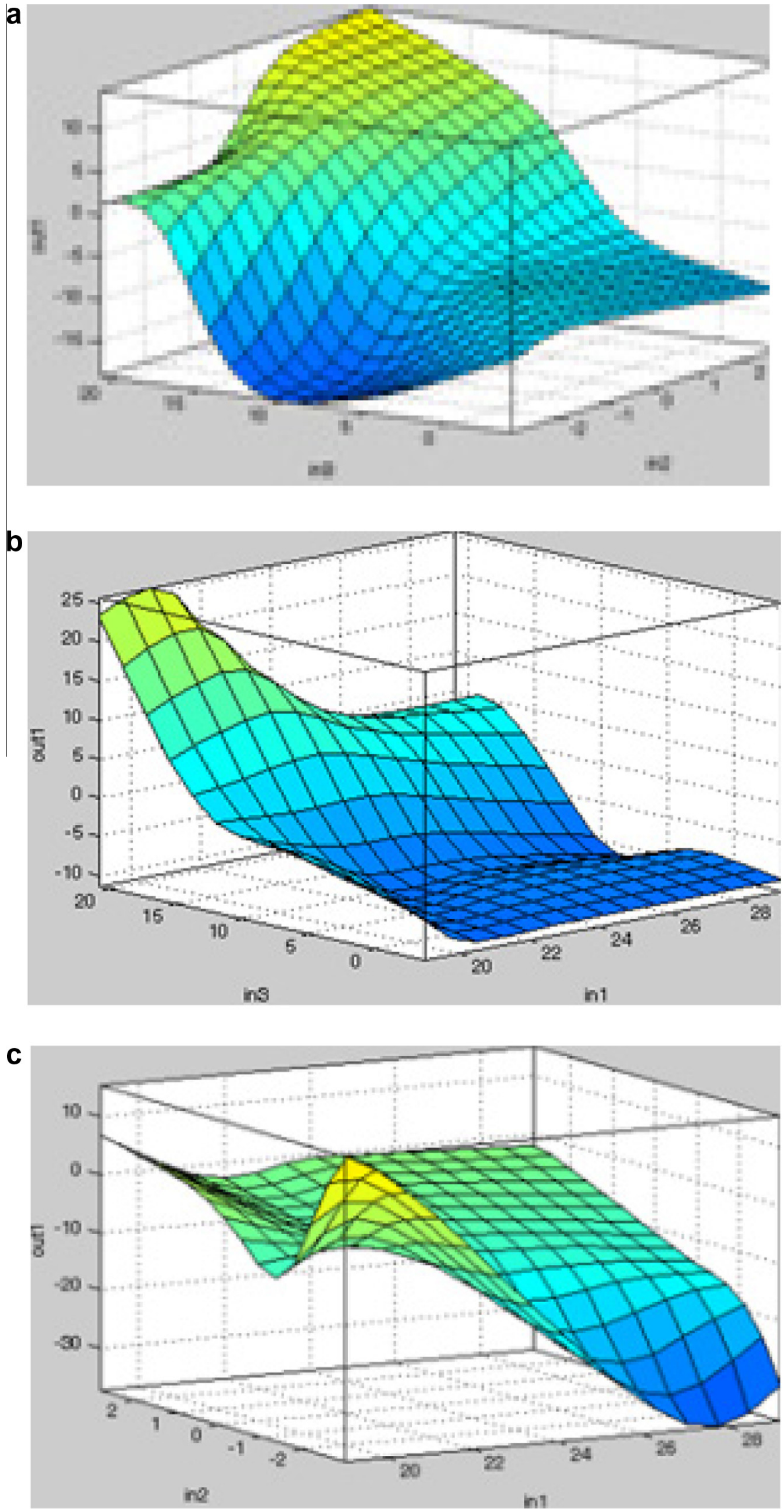

Figure 6 Diagram of relationship between different input variables (three climate indices) and output (minimum temperature): (a) NP and PNA index, (b) Nino1 + 2 and NP index, and (c) Nino1 + 2 and PNA index.

Therefore, the adaptive neuro-fuzzy inference system is one of the most appropriate modeling methods for predicting monthly minimum temperature. The following points are a number of its advantages (MATLAB):

Non-linear structure and combining fuzzy inference system with artificial neural networks.
Learning ability of the network with hybrid learning algorithm.
Ease of using the network after design and training.

2.3. Data normalization

In general, the adaptive neuro-fuzzy inference network is not particularly sensitive to non-normal inputs. However, normalized data are usually used for optimal modeling. In this research, the data are normalized between zero and one. The following relation was used for normalization:

$$x_N = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \tag{10}$$

where x_N denotes the normalized value of the input quantity. The input data matrix of the model consists of 516 rows and 3 columns. In other words, the number of observations used equal 1548 data. The percentage of the data used for training and testing were 70 and 30, respectively.

3. Results and discussion

In this research, prominent frequencies of the monthly minimum temperature of the Mashhad meteorology station were obtained together with thirteen climate indices using fast Fourier transform. The three climate indices Nino1 + 2, NP, and PNA were selected as input parameters to create the ANFIS model using expert's knowledge and correlation coefficient. The diagram of spectrum power in terms of the period of the monthly minimum temperature and three climate indices is depicted in Fig. 2. The spectrum power value is used to compare the frequencies in each diagram and also to compare two diagrams with each other. Fig. 2 illustrates the period in terms of year and the spectrum power value in the dominant frequency for the monthly minimum temperature and three climate indices.

The Nino1 + 2 pattern from the region Nino with a period equal to that of the monthly minimum temperature was selected as the first input of the model. The period of the NP pattern was also equal to that of the monthly minimum temperature (Figs. 2-b and -c). The EAWR index has a period close to that of the monthly minimum temperature in dominant frequency. The correlation of this index with other indices is not considerable. The period of the PNA index approximately equals half of that of the monthly minimum temperature. The PNA pattern possesses at least eight considerable frequency components. Using the PNA pattern causes the model to be optimum, because different frequencies exist in this pattern (Fig. 2-d). The correlation of this index with the seven climate indices used in the spectral analysis is also one of the other reasons of choosing this index in modeling the monthly minimum temperature. Table 3 shows the correlation coefficients.

The monthly minimum temperature has a period or cycle of approximately 12 years. This indicates the fact that temperature conditions repeat themselves every 12 years. The two indices Nino1 + 2 and NP also have a similar period of almost 12 years. The spectrum power value for the prominent and considerable frequency in Fig. 2-a–c is almost equal. The monthly minimum temperature lacks other periods, while the two indices Nino1 + 2 and NP have other periodic fluctuations as well. The NP index has periods of almost 4 and 6 years. These cycles have lower spectrum power. Thus, they may be overlooked.

Hence, the Nino1 + 2 and NP indices almost fully overlap with the monthly minimum temperature. The PNA index also has several periods with considerable powers. Care should be taken when using fast Fourier transform regarding the fact that the number of data used for the spectral analysis of the climate parameter should equal an integer exponent of the number 2. That is why the four initial data of climate indices and minimum temperature were left out. This means 512 data from each climate parameter were used in the spectral analysis. In case the number of data does not equal an integer exponent of the number 2, other observations are considered as zero and the spectral analysis faces a problem. The simple structure of the model is demonstrated in Fig. 3.

The training data set was used to train the ANFIS, while testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the computation of the date quality evaluation. Fuzzy system is implemented using the fuzzy inference system properties (Table 4).

In this study, we use the proposed method to train the input–output relation according to training data set. In the training phase the ANFIS firstly makes the suitable membership functions for each input. In the sequel, the membership functions are tuned according to error correction training method by using the BP algorithm. Also, the constant parameter of the linear output functions is adapt during the learning phase based on LMS algorithm. ANFIS model utilizes 100 training data over the 90 training periods. At the end of the training phase, the network error convergence curve (mean square error) of ANFIS was derived as shown in Fig. 4. Fig. 5 shows the diagram of the observed values for the monthly minimum temperature and the calculated or predicted values using the ANFIS model.

High correlation coefficient (0.987) between the observed values and the values predicted by the model and the Mean Absolute Percentage Deviations equal to 27.6 indicate an acceptable estimation of the model.

Fig. 6 depicts the input–output surface yielded. This pattern is capable of investigating the relationship among input variables. The respective surface is a complicated one, but it is evident that the surface is a combination of two input planes, each of which is determined by an output equation of a fuzzy rule.

4. Conclusion

In this research, the three climate indices Nino1 + 2, NP, and PNA were chosen as input parameters to create the ANFIS model in order to estimate and forecast monthly minimum temperature in the Mashhad meteorology station. Three properties were taken into consideration upon selecting the model inputs:

Having a frequency (period) identical or close to that of the monthly minimum temperature.
Selecting model input patterns from different areas based on Knowledge of experts.
Having a significant correlation coefficient with other climatic indices.

Research results indicated that the ANFIS can estimate and predict the monthly minimum temperature in the station under study with a correlation coefficient of 0.987. The average absolute value of the deviation percentage equal to 27.6 suggests that the system is properly trained and appropriate inputs are used for modeling. It seems that simultaneous use of expert's knowledge and mathematical methods when choosing model inputs lead to an optimal model and the model results are more reliable. Attention should be paid to the fact that as the number of inputs increases, the ANFIS system faces the curse of dimensionality owing to the existence of a huge number of rules and the model is unable to simulate the system. The number of model inputs should be reduced in order for this problem to be alleviated. Alternatively, the fuzzy clustering method should be employed to pre-process the data. Other mathematical transformations such as the Wavelet Transform may be used in spectral analysis to select model inputs. Furthermore, with regard to the period of the monthly minimum temperature of the region and the changes of sunspots, it seems that the sunspot activity could be an appropriate input for modeling the monthly minimum temperature.

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