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Time series forecasting of air temperature using an intelligent hybrid model of genetic algorithm and neural network

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Abstract

Owing to climate change, global warming, and contemporary droughts, temperature forecasting, as one of the most influential climatic parameters, produces a well-suited opportunity for executives to plan and provide the necessary preparations. The matter of time series forecasting of air temperature is one of the most intriguing issues in climate investigations. In this article, an intelligent hybrid model is presented to predict the time series of air temperature. This paper uses the idea of practicing the feature selection model based on the genetic algorithm (GA) to determine the input variables of the model and the high forecasting power of the neural network. The recommended model used the structure of the Autoregressive time series model. But, the problem of selecting the delay of the time series when they should be used in the model was done using genetic algorithm. Finally, the selected delays were used as input of the neural network model. The average monthly air temperature of Tabriz and Kermanshah stations throughout the statistical period 1980-2010 was used to assess the proposed model. The performance of the suggested model was compared with neural network models that do not use the feature selection method. The results corroborated the high accuracy of the developed model compared to the other models, indicating the significance of the problem of feature selection in predicting time series.

Keywords: Air temperature, time series, artificial neural network, genetic algorithm, feature selection

1- Introduction and literature review

Since climate has a huge influence on human social and individual life, several scientific centers around the world have started researching different climate issues. Climate weather forecasting is one of the most essential things that can be done in these centers. Many studies have been published on modeling atmospheric parameters using machine learning methods (Diez-Sierra and del Jesus, 2020, Inyurt and Sekertekin, 2019). The role of maximum temperatures in increased evaporation and transpiration(Li et al., 2020a), declined surface and groundwater (Zhou et al., 2020), the spread of multiple diseases (Bein et al., 2019), forest fires (Eskandari et al., 2020), the process of melting

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glaciers (Javadinejad et al., 2020), and the experience of drought and water deficiency (Danandeh Mehr et al., 2020) in other areas is no secret to anyone. Temperature and precipitation are the most critical and basic climatic elements that play a striking part in determining the role and distribution of other climatic elements. Because temperature performs an essential role in climatic zoning and classification, oscillations and changes are also quite mattering. Significant shifts in global warming have been considered as the most crucial indications of climate change in the modern century. Various environmental issues such as floods(Hunt and Menon, 2020), storms (Denamiel et al., 2020), aridities (Huo et al., 2013), over the extra proliferation of pests (Getahun, 2020), etc. all stem from climate change, particularly global warming. Meanwhile, the application of estimation and forecasting methods, if adequately accurate, can be beneficial in proper planning and management (Šváb et al., 2019, Sahoo et al., 2019, Leblanc, 2019, Kocharekar et al., 2019). Frequent methods of predicting climatic elements are based on the discussion of forecast maps based on data from the ground, satellite, and like stations. Extracting valuable information from the vast volume of these images by identifying and analyzing different entities in this data is challenging (Dev et al., 2016). High temperatures in road transport can further result in hazards and disasters, including the direct influence on the vehicle through the intense evaporation of gasoline and water in the vehicle (Keay and Simmonds, 2005). Weather forecasting uses non-linear and complex systems without a mathematical model. Because of the variability of the system over time, the usual predictive methods make the forecasting impossible. On the other hand, the value of weather forecasting in many areas, namely economic (Kolstad and Moore, 2020), military (Shabshab et al., 2019), agricultural affairs (Rosenzweig and Udry, 2019), etc., is apparent.

Nowadays, by developing sciences such as intelligent methods that are a potent and flexible tool, researchers are looking for methods beyond the usual ones to understand and predict critical meteorological parameters. For example, Mazurkiewicz et al. used a trained neural network to predict air parameters (Mazurkiewicz et al., 2019).

Artificial intelligence models, such as artificial neural networks (ANN), fuzzy logic, and genetic algorithms, have become a common theme of research in diverse fields today owing to their high capability in modeling complex engineering problems and nonlinear systems. There are numerous investigations in which the comparison of intelligent methods and statistical classical methods such as autoregressive integrated moving average (ARIMA), etc. in the modeling of prediction problems has been arranged and the result is higher accuracy of intelligent methods in predicting problems. For example, Praveen and Sharma used the ARIMA method to study climate diversity and its effects on crop production and predict its future (Praveen and Sharma, 2020).

One of the most prevalent intelligent models used in forecasting is artificial neural networks. This model has become the dominant approach in this field due to its high capability in obtaining multivariate nonlinear functions in problems that are affected by several different parameters in a complex and unknown way.

Jain used ANN to predict the temperature in the southern district of Georgia for the following one to twelve hours (Jain, 2003). Rehman and Mohandes revealed that neural networks can determine the solar radiation of Abha city of Saudi Arabia by the temperature and relative humidity of the statistical period 1998-2002 (Rehman and Mohandes, 2008). Senkal and Kuleli predicted solar radiation in Turkey using Resilient Back Propagation, Scaled Conjugate Gradient, sigmoid tangent transfer function in ANN and using the satellite data (Şenkal and Kuleli, 2009). Also in another study, weather observation data have been used as input parameters with the help of regression and ANN models for weather forecasting by Chen and Hu (Chen and Hu, 2019). Nezhad et al. predicted maximal temperature using neural network techniques (Nezhad et al., 2019). Where, 70% of the data were allocated in training and the rest for testing and validation. The aim of their study was to predict the maximum winter temperature in Tehran. The results of this research can be used in environmental planning such as pest and disease control, water resources management, ecological studies, etc. In south of Chile's Atacama Desert, a method for temperature prediction using ANNs and meteorological time series data relevant to this zone has been proposed (Lazzús et al., 2020).

The results of RMSE, MAE and R show that the combined ANNs and GA method is a powerful method for forecasting. In another study, drought modeling and forecasting has been done in the southern part of Iran. For this study, 29-year temperature and precipitation data were used in 28 synoptic stations in the southern part of Iran during the period 1908-2018. Modeling was performed using neural networks in MATLAB, and finally, drought-affected areas for the next 16 years were prioritized using the TOPSIS multivariate decision-making model(Sobhani and Zengir, 2020). Pita-Díaz and Ortega-Gaucin examined the relationship between temperature and precipitation changes in the Mexican state of Zacatecas on global anomalies in the agricultural sector (Pita-Díaz and Ortega-Gaucin, 2020). Asghari et al. used artificial neural networks to predict precipitation in Tabriz plain, in which the best model including of a leading network with six input groups, an output group, an intermediate layer, and the Levenberg–Marquardt algorithm was identified (ASGHARI et al., 2008). Yahya and Seker predicted future climate changes by designing and developing three ANN's approaches, with the help of weather variables (Yahya and Seker, 2019).

The application of a new method of adaptive neuro-fuzzy inference system (ANFIS) to predict air temperature was investigated by Azad et al., which discussed the improvement of ANFIS when used with genetic algorithm (GA), particle swarm optimization (PSO), ant colony optimization for continuous domains (ACOR) and differential evolution (DE). For this purpose, three inputs of various variables have been selected to predict the minimum, average and maximum air temperature per month for 34 meteorological stations in Iran. Comparison of the proposed fuzzy models shows that ANFIS with GA has the best performance in predicting maximum temperature (Azad et al., 2020).

Li et al. examined the ability of several machine learning methods based on linear regression analysis and decision tree-based methods to predict drought conditions in Northeast China (Li et al., 2020b). Predictions were made at intervals of 3, 6, 12 and 24 months. Indices were used to predict short-term and long-term drought conditions. The prediction results were such that linear regression models provide better prediction results.

The following table summarizes the mentioned background. As you can see in Table 1, most studies have used the method of artificial neural networks in predicting atmospheric parameters, and rarely in their studies, combined methods have been used. Researchers who have used artificial neural networks in combination with other tools have achieved more accurate results. With the idea of using hybrid methods, we present our proposed algorithm for better predictions.

Table 1. Atmospheric weather forecasting modeling - An overview

Authors and publication year	Method(s)	Aims
Mazurkiewicz et al.,2019	ANN's	Predicting air parameters.
Praveen and Sharma, 2020	ARIMA	Studing climate diversity and predicting its future.
Jain, 2003	ANN's	Predicting the temperature in the southern district of Georgia.
Rehman and Mohandes, 2008	ANN's	Determining the solar radiation of Abha city of Saudi Arabia.
Şenkal and Kuleli, 2009	ANN's	Predicting solar radiation in Turkey.
Chen and Hu, 2019	ANN's and regression models	Weather forecasting.
Nezhad et al., 2019	ANN's	Predicting maximal temperature.
Lazzús et al., 2020	ANN's and Meteorological Time Series data	Predicting temperature.
Sobhani and Zengir, 2020	ANN's	drought modeling and forecasting has been done in the southern part of Iran
Asghari et al., 2008	ANN's	Predicting precipitation in Tabriz plain
Yahya and Seker, 2019	ANN's approaches	predicted future climate changes
Azad et al., 2020	ANFIS, GA, PSO, ACOR, DE	Predicting air temperature
Li et al., 2020	Linear regression analysis and decision tree-based methods	Predicting drought conditions in Northeast China

Earlier research has determined that artificial neural networks are quite accurate in most cases. Therefore, considering the accuracy of these models and their increasing expansion in predicting and estimating parameters, as well as climate change and global warming in recent decades, one of the essential matters in predicting time series using neural networks is determining the structure of the model and input variables that have been less noticed in literature. In this study, the forecast of the monthly time series of atmosphere temperature by using a combined intelligent model is considered. The advanced hybrid model has two parts. In the first part, time-series data preprocessing is done. The application of a genetic algorithm-based feature selection method is considered as a proper solution for choosing input features to predict the time series of atmosphere temperature, which has been neglected in other researches. As it is mentioned in many studies, due to the existing non-linearity in climatic physics, artificial neural networks are potent tools for accurate weather forecasting (Gill et al., 2010). Since the efficiency of ANNs are highly dependent on their inputs, they can be further empowered by being combined with a well-designed genetic algorithm whose job is to determine the input variables of the model(Venkadesh et al., 2013). In this way, the hybridization of GA and ANNs produces more satisfactory results than employing ANN alone. The use of a multilayer perceptron neural network model as a nonlinear function to predict the time series is further considered.

2- Data and methodology

The first step in directing this study is to collect sufficient information about temperature parameters. The range of the statistical period is a quite significant factor in statistical studies. Forecasting models take into account mainly regional-scale parameters for forecasting, often over long periods of time (Hewage et al., 2020). In this research, the monthly temperature data of the synoptic stations of Tabriz and Kermanshah within the statistical period of 1980-2010 have been used. These data have been extracted from the website of the Meteorological Organization of the country. Kermanshah synoptic station is settled in the geographical position of 47 ˚ 09' longitude and 34 ˚ 21' latitude and at an altitude of 1319 meters above sea level. Plus, Tabriz synoptic station is settled in the geographical position of 46 ˚ 17' longitude and 38 ˚ 05' latitude and at an altitude of 1361 meters above sea level.

The problem of predicting a time series refers to a method in which the future condition of a feature is predicted based on the data of its current and past behavior. This article provides a two-step approach to develop an intelligent model for predicting the region's monthly atmosphere temperature series. The formation of the autoregressive model was used where the forecasting is made using the function f (unlike the classical model of the autoregressive, which has a linear structure, it uses the multilayered perceptron neural network, which has a nonlinear structure) as follows.

$$f: \left(T_{t-1}, T_{t-2}, \dots, T_p\right) \rightarrow T_t \tag{1}$$

T_t is the temperature of the air in month t and T_{t-j} is the temperature in j months before, which is known as the time series delay. Also, P is the order of the autoregressive time series, which defines the number of time series delays for use as the input variable, and many methods have been proposed to settle it (Shahrabi et al., 2013). In this paper, a GA-based feature selection method was used to specify the autoregressive structure and input features to forecast the atmosphere temperature. Data normalization within range of [-1,1] has been considered before applying the multilayer perceptron neural network model to increase the accuracy of the model.

2-1- Feature selection based on genetic algorithm

Feature selection is the matter of choosing a subset of input variables that have more predictive power for an output variable. Using this subset, the lowest estimate error is achieved. Several studies have confirmed that Feature selection can increase the generalizability of the model, and only part of the features present enough data to predict. If the feature is irrelevant to the objective feature of the

problem, the modeling of the objective feature cannot be altered: that is, the features are redundant. Feature selection methods have two parts. In the first part, using efficient search algorithms, subsets of the set of input features of the problem are created. In the next section, using a precise metric, the idea of the suitability of the mentioned subset should be weighed regarding its predictive power (Jain and Zongker, 1997). Feature selection methods as part of the data preprocessing can be split into two general categories:

1- Wrapper methods: These methods employ a search algorithm and use the original model that is meant for forecasting to assess the created subsets. Although these methods have a high degree of precision in picking the appropriate feature, they have a pretty high computational expense owing to the use of the original model.

2- Filter methods: These methods utilize innovative metrics to estimate the subsets formed by the search algorithm. Hence, the original model is not used in the evaluation part. Filter methods have a much lower computational cost than wrapper ones.

In this paper, the well-known Hall filter method is employed to select the structure of the air temperature time series model wherein genetic algorithm is embodied as the search filter. This algorithm is one of the most extensively used metaheuristic methods that can intelligently search the space of possible subsets of the set of main features that are the time series delays of atmosphere temperature. The genetic algorithm employs chromosomes with binary coding that have genes equal to the main input features; each chromosome representing a subset of the features. If the $j-th$ gene on the chromosome is 0, the $j-th$ feature is not in the subset, and if it is 1, the above input feature is in the subset (Liu and Setiono, 1996).

The evaluation metrics section further adopts an innovative approach aimed at selecting a subset of input features. First, the correlation between those features must be minimal (so the redundant information will be minimal). Second, their correlation with the target variable should be the highest (indicating high predictive power). To this end, we consider the $\bar{r}_{cf}$ index as the mean pair correlation of the input features in a subset with the target feature and the $\bar{r}_{ff}$ index as the mean couple correlation of the input features in the subset. Also, the evaluation metric of the j subset generated by the j chromosome is represented as $Merit_j$ and define it as:

$$Merit_i = \frac{N \times \bar{r}_{cf}}{\sqrt{N++N(N-1)\bar{r}_{ff}}} \tag{2}$$

Accordingly, we consider the chromosomal evaluation function in the genetic algorithm as the equation (2). The goal is to achieve a subset of time series delays with the highest $Merit$ function. The feature selection algorithm is presented in Figure 1.

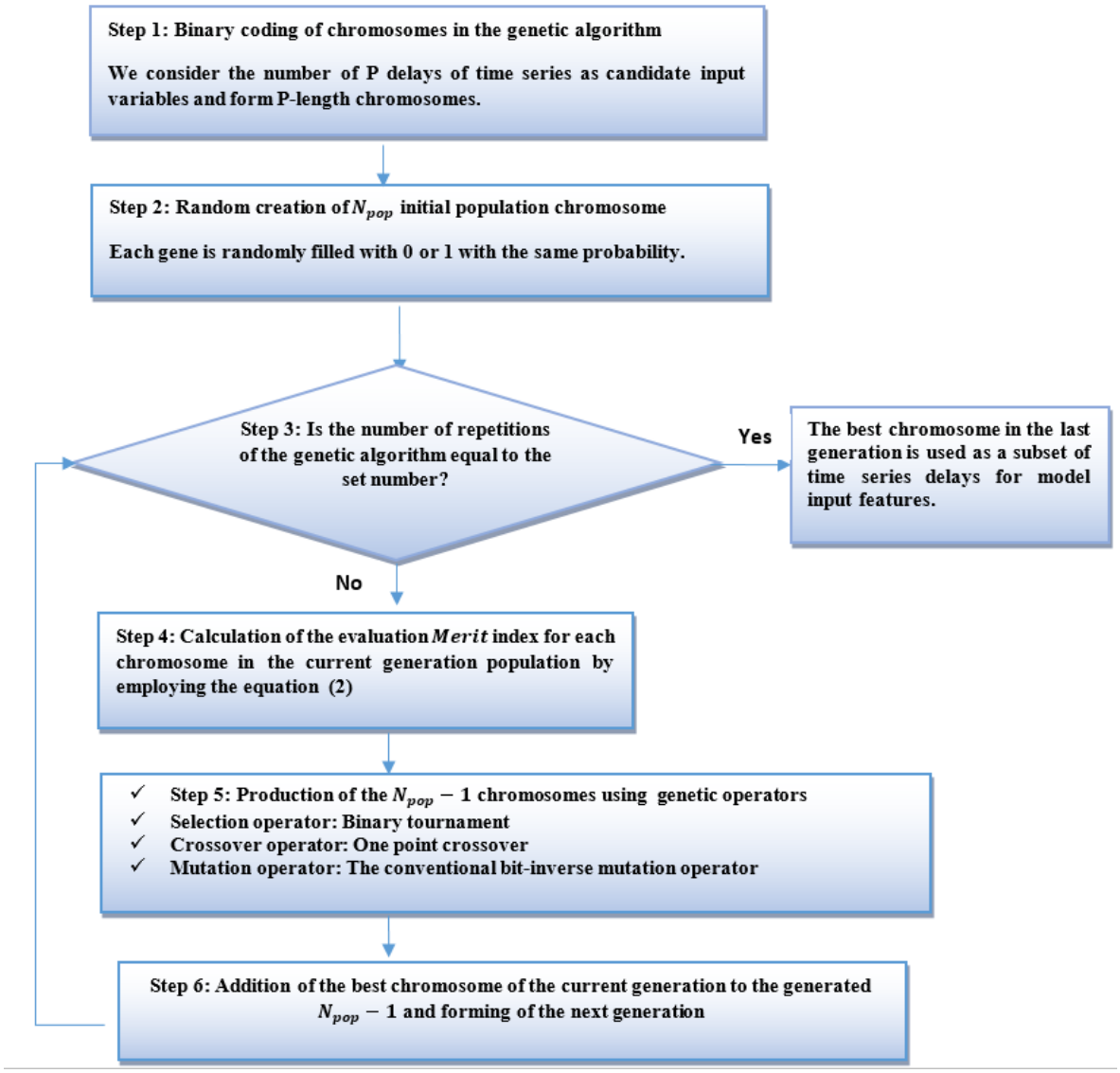

Fig 1. The algorithm provided for choosing the input features of the atmosphere temperature forecasting model

2-2- Multi-layered perceptron neural network

One of the most prevalent types of neural networks used in the domain of forecasting is the multi-layered perceptron (MLP) network, which is usually taught through the Error back-propagation algorithm. This network, which is one of the feed forward networks associated with training with supervisors and holds several layers and no memory, is extensively used in classifying patterns, approximating functions, and therefore estimating. Multilayer perceptron networks are highly able to secure multivariate nonlinear functions. These networks are proper for issues that are affected by several various parameters in a complex and unknown manner. Figure (2) displays the network structure.

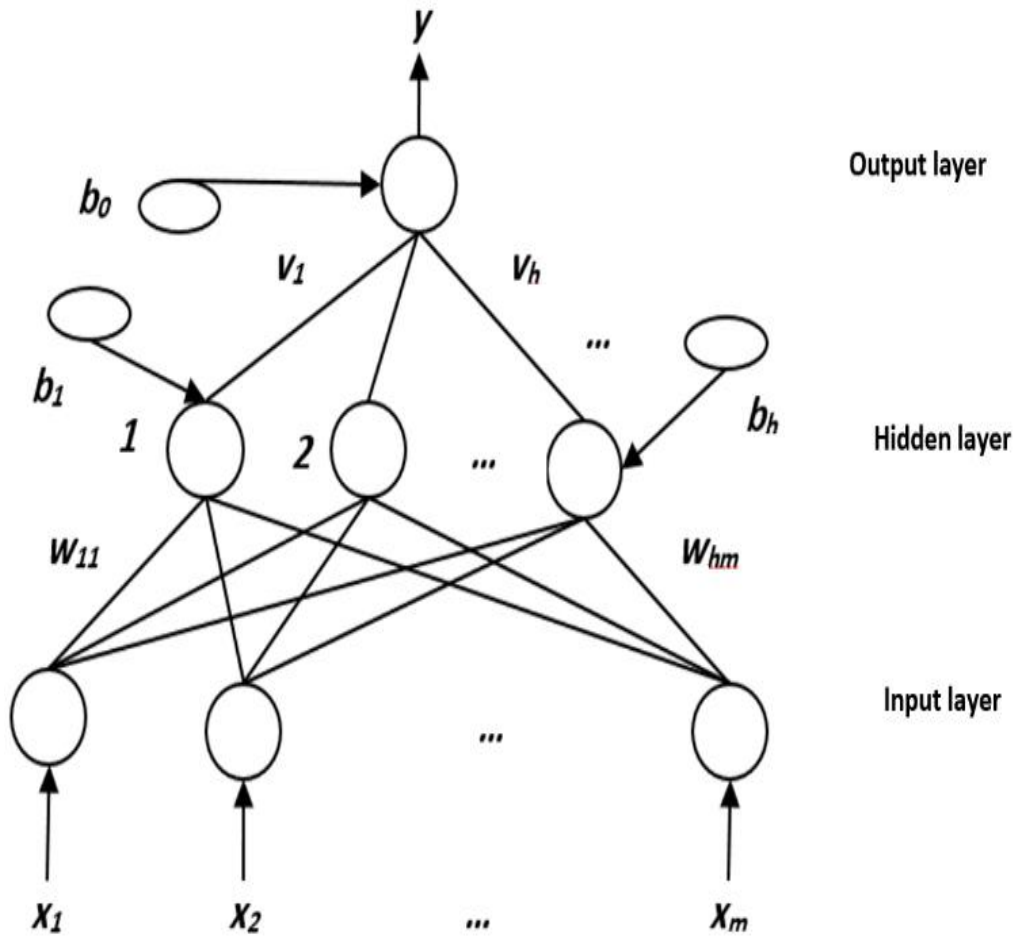

Fig 2. Common architecture of multi-layered neural networks

One method to adjust (update) the neural network communication weights is to minimize the Sum of Squares Error (SSE) objective function in the training process. That is, we renew the weights such that the difference between the system output and the actual value is minimized. Considering that the maximum reduction of a function is counterclockwise, it suffices to move in the negative direction of the SSE gradient vector. Provided that the obtained value for the $j-th$ observation (out of n) is named$\hat{Y}_j$, and the actual value is namedy_j, the SSE function is as equation (3). Figure 3 demonstrates the network training algorithm.

$$SSE = \sum_{i=1}^{n}(y_j - \hat{Y}_j)^2 \tag{3}$$

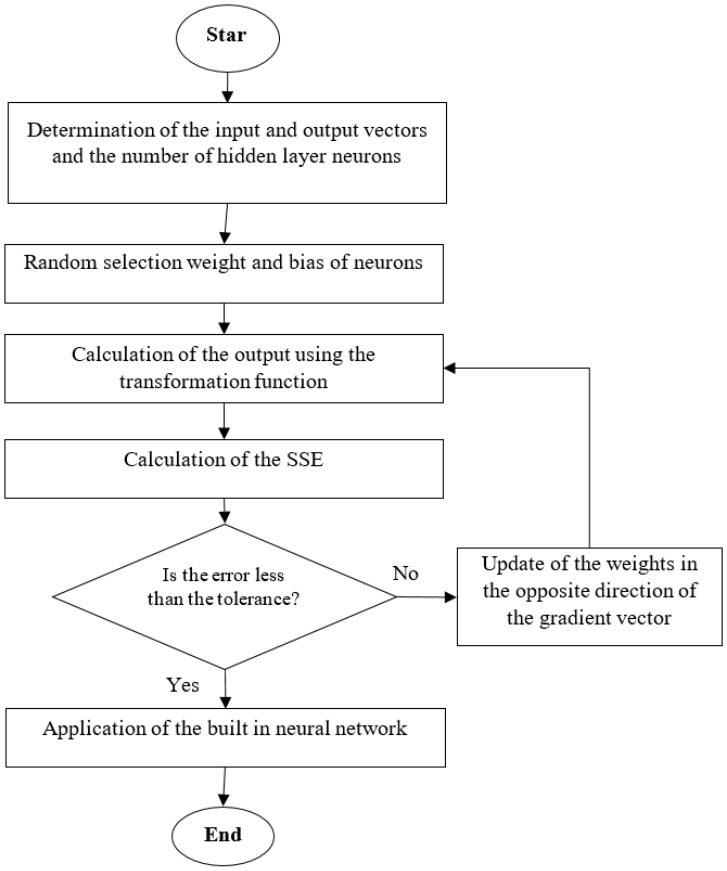

Fig 3. Artificial neural network algorithm

3- Results and discussion

In this section, the daily atmosphere temperature data of Kermanshah and Tabriz were obtained to assess the proposed model. For each data set, 80% (188) of the samples were appointed as training data. The remaining 20% (72) of the samples, on the other hand, were utilized as test data to investigate the accuracy of the model. A good fitting model is one where the difference between the actual values and predicted values for the selected model is small and unbiased for train, validation and test data sets. In this article, we have considered$RMSE$, MAE and R^2as evaluative criteria among the various evaluation metrics that existed. Most researches in this field, such as (Azad et al., 2020, Lazzús et al., 2020, Qasem et al., 2019, Stajkowski et al., 2020) have used the same metrics in their evaluation.

The most commonly used metric for regression tasks is RMSE (root-mean-square error). This is defined as the square root of the average squared distance between the actual score and the predicted score:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - p_i)^2} \tag{4}$$

Mean Absolute Error is the measure of the difference between the two continuous variables. We know that an error basically is the absolute difference between the actual values and the values that are predicted. Then, the average of all errors for each sample in a data set is considered as output. Equation (5) expresses this metric:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - p_i| \tag{5}$$

R^2 is also known as the coefficient of determination. This metric gives an indication of how good a model fits a given dataset. R^2 is always between 0 and 1 or between 0% to 100%. A value close to 1 for R^2 means a good fit, where 0 indicates that this model doesn't fit the given data and 1 indicates that the model fits perfectly to the dataset provided. R^2 is expressed as follows:

$$R^2 = 1 - \frac{\sum_i (p_i - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{6}$$

In the above relations, y_i is the actual value of the time series and p_i is the predicted value of month i. Also, $\bar{y}$ is the average of the time series for N test data. Figures 4 and 5 represent the temperature trend of Tabriz and Kermanshah stations.

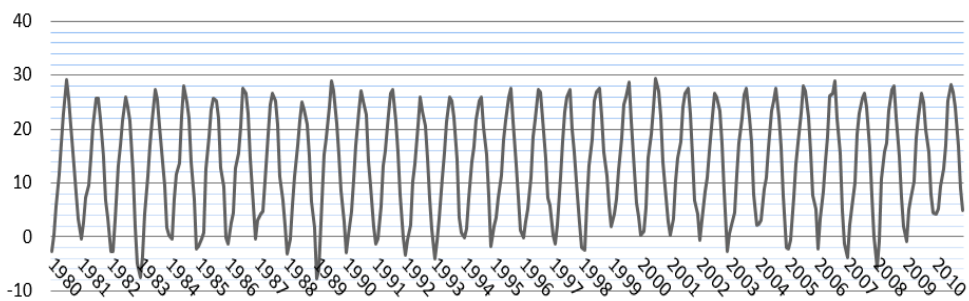

Fig 4. Time series diagram of the monthly temperature of Tabriz Synoptic Station

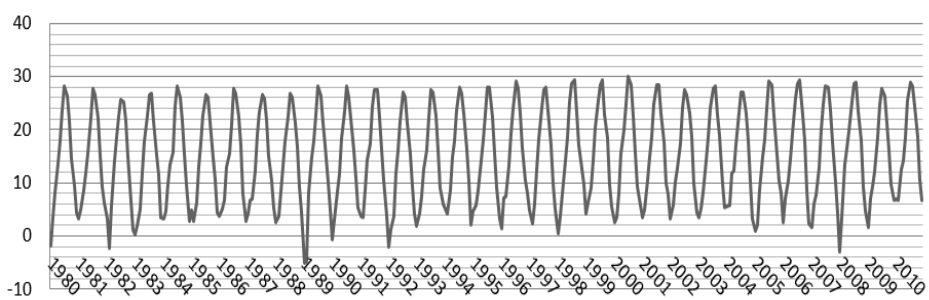

Fig 5. Time series diagram of the monthly temperature of Kermanshah synoptic

Step 1: Pre-processing of the time series data

At this stage, in the first step, the method of choosing the input features to predict the time series of atmosphere temperature was conducted using the feature selection model based on the genetic algorithm. We considered the set of input variables as 12 time-series of atmosphere temperature delays and choose the most fitting subset from them as the input variables. Table 2 lists the corresponding results.

Table 2. Implementation of results the feature selection model based on genetic algorithm for studied stations

Selected subsets for Kermanshah time- series	Selected subsets for Tabriz time series	Value	Genetic algorithm parameters
Tkermanshah__1	Ttabriz__1	0.7	Crossover
Tkermanshah__11	Ttabriz__11	0.15	Mutation
		20	#Population
Tkermanshah__12	Ttabriz__12	100	#of Generations

As shown in table 2, by performing the proposed model for the time series data of Tabriz and Kermanshah atmosphere temperatures, the 1st, $11th$, and $12th$ order delays were selected as the input variables to the forecasting model. The next stage is to normalize the data within [-1,1] interval for neural network modeling.

Step 2: Forecasting with MLP neural network

In this step, MLP single-layer neural network was implemented and trial-and-error approach was performed to determine the number of hidden layer neurons. Afterwards, the model with the least error was picked out. As a result, it was settled that the appropriate number of neurons is 6 which is shown in the network of figure 6. Table 3 further lists the suitable parameters of the implemented neural network.

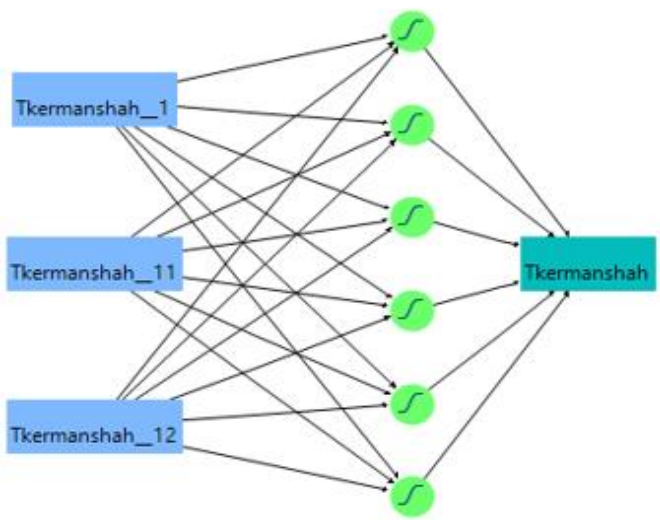

Fig 6. The structure of the MLP neural network employed to predict the time series of Kermanshah temperature

Table 3. Suitable values of neural network parameters

Parameter		**Value**
Training	Learning Rate	0.2
	Minimum Error	1e-10
	# of Epochs	100
Hidden Layer	# of Neurons	6
	Transformation Function	Hyperbolic Tangent
Output Layer	Transformation Function	Log-Sigmoid

The results of the implementation of the model are shown in figure (7). The figures give the actual and predicted values for the test and training data individually. The distribution of data around the first quarter bisector confirms the high accuracy of the predictive model. Figure (8) similarly gives the error distribution of the training and test data, most of which are nearly 0, indicating the proper performance of the model.

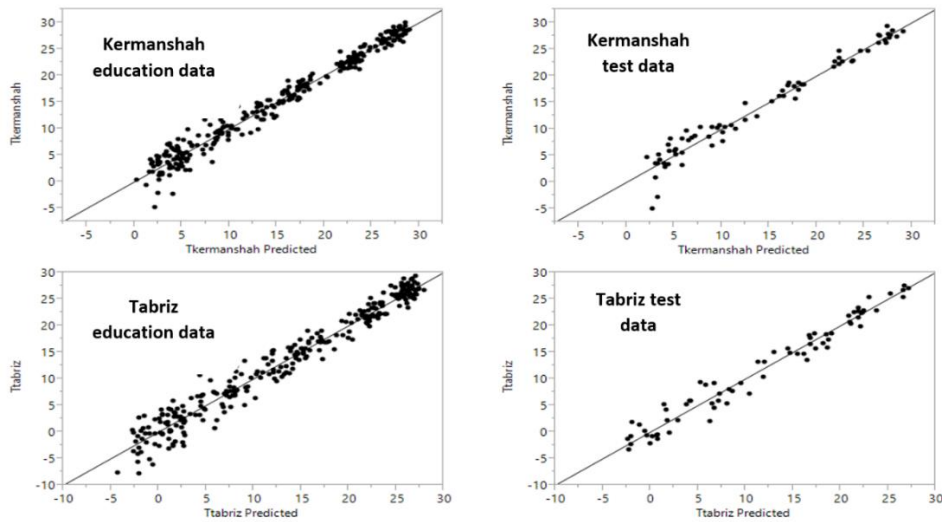

Fig 7. Actual and forecasting s values for training and test data

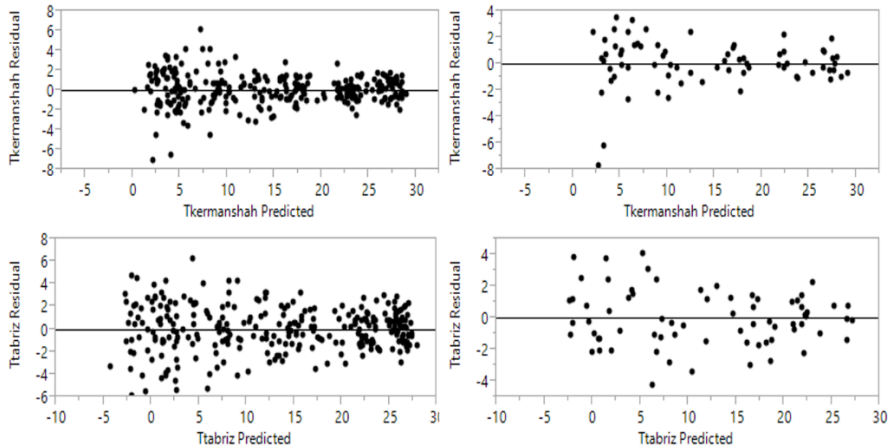

Fig 8. Error distribution of training and test data

To have a comprehensive model assessment, its performance was compared with several models lacking the feature selection method. To this end, the neural network model with the first 3 delays of the time series 'NN (3)', the model with the first 6 delays of the time series 'NN (6)' and the model with the first 12 delays of the time series 'NN (12)' were implemented for comparison. The results are presented in Table 4. For the specified models, evaluative criteria for test data are presented, attesting the generalization power of the model. The results showed the higher accuracy of the proposed model compared to its competitors. Thus, the significance of the GA-based feature selection model in time series forecasting was clearly highlighted.

Table 4. Comparison of the suggested model with other ones in terms of test data

Performance criteria	Proposed model		NN(3)		NN(6)		NN(12)	
	Tabriz	Kermanshah	Tabriz	Kermanshah	Tabriz	Kermanshah	Tabriz	Kermanshah
R^2	0.964	0.971	0.94	0.953	0.93	0.941	0.951	0.967
$RMSE$	1.722	1.77	2.05	1.94	1.86	1.82	1.81	1.89
MAE	1.391	1.223	1.49	1.54	1.51	1.42	1.43	1.36

Finally, the response curve of the neural network model proposed for predicting atmosphere temperature in Kermanshah as a function of the first and twelfth-time series delays is presented in figure 9. As can be seen, when the temperature is high the day before and 12 days before the current day's temperature was also high. The given model response curve can be used to validate the model.

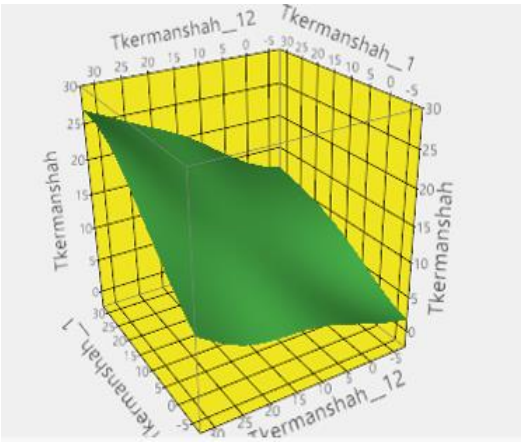

Fig 9. Time series response curve of Kermanshah synoptic station temperature concerning delays of 1st and 12th order

4- Conclusion

Temperature forecasting, which is a non-linear phenomenon that changes with time and location and is influenced by various climatic and geographical factors, is of great importance. In this study, to predict the average atmosphere temperature of Tabriz and Kermanshah cities, a hybrid intelligent model of artificial neural network and genetic algorithm was developed and its performance was evaluated using several criteria. It was shown that the proposed model has a remarkable accuracy in its predictive power. To have a comprehensive model assessment, its performance was compared with several models lacking the feature selection method. To this aim, the neural network model with the first 3 delays of the time series 'NN (3)', the model with the first 6 delays of the time series 'NN (6)' and the model with the first 12 delays of the time series 'NN (12)' were implemented for comparison. The results showed a higher accuracy of the proposed model compared to its rivals. Thus, the significance of the GA-based feature selection model in time series forecasting was clearly highlighted.

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