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Estimating of evaporation from climatic data for Konya and Karaman Regions using Adaptive neuro fuzzy interfrence ANFIS and artificial neural networks ANNs

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Abstract: Measuring and estimation of evaporation is very important for water planning, management and hydrological Practices. Evaporation can be considered as a major component of the hydrologic cycle. In this study a comprehensive investigation and comparison was achieved between different methods to estimate evaporation for two regions at Turkey which are Konya and Karaman by using different effective climatic factors at the both states . This study demonstrated on the application of two different models, adaptive neuro-fuzzy inference system (ANFIS), different types of artificial neural networks such as Levenburg-Marqudat LMNN , Scaled conjugate gradient SCGNN , radial basis function networks RBFNN and generalized regression networks GRNN for estimating daily evaporation. In the first part the ANFIS model was used by using different input combinations and by selecting different climatic data according to the correlation power between these factors with the evaporation. At the second part of this study, the ANN different models were used with different model architectures using different input combinations and different models. The ANFIS model was concluded to be more flexible than the ANN models considered, with more options of incorporating the fuzzy nature of the real-world system. The results were quite encouraging and suggest the usefulness of ANFIS based modeling technique in accurate prediction of the evaporation for both regions .

Keywords: ANFIS, ANN, LMNN, SCGNN, RBFNN, GRNN .

1.INTRODUCTION.

The rate of evaporation can be defined as the amount of water evaporated from a unit surface area per unit of time. It can be expressed as the mass or volume of liquid water evaporated per area in unit of time, usually as the equivalent depth of liquid water evaporated per unit of time from the whole area. The unit of time is normally a day. The amount of evaporation should be read in millimeters [25]. Measuring and estimation of evaporation is very important for water planning, management and hydrological Practices. Evaporation can be considered as a major component of the hydrologic cycle[3].The importance of evaporation in water resources development and management is very obvious since it affects the yield of river basins, the capacity of reservoirs, the consumptive use of water by crops and the yield of underground supplies. the estimation of this evaporation loss is very important in the planning and management of irrigation practices, and these losses should be considered in the design of various water resources and irrigation systems [28]. Estimation of evaporation has been considered as a central problem in hydrology for many years in many parts of the world, where availability of water is considered [7]. In recent two decades, modeling evaporation have been successfully used. Terzi and Erol Keskin (2005)[32] used Gene Expression Programming (GEP) for modeling evaporation as a function of air temperature, solar radiation, and relative humidity. Shirsath, and Singh (2010)[27] applied the artificial neural networks (ANN), statistical regression and climate based model for estimating of daily pan evaporation. Kumar et al (2012)[19] produced artificial neural networks (ANN) and adaptive neuro fuzzy inference system (ANFIS) models for forecasting monthly potential evaporation in Pantagar, U.S. Nagar (India) based on four explanatory climatic factors (relative humidity, solar radiation, temperature, and wind speed). Keskin, Ozlem, and Dilek (2004)[14] used the Fuzzy Logic method to estimate daily pan evaporation based on meteorological data for Lake Egirdiris and compared this with the Penman method. Kisi (2006) [15]used the ANFIS technique , ANN and SS methods for daily evaporation estimation using available climatic data. he concluded that the ANFIS model could be employed successfully in modeling evaporation processes from the available climatic data more than other techniques. Abdul Sattar et.al 2007 [1]produced a comprehensive study for Estimation of Daily Reference Evapotranspiration for Mosul Area Using different types of Artificial Neural Networks. Sameen 2013 [26]produced different types of ANNs in modeling and forecasting evaporation for hamreen reservoir northern Iraq .This study demonstrates on the application of two different models, adaptive neuro-fuzzy inference system (ANFIS), different types of artificial neural networks such as Levenburg-Marqudat LMNN , Scaled conjugate gradient SCGNN , radial basis function networks RBFNN and generalized regression networks GRNN for estimating daily evaporation in two regions at Turkey , these regions are Konya and Karaman . In the first part the ANFIS model was used by using different input combinations by selecting different climatic data according to the correlation power between these factors with the evaporation . At the second part of this study, the ANN different models were used with different model architectures using different input combinations and different models such as radial basis function networks and generalized regression networks and also by using two different algorithms in training which are The Levenberg-Marquardt (LM) algorithm and scaled conjugate gradient .

2.METHODOLOGY:

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS).

Adaptive Neuro Fuzzy Inference System (ANFIS) is a fuzzy mapping algorithm that is based on Tagaki-Sugeno-Kang (TSK) fuzzy inference system [12],[20]. ANFIS is integration of neural networks and fuzzy logic and have the potential to capture the benefits of both these fields in a single framework. ANFIS utilizes linguistic information from the fuzzy logic as well learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization. A conceptual ANFIS consists of five components: inputs and output database, a Fuzzy system generator, a Fuzzy Inference System (FIS), and an Adaptive Neural Network. The Sugeno- type Fuzzy Inference System[29] which is the combination of a FIS and an Adaptive Neural Network, was used in this study for evaporation modeling for two regions . The optimization method used is hybrid learning algorithms. An adaptive neural network is defined as a network which consists a number of nodes connected through directional links. Each of these node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of neural networks is an operation which aims to determine parameter values to fit the training data. The basic learning rule is the well-known backpropagation method which seeks to minimize some measure of error, usually sum of squared differences between network's outputs and desired outputs [13]. Most fuzzy inference systems can be classified into three types due to the types of inference operations upon "if-then rules". These types are Mamdani's system, Sugeno's system and Tsukamoto's system. The most commonly used one is Mamdani's system. Sugeno's system is more compact and computationally efficient. The output is crisp, so, without the time consuming and mathematically intractable defuzification operation, it is by far the most popular candidate for sample-data based fuzzy modeling and it lends itself to the use of adaptive techniques [29] In first-order Sugeno's system, a typical rule set with two fuzzy IF/THEN rules can be expressed as:

Rule 1: If x is A1 and y is B1,

then f1= p1x+q1y+ r1…………………..……….(1).

Rule 2: If x is A2 and y is B2,

then f2= p2x+q2y+ r2…………………………..…(2).

Figure(1) illustrates basic ANFIS structure

Each node i in the first layer which is shown in Figure(1) is an adaptive node that represents member ship functions which can be explained by generalized bell functions :

$$Z_{1,i}=\mu_1(X)=\frac{1}{1+\left|{(X-c_1)}/{a_1}\right|^{2b_1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3).$$

where X=input to the node and a1, b1 and c1=adaptable variables known as premise parameters. The outputs of this layer are the membership values of the premise part. This product represents the firing strength of a rule. The second layer consists of the nodes which multiply incoming signals and sending the product out.

$$Z_{2,1}=W_1=\mu_1(x)\mu_4(y)\ldots\ldots\ldots\ldots\ldots\ldots (4).$$

In the 3rd layer, the nodes calculate the ratio of the ith rules firing strength to the sum of all rules' firing strengths.

$$z_{3,1}=\widehat{W_1}=\frac{W_1}{W_1+W_2+W_3+W_4}\ldots\ldots\ldots\ldots (5).$$

The nodes in the fourth layer are adaptive with node functions

$$Z_{4,1}=\widehat{W_1}f_1=\widehat{W_1}(p_1X+q_1y+r_1)\ldots\ldots\ldots (6).$$

where $\widehat{W_1}$ is the output of Layer 3 and { pi, qi, r1 } are the parameter set. Parameters of this layer are referred to as consequent parameters.

The single node in the fifth layer computes the final output as the summation of all incoming signals

$$f=\sum_{i=1}^{n}\widehat{W_i}\,f_i\ldots\ldots\ldots (7).[12].$$

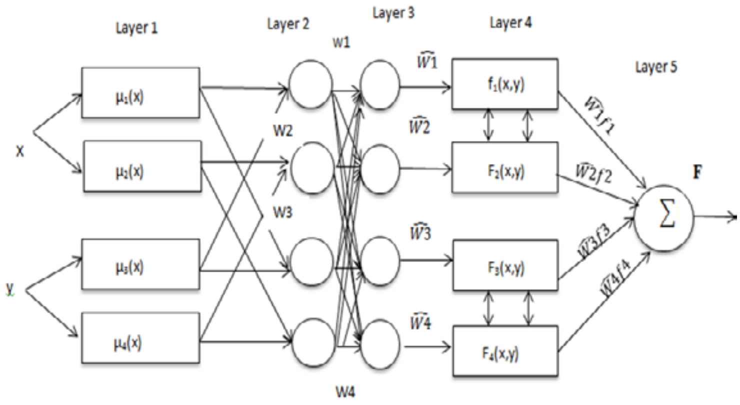


Fig (1) Structure of ANFIS Networks.

2.1. Artificial Neural Networks .

An ANN is a mathematical representation of a biological neural network which is represented at the human brain . The human brain contains billions of interconnected neurons. Due to the architecture in which the neurons are arranged and operate, a human is able to recognize patterns and process data. The ANN can do the followings 1-learning from examples.2- recognizing a pattern in the data. 3- adapting solutions over time. The application of ANNs at water resources problems and other fields is rapidly gaining popularity due to their immense power and potential in the mapping of nonlinear system data. [11],[16]). Most important properties of ANN that distinguish it from the empirical models are :a) neural networks have flexible nonlinear function mapping capability which can approximate any continuous measurable function with arbitrarily desired accuracy, whereas most of the commonly used empirical models do not have this property. B), being non-parametric and data-driven, neural networks impose few prior assumptions on the underlying process from which data are generated. Because of these properties, neural networks are less susceptible to model misspecification than most parametric nonlinear methods. There are a wide variety of algorithms available for training a network and adjusting its weights [2],[3],[24] . In this study, an adaptive technique momentum Levenberg–Marquardt based on the generalized delta rule was adopted. Also the Scaled conjugate gradient. In addition to these two training methods two another types of ANNs were used in this study which are radial basis function networks RBFNN and generalized regression neural networks GRNN . All the applied ANN different techniques are presented below .

2.1.1. Levenberg-Marquardt Neural Networks(LMNN).

The Levenberg-Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of nonlinear real-valued functions [8],[18]. It has become a standard technique for non-linear least-squares problems, widely adopted in a broad spectrum of disciplines. LM can be thought of as a combination of steepest descent and the Gauss-Newton method.[11]

2.1.2. SCALED CONJUGATE GRADIENT (SCGNN).

Scaled Conjugate Gradient algorithm is a supervised learning algorithm for feed forward neural networks, and is a member of the class of conjugate gradient methods. The Scaled Conjugate Gradient (SCG) algorithm denotes the quadratic approximation to the error E in a neighborhood of a point w by:

$$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w) y \ldots\ldots\ldots 8.$$

In order to determine the minimum to Eqw(y)the critical points for Eqw(y) must be found. The critical points are the solution to the linear system (Kisi, O ., 2005).

$$E_{qw}(y) = E''(w)y + E'(w)y \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .9$$

2.1.3.RADIAL BASIS FUNCTIONS NETWORKS(RBFNN)

Radial Basis Function type ANN owes its name to the transfer function applied at its hidden neurons RBF Networks take a slightly different approach. Their main features are:

1. They are two-layer feed-forward networks.
2. The hidden nodes implement a set of radial basis functions (e.g. Gaussian functions).
3. The output nodes implement linear summation functions.
4. The network training is divided into two stages: first the weights from the input to hidden layer are determined, and then the weights from the hidden to output layer.
5. The training/learning is very fast.
6. The networks are very good at interpolation. RBF neural network was proposed by Moody and Darken (1980). It includes three layers: an input layer, a hidden radial basis neuron layer and a linear neuron output layer. The important property of RBF networks is that the outputs of the input layer are determined by calculating the distance between the network inputs and hidden layer centers. The second layer is the linear hidden layer and outputs of this layer are weighted forms of the input layer outputs. Each neuron of the hidden layer has a parameter vector called center. A radial basis function $\emptyset$ is one whose output is symmetric around an associated center c_i. The general expression of the network can be given as:

$$\hat{y_j} = \sum_{i=1}^{I} w_{ij} \emptyset(\|x - c_i\| + \beta_j \ldots\ldots\ldots\ldots\ldots\ldots\ldots 10.$$

The norm is usually taken to be the Euclidean distance and the radial basis function is also taken to be Gaussian function and defined as:

$$\varphi(r) = \exp(-\alpha_i . \|x - c_i\|^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots 11.$$

where,

I:Number of neurons in the hidden layer ;J :is the number of neurons in the output layer ,wij :is the weight of the ith neuron and jth output;φ:is the Radial basis function;αi :is the Spread parameter of the ith neuron;xis the Input data vector ,ci : is the Center vector of the ith neuron;βj :is the Bias value of the output jth neuron and ŷj :is the Network output of the jth neuron.[21].

2.1.4. GENERALIZED REGRESSING NEURAL NETWORKS (GRNN).

A GRNN is a kind of neural networks which are a variation of the radial basis neural networks, which is based on kernel regression networks [5]. There is no need for training iterative in this kind of networks since It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function [17]. The structure of the generalized regression neural networks are composed from four layers: input layer, pattern layer, summation layer, and output layer. The first layer is fully connected to the second, pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer: S-summation neuron and D-summation neuron. The S-summation neuron computes the sum of the weighted outputs of the pattern layer while the D-summation neuron calculates the un weighted outputs of the pattern neurons. [23].

3. STUDY AREAS.

The great Konya Basin is in the Central Anatolian Plateau at a latitude of 37° and between longitudes 33° and 35° East. In it lies the Provincial Capital of Konya and the towns of Karapinar, Bor, Eregli and Karaman. It is in the Province of Konya. The Basin covers about 1 million hectares (or 2 million acres or 4 million Konya-dönüms) and is enclosed by uplands and mountains which prevent any superficial drainage to the sea. Several rivers flow into the Basin, mainly from the south and the west. the central part of the Basin is flat and consists of several plains separated by terrain elevations. The most important plains are the Konya Plain, Hotamis Plain, Karapinar Plain, Eregli Plain and Karaman Plain. These plains are about 1010 m above sea-level. The outer limits of the surveyed area are clearly defined by where the uplands rise steeply from the plain. If the rise is more gradual, an arbitrary limit is set at the 1050 m contour, where agriculture usually becomes marginal through lack of surface soil or rough terrain. Exceptionally the survey has been extended to higher levels (mainly in the east of the area). The Great Konya Basin is one of the driest parts of Turkey . By the Koppen Classification the climate is semi-arid (BSak), with cold moist winters and hot dry summers. Evaporation exceeds total precipitation largely. The mountains in the south and west cause local variations especially in wind and precipitation [31]. The second study area was Karaman state . Karaman state : Karaman is a town in south central Turkey, located in Central Anatolia, north of the Taurus Mountains, about 100 km (62 mi) south of Konya. It is the capital district of the Karaman Province. Karaman has a cold semi-arid climate under Köppen climate classification (BSk), with hot and dry summers and cold and snowy winters. Karaman is a very sunny city all year long[9]. Figure (2) shows the both study areas . The daily evaporation data for the year 2000 to 2006 approximately were used in addition to the different effective climatic data for Konya region for the same period , these factors were precipitation , vapor pressure maximum temperature ,minimum temperature ,mean temperature ,relative humidity ,wind speed, solar radiation and absolute pressure . All these factors were selected and arranged in different models after studying the correlation between them and the evaporation. The same was done for Karaman region but with extended data period from 2000 to 2010.

Fig (2) Location of Study areas .

4. Applications .

Different structures of ANN, and ANFIS models were explored with various combinations of input data to estimate evaporation. Nine different combinations of input variables were considered in the study for each case study . The considered variables were precipitation , vapor pressure , maximum temperature ,minimum temperature ,mean temperature ,relative humidity ,wind speed, solar radiation and absolute pressure . The correlation of these variables were tested with the evaporation for each region this results different input combinations and different models for each region . All the applied models were tested using coefficient of determination R^2 , Nash-Sutcliffe efficiency E_{nash} , percent bias R bias and mean absolute percent error MAPE parameters which were used as evaluation criteria. These parameters are defined as:

$$R^2 = \frac{\left(\sum_{t=1}^{n}(A_t - A_{mean})(F_t - F_{mean})\right)^2}{\sum_{t=1}^{n}(A_t - A_{mean})^2 \sum_{t=1}^{n}(F_t - F_{mean})^2} \quad \ldots\ldots 8.$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \ldots\ldots\ldots 9.$$

$$ENash = 1 - \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{\sum_{t=1}^{n}(A_t - F_{mean})^2} \ldots\ldots\ldots 10.$$

$$R\ bias = 100 * \frac{\sum_{t=1}^{n}(F_t - A_t)}{\sum_{t=1}^{n} A_t} \ldots\ldots\ldots 11.$$

where At is the actual value and Ft is the forecasted or simulated value and F_{mean}, A_{mean} are the mean value of the forecasted and actual series respectively [6],[30].

4.1 Modeling of Evaporation for Konya Region .

The daily data of the Evaporation and the effective factors such as the precipitation , vapor pressure , maximum temperature ,minimum temperature ,mean temperature ,relative humidity ,wind speed, solar radiation and absolute pressure for period between 2000-2006 were used for this study. Before starting the correlation between each variable and the evaporation was found then the input combinations for each model was set according to this correlation. Table (1) illustrates the different models for konya region .

Table(1) The applied models with different input combinations for Konya Region.

Model name	Input Combinations
M1	P,VP,T_{max},T_{min},T_{mean},H, WS, SR, AP
M2	P, T_{max},T_{min},T_{mean},H, WS, SR, AP
M3	P, T_{max},T_{min},T_{mean},H, SR, AP
M4	T_{max},T_{min},T_{mean},H, SR, AP
M5	T_{max},T_{min},T_{mean},H, SR
M6	T_{max},T_{min},T_{mean},H
M7	T_{max},T_{min},T_{mean}
M8	T_{max}, T_{mean}
M9	T_{mean}

Where P:perecipitation, VP: Vapor Pressure, Tmax, min, mean :maximum, minimum and mean temperature respectively, H:Relative humidity, WS: Wind speed , SR: solar radiation AP: absolute pressure.
The above models were tried for Adaptive neuro fuzzy interference ANFIS and artificial neural networks ANNs different models .

4.1.1 APPLICATION OF ADAPTIVE NEURO INTERFERENCE SYSTEM ON KONYA REGION.

The mentioned models at Table(1) were applied in ANFIS models for the evaporation and other climatic data for Konya region . ANFIS, model structure identification was done by subtractive clustering with a cluster radius of 0.5 and hybrid learning algorithm was used for model parameter identification. The results of this application are shown at Table(2) which shows the values of E_{nash} and R_{bias} while Figures (3)and(4) illustrate the values of R2 and MAPE respectively. The performance description is set according to [6] , Since The range of E_{nas}h lies between 1.0 (perfect fit) and $-\infty$ and the optimal value of R_{bias} is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias .

Table(2) The Evalution Parameters Results for ANFIS models on Konya.

Model Name	E_{nash}	R_{bias}
M1	0.771	1.7
M2	0.712	2.3
M3	0.78	1.65
M4	**0.93**	**0.671**
M5	0.88	1.1
M6	0.79	1.56
M7	0.811	1.4
M8	0.86	1.32
M9	0.9	0.98

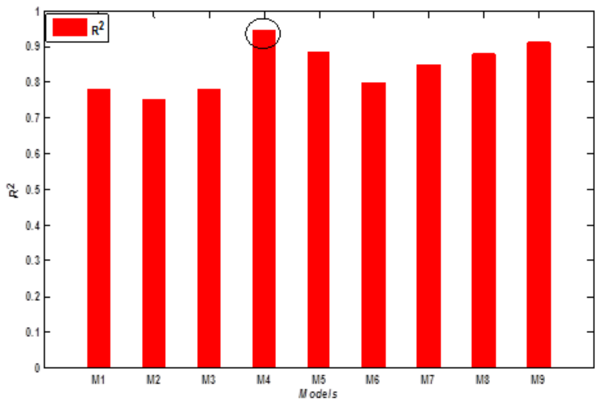
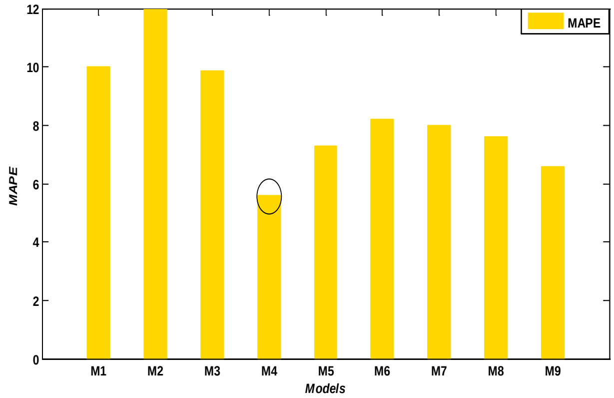


Fig (3)Values Of R^2 for ANFIS models(Konya).



Fig(4)Values of MAPE for ANFIS models(Konya).

The results indicate to a perfect fit with model no 4 (M4)which reflects the effective of the temperature as maximum ,minimum ,mean values, solar radiation ,humidity and absolute pressure in evaporation modeling .The value of R bais indicates to a small overestimation . The highest value of coefficient of determination R2 for model M4 was so encouraging (0.946)and the value of mean absolute error as a percentage was the least value among all others.

4.1.2 APPLICATION OF ARTIFICIAL NEURAL NETWORKS ON KONYA REGOIN.

4.1.2.A . APPLICATION OF LEVENBERG-MARQUARDT NEURAL NETWORKS(LMNN)ON KONYA REGION .

At this stage of the work Levenberg-Marquardt algorithm in training the artificial neural networks was used by investigating different architectures of the networks since the different input combinations as was mentioned before were applied here also. This was done by testing the best neuron numbers at the hidden layer for each different input combinations of the networks. Table (3) shows the results of E_{nash} and R_{bias} for the best structures of the different models . The best model structure is illustrated at the Table . Figures (5 and 6) show the values of R2 and MAPE for the applied models.

Table(3) The Evalution Parameters Results for LMNN models on Konya

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-5-1	0.5353	6.7532
M2	8-2-1	0.5168	6.773
M3	**7-5-1**	**0.5463**	**6.6645**
M4	6-3-1	0.5375	8.5027
M5	5-2-1	0.5383	6,4033
M6	4-5-1	0.5324	5.883
M7	3-2-1	0.4821	8.846
M8	2-3-1	0.4883	8.0616
M9	1-16-1	0.4873	7.9296

Note: Model structure represents input no. -hidden layer neurons no. -output no.

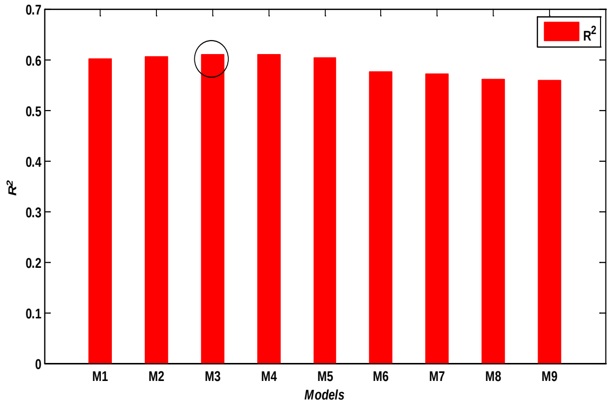


Fig (5)Values Of R^2 for LMNN models (Konya).

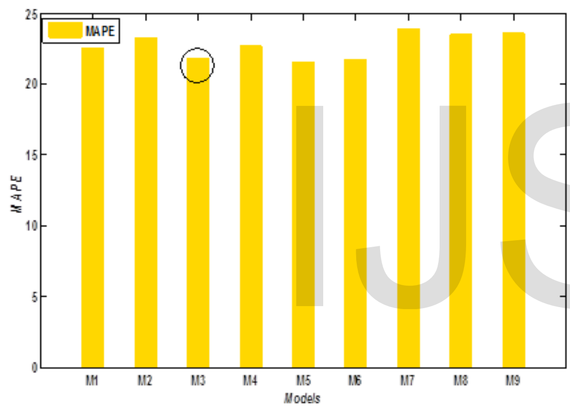


Fig (6) Values of MAPE for LMNN models(Konya).

According to the results of the evaluation parameters the model M3 which represents a model with precipitation P, ,maximum temperature Tmax, Minimum temperature Tmin, mean temperature Tmean, Humidity H, Solar radiation SR and absolute pressure, AP input combinations and by using five neurons in the hidden layer was concluded to be the best performed LMNN model with moderate success . R2 value for this model was 0.6093 with least value of MAPE among all other tested models .

4.1.2.B . Application of Scaled Conjugate Gradient (SCGNN)on Konya region .

By changing the training algorithm a new results were found for the same applied structures as an input combinations and also by testing the best neurons number at the hidden layer .The results of this type of networks after changing the training algorithm to scaled conjugate gradient are illustrated at Table (4) and Figures (7 and 8).

Table(4) The Evalution Parameters Results for SCGNN models on Konya

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-1-1	0.5689	3.8439
M2	**8-5-1**	**0.599**	**2.9297**
M3	7-9-1	0.5327	4.7297
M4	6-2-1	0.5986	3.4767
M5	5-2-1	0.5573	4.4712
M6	4-14-1	0.5214	4.0146
M7	3-2-1	0.5027	4.1504
M8	2-2-1	0.4956	5.9391
M9	1-21-1	0.4968	5.6131

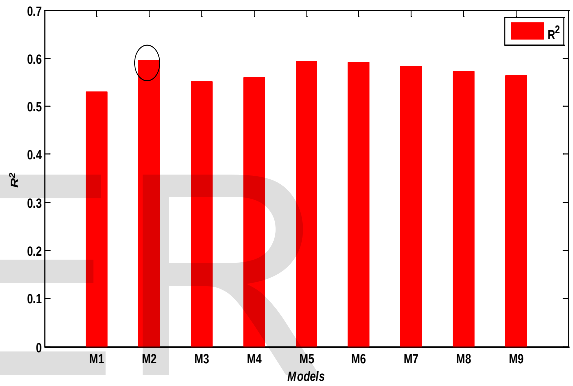
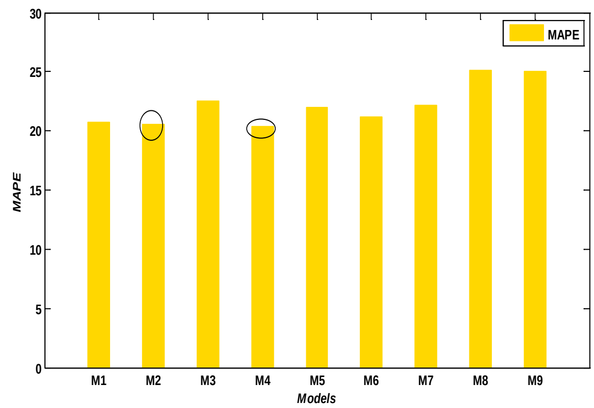


Fig (7)Values Of R^2 for SCGNN models (Konya).



Fig(8)Values of MAPE for SCGNN models(Konya).

According to the results of the evaluation parameters ,e model M2 which represents a model with precipitation P,

,maximum temperature Tmax, Minimum temperature Tmin, mean temperature Tmean, Humidity H, wind speed WS, Solar radiation SR and absolute pressure, AP input combinations and by using five neurons in the hidden layer was concluded to be the best performed SCGNN model . Figures (7) and(8) ensure the same conclusion, since the found R2 best value was 0.5951.

4.1.2.C . Application of Radial basis function neural networks (RBNN)on Konya region .

After applying a radial basis function networks the performance of the networks was improved as shown in the following table and two following figures. These results were found after testing different spread values and trying different numbers of neurons at the hidden layer . The best results for each trial is illustrated only . The results of this networks with the same input combinations are illustrated at Table (5) anf Figures (9 and 10).

Table(5) The Evalution Parameters Results for RBFNN models on Konya.

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-8-1000	0.6248	3.5487
M2	**8-8-1000**	**0.652**	**2.7095**
M3	7-8-900	0.6063	5.4203
M4	6-8-800	0.6053	4.4659
M5	5-6-1000	0.5582	6.5214
M6	4-6-1000	0.5473	5.0508
M7	3-2-500	0.4804	8.7694
M8	2-2-100	0.4747	8.6629
M9	1-2-100	0.485	8.051

Note: The structure of the model represent: Inputs no. -Spread value-no. of neurons at the hidden layer.

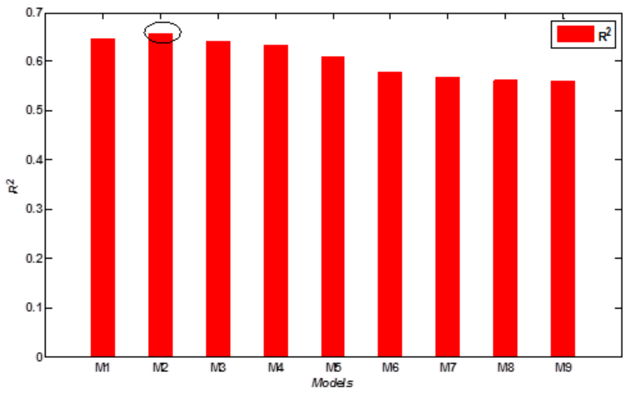


Fig (9)Values Of R^2 for RBFNN models (Konya).

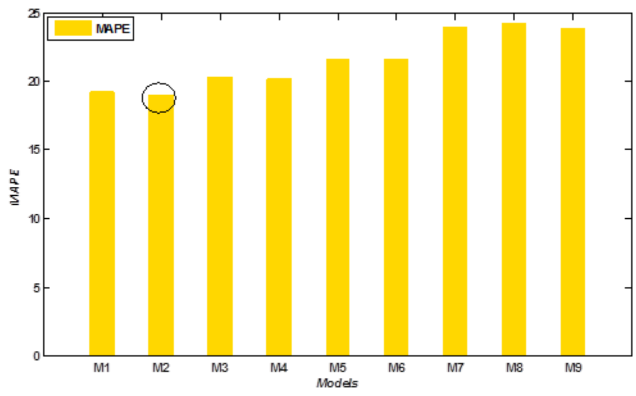


Fig (10) Values of MAPE for RBFNN models(Konya).

The best RBFNN was found to be the model M2 which represents a model with all effective factors except vapor pressure with spread value =8 and 1000 neurons at the hidden layer . The value of R2 for this model was 0.655.

4.1.2.D.Application of Generalized regression neural networks (GRNN)on Konya region .

The results of this networks with the same input combinations are illustrated at Table (6) and Figures (11 and 12).The values in the model structure column represent the best spread value after testing and trying different values.

Table(6) The Evalution Parameters Results for GRNN models on Konya.

Model Name	Model structure	E_{nash}	R_{bias}
M1	**0.3**	**0.5523**	**5.0309**
M2	0.3	0.5234	5.456
M3	1	0.4419	5.4716
M4	0.2	0.5816	4.7913
M5	0.2	0.5644	5.0517
M6	0.2	0.5464	4.8385
M7	0.2	0.5032	7.2249
M8	0.2	0.4711	6.4876
M9	0.1	0.5059	7.2267

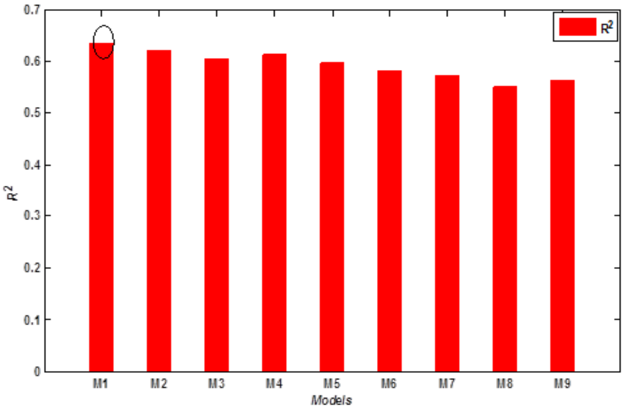


Fig (11)Values Of R^2 for GRNN models (Konya).

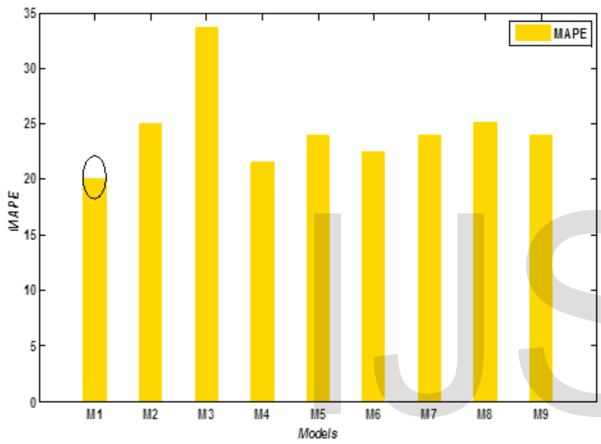


Fig (12) Values of MAPE for GRNN models(Konya).

The best tried model was M1 with all the applied factors with spread value =0.3 with R2 value =0.634.
It is clear from the applied models the effect of the climatic factors on evaporation of Konya region.

4.2 Modeling Of Evaporation for Karaman Region .

The daily data of the Evaporation and the effective factors such as the precipitation , vapor pressure , maximum temperature , minimum temperature , mean temperature, relative humidity, wind speed, solar radiation and absolute pressure for period between 2000-2010 were used for this study for Karaman region as was done for Konya . Before starting the correlation between each variable and the evaporation was also found then the input combinations for each model was set according to this correlation .Table(7)illustrates the different models for karaman region .

Table(7) The applied models with different input combinations for Karaman Region.

Model name	Input Combinations
M1	P,VP,SR,AP,WS,Tmean,Tmin,Tmax,RH
M2	P,VP,SR,AP,Tmean,Tmin,Tmax,RH
M3	P,VP,SR,Tmean,Tmin,Tmax,RH
M4	P,SR,Tmean,Tmin,Tmax,RH
M5	SR,Tmean,Tmin,Tmax,RH
M6	Tmean,Tmin,Tmax,RH
M7	Tmean,Tmin,Tmax
M8	Tmean, Tmax
M9	Tmean

The above models were tried for Adaptive neuro fuzzy interference ANFIS and artificial neural networks ANNs different models in the same way.

4.2.1 Application of Adaptive Neuro Interference System on Karaman Region.

The mentioned models at Table(7) were applied in ANFIS models for the data of evaporation and other climatic data for Karaman region .Table(8) shows the values of E_{nash} and R_{bias} while Figures (13) and (14) illustrate the values of R2 and MAPE respectively.

Table(8) The Evalution Parameters Results for ANFIS models on Karaman.

Model Name	E_{nash}	R_{bias}
M1	0.7835	-3.2111
M2	0.779	-3.28
M3	0.802	-2.7608
M4	0.768	-3.6652
M5	0.8790	1.09
M6	**0.884**	**-1.0023**
M7	0.814	-2.1137
M8	0.8236	-2.9255
M9	0.7990	-3.7118

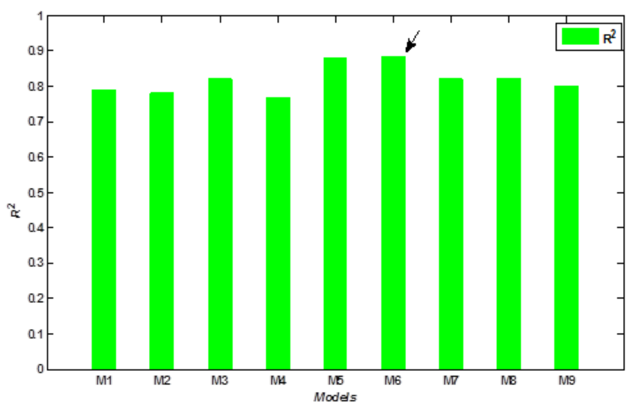


Fig (13)Values Of R^2 for ANFIS models (Karaman).

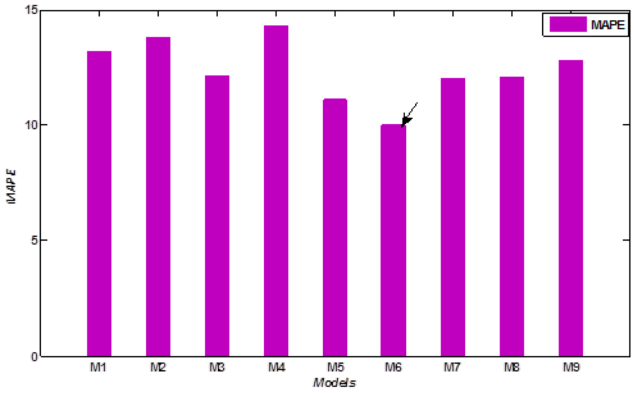


Fig (14) Values of MAPE for ANFIS models(Karaman).

From the above results it is clear that the best performance was by using model M6 with input combinations T_{max},T_{min}, T_{mean} and relative humidity since the value of evaluation parameters indicate a very good fit with a little under estimation . Value of coefficient of determination was equal to 0.885 and the value of mean absolute error as a percentage was the least one among all the other trials.

4.2.2 Application of Artificial Neural Networks on Karaman Region.

4.2.2.A . Application of Levenberg-Marquardt Neural Networks(LMNN)on Karaman Region .

The results of this networks with the same input combinations are illustrated at Table (9) and Figures (15 and16). The performance of the networks was dropped using this training algorithm if compared with the pervious method . Although of this , the best model could be decided to be M1 with all input combinations and with 4 neurons at the hidden layer . The value of R bias indicated an under estimation in all the tried models and structures.

Table(9) The Evalution Parameters Results for LMNN models on Karaman.

Model Name	Model structure	E_{nash}	R bias
M1	**9-4-1**	**0.4890**	-6.4761
M2	8-4-1	0.4708	-6.5743
M3	7-6-1	0.4676	-5.8555
M4	6-6-1	0.4422	-5.7894
M5	5-7-1	0.4205	-5.8838
M6	4-9-1	0.4044	-1.3411
M7	3-9-1	0.3703	-3.6102
M8	2-6-1	0.3908	-3.7077
M9	1-3-1	0.3812	-3.1293

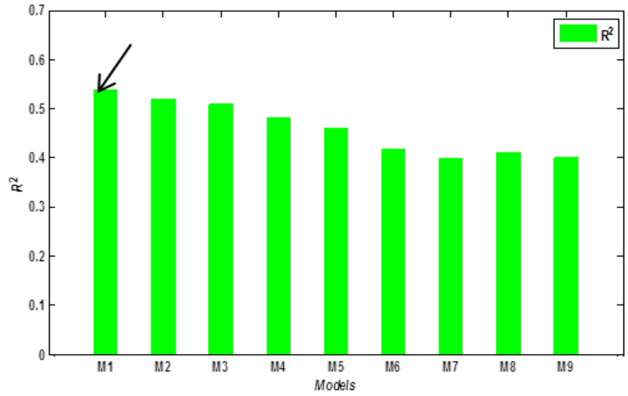
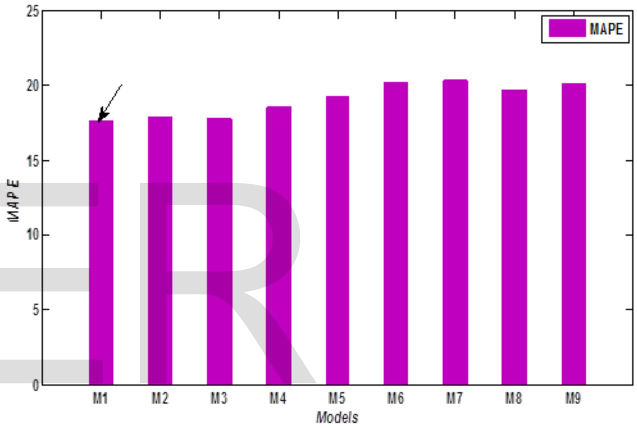


Fig (15)Values Of R^2 for LMNN models (Karaman).



Fig(16) Values of MAPE for LMNN models(Karaman).

4.2.2.B . Application of Scaled Conjugate Gradient (SCGNN)on Karaman region .

The results of this networks with the same input combinations are illustrated at Table (10) and Figures (17 and 18). Using these kinds of networks also was not so encouraging . The best model among all the applied models was found to be M4 as is indicated with bold font in the Table .

Table(10) The Evalution Parameters Results for LMNN models on Karaman.

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-2-1	0.4185	-7.9976
M2	8-8-1	0.41257	-7.9868
M3	7-2-1	0.4418	-7.8353
M4	**6-6-1**	**0.4559**	**-7.8627**
M5	5-2-1	0.4497	-7.9825
M6	4-24-1	0.4331	-4.7037
M7	3-9-1	0.4162	-6.3833
M8	2-24-1	0.4275	-6.0130
M9	1-8-1	0.4133	-5.5936

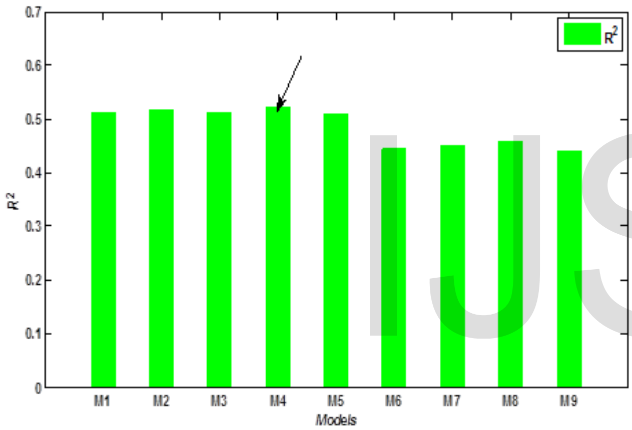
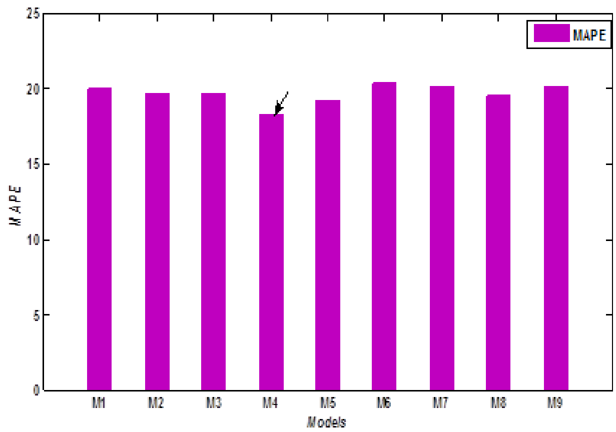


Fig (17)Values Of R^2 for SCGNN models (Karaman)



Fig(18) Values of MAPE for SCGNN models(Karaman).

4.2.2.C . Application of Radial basis function neural networks (RBNN)on Karaman region .

The results of this networks with the same input combinations with different spread values and neuron numbers at the hidden layer are illustrated at Table (11) and Figures (19 and 20).

Table(11) The Evalution Parameters Results for RBFNN models on Karaman.

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-44-700	0.5075	-7.2721
M2	8-48-1000	0.4979	-7.6198
M3	7-46-600	0.5047	-7.7608
M4	6-48-500	0.4727	-7.6652
M5	5-46-600	0.4480	-7.7779
M6	4-48-1000	0.4344	-4.9727
M7	3-10-100	0.4064	-6.1135
M8	2-4-500	0.4106	-5.9216
M9	1-2-100	0.4110	-5.7538

Note: Model structure :inputs-spread value –neurons of the hidden layer.

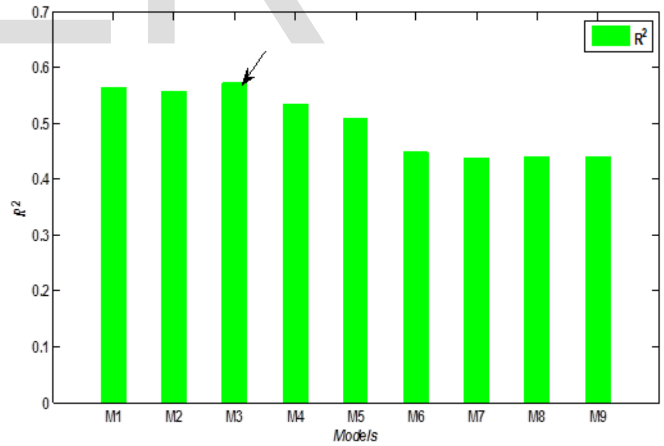
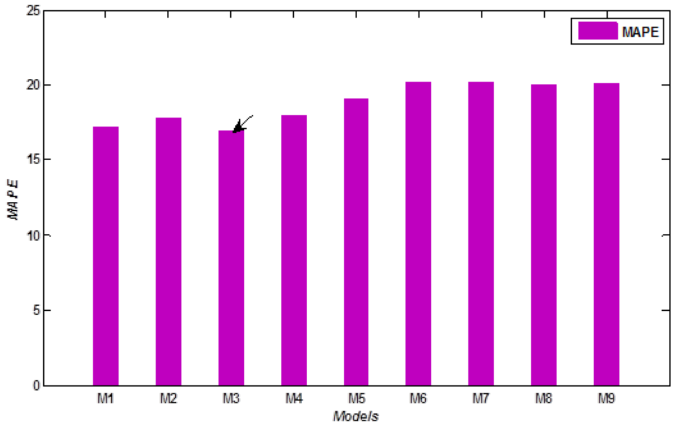


Fig (19)Values Of R^2 for RBFNN models (Karaman)



Fig(20) Values of MAPE for RBFNN models(Karaman).

As it is clear from the above results, all the models indicated to an underestimation .

4.2.2.D . Application of Generlized regression neural networks (GRNN)on Karaman region .

The results of this networks with the same input combinations and different spread values are illustrated at Table (12) and Figures (21 and 22).

Table(12) The Evalution Parameters Results for RBFNN models on Karaman.

Model Name	Model structure	E_{nash}	R_{bias}
M1	9-0.3-1	0.157	1.0096
M2	**8-0.4-1**	**0.1682**	**1.4649**
M3	7-0.1-1	0.075	-1.2482
M4	6-0.1-1	0.0715	-0.7821
M5	5-0.1-1	0.0619	-1.3736
M6	4-0.3-1	0.1466	1.5182
M7	3-0.1-1	0.0468	-0.0609
M8	2-0.1-1	0.0567	-1.1091
M9	1-0.2-1	0.1606	0.88

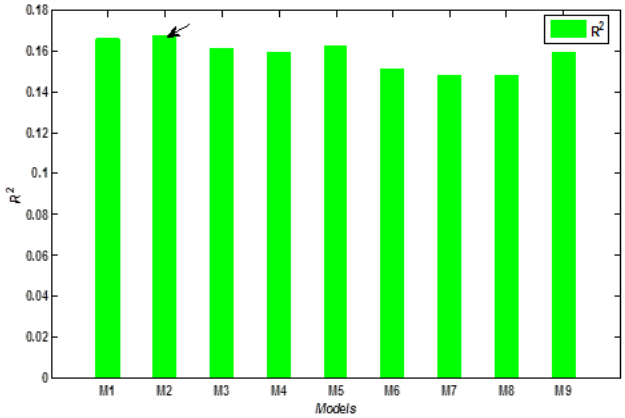
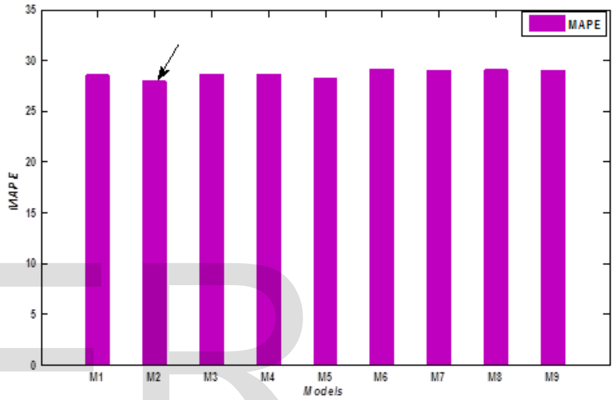


Fig (21)Values Of R^2 for GRNN models (Karaman).



Fig(22) Values of MAPE for GRNN models(Karaman).

The results of using generalized regression networks in modeling evaporation for Karaman region was not good. This is clear from E_{nash} and coefficient of determination R2values especially since the best caught value of R2 was 0.1674. Among all the applied models with different structures and different types of networks, the performance of adaptive neuro interference system ANFIS models were the best and the ANFIS model was capable to describe the evaporation at both Konya and Karaman regions .

Conclusions :

ANFIS and different ANN models have been proposed and emerged as an alternative approach of evaporation estimation for two case studies which are Konya and Karaman regions at Turkey . The back propagation multilayer perception ANN with two training algorithms and two another types of ANN models which are RBFNN and GRNN were used for estimation of the evaporation at both states . Both ANFIS and ANN models were applied using different parameters as input for models for the prediction of evaporation. The study consisted a comprehensive investigation of number of neurons at the hidden layer for LMNN, SCGNN and RBFNN s . Also different values of spread were tested for both RBFNN and GRNNs. The study concluded that combination of different input parameters provides better performance of model for estimation the evaporation rather than individual parameters. The outcome of the study provided an impetus to the potential use of ANFIS approach rather than others for prediction the evaporation for both states. The ANFIS model was concluded to be more flexible than the ANN models considered, with more options of incorporating the fuzzy nature of the real-world system. The results are quite encouraging and suggest the usefulness of ANFIS based modeling technique in accurate prediction of the evaporation as an alternative to other traditional approaches. This study also concluded that a combination of mean max, min air temperature, precipitation , solar radiation , relative humidity and absolute pressure provides better performance in predicting the evaporation of Konya region while for Karaman the combination of max, min, mean air temperature and relative humidity only provided the best evaporation estimation.

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