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PRECIPITATION PREDICTION MODEL WITH GENETIC EVALUATIONARY PROGRAMMING

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Abstract

The aim of this study was to develop an optimum precipitation prediction model, based on genetic evaluationary programming (GEP) and artificial neural network (ANN). The methodologies were applied to predict precipitation in Eğirdir located in the Lakes District of Turkey. The precipitation values of Eğirdir station were predicted using precipitation values of Isparta and Senirkent stations located in same region. For monthly precipitaion predictions, the data were taken from Turkish State Meteorological Service. The used data covered 36 years period during 1975-2010 for monthly precipitations. The GEP and ANN models were developed using different combinations of input variables. The comparison of historical records and models showed a better agreement in the GEP models than ANN models. With the help of GEP model for integrated precipitaton prediction, it is possible to estimate missing or unmeasured data and it wasgood at prediction of min and max precipitations.

Keywords: Monthly precipitation, Genetic Evaluationary Programming, Artificial Neural Networks, Eğirdir

GENETİK EVRİMSEL PROGRAMLAMA İLE YAĞIŞ TAHMİN MODELİ

Özet

Bu çalışmanın amacı Genetik Evrimsel Programlama (GEP) ve Yapay Sinir Ağları (YSA) yöntemlerini kullanarak en uygun yağış tahmin modelini geliştirmektir. Söz konusu metotlar Türkiye'de Göller Bölgesinde yeralan Eğirdir'e düşen yağışı tahmin etmek için kullanılmışlardır. Eğirdir'e ait yağış verileri aynı bölgede yeralan Isparta ve Senirkent istasyonlarının yağış verileri kullanılarak tahmin edilmiştir. Aylık yağış tahminleri için veriler Meteoroloji Genel Müdürlüğü'nden alınmıştır. Kullanılan meteorolojik veriler 1975 yılından 2010 yılına kadar olan 36 yıllık periyottan oluşmaktadır. GEP ve YSA modelleri için farklı girdi değişkenleri denenerek en uygun girdi seti elde edilmeye çalışılmıştır. Model sonuçları ile tarihi yağış kayıtları mukayese edildiğinde GEP modellerinin YSA modellere göre daha iyi sonuçlar verdiği görülmüştür. GEP ile geliştirilen yağış modeli sayesinde eksik ya da ölçülmemiş yağış verilerinin tahmini aynı zamanda en düşük ve en yüksek yağış verilerinin tahmini kolaylıkla yapılabilecektir.

Anahtar kelimeler: Aylık Yağış, Genetik Evrimsel Programlama, Yapay Sinir Ağları, Eğirdir

1. INTRODUCTION

The precipitation is an important meteorological variable in hydrological circulation. The precipitation formation and prediction have complex physics. In drought regions, this variable is mostly important for agriculture and water resources management, and for this reason, in recent years, a number of studies have been realized on improving precipitation prediction.

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In planning of the water structures, the future predictions based on the past records are necessary for the assessment of design criterion. The identification of suitable generation models for future precipitations is an important precondition for successful planning and management of water resources. In particular manner, missing data filling or prediction of data can be achieved through artificial intelligent modeling techniques (Genetic Evaluation Programming, Artificial Neural Networks, Adaptive Neural Based Fuzzy Inference Systems, and Fuzzy Logic etc.). Such modeling studies help to predict future likely replicates of possible precipitations for the design hydrologist.

More recently, artificial intelligence systems have gained attention. In the artificial intelligence models the overall error is not considered as globally in the stochastic methods but propagated to each variable in different proportions depending on the significance of the hydrological factor in the prediction process. The comparison is based on the prediction graphs and the root mean square errors. On the other hand, artificial intelligence models have also been used by many researchers in hydrology (Imrie et al., 2000, Zealand et al., 1999, Luk et al., 2000, Jervase et al., 2002, Dibike and Solomatine, 2001, Braddock et al., 1998, Keskin and Terzi, 2006).

Genetic evolutionary programming (GEP) is a method based on evolutionary algorithm basis. In this modeling, the optimal model solution is tried to be explained with the genetic algorithms produced starting from the theory of evolution.

The first genetic programming had been begun by mathematician Nils AallBaricelli through the use of evolutionary algorithms for evolution modeling in 1954. The genetic algorithms for the solution of optimization problems have become increasingly important in later years. The Gene Expression Programming developed by Ferraira (2001) is to use together genetic algorithms and genetic programming modeling. The different GEP applications used by many researchers are available in the field of hydrology nowadays. (Ghorbani et al., 2010; Teegavarapu et al., 2009). Güven and Aytek (2009) have used the GEP approach in storage-discharge relationship modeling. They have suggested this approach as alternative to conventional methods because of giving better results. Ghani and Azamathull (2011) were modeled sediment movement in waste water pipe systems by using GEP. Whigham and Crapper (2001) have predicted daily rainfall and flow series for two different basins using

GEP. They stated that this method is very good for hydrologic models, in runoff modeling especially. Rodriguez et al., (2012), have estimated runoff by using genetic algorithms and total precipitation records in a basin in Mexico. Hashmi et al., (2011) have tried to estimate rainfall using GEP and artificial neural networks. They said that these models gave similar results, but GEP model has better results than ANN model. Reddy and Ghimire (2009) have used the M5 model tree and GEP to estimate the amount of suspended material in streams. They compared this model with multilinear regression analysis and sediment charts. They stated that results of the M5 tree are better than GEP.

Zahiri and Azamathull (2012) used the linear genetic programming and M5 tree model to estimate flow in the composite channels. They stated that linear genetic programming gave better results according to 98% coefficient of determination.

Artificial neural networks (ANN) reconstruct links between input–output pairs for the system being modeled. The ANN has to be trained in order to generate the desired output. It was shown that artificial neural networks have been given useful results in many fields of hydrology and water resources research (Chen et al. 2006, Tingsanchali and Gautam, 2000). Teegavarapu and Chandramouli (2005) were used an data driven approach (i.e. ANN) to estimate missing precipitation data. They used historical precipitation data from 20 rain gauging stations in the state of Kentucky, USA. Ahmad and Simonovic (2005) showed a general framework for developing a runoff hydrograph using artificial neural network approach. They found that correlation between observed and simulated values of peak flow and time of peak was 0.99 and 0.88, respectively. Ramirez et al. (2005) proposed an artificial neural network (ANN) technique to construct a nonlinear mapping between output data from a regional ETA model ran at the Center for Weather Forecasts and Climate Studies/National Institute for Space Research/Brazil, and surface rainfall data for the region of Sao Paulo State in Brazil. They said that ANN results were superior to the ones obtained by the linear regression model thus revealing a great potential for an operational suite.

The main purpose of this paper is to develop the best methodology between GEP and ANN models to predict Eğirdir's precipitation collectively for a longer period (several months) by using historical measured monthly precipitation data of Isparta and Senirkent. The ANN models had been purposed Taylan and Küçükyaman (2011) for this region. In this study these

ANN models were compared GEP models. The measurement period is over a long span as inputs and outputs. All inputs and output variables were taken as monthly precipitation data and different hydrological or meteorological variable was not used.

2. METHODS

2.1. Genetic Evolutionary Programming

The algorithm of Genetic Evolutionary Programming consists of constant number and same long linear chromosomes which could be reconstituted by the computer program. The created chromosomes can be expressed as "Description Trees" (DT) in the form of different shapes and sizes by GEP's operator and processors. The GEP algorithm is reached target functions and values (Fitness), through new chromosomes obtained randomly by using one or more genetic operators such as The Genetic Algorithm (Genetic Algorithm GA) and The Genetic Programming (Genetic Programming GP) algorithms. The resulting new populations are algorithm that gives the most suitable function for target value (Ferreira, 2001).

The most of the genetic operators which has been used in GA and GP are used in the GEP with minor changes. As GP, GEP also has the basic five components: function settings, constants, fitness function, control parameters and stopping conditions. These components must be decided in solving a problem when used the GEP. The GEP use the fixed-length strings in its solutions, later evolving suitability, in different sizes and shapes are expressed as description tree.

In GEP algorithm, all of the problems which is from the most simple to the most complex are expressed as a description trees. The Description trees occur operators, functions, constants and variables. For example the GEP variables as {+, -, *, /, sqrt, 1, a, b, c, d, sin, cos} might be in a chromosome list. Here, when a chromosome is created as “sqrt.*.+.*.a.*.sqrt.a.b.c./.1.-.c.d”, "." was used to separate each gene and easy to read, "sqrt" means square root operation, "1" is a fixed number, "+,-,*" are the algebraic expressions, "a, b, c, d" refers to constants.

The relationships between variables are expressed as the Karva notation by Candida Ferreira which improves the GEP algorithm. According to Karva notation "explanation tree" is expressed as (AA). The description tree which is belonging to evolutionary genetic programming formed according to Karva notation is shown in Figure 1 (Ferreira, 2001).

Figure

1. The map of region

The mathematical expression of description tree in Figure 2, is expressed as following equation:

$$\frac{a \cdot b}{c} + \sqrt{d - e} \qquad (1)$$

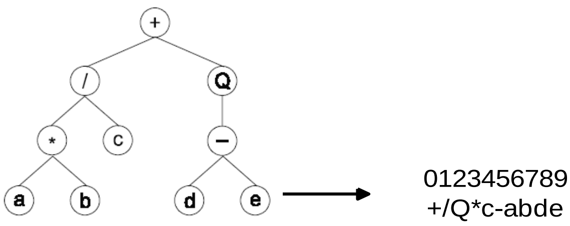

Figure 2. An example of mathematical description tree

2.2. Artificial Neural Networks

Neural Networks are promising new generation of information processing systems that demonstrate the ability to learn, recall, and generalize from training patterns or data. Artificial neural networks (ANNs) are systems that are deliberately constructed to make use of some organizational principles resembling those of the human brain. ANNs are inspired by modelling networks of real (biological) neurons in the brain. Hence, the processing elements in ANNs are also called artificial neurons, or simply neurons. Fig.3 shows a simple mathematical model of biological neuron proposed by McCulloch and Pitts (1943) [13], usually called an M-P neuron. In this model, the its processing element computes a weighted sum of its inputs and outputs y_i=1 (firing) or 0 (not firing) according to whether this weighted input some is above or below a certain threshold θi:

$$y_i(t+1) = a\left(\sum_{j=1}^{m} w_{ij} x_j(t) - \theta_i\right) \qquad (2)$$

$$a(f) = \begin{cases} 1 & if\ f \geq 0 \\ 0 & otherwise \end{cases} \qquad (3)$$

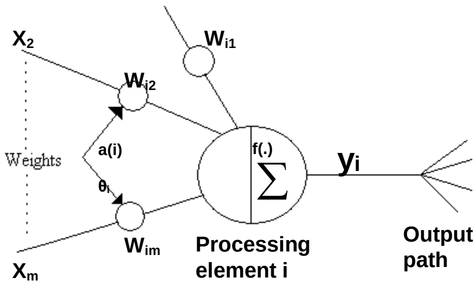

Figure 3. Schematic diagram of a McCulloch and Pitts neuron

where the activation function a(f) is a unit step function. The weight w_{ij} represents the strength of the synapse (called the connection or link) connecting neuron j (source) to neuron i(destination).A positive weight corresponds to an excitatory synapse, and a negative weight corresponds to an inhibitory synapse. If w_{ij}=0, then there is no connection between the two neurons. In Equation (2), it is assumed that a unit relay elapses between the time instants t and (t+1). This assumption will also be used in our further discussion of this subject. Although simplicity models a biological neuron as a binary threshold unit, a McCulloch-Pitts neuron has substantial computing potential. It can perform the basic logic operations NOT, OR, and AND when weights and thresholds are selected accordingly. Since any multivariable combinational function can be implemented by these basic logic operations, a synchronous assembly of such neurons is capable of performing universal computations, much like an ordinary digital computer (Lin and Lee, 1996).

3. STUDY AREA AND DATA

The models were developed to predict precipitation in Eğirdir in the Lakes District in southern part of Turkey. Lakes District is lying at south of Mediterranean in Turkey. Its surface area is 8.933 km^2 and it is located in the 30^{o}20' – 31^{o}33' east longitudes and 37^o 18'– 38^{o}30' north latitudes. The altitude of district is 1050 m. As a result of climatologically analysis of long period observations, both Mediterranean climate and terrestrial climate are seen in region. Therefore, characteristics of both climates are observed. Sum of mean annual precipitation is 551.8 mm/m^2. The best part of precipitation is in the winter and spring months (72.69%). Summer and autumn months are rather drought (29.31% of total precipitation).

The ANN model for study region had been applied Taylan and Küçükyaman (2011). They found that ANN (2,5,1) model was good at predicting of precipitation in Eğirdir. Monthly precipitation data from the Eğirdir, Isparta and Senirkent stations were taken from Turkish State Meteorological Service. The study region map was given in Fig. 1. The data period was consisting of monthly precipitations between 1975-2010 years. The mean monthly precipitation values for Isparta, Eğirdir and Senirkent were measured as 55,96 mm, 68,79 mm and 43,26 mm, respectively.

4. RESULTS AND DISCUSSIONS

In this study, monthly mean precipitation values of Isparta (Centrum), Eğirdir and Senirkent in Lakes District, Turkey have been obtained from Turkish State Metrological Service for precipitation prediction modeling.

The data belonging to the period between 1975 and 2003 years were used to develop the training part of the GEP and ANN models. The remaining data (2004 – 2010) were used to test period. The adequacy of the precipitation models were evaluated by estimating the coefficients of determination (R^2) and mean square error (MSE) defined based on the precipitation prediction errors as,

$$R^2 = \frac{P_o - P}{P_o} \tag{4}$$

$$P_o = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - P_{(mean)}\right)^2 \tag{5}$$

$$P = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - P_{i(predicted)}\right)^2 \qquad (6)$$

Where n is the number of observed or historical data, P_i and $P_{i(predicted)}$ were historical monthly precipitation values and developed model results, respectively. P_{mean} was the mean value of historical precipitation data. The mean square error (MSE) is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - P_{i(predicted)}\right)^2 \qquad (7)$$

In models, the input layer consisted of previous monthly precipitation values for Senirkent and Isparta Stations (P_{t-2}, P_{t-1}, P_t). The output layer contained a single precipitation value (PE_t) for Eğirdir at time t in models. The some models which have different input combinations were examined. PS_{t-2}, PS_{t-1}, PS_t showed monthly precipitation values for Senirkent in time t-2, t-1 and t, respectively. In the same way, PI_{t-2}, PI_{t-1}, PI_t showed monthly precipitation values for Isparta in time t-2, t-1 and t, respectively. In study, only historical precipitation values as hydrological and meteorological parameter were used to predict Eğirdir precipitation values in time t.

In first section of this study the GEP models were developed. The five steps were taken into account in GEP modeling . The first is to choose the fitness function. For this study, the R-square based fitness function was selected. This function has a very wide range of applications in engineering area. It is usually required a model with a high value of R-square. The second step is to select the set of inputs and the set of functions . The input set is consisted of the selected variables, giving as {PS_t, PS_{t-1}, PS_{t-2}, PI_t, PI_{t-1}, PI_{t-2}}. The four basic arithmetic operators F = {+,-, *, /} and some mathematical functions {power, √, e^x, ln(x), log(x), 10^X, sin, cos, tan } were used in this study.The third step is to choose the chromosomal architecture: the length of the head = 8 and the number of genes per chromosome = 3 in this study. The fourth step is to choose the kind of linking function. In this problem, the sub-expression trees were linked by addition. And final step, is to choose the set of genetic operators and their rates. The genetic parameters used in this study were given in Table 1.

Table 1. GEP model parameters

Number of chromosomes	50
Number of genes	3
Linkingfunctions	+
Head size	8
Mutation rate	0,044
One -pointrecombination rate	0,3
Two –pointrecombination rate	0,3
Gene recombination rate	0,1
Gene transposition rate	0,1

The mean square error (MSE) and R^2values of the training and testing sets of each model were given in Table 2 according to Equation (4) and (7).

Table 2. The GEP model structures and R^2 - MSE values for training and testing sets

Inputs	Basic arithmetic operators (+,-,*,/)									In training sets		In testing sets	
	+,	po	√	e	ln(	log(	1	si	c	ta	R^2	MSE	R^2	MSE
PS_t, PI_t	+	+	+	+	+	+	+	+	+	+	0,761	1270,6	0,821	933,9
PS_t, PS_{t-1}, PI_t	+	+	+	+	+	+	+				0.753	1311,0	0.865	706,0
PS_t, PS_{t-1}, PI_t, PI_{t-1}	+	+	+	+	+	+	+	+	+	+	0.775	1203,9	0.855	755,5
PS_t, PS_{t-1}, PS_{t-2}, PI_t,	+	+	+	+	+	+	+	+	+	+	0.774	1202,0	0.802	1035,
PS_t, PS_{t-1}, $PS_{t-2}PI_t$,	+	+	+	+	+	+	+	+	+	+	0.758	1309,8	0.874	655,2
PS_t, PS_{t-1}, PI_t, PI_{t-1},	+	+	+	+	+	+	+				0.750	1324,6	0.865	702,0
PS_t, PI_t, PI_{t-1}, PI_{t-2}	+	+	+	+	+	+	+	+	+	+	0.787	1130,4	0.850	782,8

As seen from Table 2, when the developed models were examined, it was shown that the model with input combinations of PS_t, PI_t, PI_{t-1}, PI_{t-2} precipitation values had the highest R^2 (0.787) and the lowest MSE (1130,42 mm/month) for training set and the model with input combinations of PS_t, PS_{t-1}, $PS_{t-2}PI_t$, PI_{t-1}, PI_{t-2} precipitation values had the highest R^2 (0.874) and the lowest MSE (655,22 mm/month) for testing set, respectively. The worse performances were provided by the input combinations of PS_t, PS_{t-1}, PI_t, PI_{t-1}, PI_{t-2} for training set (R^2=0,750 and MSE=1324,68), and by the input combinations of PS_t, PS_{t-1}, PS_{t-2}, PI_t, PI_{t-1} for testing set (R^2=0,802 and MSE=1035,71) .

In second section of this study, in ANN modeling, ANN(i,j,k) indicates a network architecture with i, j and k neurons in input, hidden and output layers, respectively. Herein, i were 2, 3, 4, 5, 6 and 7; j assumes different neuron values for one hidden layer whereas k=1 was adopted for output in order to decide about the best ANN model alternative. The numbers of hidden layer neurons were selected by trial and error. Prior to execution of the model, standardization of the data, X_i, (i = 1,2, …,n) was done according to the following expression such that all data values fall between 0 and 1.

$$x_i = (X_i - X_{\min})/(X_{\max} - X_{\min}) \qquad (8)$$

where x_i is the standardized value of the X_i, X_{max} and X_{min} are the maximum and minimum measurement values. Such standardization procedure renders the data also into dimensionless form. For ANN models the learning rate and momentum parameters affect the speed of the convergence of the back-propagation algorithm. A learning rate of 0.001 and momentum 0.1 were fixed for selected network after training and model selection is completed.

To compare of models performances R^2 and MSE values calculated according to Equation (4) and (7) were given in Table 3.

Table 3. The ANN model structures and R^2 – MSE values for training sets and testing sets.

Inputs	Model	In training		In testing sets	
		R^2	MSE	R^2	MSE
PS_t, PI_t	(2,4,1)	0.795	1088.9	0.767	1158.1
PS_t, PS_{t-1}, PI_t	(2,5,1)	0.833	883.0	0.715	1489.1
PS_t, PS_{t-1}, PI_t, PI_{t-1}	(2,5,1)	0.831	893.7	0.845	1572.0
PS_t, PS_{t-1}, PS_{t-2}, PI_t, PI_{t-1}	(2,5,1)	0.841	844.9	0.523	2488.6
PS_t, PS_{t-1}, $PS_{t-2}PI_t$, PI_{t-1},	(2,5,1)	0.830	900.9	0.529	2456.2
PS_t, PS_{t-1}, PI_t, PI_{t-1}, PI_{t-2}	(2,6,1)	0.841	844.8	0.699	1571.2
PS_t, PI_t, PI_{t-1}, PI_{t-2}	(2,6.1)	0.830	903.2	0.530	2450.6

It was seen from Table 3 that PS_t, PS_{t-1}, PI_t, PI_{t-1} input variables were to give the best results (R^2=0,831and MSE=893,7 for training set and R^2=0,845 and MSE=1572 for testing set). In this model structure were formed by four inputs, five hidden layer neurons and one output neuron. According to this model, it was enough to know precipitations values of Senirkent and Isparta stations in t and t-1 times for Eğirdir precipitation in t time. For this model structure R^2 value of testing sets were higher than others. This situation showed that selected model architecture was the best one.

Comparing the performance of the GEP and ANN models, the performance indices revealed that the GEP models are generally better than ANN models for testing sets. It was shown that GEP model with PS_t, PS_{t-1}, $PS_{t-2}PI_t$, PI_{t-1}, PI_{t-2} precipitation values had the highest R^2 (0.874) and the lowest MSE (655,22 mm/month) in all models. The results of the best GEP model were plotted against observed monthly precipitation for training and testing sets in Fig. 4. The GEP model had a good correlation with observed precipitation values. The min and max precipitations were well predicted by the GEP model.

The formula obtained from the GEP model developed for Eğirdir is given as:

$$PE_t = \frac{\tan(\sin((PI_{t-2})+(PS_{t-2}))+(PI_t)}{e^{(PS_{t-2})}} + \frac{\log(\sqrt{10^{(PS_t)}-10^{\sin((PS_{t-1})-(PI_{t-1}))}}}{log10} + ((PI_t) - \sin\Big(\big((PI_{t-1}) - ((PT_{t-2}) - (PI_{t-1}))\big)\Big) - ((PS_{t-2}) * (PI_{t-1}))) \quad (9)$$

in which PS_{t-2}, the previous 2-month precipitation for Senirkent (mm/month); PS_{t-1}, the previous 1-month precipitation for Senirkent (mm/month); PS_t, precipitation for Senirkent (mm/month) in t time; PI_{t-2}, the previous 2-month precipitation for Isparta (mm/month); PI_{t-1}, the previous 1-month precipitation for Isparta (mm/month); PI_t, precipitation for Isparta (mm/month) in t time; PE_t ,precipitation for Eğirdir (mm/month) in t time, respectively.

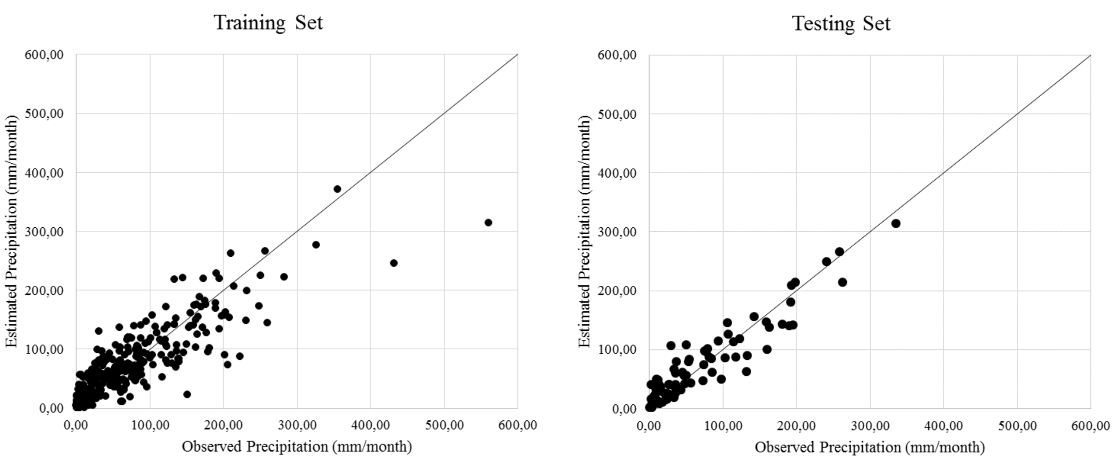

Figure 4. Scatter diagrams between the GEP model (PS_t, PS_{t-1}, PS_{t-2} PI_t, PI_{t-1}, PI_{t-2}) and the observed monthly precipitation for training and testing sets

As shown in Figure 4 the GEP model comparison plot was uniformly distributed around 45° straightlines, that means there were no bias effects in the models for training and testing sets. The time series of the GEP and ANN models together with the montly precipitation values were shown in Figure 5, which shows a good agreemen between the GEP and ANN models and precipitation values. When results of the GEP and ANN models were compared to montly precipitation values for testing set, it could be said that the GEP model was a little beter than the ANN model.

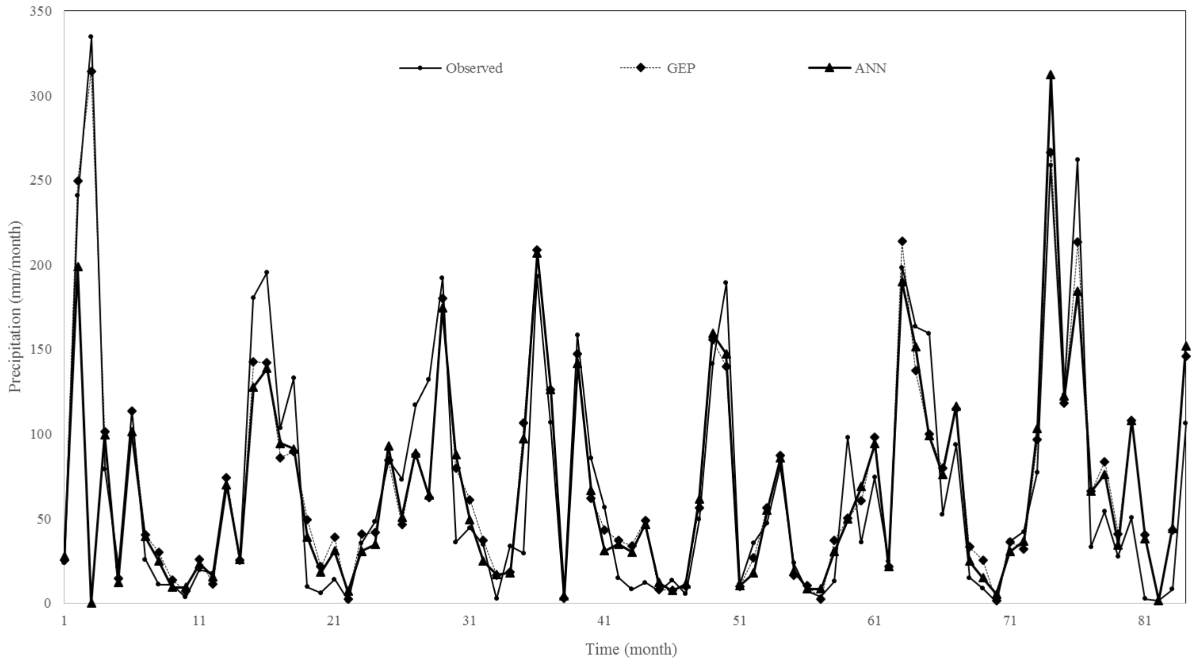

Figure 5. Time series of estimatedandobservedmonthlyprecipitationvaluesfortesting set

5. CONCLUSION

In the present study, precipitation prediction for Eğirdir in Lakes District, Turkey was realized using GEP and ANN methods. The different input combinations were examined to predict the best results. The most suitable model was selected by comparing observed and predicted values. The highest R^2 values and the lowest MSE values were obtained for PS_t, PS_{t-1}, $PS_{t-2}PI_t$, PI_{t-1}, PI_{t-2} input set in GEP model. The developed GEP models were found suitable to predict effectively for extreme points. It was found that the GEP model gave better results than the ANN model.Although, precipitation predicting is real problem for local administrations and water resources planners in areas in which drought is a serious problem, especially. This paper presents an applicable approximation by using GEP. Also, the obtained GEP model formula can be used to estimate precipitation of Eğirdir. Although the formula was obtained for Eğirdir, it could be adapted by using different parameters for study region.

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