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Evaluation of Adaptive Neuro-Fuzzy Inference System Models in Estimating Saffron Yield Using Meteorological Data

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ABSTRACT

Saffron is one of the most valuable agricultural and medicinal plants of the world and has a special place in Iran's export of products. Presently, Iran is the world's largest producer and exporter of saffron and more than 93/7% of the world production belongs to Iran. However, despite the long history of saffron cultivation and its value-added in comparison to many of the other crops in the country, a lower share of new technologies is assigned to it, and its production is mainly based on local knowledge. This study aimed to develop and evaluate the performance of Adaptive Neuro-Fuzzy Inference System model (ANFIS) in calculating the yield of saffron using meteorological data from 20 synoptic stations in the province, including evapotranspiration, temperature (maximum, minimum), the mean relative humidity, and rainfall. To this end, by using software Wingamma, data and parameters were analyzed and the best combinations of inputs to the model were determined. In order to assess the models, statistical parameters of correlation coefficient, the mean absolute error, and mean square error were used to predict the performance of the plant. ANFIS model was most effective when the data of total minimum temperature, precipitation, evapotranspiration, and relative humidity of autumn were used as independent variables for forecasting yield (R^2= 0.5627, RMSE= 2.051 kg ha^{-1}, and MAE = 1.7274 kg ha^{-1}) .

Keywords: ANFIS model, Forecasting yield, Gamma test, Regression.

INTRODUCTION

Saffron (Corcus sativus) is an Iridaceous plant, which is one of the most expensive spices in the world and it has great nutritional and medicinal value (Leffingwell, 2008). This plant is considered as a strategic product in Iran and its agricultural history dates back more than 2,500 years ago (Sharrif Moghaddasi, 2010). Saffron cultivation history is more than 2500 years ago. Apparently, this plant is native to Greece and Mediterranean regions, but some believe that the primary site of it, but currently its producton is limited in South Khorasan and some other regions including Fars, Kerman, Yazd, and Khorasan Razavi Provinces. Among the various agricultural products, saffron is a traditional crop. Annually, Iran produces more than 200 tons of saffron, while it has 90 percent of cultivate area of the world and 93.7 of production (Behdani *et al*., 2010).

About 85 thousand households in southern and central Khorasan Province are involved in saffron production and, according to statistics, this region is considered the most important and prominent exporter of this crop. Gross value of production of saffron in South Khorasan Province is about 17% of the agricultural sector. The climate of the region is considered as the most important factor in agricultural production and,

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therefore, climate change is a major deterrent to the development of agriculture. Given the growing crisis related to rainfall in the region and especially in this study, it is of great interest to select appropriate strategies to maximize the performance of products.

In recent years, due to the severe shortage of quality water resources, growth or cultivation of plants and crops in different parts of the world, and especially in the arid and semi-arid areas, is designed based on the availability of water resources. Principally, in many cases, the efficiency of crop production per cubic meter of water is calculated (Koozegaran *et al.* 2010). Despite tolerance of this plant to low water conditions, climate change in recent years in different parts of the world, severely affected the plant growth. The results of studies on the relationship between climatic data and crop yield and area under cultivation indicate the effect of temperature and rainfall changes on the mean and variance of crop yield are effected. So that the average crop yield increases with more rainfall and degree higher temperatures decrease or in other words, increasing rainfall reduces the variability of crop yield and increasing temperature increases the variability of crop yield (Adams, 2000).

Today, artificial intelligence is used in all human needs and is rapidly developing. One of the most important results of this research is the use of artificial intelligence in predicting the performance of strategic and sensitive saffron crop for economic planning. Since the economic livelihood of a large number of families in the provinces of Khorasan Razavi and South Khorasan, and other parts of Iran, depends on this crop., decision makers using existing data and using this tool can help reduce uncertainty and risk for this product

In one study, the ability of the technology of Artificial Neural Network (ANN) and Fuzzy Inference System (ANFIS) using meteorological and annual data to predict dry land wheat yield in the province was studied (Khashei-Siuki *et al*., 2011). Based on the results of the model ANFIS, when the temperature (maximum, minimum and dew point) were used as independent variables to predict the best performance was obtained. In this study, the model input was considered on an annual basis, but it seems that Hosseini *et al*, showed that average monthly parameters predict changes of performance (Khashei *et al*., 2011).

Moghadam Nia and colleagues (Moghadamnia *et al*., 2009) in a study to estimate of evaporation by artificial neural network (ANN) and Adaptive neuro-fuzzy inference system (ANFIS) used gamma test to select the best combination of input data and determine the number of data the model used for calibration. In fact, the validity of the test data was examined.

The fuzzy inference systems are not much used in predicting crop yield, but one of the other applications of this system can include agricultural sector, especially in the field of water engineering: Hashemi Najafi *et al*. (2007) used adaptive neural fuzzy inference systems to estimate evapotranspiration reference plant in Ahvaz. The results showed that the precision of neural fuzzy inference system model in comparison to experimental methods is high and has high potential to predict evapotranspiration of reference crop. Jia Bing (2004), estimated the evapotranspiration of this reference crop in China using fuzzy logic and artificial neural network and the combination of these two models, and compared the results with Penman-Monteith (FAO) method. He concluded that the number of sunshine hours and the maximum temperature in ANFIS model as input data can provide better results and comparative advantages compared to ANFIS and ANN model. Seifi and Riahi.,(2020) estimated daily reference evapotranspiration using hybrid gamma test-least square support vector machine, gamma test-ANN, and gamma test-ANFIS models in an arid area of Iran.

Zare Abyaneh *et al.* (2010) evaluated the neural systems in reducing estimation parameters of evapotranspiration of the reference crop for this purpose, using

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Pearson, six meteorological parameters needed in the Penman-Monteith FAO, including maximum and minimum temperatures, relative humidity values, the minimum and maximum wind speed at a height of two meters and daily sunshine hours as four scenarios (known as 1, 2, 3, and 4). Applying these scenarios based on intelligent models of artificial neural network and adaptive fuzzy inference system in MATLAB software, evapotranspiration of reference crop of the region was estimated. In order to evaluate the results of each of the scenarios used, the actual values of reference evapotranspiration (lysimeter) were used. The results showed that increasing the number of data at input layer did not necessarily lead to improved results of smart model and Neural Network model after 26 computational iterations in comparison with adaptive fuzzy inference system with 40 computational iterations achieved good results and faster.

Given the importance of saffron in terms of economic, export, employment, and pharmaceutical applications, more accurate performance prediction of it is very important and provides decision possibility on the potential of the region to anticipate credits for the purchase of a guarantee of the product or providing the necessary measures to provide the needed labor force, especially in harvesting saffron, which is a labor-consuming activity. On the other hand, more exact forecasts of saffron performance ensures the interests of all those involved in the industry and, ultimately, meeting the national interest. Study of Riahi Modavar *et al*. (2017) indicated that decision makers and agricultural developers should consider confidence intervals in the prediction in order to make more realistic policies instead of using unique yield value. Also, it can be concluded that the Monte-Carlo uncertainty analysis combined with artificial neural network can provide uncertainty bounds for black box prediction models and it can be used for more realistic decision making.

Up to now, other conventional methods have been used for prediction of saffron yield, and the use of artificial neural network is a different way for this purpose. In this research, the saffron performance is predicted using fuzzy inference systems. Given the diversity of input data and proper operation of these systems, we try to have a reliable estimation of performance of saffron at its main production regions.

MATERIALS AND METHODS

Fuzzy Inference System (FIS)

Fuzzy Inference System maps an input space to an output space. The primary mechanism for doing it is a series of if-then fuzzy rules. In general, a fuzzy inference system is composed of five main blocks.

Base of Act: That contains a number of fuzzy if-then rules.

Database: That defines membership functions of fuzzy sets used at the rules.

Decision Unit: That applies Inference operations on rules.

Interface of Fuzzy-Builder: That changes the actual inputs to the degree of conformity to the linguistic values.

Interface of Non-Fuzzy-Builder: That take the results of fuzzy inference to the actual outputs.

Usually, a knowledge base is made of a combination of database and rule base.

ANFIS is a powerful universal approximation tool for vague and fuzzy systems (Lee, 2000). The basic structure of adaptive network consists of two main conceptual parts: a FIS, which is made up of three components: a rule base, a database, a reasoning mechanism demonstrated in the Figure 1 schematically, and a learning mechanism consisting of a multilayer feed forward network (Nayak *et al.*, 2004).

Neural-Fuzzy Network

In Neural- Fuzzy Network, at first, the neuronal part is used for learning and classification capabilities and to link reform

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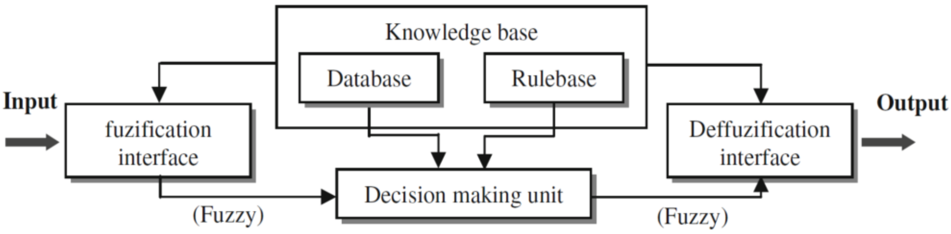

Figure 1. Fuzzy inference system with crisp output (Kholghi and Hosseini, 2009).

model. The neural part of network automatically creates fuzzy logic rules and membership functions during the learning period. In addition, even after learning, neural networks continue to modify membership functions and fuzzy logic rules, so that from its input signal, learns more and more. On the other hand, the fuzzy logic for inference and for providing a non-fuzzy output is used (Joorabyan and Hooshmand, 2002).

Adaptive Neuro-Fuzzy Inference System (ANFIS)

The combination of fuzzy systems that are based on logical rules and method of artificial neural networks that can extract knowledge from numerical data has led to the adaptive neural-fuzzy inference system. This system is a feedback network of multi-layer that uses neural network learning algorithms to design nonlinear mapping between input and output space. ANFIS with respect to the ability to combine the power of language in a fuzzy system with numerical ability of a neural network has shown that the model is very powerful in non-linear processes.

Karamooz *et al*. (2005) consider ANFIS a capable model in designing nonlinear mapping between input and output spaces with successful applications in modeling and control of complex systems. The main teaching method in this system is post-propagation method that is a combination with the lowest sum of squared errors. At sum of ANFIS, a 5-layer structure with a number of input variables was used and each entry was with a member of two or more functions. The structure of the system was selected with inputs, the input and output membership functions, rules, and membership function.

Today, with the use of these systems, many studies have been done in the field of science. The use of these systems in Iran, especially in agricultural sciences, is at the beginning, however, due to the ability of modeling complex processes whose number of influencing factors is high, they provide the possibility of widespread use in agricultural science (Taherhoseini *et al*., 2007).

Gamma Test

Their correct understanding from the nonlinear issues and being complex of prior information of model is one of the abilities of the smart models is one of the abilities of the smart models. However, determination and selection of the most important and effective parameters of an unknown nonlinear function at simulation models is one of the most difficult stages of development of a model. In this regard, a new method, namely, gamma test is used for this purpose.

The test is a powerful tool to find the best combination of input at non-linear modeling that examines creating a smooth model even before creating the model. With this combination, the importance of input parameters, the best possible combination for the training model can be achieved. Since, in general, the gamma test requires no assumptions about the population under

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study, it is a non-parametric statistical method and its results, regardless of the specific test, are used to build the model (Jones *et al*., 2002). Basically, this test shows that the output of the variance that we cannot calculate its with each paved model on inputs. Therefore, Gamma calculation is a simple form of error deviation that shows the estimated error rate (error variance) with respect to the actual data. This estimate is called gamma statistics (Γ).

Various reasons are responsible for errors in the measured data sets. Some of these reasons can be pointed out: (Jones *et al*., 2002):

- The lack of precision in the measurement.
- The relationship between the input and output data is not smooth.
- All factors affecting output are not considered at input.

The Study Area

The study was done in 2013 on the basis of climate data related to provinces of South Khorasan and Khorasan Razavi as the most important areas for saffron cultivation in Iran. Figure 2 shows the location of different cities in the two provinces studied. The 20-year data in this study is from Meteorological Stations and Agriculture Organization of Khorasan. Meteorological data used in this study include total minimum temperature, total maximum daily temperature, total daily humidity in the growth period, total rainfall and evapotranspiration that was prepared as input and yield models from Agriculture Organizations and Statistics of the Ministry of Agriculture and were used as the outgoing model.

Table 1 shows the scope and the statistical properties of meteorological parameters such as total minimum Temperature (Tmin), maximum Temperature (Tmax), Evapotranspiration ((ET Precipitation (Pr), Telative Humidity (RH), and the Yield of saffron (Yield), were measured. One of the characteristics of saffron, unlike other agricultural products, is that it gives a yield at the beginning of cultivation and then continues to grow and develop. Any irrigation then harvesting has a direct impact on crop yield in the next year. Therefore, in this study, we arranged the meteorological parameters in proportion to the performance of the following year (Nekouei *et al*., 2014).

Pre-Processing of Gamma Test

At this stage, using existing

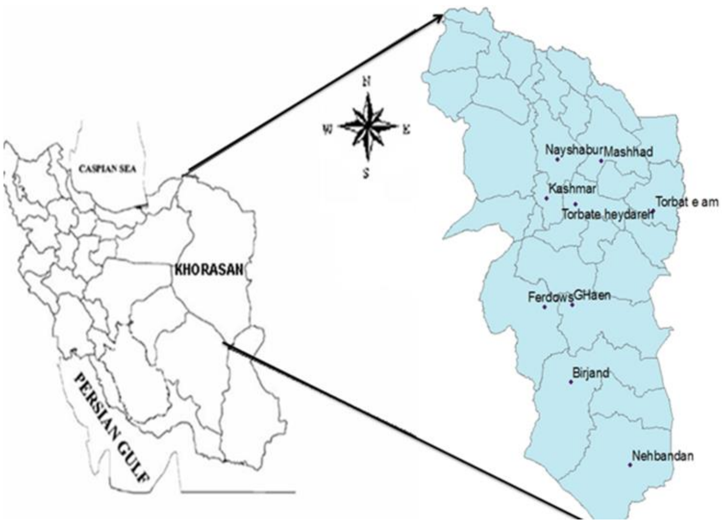

Figure 2. Location of the study area.

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Table 1. Range and statistical characteristics of the collected data set.

Row	Parameter	STDEV	Max	Min	Average
1	Tmin total (°C)	785.05	5138.1	1850.7	3383.79
2	Tmax total (°C)	1771.005	10445.4	2866.2	7987.27
3	Pr total (mm d^{-1})	77.5534	390	14	189.47
4	ET total (mm d^{-1})	322.4995	2316.95	208.7	1508.06
5	RH total (%)	5023.393	23193.6	1900.28	13779.55
6	Yield (kg ha^{-1})	2.162	6.94	0.3	3.843

meteorological parameters (Tmin, Tmax, P, ET, RH) and taking into account all factors combined, 86 different input combinations were randomly selected and defined for the application WinGamma. In this research, meteorological parameters were considered seasonally and in some cases on a monthly basis. Symbols Psp, Psu, Pau, Pwi, and Ptotal represent the total rainfall in the spring, summer, autumn, winter, and per year. ETsp (Total Evapotranspiration in the spring), ETsu (Total Evapotranspiration in the summer), ETau (Total Evapotranspiration in autumn), ETwi (Total Evapotranspiration in the winter), ETtotal (Total Evapotranspiration year), RHsp (Total Humidity in the spring), RHsu (Total Humidity in the summer), RHau (Total Humidity in autumn), RHw (Total Humidity in winter), RHtotal (Total RH year), Tmin sp (Total at least in the spring), Tmin su (Total at least in summer), Tmin Mehr (Total at least in October), Tmin Aban (Total minimum temperature in November), Tmin Azar (Total minimum temperature in December), Tmin Dey (Total minimum Temperature in December), Tmin Bahman (Total minimum Temperature in the month of January), Tmin Esfand (Total Minimum Temperature in March), Tmin total (Total of at least a year), Tmax sp (Total maximum Temperature in the spring), Tmax su (Total maximum Temperature in summer), Tmax Mehr (Total maximum Temperature in the month of October), Tmax Aban (Total maximum Temperature in November), Tmax Azar (Total maximum Temperature in the month of December), Tmax Dey (Total maximum Temperature in December), Tmax Bahman (Total maximum Temperature in the month of January}, Tmax Esfand (Total maximum Temperature of the month March}, Tmax total (Total maximum Temperature in the year). Table 2 has introduced all combinations tested. These statistic gamma values, the standard error, and the slope of the regression line were estimated. It is clear that among the possible compounds, some compounds with more effective parameters on saffron yield will be more important.

By calculating delta and gamma values from the input and output parameters, their distribution was plotted around the regression line for the selected composition. In this regard, the greater the accumulation of points in the wedge-shaped margins around the gamma axis, the greater the number of points that have different outputs for the same inputs.

Regression Model

Most meteorological models of agricultural yield are statistical and experimental models. Its main characteristics are simple and direct connection between the yield and one or more environmental parameters. Among these models, regression models are most widely used and many studies have been done in this field. In the current research, we studied prediction of crop yield and the relationship between meteorological parameters as independent variables and yield as the dependent variable and compared this model with fuzzy inference systems and multivariate regression model using the software sigmasat 3 0.5.

Evaluation Criteria Investigation

The data of network was divided into three parts, of which 60 percent of data was used

Table 2. Combination tested in gamma test.

Parameters	NC [a]	Parameters	NC [a]
$P_{sp}-P_{su}-P_{au}-P_{wi}$	1	$P_{sp}-P_{su}-P_{au}-P_{wi}-H_{sp}-H_{su}-RH_{au}-RH_{wi}$	2
$T_{\text{max Mehr}}-T_{\text{max Dey-}}P_{\text{au-}}P_{wi}-ET_{au}-ET_{\text{wi-}}y$	3	$P_{sp}-P_{su}-P_{au}-P_{wi}-y$	4
$P_{sp}-P_{su}-P_{au}-P_{wi}-RH_{sp}-RH_{su}-RH_{au}-RH_{wi}-y$	5	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{au}-P_{wi}-ET_{au}-ET_{wi}$	6
$ET_{SP}-ET_{su}-ET_{au}-ET_{wi}$	7	$ET_{SP}-ET_{su}-ET_{au}-ET_{wi}-RH_{sp}-RH_{su}-RH_{au}-RH_{wi}$	8
$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{\text{au-}}P_{wi}-ET_{au}-ET_{\text{wi-}}y$	9	$ET_{SP}-ET_{su}-ET_{au}-ET_{w}-y$	10
$ET_{SP}-ET_{su}-ET_{au}-ET_{wi}-RH_{sp}-RH_{su}-RH_{au}-RH_{wi}-y$	11	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{\text{au-}}P_{wi}\ RH_{au}-RH_{wi}$	12
$RH_{sp}-RH_{su}-RH_{au}-RH_{wi}$	13	$T_{\text{min total}}-T_{\text{max total}}-P_{total}-ET_{total}$	14
$T_{\text{max Bahman}}-T_{\text{max Esfand}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}\ ET_{wi}-RH_{wi}-y$	15	$RH_{sp}-RH_{su}-RH_{au}-RH_{wi}-y$	16
$T_{\text{min total}}-T_{\text{max total}}-P_{total}-ET_{total}-y$	17	$T_{\text{min Bahman}}-T_{\text{min Esfand}}-P_{au}-y\ -\ -T_{\text{min Dey}}-T_{\text{min Azar}}\ T_{\text{min Mehr}}-T_{\text{min aban-}}T_{\text{min sp}}-T_{\text{min su}}$	18
$T_{\text{min total}}-T_{\text{max total}}-P_{total}-ET_{total}-RH_{total}$	19	$P_{total}-ET_{total}$	20
$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-P_{au}-RH_{au}$	21	$T_{\text{min total}}-T_{\text{max total}}-P_{total}-ET_{total}-RH_{total}-y$	22
$P_{total}-ET_{total}-y$	23	$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-P_{au}-RH_{au}-y$	24
$P_{sp}-P_{su}-P_{au}-P_{wi}-ET_{SP}-ET_{su}-ET_{au}-ET_{wi}$	25	$P_{sp}-P_{su}-ET_{SP}-ET_{su}-y$	26
$T_{\text{max Mehr}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{au}-RH_{au}-ET_{au}$	27	$ET_{SP}-ET_{su}-ET_{au}-ET_{wi}-yP_{sp}-P_{su}-P_{au}-P_{wi}-$	28
$P_{sp}-P_{su}-RH_{sp}-RH_{su}$	29	$T_{\text{min Bahman}}-T_{\text{min Esfand}}-T_{\text{min Dey-}}T_{\text{min Azar}}-T_{\text{min Mehr}}-T_{\text{min Aban-}}T_{\text{min sp}}-T_{\text{min su}}$	30
$P_{total}-ET_{total}-RH_{total}$	31	$P_{sp}-P_{su}-RH_{sp}-RH_{su}-y$	32
$T_{\text{min Bahman}}-T_{\text{min Esfand}}-y-T_{\text{min dey}}T_{\text{min Azar}}-T_{\text{min Mehr}}-T_{\text{min Aban-}}T_{\text{min sp}}-T_{\text{min su}}$	33	$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-P_{au}-RH_{au}-ET_{au}-y$	34
$P_{sp}-P_{su}-ET_{SP}-ET_{su}-RH_{sp}-RH_{su}$	35	$T_{\text{max Bahman}}-T_{\text{max Esfand}}T_{\text{max dey}}T_{\text{max Azar}}-T_{\text{max Mehr}}-T_{\text{max Aban-}}-T_{\text{max sp}}-T_{\text{max su}}$	36
$RH_{total}-yP_{total}-ET_{total}$	37	$P_{sp}-P_{su}-ET_{SP}-ET_{su}-RH_{sp}-RH_{su}-y$	38
$y-T_{\text{max Bahman}}-T_{\text{max Esfand}}-T_{\text{max dey}}-T_{\text{max Azar}}-T_{\text{max Mehr}}-T_{\text{max Aban}}-T_{\text{max sp}}-T_{\text{max su}}$	39	$T_{\text{min sp}}-T_{\text{min su}}-T_{\text{max sp}}-T_{\text{max su}}-P_{sp}-P_{su}$	40
$T_{\text{min sp}}-T_{\text{min su}}-ET_{SP}-ET_{su}$	41	$T_{\text{min Bahman}}-T_{\text{min Esfand}}-P_{au}-T_{\text{min Dey-}}T_{\text{min Azar}}\ T_{\text{min Mehr}}-T_{\text{min Aban-}}T_{\text{min sp}}-T_{\text{min su}}$	42
$T_{\text{min sp}}-T_{\text{min su}}-T_{\text{maxsp}}-T_{\text{max su}}-P_{sp}-P_{su}-y$	43	$T_{\text{min sp}}-T_{\text{min su}}-ET_{SP}-ET_{su}-y$	44
$T_{\text{min Bahman}}-T_{\text{min Esfand}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-P_{sp}-ET_{sp}-RH_{sp}-y$	45	$P_{sp}-P_{su}-ET_{SP}-ET_{su}$	46
$T_{\text{maxsp}}-T_{\text{max su}}-P_{sp}-P_{su}-RH_{sp}-RH_{su}$	47	$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{max Mehr}}-T_{\text{max Aban}}-P_{sp}-P_{su}$	48
$T_{\text{min Mehr}}-T_{\text{min Dey}}-T_{\text{min Bahman}}-T_{\text{max Mehr}}-T_{\text{max Dey}}-T_{\text{max Bahman}}$	49	$T_{\text{max sp}}-T_{\text{max su}}-P_{sp}-P_{su}-RH_{sp}-RH_{su}-y$	50
$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{max Mehr}}-T_{\text{max Aban}}-P_{sp}-P_{su}-y$	51	$T_{\text{min Mehr}}-T_{\text{min Dey}}-T_{\text{min Bahman}}-T_{\text{max Mehr}}-T_{\text{max Dey}}-T_{\text{max Bahman-}}y$	52
$ET_{SP}-ET_{su}-RH_{sp}-RH_{su}$	53	$T_{\text{max Bahman}}-T_{\text{max Esfand}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}-ET_{wi}-RH_{wi}$	54
$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{au}$	55	$ET_{SP}-ET_{su}-RH_{sp}-RH_{su}-y$	56
$T_{\text{max Mehr}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{au}-RH_{au}-ET_{au}-y$	57	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{au}-y$	58
$ET_{au}-ET_{wi}-RH_{au}-RH_{wi}$	59	$T_{\text{min Dey}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}-P_{wi}-RH_{wi}$	60
$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-ET_{au}$	61	$ET_{au}-ET_{wi}-RH_{au}-RH_{wi}-y$	62
$T_{\text{min dey}}-T_{\text{min bahman}}-T_{\text{min esfand}}-P_{wi}-RH_{wi}-y$	63	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-ET_{au}-y$	64
$RH_{sp}ET_{SP}-T_{\text{min sp}}-T_{\text{maxsp}}-P_{sp}-$	65	$T_{\text{max Dey}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-RH_{wi}$	66
$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-RH_{au}$	67	$T_{\text{min sp}}-T_{\text{maxsp}}-P_{sp}-ET_{SP}-RH_{sp}-y$	68
$T_{\text{max Dey}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-P_{wi}-RH_{wi}-y$	69	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-RH_{au}-y$	70
$T_{\text{min su}}-T_{\text{max su}}-P_{su}-ET_{su}-RH_{su}$	71	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-P_{\text{au-}}P_{wi}-RH_{au}-RH_{wi}-y$	72
$T_{\text{min mehr}}-T_{\text{min dey}}-T_{\text{max mehr}}-T_{\text{max dey-}}P_{\text{au-}}P_{wi}$	73	$T_{\text{min su}}-T_{\text{max su}}-P_{su}-ET_{su}-RH_{su}-y$	74
$T_{\text{min Bahman}}-T_{\text{min Esfand}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-P_{sp}-ET_{sp}-RH_{sp}$	75	$T_{\text{min Mehr}}-T_{\text{min Dey}}-T_{\text{max Mehr}}-T_{\text{max Dey}}-P_{au}-P_{wi}-y$	76
$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}$	77	$T_{\text{min Mehr}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}-T_{\text{max Mehr}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-P_{wi}-y$	78
$T_{\text{min mehr}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}-T_{\text{max Mehr}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-P_{wi}$	79	$T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{max Aban}}-T_{\text{max Azar}}-y$	80
$T_{\text{max Mehr}}-T_{\text{max Dey-}}P_{\text{au-}}P_{wi}-ET_{au}-ET_{wi}$	81	$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{min Dey}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}-y$	82
$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-T_{\text{min Dey}}-T_{\text{min Bahman}}-T_{\text{min Esfand}}$	83	$T_{\text{max Mehr}}-T_{\text{max Aban}}-T_{\text{max Azar}}-T_{\text{max Dey}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}-y$	84
$T_{\text{max Mehr}}-T_{\text{max Aban}}-T_{\text{max azar}}-T_{\text{max Dey}}-T_{\text{max Bahman}}-T_{\text{max Esfand}}$	85	$T_{\text{min Mehr}}-T_{\text{min Aban}}-T_{\text{min Azar}}-P_{au}-RH_{au}-ET_{au}$	86

[a] Number of combination

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for network training, 20 percent for the validation of software used to calibrate the model of neural network, and 20% for testing and evaluation of model (Khashei *et al*., 2011). In order to obtain the consistency of the model, all data sets were normalized first in the range of 0 to 1 and then returned to the original values after simulation by using the equation of Doğan (Doğan, 2008):

$$X_{norm} = \left[\frac{X - X_{min}}{X_{max} - X_{min}}\right] \times 0.8 + 0.1 \quad (1)$$

Where, X is original value, Xmin and Xmax are minimum and maximum values in the series, respectively, Xnorm is the normalized value, and 0.8 and 0.1 are scaling factors. Different values may be assigned for the scaling factors. However, there is no proposed rule on standardization approach that can be used in particular circumstances. In this study, the scaling factors were selected as 0.8 and 0.1, respectively (Khashei-Siuki, *et al*., 2011).

Therefore, based on the basic assumption of normality of the parameters used in the fuzzy inference system, at first the meteorological parameters and functions in saffron were examined in terms of normality. Thus, in order to evaluate the model, we used statistical parameters of the coefficient of determination (R^2), Root Mean Square Error (RMSE), and the Mean Total Error (MAE).

$$R^2 = \frac{\left[\sum_{i=1}^{N}\left(P_i - \overline{P}\right)\left(O_i - \overline{O}\right)\right]^2}{\sum_{i=1}^{N}\left(P_i - \overline{P}\right)^2 \sum_{i=1}^{N}\left(O_i - \overline{O}\right)^2} \quad (2)$$

$$\text{RMSE} = \left[N^{-1}\sum_{i=1}^{N}(P_i - O_i)^2\right]^{0.5} \quad (3)$$

$$\text{MAE} = \frac{1}{N}\sum_{i=I}^{N}\left|O_i - P_i\right| \quad (4)$$

Where, N is the Number of observations, P_i is the estimated values, and O_i is the Observed values, while $\overline{P}$, $\overline{O}$ are the means of P_i and Oi, respectively. After determining the exact model in this study, calculations were performed using the ANFIS Toolbox at software MATLAB7.

RESULTS AND DISCUSSION

Gamma Test and Selection of Appropriate Combinations

Gamma test for all compounds in Table 2 were calculated. The best combinations based on value of gamma statistics and also combinations with gamma statistics values close to each other are in Table 3.

In this study, the basis for selecting the optimum combination is the minimal gamma statistics value. According to the results obtained from gamma test in Table 3, composition 11 with the lowest amount of gamma statistics shows the large effect of total relative humidity and evapotranspiration of four seasons as the input of the scenario on the output of the model (saffron yield).

Inference System Performance Evaluation in Predicting Crop Yield

Different membership functions, fuzzy rules, and epoch numbers were considered variable to reach the best combinations of independent variables (list of modes are presented in Table 3). The performances of all models were traced accordingly to find the best model for predicting saffron yield in Khorasan Province of Iran based on the ANFIS methodology.

Fuzzy membership functions can take many forms, but simple straight line triangular and Gaussian functions are most common (Kisi and Oztork, 2007). Table 4 and Figure 3 are due to testing part of the data set and the statistical performances of these models corresponding to different input layers. Results indicate that the ANFIS model does not provide the most accurate saffron yield estimation.

Table 4 shows the membership function type, the number of membership functions,

Table 3. Gamma test results to determine the optimal model to predict crop yield Gamma test results to determine the optimal model to predict crop yield.

Parameters Input	Gamma statistic	Number of combination
ET_{SP}-ET_{su}-ET_{au}-ET_{wi}-RH_{sp}-RH_{su}-RH_{au}-RH_{wi}	0.008764	8
$T_{min\ Bahman}$-$T_{min\ Esfand}$-$T_{max\ Bahman}$-$T_{max\ Esfand}$-P_{sp}-ET_{sp}-RH_{sp}-y	0.00967	45
$T_{max\ sp}$-$T_{max\ su}$–$T_{max\ Mehr}$–$T_{max\ Aban}$–$T_{max\ Azar}$-$T_{max\ Dey}$-$T_{max\ Bahman}$- $T_{max\ Esfand}$	0.010949	81
P_{au}- P_{wi} RH_{au}-$RH_{wi}$$T_{min\ Aban}$-$T_{min\ Azar}$-$T_{max\ Aban}$-$T_{max\ Azar}$-	0.011454	59
$T_{min\ Aban}$-$T_{min\ Azar}$-$T_{max\ Aban}$-$T_{max\ Azar}$-P_{au}- P_{wi}-RH_{au}-RH_{wi}-y	0.012785	72
P_{sp}-$P_{su}$$T_{min\ Mehr}$-$T_{min\ Aban}$-$T_{max\ Mehr}$-$T_{max\ Aban}$-	0.013507	63
y-ET_{au}-$RH_{au}$$P_{au}$$T_{max\ Azar}$$T_{max\ Mehr}$-$T_{max\ Aban}$-	0.013751	39
$T_{max\ sp}$-$T_{max\ su}$–$T_{max\ Mehr}$–$T_{max\ Aban}$–$T_{max\ Azar}$-$T_{max\ Dey}$-$T_{max\ Bahman}$- $T_{max\ Esfand}$-y	0.01449	82
ET_{SP}-ET_{su}-ET_{au}-ET_{wi}-yP_{sp}-P_{su}- P_{au}-P_{wi}-	0.015436	28
RH_{au}-$ET_{au}$$P_{au}$-$T_{min\ Azar}$ $T_{min\ Mehr}$-$T_{min\ Aban}$-	0.018415	24

Table 4. Statistical representation of the membership function type for ANFIS model to predict the performance of saffron.

Scenario type	Membership function type	Optimized model	No of membership function	R^2	RMSE (kg ha^{-1})	MAE (kg ha^{-1})
A	Trimf	Hybrid	22222222	0.3543	2.1841	1.8326
B	Trimf	Hybrid	22222222	0.2277	2.7734	2.2758
C	Trimf	Hybrid	2 2 2 2 2 2 2 2 2	0.0147	2.318	2.056
D	Gus2mf	Backpropa	2 2 2 2 2 2 2 2	0.1255	2.8765	2.4358
E	Gus2mf	Backpropa	2 2 2 2 2 2 2 2 2	0.0888	2.9075	2.438
F	Gus2mf	Backpropa	2 2 2 2 2 2	0.1154	2.6649	2.2038
G	Gus2mf	Backpropa	2 2 2 2 2 2	0.5627	2.0511	1.7274
H	Trimf	Backpropa	2 2 2 2 2 2 2 2 2 2	0.3156	3.8521	3.4282
I	Trimf	Backpropa	2 2 2 2 2 2	0.3156	3.8521	3.4282

and evaluation criteria of model for 10 different scenarios by fuzzy inference system. The results of the study on the ANFIS model showed that in this scenario model G is closer to the corresponding observed yield values than those of the other models. As seen from the fit line equations (P= a+bO) in the scatter plots, the a and b coefficients for the models are closer to the 0 and 1, respectively, than those of the other models. Model G (total of at least three months of October, November, and December and autumn rainfall and evapotranspiration and relative humidity) with (R^2= 0.5627, RMSE= 0.2.051 kg ha^{-1}, and MAE= 0.1.7274 kg ha^{-1}) has the highest correlation coefficient compared to other scenarios. In other words, this scenario is closely related to the performance, and scenario C (with R2= 0.8499 and RMSE = 0.730 Kg.ha-1 and MAE = 0.55 Kg.ha-1) has the lowest correlation coefficient. Scenario A has a high correlation coefficient (R^2= 0.3543, RMSE= 2.1841 kg ha^{-1}, and MAE= 1.8326 kg ha^{-1}). In general, this model is less accurate in predicting crop yield and cannot be used to predict performance. In fuzzy inference system, one can use different membership functions which may affect the final result. At this stage, each of the scenarios with various membership functions such as Gaussian, triangular test, and the best results are shown in Table 4. As shown in Table 4, triangular membership function has better results than Gaussian. In this research, the efficiency of fuzzy methods was investigated and the results were compared. Another method in eper system is the use

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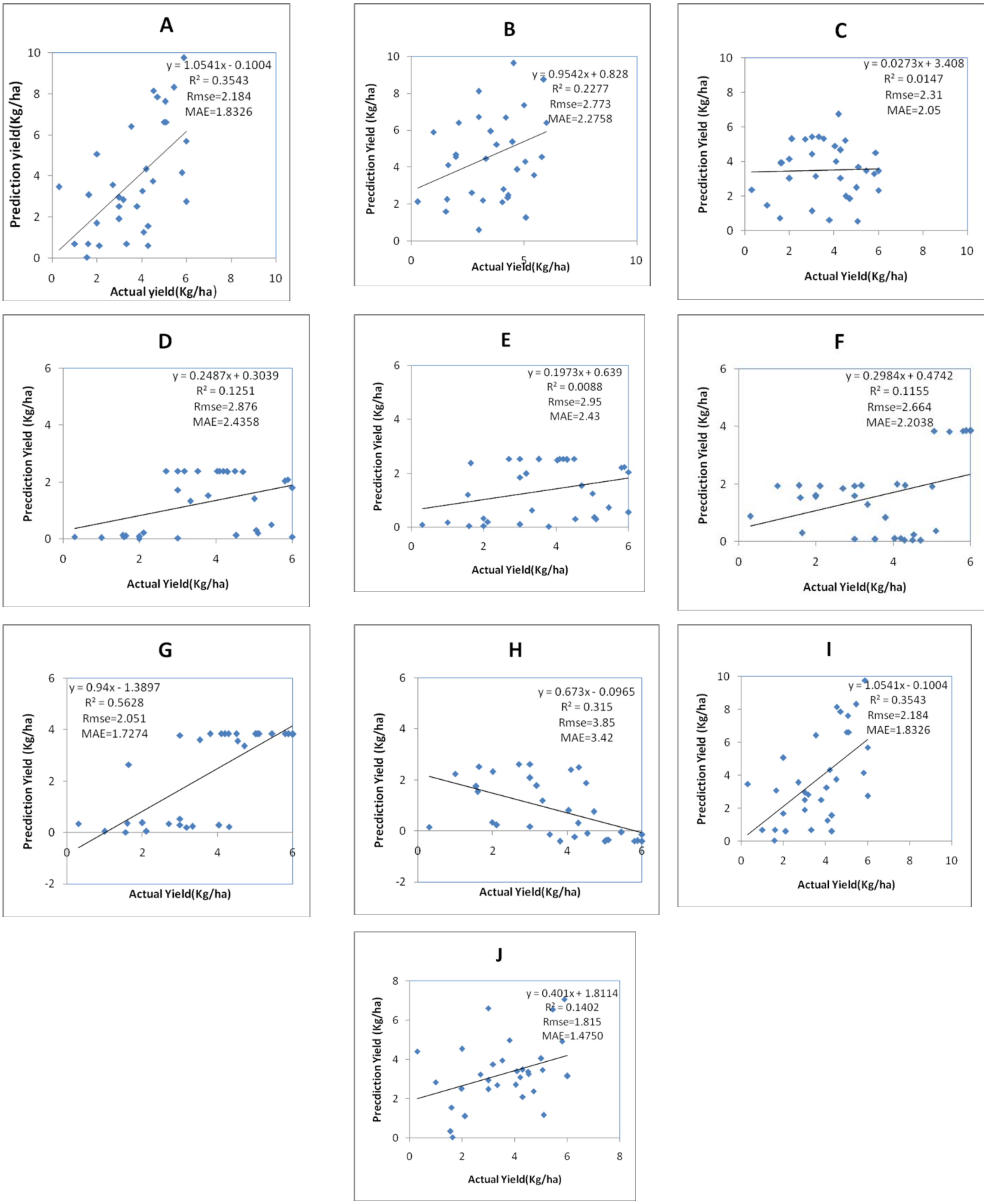

Figure 3. Comparison of the observed and predicted yield of saffron (kg per ha) for test data in different scenarios of ANFIS (A, B, C, D, E, F, G, H, I,).

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of artificial neural network method. In this regard, a study conducted by Nikoei *et al*. (2014) and results of their study showed that the neural network model can accurately measure saffron yield with the help of meteorological data the result of ANN is better than ANFIS model.

According to Table 4, in running the ANFIS model, when the number of membership functions increases, it means that the input number must be changed to the same number of membership function numbers to the fuzzy parameter by that function. This increases with the execution running time of the model. For this reason, more than two membership functions were not possible in the model implementation.

Evaluation of Linear Regression to Determine Crop Yield

The aim of this section is to compare the accuracy of linear regression and fuzzy neural network with on the same data. Undoubtedly, the need for more accurate and more favorable results from the regression model is further processing data to prepare them for use in the regression model. To calculate the crop yield in regression model, we used from the three collections of data for training, validation and test in ANFIS model. The results of the regression model, in scenarios are presented in Table 5. The results showed that scenario "I" in regression model has a more suitable accuracy than another scenario. "A" scenario also has the lowest coefficient of correlation

Table 5. Statistical representation of the regression model type in scenarios to predict.

Regression equation	MAE [a]	RMSE [b]	R2 [c]	T S [d]
$y= -5.077+0.00241*et_{sp}+0.000566*et_{su}-0.000724*et_{au}+0.00912*et_{wi}+0.00019*rh_{sp}+0.000833*rh_{su}+0.000237*rh_{au}+0.000431*rh_{wi}$	0.6875	0.8996	0.6613	A
$y= 12.08-0.00149*tmax_{sp}-0.00136*tmax_{su}-0.000934*tmax_{Mehr}-0.000209*tmax_{Aban}-0.0021*tmax_{Azar}+0.00259*tmax_{Dey}+0.000726*tmax_{Bahman}$	0.6030	0.7416	0.7665	B
$y= 12.049-0.00149*tmax_{sp}-0.00135*tmax_{su}-0.000935*tmax_{Mehr}-0.000211*tmax_{Aban}-0.00209*tmax_{Azar}+0.00259*tmax_{Dey}+0.00072*tmax_{Bahman}+0.0000923*tmax_{Esfand}+0.00582*y$	0.6025	0.7412	0.767	C
$y= 2.032-0.00281*tmin_{Aban}-0.00415*tmin_{Azar}+0.00124*tmax_{Aban}+0.000599*tmax_{Azar}+0.01799*pau+0.00166*pwi+0.000371*rhau+0.0000302*rhwi$	0.5739	0.7364	0.7715	D
$y= 2.801-0.00194*tmin_{Aban}-0.000122*tmin_{Azar}-0.00163*tmax_{Aban}+0.024*tmax_{Azar}+0.00299*p_{au}+0.000264*rh_{au}-0.00752*y$	0.6308	0.7933	0.7385	E
$y= 4.327-0.00231*tmin_{Mehr}-0.0031*tmin_{Aban}-0.000732*tmax_{Mehr}-0.000223*tmax_{Aban}+0.011*p_{sp}-0.00497*p_{su}$	0.6298	0.8303	0.7130	F
$y= 2.286-0.00192*tmin_{Mehr}-0.00188*tmin_{Aban}-0.00429*tmin_{Azar}+0.018*p_{au}+0.00187*et_{au}+0.000187*rh_{au}$	0.5224	0.6186	0.8419	G
$y= 0.53-0.000195*tmin_{Bahm}+0.000857*tmin_{esfan}+0.0018*tmax_{Bahmaan}+0.000157*tmax_{Esfand}+0.0202*p_{sp}+0.00203*et_{sp}+0.0000348*rh_{sp}+0.0104*y$	0.6227	0.7593	0.7689	H
$y= 2.077-0.00186*tmax_{Mehr}-0.000462*tmax_{Aban}-0.00149*tmax_{Azar}+0.0214*p_{au}+0.00334*et_{a}u+0.000408*rh_{au}+0.0147*y$	0.4514	0.5588	0.8886	I
$y = 0.225+0.0087*p_{sp}-0.00454*p_{su}+0.0242*p_{au}+0.00257*p_{wi}+0.00146*et_{sp}-0.000635*et_{su}+0.00239*et_{au}+0.00626*et_{wi}-0.0125*y$	0.5092	0.6490	0.8226	j

[a] The mean total error (MAE), [b] root mean square error (RMSE), [c] coefficient of determination (R2), [d] Type of Scenario(TS).

compared to other scenarios. The results showed that regression models have a higher accuracy than ANFIS model..

Predicting the yield of agricultural crops, especially for strategic crops such as saffron, can be used in planning and preparing managers to provide liquidity to buy products from farmers and provide space suitable for warehousing to help them. In addition, at the senior management level, knowledge and forecasting of the amount of agricultural production can be decisive in the pricing and the amount of imports and exports of products.

One of the problems of expert systems is their execution time for learning stage. In ANFIS models, as the number of model inputs increases, unlike neural networks, the model accuracy decreases due to increasing execution time and decreasing the model training phase. In this regard, reducing the number of membership functions can play a significant role in the output of the model and increase the performance of the model. The efficiency of artificial intelligence models can be increased by using automatic optimization methods. In these methods, a meta-heuristic optimization algorithm is usually associated with the artificial intelligence model and model parameters such as type and number of membership functions and determines the specific algorithm and tries to minimize the model error, i.e. the difference between the predicted data and the actual data value (Dehghani e*t al*., 2019).

CONCLUSIONS

The aim of this study was to predict the performance of saffron and evaluate the performance of fuzzy neural network that gave those results. Results showed that fuzzy neural network predicted the yield of saffron with a relatively high precision. The high accuracy of Fuzzy Neural Network makes this model suitable for different areas of timing, design, and politics. Besides, since it is easy to measure rainfall and there are various rain-gauge stations in all parts of the country and the saffron yield is strongly dependent on rainfall, we can estimate easily the saffron yield in different parts of the country using fuzzy neural network based on the data available in the meteorological stations. However, the results showed that regression model had a higher accuracy than ANFIS model.

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ارزیابی مدلهای سیستم استنتاج عصبی و فازی تطبیقی در برآورد عملکرد زعفران با استفاده از داده های هواشناسی

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چکیده

زعفران به عنوان با ارزش ترین محصول کشاورزی و پزشکی جهان است که در صادرات محصولات صنعتی ایران جایگاه ویژه ای دارد. اکنون ایران بزرگترین تولید کننده و صادر کننده زعفران در جهان است ، به طوری که بیش از ۷/۹۳ درصد از تولید جهانی این محصول گرانبها به ایران اختصاص یافته است ، اما با وجود قدمت زعفران کشت زراعی و ارزش افزوده این محصول در مقایسه با بسیاری از محصولات زراعی فعلی در کشور ، بخش کمتری از فناوریهای جدید به آن اختصاص داده شده است ، و تولید آن عمدتا بر اساس دانش محلی است. این مطالعه با هدف توسعه و ارزیابی عملکرد مدل سیستم استنتاج عصبی و فازی تطبیقی (ANFIS) در محاسبه عملکرد زعفران بر پارامترهای اقلیمی انجام شده است. از داده های هواشناسی ۲۰ ایستگاه سینوپتیک استان های خراسان رضوی و جنوبی استفاده شده است ، از جمله تبخیر و تعرق ، دما (حداکثر ، حداقل) ، میانگین رطوبت نسبی و بارندگی. برای این منظور بااستفاده از نرم افزار Wingamma داده ها و پارامترها مورد بررسی قرار گرفت و بهترین ترکیب ورودی ها به مدل تعیین شد. برای ارزیابی مدلها از پارامترهای آماری ضریب همبستگی ، میانگین خطای مطلق و میانگین مربعات خطا برای پیش بینی عملکرد محصول استفاده شده است. در مدل ANFIS هنگامی که از کل داده ها حداقل دما ، بارش ، تبخیر و تعویض و رطوبت نسبی پاییز به عنوان متغیرهای مستقل در عملکرد پیش بینی استفاده شده است ($R^2 = 0.5627$ و RMSE = 2.051 Kg.ha-1 و MAE = 1.7274 Kg.ha-1)) مؤثرترین مدل بودند

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