

Application of ANFIS and linear regression models to analyze the energy and economics of lentil and chickpea production in Iran

Authors

Behzad Elhami^a
 Asadollah Akram^a
 Majid Khanali^{a*}
 Seyed Hashem Mousavi-Avval^a

^a Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran

ABSTRACT

In the present study, the energetic and economic modeling of lentil and chickpea production in Esfahan province of Iran was conducted using adaptive neuro-fuzzy inference system (ANFIS) and linear regression. Data were taken by interviewing and visiting of 140 lentil farms and 110 chickpea farms during 2014-2015 production period. The results showed that the yield and total energy consumption were calculated 2,023 kg ha⁻¹ and 32,970.10 MJ ha⁻¹, respectively for lentil; and 2,276 kg ha⁻¹ and 33,211.18 MJ ha⁻¹, respectively for chickpea. Energy use efficiency was found to be 0.9 for lentil and 1.02 for chickpea; while benefit-cost ratio (BCR) were obtained 1.60 for lentil and 1.74 for chickpea. Regression results demonstrated that the coefficient of determination (R²) were 0.92 for lentil and 0.89 for chickpea. In addition, in regression estimated model in terms of BCR, R² were obtained as 0.86 for lentil and 0.72 for chickpea. In modeling of yield using the best ANFIS model, R² were calculated 0.99 and 0.98, respectively for lentil and chickpea. Finally, for evaluation of crops BCR by best ANFIS model, R² were determinate as 0.94 and 0.91 for lentil and chickpea, respectively. It was concluded that ANFIS model could better predict the energy output and BCR than that of linear regression model.

Article history:

Received : 20 February 2016
 Accepted : 1 June 2016

Keywords: Energy Use Efficiency, Linear Regression, Prediction, Cobb-Douglas Model.

1. Introduction

Lentil (*Lens culinaris*) and chickpea (*Cicer arietinum*) from legume family, are important dietary sources of protein, fiber, energy and minerals for both humans and animals [1]. Based on the FAO statistics [2], Iran ranked as the 11th and 7th largest producer of lentil and chickpea, respectively. Total production of these crops in Iran were 334000 ton [3]. About

12% from total lentil and chickpea production in Iran is produced in Esfahan province [3].

The relationship between agriculture and energy is very close due to the fact that, agriculture itself is an energy user and energy supplier in the form of bio-energy [4]. The energy consumption in agricultural sector is affected profoundly by the amount of arable land area, the size of the population occupied in agriculture land and the level of mechanization [5]. A major part of the consumed energy in agriculture is used in direct form such as diesel fuel, water for irrigation, electricity and human labor, while

*Corresponding author: Majid Khanali
 Address: Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran
 E-mail address: khanali@ut.ac.ir

Based on a review of literature, increase in the crop yields was mainly due to improve crop varieties [7]. Also, energy is a fundamental part of economic expansion because it provides essential services that maintains the economic activity and increases the quality of human life [8, 9].

There are several parametric, such as linear regression, and non-parametric techniques, such as adaptive neuro-fuzzy inference system (ANFIS), to measure the efficiency of agricultural production systems.

Moreover, there are several studies to identify the relationship between energy consumption from different inputs and yield values of crop production using parametric techniques [10, 11, 12]. Rafiee et al. [4] used linear regression analysis in the Cobb-Douglas (CD) form. They reported that farmyard manure (FYM), water for irrigation, electricity, chemical fertilizer and human labor energy inputs had significantly positive effect on yield.

ANFIS, a branch of artificial intelligence (AI), is a multilayer feed-forward network which is applying to map an input space to an output space using a combination of fuzzy systems and artificial neural networks (ANNs) [13]. It is a beneficial method to solve non-linear problems and can be applied in engineering applications where classical approaches fail or they are too complicated to be used [14]. Some researchers have applied ANFIS for modeling of energy consumption and crop yield [13, 15, 16]. Naderloo et al. [17] evaluated ANFIS model to predict the grain yield of irrigated wheat base on energy consumption parameters. Their results showed that, the using ANFIS with several layers could predict the grain yield with good accuracy.

The main objective of this study is to predict crops yield based on energy inputs and BCR based on cost inputs for lentil and chickpea production systems. For this purpose, linear regression and ANFIS were applied. Also, these techniques were compared to find the superior approach.

Abbreviations

AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
BCR	Benefit–cost ratio
CD	Cobb-Douglas
DW	Durbin-Watson

ER	Energy ratio
EP	Energy productivity
FYM	Farmyard manure
MAPE	Mean absolute percentage error
MF(s)	Membership function(s)
MPP	Marginal physical productivity
NEG	Net energy gain
OLS	Ordinary least square
RMSE	Root mean square error
RTS	Return to scale
SE	Specific energy
TSK	Takagi–Sugeno–Kang

2. Materials and methods

2.1. Case study and data collection

The study was carried out in Isfahan Province of Iran. The province is located in the center of Iran, within 49° 36' and 55° 32' east longitude and 30° 42' and 34° 30' north latitude [18]. The total farming area of the province is 280364 ha and the sum of farming area of lentil and chickpea is 6221 ha with the share of 2.22 % [3]. The data was collected from 140 lentil producers and 110 chickpea producers using face to face questionnaire method and interviewing with the farmers in the cropping season of 2014-2015. The sample size was calculated using the Cochran method [12]:

$$n = \frac{N \times S^2 \times t^2}{(N - 1)d^2 + (S^2 \times t^2)} \quad (1)$$

where ' n ' is the required samples size, ' N ' denotes the number of target population, ' S ' presents the standard deviation of sample mean, ' t ' denotes the t value at 95% confidence limit (1.96), and ' d ' presents the precision ($\bar{x} - \bar{X}$). The allowable error was defined in the sample size as 5% for 95% confidence.

The surveyed data consisted of the amount of energy inputs, the yield produce and the production costs per hectare for lentil and chickpea production. The energy inputs were diesel fuel, human labor, water for irrigation, electricity, machinery, seed, FYM, nitrogen (N), phosphate (P₂O₅), potassium (K₂O), herbicide, insecticide and fungicide. On the other hand, the outputs were lentil and chickpea grain production. Energy coefficients were applied to convert energy inputs into their energy equivalents [19]. Energy coefficients corresponded to different inputs and output, in lentil and chickpea production, are presented in

Table 1. Energy equivalent of inputs such as electricity, seed, diesel fuel, chemicals, chemical fertilizers and FYM used in lentil and chickpea production were converted to energy value (MJ ha^{-1}) by multiplying the quantity of the materials used in the farms by the corresponding energy coefficients. For example, the labor energy consumption (MJ ha^{-1}) was calculated by multiplying the total amount of labor hours during production period (h ha^{-1}) with its energy coefficient (1.96 MJh^{-1}). Also, the output energy was estimated by multiplying the yields by the energy coefficients of lentil and chickpea grains.

Energy coefficient of irrigation water and machinery are estimated based on the literature [20, 21].

2.2. Calculation of energy and economic indices

To calculate the energy input and output values, energy ratio (ER), i.e. energy use efficiency, net energy gain (NEG), energy energy productivity (EP) and specific energy (SE) indices were calculated as follow [12, 19].

$$ER = \frac{\text{Output Energy (MJ ha}^{-1}\text{)}}{\text{Input Energy (MJ ha}^{-1}\text{)}} \quad (2)$$

$$NEG = \text{Output Energy (MJ ha}^{-1}\text{)} - \text{Input Energy (MJ ha}^{-1}\text{)} \quad (3)$$

Table 1. Energy equivalent of inputs and outputs in lentil and chickpea productions

Input - output(unit)	Energy equivalent (MJ per unit)	References
1.Inputs		
Lentil seed (kg)	14.7	[19]
Chickpea seed (kg)	14.7	[19,20]
Chemical fertilizer (kg)		
Nitrogen(N)	78.1	[19,21]
Phosphate(P ₂ O ₅)	17.4	[19,21]
Potassium(K ₂ O)	13.7	[19,21]
FYM (kg)	0.3	[11]
Machinery (kg)		
Tractor	138	[19,21]
Plow	180	[19]
Disk	149	[19]
Boundaries	160	[19]
Leveler	149	[19]
Planter	133	[19]
Sprayer	129	[19]
Rotary Hoes	148	[19]
Thrashing(h)	62.7	[19]
Chemicals(kg)		
Herbicide	238	[5,10]
Insecticide	101.2	[5,10]
Fungicide	216	[5,10]
Diesel(L)	47.8	[10,27]
Labor(h)	1.96	[10,27]
Electricity(KWh)	11.93	[11,16]
2.Outputs (kg)		
Lentil	14.7	[19]
Chickpea	14.7	[19,20]

$$EP = \frac{\text{Product output}(kg\ ha^{-1})}{\text{Energy input}(MJ\ ha^{-1})} \quad (4)$$

$$SE = \frac{\text{Energy input}(MJ\ ha^{-1})}{\text{Product output}(kg\ ha^{-1})} \quad (5)$$

Total costs in a production system consist of the fixed and the variable costs. The fixed costs include costs of land renting and depreciation of farm machineries during the production period. The variable costs include the cost of used materials and inputs, including, seed, chemicals, fertilizers, diesel, electricity, labor and machinery rent. All prices of inputs and outputs were taken from market. All cost data were calculated per hectare and applied to obtain the economic indices. Therefore, the impure production value, pure profit, impure profit, BCR and economic productivity were calculated as follow [6, 21]:

$$\begin{aligned} &\text{Impure production value} \\ &= \text{Crop yield}(kg\ ha^{-1}) \\ &\times \text{Crop price}(\$ kg^{-1}) \end{aligned} \quad (6)$$

$$\begin{aligned} &\text{Pure profit} \\ &= \text{Total production value}(\$ ha^{-1}) \\ &- \text{Total production cost}(\$ ha^{-1}) \end{aligned} \quad (7)$$

$$\begin{aligned} &\text{Impure profit} \\ &= \text{Total production value}(\$ ha^{-1}) \\ &- \text{Variable cost of production}(\$ ha) \end{aligned} \quad (8)$$

$$\begin{aligned} &\text{BCR} \\ &= \frac{\text{Total production value}(\$ ha^{-1})}{\text{Total production cost}(\$ ha^{-1})} \end{aligned} \quad (9)$$

$$\begin{aligned} &\text{Economic productivity} \\ &= \frac{\text{Crop yield}(Kg\ ha^{-1})}{\text{Total production cost}(\$ ha^{-1})} \end{aligned} \quad (10)$$

2.3. Linear regression modeling

In order to specify the effects of energy inputs on yield as well as the as well as cost inputs on BCR, the mathematical models needs to be identified. In this respect, the production function of Cobb-Douglas was selected as the best function in terms of statistical significance and expected signs of the

parameters. This function can be expressed as follows:

$$Y = f(x)\exp(u) \quad (11)$$

This function has been used in several researches to analyze the relationship between energy inputs and yield and cost inputs and output [22, 23]. It can be expanded in the following form;

$$\begin{aligned} \ln Y_i &= \alpha + \sum_{j=1}^n \alpha_j \ln(X_{ij}) + e_i \quad i \\ &= 1, 2, \dots, n \end{aligned} \quad (12)$$

In this study, Eq. (12) can be stated in the following forms:

$$\begin{aligned} \ln Y_1 &= \alpha_0 + \alpha_1 \ln x_1 + \alpha_2 \ln x_2 \\ &+ \alpha_3 \ln x_3 + \alpha_4 \ln x_4 \\ &+ \alpha_5 \ln x_5 + \alpha_6 \ln x_6 \\ &+ \alpha_7 \ln x_7 + \alpha_8 \ln x_8 \\ &+ \alpha_9 \ln x_9 \\ &+ \alpha_{10} \ln x_{10} \\ &+ \alpha_{11} \ln x_{11} + e_i \end{aligned} \quad (13)$$

$$\begin{aligned} \ln Y_2 &= \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \\ &\beta_3 \ln x_3 + \beta_4 \ln x_4 + \beta_5 \ln x_5 + \\ &\beta_6 \ln x_6 + \beta_7 \ln x_7 + \beta_8 \ln x_8 + \\ &\beta_9 \ln x_9 + \beta_{10} \ln x_{10} + \beta_{11} \ln x_{11} + e_i \end{aligned} \quad (14)$$

In Eq.(13), lentil and chickpea yields (Y_1) were considered functions of seed, nitrogen, phosphate, potassium, FYM, chemicals, machinery, diesel fuel, human labor, water and electrical energies.

In Eq. (14), lentil and chickpea BCRs (Y_2) were considered functions of total production costs.

In this study, the output considered zero for zero inputs.

Marginal physical productivity (MPP) technique based on response coefficient of inputs was applied to assess the sensitivity of a specific energy inputs on the production as well as cost input on BCR. The MPP of a factor insinuates the change in the total output with a unit change in the factor input, knowing that geometric mean level are fixed at all other factors [24]. The MPP of the various inputs was calculated as follows [22]:

$$MPP_{x_j} = \frac{GM(Y)}{GM(X_j)} \times \alpha_j \quad (15)$$

where MPP_{x_j} is the marginal physical

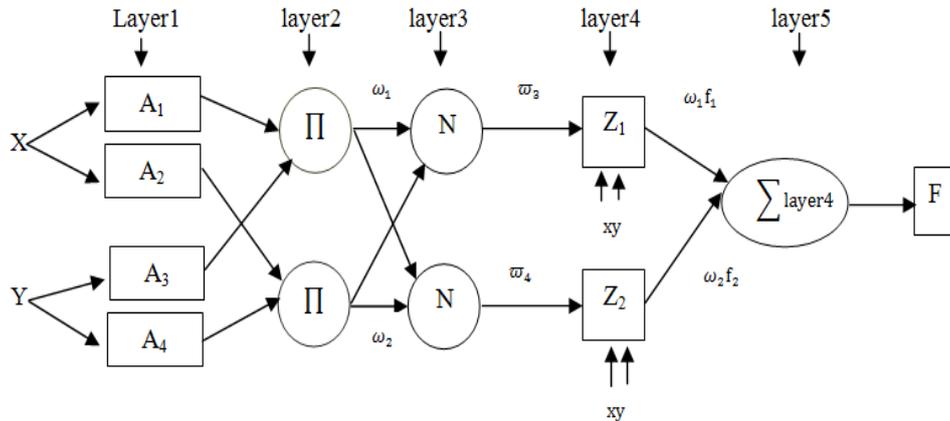


Fig. 1. Adaptive neuro-fuzzy inference system structure

productivity of j^{th} input, a_j is the regression coefficient of j^{th} input based on Eq. (13), $GM(Y)$ is the geometric mean of yield and $GM(X_j)$ is the geometric mean of j^{th} input energy per hectare.

Basic information on energy, cost inputs, crops yield and BCR were entered into Excel's spreadsheet and modeled using SPSS V.20 software program.

2.4. ANFIS

ANFIS is a multilayer feed-forward network which is used to scheme an input space to an output space by incorporation of ANN learning algorithms and fuzzy logic. Learning algorithms used in ANFIS are hybrid and propagation. The hybrid system is a blend of propagation and least squares method [25]. As can be seen in Fig. 1, a typical ANFIS structure is including five layers. The first layer consists of membership functions (MFs). The most common MF encompasses bell-shaped, Gaussian and triangular. The second layer calculates the firing robustness of a rule multiplication. The third layer indicates outputs called normalized firing strengths. The output of the fourth layer is composed of a linear combination of the inputs multiplied by the normalized firing strength ω . The fifth layer is the simple summation of the outputs of the fourth layer [13]. In this study Takagi–Sugeno–Kang (TSK) fuzzy model was applied. TSK fuzzy model is similar to Mamdani type inference systems in many ways as progressive lattice structure. Privilege of TSK model than Mamdani method is that, it is simpler and acts easily with linear techniques, it is computationally efficient and well suited to mathematical analysis [26].

The most fundamental restriction of standard

ANFIS models relates to the number of input variables. When the number of ANFIS inputs is more than 5, ANFIS is failed in analysis due to increased computational time and rule numbers. Because of the high number of inputs, a standard ANFIS could not be employed for the modeling of the desired parameters, such as crops yield and the BCR. Therefore, in order to predict each of the desirable outputs, i.e., yield and BCR values of lentil and chickpea, we selected the best ANFIS topology through different architecture of ANFIS. ANFIS programming was done in MATLAB V7.14 (R2012a) environment.

2.5. Comparison between linear regression and ANFIS model

The performance of ANFIS and regression model was compared using the coefficient of determination (R^2), the root mean square error (RMSE) and mean absolute percentage error (MAPE) expressed below [27, 28]:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^n (t_i - z_i)^2}{\sum_{i=1}^n t_i^2} \right] \quad (16)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - z_i)^2} \quad (17)$$

$$MAPE(\%) = \frac{100}{n} \sum_{i=1}^n \left| \frac{(t_i - z_i)}{t_i} \right| \quad (18)$$

where ' t_i ' and ' z_i ' denote the actual and the predicted output sets and ' n ' presents the number of the points in the data set.

3. Results and discussion

3.1. Energy flow of lentil and chickpea production

The inputs used in crops production, their energy equivalents and the relevant energy indices are shown in Table 2. The results indicated that the total energy used in various operations during lentil and chickpea production were 32970.10 MJ ha⁻¹ and 33211.18 MJ ha⁻¹, respectively. The average lentil and chickpea yields in studied region were about 2023 kg ha⁻¹ and 2276 kg ha⁻¹, respectively. With respect to the obtained results, shown in Table 2 and Fig.2, among the different energy sources, chemical fertilizers, electricity, diesel fuel and water for irrigation have the highest contribution to energy consumption in both crops. In lentil production, the magnitude and contribution of chemical fertilizers, electricity, diesel fuel and water for irrigation were respectively 10537.92 (42%), 6780 (20.56%), 5181.17 (15.71%) and 3957.21 (12%) MJ ha⁻¹ of total energy consumption; whereas the corresponding values in chickpea production calculated as 9808.65 (39.88%), 6818.71(20.53%), 5645.18 (17%) and 3557.92 (10.71%) MJ ha⁻¹, respectively. Koocheki et al. [29] reported that diesel fuel energy made up 24.36% of total energy, followed by water for irrigation (18.79%), chemical fertilizers (18.52%) and electricity (13.27%) during production period in lentil in

Khorasan Razavi province of Iran. In contrast, Patil et al. [30] in India claimed that the greater shares of input energy in chickpea production were observed for human labor and bullock pair (28.53%), as majority of operations were done with this force. Following human labor and bullock pair, seed (25.78%), chemical fertilizer (22.28%) and pesticides (14.85%) were the main energy consuming inputs in their study. The cause of difference between our study the difference between mentioned study and our study was the using of women labor (11%) and bullock pair (10%) instead of machinery.

Application of integrated nutrient managements, new machineries and irrigation pumps with more energy efficiency can be used to reduce the amount of chemical fertilizers, diesel fuel and electricity, respectively. ER for lentil and chickpea were calculated as 0.90 and 1.02, respectively, showing the inefficient use of energy in lentil production. Raising crop yield as well as decreasing energy consumption are pathways to boost energy ratio. Other authors reported similar results such as ER of 1.79 for lentil [29], 3.04 for chickpea [31], 0.95 for potato [6], 3.02 for canola [11] and 1.16 for apple [4]. Finally the results showed that SE, NEG and EP were calculated respectively as

Table 2. Amounts of inputs and their energy equivalences in lentil and chickpea productions

Inputs (Unit)	Quantity per unit area (ha)		Total energy equivalent (MJ ha ⁻¹)	
	Lentil	Chickpea	Lentil	Chickpea
Crops				
A. Inputs				
1- Seed (kg)	74.78	65.99	1099.35	970.06
2- Chemical Fertilizers (kg)				
a) Nitrogen	134.31	125.59	10537.92	9808.65
b) Phosphorus (P ₂ O ₅)	131.35	134.27	2285.61	2336.34
c) Potassium (K ₂ O)	75.28	81	1031.34	1109.70
3-FYM (kg)	892.75	1636.36	267.85	490.90
4- Chemical (kg)				
a) Herbicide	2.07	1.37	494.37	328.30
b) insecticide	3.05	1.91	309.38	193.50
c) fungicide	-	3.14	-	678.68
5- machinery (kg)	5752.96	4433.91	631.70	799.24
6- Diesel fuel (L)	108.39	118.10	5181.17	5645.18
7- human labor (h)	201.10	241.8	394.17	473.64
8- Water for irrigation (m ³)	314.50	289.27	3957.21	3557.92
9- Electricity (kWh)	565	568.24	6780	6818.72
Total energy input			32970.10	33211.18
B. Outputs				
1- Yield (kg)	2023.57	2276.36	29746.50	33462.54

as 16.29 MJ kg^{-1} , 0.06 kg MJ^{-1} and $-3223.61 \text{ MJ ha}^{-1}$ for lentil production; and 14.54 MJ kg^{-1} , 0.06 kg MJ^{-1} , and $251.36 \text{ MJ ha}^{-1}$ for chickpea production in Isfahan province (Table 3).

3.2. Economic analysis for lentil and chickpea production

Total cost of lentil and chickpea production, total value of production and economic indices were calculated (Table 4). The fixed and variable costs were calculated separately. The results revealed that the total cost of production for lentil and chickpea were 1557.24 and $1447.23 \text{ \$ ha}^{-1}$, respectively; furthermore, calculating impure production value with multiplying the crops yield by their sale prices, the corresponding values for lentil and chickpea production were 2358.42 and $2238.34 \text{ \$ ha}^{-1}$. Variable cost contributes as 71 % and 81% from total cost for lentil and chickpea production. As can be seen from Table 4, human labor had the highest share of variable cost for both lentil and chickpea production.

Similar results were found by Mohammadi et al. [10] for kiwifruit production and Tabatabaie et al. [32] for prune in Iran. The key factor to attain sustainable innovations in cropping techniques and management systems is farmer's economic interests and sustainability of local ecological systems [33]. BCR of higher than one revealed that both lentil and chickpea products were relatively profitable in the study area (Table 4). In the literature, BCR was reported as 1.09 for potato [6], 2.58 for cucumber [7], 1.74 for strawberry [19] and 1.62 for tangerine [34]. Also, productivity was found to be $1.29 \text{ kg \$}^{-1}$ for lentil; whereas this amount was $1.57 \text{ kg \$}^{-1}$ for chickpea. The pure return of 947.13 and $1072.32 \text{ \$ ha}^{-1}$ were calculated by subtracting the total cost of production from the total value of production per hectare (Table 4).

3.3. Econometric model of energy and crops yield

For investigating the relationship between energy inputs and yield of any of the products (Table 5 and Eq.13), the CD production

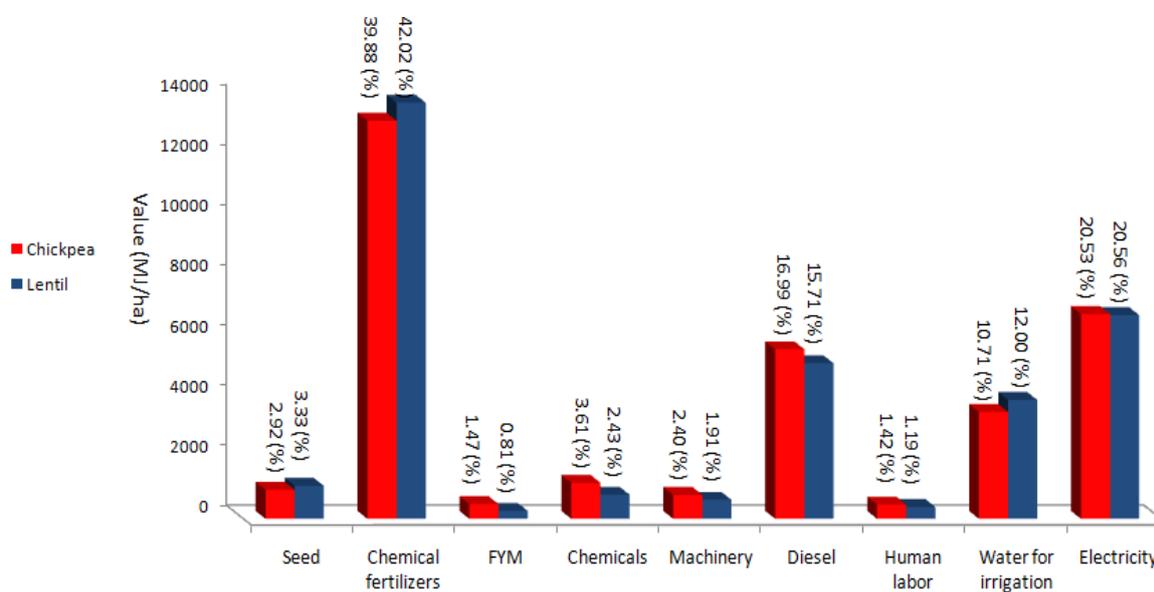


Fig.2. Distribution of energy consumption for chickpea and lentil productions

Table 3. Energy indices in lentil and chickpea productions

Item	Unit	Lentil production	Chickpea production
1. Energy ratio	-	0.90	1.02
2. Specific energy	(MJ kg^{-1})	16.29	14.54
3. Energy productivity	(kg MJ^{-1})	0.062	0.069
4. Net energy gain	(MJ ha^{-1})	-3223.60	251.36

Table 4. Economic analysis of lentil and chickpea productions

Cost and return components (Unit)	Lentil production	Chickpea production
A. Revenue		
Sale price (\$ kg ⁻¹)	1.165	0.983
Impure value of production (\$ ha ⁻¹)	2358.42	2238.34
Subsidiary value of production (\$ ha ⁻¹)	145.95	281.21
Total value of production	2504.37	2519.55
B. Costs	1557.24	1447.23
B.1. Variable cost (\$ ha ⁻¹)	1107.96	1166.63
1- Seed	73.30 (6.6%)	53.35 (4.6%)
2- Chemical Fertilizers		
a) Nitrogen	44.47 (4.07%)	35.33 (3.02%)
b) Phosphorus	48.36 (4.36%)	40.83 (3.49%)
c) Potassium	49.30 (4.44%)	28.01 (2.40%)
3- FYM	131.07 (11.82%)	140.60 (12.05%)
4- Chemical		
a) Herbicide	22.05 (1.99%)	12.92 (1.10%)
b) insecticide	42.48 (3.83%)	19.26 (1.65%)
c) fungicide	-	16.95 (1.45%)
5- Machinery	217.72 (19.65%)	287.22 (24.61%)
6- Diesel fuel	18.66 (1.68%)	19.47 (1.66%)
7- human labor	408.17 (36.83%)	465.66 (39.91%)
8- Electricity	52.38 (4.72%)	47.75 (4.09%)
B.2. Fixed cost (\$ha ⁻¹)	449.28	280.60
C. Economic indices		
1. Pure return (\$ ha ⁻¹)	947.13	1072.32
2. Impure return (\$ ha ⁻¹)	1396.41	1352.92
3. BCR	1.60	1.74
4. Productivity (kg \$ ⁻¹)	1.29	1.57

function was developed using ordinary least square (OLS) estimation technique. Autocorrelation test was accomplished using Durbin-Watson (DW) test [35]. The test result indicated that DW value was, respectively, 1.76 and 1.66 for lentil and chickpea in Eq. (13), indicating that there was no autocorrelation between the model variables. Accordingly, the yield values were assumed to be a function of seed, nitrogen, potassium, phosphate, FYM, human labor, machinery, chemicals, water for irrigation and electricity. As can be seen in Table 5 for lentil production modeling, the contributions of seed, diesel, machinery, labor and water for irrigation energies were statistically significant at 1% level. According to the second column of Table 5, human labor had the highest elasticity on lentil yield. It demonstrates that a

1% increase in the energy human labor input led to 0.72% increase in yield in these conditions. On the other hand, the impact of nitrogen and FYM energies on lentil yield were estimated statistically insignificant. Summing the regression coefficients of lentil production modeling, return to scale (RTS) was obtained as 1.15 and revealed that a 1% increase in total energy inputs would lead to increasing the lentil yield by 1.15%. Also, for chickpea model, human labor had the highest impact (0.24) among other inputs, indicating that a 1% increase in the machinery energy input would lead to 0.24% increase in chickpea yield. On the other hand, the impacts of FYM and water for irrigation energies on chickpea yield were estimated statistically insignificant with a negative sign. The value of RTS for chickpea production modeling was

Table 5. Econometric estimation and sensitivity analysis results of energy inputs on yield of lentil and chickpea productions

Endogenous variable: Yield	Lentil			Chickpea		
	Coefficient	<i>t</i> -Ratio	MPP	Coefficient	<i>t</i> -Ratio	MPP
Model 1: $\ln Y_1 = \alpha_0 + \alpha_1 \ln x_1 + \alpha_2 \ln x_2 + \alpha_3 \ln x_3 + \alpha_4 \ln x_4 + \alpha_5 \ln x_5 + \alpha_6 \ln x_6 + \alpha_7 \ln x_7 + \alpha_8 \ln x_8 + \alpha_9 \ln x_9 + \alpha_{10} \ln x_{10} + \alpha_{11} \ln x_{11} + e_i$						
Exogenous variables						
Constant	942.73	15.29 ^a		1674.57	26.05 ^a	
Seed (X ₁)	0.23	5.04 ^a	0.34	0.07	1.56	0.17
Nitrogen (X ₂)	-0.00007	-0.03	-0.0002	0.007	1.78	0.01
Phosphorus (X ₃)	0.01	1.01	0.03	0.01	1.25	0.04
Potassium (X ₄)	0.02	2.716 ^b	0.54	0.02	1.63	0.12
FYM (X ₅)	-0.01	-1.86 ^b	-0.57	-0.0004	-0.15	-0.79
Chemicals (X ₆)	0.04	1.40	0.19	0.02	1.28	0.16
Machinery (X ₇)	0.08	3.54 ^a	0.49	0.04	2.50 ^b	0.68
Diesel fuel (X ₈)	0.04	4.86 ^a	0.08	0.02	4.95 ^a	0.15
human labor (X ₉)	0.72	3.92 ^a	0.92	0.24	1.92 ^b	0.39
Water for irrigation (X ₁₀)	0.01	2.75 ^a	0.02	-0.01	-1.17	-0.03
Electricity (X ₁₁)	0.00003	0.008	0.0001	0.02	2.83 ^a	0.03
Durbin-Watson	1.76			1.66		
Return to scale ($\sum_{i=1}^n \alpha_i$)	1.15			0.44		

^a Indicates significance at 1% level.

^b Indicates significance at 5% level.

obtained as 0.44, by gathering the regression coefficients located in the fifth column of Table 4. These results indicate that a 1% increase in all the energy inputs would result only by 0.44% increase in the chickpea production. Mohammadshirazi et al. [34] reported that impact of chemical fertilizers, water for irrigation and electricity energies were statistically significant at the 1% level on the tangerine yield. The MPP value of model variables is shown in the third and sixth columns of Table 5. As can be seen, the highest MPP value was calculated as 0.92 for human labor used for lentil production modeling and 0.68 for machinery in chickpea production modeling. This implies that, an additional use of 1 MJ ha⁻¹ in the human labor would cause to additional increase in lentil yield by 0.92 kg ha⁻¹ and 1 MJ ha⁻¹ increasing in machinery energies lead to additional increase in chickpea yield by 0.68 kg ha⁻¹.

3.4. Econometric model estimation of BCR

Relationships between input costs and BCR

for lentil and chickpea production were estimated using CD production function using Eq. (14). BCR values of lentil and chickpea production were regarded to be a function of all the fixed and variable costs. Using Eq.(14), DW was obtained as 2.16 and 1.81 for lentil and chickpea production, respectively. Therefore, there was no autocorrelation at 99% confidence level. According to Table 6 for lentil production modeling, the contribution of FYM, diesel fuel land renting were statistically significant at 1% level. Moreover, seed, FYM, chemicals, machinery, human labor and rant land are significant for chickpea production modeling at 1% level. The impact of seed, total chemical fertilizers (nitrogen, phosphate and potassium), chemicals, electricity and machinery had an insignificant relationship with BCR in lentil production modeling; while, in chickpea production modeling, electricity, nitrogen, phosphate, machinery and electricity showed an insignificant relationship with BCR; therefore, the increase or decrease of these factors has no influence on BCR. Banaeian

Table6. Econometric estimation results of cost inputs on BCR for lentil and chickpea productions

Endogenous variable: Benefit-cost ratio	Lentil		Chickpea	
	Coefficient	t-Ratio	Coefficient	t-Ratio
Model 2: $\ln Y_2 = \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \ln x_3 + \beta_4 \ln x_4 + \beta_5 \ln x_5 + \beta_6 \ln x_6 + \beta_7 \ln x_7 + \beta_8 \ln x_8 + \beta_9 \ln x_9 + \beta_{10} \ln x_{10} + \beta_{11} \ln x_{11} + e_i$				
Exogenous variables:				
Constant	0.488	0.92	5.29	3.56 ^a
Seed (X ₁)	0.0000010	0.39	-0.000013	-3.49 ^a
Nitrogen (X ₂)	-0.0000046	-1.60	-0.0000019	-0.36
Phosphorus (X ₃)	-0.0000015	-0.73	-0.0000063	-1.12
Potassium (X ₄)	0.0000005	0.396	-0.000010	-2.47 ^b
FYM (X ₅)	-0.0000027	-4.23 ^a	-0.0000022	-3.17 ^a
Chemicals (X ₆)	-0.000001	-0.56	-0.0000073	-3.63 ^a
Machinery (X ₇)	-0.00000013	-0.40	0.000000097	0.39
Diesel fuel (X ₈)	0.000065	6.56 ^a	-0.0000090	-2.69 ^b
human labor (X ₉)	0.00000088	1.46	0.0000025	7.54 ^a
Electricity (X ₁₀)	-0.0000066	-2.03 ^b	-0.0000037	-0.76
Rant land (X ₁₁)	-0.00000052	-33.07 ^a	-0.00000021	-6.64 ^a
Durbin–Watson	2.16		1.81	
Return to scale ($\sum_{i=1}^n \alpha_i$)	0.00005		-0.00005	

et al. [19] estimated that human labor, total fertilizer, transportation and installation of equipment were significant on strawberry yield at 1% level while the impacts of water for irrigation, diesel fuel and electricity energies were insignificant on yield.

3.5. Evaluation of ANFIS models for energy and crops yield

Figures 3 and 4 illustrate the best ANFIS topology for modeling chickpea yield and lentil yield, respectively. These topologies consisted of seven standard ANFIS networks at three stages. At the first stage, the inputs were entered into four standard ANFIS sub-networks. At the second stage, ANFIS 1 and ANFIS 2 sub-networks were entered to ANFIS 5; similarly, the predicted values of ANFIS 3 and ANFIS 4 composed the ANFIS 6, and finally at the third stage, the chickpea yield was predicted by ANFIS 7.

As can be seen in Table 7 for both of the ANFIS models, a collection of adjustments contains the number of MFs, types of MFs and number of epochs. Accordingly, hybrid learning algorithm was chosen to determine the relationship between input variables and output in both ANFIS models. All of the MFs were tested to create the best

ANFIS network. In both ANFIS structures, the Gbell and linear MFs were selected for input and output MFs, respectively. The best solution was obtained by 100 epochs. The main difference between these two ANFIS structures was in the number of input MFs. For the best ANFIS topology of chickpea yield, ANFIS 2, 3 and 4 sub-networks included three input parameters, thus the number of MFs was chosen to be 4-3-3. For ANFIS 1 and ANFIS 5–7 sub-networks there were only two inputs so the number of MFs was chosen as 7–7. However, in best ANFIS topology of lentil yield, ANFIS 4 contained four input parameters. Also in ANFIS 3 three inputs were entered, so the number of MFs was selected as 4-3-3.

It is noted that the number of MFs assesses the total number of parameters in the network which should be less than number of training data pairs. In this study, for the best ANFIS topology of both the crops, the total number of training data pairs in final ANFIS was assessed as 128 and the total number of parameters was 123 in the maximum of situation, demonstrating that, the number of input MFs was selected appropriately. Finally, for the better comparison of the best ANFIS topologies for lentil and chickpea yields, MAPE was employed. These values were

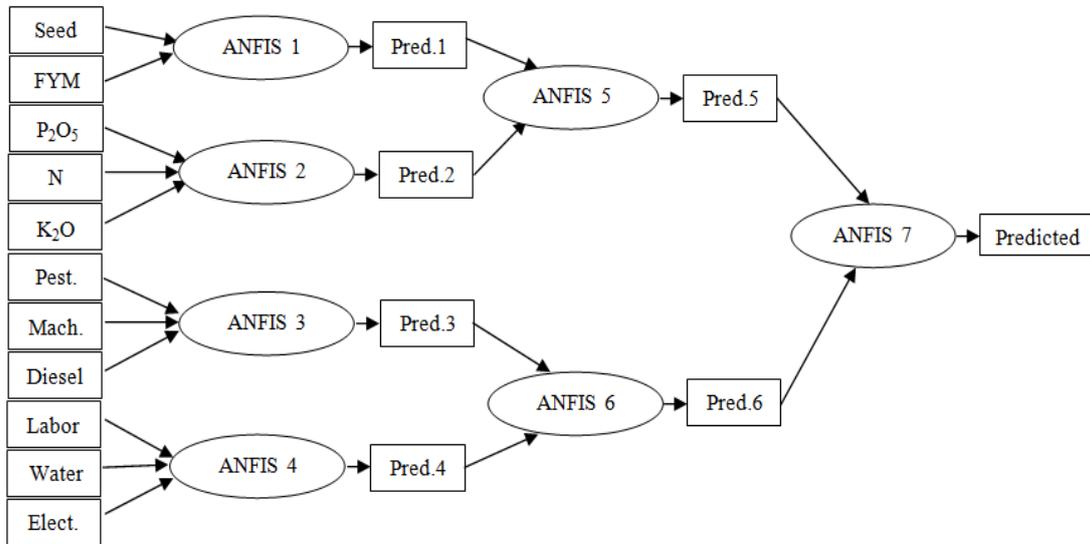


Fig. 3. The best topology of ANFIS model to predict chickpea yield

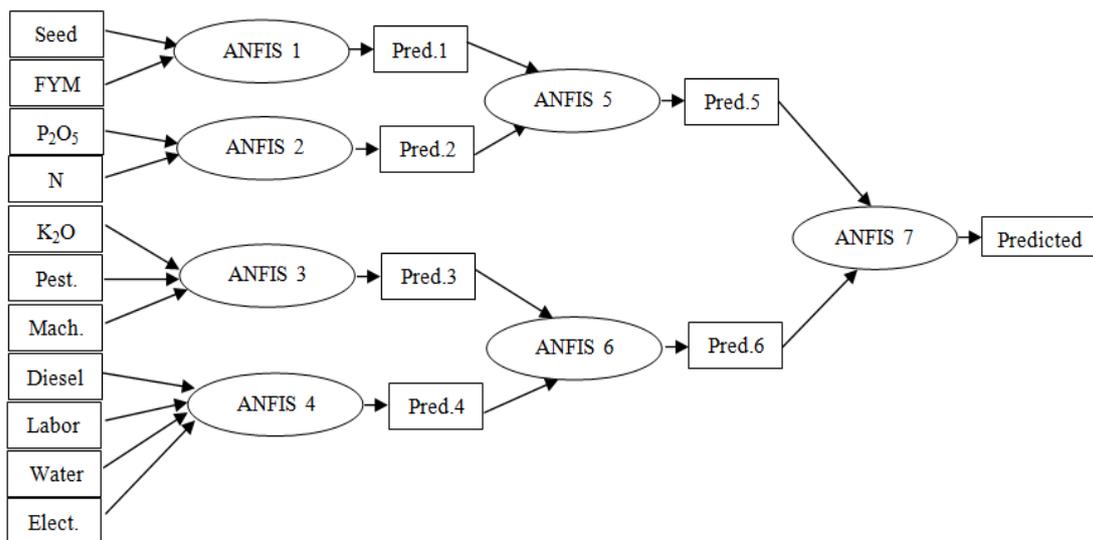


Fig. 4. The best topology of ANFIS model to predict lentil yield

Table 7. The characteristics of the best structure of final ANFIS architecture for yield of lentil and chickpea productions

Item	Lentil/Chickpea	Lentil	Chickpea	Lentil	Chickpea	Lentil	Chickpea	MAPE(%)		
	Type of MF	Number of MF	Number of MF	Learning method	MAPE(%)					
	Input Output	Input Epoch	Input Epoch							
ANFIS1	Gbell	Linear	7,7	100	7,7	100	Hybrid	Hybrid	0.49	0.91
ANFIS2	Gbell	Linear	7,7	100	4,3,3	100	Hybrid	Hybrid	1.02	1.03
ANFIS3	Gbell	Linear	4,3,3	100	4,3,3	100	Hybrid	Hybrid	1.71	0.42
ANFIS4	Gbell	Linear	2,2,2,2	100	4,3,3	100	Hybrid	Hybrid	0.17	0.79
ANFIS5	Gbell	Linear	7,7	100	7,7	100	Hybrid	Hybrid	0.23	0.50
ANFIS6	Gbell	Linear	7,7	100	7,7	100	Hybrid	Hybrid	0.12	0.21
ANFIS7	Gbell	Linear	7,7	100	7,7	100	Hybrid	Hybrid	0.02	0.09

were obtained as 0.02 % for final ANFIS of lentil yield and 0.09 % for the final ANFIS of chickpea yield. It indicates that the accuracy of ANFIS modeling for lentil yield is more than that of chickpea yield. Khoshnevisan et al. [13] reported that for the two investigated ANFIS networks with seven and eight standard ANFIS, MAPE values for final ANFIS were estimated at 0.2% and 0.2%, respectively.

3.6. Appraisal of ANFIS models for BCR modeling

Aiming at more accurate prediction of BCR in this study, the best ANFIS topologies for BCR modeling in chickpea and lentil production are shown in Figs. 5 and 6, respectively. Also relevant information about developed ANFIS models illustrated in Table 8.

The combination of Gbell and linear MFs were selected for values of input and output. The best ANFIS topology for chickpea crop obtained from an eight layers ANFIS. Eleven input variables divided into five groups and each group was selected as an input for ANFIS models of 1 to 5. Outputs for the models 1 and 2 entered into the ANFIS 6, and outputs 3, 4 and 5 entered into the ANFIS 7 and finally ANFIS 6 and 7 have been entered as input to ANFIS 8. On the other hand, in best ANFIS topology of lentil, as shown in Fig.6, input variables divided into three groups and each group is selected as the input ANFIS 1 to 3. Output ANFIS 1 to 3 selected as input and output ANFIS 4 is considered as BCR of lentil production. The best solution was calculated by 100 epochs and hybrid learning algorithm. The number of input MFs is determinative of the total number of

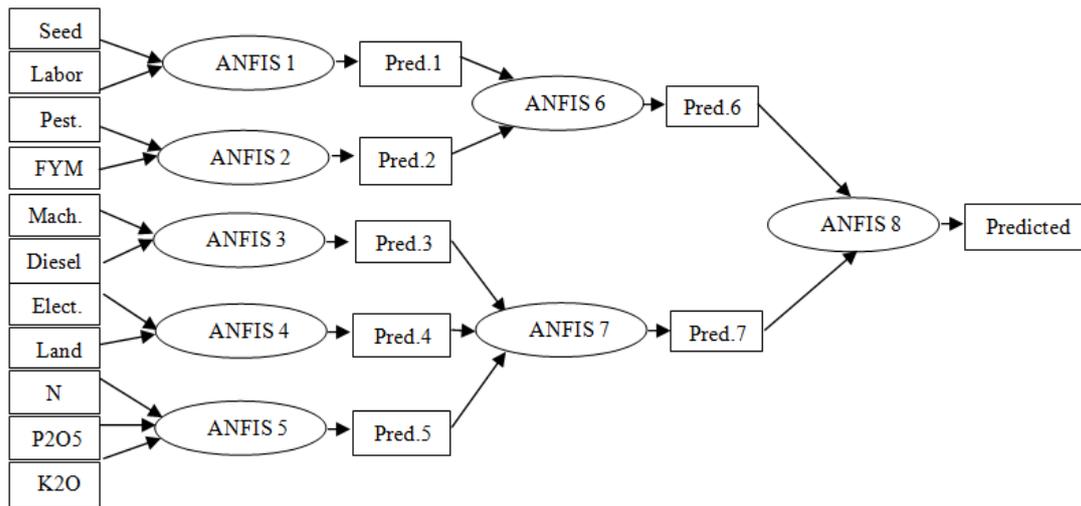


Fig. 5. The best topology of ANFIS model to predict BCR of chickpea

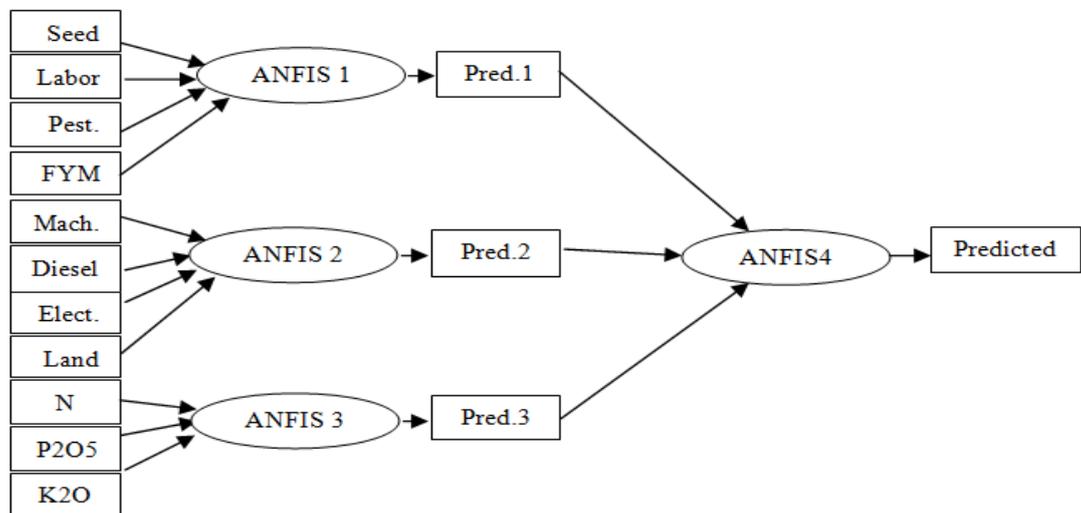


Fig. 6. The best topology of ANFIS model to predict BCR of lentil

parameters. These parameters should not be more than the number of training data. In the best ANFIS topology for lentil production, the number of input MFs was determined as 4-3-3 for ANFIS 1 and 2; and as 2-2-2-2 for ANFIS 3 and 4.

Finally, the MAPE was obtained as 0.29% for the final ANFIS for predicting BCR of lentil production and 0.48% for the final ANFIS for predicting BCR of chickpea production. This result showed that the accuracy of ANFIS for modeling BCR of lentil is more than BCR for chickpea production.

3.7. Comparison of linear regression and ANFIS for prediction of yield and BCR

In this study, ANFIS modeling was applied to predict crop yield and BCR, and then the linear regression analysis was used to test the validity and significance of the model. According to Table 9, it can be concluded that the ANFIS model gives superior results than linear regression model.

In the comparison between linear regression and ANFIS about lentil yield, R^2 was obtained as 0.92 for regression and 0.999 for the final ANFIS model; moreover, RMSE was calculated as 1.15 and 0.046 for the respective models. Comparing the model performances in chickpea yield prediction the results revealed that, R^2 was 0.89 and 0.986 for regression and ANFIS modeling, respectively. The results of BCR modeling showed in Table 8. It can be noted that, final ANFIS with higher R^2 and lesser RMSE achieved better results than the linear regression analysis.

Sefeedpari et al. [16] have done a similar work for modeling output energy based on fossil fuels and electricity energy consumption on dairy farms of Iran. Performance measure in the comparison process between the linear regression and ANFIS models was done using R^2 and RMSE. The R^2 and RMSE values were found to be 0.79 and 0.11 by final ANFIS, and also, 0.11 and 0.22 by linear regression model, respectively. Therefore, ANFIS topology can accurately model outputs in agricultural production systems; because measuring the input parameters is difficult and in the most cases is not precise [36].

4. Conclusion

This study predicted the output energy and benefit to cost ratio of lentil and chickpea production in Esfahan province of Iran. The energy balance of these two crops revealed that the total input and output energies were respectively 32970.10 and 29476.50 MJ ha⁻¹ for lentil production; and the respective values were 33211.18 and 33462.52 MJ ha⁻¹ for chickpea production. The results clearly revealed that the total energy consumption for both the crops was dominated by N based fertilizer and electricity. Therefore, management of fertilizer consumption needs to be given a higher priority. From economic point of view, the mean total production value and costs were respectively 2504.37\$ ha⁻¹ and 1557.24 \$ ha⁻¹ for lentil; and 2519.55 \$ ha⁻¹ and 1447.23 \$ ha⁻¹ for chickpea. Human labor was the most influential factor in production costs. The average of the energy and

Table 8. The characteristics of the best structure of final ANFIS for BCR of lentil and chickpea productions

Item	Lentil		Chickpea				Lentil / Chickpea		Lentil / Chickpea			
	Type of MF Input	Type of MF Output	Number of MF Input	Number of MF Output	Type of MF Input	Type of MF Output	Learning method	Learning method	MAPE (%)	MAPE (%)		
ANFIS1	Gbell	Linear	2,2,2,2	100	Gbell	Linear	7,7	100	Hybrid	Hybrid	0.61	1.46
ANFIS2	Gbell	Linear	2,2,2,2	100	Gbell	Linear	7,7	100	Hybrid	Hybrid	0.75	1.38
ANFIS3	Gbell	Linear	4,3,3	100	Gbell	Linear	7,7	100	Hybrid	Hybrid	0.82	1.35
ANFIS4	Gbell	Linear	4,3,3	100	Gbell	Linear	7,7	100	Hybrid	Hybrid	0.29	1.25
ANFIS5					Gbell	Linear	4,3,3	100		Hybrid		1.16
ANFIS6					Gbell	Linear	7,7	100		Hybrid		0.91
ANFIS7					Gbell	Linear	4,3,3	100		Hybrid		0.77
ANFIS8					Gbell	Linear	7,7	100		Hybrid		0.48

Table 9. Performance of regression and ANFIS models

Item	Lentil yield		Chickpea Yield		Lentil BCR		Chickpea BCR	
	R ²	RMSE	R ²	RMSE	R ²	RMSE	R ²	RMSE
Regression	0.92	1.15	0.89	1.62	0.86	2.45	0.72	4.12
ANFIS1	0.980	0.067	0.866	2.278	0.72	4.75	0.35	9.15
ANFIS2	0.946	0.078	0.835	2.575	0.64	5.15	0.39	9.02
ANFIS3	0.920	0.090	0.941	0.080	0.51	6.25	0.44	8.15
ANFIS4	0.993	0.054	0.892	1.560	0.94	0.075	0.53	7.15
ANFIS5	0.990	0.060	0.914	1.250			0.67	5.88
ANFIS6	0.998	0.050	0.981	0.065			0.72	3.59
ANFIS7	0.999	0.046	0.986	0.053			0.85	2.45
ANFIS8							0.91	1.25

economic indices, i.e. ER, SE, BCR and productivity were respectively found to be 0.90, 16.29 MJ kg⁻¹, 1.60 and 1.29 kg \$⁻¹ for lentil crop; and 1.02, 14.54 MJ kg⁻¹, 1.74 and 1.57 kg \$⁻¹ for chickpea crop. The results indicated that the cultivation of chickpea compared to lentil is more affordable. The result of regression models indicated that the human labor and seed energies had the highest elasticity on lentil yield, diesel and electricity on chickpea yield and FYM and land renting on any two model of BCR. The best ANFIS topology for modeling of lentil yield in this study was a model with seven sub-ANFIS networks at three stages with R² and RMSE values as 0.99 and 0.046, respectively. A comparison between the linear regression and ANFIS modeling techniques showed that ANFIS with better results of statistical indices, compared to linear regression was more effective to model and predict yield and BCR.

Acknowledgments

The financial support provided by the University of Tehran, Iran, is duly acknowledged.

References

- [1] Torres J., Rutherford S.M., Muñoz LS, Peters M., Montoya CA., The impact of heating and soaking on the in vitro enzymatic hydrolysis of protein varies in different species of tropical legumes, *Food Chemistry*, 194, (2016) 377–382.
- [2] Food and Agricultural Organization (FAO), (2008), www.fao.org.
- [3] Anonymous. Annual agricultural statistics, Ministry of Jihad-e- Agriculture of Iran, (2014), www.maj.ir.
- [4] Rafiee S., Mousavi Avval S.H., Mohammadi A., Modeling and sensitivity analysis of energy inputs for apple production in Iran, *Energy*, 35, (2010) 3301-3306.
- [5] Alam M.S., Alam M.R., Islam K.K., Energy flow in agriculture: Bangladesh, *American Journal of Environment Science*, 1(3), (2005) 213-320.
- [6] Zangeneh M., Omid M., Akram A., A comparative study on energy use and cost analysis of potato production under different farming technologies in Hamadan province of Iran, *Energy*, 35, (2010) 2927-2933.
- [7] Mohammadi A., Omid M., Economical analysis and relation between energy inputs and yield of greenhouse cucumber production in Iran, *Applied Energy*, 87, (2010) 191–196.
- [8] Thankappan S., Midmore P., Jenkins T., Conserving energy in small holder agriculture: a multi-objective programming case-study of northwest India, *Ecological Economics*, 56, (2005) 190-208.
- [9] Baruah D.C., Dutta P.K., An investigation into the energy use in relation to yield of rice (*Oryza sativa*) in Assam, India. *Agriculture, Ecosystems and Environment*, 120, (2007) 185-191.
- [10] Mohammadi A., Rafiee S., Mohtasebi S.S., Rafiee H., Energy inputs-yield relationship and cost analysis of kiwifruit production in Iran, *Renewable Energy*, 35, (2010) 1071-1075.
- [11] Mousavi-Avval S.H., Rafiee S., Jafari A., Mohammadi A., Energy flow modeling and sensitivity analysis of inputs for canola production in Iran, *Journal of Cleaner Production*, 19, (2011) 1464-1470.

- [12] Ghasemi Mobtaker H., Keyhani A., Mohammadi A., Rafiee S., Akram A., Sensitivity Analysis of Energy Inputs for Barley Production in Hamedan Province of Iran, *Agriculture, Ecosystems and Environment* (2010) 137:367-372.
- [13] Khoshnevisan B., Rafiee S., Omid M., Mousazadeh H., Prediction of Potato Yield Based on Energy Inputs Using Multi-Layer Adaptive Neuro-Fuzzy Inference System, *Measurement* (2014) 47:521–530.
- [14] Cheng C.B., Cheng C.J., Lee E.S., Neuro-Fuzzy and Genetic Algorithm in Multiple Response Optimization. *Computers and Mathematics with Applications* (2002) 44:1503–1514.
- [15] Al-Ghandoor A., Phelan P.E., Villalobos R., Phelan B.E., Manufacturing Aggregate Energy Intensity Decomposition, The Application of Multivariate Regression Analysis, *International Journal Energy Research* (2008) 32: 501–513.
- [16] Sefeedpari P., Rafiee S., Akram A., Pishgar Komleh S.H., Modeling Output Energy Based on Fossil Fuels and Electricity Energy Consumption on Dairy Farms of Iran, Application of Adaptive neural-fuzzy inference system technique, *Computers and Electronics in Agriculture* (2014) 109: 80–85.
- [17] Naderloo L., Alimardani R., Omid M., Sarmadian F., Javadikia P., Torabi M.Y., Alimardani F., Application of ANFIS to Predict Crop Yield Based on Different Energy Inputs, *Measurement* (2012) 45:1406– 1413.
- [18] Statistical Yearbook of Esfahan Province in Iran (amar.org.ir/english/Iran-Statistical-Yearbook) (2013).
- [19] Banaeian N., Omid M., Ahmadi H., Energy and Economic Analysis of Greenhouse Strawberry Production in Tehran Province of Iran, *Energy Conversion and Management* (2010) 52: 1020–1025.
- [20] Kitani O., Energy and Biomass Engineering. In, *CIGR Handbook of Agricultural Engineering*, St. Joseph, MI, ASAE (1999) 330.
- [21] Pishgar-Komleh S.H., Keyhani A., Mostofi-Sarkari M.R., Jafari A., Energy and Economic Analysis of Different Seed Corn Harvesting Systems in Iran, *Energy* (2012) 43: 469-476.
- [22] Singh G., Singh S., Singh J., Optimization of Energy Inputs for Wheat Crop in Punjab, *Energy Converse Management* (2004) 45: 453–465.
- [23] Hatrili S.A., Ozkan B., Fert C., Energy Inputs and Crop Yield Relationship in Greenhouse Tomato Production, *Renewable Energy* (2006) 31: 427–438.
- [24] Ghasemi Mobtaker H., Akram A., Keihani A., Economic Modeling and Sensitivity Analysis of the Cost Inputs for Alfalfa Production in Iran, A Case Study from Hamedan Province, *Ocean Journal of Applied Sciences* (2010) 3: 313-319.
- [25] Ubeyli E.D., Adaptive Neuro-Fuzzy Inference System Employing Wavelet Coefficients for Detection of Ophthalmic Arterial Disorders, *Expert Systems with* (2008) 34: 2201–2209.
- [26] Singh R., Kainthola A., Singh T.N., Estimation of Elastic Constant of Rocks Using an ANFIS Approach, *Applied Soft Computing* (2012) 12: 40–45.
- [27] Khoshnevisan B., Rafiee S., Omid M., Yousefi M., Movahedi M., Modeling of Energy Consumption and GHG (greenhouse gas) Emissions in Wheat Production in Esfahan Province of Iran Using Artificial Neural Networks, *Energy* (2013a) 52: 333-338.
- [28] Safa M., Samarasinghe S., Determination and Modeling of Energy Consumption in Wheat Production Using Neural Networks, A Case Study in Canterbury Province, New Zealand, *Energy* (2011) 36: 5140-5147.
- [29] Koocheki A., Ghorbani R., Monadi F., Alizadeh Y., Moradi R., Pulses Production Systems in Term of Energy Use Efficiency and Economical Analysis in Iran, *International Journal of Energy Economics and Policy* (2011) 4(1): 95-106.
- [30] Patil S.L., Mishra P.K., Loganandhan N., Ramesha M.N., Math S.K.N., Energy, Economics and Water Use Efficiency of Chickpea (*Cicer arietinum* L.) Cultivars in Vertisols of Semi-Arid Tropics, *Indian Machineries Research Communication*, (2014) 107:656-664.
- [31] Yousefi M., Damghani A.M., Evaluation of Energy Flow and Indicators of Chickpea under Rainfed Condition in Iran, *International Journal of Farming and Allied Sciences* (2012) 1(2): 57- 61.
- [32] Tabatabaie S.M.H., Rafiee S., Keyhani A., Ebrahimi A.H., Energy and Economic Assessment of Prune Production in Tehran Province of Iran, *Journal of Cleaner Production* (2013) 39: 280-284.

- [33] Zhang L.X., Song B., Chen B., Energy-Based Analysis of Four Farming Systems, Insight into Agricultural Diversification in Rural China, *Journal of Cleaner Production* (2012) 28: 33-44.
- [34] Mohammadshirazi A., Akram A., Rafiee S., Mousavi-Avval S.H., Bagheri Kalhor E., An Analysis of Energy Use and Relation between Energy Inputs and Yield in Tangerine Production, *Renewable and Sustainable Energy Reviews* (2012) 16:4515–4521.
- [35] Cetin C., Vardar A., An Economic Analysis of Energy Requirements and Input Costs for Tomato Production in Turkey, *Renewable Energy* (2008) 33: 428-433.
- [36] Khoshnevisan B., Rafiee S., Mousazadeh H., Environmental Impact Assessment of Open Field and Greenhouse Strawberry Production, *European Journal Agronomy* (2013b) 50: 29-37.