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Energy audit of Iranian kiwifruit production using intelligent systems

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ABSTRACT

Optimizing the energy flows of agricultural production is a concern in order to find the most appropriate mix of agricultural inputs, which would in turn minimize energy consumption and maximize energy output. Thus, the aim of this study is to model the energy flows of kiwifruit production in Guilan province of Iran (as a case study) using Artificial Neural Network (ANN) + Genetic Algorithm (GA) modeling and Multiple Linear Regressions (MLR) + GA modeling. The results indicated that the highest energy consumption were attributed to electricity and chemical fertilizers with the shares of 42% and 25%, respectively. Energy indices such as energy use efficiency, energy productivity, specific energy and net energy were determined to be 0.48, 0.25 $kgMJ^{-1}$, 4.01 $MJkg^{-1}$, and -54,644 $MJha^{-1}$. The performance indices such as coefficient of determination (R^2) and efficiency (EF) for the best MLR model were determined to be 0.61 and 0.60%, respectively. Moreover, the same indices for the best developed ANN model were 0.73 and 0.72%, respectively. Overall, it was concluded that the ANNs models could better predict the energy output than the MLRs models and the performance of ANN highlighted that this model may be applied to prognosticate the energy output of kiwifruit production. To conclude, a comparison between ANN + GA and MLR + GA clearly demonstrated the better performance of ANN + GA to optimize the energy flows of Iranian kiwifruit production.

1. Introduction

Energy audit of agricultural systems is one of the main factors for sustainable production assessment [1]. In fact, it is the first step to assess how much energy the production system consumes and determine what measures can be taken to make the system more energy efficient. Energy audit reveals energy hotspots and it can contribute to saving significant amounts of energy and money over a certain period of time [2].

Energy consumption in Iranian fruit production is not efficient and there is a high degree of inefficiency at all the stages of the production cycle [25]. On the other hand, modeling the energy flows of agricultural production is a difficult task, simply due to different interactions between the inputs. In recent years, mathematical models have been widely used to evaluate the energy audit of agricultural production [3,4]. Several researchers have used multiple linear regressions (MLRs) models to model the energy consumption of crop production such as canola [5], peach [6], mushroom [7], lentil and chickpea [8], and watermelon [4]. Table 1 shows the summary of the literature on the energy modeling of crop production from 2012 to now. In a study conducted by Ref. [25]; the impacts of energy inputs on apple yield were studied using MLR. The authors reported that the impact of energy inputs included chemical fertilizer, electricity, farmyard manure, water for irrigation and human labor were significantly positive on the apple yield. In another study, MLR modeling was used to study the impact of each energy input on the pear production In Iran. The researchers concluded that the energy inputs of human labor, gasoline, chemical fertilizer, farmyard manure, biocide and electricity had significantly positive impact on the pear yield [11].

There have been a number of recent studies in which the authors have used Artificial Neural Network (ANN) for predicting energy output of some agricultural production such as basil [26], tea [27], and wheat [28]. Ref. [23] employed ANN to predict the energy output of grape production in West Azerbayjan of Iran. The authors claimed that this method can be used to prognosticate the energy output for grape production in the studied region.

Optimizing the energy flows of agricultural production is a concern in order to find the most appropriate mix of agricultural

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Table 1
Summary of the literature on the energy modeling of crop production (from 2012 to now).

Authors	Crop's name	Modeling	Optimization	Energy consumption hotspot
[9]	Plum	MLR	–	Electricity and water
[10]	Alfalfa	MLR	–	Electricity and chemical fertilizers
[11]	Pear	MLR	–	Electricity and water
[12]	Wheat	ANN	–	Electricity and chemical fertilizers
[13]	Tangerine	ANN	–	Chemical fertilizer and human labor
[7]	Mushroom	MLR	–	Compost and diesel fuel
[14]	Potato	ANN	–	Electricity and nitrogen fertilizers
[15]	Grapefruit	MLR	–	Chemical fertilizers and diesel fuel
[16]	Saffron	MLR	–	Seeds and chemical fertilizer
[17]	Apple	ANN	–	Water and diesel fuel
[18]	Corn silage	MLR	–	Chemical fertilizers and water
[19]	Orange	MLR	–	Chemical fertilizers and biocide
[20]	Watermelon	MLR	GA	Water and plastic
[21]	watermelon	ANN	–	Chemical fertilizers and diesel fuel
[22]	Kiwifruit	ANN	–	Nitrogen fertilizers and diesel fuel
[23]	Grape	ANN	–	Chemical fertilizers and water
[24]	Canola	MLR	GA	Chemical fertilizers and diesel fuel
Current Study	**Kiwifruit**	**MLR and ANN**	**GA**	**-**

inputs, which would in turn minimize energy consumption and maximize energy output. The implementation of ANN alongside the other models can contribute to better optimize the production system [29]. Specifically, reviewing the literature indicated that many researchers have reported the successful application of ANN and **Genetic Algorithm** (GA) for optimization of some production systems like optimization of solar systems [30], electrical energy consumption [31], biogas production [32], and biodiesel production [33]. However, the combination of ANN and GA in the energy modeling of fruit systems has not yet been investigated. Therefore, the aim of the current research is to predict and optimize the energy flows of Iranian kiwifruit production in Guilan province of Iran (as a case study) using ANN approach and GA modeling. In addition, the results are compared with the results obtained from application of MLR + GA.

2. Materials and methods

2.1. Selection of case study area and data collection

This research was conducted in Talesh city of Gulian province of Iran. In Iran, there are more than 10,156 ha cultivated with kiwifruit, and Guilan province is the second largest producer of kiwifruit (Ministry of Jihad-e-Agriculture of Iran [53]).

The sample size was determined using Cochran method [34]. Accordingly, the primary data used for this research collected through face-to-face interviews with 84 kiwifruit producers in the 2012–2013. The questionnaires included total inputs and output of production in the studied region. Data for the inputs-output of kiwifruit production were taken from our previous research [35].

2.2. Energy inputs-output analysis

The main energy inputs for kiwifruit production in the studied region included human labor, machinery, diesel fuel, chemical fertilizer, biocide, irrigation water, farmyard manure and electricity. Energy output was considered as kiwifruit yield. The equivalences of energy inputs and output for kiwifruit production were obtained from: Refs. [10,36,37] and [12]. Accordingly, the energy equivalences of human labor was 1.96 $MJhr^{-1}$, machinery was 62.7 $MJhr^{-1}$, diesel fuel was 56.31 MJL^{-1}, nitrogen fertilizer was 66.14 $MJkg^{-1}$, phosphate fertilizer was 12.44 $MJkg^{-1}$, potash fertilizer was 11.15 $MJkg^{-1}$, sulfur fertilizer was 1.12 $MJkg^{-1}$, biocide was 120 $MJkg^{-1}$, irrigation water was 1.02 MJ/m^3, farmyard manure was 0.3 $MJkg^{-1}$ and electricity was 11.93 $MJkWh^{-1}$. Moreover, in this study, the energy indices such as energy use efficiency, energy productivity, specific energy and the net energy were investigated [38,39].

2.3. Multi linear regression modeling

In this study, an MLR model was developed based on the eight independent variables (energy inputs) and one dependent variable (energy output) by the analysis of variance using MATLAB vR2014b (Math works Inc, US) software according to equations (1) and (2):

$$E_i = a_0 + \sum_{j=1}^{n} \alpha_j x_{ij} + e_i \quad i = 1, 2, \ldots, n \tag{1}$$

$$Ei = a_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_5 x_5 + \alpha_6 x_6 + \alpha_7 x_7 + \alpha_8 x_8 + e_i \tag{2}$$

where E_i denotes the energy output of the ith orchard; x_{ij} the vector of inputs used in the production process; a_0 the constant term; *aj* represents coefficients of inputs which are estimated from the model and e_i is the error term.

Accordingly, x_1: human labor, x_2: machinery, x_3 diesel fuel, x_4: chemical fertilizer, x_5: biocide, x_6: water, x_7: electricity and x_8: farmyard manure are the energy inputs. The percentage contributions (PC) for the developed model were calculated as follows:

$$PC_i = \frac{SS_i}{SS_T} \times 10 \tag{3}$$

where, SS_i and SS_T are the sum of squares of the term of the model and total sum of square of the model, respectively.

2.4. Artificial Neural Networks modeling

Multilayer perceptron (MLP) is a feed-forward layered network with one input layer, one output layer, and some hidden layers [40,41]. Fig. 1 displays the structure of the developed MLP model. Every node computes a weighted sum of its inputs and passes the sum through a soft nonlinearity [42]. The soft nonlinearity or activity function of neurons should be non-decreasing and differentiable [43]. Unipolar sigmoid is one of the most popular functions

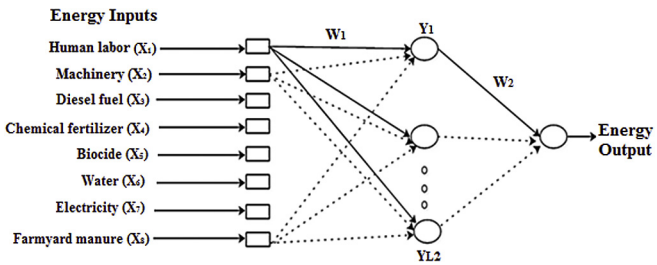

Fig. 1. Structure of MLP neural network for energy inputs-output in Iranian kiwifruit production.

which was calculated as [44]:

$$f(\theta) = \frac{1}{1 + e^{-\theta}} \tag{4}$$

In this study, the energy inputs are considered as the inputs for MLP neural networks and energy output was the energy output of kiwifruit production. The goal was to obtain the fit MLP model by finding the best weights between nodes of the inputs and hidden layers (W_1) and between nodes of the hidden and output layer (W_2). The optimal weights are obtained through neural network training algorithm with a hidden layer. In order to achieve appropriate error performance for the training set, the numbers of neurons in the hidden layer (L_2) were obtained by trial and error [45]. Each of the weights is updated in equations (5) and (6).

$$W_1(n+1) = W_1\,(n) - \eta\frac{\partial E}{\partial W_1} + \alpha(W_1(n) - W_1(n-1)) \tag{5}$$

$$W_2(n+1) = W_2\,(n) - \eta\frac{\partial E}{\partial W_2} + \alpha(W_2(n) - W_2(n-1)) \tag{6}$$

where n, E, η and α are the number of training iterations, the error, the learning rate and the momentum factor, respectively. A computer code was developed by MATLAB vR2014b (Math works Inc, US) software to apply the analysis.

2.5. Model performance indices

Three criteria were used to evaluate the performances of the MLR and ANN models. These Model performance indices were coefficient of determination) R^2 (, model efficiency (EF), mean absolute percentage error (MAPE) that are defined as equations (7)–(9) [46]:

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(E_{ai} - \overline{E_{ai}}\right) \times \left(E_{pi} - \overline{E_{pi}}\right)\right)^2}{\sum_{i=1}^{n}\left(E_{ai} - \overline{E_{ai}}\right)^2 \times \sum_{i=1}^{n}\left(E_{pi} - \overline{E_{pi}}\right)^2} \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E_{ai} - E_{pi}}{E_{ai}}\right| \times 100 \tag{8}$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}\left(E_{ai} - E_{pi}\right)^2}{\sum_{i=1}^{n}\left(E_{ai} - \overline{E_{pi}}\right)^2} \tag{9}$$

where, E_a and E_p are the actual and the predicted energy output, respectively, i (1, …, n) is the number of patterns. The model with the smallest MAPE and the largest EF and R^2 is selected as the best.

2.6. Genetic algorithm

In order to optimize the energy flows of kiwifruit production in Iran, genetic algorithm approach was applied. In other words, the purpose of optimization in this study was to find the best levels of the energy inputs in order to achieve the highest energy output. In this study, binary genetic algorithm procedure was employed (Fig. 2). Moreover, the trained MLP neural network and the extracted regression model were used as the fitness functions. The energy output was defined as the fitness and the energy inputs were considered as optimization variables. In this research, the minimum and maximum values for energy consumption of Iranian kiwifruit production were verified by local experts. These values were considered as the lower and upper bounds in the GA model. Table 2 shows the upper and lower bounds for the optimization issue in Iranian kiwifruit production.

The population size of initial people assumed 80 samples. The maximum number of interactions was equal to 50 sets of initial solutions ($x_1^0\ x_2^0\ x_3^0\ x_4^0\ x_5^0\ x_6^0\ x_7^0\ x_8^0$) which were randomly generated. Each solution in the population is called a chromosome [48]. The fitness of each chromosome was calculated by the MLR and the ANN models. The chromosomes were arranged in an ascending order in terms of their fitness and 50% of their initial chromosomes were selected to produce the next generation. The parents from the remaining population were chosen through tournament selection procedure. Uniform crossover procedure was employed to produce the new offspring and the next generation. The mutation rate was considered to be 30%. Overall, 20% of the bits in the new generation were randomly changed from 0 to 1, or vice versa.

The production of new generation continued until a better solution was found. The computer code for the genetic algorithm was developed in MATLAB programming environment as demonstrated in Fig. 2.

3. Results and discussion

3.1. Energy results

Fig. 3 shows the amounts of energy inputs for kiwifruit production in Guilan province of Iran. The results showed that the highest energy consumption was attributed to electricity with the value of 43,169.55 $MJha^{-1}$. Chemical fertilizers were the second largest energy consumer during kiwifruit production with a share of 25% (25,954.70 $MJha^{-1}$). It was in agreement with Refs. [49–51]; and Ref. [52] who suggested that the chemical fertilizers were one of the most widely energy consumer in rice, peanut, tea, and olive production in Northern Iran. In this area, consuming the relatively large number of application of chemical fertilizers for kiwifruit production were the remarkable point, a way that average the number of chemical fertilizer was about 2.24 times.

Irrigation water was the third input in terms of energy consumption and it was consumed approximately 12916.71 $MJha^{-1}$ (12% of total energy inputs). Sandy soil of kiwifruit orchards in this region is one of the main reasons for relatively high consumption of irrigation water [53]. Diesel fuel was the fourth input with the highest energy consumption in kiwifruit production and its energy consumption was determined to be 11,381.84 $MJha^{-1}$ (11% of total energy input). According to relatively high consumed water and using of electric motor in this area, diesel fuel was not used for pumping.

Human labor, farmyard manure, machinery and biocide were known as the lowest energy consumers with the shares of 5%, 3%, 2% and less than 1%, respectively. The numbers of spraying and weeding were 1.22 and 2.97 times, respectively.

Table 3 displays a comprehensive summary of energy indices for

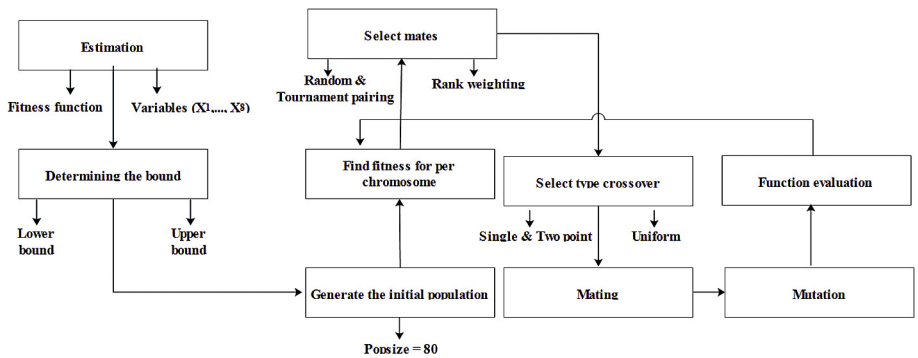

Fig. 2. System boundary of genetic algorithm procedure [47].

Table 2
The lower and upper bounds for the optimization issue in Iranian kiwifruit production.

Input parameters	Lower bound (MJha^{-1})	Upper bound (MJha^{-1})
Agricultural machinery	200	90,000
Diesel fuel	500	65,000
Electricity	0	95,000
Chemical fertilizer	0	50,000
Water	0	40,000
Biocide	0	15,000
Farmyard manure	0	40,000
Human labor	100	50,000

some crops production in the Northern parts of Iran. The total energy input for kiwifruit production in Guilan province of Iran was determined to be 104,156.03 MJha^{-1} that it was higher than that of energy input for some of crops production in the Northern parts of Iran such as olive, rice and peanut in Guilan, kiwiftuit in Mazandaran, and peach in Golestan [6,49,51,52,54]. The consuming of relatively high levels the chemical fertilizer and electricity was one of the most important causes in high energy consumption in kiwifruit production.

The energy use efficiency for kiwifruit production was determined to be 0.48. The comparison of the results shows that the energy use efficiency of kiwifruit production was lower than that of olive, rice and peanut in Guilan, kiwifruit in Mazandaran, and peach production in Golestan province of Iran [6,49,51,52,54]. One of the most important reasons of lower energy efficiency in kiwifruit production in Guilan province can be refer to relatively high consumption of irrigation water and electricity. Moreover, the amount of chemical fertilizer consumption was higher than the other crops like olive, tea, peanut, rice, and peach [6,49–52]. The average of energy output of kiwifruit production in Guilan province of Iran was equal to 26,059 MJha^{-1}. Given the relatively high performance of this product in area, energy productivity (0.25 kgMJ^{-1}) was more than those of for rice and peanuts production [51,52] and less than kiwifruit in Mazandaran, tea in Guilan and peach in Golestan [6,50,54]. In addition, specific energy and net energy in this area were determined to be 4.01 MJkg^{-1} and -54,643.89 MJha^{-1}, respectively.

The contributions of direct and indirect energy for kiwifruit production in Guilan province were equal to 73,088.30 and 31,067.74 MJha^{-1}, respectively. The amounts of renewable and non-renewable energy were 21,826.20 and 82,329.84 MJha^{-1}, respectively. The consumption of renewable energy in this study was more than of many crops in Northern Iran [6,11,49–52,54]. One of

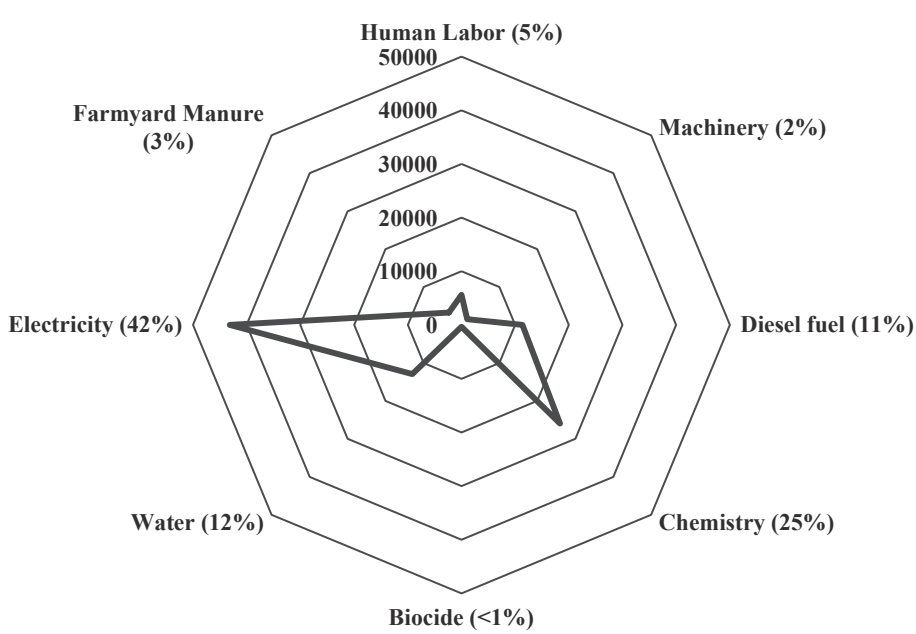

Fig. 3. The values of energy inputs for kiwifruit production (MJha^{-1}).

Table 3
Energy indices for some crops production in the Northern parts of Iran.

Energy indices	Unit	Kiwifruit in Guilan (The results of this study)	Kiwifruit in Mazandaran [54]	Olive in Guilan [49]	Tea in Guilan [50]	Rice in Guilan [51]	Peanut in Guilan [52]	Peach in Golestan [6]
Total energy input	$MJha^{-1}$	104156.03	30285.62	20,000	39060.60	39,333	19407.36	37,536
Total energy output	$MJha^{-1}$	49512.14	46639.85	24,800	8593.33	60179.49	76751.70	20644.8
Energy efficiency	–	0.48	1.54	1.24	0.22	1.53	3.92	0.55
Energy productivity	$kgMJ^{-1}$	0.25	0.81	0.11	0.28	0.09	0.16	0.29
Specific energy	$MJkg^{-1}$	4.01	1.23	10.50	3.63	11.09	6.06	3.41
Net energy	$MJha^{-1}$	−54643.89	16354.23	−2544.88	−30421.78	21,008	56744.34	16642.03
Direct energy	$MJha^{-1}$	73088.30	9110.45	6645.64	13843.71	19,388	12958.36	19138.06
Indirect energy	$MJha^{-1}$	31067.74	21275.17	9036.66	25216.89	19,946	6494	18,404
Renewable energy	$MJha^{-1}$	21826.20	7713	2010.83	6761.57	4411	1510.11	6623.54
Non-renewable energy	$MJha^{-1}$	82329.84	22572.62	13671.13	32299.03	34922	17897.25	30918.53

the most important reasons for relatively high share of renewable energy was the relatively high farmyard manure consumption in the studied region (see Fig. 4).

3.2. Correlation between orchard size and energy inputs-output

Table 4 shows the correlation between orchard size and energy inputs-output for kiwifruit production. The results showed that there was an inverse correlation between orchard size with energy inputs ($r = -0.12$) and energy output ($r = -0.30$). A direct correlation was found between the energy inputs with energy output ($r = 0.21$). It means that, with the addition of energy consumption in some of inputs (machinery, diesel fuel, manure and chemical fertilizer), the energy output can be improved (Table 4).

3.3. MLR results

Before establishing the regression relationship through the analysis of variance, the normality of the output data was analyzed using Anderson-Darling normality test, the results of which indicated that the data are in fact normal (level of significance, Pvalue = 0.05) (see Fig. 5).

Table 4
Correlation between orchard size and energy input and output.

Correlation	Area	Energy inputs	Energy output
Area	1.00	−0.12	−0.30
Energy inputs	−0.12	1.00	0.21
Energy output	−0.30	0.21	1.00

Table 5 shows the impacts of energy inputs on the energy output of Iranian kiwifruit production. The results of MLR model demonstrated that the energy inputs such as electricity, chemical fertilizers, diesel fuel and machinery had the highest impacts on the energy output of kiwifruit production. In addition, according to the coefficient of the developed MLR model, the use of extra energy in the above mentioned energy inputs had a positive effect on the energy output. The results of the coefficient of determination) R^2 (indicated that the developed MLR model can explain 60% of the variability in the energy output. On the other hand, due to value of the VIF being less than 5, the correlations between inputs were very low, which indicates that it was suitable for regression model. The contribution percent (PC) of energy inputs such as diesel fuel, machinery, electricity, manure and chemical fertilizer were

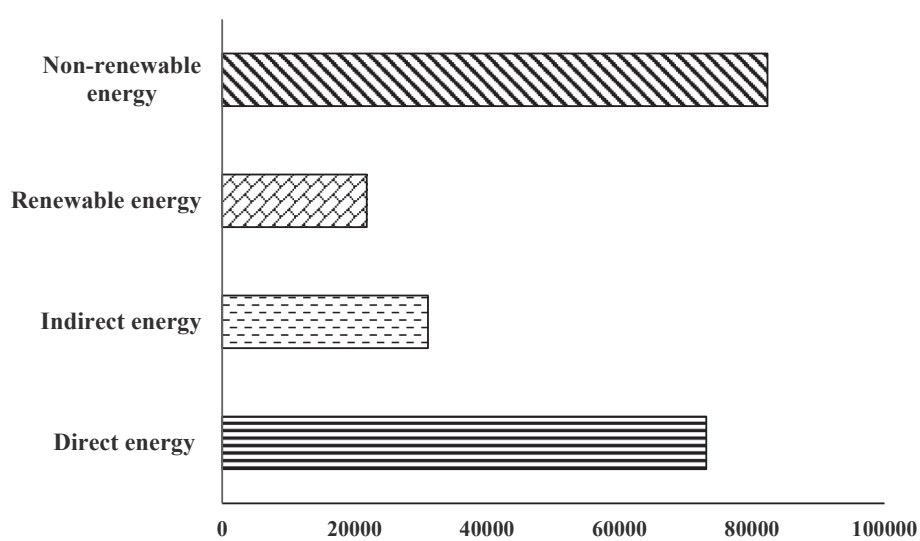

Fig. 4. Comparison of different forms of energy for Iranian kiwifruit production ($MJha^{-1}$).

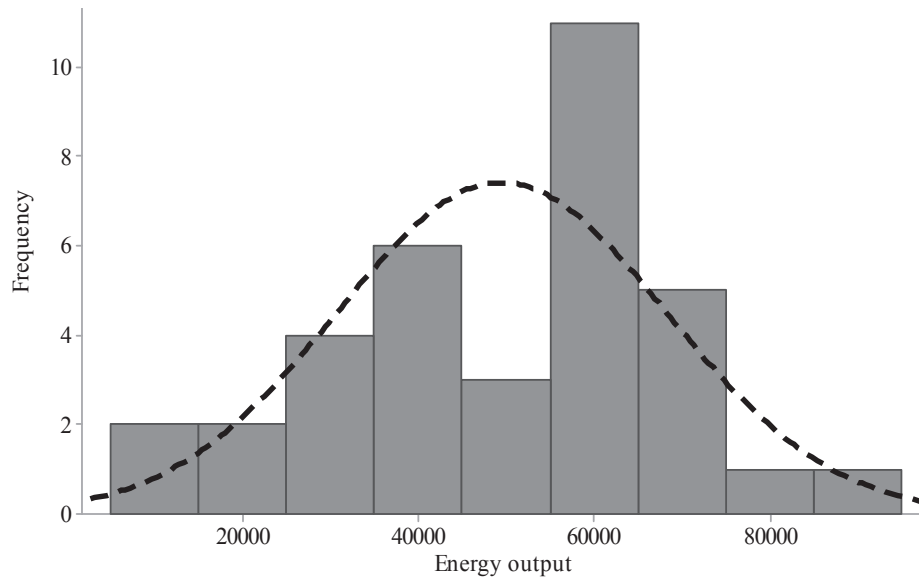

Fig. 5. Normal distribution test for energy output data in kiwifruit production.

Table 5
The impacts of energy inputs on the energy output in Iranian kiwifruit production.

Item	Coefficient	Contribution (%)	t-ratio	P-Value	VIF
Human labor	- 0.18	0.08	−0.58	0.565	1.49
Machinery	9.25	18.14	3.81	0.001	1.27
Diesel fuel	1.11	20.64	2.28	0.03	1.43
Chemical fertilizers	0.68	5.18	3.14	0.004	1.36
Biocides	- 3.82	2.41	−0.89	0.380	1.26
Water	- 0.15	0.21	−0.88	0.358	1.38
Electricity	0.43	8.51	2.92	0.007	1.49
Manure	2.80	5.96	2.00	0.056	1.45
Error	–	38.86	–	–	–
Total	–	100	–	–	–
R^2	0.61				
Durbin- Watson	1.80				

determined to be 20.64, 18.14, 8.51, 5.96 and 5.18%, respectively.

3.4. ANN results

Based on the universal approximation theorem, a neural network with a single hidden layer and sufficiently a large number of neurons can well approximate any arbitrary continuous function [55]. In this study, the number of neurons in the hidden layer was determined using a trial-and-error method and by setting marquardt adjustment parameter (μ), epoch size constant and performance goal to 0.001, 5000 and 0.001, respectively. The process was repeated several times, once for each set of data. The purpose of applying the MLP model in this study was to estimate the accuracy of its prediction of the energy output in the process of kiwifruit production in Guilan province of Iran.

Table 6 displays the process of determining the optimal number of neurons using performance indices. The results indicated that the optimal number of neurons in the hidden layer with regards to the model performance indices for the training phase was 25 neurons. This implies that the ANN model with the 8-25-1 structure was the optimal model for prognosticating the energy output of Iranian kiwifruit production. The best developed model to predict the Iranian tangerine yields based on the energy inputs was reported to be an ANN model with the 10–8–5 structure [13]. Ref. [23] developed an ANN model with one hidden layer (14 neurons) and two output layers that could predict Iranian grape production.

Table 7 displays the performance indices of the optimal developed ANN model. The performance parameters such as R^2 and model efficiency were determined to be 0.73 and 0.72, respectively. In addition, the error parameter of MAPE was computed 21.77%, respectively.

3.5. The comparison between MLR and ANN modeling

As another aim of this study, the accuracy rate of MLR and ANN modeling for predicting the energy output of kiwifruit production in Iran were compared to one another. Different values of the performance indices at different phases of training (80% of the data), testing (20% of the data) and the total in MLR and ANN

Table 7
Performance indices of the optimal ANN model.

Parameters	Train	Test	Total
R^2	0.80	0.61	0.73
Model efficiency (%)	0.78	0.60	0.72
MAPE (%)	19.36	31.42	21.77

Table 6
The process of determining the optimal number of neurons using performance indices.

Parameters	Number of neurons in hidden layer									
	5	10	15	20	25	30	35	40	45	50
R^2	0.58	0.62	0.68	0.52	0.80	0.67	0.72	0.71	0.68	0.76
Model efficiency (%)	0.59	0.60	0.56	0.51	0.78	0.67	0.64	0.59	0.64	0.75
MAPE (%)	25.65	31.05	25.03	29.40	19.36	25.35	21.17	35.90	21.11	21.10

Table 8
Comparison between the optimal developed MLR and ANN models.

Type of model	Parameters	Train	Test	Total
ANN Modeling	R^2	0.80	0.61	0.73
	Model efficiency (%)	0.78	0.60	0.72
	MAPE (%)	19.36	31.42	21.77
MLR Modeling	R^2	0.59	0.67	0.61
	Model efficiency (%)	0.59	0.60	0.60
	MAPE (%)	25.65	24.06	25.33

models were included in the comparison. The results showed that the coefficient of determination) R^2 (for the ANN and MLR models were 0.73 and 0.61, respectively, (Table 8). In addition, error parameter of MAPE for the developed ANN model was less than that of the MLR model. Ultimately, it was concluded that the ANN model could better predict the energy output than the MLR model and the performance of ANN highlighted that this model can be applicable in order to prognosticate the energy output of kiwifruit production. Table 9 presents the statistical variables of actual and predicted values for the MLR and ANN models in different phases of the process.

3.6. Optimization using genetic algorithm

At this stage, the optimal fitness function (energy output) for the MLR and ANN models were determined by considering the levels of

Table 9
Statistical variables of actual and predicted values for the MLR and ANN models (MJha-1).

Phase		Modeling	Average	Statistical parameters					
				Std	Minimum	Maximum	Sum	Skewness	Kurtosis
Train	Actual value	–	49755.83	18992.75	7916.67	85500.00	1393163.13	−0.35	2.43
	Predicted value	ANN	48661.80	14511.21	17116.50	76415.44	1362530.35	−0.09	2.43
		MLR	25716.65	14740.05	20835.52	77923.56	1389931.79	−0.08	2.41
Test	Actual value	–	48537.40	19478.42	13255.81	71250.00	339761.77	−0.68	2.57
	Predicted value	ANN	45525.82	13512.27	25980.85	68259.47	318680.76	0.28	2.49
		MLR	47967.96	16503.69	22543.29	70957.43	335775.722	- 0.17	2.04
Total	Actual value	–	49512.14	18805.76	7916.67	85500.00	1732924.89	−0.41	2.47
	Predicted value	ANN	48034.60	14179.62	17116.50	76415.44	918825.93	−0.01	2.41
		MLR	49305.93	14868.20	20835.52	77923.56	1681211.11	−0.10	2.34

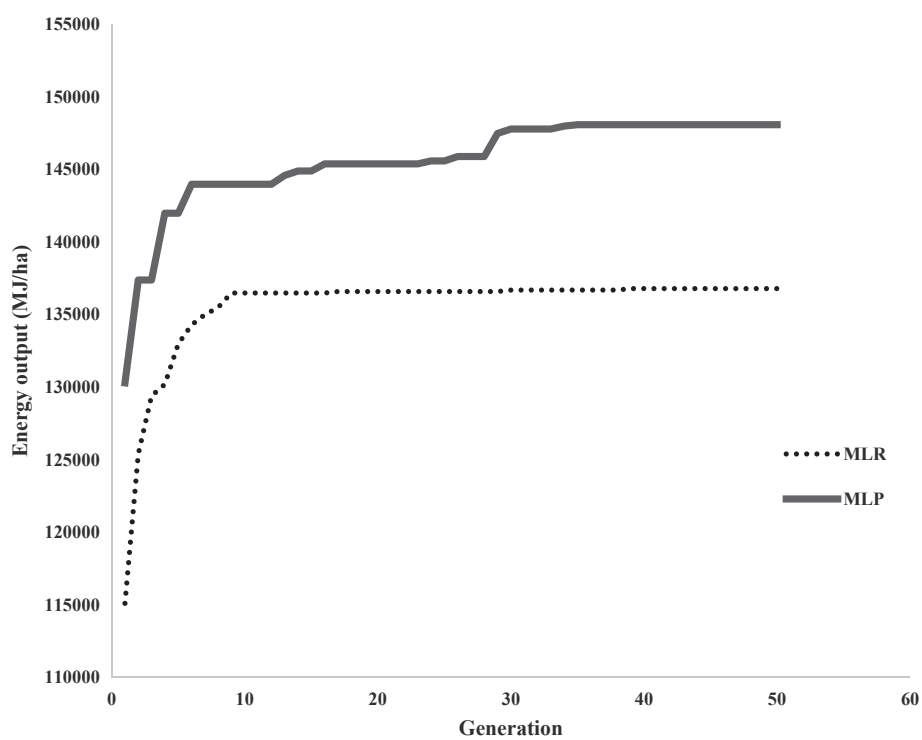

Fig. 6. Convergence graph of the GA for MLR and MLP models.

Table 10
The optimal energy inputs to achieve the highest energy output for Iranian kiwifruit production (MJha-1).

Fitness function	Human	Machinery	Diesel	Chemical fertilizer	Biocide	Water	Electricity	Manure	Energy output
ANN	30447.07	16235.40	39701.90	3116.20	353.20	14621.85	12406.32	3040.67	148135.45
MLR	8285.77	4682.66	22305.44	48263.08	233.18	3445.25	93949.40	6323.08	136839.12

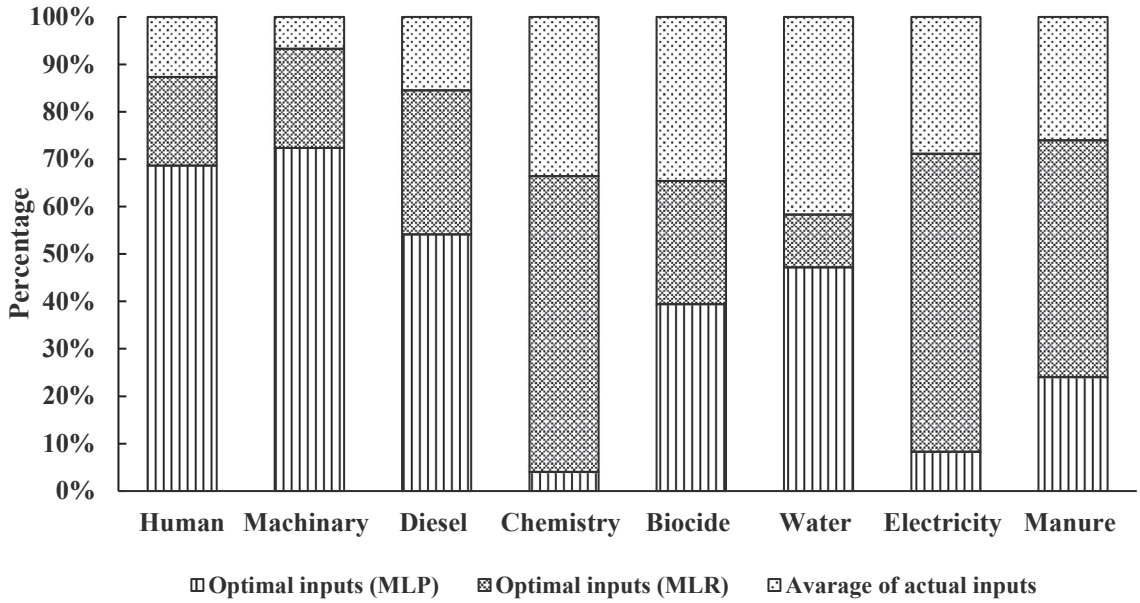

Fig. 7. Actual and optimal inputs for kiwifruit production based on the MLR and ANN models.

Table 11
Comparing the energy efficiency improvement through MLR + GA and ANN + GA.

	Energy inputs ($MJha^{-1}$)	Energy output ($MJha^{-1}$)	Energy efficiency	Energy use efficiency improvement ((Optimum-Actual)/Actual*100)
Actual production	104156.03	49512.14	0.48	-
Optimum production (ANN)	105300.76	148135.45	1.40	191.66%
Optimum production (MLR)	187487.86	136839.12	0.72	50%

input variables through genetic algorithm. Fig. 6 shows the convergence graph of the genetic algorithm to find the optimal solution for the developed MLR and ANN models. This figure shows that GA converged after the 17th and 35th generations of solutions. The values of optimal kiwifruit energy output for the MLR and ANN using GA were determined to be 136,839.12 and 148,135.45 $MJha^{-1}$, respectively.

The results of GA optimization through the application of the MLP neural network and MLR as the fitness function are presented in Table 10. The improvement of the actual energy compared with the optimal energy in the MLR and ANN models were 26% and 66%, respectively. The maximum values of output energy for both the MLR and ANN models were more than the upper limit of the average of observed energy output (49,512.13 $MJha^{-1}$) in kiwifruit production. Moreover, the optimal amount of energy obtained through GA was 7.6% higher for ANN than for the MLR, simply because the ANN model is able to accurately estimate the nonlinear behavior of the output, contrary to the MLR model which acts as a linear function. Fig. 7 displays the comparison between the actual and optimal energy inputs for MLR and ANN models using GA.

Table 11 shows a comprehensive summary of energy indices for GA + MLR and ANN + GA. As previously mentioned, the energy use efficiency of Iranian kiwifruit production was 0.48. However, the GA + MLR and ANN + GA results indicated that the energy use efficiency can be improved to 0.72 and 1.40, respectively. In the other words, there was a possibility of improving the energy use efficiency up to 192% and 50% by implementing the ANN and MLR models, respectively. Ref. [24] investigated the application of multi-objective genetic algorithms and MLR model for optimization of energy consumption in canola production in Iran. The results showed that the actual and optimum energy efficiency were 3.8 and 4.9, and the percentage of energy use efficiency improvement was equal to 30.3%.

4. Conclusion

This study evaluated the potential of MLR and ANN models to predict the energy flows of Iranian kiwifruit production. Moreover, the potential of MLR + GA and ANN + GA were compared in terms of optimization of energy flows. It is important to note that the current study is the first research on the application of ANN + GA for energy optimization of fruit production systems. The results indicated that the energy use efficiency of Iranian kiwifruit production was 0.48. It implies that the energy consumption in kiwifruit production in Iran is not efficient and there is a high degree of inefficiency at some of the stages of the production chain. However, the results obtained from the application of GA + MLR and ANN + GA demonstrated that this rate may be improved to 0.72 and 1.40, respectively. It was hence concluded that both ANN and ANN + GA have great potential for predicting and optimizing the energy flows of kiwifruit production. Many fruit production systems could benefit from using ANN + GA methodology for the optimization of energy flows.

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