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Modeling and optimization of CO_2 emissions for tangerine production using artificial neural networks and data envelopment analysis

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Abstract

The aims of this research were to scrutinize CO_2 emissions based on different size levels of orchards, modeling and optimization of CO_2 emissions using artificial neural network (ANN) and data envelopment analysis (DEA) for tangerine production in Guilan province, Iran. The results revealed that the total CO_2 emissions and yield were calculated about 622 $kgCO_{2eq.}$ ha^{-1} and 49 ton ha^{-1}, respectively. Also, the large orchards had the highest emissions and yield among all of the groups. The results of ANN modeling indicated that the best topology was 8-4-1 for prediction of tangerine yield based on emission inputs. Also, the R^2, RMSE and MAPE (%) of the best structure was computed as 0.964, 0.111 and 0.312, respectively. Based on DEA approach, the mean of technical, pure technical and scale efficiency was found to be 0.802, 0.890 and 0.894, respectively. In optimal units, the total CO_2 emissions were calculated as 483.83 $kgCO_{2eq.}$ ha^{-1}. The results indicated that optimization of CO_2 emissions by the DEA can reduce the total emissions about 138 $kgCO_{2eq.}$ ha^{-1} and the reduction of electricity consumption had the highest positive effect in CO_2 emissions reductions.

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Introduction

Tangerine (*Citrus tangerine*) is an orange-colored citrus fruit which is closely related to the mandarin orange (*Citrus reticulate*) (Penjor *et al.,* 2013). China, Spain, Brazil, Japan, Turkey, Italy and Egypt are the main orange producers. After the mentioned countries, Iran has the eighth place of tangerine production in the world (FAO, 2011). Production, formulation, storage, distribution of these inputs and application with tractorized equipment lead to combustion of fossil fuel, and use of energy from alternate sources, which also emits CO_2 and other greenhouse gases (GHGs) into the atmosphere. Thus, an understanding of the emissions expressed in kilograms of carbon equivalent (kg CE) for different tillage operations, fertilizers and pesticides use, supplemental irrigation practices, harvesting and residue management is essential to identify C-efficient alternatives such as biofuels and renewable energy sources for seedbed preparation, soil fertility management, pest control and other farm operations (Lal, 2004). Intensifying global focus on the environmental responsibility has forced industries and policy makers to develop strategies to decrease the production of harmful emissions (Pishgar-Komleh *et al.,* 2013). The contribution of global agriculture to air pollution accounts for about 5-13.5% of annual GHG emissions (Safa and Samarasinghe, 2012). So, the survey of GHG emissions (especially CO_2 emissions) is very important for agriculture activity. Models are the only practical way to quantify the net effect of farm practices on Greenhouse Gas (GHG) emissions or to assess climate change mitigation measures (Dyer *et al.,* 2010). Artificial neural networks (ANN) are used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural system. The predictive ability of an ANN results from the training on experimental data and then validated by independent data (Deh Kiani *et al.,* 2010). An ANN has the ability to re-learn and improve its performance if new data are available. In the recent year, the ANN methods were used for modeling of GHG emissions in the agricultural activity. Khoshnevisan *et al.* (2014a) examined the ANN model for GHG emissions of potato production in Esfahan province of Iran. Their results indicated that the structure had the best topology for prediction of yield based CO_2 emissions of each input. In another study, Nabavi-Pelesaraei *et al.* (2013) investigated the GHG emissions of eggplant production and determination of the best model for CO_2 emissions using ANN method. Optimization (alternatively, optimization or mathematical programming) is the selection of a best element (with regard to some criteria) from some set of available alternatives. Data Envelopment Analysis (DEA) is a non-parametric technique of frontier estimate which is used extensively in many settings for measuring the efficiency and benchmarking of decision making units (DMUs) (Adler *et al.,* 2002). Although DEA wasn't used directly for CO_2 emissions optimization in agriculture crops but the effect of energy optimization in CO_2 emissions was considered in recent years. Mohammadi *et al.* (2013) used DEA and life cycle assessment for determination of potential GHG reductions in soybean farming. Khoshnevisan *et al.* (2014b) computed the CO_2 emissions reduction by improving energy use efficiency using DEA for strawberry production. In another study, the reduction of GHG emission determined by the DEA approach after optimization of energy consumption for orange production (Nabavi-Pelesaraei *et al.,* 2014).

The present study applies ANN and DEA methodology with the aim of modeling and performing CO_2 emissions in tangerine production in the north of Iran. Additionally, a technical efficiency study is undertaken in order to detect inefficient tangerine orchardists and benchmark target input consumption levels for the inefficient producers.

Materials and methods

2.1. Sampling design

This research was conducted in Guilan province as one of the main agricultural production areas of Iran.

This province is located in the North of Iran, within 36° 34′ and 38° 27′ north latitude and 48° 53′ and 50° 34′ east longitude (Anon, 2013). Data were collected from the growers of 60 tangerine orchards using a face-to-face questionnaire which was carried out in July and August 2013. The sample size of orchards in the research area was calculated using the Cochran method that is one of the stratified random sampling techniques (Snedecor and Cochran, 1988).

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

Where *n* is the required sample size; *s*, the standard deviation; t, the value at 95% confidence limit (1.96); *N*, the number of holding in the target population and *d*, the acceptable error (permissible error 5%). For the calculation of sample size, criteria of 5% deviation from population mean and 95% confidence level were used. In this study, the sample size was calculated 53 but it was considered to be 60 to ensure the accuracy. In order to estimate the reliability of a psychometric test for samples, the Cronbach method was utilized (Cronbach, 1951). The results of this testing indicated that Cronbach's alpha of questionnaire 83%. Also, the quality of orchardists answers was investigated by regional experts.

CO_2 emissions of inputs

The coefficient standard of emissions was used for estimation of CO_2 emissions for each input (Table 1). In this study, machinery, diesel fuel, chemical fertilizers (including: nitrogen, phosphate and potassium), pesticides (including: insecticides and fungicides) and electricity were found as manufacturer CO_2 emissions in tangerine production. The CO_2 coefficient of machinery input consists of manufacturing and applying the machinery on the orchard. For calculation of CO_2 emissions, the first step was to determine the input quantity based on units of each input as shown*2.3. ANN design.*

An ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. ANNs have been applied when there is no theoretical evidence about the functional forms. Therefore, ANNs are data-based, rather than model-based. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems (Ghodsi *et al.,* 2013). The ANN modeling was made in three sections including: input layer (the all of effective inputs to outputs), one or several hidden layers and output layer. For the modeling of CO_2 emissions, the all of inputs were selected as input layer and tangerine yield was chosen as the output layer in this study. Also, the Levenberg-Marquardt learning algorithm was applied for training ANN. Moreover, determination of the coefficient (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) was computed for validate the fitted model.

These mentioned above statistical indices can be expressed as (Zangeneh *et al.,* 2011; Khoshnevisan *et al.,* 2014a).

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

$$RMSE = \sqrt{\frac{1}{n} \sum_{i}^{n} (t_i - z_i)^2} \quad (3)$$

$$MAPE(\%) = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{t_i - z_i}{t_i} \right| \quad (4)$$

Sensitivity Analysis

Sensitivity Analysis via ANN (SAANN) can rank and select the major and input variables through its analysis. SA with partial differential is based on a calculation of input, weights and output variables from the ANN simulation. The calculation of sensitivity, S is as follows (Sung, 1998).

$$S = \frac{\partial O}{\partial I} = O' \left(\sum_{J=1}^{J} w_{ij}^1 \; H' \; w_{ij}^2 \right) \quad (5)$$

$$S = \frac{\partial f(O)}{\partial X} \sum_{J=1}^{J} \left(w_{ij}^1 \; \frac{\partial f(H)}{\partial X} w_{ij}^2 \right) \quad (6)$$

Where *O* is output and *H* is a hidden node that has to be differentiated, w_{ij}^1 and w_{ij}^2 are the weights with respthe the hidden layerirst and second connection of hidden layer. The first connection is for input and hidden layer and the second connection is for hidden node and the output layer (Sung, 1998).

Data envelopment analysis (DEA)

DEA as a very useful management and decision tool, has found surprising development in theory and methodology and extensive applications in the range of the whole world since (Wang *et al.,* 2005). Given a sample of the DMUs, the purpose of the DEA is to establish the relative efficiency of each DMU within a sample (Heidari *et al.,* 2012). In DEA method an inefficient unit can be made efficient either by reducing the input level while the output is fixed (input oriented), or by increasing the output level while input is fixed (output oriented) (Mousavi-Avval *et al.,* 2011). DEA has two models including CCR and BCC models. The CCR DEA model assumes constant returns to scale. It measures the technical efficiency by which the DMUs are evaluated for their performance (Cooper *et al.,* 2007). While, the BCC DEA model assumes variable returns to scale conditions. Therefore this model calculates the technical efficiencies of DMUs under variable return to scale conditions. It decomposes the technical efficiency into pure technical efficiency for management factors and scale efficiency for scale factor relative to other DMUs in a sample (Mobtaker *et al.,* 2012).

Technical efficiency

The technical efficiency can be expressed by the ratio of the sum of the weighted outputs to the sum of weighted inputs and mathematically can be shown as follows relation (Nassiri and Singh, 2009).

$$TE_j = \frac{u_1 y_{1j} + u_2 y_{2j} + \dots + u_n y_{nj}}{v_1 x_{1j} + v_2 x_{2j} + \dots + v_m x_{mj}} = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \qquad (7)$$

Where, u_r, is the weight given to output n; y_r, is the amount of output n; v_s, is the weight given to input n; x_s, is the amount of input n; r, is the number of outputs ($r = 1, 2, \dots, n$); s, is the number of inputs ($s = 1, 2, \dots, m$) and j, represents j^{th} of DMUs ($j = 1, 2, \dots, k$). Eq. (2) is a fraction problem, so it can be translated into a linear programming problem which is introduced by Charnes *et al.* (1978).

$$\begin{aligned} &\text{Maximize } \theta = \sum_{r=1}^{n} u_r y_{rj} \\ &\text{Subjected to } \sum_{r=1}^{n} u_r y_{rj} - \sum_{s=1}^{m} v_s x_{sj} \le 0 \qquad (8) \\ &\sum_{s=1}^{m} v_s x_{sj} = 1 \\ &u_r \ge 0,\ v_s \ge 0,\ \text{and } (i \text{ and } j = 1, 2, 3, \dots, k) \end{aligned}$$

Where θ is the technical efficiency, Model (3) is known as the input oriented CCR DEA model assumes constant returns to scale (CRS) (Avkiran, 2001).

2.7. Pure technical efficiency

Pure technical efficiency is technical efficiency of BCC model. The input-oriented BCC model evaluates the efficiency of DMUs by solving the following function (Mobtaker *et al.,* 2012)

$$\begin{aligned} &\text{Maximize} \quad z = uy_i - u_i \\ &\text{Subjected to} \quad vx_i = 1 \qquad (9) \\ &-vX + uY - u_o e \le 0 \\ &v \ge 0,\ u \ge 0 \text{ and } u_o \text{ free in sing} \end{aligned}$$

Where z and u_o are scalar and free to sign; u and v are output and input weight matrixes, and Y and X are the corresponding output and input matrixes, respectively. The letters x_i and y_i refer to the inputs and output of ith DMU.

Scale efficiency

Scale efficiency shows the effect of DMU size on the efficiency of the system. Simply, it indicates that some part of inefficiency refers to the inappropriate size of DMU, and if DMU moved toward the best size the overall efficiency (technical) can be improved at the same level of technologies (inputs) (Nassiri and Singh, 2009).

The scale efficiency can be obtained by following a formula:

$$\text{Scale efficiency} = \frac{\text{Technical efficiency}}{\text{Pure technical efficiency}} \qquad (10)$$

The level of each inefficient unit was calculated from CO_2 emissions saving target ratio (CSTR). In this study, CSTR index was used for the first time for emissions of agricultural units. It should be noted, CSTR was created from similar index called energy saving target ratio; Which the several studies were used in energy optimization by DEA (Mousavi-Avval *et al.,* 2011; Mobtaker *et al.,* 2012; Nabavi-Pelesaraei *et al.,* 2014).

The formula is as follows:

$$CSTR_j = \frac{(CO_2\ emissions\ \ saving\ target)_j}{(Actual\ energy\ input)_j} \qquad (11)$$

Where CO_2 emissions saving target are the total reducing amount of input that could be saved without decreasing the output level and *j* represents *j*th DMU.

Basic information on CO_2 emissions inputs in tangerine production was entered into Excel 2010 spreadsheets, and Frontier Analyst 4 and Matlab 7.2 (R2012a) software package.

Results and Discussion

3.1. CO_2 emissions of tangerine production

The result of CO_2 analysis is demonstrated in Table 2 based on orchard size levels. For this purpose, tangerine orchards were classified into 3 categories including a): small orchards (<1 hectare), b): medium orchards (between 1 and 3 hectares) and C): large orchards (>3 hectare). The results revealed that the total CO_2 emissions was calculated about 622 $kgCO_{2eq.}\ ha^{-1}$. Large orchards had higher total CO_2 emissions from other orchards with 686.75 $kgCO_{2eq.}\ ha^{-1}$. The share of nitrogen had the highest for CO_2 emissions among all inputs with 43.25%. The reason of this result was the inappropriate horticultural system specially in allocation of chemical fertilizers in Guilan province, Iran. Because, the local orchardists believed that the increase of chemical fertilizers is equal in obtaining more yield. This opinion was formed from many years ago in studied area. So, it's suggested the promotional activities should be increased in the studied area specially about consumption of inputs. The ANOVA test results indicated the difference of CO_2 emissions was significant for three groups orchards.

Moreover, Fig 1 displays the tangerine yield of three groups orchards. The mean of total tangerine yields was found to be about 49 ton ha^{-1}. As can be seen Fig 1, the large orchards had the first place for mean of tangerine yield with 54.54 ton ha^{-1} in Guialn province, Iran. Also, the small orchards with 35.9 ton ha^{-1} had the lowest average of the yield among three groups orchards.

Table 1. CO_2 emission coefficients of agricultural inputs.

Input	Unit	CO_2 Coefficient ($kg\ CO_{2eq.}\ unit^{-1}$)	Reference
1. Machinery	MJ	0.071	(Dyer and Desjardins, 2006)
2. Diesel fuel	L	2.76	(Dyer and Desjardins, 2003)
3. Chemical fertilizers			
(a) Nitrogen	kg	1.3	(Khoshnevisan *et al.,* 2014b)
(b) Phosphate (P_2O_5)	kg	0.2	(Nabavi-Pelesaraei *et al.,* 2014)
(c) Potassium (K_2O)	kg	0.2	(Pishgar-Komleh *et al.,* 2013)
4. Pesticides			
(a) Insecticide	kg	5.1	(Lal, 2004)
(b) Fungicide	kg	3.9	(Lal, 2004)
5. Electricity	kW h	0.608	(Nabavi-Pelesaraei *et al.,* 2014)

Evaluation and analysis of ANN model

The ANN was used for modeling of CO_2 emissions in tangerine production. Based on inputs and outputs of modeling and Levenberg-Marquardt Learning Algorithm, 8-4-1 structure was computed as the best topology (Fig 2). Actually, the best structure can predict the tangerine yield based on CO_2 emission input. In this study, 75% of total units was used for modeling and the remaining unit was considered for model testing. Also, the results of the best topology are illustrated in Table 3. This topology had the highest R^2 and lowest RMSE and MAPE for tangerine production. Accordingly, the R^2, RMSE and MAPE (%) was calculated as 0.964, 0.111 and 0.312%, respectively. The high rate of R^2 illustrated the strong relationship was between CO_2 emissions and tangerine yield in ANN model.

Table 2. CO_2 emissions of inputs in tangerine based on different orchard size levels.

Items	Orchard size groups (ha)			Average (kg $CO_{2eq.}$ ha^{-1})	Percentage (%)
	Small (<1)	Medium (1-3)	Large (>3)		
1. Machinery	62.60^a	90.24^b	94.67^b	88.22	14.18
2. Diesel fuel	49.07^a	73.03^b	72.22^b	70.50	11.33
3. Chemical fertilizers					
(a) Nitrogen	231.46^a	262.71^b	319.27^c	269.01	43.25
(b) Phosphate (P_2O_5)	12.13^a	26.42^b	29.25^c	25.47	4.09
(c) Potassium (K_2O)	56.07^a	68.68^a	65.00^a	66.81	10.74
4. Pesticides					
(a) Insecticide	2.90^a	5.14^{ab}	6.14^b	5.09	0.82
(b) Fungicide	5.57^a	13.47^b	14.42^b	12.83	2.06
5. Electricity	82.05^a	83.99^a	85.77^a	84.10	13.52
Total CO_2 emissions	501.86^a	623.69^b	686.75^b	622.02	100

Note: Different letters show significant difference of means at 5% level.

Khoshnevisan *et al.* (2014a) reported the ANN model with 12-8-2 structure was the best one for predicting the potato output energy and total GHG emission.

Table 3. The best result of different arrangement of model.

Items	CO_2 emissions
R^2	0.964
RMSE	0.111
MAPE (%)	0.312

SAANN Results

The sensitivity analysis of emissions inputs was calculated using the best structure. The results of SAANN are demonstrated in Fig 3. Based on the results, the highest sensitivity belonged to electricity with 0.081; followed by insecticide with 0.046 and diesel fuel with 0.040. In other words, an additional use of 1 $kgCO_{2eq.}$ of each electricity, insecticide and diesel fuel emissions, would lead to an additional increase in tangerine yield by 0.081, 0.046 and 0.040 kg, respectively.

Efficiency estimation of orchardists

Fig 4 displays the results of BCC and CCR models in DEA for separation inefficient from efficient units. The results revealed that 38 units were efficient based on pure technical efficiency (about 63%); While, score of technical efficiency was 1 for 28 orchardists (about 47%). Because, the CCR model had less flexibility toward BCC model from computing efficiency point of view. Obviously, the number of efficient units for scale efficiency had 28 units. Moreover, the distribution of efficiency score in two-tenths of the interval from 0.4 to 1 are demonstrated in Fig 4. With respect to above-mentioned sentence, the number of units with low scores in technical efficiency had more than pure technical efficiency.

The summarized statistics for the three estimated measures of efficiency are given in Table 4. The results indicated that the average of technical, pure technical and scale efficiency was calculated as 0.802, 0.890 and 0.894, respectively. Technical efficiency had the highest standard deviation with; Because, the technical efficiency varied from 0.361 to 1. As can be seen in Table 4, the maximum rate of three estimated measures was 1. The wide variation in the technical efficiency of orchardists indicated that all the orchardists were not fully aware of the right production techniques or did not apply them at the proper time, in the optimal quantity (Mousavi-Avval *et al.*, 2011).

Mousavi-Avval *et al.* (2011) calculated the mean of technical, pure technical and scale efficiency about 0.78, 0.90 and 0.87 for apple production from the energy input point of view, respectively.

Table 4. Average technical, pure and scale efficiency of tangerine orchardists.

Particular	Average	SD	Min	Max
Technical efficiency	0.802	0.218	0.361	1.00
Pure technical efficiency	0.890	0.169	0.499	1.00
Scale efficiency	0.894	0.140	0.532	1.00

Optimum CO_2 requirement and saving CO_2 emissions

The allowable rate of CO_2 emissions was determined based on BCC model for tangerine production and their results are given in Table 5. The total CO_2 emissions of inputs were calculated as 483.83 $kgCO_{2eq.}$ ha^{-1}. Accordingly, the rate of saving CO_2 emissions was found to be 138.18 $kgCO_{2eq.}$ ha^{-1}. As can be seen, the nitrogen (with 42.85%) had the highest contribution of total saving CO_2 emissions, followed by electricity (with 16.48%) and machinery (with 12.16%). The results obtained from three reasons a): excessive use of chemical fertilizers (mainly nitrogen) b): applying inappropriate electro pumps with high power. C): utilizing non-standard machinery with a high depreciation in the studied area. So, it's suggested, the inefficient units should be closed to efficient units of nitrogen, electricity and machinery consumption. For this purpose, the use of nitrogen should be monitored by local experts. With respect to the rainy weather of Guilan province, the applying droplet irrigation system was useful to reduce electricity consumption for tangerine production. Furthermore, existence of test centers can be effective for standard machinery importation in studied area and total machinery use can be reduced by timely maintenance and management of machinery during the utile life.

Table 5. Optimum CO_2 emissions requirement and saving CO_2 emissions for tangerine production.

Input	Optimum CO_2 emissions requirement ($kg\ CO_{2eq.}\ ha^{-1}$)	Saving CO_2 emissions ($kg\ CO_{2eq.}\ ha^{-1}$)	Saving CO_2 emissions (%)	Contribution to the total savings CO_2 emissions (%)
1. Machinery	71.41	16.81	19.05	12.16
2. Diesel fuel	54.61	15.88	22.53	11.50
3. Nitrogen	209.80	59.21	22.01	42.85
4. Phosphate	19.96	5.50	21.61	3.98
5. Potassium	53.96	12.85	19.23	9.30
6. Insecticide	3.86	1.22	24.07	0.89
7. Fungicide	8.90	3.93	30.62	2.84
8. Electricity	61.33	22.77	27.08	16.48
Total energy	483.83	138.18	22.22	100

Nabavi-Pelesaraei *et al.* (2014) reported the GHG emissions can be reduced about 184 $kgCO_{2eq.}$ ha^{-1} by optimization of energy consumption for orange production using DEA. In another study, Khoshnevisan *et al.* (2014b) reported the energy optimization by the DEA can reduce CO_2 emissions of strawberry production about 5774 $kgCO_{2eq.}$ ha^{-1}.

Setting realistic input levels for inefficient orchardists

Table 6 showed the score of pure technical efficiency, actually and optimum CO_2 emissions for each inefficient orchardists in tangerine production. Also, the CSTR (%) are given in the last column of Table 6. The results indicated that the average of CSTR percentage was 41% (with standard deviation 15%) for 22 inefficient units. Obviously, the high rate of CSTR revealed the difference between inefficient and optimal condition was higher in the studied area. So, the consumption of inputs based on DEA optimal units can reduce the CO_2 emissions for tangerine production, significantly. Also, the average of pure technical efficiency was found to be 0.70 (with standard deviation 0.14). As mentioned above, good promotion activity for applying appropriate inputs and use the standard machinery can be helped to optimization of CO_2 emissions in tangerine production in Guilan province, Iran. On the other hand, adequate supervisory authorities can be effective to achieve these objectives.

Table 6. The source wise actual and target CO_2 emissions for inefficient orchardists in the tangerine production (based on BCC Model).

DMU	PTE *	Actual CO_2 emissions (kg $CO_{2eq.}$ ha^{-1})								Optimum CO_2 emissions (kg $CO_{2eq.}$ ha^{-1})								CSTR (%)
		Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Insecticide	Fungicide	Electricity	Machinery	Diesel fuel	Nitrogen	Phosphate	Potassium	Insecticide	Fungicide	Electricity	
5	0.521	138.92	135.69	308.62	51.07	68.43	5.12	20.26	35.31	65.19	69.76	160.79	26.61	21.61	2.67	9.01	18.40	51
8	0.624	64.31	157.40	308.62	5.81	68.43	8.77	13.50	363.19	40.10	48.21	192.42	3.62	27.08	2.39	2.44	226.45	45
11	0.632	123.48	59.70	308.62	22.03	91.23	4.87	25.32	1.35	60.52	31.63	195.02	13.92	45.84	2.05	5.11	0.85	44
14	0.722	154.35	77.34	154.31	33.64	68.43	7.92	15.19	2.27	69.09	54.49	111.40	24.29	49.40	3.42	6.35	1.64	38
15	0.694	92.61	70.56	308.62	34.25	91.23	4.99	40.51	0.00	60.55	34.43	214.03	14.11	63.27	2.19	5.47	0.00	39
18	0.516	77.18	77.34	351.32	23.24	68.43	4.32	3.38	4.54	39.85	30.55	181.42	8.43	27.57	1.33	1.74	1.89	52
24	0.885	123.48	82.43	385.77	22.03	91.23	7.00	25.32	3.53	88.61	68.33	311.53	19.48	80.70	6.19	12.76	3.12	20
25	0.935	90.04	84.81	462.93	22.03	57.02	7.79	13.50	121.06	80.28	74.75	297.20	20.60	53.33	6.14	12.63	113.23	23
26	0.607	77.18	63.10	617.23	34.86	57.02	4.51	13.50	1.36	17.88	20.94	258.49	1.00	34.60	0.68	1.00	0.83	61
29	0.712	77.18	37.99	617.23	11.01	79.83	4.51	10.13	0.00	16.09	25.81	276.36	1.00	56.81	0.82	1.00	0.00	55
30	0.674	72.03	40.71	462.93	56.88	114.04	5.30	6.75	0.00	15.50	27.42	282.27	1.00	64.18	0.87	1.00	0.00	48
34	0.643	154.35	73.95	154.31	39.15	79.83	6.39	18.23	3.03	77.54	47.53	99.17	21.78	51.31	4.11	10.48	1.95	41
35	0.892	123.48	62.42	154.31	38.05	125.45	4.51	12.15	1.82	108.38	55.65	137.57	29.62	100.93	4.02	9.82	0.82	14
36	0.889	90.04	102.45	462.93	22.03	62.72	7.67	13.50	258.27	80.06	74.75	298.09	19.59	55.77	5.54	12.01	229.65	24
39	0.499	77.18	102.45	385.77	22.03	102.64	5.24	12.15	16.48	38.51	29.75	192.50	10.99	12.13	1.85	3.99	8.22	59
41	0.519	92.61	223.21	308.62	42.08	102.64	5.18	42.54	567.49	48.07	58.91	160.17	13.46	32.09	2.06	3.39	259.43	58
48	0.763	82.32	101.09	308.62	22.03	79.83	3.90	3.04	151.33	62.81	70.69	192.94	16.04	60.91	2.97	2.32	115.47	30
51	0.506	123.48	86.84	231.46	33.15	96.94	7.06	15.19	453.99	62.51	40.11	117.17	12.61	48.33	2.81	6.69	28.07	70
53	0.915	123.48	76.67	308.62	26.43	91.23	6.22	28.36	4.04	98.41	70.11	255.69	24.17	83.43	5.69	11.93	3.69	17
54	0.853	102.90	57.33	385.77	34.86	85.53	5.05	13.50	11.10	87.80	48.91	189.59	27.43	59.32	4.31	11.34	1.03	38
57	0.669	64.31	131.62	308.62	5.81	68.43	10.05	13.50	706.21	41.32	61.70	206.50	3.89	28.43	2.39	1.70	335.32	48
58	0.736	123.48	67.17	308.62	30.76	136.85	5.72	17.22	5.45	90.87	49.43	225.95	22.64	83.56	4.21	10.67	4.01	29
Ave.	0.70	102.20	89.65	345.63	28.78	85.79	6.00	17.13	123.26	61.36	49.72	207.10	15.29	51.85	3.12	6.49	61.55	41
S.D.	0.14	28.17	41.91	125.14	12.89	21.37	1.63	10.10	210.50	26.73	17.55	62.86	9.15	22.56	1.71	4.37	104.16	15

* Pure Technical Efficiency (PTE).

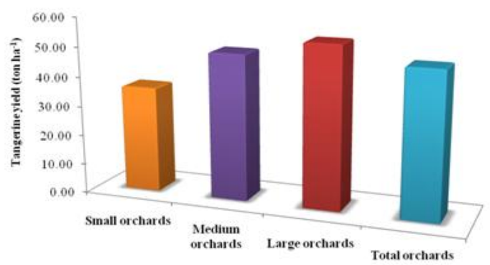

Fig. 1. The tangerine yield of orchard size groups.

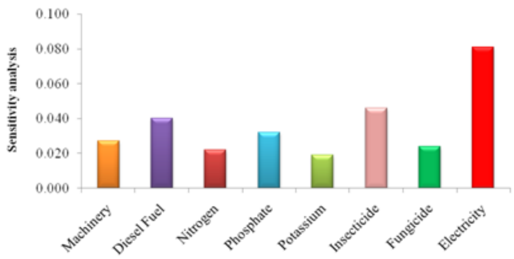

Fig. 3. Sensitivity analysis of CO_2 emissions inputs in tangerine production.

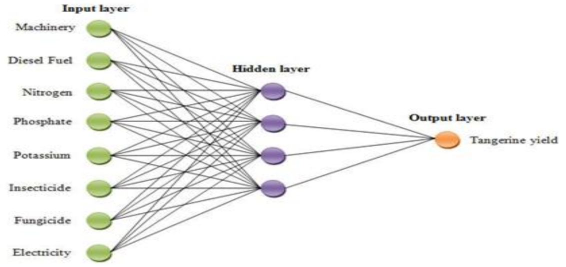

Fig. 2. Schematic diagram of ANN model with 8-4-1 structure.

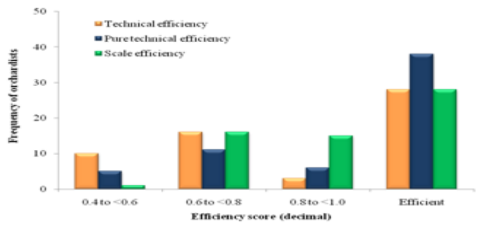

Fig. 4. Efficiency score distribution of tangerine producers for CO_2 emissions.

Conclusions

The main objective of this study was to survey CO_2 emissions of tangerine production and determination of ANN modeling based on emission inputs and tangerine yield in Guilan province of Iran. Also, the other target of this research was to investigate CO_2 emission optimization by DEA non-parametric method.

So the following conclusions are drawn from thepresent study.

The average of total CO_2 emissions and the yield of tangerine production was about 622 $kgCO_{2eq.}$ ha^{-1} and 49 ton ha^{-1}, respectively. Based on the segmentation of orchard size, the highest share of total CO_2 emissions and yield belonged to the large farms and wasn't significant among three groups orchards.

The ANN model with 8-4-1 structure was determined as the best topology for prediction of tangerine yield based CO_2 emission inputs. Also, the highest R^2 (with 0.964), lowest RMSE (with 0.964) and MAPE (with 0.964) were obtained by ANN model.

With respect to SAANN, the electricity, insecticide and diesel fuel were the most sensitive CO_2 emission inputs to tangerine yield, respectively.

The average of technical, pure technical and scale efficiency scores was calculated as 0.802 (with standard deviation 0.218), 0.890 (with standard deviation 0.169) and 0.894 (with standard deviation 0.140), respectively.

The optimum CO_2 emissions were computed about 484 $kgCO_{2eq.}$ ha^{-1} using DEA. So, the saving CO_2 emissions were found to be about 138 $kgCO_{2eq.}$ ha^{-1}. The high effect on saving total CO_2 emissions belonged to nitrogen with 42.85% of total saving; followed by electricity and machinery.

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