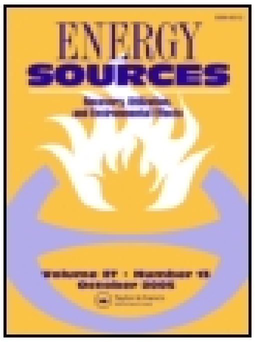

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Energy consumption forecasting in agriculture by artificial intelligence and mathematical models

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ABSTRACT

Energy management and reduction of CO_2 emission lead to many investigates about energy input–output analyses especially in agricultural sector. The main objectives of this study are to assess the energy use pattern and to select the best method among Cobb–Douglas (CD), multiple linear regressions (MLR), multilayer perceptron (MLP), radial basis function (RBF) and support vector machine (SVM) models to estimate potato output energy in Jiroft city, located in the south of Kerman province, Iran. Data were collected with questioner method from expert farmers. Results indicated that the average of total input energy is about 84309.43 MJ ha^{-1} and the average of total output energy is 130217.14 MJ ha^{-1}. Irrigation water (36%) and fertilizers (26%) were found to be the most important energy inputs in potato production. Unlike most literature reviews, in this study for better and more accurate model evolutions in energy forecasting, five different sizes of training selection (TS) were used: 50%, 60%, 70%, 80% and 90%. Some statistical indexes (RMSE, MAPE, and R^2) of the different data selection calculated from *k*-fold in two training sets. The results showed that RBF model has a great prediction performance at all different values of training data selection. The average value of R^2 was found to be more than 0.98. Between SVM and MLP models, the test performance will be improved by size reduction of training selection. Thus, the RBF model is chosen as the best model for fitting and modeling the output energy of potato production.

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Introduction

Potato (*Solanum tuberosum L.*) grows under a wide range of climatic and farm conditions. Potato is not only one of the most important global food crops but also it has one of the heaviest demands for fertilizer inputs versus other crops (Omid et al. 2011; Zangeneh, Omid, and Akram 2010). This cultivation plays a key role in the food security of Iranian households and recent governmental economic policies have increased attention on these agricultural products (Mardani and Salarpour 2015). In Iran, the total production of potato was about 4995327 tons in the year of 2015–2016 (Anonymous, 2015).

Nowadays, energy is an important issue in the world, especially in agriculture and industrial production. As we know, agriculture uses energy and also supplies energy as bio-energy (Horsfield and Williams 2007; Pahlavan, Omid, and Akram 2011). Demand for energy in agriculture is rapidly increasing (Canakci and Akinci 2006). The major input sources for energy are human, fertilizer, machinery, electricity, etc. They fall into two categories: renewable and

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non-renewable (Durusoy et al. 2011; Heidari and Omid 2011; Zangeneh, Omid, and Akram 2010). Energy management, reduction the negative environmental problems and also increasing the efficiency and security of agricultural productions caused many investigates about energy input-output analyses in agriculture (Hatirli, Ozkan, and Fert 2006; Ozkan et al. 2004). Studies on energy-use pattern and benchmarking with data envelopment analysis (DEA) method (Bolandnazar, Keyhani, and Omid 2014), using artificial neural network (ANN) (Khoshnevisan et al. 2013; Taki et al. 2018a), adaptive neuro-fuzzy inference system (ANFIS) models (Landeras et al. 2012; Shiri et al. 2013), and multi-layer adaptive neuro-fuzzy inference system (Khoshnevisan et al. 2014) were conducted in order to determine suitable combination of input product and optimize them.

The modeling of energy required in agricultural activity can correct the pattern of input consumption and grow clean products. In addition, the energy resources can be saved by energy modeling. The advanced models can give satisfactory predictions in the studied region and appear to be a suitable tool for prediction of energy required. Many studies have conducted experiments on energy use in agriculture (Gezer, Acaroglu, and Haciseferogullari 2003; Taki et al. 2018b; Taki and Yildizhan 2018).

The number of scientists and engineers who are interested in modeling of energy consumption and related environmental effects has increased sharply in recent years (Al-Ghandoor et al. 2009; Yildizhan and Taki 2018). In energy subject, a wide range of models have been applied from geological models in research on natural resources to modeling the future energy demand (Safa and Samarasinghe 2011). In the past, regression analysis was the usual modeling technique that applied in energy researches. Recently, neural networks (NN) have been increasingly applied in energy researches (Sözen 2009). ANNs have been widely used to predict the energy consumption, energy demand, environmental problems, etc. The relative performance of ANN over traditional statistical methods is reported by Zhang, Patuwo, and Hu (2001). Several researches have applied ANNs for classification, prediction, and solving problems in the field of energy. Khoshnevisan et al. (2014) used ANN for prediction of the output energy and greenhouse gas (GHG) emissions in potato production in Iran (Khoshnevisan et al. 2014). Pahlavan, Omid, and Akram (2012) applied ANN model to predict greenhouse basil production. Safa and Samarasinghe (2011) applied ANN for determination and modeling the energy consumption in wheat production. They compared ANN with multiple linear regression (MLR) model. They found that ANN can predict energy consumption better than regression models.

In this study, the models are developed based on artificial intelligence for predicting the output energy of potato crop. One of the models employed radial basis function (RBF) as the active function for ANN and other models used multilayer perceptron (MLP) as a class of feedforward artificial neural network. As an alternative to ANN, support vector machine (SVM) suggested by Vapnik (1998) is a powerful tool for nonlinear classification, regression, and time series prediction (Wang, Men, and Lu 2008). SVMs belong to kernel-based learning approaches and have obtained wide popularity. SVMs are a kind of supervised machine learning system that applies a linear high-dimensional hypothesis space called feature space. The basic idea of SVM is provided by the use of kernel functions that implicitly map the data to a higher-dimensional space. This makes SVM as a powerful tool for modeling the nonlinear complex environmental problems (Bhagwat and Maity 2012). Yousefi et al. (2015) applied support vector regression (SVR) methodology for prediction the output energy in rice production. Results showed that SVR can serve as a promising alternative for existing prediction models. In all the above literatures, there is not any research which applied SVM for energy prediction of potato production. Therefore, the main goal of this study is to use SVM and make a comparison with other models such as Cobb–Douglas (CD), RBF-MLP, and MLR to show the ability of these models for prediction of the output energy of potato production. Selecting the best model can help the farmers and other researchers to estimate the output energy and also total yield of potato production for every year to manage the all inputs with high efficiency.

Materials and methods

Case study selection and data processing

This study was conducted in Kerman province, the first largest province of Iran (180,726 km^2), and specifically in the city of Jiroft in the south of the province (28° 40′ N, 57° 44′ E). The Southeast of Kerman province with a total production of 311892 ton from 9706 ha is considered as one of the main fertile regions in potato production (Anonymous, 2015). Accordingly, this study focused on potato production in Jiroft. Initial data were gathered by sending questionnaires to potato producers in the region. The questionnaires were designed to obtain information about all types of agricultural inputs, energy carriers, and equipment and machines used. Then, collected data were used in further steps.

Input–output energy in potato production

Energy flow assessment in a production system needs to calculate the input–output energies. To deal with this part, energy coefficients were taken into account to convert all agricultural inputs to their energy equivalent. The energy conversion factors presented in Table 1 were utilized to estimate the total energy consumption in potato production in the surveyed area. In other words, each input was converted to its energy equivalent by multiplying the application rate of agricultural inputs used within the system by its energy coefficient.

The cultivation of potato in this region depends heavily on the water extracted from agricultural wells because the weather is warm and relatively humid. The average depth of these wells is about 120 m, so that a high amount of energy is needed for water extraction. Energy needed for irrigation system was calculated as follows:

$$DE = \frac{\gamma g H Q}{\varepsilon_p \varepsilon_q} \tag{1}$$

where DE presents direct energy (J ha^{-1}), g is acceleration due to gravity (m s^{-2}), H is total dynamic head (m), Q is volume of required water for one cultivating season (m^3 ha^{-1}), γ is density of water (kg m^{-3}), ε_p is electrical pump efficiency (reported to be 70–90% in the literature while it was calculated as 44% in the region) and ε_q is total power conversion efficiency (18–20%) (Kitani 1999).

Table 1. Energy coefficients of different inputs used and outputs in potato production.

	Unit	Energy equivalent (MJ Unit^{-1})	References
A. Inputs			
1. Human labor			
Woman	h	1.57	Yaldiz et al. (1993)
Man	h	1.96	Yaldiz et al. (1993)
2. Diesel fuel	L	56.31	Khoshnevisan et al. (2013a)
3. Machinery		64.8	Bolandnazar, Keyhani, and Omid (2014)
4. Fertilizers			
Nitrogen (N)	kg	66.14	Bolandnazar, Keyhani, and Omid (2014)
Phosphate (P_2O_5)	kg	12.44	Bolandnazar, Keyhani, and Omid (2014)
Potassium (K_2O)	kg	11.15	Bolandnazar, Keyhani, and Omid (2014)
Microelements	kg	120	
5. Farmyard manure	kg	0.3	Mousavi-Avval, Rafiee, and Mohammadi (2011b)
6. Chemicals			
Fungicide	kg	216	Ozkan, Fert, and Karadeniz (2007)
Insecticide	kg	101.2	Ozkan, Fert, and Karadeniz (2007)
Herbicide	kg	238	Ozkan, Fert, and Karadeniz (2007)
7. Seeds	kg	3.6	Ozkan et al. (2004)
8. Water for irrigation	m^3	1.02	Bolandnazar, Keyhani, and Omid (2014)
B. Output			
Potato	kg	3.6	Esengun et al. (2007)

Cobb–Douglas modeling (CD)

In this study, CD modeling was used for assessment the effects of all inputs energy on different potato cultivars. The final model of CD based on the all inputs can be assumed as follows (Beigi, Torki Harchegani, and Ebrahimi 2016):

$$lny_i = p_0 + p_1 lnx_1 + p_2 lnx_2 + p_3 lnx_3 + \ldots + p_8 lnx_8 + \varepsilon_i \tag{2}$$

where p_0 is constant and ε_i is error coefficient, y_i is the output energy of farm i_{th}, and also x_{ij} shows all the inputs used for potato production and, p_1, p_2,…, p_8 are the coefficients of regression model for all the energy inputs.

In this study, return to scale indicator was used to show the effects of inputs changes on output level. This index was calculated by adding the all regression coefficients used in Equation (2) (Ghasemi Mobtaker et al. 2012). In the next level, marginal physical productivity (MPP) was used for evaluate the sensitivity analysis of output based on inputs level. In this method, by increasing one unit of an input, its effect on output was evaluated when the other inputs were fixed (Soltanali et al. 2016). For MPP evaluation, the following equation was used (Royan et al. 2012):

$$MPP_{Xj} = \frac{GM(Y)}{GM(X_j)} \times a_j \tag{3}$$

Multi-layer perceptron neural networks (MLPNN) model

Multilayer perception (MLP) neural network with back propagation algorithm was used to predict daily and monthly solar radiation in some researches (Asadi, Amiri, and Mottahedi 2014). MLP neural network is a predicted method and composed of at least three layers. The first layer is the input layer whose size is equivalent to the number of features intended for the prediction. There is a weight equivalent to each input (Taki, Ajabshirchi, and Mahmoudi 2012a). The hidden layer is formed by some neurons. The present research evaluated 3, 5, …, 13 neurons in hidden layer. The output layer was supposed to include a neuron since the objective of the present study was to predicted output energy of potato production. The transfer function of output layer was sigmoid type. Two functions, sigmoid and hyperbolic tangent, were evaluated as transfer function for the hidden layer:

$$\text{out} = \frac{1}{1 + e^{-\sum^{F_i w_{ij} + b}}} \tag{4}$$

$$\text{out} = \frac{2}{1 + e^{-\sum^{2F_i w_{ij} + b}}} - 1 \tag{5}$$

where F_i, b, and w_{ij} denote ith input, bias, and weight of jth neuron, respectively (Chen, Cowan, and Grant 1991; Taki, Ajabshirchi, and Mahmoudi 2012b). The optimum weights and biases in MLP model were derived by training functions. In this research, two functions were used, Bayesian regularization back-propagation (Trainbr) and Levenberg–Marquardt back-propagation (Trainlm), for the training and optimization of network weights.

Radial basis function neural networks (RBFNN)

In this research in addition to MLP neural network model, we used the radial basis function neural network (RBFNN) due to its superiority over the MLP model. The advantages of RBF, compared to MLP, include high-speed learning, the lack of the local minima problems and the simple and fixed three-layer architecture (Haykin 2009; Rohani, Abbaspour-Fard, and Abdolahpour 2011). The

Gaussian activation function is used as the activation functions in the hidden layer. The hidden layer transforms the input vector using activation function. The output layer plays the role of the linear combiner. The output of the RBF network is computed as follows:

$$Y = \sum_{j=1}^{L_2} w_j \phi(\|x - c_k\|) \tag{6}$$

where w_j is the connection weight from the jth hidden neuron to the output neuron, c_k is prototype of center of the jth hidden neuron, $\|.\|$ is the Euclidean norm and finally L_2 is the number of neurons in the hidden layer. The Gaussian function is as follows:

$$\phi(r) = e^{-\frac{r^2}{2\sigma^2}} \tag{7}$$

where r is the distance of the input vector x from center c and σ is the parameter to control the smoothness of the interpolating function. The RBF neural network trained uses the Levenberg–Marquardt (LM) training algorithm because the results of other studies showed that the LM has fast convergence rate and good performance in prediction (Cao, Xin, and Yuan 2016; Iliyas et al. 2013).

Multiple linear regression (MLR) model

In this research, MLR model as specified in Equation (7) for predicting the output energy of potato production (Suykens and Vandewalle 1999):

$$Y = \Psi_0 + \sum \Psi_i x_i + \sum \Psi_{ij} x_i x_j + \sum \Psi_{ii} x_i^2 + \varepsilon \tag{8}$$

where ε is the error of the model ψ_0 is constant coefficient of the MLR model, and ψ_i, ψ_{ii} and ψ_{ij} are the linear, quadratic, and interaction coefficients of the MLR model, respectively. In this study, stepwise method was applied for selecting the best form of the MLR model. The suitable predictor variables were selected among the six different predictors. The sum of square error (SSE) was used as selection criteria. The t-test and F-test were used to assess the significance of regression coefficients in the selected MLR model.

Support vector machine (SVM) model

The SVM in this study convert quadratic optimization difficulty to a linear subject. The SVM model considers such as dataset $\{(x_1, y_1), (x_2, y_2, \ldots, (x_n, y_n)\}$with the below nonlinear function (Jung, Kim, and Heo 2015):

$$f(x) = \langle w, \mathrm{M}(x) \rangle + z \tag{9}$$

where $M(x)$ is the nonlinear function that carries out a regression, z and w are bias and weight vector, respectively. Cao, Xin, and Yuan (2016) presented an optimization SVM forum as:

$$\left\{ \begin{array}{c} \min\limits_{w,b,e} J(w,e) = \frac{1}{2}\|w\|^2 \ + \ \frac{1}{2}\gamma \sum\limits_{k=1}^{N} e_k^2 \\ s.t. y_k = \langle w, \Phi(x_k) \rangle + b + e_k, \ \mathrm{k} = 1, 2, \ldots, \mathrm{k} \end{array} \right\} \tag{10}$$

where $(\gamma \geq 0)$ is a regularization parameter and $e_k$is the error of regression for N training. Lagrange function was used for solving the optimization problem (Suykens and Vandewalle 1999):

$$L(w, b, e, \alpha) = \frac{1}{2}\|w\|^2 + \frac{1}{2}\gamma \sum_{k=1}^{N} e_k^2 - \sum_{k=1}^{N} \alpha_k \{\langle w, \Phi(x_k) \rangle + b + e_k - y_k\} \tag{11}$$

where α_k is the Lagrange multiplier and support vector can make the Lagrange multiplier not equal 0. More details about SVM structure can be seen in Cao, Xin, and Yuan (2016; Arabloo et al. 2015).

k-Fold cross validation

The results of the neural network models are dependent on the data set used in the training step. Therefore, the results of the neural network are different in each repetition and random selection of data (Taki et al. 2018a). In this study, *k*-fold cross-validation method was used for better estimation of neural network model and evaluation of stability and generalizability. The steps to implement it are such that the data sets are randomly placed next to each other and then divided into five equal parts (k = 5). In the following, one part of the data is allocated to test and the k - 1 remainder to training. In the end, the performance of the model is evaluated by averaging its errors obtained from different runs.

Evaluation the performance of the models

To evaluate the predictive capability of the models and optimization, the comparison between actual energy values (y_a) and its predicted values (y_p) was used. For this purpose, the statistical analysis of mean y_a and variance y_p was used. The hypothesis of null and one was defined by (Taki, Ajabshirchi, and Mahmoudi 2012b)

$$\begin{cases} H_0: \overline{y_a} = \overline{y_p} \\ H_1: \overline{y_a} \neq \overline{y_p} \end{cases} and \begin{cases} H_0: \sigma^2_{y_a} = \sigma^2_{y_p} \\ H_1: \sigma^2_{y_a} \neq \sigma^2_{y_p} \end{cases} \tag{12}$$

Paired t-test and F-test were used to evaluate the equality of mean and variance in a 5% significant level. The non-reject of the null hypothesis implies the ability of the neural network to produce similar predicted data to real data. In addition, three criteria of RMSE, MAPE, and R^2 were also used to evaluate the accuracy of the final model (Taki et al. 2012c; Zarifneshat et al. 2012):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{ai} - y_{pi}\right)^2}{n}} \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{ai} - y_{pi}}{y_{ai}}\right| \tag{14}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(y_{ai} - \overline{y_a}\right)\left(y_{pi} - \overline{y_p}\right)}{\sum_{i=1}^{n}\left(y_{ai} - \overline{y_a}\right)\sum_{i=1}^{n}\left(y_{pi} - \overline{y_p}\right)}\right]^2 \tag{15}$$

Results and discussion

An overview of energy flow in potato cultivation

An analysis of energy inputs and outputs flow in potato cultivation in the area selected for this study revealed a high level of energy consumption, especially for energy from non-renewable sources. Table 2 summarizes the outcomes of the energy analysis for potato cultivation. The average of energy inputs was calculated as 84309.43 MJ ha^{-1} but it ranged from 67442 to 100821 MJ ha^{-1}. This difference is significant and it demonstrates that the energy consumed in potato cultivation in this region is not effective. The results also revealed that under different farm management systems, different amounts of energy were consumed. The results depicted in Table 2 show that the energy consumption from different sources varied from farm to farm. The results of the present study are compatible with other studies conducted in different parts of Iran in which the authors found that

Table 2. Energy inputs and output for potato production.

Inputs (unit)	Average of energy equivalent (MJ ha^{-1})	Standard deviation (SD)
A. Inputs		
1. Human labor (h)		
Woman	504.10	181.97
Man	2094.18	374.08
2. Diesel fuel (L)	7798.94	2057.63
3. Machinery (h)	897.02	243.36
4. Fertilizers (kg)		
Nitrogen (N)	13625.78	2902.71
Phosphate (P_2O_5)	1399.50	286.73
Potassium (K_2O)	1361.89	272.89
Micro	1317.43	446.75
5. Farmyard manure	4015.71	764.50
6. Water for irrigation (m^3)	31509.90	6125.84
7. Chemicals (kg)		
Fungicide	515.31	139.23
Insecticide	226.98	78.74
Herbicide	461.55	285.25
8. Seeds (kg)	18581.14	1263.73
The total energy input (MJ)	84309.43	7763.23
B. Output		
Potato (kg)	130217.14	18804.58

most of the farmers in Iran were not aware of better farm management methods especially in regards to the management of agricultural inputs. Consequently, a high degree of inefficiency can be seen in Iranian farm management system (Khoshnevisan et al. 2013a; Mousavi-Avval, Rafiee, and Mohammadi 2011b; Nabavi-Pelesaraei et al. 2014).

An examination of specific results of the energy inputs and outputs analysis (Figure 1) provides further details about potato cultivation in the surveyed region. Irrigation water and fertilizers are the most important energy inputs in potato cultivation. The energy required for irrigation is a type of direct energy because it refers to the energy consumed for extraction water from wells. Water, which is an increasingly sensitive issue, is generally extracted from local wells using electric pumps. The use of electric pumps means that electrical consumption is high in irrigation systems. Irrigation water accounted for 36% of the total input energy followed by fertilizers (26%) and seed (22%).

In the present study, unlike the previous ones, conventional methods such as CD and MLR in two stages of training and testing are evaluated. Soft computing methods such as RBF, MLP and SVM are also used to compare their performance in energy prediction with conventional methods.

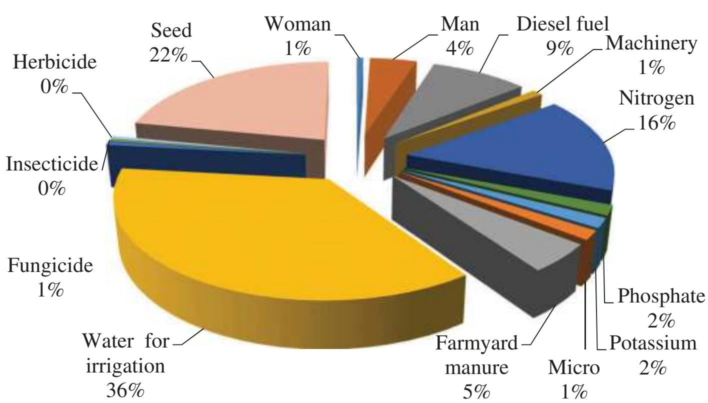

Figure 1. Contribution of inputs to the total energy consumption.

Cobb-Douglas (CD) model

The CD model is a well-known method for energy prediction. But in most cases, all of the available data sets are used to estimate its coefficients. However, this may cause the over fitting problem. The results of this paper also confirmed this fact. For calibrating the CD model coefficients, 80% of the total data were chosen randomly. Because of random selection, there may be a little difference in the calibration results of model coefficients. The values of mean standard deviations, RMSE, MAPE, and R^2 of model support this idea. Therefore, for better evaluation the k-fold cross-validation method, which explained in the materials and methods, is applied. The average results of the RMSE, MAPE, and R^2 of the CD models are presented in Table 3.

It is necessary to repeat that the CD model has been used linearly in most cases. However, the results show that in addition to model linear form, the other forms can also be used. As shown in the results, the quadratic form of the CD model has more capability for energy prediction. This subject has been dissolved by many researchers. The main reason for choosing the quadratic model was its low error average in both of calibration (training) and test levels compared to other models. As shown in Table 3, the type of model calibration data set (training) has an effect on the values of the CD model coefficients and consequently affects its performance of training and testing levels. Therefore, 50–90% of entire randomized data sets were evaluated and surveyed for training and calibrating the CD model (Table 4). As the results show, by decreasing the size of data set, the CD model performance improves at the training level, while the performance of test level decreases. This is due to the fact that the model coefficients fit better for less data. In the opposite side, because of not using the entire data in coefficient estimations, the prediction performance weakens in the test level.

MLR model

The MLR model is another option for energy modeling. Compared to the CD model, the MLR model has been less used in energy estimates. In Table 5, four different forms of the MLR model such as linear, interactions, reduced quadratic, and quadratic are considered. The results indicated that reduced quadratic model is the best model for the MLR. A comparison between the performance of both CD and MLR models shows that the MLR model is much better than the CD model at the training level, in the way that the MLR quadratic model has an error of almost zero at the training level. It shows that the MLR model is more subjected to over fitting than CD model, because the results of the test level were very frustrating compared to the training level. Red quadratic model is the only model which has acceptable results at training and testing levels.

Table 3. The evaluation results of different forms of CD model.

	Train			Test		
Model	RMSE	MAPE	R^2	RMSE	MAPE	R^2
Linear	11.18 ± 0.76	7.04 ± 0.50	0.68 ± 0.03	13.13 ± 1.99	8.29 ± 1.33	0.59 ± 0.13
2FI	9.51 ± 0.44	6.04 ± 0.74	0.74 ± 0.02	11.89 ± 2.67	7.92 ± 1.40	0.64 ± 0.16
Red. quadratic	9.04 ± 0.55	5.53 ± 0.36	0.77 ± 0.03	12.04 ± 1.66	7.89 ± 1.02	0.64 ± 0.13
Quadratic	8.85 ± 0.45	5.42 ± 0.28	0.78 ± 0.03	11.65 ± 1.55	7.31 ± 1.00	0.72 ± 0.12

Table 4. Evaluation the CD quadratic model vs. the size of training data set.

	Train			Test		
	RMSE	MAPE	R^2	RMSE	MAPE	R^2
90	8.94 ± 0.80	5.53 ± 0.12	0.77 ± 0.03	10.51 ± 2.87	7.30 ± 1.97	0.73 ± 0.12
80	8.85 ± 0.45	5.42 ± 0.28	0.78 ± 0.03	11.65 ± 1.55	7.31 ± 1.00	0.72 ± 0.12
70	8.84 ± 0.75	5.32 ± 0.48	0.78 ± 0.02	12.25 ± 0.94	7.82 ± 0.52	0.69 ± 0.05
60	8.73 ± 1.30	5.12 ± 0.74	0.79 ± 0.05	12.56 ± 1.30	7.97 ± 0.95	0.66 ± 0.08
50	7.66 ± 1.84	4.64 ± 1.01	0.83 ± 0.07	15.82 ± 0.82	8.65 ± 1.88	0.52 ± 0.28

Table 5. The results of MLR model.

	Train			Test		
Model	RMSE	MAPE	R^2	RMSE	MAPE	R^2
Linear	9.03 ± 0.40	5.64 ± 0.29	0.77 ± 0.02	10.78 ± 1.36	6.92 ± 1.00	0.66 ± 0.12
2FI	1.15 ± 1.59	0.66 ± 0.89	0.99 ± 0.03	208.90 ± 120	121 ± 140	0.17 ± 0.15
Red. quadratic	7.76 ± 0.68	4.66 ± 0.44	0.83 ± 0.03	11.90 ± 1.98	1.36 ± 0.50	0.66 ± 0.13
Quadratic	0.00 ± 0.00	0.00 ± 0.00	0.99 ± 0.00	85.25 ± 56.22	52.60 ± 35.33	0.15 ± 0.16

Table 6 shows the evaluation results of training data sets on the performance of the MLR model are presented at training and testing levels. The results are similar to ones of the CD model. It means that by size reduction of the training or calibration data set, the performance of the training level has an ascending trend while the performance of the test level has a descending trend. Thus, the MLR model has a weak generalizability capability.

Soft computing models

Nowadays, most researchers interested in using soft computing techniques for estimating the energy flow. However, in most studies, MLP has been used. In this paper, the RBF neural network and SVM techniques are used as alternative soft computing methods. It has been tried to compare the performance of these methods with conventional ones such as CD and MLR.

Optimizing the RBF parameters

The number of neurons in the hidden layer, the spread parameter (S), and the type of training algorithm are the most important parameters that affect the performance of the RBF model. Figure 2 shows the effect of these parameters on R^2 index between real and predicted values in training, testing, and total levels. Different values of S (0.1 to 10) were evaluated and the best result for all possible status was 0.1. As can be seen, with increasing the number of neurons, the performance of the RBF neural network improves during the training level. Although this fact is totally different during the test level, particularly for the Trainlm training algorithm. Comparison of the prediction performance of the RBF model with supporting of two training algorithms indicates that Trainbr can have the best prediction performance for energy flow. Because for the number of neurons greater than or equal to 5, the values of R^2 were very close to each other at training and testing levels, and also its value is pretty close to one. As a result, the RBF model is used to predict potato energy flow with hidden sizes = 5, S = 0.1, and Trainbr training algorithm for obtaining the best results.

Optimizing the MLP parameters

The parameters that most affected the prediction function of MLP neural network are consisted of the number of neurons in hidden layer, the type of training algorithm, and the type of activating function in the neurons of hidden layer. In designing neural network, only one hidden layer is used, because MLP neural network with sufficient neuron in hidden layer can estimate every continuous

Table 6. The evaluation results of MLR quadratic model vs. the size of training data set.

	Train			Test		
Data	RMSE	MAPE	R^2	RMSE	MAPE	R^2
90%	7.79 ± 0.42	4.63 ± 0.26	0.83 ± 0.02	11.32 ± 2.79	7.20 ± 1.90	0.72 ± 0.16
80%	7.76 ± 0.68	4.66 ± 0.44	0.83 ± 0.03	11.90 ± 1.98	7.36 ± 0.50	0.66 ± 0.13
70%	7.46 ± 0.88	4.48 ± 0.54	0.83 ± 0.04	12.80 ± 2.37	7.92 ± 1.48	0.61 ± 0.08
60%	6.99 ± 1.18	4.21 ± 0.64	0.86 ± 0.04	13.82 ± 3.37	8.61 ± 2.24	0.56 ± 0.12
50%	5.28 ± 1.49	3.22 ± 0.89	0.92 ± 0.04	21.14 ± 8.75	12.17 ± 4.95	0.38 ± 0.19

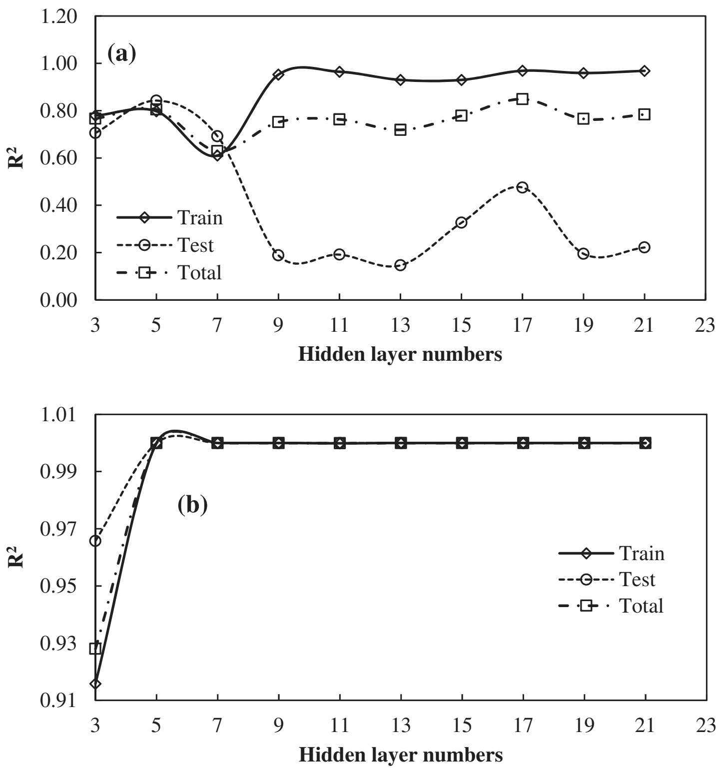

Figure 2. R^2 changes of RBF model with Trainlm (a) and Trainbr (b).

function with any complexity degree. (Rohani, Abbaspour-Fard, and Abdolahpour 2011). Figure 3 illustrates the R^2 value changes of MLP neural network in two levels of test and train for different values of parameters.

As it is confirmed by the results, with increasing the number of neurons, R^2 value has almost an increasing trend at the test level. It means that the neural network can better discover the relation between input and output variables with increasing the number of neurons. However, for having the appropriate model without confronting to any over fitting problem, the test level function must be considered as well. With considering all aspects, we used MLP neural network with nine neurons in hidden layer, activating function of tangent sigmoid (Tansig) with training algorithm of Trainbr (Bayesian regulation) for prediction of energy flow of potato. However, in previous studies, only the training algorithm of Trainlm was used and there is not any functional comparison between Trainlm and Trainbr training algorithms.

Optimizing the SVM parameters

In present study, SVM is also used as an alternative method for soft computing. The type of Kernel function has much influence on prediction performance of SVM model. In this paper, four types of Kernel function are evaluated: linear, second-order polynomials (Poly2), third-order polynomial (Ploy3), and Gaussian (rbf). The results of applying these kernel functions at three levels of training, test, and total are shown in Figure 4. The best results will be obtained only by considering the results of training level of Poly3 Kernel function. The test level of linear and second-order polynomial Kernel functions has almost similar R^2 values, but according to total result, the -order polynomial Kernel function is selected as the best function.

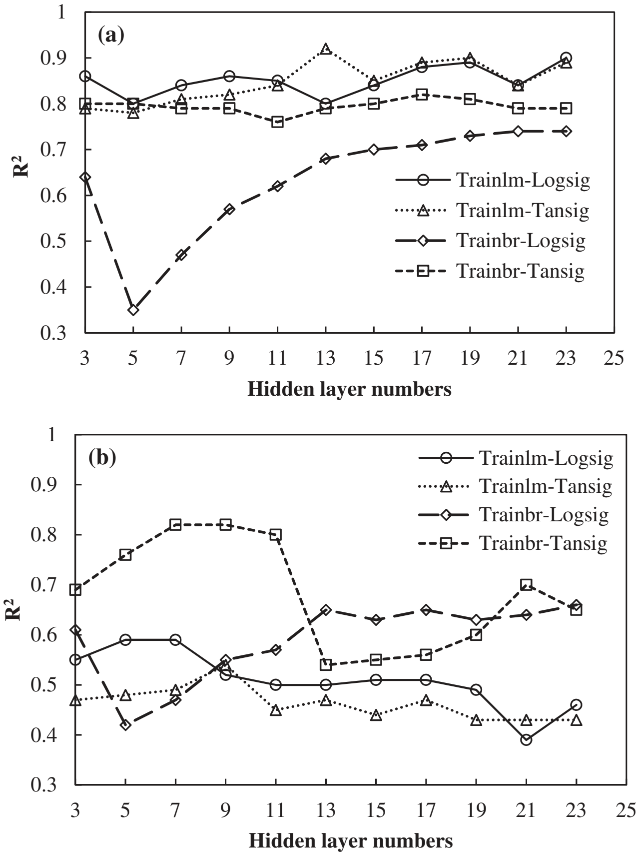

Figure 3. The changes of R^2 values of MLP model for different parameters in train (a) and test (b) levels.

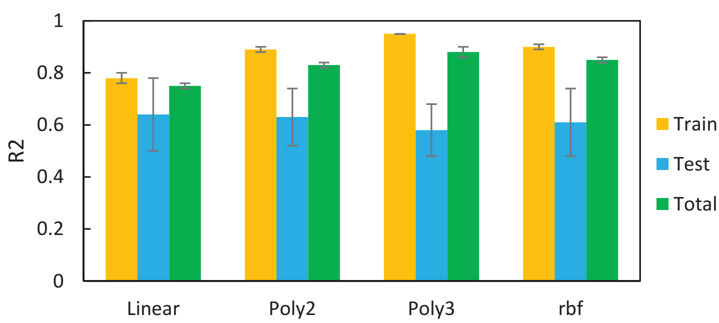

Figure 4. SVM model performance for different Kernel functions.

Comparison of soft computing models performance

In the previous section, the optimized parameters of soft computing methods including RBF, MLP and SVM were found. Unlike most of studies in literature review, for better and more accurate model evolutions in estimating energy flow, the different sizes of training selection (TS) are used in current paper. Hence, 50, 60, 70, 80, and 90% of all data are selected randomly. The results of RMSE, MAPE, and R^2 of the different data selection obtained from k-fold in two levels of training and test are displayed in Table 7.

Table 7. The results of soft computing evaluation vs. the size of training data selection.

		Train			Test		
TS*	Model	RMSE	MAPE	R^2	RMSE	MAPE	R^2
90	RBF	0.53 ± 0.80	0.22 ± 0.34	0.99 ± 0.00	0.52 ± 0.98	0.27 ± 0.47	0.99 ± 0.00
	MLP	9.26 ± 1.11	5.95 ± 0.86	0.79 ± 0.01	9.64 ± 2.89	6.22 ± 1.87	0.74 ± 0.17
	SVM	4.25 ± 0.32	2.54 ± 0.13	0.95 ± 0.00	12.91 ± 4.25	8.31 ± 3.05	0.59 ± 0.22
80	RBF	1.11 ± 3.28	0.59 ± 2.02	0.98 ± 0.12	1.11 ± 3.46	0.62 ± 2.09	0.98 ± 0.09
	MLP	8.97 ± 1.16	5.76 ± 0.86	0.80 ± 0.02	10.95 ± 1.77	7.12 ± 1.24	0.65 ± 0.11
	SVM	4.12 ± 0.39	2.51 ± 0.16	0.95 ± 0.00	12.39 ± 1.68	7.85 ± 1.16	0.57 ± 0.10
70	RBF	0.33 ± 0.68	0.14 ± 0.29	0.99 ± 0.00	0.37 ± 0.92	0.16 ± 0.35	0.99 ± 0.01
	MLP	8.33 ± 1.43	5.33 ± 1.05	0.82 ± 0.04	11.40 ± 1.57	7.39 ± 1.11	0.64 ± 0.10
	SVM	3.83 ± 0.59	3.83 ± 0.59	0.96 ± 0.01	12.83 ± 1.44	8.18 ± 0.93	0.55 ± 0.10
60	RBF	0.26 ± 0.64	0.11 ± 0.30	0.99 ± 0.00	0.29 ± 0.87	0.13 ± 0.40	0.99 ± 0.00
	MLP	8.97 ± 2.52	5.81 ± 1.85	0.82 ± 0.05	12.15 ± 1.76	7.90 ± 1.48	0.62 ± 0.08
	SVM	3.71 ± 0.73	2.23 ± 0.39	0.96 ± 0.01	12.63 ± 1.17	8.13 ± 0.86	0.56 ± 0.07
50	RBF	0.22 ± 0.62	0.09 ± 0.28	0.99 ± 0.00	0.19 ± 0.55	0.09 ± 0.31	0.99 ± 0.00
	MLP	9.69 ± 2.16	6.41 ± 1.66	0.81 ± 0.03	12.14 ± 1.38	7.87 ± 1.09	0.63 ± 0.06
	SVM	3.33 ± 0.83	2.12 ± 0.41	0.97 ± 0.01	12.99 ± 1.09	8.27 ± 0.82	0.54 ± 0.07

The results show that RBF model at all different values of training data selection has a great prediction performance, as the average value of R^2 is more than 0.98. Even in smaller sizes, the performance of RBF model is better than others. In SVM and MLP models, the test performance will be improved by size reduction of training selection, while the test performance will be weakened. Thus, in comparison with RBF, both MLP and SVM can be more subjected to over fitting problem. Therefore, by comparing the results of three above methods and also CD and MLR, the RBF neural network is chosen as the best model for fitting and estimating the energy flow of potato.

Conclusions

Thus, based on this study, the following conclusions can be drawn:

(1) Energy consumption in potato production calculated about 84309.43 MJ ha^{-1} and average of total output energy was 130217.14 MJ ha^{-1}.
(2) About 80% of total input energy in this cultivation was consumed in irrigation system (36%), fertilizer (26%) and seeds (22%).
(3) Comparing the results of CD, MLR, RBF, MLP, and SVM models indicated that the RBF is the best model for output energy prediction.
(4) The results of RMSE, MAPE, and R^2 of the different randomized data set (50, 60, 70, 80, and 90%) obtained from *k*-fold in train and test phases showed that RBF model, at all different values of training data set has a better prediction performance (R^2 = 0.98).
(5) MLP and SVM in comparison with RBF can be more applied to solve the over fitting problem.

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