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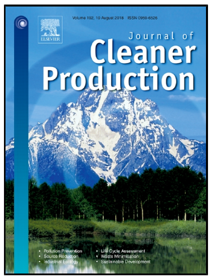

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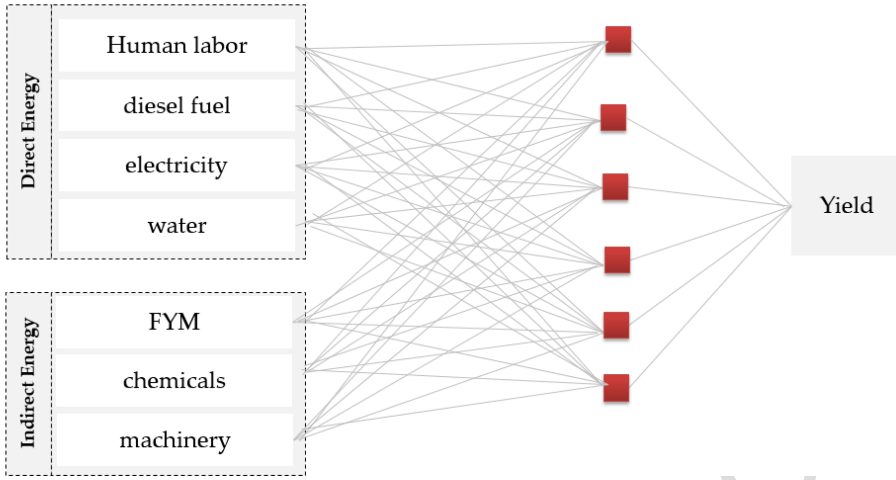

Topology of a simple artificial neural network

Sensitivity analysis of energy inputs in crop production using artificial neural networks

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Abstract

Sensitivity analysis establishes priorities for research and allows to identify and rank the most important factors which lead to great improvements in output factors. The aim of this study is to examine sensitivity analysis of inputs in grape production. We are proposing to perform sensitivity analysis using partial rank correlation coefficient (PRCC) which is the most reliable and efficient method, and we apply this for the first time in crop production. This research investigates the use of energy in the vineyard of a semi-arid zone of Iran. *Energy use efficiency*, *energy productivity*, *specific energy* and *net energy* were calculated. Various artificial neural network (ANN) models were developed to predict grape yield with respect to input energies. ANN models consist of a multilayer perceptron (MLP) with seven neurons in the input layer, one and two hidden layer(s) with different number of neurons, and an output layer with one neuron. Input energies were labor, machinery, chemicals, farmyard manure (FYM), diesel, electricity and water for irrigation. Sensitivity analysis was performed on over 100 samples of parameter space generated by Latin hypercube sampling method, which was then fed to the ANN model to predict the yield for each sample. The PRCC between the predicted yield and each parameter value (input) was used to calculate the sensitivity of the model to each input. Results of sensitivity analysis showed that machinery had the greatest impact on grape yield followed by diesel fuel and labor.

Keywords: Grape production, artificial neural networks, sensitivity analysis, energy efficiency

1. Introduction

Agriculture and energy are closely related since efficient use of energy is a key factor in sustainable agricultural production. Increasing requirement of higher food production has led to intensive use of agricultural and natural resources (Khoshroo, 2014). However, bio-energy has placed agriculture in the position of energy consumer and energy supplier (Esengun et al., 2007). Efficient energy use in agriculture is a pathway toward decreasing environmental hazards and improving agricultural sustainability (Izadikhah and Khoshroo, 2018).

Energy demand in agriculture can be classified into direct and indirect energies or renewable and non-renewable energies (Ozkan et al., 2004a). Direct energy consists of human labor, diesel fuel, electricity and water for irrigation, while farmyard manure (FYM), chemicals and machinery are considered indirect energy. Renewable energy includes human labor, FYM and water for irrigation whereas machinery, diesel fuel and chemicals are considered non-renewable forms of energy (Demircan et al., 2006; Ozkan et al., 2004a).

The established method to determine energy efficiency of production systems is the input-output analysis. Using this type of analysis, researchers have studied energy consumption in the production of fruits such as citrus (Ozkan et al., 2004), grape (Ozkan et al., 2007), apple (Gokdogan and Baran, 2017; Taghavifar and Mardani, 2015), prune

(Tabatabaie et al., 2013), walnut (Khoshroo and Mulwa, 2014) and pomegranate (Houshyar et al., 2017).

Modeling crop yield based on energy consumption is an interesting issue for researchers. Prediction of agricultural production is useful for farmers, governments, and agribusiness industries. It helps farmers to make marketing decision. Government requires forecasts of the crop yield to implement policies that provide technical and market support for the agricultural sector. Processors of food, and others in the marketing chain, need forecasts for their purchasing and storing decisions.

Various approaches and methods have been used to model energy consumption (Arabi et al., 2017; Jebaraj and Iniyan, 2006; Laha and Chakraborty, 2017; Say and Yücel, 2006; Tso and Yau, 2007). Traditionally, econometric models, based on Cobb-Douglass production function were the most popular modeling technique for investigating functional relations between input energy and various crop yield (Hamedani et al., 2011; Hatirli et al., 2006; Houshyar et al., 2015).

Artificial neural networks (ANNs) have received great interest in various research fields such as engineering (Ahmadi, 2011, 2012; Ahmadi, M.H. et al., 2015; Jani et al., 2017; Rafiq et al., 2001; Shafiei et al., 2014), energy (Kalogirou, 2001; Olatomiwa et al., 2016), petroleum and gas (Ahmadi and Ebadi, 2014; Ahmadi et al., 2014a; Ahmadi et al., 2014b; Ahmadi et al., 2014c; Ahmadi, M.A. et al., 2015) and agriculture (Jayas et al., 2000; Moldes et al., 2017; Soltanali et al., 2017). ANNs provide a powerful and flexible tool for modeling complex systems (Catalão et al., 2011). ANNs are data driven and distribution free; therefore, they can approximate non-linear functions and solve the problems where input-output relationship is not easily computable (Sözen, 2009).

Several researches have used ANN to predict crop yield or output energy in various crops such as wheat (Safa and Samarasinghe, 2011), basil (Pahlavan et al., 2012), kiwifruit (Soltanali et al., 2017) and paddy (Taheri-Rad et al., 2017).

Sensitivity analysis is performed in crop production to determine the most important inputs which lead to the highest increase in yield. Marginal Physical Productivity (MPP) is perhaps one of the most common methods for sensitivity analysis in the econometric models (Mobtaker et al., 2010; Mohammadshirazi et al., 2012; Singh et al., 2004). Some researchers have studied sensitivity analysis of energy input in ANN models using NeuroSolution software (Khoshnevisan et al., 2013; Pahlavan et al., 2012). The current paper applies Partial Rank Correlation Coefficient (PRCC) to study the priority of energy inputs on crop yield improvement. PRCC searches the whole parameter space of a model with the fewest number of simulations. PRCC is the most efficient and reliable method of sensitivity analysis among the sampling-based indices (Marino et al., 2008; Saltelli and Marivoet, 1990). To the best of our knowledge, PRCC has not been used for sensitivity analysis in crop production.

The main objective of this study is to find the most important factors influencing the grape yield; hence, farmers and policy makers can focus on these factors to increase the energy efficiency.

The remaining part of this paper is organized as follows: Section 2 describes the data collection and the method used for this analysis including the development of artificial neural networks. Section 3 discusses the results. Sensitivity analysis of grape production is also discussed in this section. Section 4 makes conclusions and provides direction for future research.

2. Methods

2.1. Artificial neural networks

ANNs are networks of interconnected processing units which were inspired by the biological structures in the human brain (Haykin, 1999). Each of the processing units is called neuron. Neurons are organized in a way that defines network architecture. Multi-Layer Perceptron (MLP) is the most common type of feed forward neural networks. In a MLP, neurons are often arranged as an input layer, one or more hidden layer, and an output layer (Catalão et al., 2011). The neuron output is produced by processing the weighted inputs through linear or non-linear transfer functions (Basheer and Hajmeer, 2000). The error calculated during training step is distributed through the network and adjust connection weights between neurons (Haykin, 1999). In the feed forward networks, the most common method for obtaining minimum error is back propagation (BP) algorithm. BP uses a gradient descent technique and tends to converge slowly. Adding a momentum term is an efficient way to speed up the algorithm. Gradient descent with momentum (GDM) algorithm increases the performance of standard BP algorithm. The momentum term helps to avoid local minima, improve learning speed, and stabilize convergence (Omid et al., 2009; Ramedani, 2013).

The process of weight update in the n^{th} iteration of GDM algorithm is performed by the following equation (Omid et al., 2009; Ramedani et al., 2013):

$$w_{ji}^{n} = w_{ji}^{n-1} + \Delta w_{ji}^{n} \tag{1}$$

and weights are adapted by:

$$\Delta w_{ji}^{n} = \eta \delta_j^n o_i^n + \alpha \Delta w_{ji}^{n-1} \tag{2}$$

Where w_j denotes the weight between *j*th neuron of the following layer and the *i*th neuron of the previous layer. The error signal of *j*th neuron is shown by δ_j. 0_i represents output of the *i*th neuron of the previous layer. Also, Δw_{ji}^{n} is the gradient vector associated with the weights and η and α are the learning rate and momentum. Figure 1 presents the steps of implementing an ANN with back-propagation algorithm.

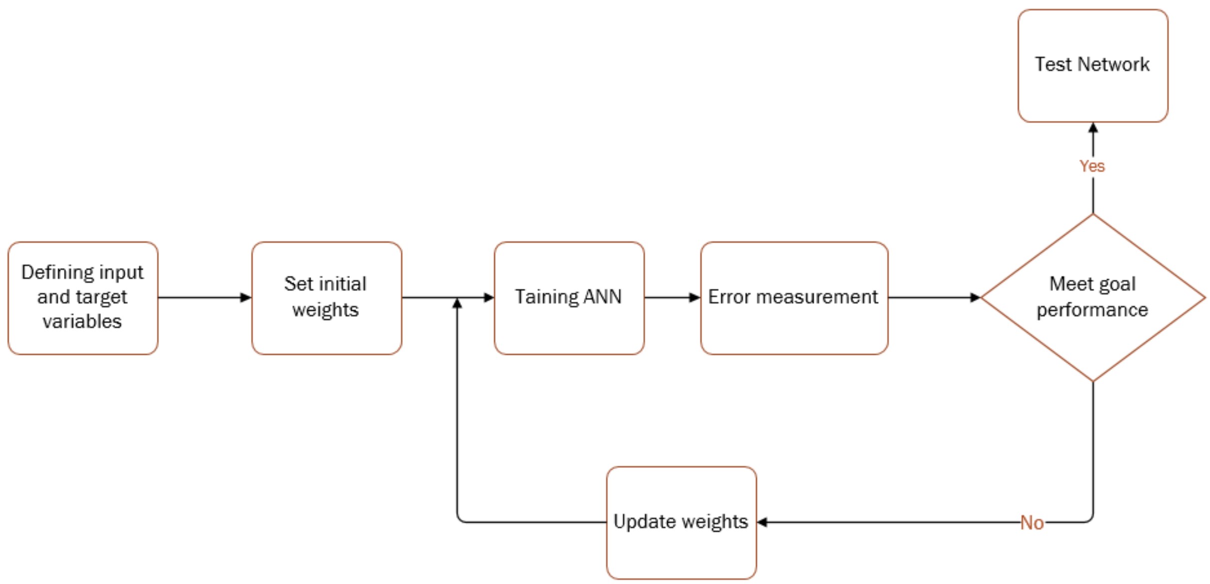

Figure 1. Flowchart of BP-ANN

In order to estimate grape production yield, several feed forward neural networks have been designed and trained to find the one that has the best accuracy. Data were shuffled and divided into two sets: training set (seventy percent of data) and test set (thirty percent of data). Artificial neural networks a learning machine technique is used to dealing with nonlinear and complex relationships between inputs and output for model, as an example Figure 2 illustrates the topology of a case with three-layer MLP network with seven neurons in the input layer and one neuron in the output layer.

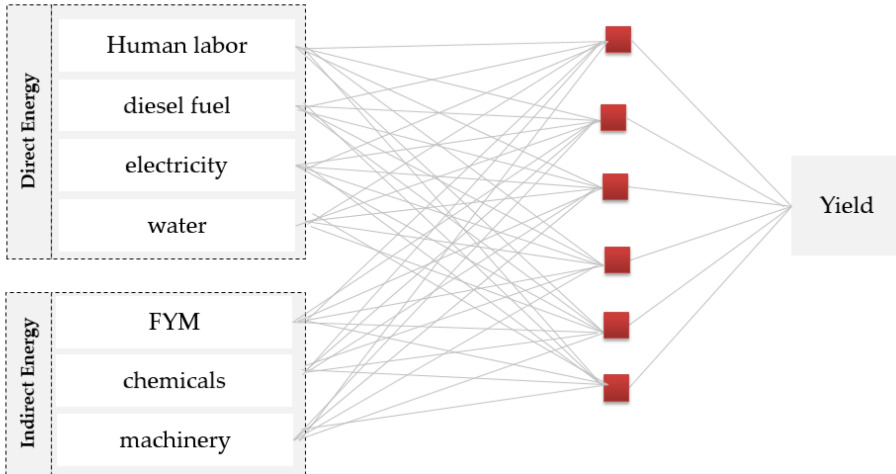

Figure 2. Topology of a simple artificial neural network

2.2. Statistical Analysis

To evaluate the performance of developed ANN models, correlation coefficient (r) was calculated using the following equation (Mayer and Butler, 1993; Wallach and Jones, 2006):

$$r = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})(\hat{Y}_i - \bar{\hat{Y}})}{\sqrt{\sum_{i=1}^{N}[(Y_i - \bar{Y})^2]\sum_{i=1}^{N}[(\hat{Y}_i - \bar{\hat{Y}})^2]}} \tag{3}$$

Where N is the number of samples, Y_i is the observed output for sample i, $\hat{Y}_i$ is the estimated output for sample i, $\bar{Y}$ is the average value for Y_i, and $\bar{\hat{Y}}$ is the average value for $\hat{Y}_i$. Correlation coefficient measures the statistical relationship between the predicted values and observed (actual) data.

2.3. Sensitivity analysis

Sensitivity analysis establishes priorities for research (Cariboni et al., 2007) and allows to identify and rank the most important factors which lead to great improvements in the output factor (Marino et al., 2008). Sensitivity analysis was performed using partial rank correlation coefficient (PRCC) (Helton et al., 2006; Rummel, 1976) over 100 samples of parameter space generated by Latin hypercube sampling method (LHS) (McKay et al., 1979). LHS divides each parameter distribution to N equal probability intervals, where N is the number of needed samples. Each interval is then sampled randomly, but exactly once, to generate N values. A sample can be created by selecting a value from each parameter set. Once a value is selected from a parameter set, it is removed from the set (sampling without replacement).

After generating samples, the trained ANN model from the previous section is used to predict the output of each sample. The PRCC between the predicted output and each parameter value can then be used to calculate the sensitivity of our model to each input.

3. A real application: Modeling and sensitivity analysis of input energies in grape production

Grape (*Vitis vinifera* L.) has an important position in horticultural and beverage industries. Fruits are composed of water, sugars, amino acids, minerals and micronutrients. Grape is a commercial source of tartaric acid and is also rich in malic acid (Kole, 2007). World grape production in 2016 was approximately 75.8 Mt, with leading grape-producing countries being China, Italy, USA, France, Spain, Turkey, India and Iran (OIV, 2017). Grape production exceeded 3.16 Mt in Iran, ranking second in fruit production table (MAJ, 2015).

3.1. Data collection and energy analysis

In this study, data were collected from grape vineyards in Fars province, Iran. The research was carried out in the form of interviews, during which questionnaires were filled. Fars province had the highest share of grape production in Iran (16%) with 506,000 tons production (MAJ, 2015).

Table 1. Energy equivalents for agricultural input resources and yield output

Variables	Unit	Energy equivalent (MJ Unit^{-1})	References
Inputs			
Human labor	hr	1.96	(Khoshroo and Izadikhah, 2018; Ozkan et al., 2004b);
Machinery	hr	62.7	(Ozkan et al., 2004a; Ozkan et al., 2004b)
Chemicals	Kg		
- Insecticides		101.2	(Mohammadi et al., 2010a; Rafiee et al., 2010)
- Fungicides		216	(Mohammadi et al., 2010a; Rafiee et al., 2010)
- Herbicides		238	(Mohammadi et al., 2010a; Rafiee et al., 2010)
Farmyard manure	Kg	0.3	(Beheshti Tabar et al., 2010; Ozkan et al., 2004a)
Diesel fuel	L	56.31	(Kitani, 1999; Ozkan et al., 2004a)
Electricity	kWh	11.93	(Mousavi-Avval et al., 2011; Pahlavan et al., 2012)
Water for irrigation	m3	1.02	(Erdal et al., 2007; Khoshroo et al., 2018)
Outputs			
Grape	Kg	11.8	(Ozkan et al., 2007)

Data were obtained using face-to-face interviews with 41 selected grape farmers and responses were filled in an interview schedule. The inputs used in grape production in the surveyed area were specified for the calculation of energy equivalences in the study.

The input energy sources for grape production were human labor, machinery, diesel fuel, chemicals, farmyard manure (FYM), water for irrigation and electricity, while output energy source was the grape yield. Table 1 demonstrates energy equivalents for the different input and output sources.

To determine pattern of energy use in grape production, the following energy indicators were computed (Demircan et al., 2006):

$$EUE = \frac{E_{out}}{E_{in}} \quad (4)$$

$$EP = \frac{GY}{E_{in}} \quad (5)$$

$$SE = \frac{E_{in}}{GY} \quad (6)$$

$$NE = E_{out} - E_{in} \quad (7)$$

Where EUE is *Energy Use Efficiency*; EP is *Energy Productivity*; SE is *Specific Energy* and NE is *Net Energy*. Also, E_{in} is energy input (MJ ha^{-1}), E_{out} is energy output (MJ ha^{-1}) and GY is grape yield (kg ha^{-1}).

3.2. Results and discussion

3.2.1. Analysis of energy consumption in grape production

Table 2 presents average values and variation of input energies and crop yield in grape production. Average human labor used was 2465.68 MJ ha^{-1}. The source of human labor in the surveyed vineyards was mainly from hired workers. The highest contribution of human labor was found in farmyard manure application (25.17%), followed by harvesting (24.02%), land preparation (21.45%) and pruning (14.17%) operations. The results showed that the required machinery power in grape production was 1630.2 MJ ha^{-1}. This power was applied for chemical spraying. Most of the required machinery in the studied region was rented machinery. The total energy consumption of grape production was about 45003 MJ ha^{-1} and the total output energy reached 184096 MJ ha^{-1}.

Table 2. Statistical measures for energy inputs and output in grape production

Variables	Average	Std. Dev.	Min	Max
Inputs (MJ ha^{-1})				
Human labor	2465.68	628.65	1364.16	4029.11
Machinery	805.86	442.58	282.15	2142.25
Chemicals	1856.30	1497.87	0	4814
Farmyard manure	4568.26	2090.89	2000	12000
Diesel fuel	2597.54	2414.51	406.24	14734.45
Electricity	23415.86	9798.44	6282.68	43193.42
Water for irrigation	9593.64	5822.39	1615.68	26928
Output(kg ha^{-1})				
Grape	15344.56	8272.86	2500	36666.67

The percentage distribution of energy related to the inputs is illustrated in Figure 3. Among different energy sources, electricity energy had the highest share of energy consumption (48.5%) in grape production. Water for irrigation ranked second with 21.5% in the total energy input. These results are consistent with the finding that irrigation energy consumes the greatest part of total energy inputs in Iranian agriculture (Beheshti Tabar et al., 2010).

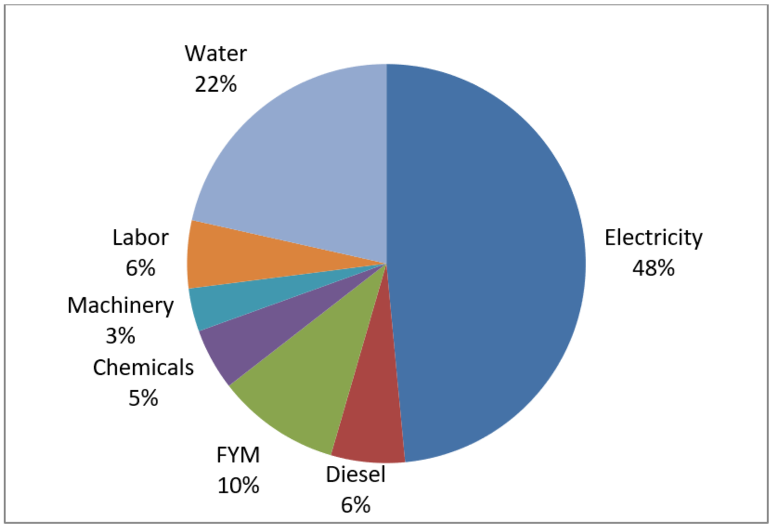

Figure 3. Percentage distribution of energy consumption in grape production

Table 3 presents the energy indicators in grape production. Energy use efficiency was achieved 4.09, indicating that output energy is higher than input energy. Meanwhile, energy productivity, specific energy, and net energy were calculated 0.35 kg MJ^{-1}, 2.88 MJ kg^{-1}, and 139093.16 MJ ha^{-1}, respectively.

The distribution of input energy in grape production, based on *Direct Energy* (DE), *Indirect Energy* (IDE), Renewable Energy (RE), and *Non-Renewable Energy* (NRE) forms is shown in Table 3. Results revealed that direct energy had higher share (81.39%) in the total energy consumption compared to the indirect energy (18.61%).

Results also showed the higher rate of non-renewable energy (63%) in comparison with renewable energy (37%). The high share of non-renewable energy in the total energy consumption leads to a decreased sustainability in grape production.

Table 3. Energy indicators in grape production

Items	Unit	Quantity
EUE		4.09
EP	kg MJ^{-1}	0.35
SE	MJ kg^{-1}	2.88
NE	MJ ha^{-1}	139093.16
DE [a]	MJ ha^{-1}	36628.09
IDE [b]	MJ ha^{-1}	8374.92
RE [c]	MJ ha^{-1}	16682.73
NRE [d]	MJ ha^{-1}	28320.28
Total energy input	MJ ha^{-1}	45003.01

3.2.2. ANN models: Development and evaluation

In order to model grape yield based on input energies, several ANN models were developed. Labor, machinery, chemicals, FYM, diesel, electricity and irrigation water energies are included as input to ANN models while the grape yield has been chosen as the desired output variable. To come up with a proper architecture for our ANN model (i.e., the number of hidden layers and the number of neurons comprising each layer), we designed multiple networks were designed and trained to compare their prediction performance. As mentioned in Section 2.3, the correlation coefficient was used to evaluate the performance of designed ANN models. Figure 4 shows the mean and standard deviation of correlation coefficient between the observed (actual) data and the predicted values by ANN models for 17 different network architectures each trained 10 times independently. In this figure, [4 , 0] denotes a network with one hidden layer comprising of 4 neurons and [2 , 8] denotes a network with two hidden layers: first with 2 neurons and the second with 8. Since the size of problem is small, as Figure 4 shows, most of architectures have similar performance. The 7-6-1 architecture was chosen, the one with the highest mean correlation coefficient and the least standard deviation. Low standard deviation indicates the robustness of the performance of this architecture, since it has consistently provided reasonable predictions. This architecture had an input layer with seven neurons, one hidden layer with six neurons, and an output layer with a single neuron.

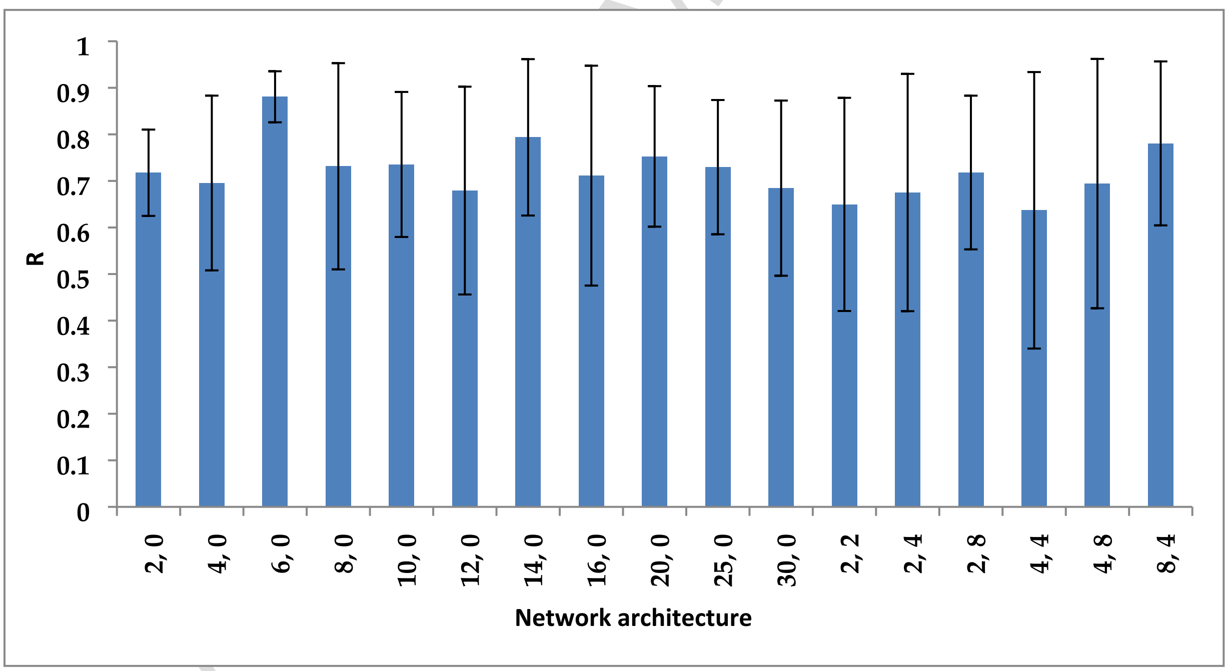

Figure 4. ANN performance of grape yield estimations for various network structures

Figures 5a and 5b demonstrate the performance of our ANN model over randomly sampled training and test sets. It is worth mentioning that there should be several uncontrolled factors that influence the yield (Safa and Samarasinghe, 2011), therefore, the results of this model seem plausible.

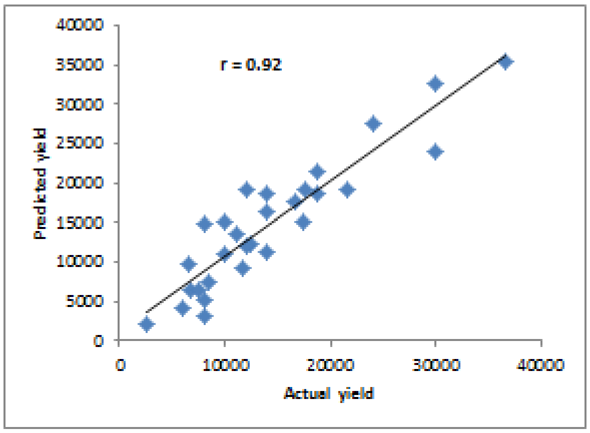

Figure 5a. Relationships between the actual and ANN model predicted grape yield (Training data)

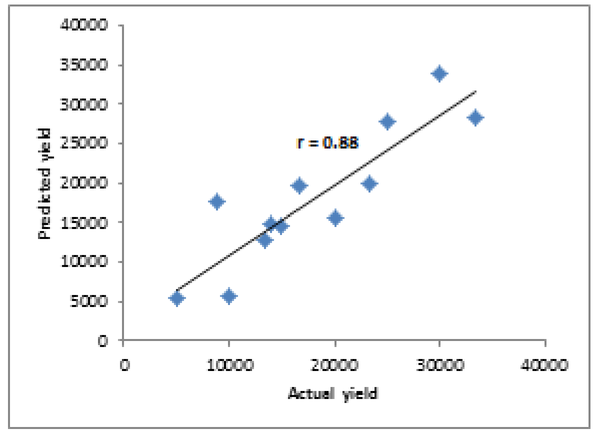

Figure 5b. Relationships between the actual and ANN model predicted grape yield (Test data)

3.3.3 Sensitivity analysis

After generating 100 samples of parameter space by using Latin hypercube sampling method, we use the trained ANN model to predict the output of each sample. Then, to determine the sensitivity of our developed model to each input, the PRCC between the predicted grape yield and each input is calculated. Figure 6 depicts the share of each input factor of developed ANN model on output factor (grape yield). According to the results (Figure 6), machinery showed the greatest impact on the grape yield followed by diesel and labor. Results showed the sign of PRCC was negative for chemicals, FYM, irrigation water and electricity. It indicated the excessive use of these energy resources in the studied region with negative impact on grape yield.

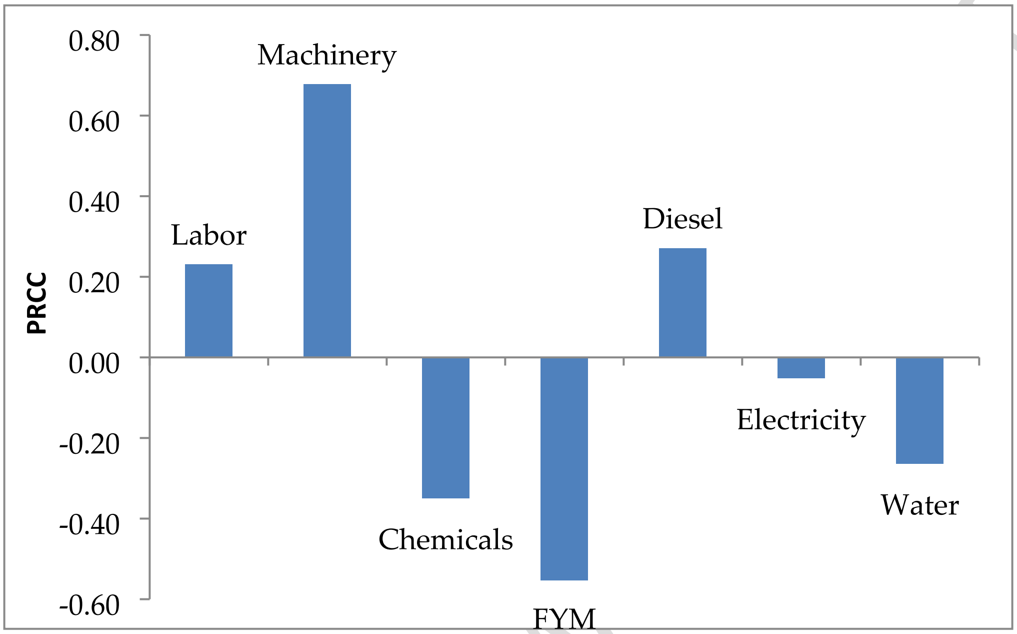

Figure 6. Sensitivity analysis of various inputs on grape yield

4. Conclusion and direction for future research

Modern crop production requires significant amount of energy. Efficient energy use in agriculture is a necessary step towards decreasing environmental issues and increasing agricultural sustainability. Thus, finding the important factors contributing on crop yield is important. Prediction of crop yield based on energy use is important for farmers, governments, and agribusiness industries. Artificial neural networks a learning machine technique is used to dealing with nonlinear and complex relationships between inputs and output. Therfore, to predict grape yield with respect to input energies, various multi-layer perceptron ANN models were developed with one and two hidden layers. The best ANN model had 7-6-1 topology with high correlation coefficient between predicted values and observed data. Sensitivity analysis of input parameters was determined using partial rank correlation coefficient (PRCC). It showed that machinery had the greatest impact on yield. Therefore, agricultural mechanization is the first priority for increasing grape yield in the studied region. This study can be generalized for semi-arid regions with the same latitude, but the impact of climate change that may affect results, requires further investigation.

In many real applications data reported are not crisp data, hence, future research could focus on including the uncertainty and develop a fuzzy network for the proposed ANN.

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