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Full Length Research Paper

Assessment of machinery energy ratio in potato production by means of artificial neural network

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A single hidden layer Artificial Neural Network (ANN) model was developed to estimate a machinery energy ratio (MER) indicator, used to characterize and assess mechanization status of potato farms in Iran with a view point of energy expenditure in farm machinery. A wide range of variables of farming activities were examined. Initially, 90 attributes were used as input variables to predict desired MER output. Using regression analysis, 13 inputs were finally selected to model MER. Performance of developed ANN model was evaluated with various statistical measures including the coefficient of determination (R^2), mean absolute percentage error (MAPE), mean squared error (MSE) and mean absolute error (MAE). The optimum ANN model had a 13 - 4 - 1 configuration. The values of the optimum model's outputs correlated well, with R^2 of 0.98. Value of MAPE calculated as 0.0001 for best ANN model, which indicate superiority of this model over other prediction models. Sensitivity analyses were also conducted to investigate the effects of each input item on the output value. Since the ANN model can predict this mechanization indicator for a target farming system in Hamadan province of Iran, it could be a good estimator for appraising mechanization of other regional farms. Also it overcomes some of the limitations of using simple data available from local databases as inputs that may contain errors.

Key words: Potato, agricultural mechanization, machinery energy ratio, Artificial Neural Network.

INTRODUCTION

In order to maximize the efficiency of new agricultural technology to farms in a target region, the farming system of the region should be first characterized, especially to identify possible resource constraints and to capture the diversity of farming systems (Sims, 1987; Collado and Calderon, 2000; Oida, 2000). Monitoring the mechanization status of target region, in combination with other agronomic indicators such as productivity potential (Garcia et al., 2005), would result in a better assessment of the sustainability of the farming system. The purpose of this study was to develop an Artificial Neural Network (ANN) model to predict a mechanization indicator based on energy and power consumption. The potential practical application of this work is mapping the proposed mechanization indicator for a much wider area without direct calculations using the proposed method. Further analysis based on the interrelation between the produced data with complementary parameters already available in local databases, would contribute to assess the mechanization status in the whole region.

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Abbreviations: ANN, artificial neural network; **MER,** machinery energy ratio; **MAPE,** mean absolute percentage error; **MSE,** mean squared error; **MAE,** mean absolute error; **R^2,** coefficient of determination.

MATERIALS AND METHODS

Data source and processing

The study was carried out on potato farms in Hamadan, Iran. Hamadan province has 1.2% of total area of the country and located in the west of Iran, within 36° 40′ latitude and 48° 31′ longitudes. The total area of the Hamadan province is 1,494,400 ha, and the farming area is 660,000 ha, with a share of 44.16% (Anonymous, 2005). Data were collected from the farmers by using a face to face questionnaire performed in July 2009. The data collected belonged to the production period of 2008 - 2009. The

Table 1. Description of input items.

Input category	Example
Social issues	Farmer age, school years, agricultural experience, number of land plot, average agricultural output, etc.
Asset	Total Farm size (ha), Area under potato production (ha), machinery used (units, type, model), tractors (model, old, power), etc.
Farming strategies	Farming method (type of tillage operation, sequence), number of irrigation, number of potato land plots, etc.
Production factors	Working hours of labor and farm machinery, inputs for crop production (seeds, agrochemicals, fertilizers, etc.), yield (tones ha^{-1}), etc.
Finance	Unitary costs for crop production, fixed and variable cost ($\$ ha^{-1}$ and $\$ kg^{-1}$), cost of fixed labor per year, etc.
Policy support	Subsidizing source, number of subsidized chemical fertilizers, etc.

size of sample of each stratification was determined using Equation (1) derived from Neyman technique (Mohammadi and Omid, 2010).

$$n = \frac{\sum N_h S_h}{N^2 D^2 + \sum N_h S_h^2} \quad (1)$$

Where n is the required sample size; N is the number of holdings in target population; N_h is the number of the population in the h stratification; S_h is the standard deviation in the h stratification, S^2_h is the variance of h stratification; d is the precision $(x- X)$; z is the reliability coefficient (1.96 which represents the 95% reliability); $D^2 = d^2/z^2$.

The permissible error in the sample size was defined to be 5% for 95% confidence, and total sample size was calculated as 68 samples. The data consist of about 300 attributes for each farm classified in 6 categories; these categories have been shown in Table 1. The prevailing farming system in the region of study is characterized by the use of tractors as main power source, as encouraged by the government in response to the restriction of timeliness of seasonal farm works, to increase agricultural production and productivity, and labor shortage trends. Land tenure varies from 5 to 100. Sample farming area selected for the study was 1545 ha representing a big part of the target farming system of potato production in Hamadan. The mechanization indicator, Machinery Energy Ratio (MER), was chosen because it would allow us to identify which farming systems in the region would benefit from mechanization and to estimate the intensity of mechanization as part of an agricultural modernization program. The Artificial Neural Network (ANN) model gives estimations of the mechanization indicator using limited data available from the target region, without the need to calculate them directly, which would require more data. The model is based on statistical analyses of actual data, and enables us to distinguish between necessary and unnecessary items of raw data. A fundamental hypothesis of this study is being feasible to train an ANN model to establish a non-explicit function, which corresponds to the ANN network itself, between a selected set of simple inputs, such as farm size and number of tractors owned, and the mechanization indicator as the outputs.

To assess the technological status and the agricultural production strategies, the farming system was analyzed according to its energy input-output flow and consumption of power for various farming operations. In the case of input-output energy flow, firstly, the amounts of inputs (chemicals, human labor, machinery, seed, manure, fertilizers, fuel, electricity and irrigation water) used in the production of potato were specified in order to calculate the energy equivalences in the study. The units in Table 2 were used to find the input and output energy equivalent (Mohammadi and Omid, 2010; Kocturk and Engindeniz, 2009; Dagistan et al., 2009). Basic information on energy inputs and potato yields were entered into Excel 2007 and SPSS 16 spreadsheets. Based on the energy equivalents of the inputs and output (Table 2), the MER can be calculated. Technical information on the type of machinery found in this region, such as fuel consumption and power rate, was obtained from the information obtained by questionnaire method.

Input and output parameters

Based on input items availability and how representative they were of all the data, a set of input attributes, including 94 items, were chosen as the first candidate set of the input items for estimating output. Using a regression method (Forward method) different collection of input items were selected for MER. Because the items have different scales, the data were normalized by converting them using natural logarithm to maintain the neural network sensitivity (Drummond et al., 2003; Abdullakasim et al., 2005; Zhang et al., 1998). Finally, based on the responses of the ANN model, 13 input parameters produced output. These parameters correlated well with the calculated output and a wide range of response values of the model's output was selected for estimating MER. Table 3 shows the selected parameters fed into the ANN model during the training process. These items represent key factors of the farming system and were identified as factors in the mechanization status. They produced superior performance during the training process.

Machinery energy ratio (MER) indicates the investment in machinery energy in comparison with the other input energy sources required for crop production as described (Collado and Calderon, 2000). The ratio is useful for comparing the contributions of mechanization among the individual farms. MER is defined by Equation (2):

$$MER = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{M_{e(i)}}{T_{e(i)}}\right) \quad (2)$$

Where n is the number of farms, MER is Machinery energy ratio, ratio between machinery energy and total input energy and $T_{e(i)}$ and $M_{e(i)}$ are the total input energy (from labor, machinery, seeds, fertilizers, agrochemicals, etc.) and the overall input energy due to machinery in the production unit \`a\`, respectively.

Artificial Neural Network model

The ANN models were developed using the NeuroSolutions 5.07

Table 2. Amounts of inputs and output with their equivalent energy.

Quantity	Unit	Values			
		Energy equivalent ($MJ\ unit^{-1}$)	**Quantity per unit area (ha)**	**Total energy equivalent ($MJ\ ha^{-1}$)**	**Total energy input (%)**
Inputs					
Human labor	h	1.96	534.95	1048.50	0.69
Machinery	h	62.7	47.24	2962.42	1.94
Diesel fuel	L	56.31	504.98	28435.47	18.58
Fertilizers	kg		918.00	37951.32	24.79
(a) Nitrogen (N)		66.14	498.16	32948.42	21.52
(b) Phosphate (P_20_5)		12.44	249.26	3100.85	2.03
(c) Potassium (K_2O)		11.15	170.58	1902.05	1.24
Farmyard manure	kg	0.30	10411.7	3123.52	2.04
Chemical	kg		4.43	820.7	0.53
(a) Insecticides		101.20	1.49	151.42	0.09
(b) Herbicides		238.00	1.44	343.70	0.23
(c) Fungicides		216.00	1.50	325.58	0.2
Water for irrigation	m^3	1.02	7470.37	7619.77	4.98
Electricity	kWh	11.93	4696.01	56023.51	36.60
Seed	kg	3.6	4190.58	15086.11	9.85
Total energy input	MJ			153071.4	100.0
Output					
Potato	kg	3.6	43661.76	157182.35	
Total energy output	MJ			157182.35	

Table 3. Selected input items for MER.

Inputs	Output
1	Number of labors for hand collecting and bagging potato per hectare
2	Required time for hand collecting and bagging potatoes per hectare
3	Distance of potato transportation (m)
4	Total number of nitrogen fertilizer (50 kg bag)
5	Amount of insecticides ($L\ ha^{-1}$)
6	Average quantity of water per shaft (inches)
7	Total hours of farm machinery work ($h\ ha^{-1}$)
8	Equal energy of farm machinery ($MJ\ ha^{-1}$)
9	Total input energy ($MJ\ ha^{-1}$)
10	Energy productivity ($kg\ MJ^{-1}$)
11	Total direct energy ($MJ\ ha^{-1}$)
12	Total renewable energy ($MJ\ ha^{-1}$)
13	Total non-renewable energy ($MJ\ ha^{-1}$)

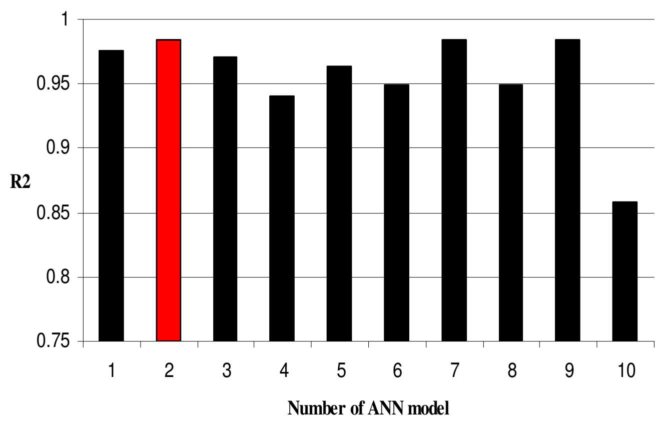

Figure 1. Correlation between the ANN model's outputs and calculated outputs.

software package. During the calibration process, 80 different architectures were trained. A variant of the back propagation learning algorithm, namely Gradient Descent with Momentum (GDM), were applied. The ANN models were trained to output this indicator from the data of the 13 input parameters. The validity of the model was checked by comparing its output values with those calculated using Equation (2), mean squared error (MSE), mean absolute error (MAE), coefficient of determination (R^2), and mean absolute percentage error (MAPE) as given by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|\text{Actual value}_i - \text{Estimated value}_i\right|}{\text{Actual value}_i}100\right)$$

(3)

RESULTS AND DISCUSSION

Number of hidden units

To determine the optimal architecture of the ANN, various one and two hidden layer architectures with hidden units ranging from one to twenty were trained, tested and validated. The validation subset contained ten patterns that were not used in the training and testing phases. This subset was used to test the correlation between the values of the outputs given by the ANN model and those obtained from Equation (2). Using Equation (2), the actual value of MER was calculated as 0.023. Figure 1 shows the correlation between the model's outputs and calculated output. In general, one hidden layer networks having two to eight hidden units showed better performance. Among these, a single hidden layer with four neurons was finally selected, because the number of hidden units should be as few as possible (Zhang et al., 1998). The performance of various ANN models is presented in Table 4. The best coefficient of determination (R^2) between the output of the ANN model (predicted) and the actual (calculated) value of MER indicator was 0.984, as highlighted in red in Figure 1.

Figure 2 shows the MAPE of MER calculated from Equation (3) for each validation pattern, obtained by comparing the outputs of the best ANN model of every desired output and the actual outputs calculated using Equation (2). The wide range of the actual output values for the MER (from 0.483 to 0.726) in the studied farming system suggests that this ANN model may be applied to other regions in the country with conditions similar to those in this study.

Input parameters of MER

According to the results obtained in the case of input parameters of MER, as shown in Table 3, some technical factors were selected. Because of semi mechanized structure of potato production in Hamadan province of Iran using human labor in production process especially in harvesting process items such as number of labors for hand collecting and bagging potato per hectare and required time for hand collecting and bagging potatoes per hectare have being selected as input items for this index, increasing mechanization and reducing labor in all sections of production can improve the MER, which will introduce high level of mechanization in all phases of potato production. Transportation is a main item in harvesting potatoes, storing in suitable condition even in distant store and consignment to market, should be considered in assessment of MER. Potato is a great consumer of chemical fertilizers and insecticides, they are utilized several times in each stead, scattering these materials requires tractors for long time and as well as diesel fuel which can influence MER. Shaft capacity and amount of pumped water has positive effect on fuel consumption of pump which increase and decrease MER. Calculation of MER depend on equivalent of machinery energy and total hours of farm machinery work (h ha^{-1}) and diesel fuel consumption subsequently. Because of the high importance of energy role in agricultural sector, particularly in potato production energy indicators are selected for justifying MER.

Sensitivity analysis

In order to assess the predictive ability and validity of the developed ANN model, a sensitivity analysis was performed using the best network selected. The robustness and sensitivity of the model were determined by examining and comparing the output produced during the validation stage with the calculated values. The ANN model was trained by withdrawing each input item one at a time while not changing any of the other items for every pattern. Result of this sensitivity analysis is shown in Figure 3. According to obtained results the share of each input item of developed ANN model on desired output can be seen clearly.

Table 4. Alternative configuration of ANN models for estimating MER.

Model	# hidden layer	Neurons	MSE	MAE	MAPE	R^2
1	1	2	0.0059	0.0602	1.6904	0.976
2	1	4	0.0053	0.0491	0.0001	0.984
3	1	5	0.0121	0.0840	2.2455	0.971
4	1	8	0.0288	0.1157	3.1186	0.940
5	1	11	0.0118	0.0802	2.1730	0.964
6	1	15	0.0122	0.0851	2.3695	0.949
7	1	20	0.0045	0.0497	1.3688	0.984
8	2	4-2	0.0218	0.1119	3.0388	0.949
9	2	5-3	0.0066	0.0555	1.5341	0.984
10	2	7-4	0.0340	0.1484	3.9089	0.858

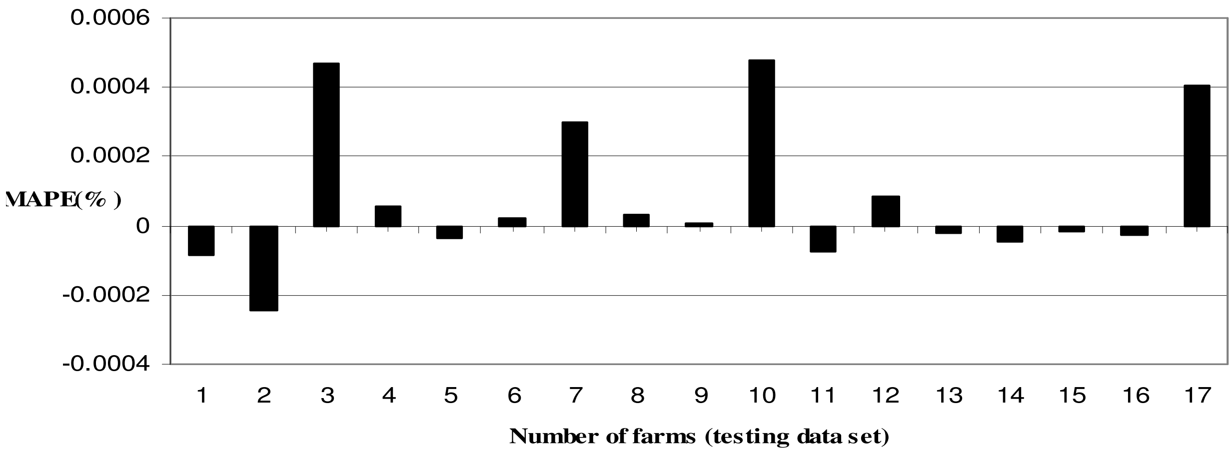

Figure 2. MAPE in the MER estimation over the test set.

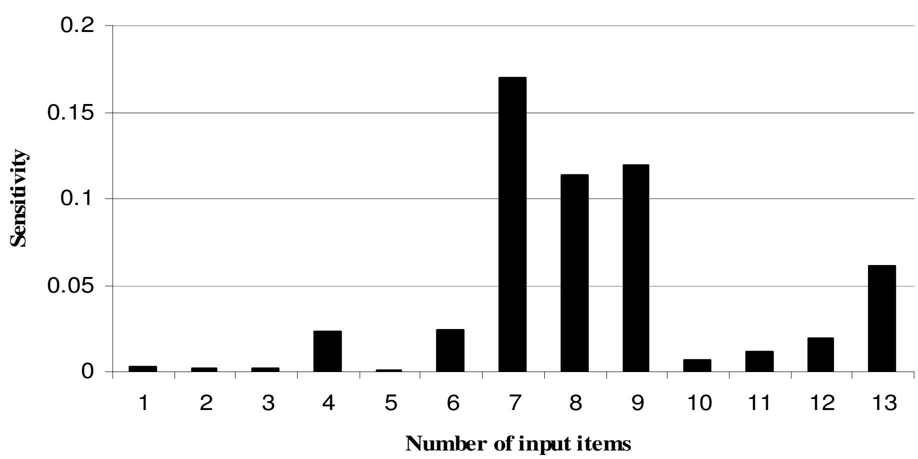

Figure 3. Sensitivity analysis of input items on MER.

Conclusions

Based on the results of this paper it can be stated that:

1. The developed ANN model predicted well the mechanization indicator, Machinery Energy Ratio (MER), for the potato farms in the study area in Iran. The models are based on a single hidden layer artificial neural network. Topology of the optimum model was 13 - 4 -1.
2. The correlation between the model's output, that is; predicted values, and the calculated values of the indicator was quite strong according to the results after the validation phase (10 cases), as described in the article ($R^2 = 0.984$).
3. The developed Mechanization Indicator may provide sufficient information to identify the target farming system as well as to assess their mechanization status.

We recommend that the ANN model is tested using specific inputs from different farming systems in other regions of the country, especially where the tractor type described in this study is not the main power source. Further practical application of this work includes generating a map of mechanization indicators for a much wider area. Analyzing the interrelation between the base-line data, in conjunction with available farm monitoring reports could allow resolving indications of average effectiveness of energy conversion, to identify priority areas to replace obsolete agricultural machinery, as well as, to asses the suitability of introducing new tractor units in the region.

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