Middle-East Journal of Scientific Research 25 (8): 1664-1681, 2017
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2017.1664.1681

Prediction of Consumption of Energy for Land Leveling on Irrigation Farms with Environmental Indicators Using ANFIS and Regression

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Abstract: Land leveling is one of the most important steps in soil preparation for agricultural processes. In this regard, different considerations are required to satisfy energy consumption and environmental urges as well as financial aspects. On the other hand, energy conservation is regarded as one of the most important factors in agricultural sector mainly due to its relation to pollution which is a result of fossil fuel (particularly gasoline) usage. The objective of this research was to develop three methods including artificial bee colony algorithm (ABC-ANN), regression and adaptive neural fuzzy inference system (ANFIS) to predict the environmental indicators for land leveling and to analyses the sensitivity of these parameters. So, several soil properties such as soil, cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, sand percent and soil swelling index in energy consumption were investigated. A total of 90 samples were collected from 3 land areas with the selected grid size of (20×20m). Acquired data were used to develop accurate models for labor, energy (LE), fuel energy (FE), total machinery cost (TMC) and total machinery energy (TME). By applying the three mentioned analyzing methods, the results of regression showed that, only three parameters of sand percent, slope and soil, cut/fill volume had significant effects on energy consumption. According to the all developed models (Regression, ANFIS and ABC-ANN) had satisfactory performance in predicting aforementioned parameters in various field conditions. The adaptive neural fuzzy inference system (ANFIS) has the most capability in prediction according to least RMSE and the highest R^2value of 0.0143,0.9990 for LE. The ABC-ANN has the most capability in prediction of the environmental and energy parameters with the least RMSE and the highest $R^2$with the related values for TMC, FE and TME (0.0248, 0.9972), (0.0322, 0.9987) and (0.0161, 0.9994), respectively.

Key words: Energy · ANFIS · Regression · Land levelling · Environmental indicators · Artificial bee colony algorithm

INTRODUCTION

Agriculture, which is the most important sector in the production of food in the world, is also a big consumer of energy. Energy is needed in agriculture to produce food to feed the ever increasing world population. Tillage operation and cultivation in a farming season consists of plowing, preparing the seed bed, leveling, cultivating, covering the seed, making the irrigation furrow and sometimes application of fertilizer. Machines used for these types of operation consist of different kinds of plowshare, land leveling, planter and forever. Each of the mentioned equipment has to be attached to the grader and used in farmland to accomplish the specified operation. In the agricultural sector, like other fields, energy is regarded as one of the most important parameters. However, the inherent disadvantage of using fossil fuels (particularly gasoline) as an energy source is pollution.

One-third of arable lands are already contaminated; therefore, the use of polluted lands will have to feature highly in modern agriculture [1]. There are also other issues to consider, such as cost–benefit analysis, the possible entry of pollutants into the photoproduct's, certification and marketing of such products, in order to achieve the large-scale exploitation of polluted lands [1]. Therefore, land leveling which is one of the heaviest and costly operations among agricultural practices that need substantial amounts of energy, got into limelight [2].

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Finding the relationship between energy consumption and land leveling parameters is necessary for prediction and optimization of the amount of energy needed in a particular land and achieving sustainable agriculture and also for reducing the ensuing pollutions. The best choice is finding an ideal and optimum way through which all pros and cons can be considered so it will be easier to compromise. In the following some of the highlighted results reported by researchers will be presented. It is anticipated that environmental conservation and market globalization will be dependent on food security in the future [3]. Even if developing and improving strategies continue and led to some worthwhile effects, there would be some undesirable effects remaining [4].

Furthermore, Environmental Impact Assessment (EIA) involves the investigation and estimation of scheduled events with a view to ensuring environmentally sound and sustainable agriculture [5]. Considering individual, social, financial and agronomic aspects of environmental conservation will improve farmers' awareness of benefits ant their willingness of using laser land levelling for water and soil management [6]. In order to forecast the oven-dried bulk density from soil samples, a stepwise multiple regression process was established [7]. The fuzzy logic method was first developed to explain the human thinking and decision system by Zadeh [8]. Several studies have been carried out using fuzzy logic in agriculture. Recently, adaptive Neuro fuzzy inference system (ANFIS), which is a combination of the ANN and fuzzy logic methods, has been used for many applications such as, database management, system design and planning/forecasting of the mechanization [9,10,11].

ANFIS is one of hybrid Neuro-Fuzzy Inference expert systems and it works in Takagi-Sugeno-type Fuzzy Inference System, which was developed by Jang [12]. This method has a similar structure to a Multilayer Feed Forward Neural Network but the links in an ANFIS only indicate the flow direction of signals between nodes and no weights is associated with the links. Through fuzzy language instructions, when ANNs is created in form of trained connections and weights, an Adaptive Network-based Fuzzy Inference System (ANFIS) will be developed and it will connect the input and output data [13].

It is broadly believed that an ANFIS model is livelier than an ANN model [14]. Reviewing the literature shows that there are several studies in profitability of application of ANN and ANFIS models in agricultural activities.The goal of this method is to find a model or a mapping that correctly associates the inputs (descriptors) with the target (activity). It simulates an optimization problem by analogizing variables to colony and imperial countries. Moumenis *et al*., [15] used ANNs and ANFIS for calculation of subsurface water level in paddy fields of plain areas [15]. ICA is obtainable through Atashpaz-Gargari and Lucas in [16] and is based on socio-political evolution process [17]. The algorithm has several advantages in resolving engineering optimization complications such as data clustering [18], Nash balance point attainment [19], ANN training [20], composite constructions [21], production administration complications [22], optimization complications [23].

Since, land leveling with machines requires considerable amount of energy, optimizing energy consumption in land leveling operation is of a great importance. So, three approaches comprising: ABC-ANN, ANFIS as powerful and intensive methods and regression as a fast and simplex model have been tested and surveyed to predict the environmental indicators for land leveling and determine the best method. Hitherto, only a limited number of studies associated with energy consumption in land leveling have been done. In mentioned studies energy was a function of the volume of excavation (cut/fill volume). Therefore, in this research, energy and cost of land leveling are functions of all the properties of the land including slope, coefficient of swelling, density of the soil, soil moisture, special weight and swelling index which will be thoroughly mentioned and discussed. In fact, predicting minimum cost of land leveling for field irrigation according to the field properties is the main goal of this research which is in direct relation with environment and weather pollution.

MATERIALS AND METHODS

Case Study Region: In order to verify the accuracy and feasibility of the proposed linear programming model, a case study was specified based on the proposed land leveling project in the district of Karaj, Iran. The study farm was a 70 ha area and it was located in the west of Iran, between 31° 28' 42" north latitude and 48° 53' 29" east longitude. Topography of the farm was done at a scale of 1:500. The outputs of the plan were length, width and height of points (coordinates of x, y and z). The grid size in the region was 20 m* 20 m and samples were collected from two plantation sites at two different depths including surface soil (0-10 cm) and subsurface soil (10-30 cm). A total of 90 samples (30 from each plantation site and 15 from each soil depth) were collected from 3 land areas. Then every five samples were mixed together to prepare one sample. In this way a total of 90 samples were reduced to 18 composite soil samples for convenient laboratory analyses. In the laboratory, collected moist soil samples were firstly sieved through 10 mm mesh sieve to remove gravel, small stones and coarse roots and then passed through a 2 mm sieve. Then the sieved samples were dried under room temperature and moisture content of soil samples was determined. At this time, soil texture, soil bulk density and soil optimum density were determined.

Land Leveling on Irrigation Farms and Related Method: In surface irrigation, such as basin border and furrow irrigation he fields slope must be considered. Preparing the irrigation plot in a way that is caused uniform distribution of irrigation water on the field necessitate ensuring the optimal slope for water movement across a field during irrigation. The design slope for graded irrigation methods should be equal to or less than the maximum recommended irrigation grade for the particular soil. The maximum slope recommended for irrigation methods is as follow:

Borders for non-sod-forming crops, such as alfalfa or grain is 2%, borders for erosion-resistant grass or grass-legume crops or for non-sod-forming crops on sites where water application by the border method is not required until after good crop stands have been established is 4%. This is 3% for furrows and 8% for Corrugations in case where potential of rainfall erosion is great. Finally, the slope of furrows is 0.5%, for borders with sod-forming grasses is 2% and for other crops is 0.5%on slopes in the direction of irrigation of more than 0.5 percent [24].

Multiple Linear Regressions: Regression analysis is a very useful statistical approach to find relationships between inputs and outputs. Most of regression models contain more than one regression variable which are called multiple regression models [25]. A multiple linear regression model can be formulated as follows:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k + \varepsilon \quad (1)$$

Where: Y denotes the dependent variable, k presents the number of independent variables, xj denotes the independent variable for j= 0,1,., k; j presents the regression coefficient for j=0,1,., k; and ? is the error term. For developing the regression model, inputs were cut soil, specific gravity, density, moisture content, slope, soil type and inflation rates; while, the outputs were fuel energy, labor, energy, energy, machinery cost, total energy. So, in this form, the multiple regression analysis is used to model the functional relationships between input variables and output variables.

Adaptive Neural Fuzzy Inference System (ANFIS): ANFIS is a suitable and well known technique for modelling complex systems which confront with uncertainty [26,27]. By using hybrid learning methodology, it gives the mapping relation between the input and output data and specifies the best distribution of membership functions [28]. By combining the ANN and fuzzy logic, ANFIS has many advantages of fuzziness [29]. Combination of these two techniques makes the ANFIS modeling to be more systematic and also to be less dependent to expert knowledge [26,27]. The ANFIS technique developed by Jang [30] is the implementation of a fuzzy inference system to adaptive networks for developing fuzzy rules with proper membership functions to have required inputs and outputs. As such, ANFIS relies on the fuzzy If-Then rule statements, as the main problem in formulating fuzzy systems, to develop an effective tool, which uses ANN learning ability for automatically creating such fuzzy statements and optimizing the parameters. In fact, the ANFIS model is a neural-fuzzy approach. For the sake of simplification, one can assume that the inference system has two inputs, (soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, sand percent and soil swelling index) and Y and an output,(labor, energy (LE), fuel energy (FE), total machinery cost (TMC) and total machinery energy (TME)). For a first-order takagi-sugeno fuzzy model, a set of basic rules can be founded upon two rules, if the fuzzy system shows the following:

$$??_1 = ??_1?? + ??_1?? + ??_1 \ldots\ldots \quad (2)$$

$$??_2 = ??_2?? + ??_2?? + ??_2 \ldots\ldots \quad (3)$$

Rule 1: if X is equal to A_1 and Y is equal to B_1, then $??_1 = ??_1?? + ??_1?? + ??_1$

Rule 2: if X is equal to A_2 and Y is equal to B_2, then $??_2 = ??_2?? + ??_2?? + ??_2$

Were pi, Qi and RI (I=1, 2) are the linear parameters in the consequent part of the first-order Takagi-Sugeno fuzzy model.The tagaki-sugeno type fuzzy inference system (T-S FIS) is generally the heart of an ANFIS model. Sequential mapping procedure of ANFIS as a multilayer feed-forward network, with 2 inputs, is shown in (Fig. 1). Basic first order ANFIS architecture consists of 5 layers. For simplicity, the ANFIS with two

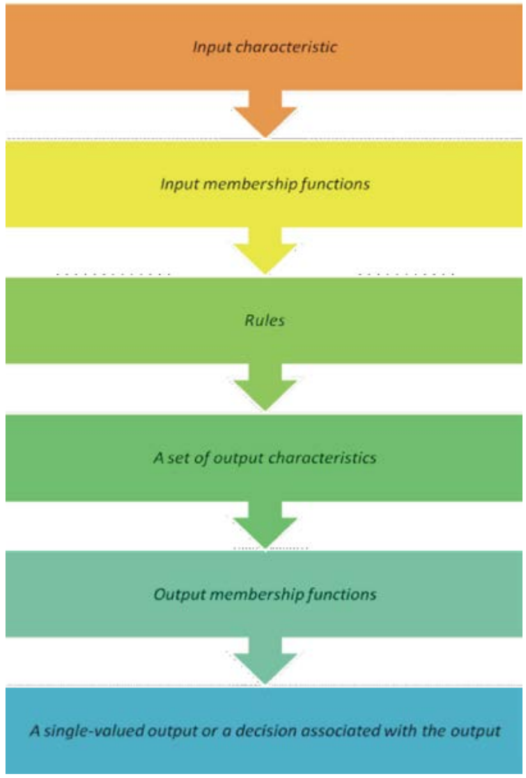

Fig. 1: ANFIS mapping procedure.

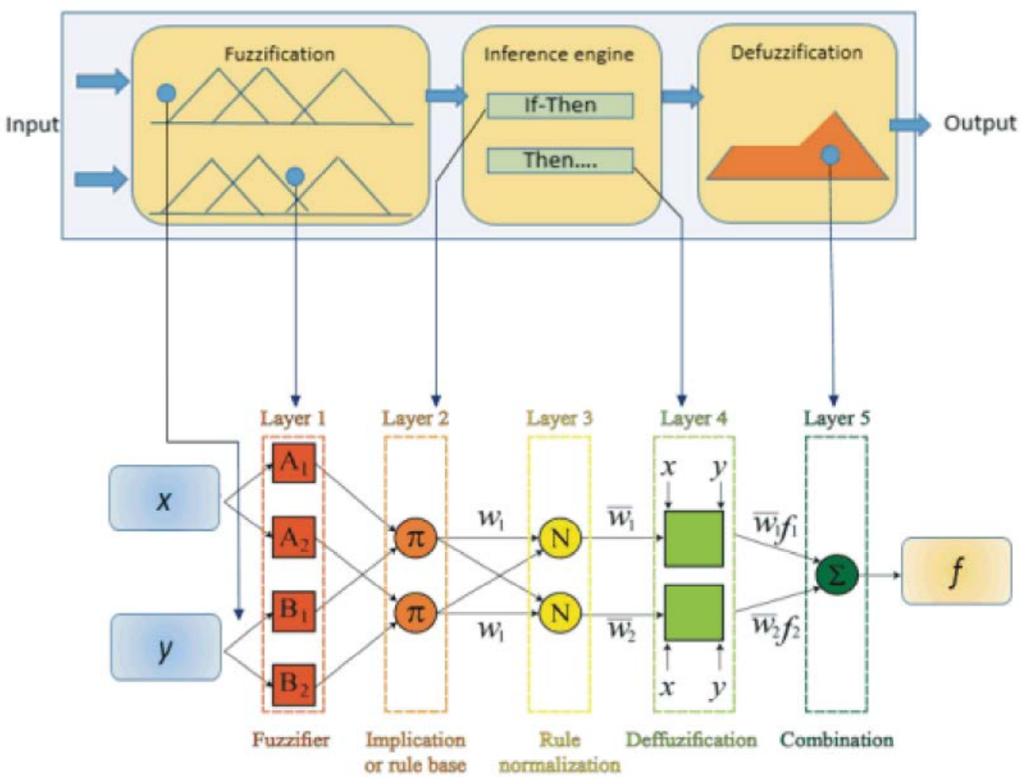

Fig. 2: ANFIS model structure.

Table 1: ANFIS parameters.

ANFIS parameter	Value/type
Generation FIS type	genfis3
Number of input variables	7
Type of MF	gbell
Number of clusters	15
Epoch	100
Error goal	0
Train percentage	80%

inputs x and y and one output f is illustrated in (Fig. 2). First layer (Input nodes): each layer of this node produces membership values belonging to each of the fuzzy sets via membership function:

$??_{1,i}$ = $??_{??}$???????? = 1, 2…….. (4)

Where x and y are non-fuzzy inputs related to me, AI and Bi (small, large, etc.) as linguistic labels which are respectively identified through ?????? and ?????? appropriate membership functions. At this stage, Gaussian falsification and bell-shaped functions are usually used. The parameters of these member functions, which are recognized as primary parameters (Table 1), should be first identified. Second layer (rule nodes): in the second layer, the operator "AND" is used to find the output (firing strength) which represents the antecedent of the rule. Firing strength is used to describe the degree to which the antecedent satisfies a fuzzy rule, shaping the output function of the same rule. As a result, $O_{2,k}$ outputs of this layer, are the results of the multiplication of the degrees related to the first layer. Third layer (average nodes): the main purpose in the third layer is to determine the ratio of me-the rule firing strength to the total firing strength. Therefore, ??, the normalized firing strength would be as follows:

$??_{3,i}$ = $??_{??}$ =☻ i=1, 2, 3, 4……… (5)

Fourth layer (consequent nodes): the node function of the fourth layer calculated the distribution of me-the rule in the final output, defining it as the following relation:

$??_{4,i}$ = $??_{??}$$??_{??}$ = $??_{??}$?? + $??_{??}$?? + $??_{??}$ i=1, 2, 3, 4………(6)

Where ???? is the output of I-the node from the previous layer, {pi, Qi, RI} are coefficients of this linear combination as well as the set of parameters of the consequent part of the Takagi-Sugeno fuzzy model.

Fifth layer (output nodes): this single node computes the total output by submitting all of the input signals. As a result, in the layer of the defuzzification process, the fuzzy results are converted into non fuzzy formats.

☻………. (7)

This network is trained based on learning under supervision. Thus, the focus of this study is on training, adaptive networks capable of estimating unknown functions resulted from training information and finding accurate values for the above parameters.

Performance Evaluation: To evaluate the performance of developed regression and ANFIS models, various criteria were calculated. Root mean square error (RMSE) which is a well-known standard error is often used as a criterion to compare error aspects in various models. Another criterion is coefficient of determination (R^2) which is a method to calculate a standard error in estimating methods that shows the normal difference of real data from the estimated data. The expressions for these statistical measures are given below:

☻……. (8)

☻……… (9)

Where:
N: The number of test observation
☻: The value of the variable being modeled (observed data)
☻: The value of variable modeled by the model (predicted)
☻: The mean value of the variable
o: observed value;
p: predicted or estimated values

RESULTS

Results of Regression

Mathematical Model: A total of 431 tests with three replications were performed for finding appropriate models of LE, FE, TMC and TME. A set of different polynomial models was analyzed by using design expert software. In order to optimize and reduce the number of candidate regressors, a stepwise regression algorithm, as a most widely used variable selection technique [31] was then applied.

Table 2: Analysis of variance (ANOVA) for labor energy (LE), fuel energy (FE), total machinery cost (TMC) and total machinery energy (TME) models.

Model	Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F
LE Model	Model	1.24^{11}	3	4.15^{10}	5523.914	< 0.0001
	Slope	1.85^{9}	1	1.85^{9}	246.7733	< 0.0001
	Cut-Fill Volume (V)	1.21^{11}	1	1.21^{11}	16149.7	< 0.0001
	Soil Swelling Index (SSI)	2.61^{8}	1	2.61^{8}	34.70285	< 0.0001
FE Model	Model	1.84^{13}	3	6.15^{12}	4632.446458	< 0.0001
	Slope	3.43^{11}	1	3.43^{11}	258.640572	< 0.0001
	V	1.78^{13}	1	1.78^{13}	13457.37208	< 0.0001
	% Sand	3.28^{10}	1	3.28^{10}	24.73922519	< 0.0001
TMC Model	Model	1.16^{19}	3	3.88^{18}	4751.319	< 0.0001
	Slope	1.8^{17}	1	1.8^{17}	220.2573	< 0.0001
	V	1.13^{19}	1	1.13^{19}	13881.29	< 0.0001
	SSI	2.21^{16}	1	2.21^{16}	27.00684	< 0.0001
TME Model	Model	6.64^{16}	3	2.21^{16}	5653.467	< 0.0001
	Slope	9.6^{14}	1	9.6^{14}	245.4494	< 0.0001
	V	6.47^{16}	1	6.47^{16}	16537.35	< 0.0001
	SSI	1.44^{14}	1	1.44^{14}	36.87527	< 0.0001

Labor Energy: ANOVA table was carried out using design expert software to determine the level of significance effects of the moisture content, soil cut/fill volume, soil compressibility factor, specific gravity, slope, sand percent and soil swelling index on LE (Table 2). The results showed that significant effects of the moisture content, soil, cut/fill volume, soil compressibility factor, specific gravity, slope, sand percent and soil swelling index of LE at a probability value (< 0.0001). Soil compressibility factor, specific gravity, moisture content and sand percent, had no significant effect on LE. Moreover the ANOVA table revealed a significant effect between interactions of these parameters at various probability value (lower than 0.05). (Fig. 3a) illustrates the effects of studied parameters and their interactions on LE.By increasing cut soil volume, time of used machinery increases and consequently it increases fuel energy. Moreover, increasing the time of machinery using increases the labor requirement for operation. So, energy consumption by labor increases. On the other hand by decreasing the cut soil volume, human labor requirement also decreases. Another important parameter is slope. As presented in (Fig. 3a), by increasing the slope in land leveling operation, labor requirement also increases. This can be interpreted by increasing the time of machinery application in this operation. Also, (Fig. 3a) reveals that increasing soil swelling index (SSI) also increases labor energy. This means that, by increasing soil swelling index (SSI), more machinery is required for land leveling and consequently labor energy requirement also increases. Another reason is that increasing of plowing depth would cause an increase of soil tear, bulk and mass, so that more power is needed to cut the soil. Increasing the soil mass gathered around the moldboard causes the lateral pressure on the soil, consequently the friction between runner and furrow surface increases.

Fuel Energy (FE): ANOVA Table was carried out using design expert software to determine significance effects of moisture content, soil cut/fill volume, soil compressibility factor, specific gravity, slope, sand percent and soil swelling index on FE. All model-F values are presented in (Table 2) indicated a great significance (á<0.0001) for all developed regression models in rejecting the null hypothesis. All models have significant p-value. (Fig.3b) illustrates the perturbation plot of parameters affecting on FE of the seven parameters of soil and land characteristics (moisture, density, soil compressibility factor, land slope, soil type and embankment volume), three factors of slope, cut-fill volume (V) and sand percent have the most significant effect on FE in land leveling.

Total Machinery Cost (TMC) and Total Machinery Energy (TME): (Table 2) shows the results of ANOVA related to the effects of soil moisture content, soil cut/fill volume, soil compressibility factor, specific gravity, slope, sand percent and soil swelling index on TMC and TME. Results showed that the parameters had a significant effect except soil compressibility factor, specific gravity, moisture content and sand percent. Also, interaction of soil, cut/fill volume, slope and soil swelling index (SSI) were significant. While interaction between soil

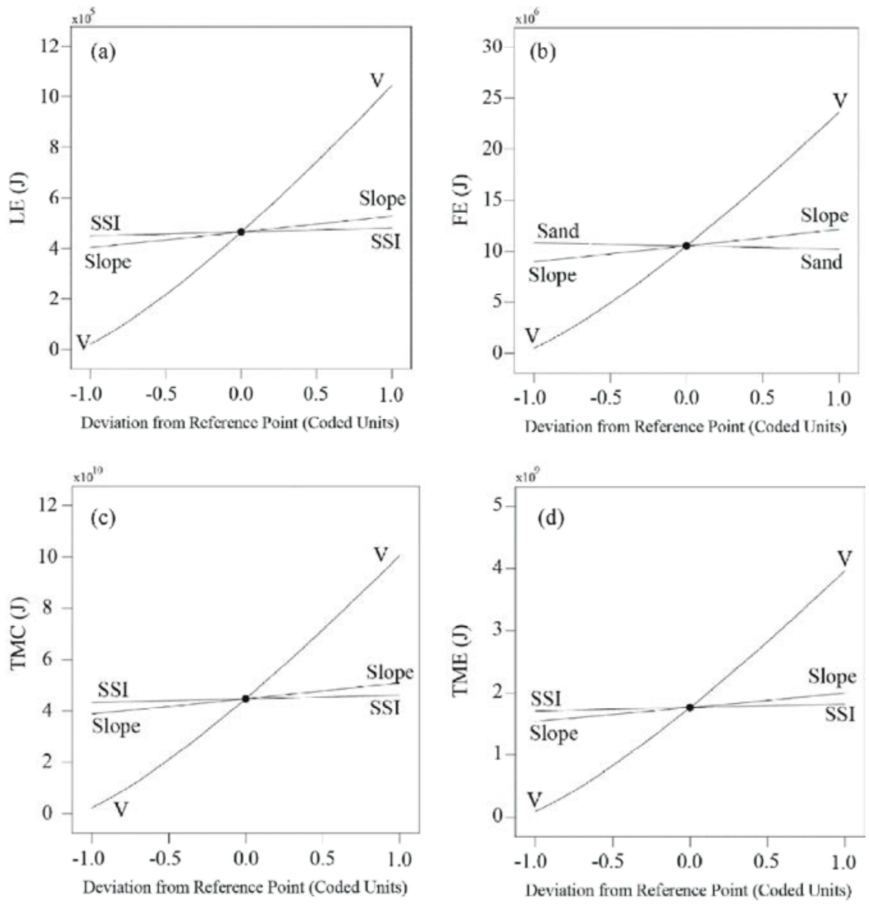

Fig. 3: Trace plot of a) Labor energy, b) Fuel energy, c) Total Machines cost and d) Total machines energy.

compressibility factor, specific gravity, moisture content and sand percent had not significant effect. So that the results show the relationship of land leveling in the energy with the slope of the land, swelling coefficient and soil type is signed. By increasing land slope, volume of excavation and embankment increases and the number of sweep and distance traveled leveling machines also increases and fuel consumption increases. Increase in soil swelling factor, increases the volume of the embankment and increase in volume of the embankment also increases the demand for fuel and energy. Heavy clay soils and soil adhesion at wet mode needs more machines and move the car to be faced with a larger resistance leveling and cause more consumption of fuel and energy. The trace plot helps to compare the effect of all the independent variables at a particular point in the design space. A relatively flat line shows insensitivity to change in that particular factor. The response traces plot for the LE, FE, TMC and TME are shown in (Fig. 4a to Fig. 4d). The vertical axis is the predicted values and the horizontal axis is the incremental change made in factors included in the final equation model. Moreover, the scatter plots of actual values of the response of interest vs. predicted values using final models are displayed in (Fig. 5a to 5d). The strong nonlinear effect of cut-fill volume of the all responses of interest is conspicuous (Fig. 4a to Fig. 4d). As appreciated from the (Fig. 5a to 5d), energy and cost increase with increased cut-fill volume as the major effect. All responses of interest are moderately affected by the slope. Additionally, it is perceived that the increase of the slope led to increased energy and cost. The most appropriate power transformation (lambda) for responses is detected by the Box-Cox diagram that results the minimum residual sum of squares in the transformed model (Fig. 4a). Scatter plots of Actual vs. Predicted for regression model (Fig. 5a-d) show the actual predicted response versus the predicted ones. As the predicted values come closer to the actual values, the points on the scatter plot fall closer around the regressed diagonal line.

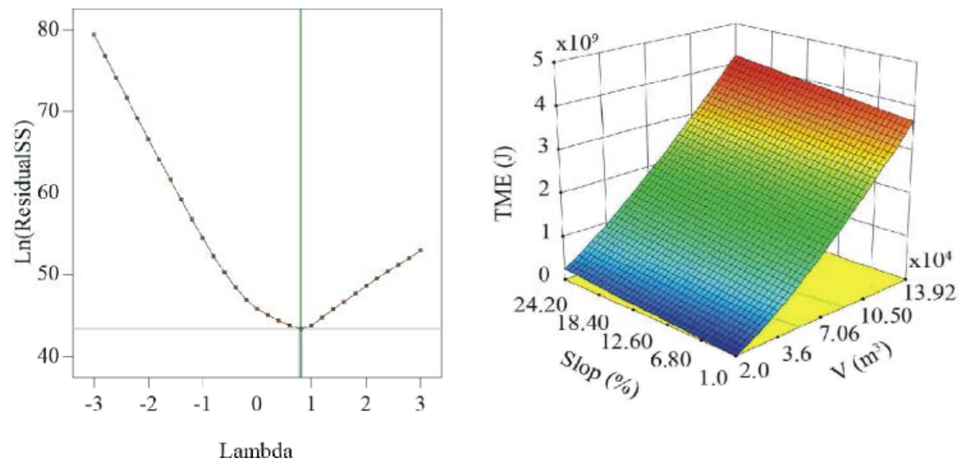

Fig. 4: Box-Cox plot of b) surface plot of Total machines energy versus slop and volume

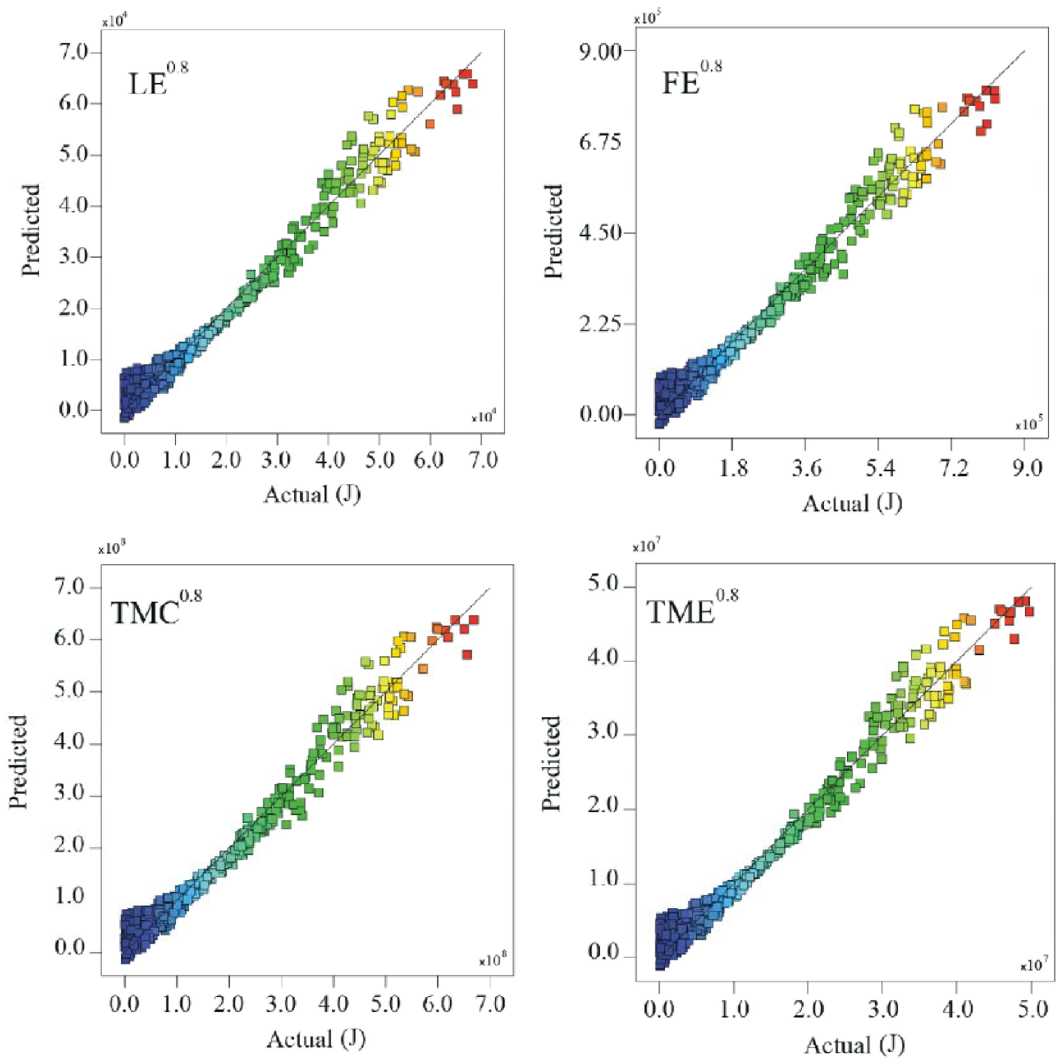

Fig. 5: Scatter plots of Actual vs. Predicted using regression models for a) Labor energy, b) Fuel energy, c) Total Machines cost and d) Total machines energy

Because the points are all very close to the line, you can see that the models predict targets well. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. The fitted nonlinear equations for the all response of interest, including LE, FE, TMC and TME are represented in Eqs.10-13, respectively, in which the coefficients are provided in coded units. The coded equation is more easily interpreted. The coefficients in the actual equation compensate for the differences in the ranges of the factors as well as the differences in the Effects. For final LE, TMC and TME models only three variables, including slope, cut-fill volume (V) and soil swelling index (SSI) have significant effects. Although, in FE model the effect of Soil Swelling Index (SSI) is not significant and has been replaced by the percentage of soil Sand. Energy consumption in land leveling (labor, energy) is a nonlinear function of the soil compressibility factor and slope (Equation 10). Energy consumption in land leveling (fuel energy) is a nonlinear function of the soil compressibility factor and slope (Equation 11). Energy consumption in land leveling (Total Machinery Cost) is a nonlinear function of the soil compressibility factor and slope (Equation 12). Energy consumption in land leveling (total machinery energy) is a nonlinear function of the soil compressibility factor and slope (Equation 13). The value of each coefficient variable in the equation represents the effect of the variable in the function.

$$(LE)^{0.8} = 34161.36 + 3639.90*Slope + 31173.94*V+911.96 * SSI \quad (10)$$

$$(FE)^{0.8} = 4.148^{5}+ 49590.44 * Slope + 3.782^{5}* V -10008.33 * Sand \quad (11)$$

$$(TMC)^{0.8}= 3.319^{8}+ 3.587^{7}* Slope + 3.015^{8}* V+ 8.393^{6}* SSI \quad (12)$$

$$(TME)^{0.8}= 2.494^{7}+2.621^{6}* Slope +2.277^{7} * V+6.787^{5}* SSI \quad (13)$$

Results of ANFIS: In this section the results of ANFIS models for prediction of LE, FE, TMC and TME are presented. A code was written in MATLAB programming language for the ANFIS model simulations. Different ANFIS structures were tried using the code and the appropriate representations were determined.

Labor Energy (LE): Table 3 demonstrated the statistical indicators (RMSE and R^2) for two types of learning methods (Hybrid and back propagation). The results revealed that both methods used in this study had a satisfactory. The results revealed that both methods used in this study had a satisfactory performance for labor energy. But back propagation had better performance. Average R^2 value in the FIS model for prediction of Labor energy was found to be 0.9948 and 0.9944 in Mamdani and Sugeno models, respectively. While in back propagation model it was calculated as 0.9921 and 0.9921, respectively. Fig. 7 shows the mapping between experimental and simulated values by ANFIS in the case of 86 testing data points. There is satisfactory mapping which approves the promising applicability of ANFIS model for the labor energy. Moreover, Fig. 6 shows the predicted values by ANFIS versus experimental values. Close scattering around unity slope line confirms the satisfactory performance of developmental models. The obtained results are better than the other studies in term of MSE and R^2 like [32] and [33] who used ANN.

Table 3: Calculated statistical criteria for prediction of labor energy using / fuel energy different combination of optimization methods and FIS types.

Optimization method		Fis type	MSE			R^2		
			Min.	Ave.	Max.	Min.	Ave.	Max.
Labor E.	Hybrid	Mamdani	0.0006	0.0013	0.0033	0.986	0.995	0.997
		Sugeno	0.0006	0.0013	0.0033	0.986	0.994	0.997
	Backpropagation	Mamdani	0.0008	0.0010	0.0041	0.983	0.992	0.996
		Sugeno	0.0009	0.0015	0.0041	0.983	0.992	0.996
Fuel E.	Hybrid	Mamdani	0.0012	0.0018	0.0037	0.985	0.993	0.995
		Sugeno	0.0011	0.0017	0.0039	0.984	0.992	0.995
	Backpropagation	Mamdani	0.0012	0.0027	0.0056	0.977	0.989	0.995
		Sugeno	0.0012	0.0027	0.0056	0.977	0.989	0.995

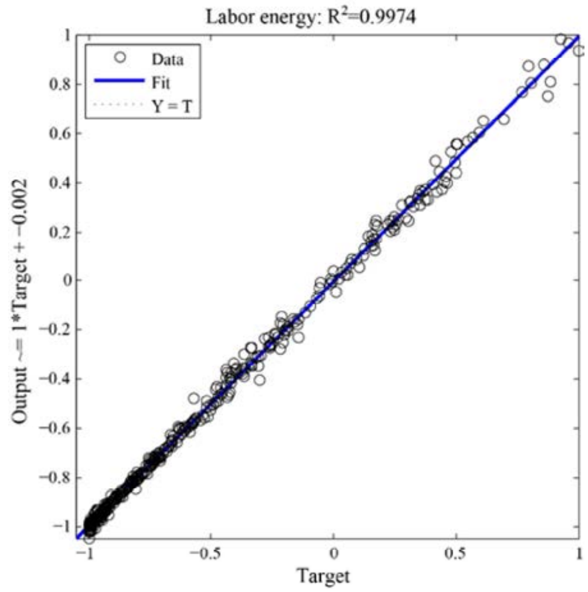

Fig. 6: Scatter plot for the predicted model and actual values of a) Labor energy

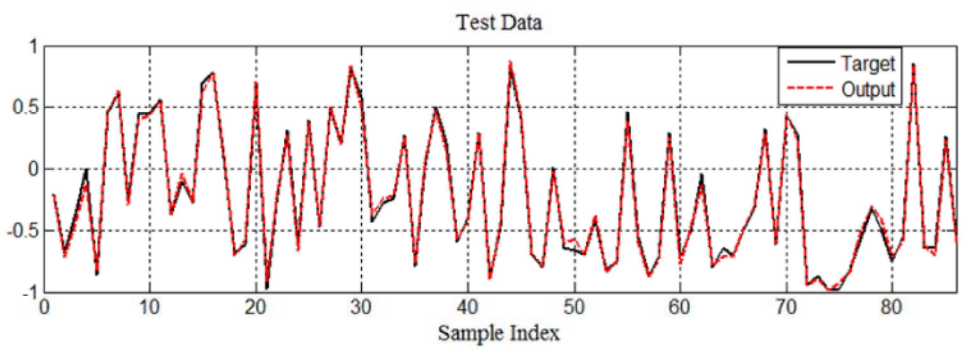

Fig. 7: Mapping between experimental and predicted values by ANFIS algorithm in the case of 86 data points for Labor energy.

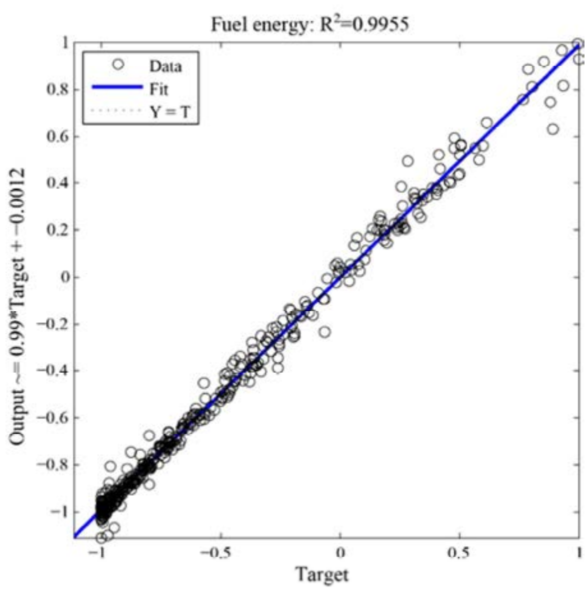

Fig. 8: Scatter plot for the predicted model and actual values of b) Fuel energy

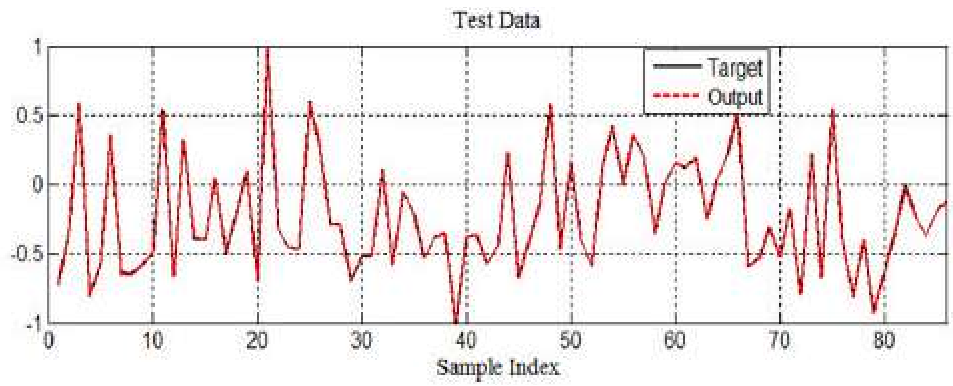

Fig. 9: Mapping between experimental and predicted values by ANFIS algorithm in the case of 85 data points for Fuel energy.

Table 4: Calculated statistical criteria for prediction of total machinery cost /energy using different combination of optimization methods and FIS types.

Optimization method		Fis type	MSE Min.	MSE Ave.	MSE Max.	R^2 Min.	R^2 Ave.	R^2 Max.
Cost	Hybrid	Mamdani	0.0012	0.0019	0.0039	0.984	0.9921	0.995
		Sugeno	0.0012	0.0018	0.0039	0.983	0.9922	0.995
	Backpropagation	Mamdani	0.0014	0.0025	0.0046	0.980	0.9894	0.994
		Sugeno	0.0014	0.0025	0.0046	0.980	0.9895	0.994
Energy	Hybrid	Mamdani	0.0006	0.0012	0.0035	0.986	0.9950	0.997
		Sugeno	0.0006	0.0012	0.0036	0.985	0.9952	0.998
	Backpropagation	Mamdani	0.0006	0.0018	0.0039	0.984	0.9925	0.997
		Sugeno	0.0008	0.0018	0.0039	0.984	0.9926	0.997

Fuel Energy (FE): To select the best model of ANFIS for FE, it was applied with two methods of optimization (Hybrid and back propagation). The optimization methods and statistical criteria (RMSE and R^2) illustrated in (Table 3). A statistical criterion for prediction of fuel energy reveals that FIS model is superior to back propagation model. Average R^2 value in the FIS model for prediction of fuel energy was found to be 0.9927 and 0.9922 in Mamdani and Sugeno models, respectively. While in back propagation model it was calculated as 0.9891 and 0.9892, respectively. Fig. 9 represents the mapping between experimental and predicted values. Furthermore, a robust correlation was established between measured and predicted slippage values which are explained in (Fig. 8). It is clear from Fig. 9 that ANFIS revealed good results; it can be used as an acceptable tool in the prediction of fuel energy under different field conditions.

Total Machinery Cost (TMC): Table 4 illustrates the learning methods and statistical parameters of ANFIS models. As a whole, both approaches demonstrated satisfactory results for prognostication of total machinery cost. A statistical criterion for the prediction of total machinery cost reveals that FIS model is superior to back propagation model. Average R^2 value in the FIS model for the prediction of total machinery cost was found to be 0.9921 and 0.9922 in Mamdani and Sugeno models, respectively. While in back propagation model it was calculated as 0.9894 and 0.9895, respectively. Fig. 11 represents the mapping between experimental and predicted values. Furthermore, a robust correlation was established between calculation and predicted Total machinery cost a value which is explained in (Fig. 10). It is clear from Fig. 11 that ANFIS revealed good results; it can be used as an acceptable tool in the prediction of total machinery cost under different field conditions.

Total Machinery Energy (TME): As presented in Table 4, statistical criteria for the prediction of total machinery, energy reveals that FIS model is superior to back propagation model. Average R^2 value in the FIS model for the prediction of total machinery, energy was found to be 0.9950 and 0.9952 in Mamdani and Sugeno models,

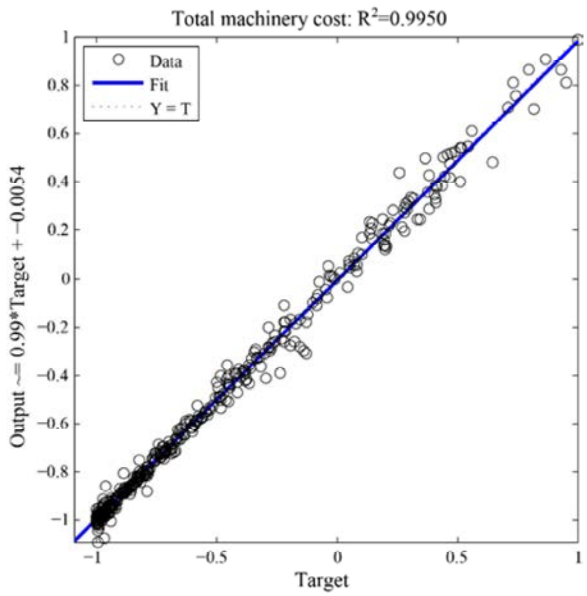

Fig. 10: Scatter plot for the predicted model and actual values of b) total machinery cost.

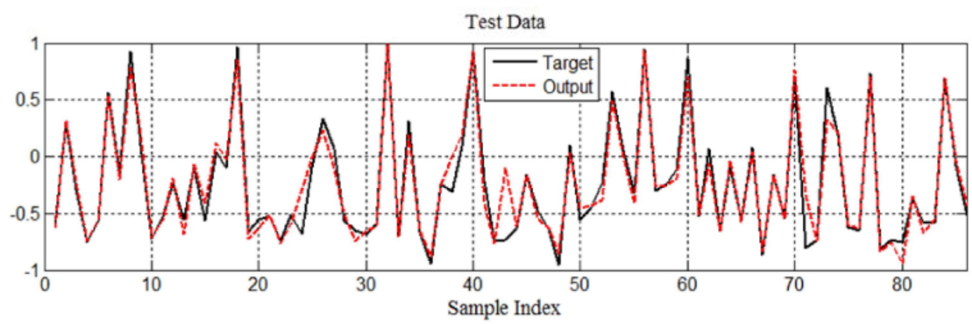

Fig. 11: Mapping between experimental and predicted values by ANFIS algorithm in the case of 85 data points for total machinery cost.

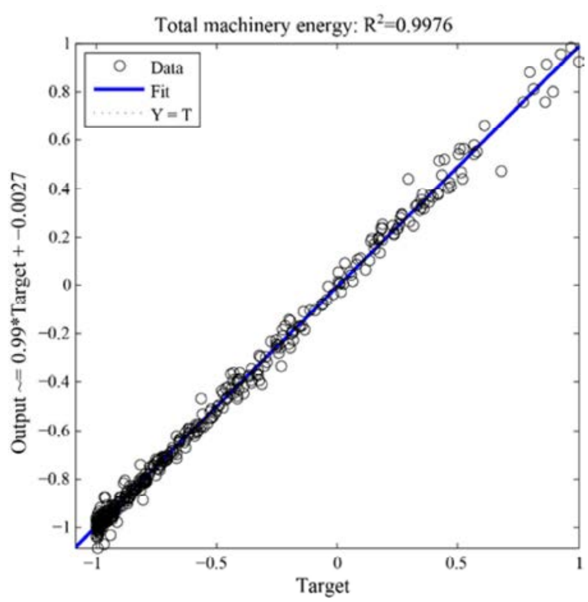

Fig. 12: Scatter plot for the predicted model and actual values of b) total machinery.

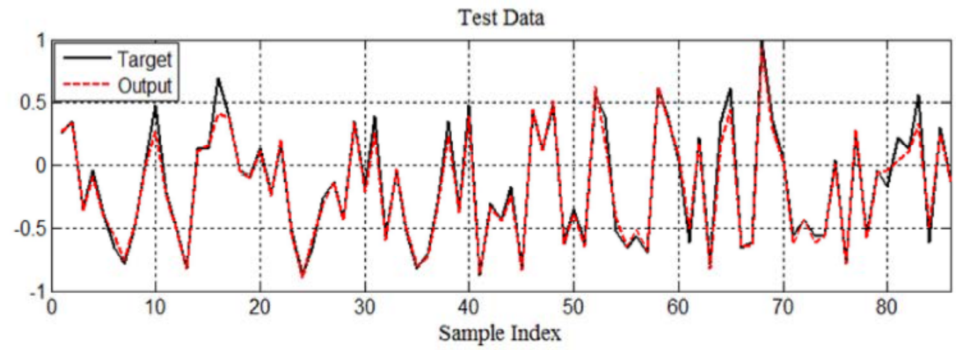

Fig. 13: Mapping between experimental and predicted values by ANFIS algorithm in the case of 86 data points for Total Machinery Energy.

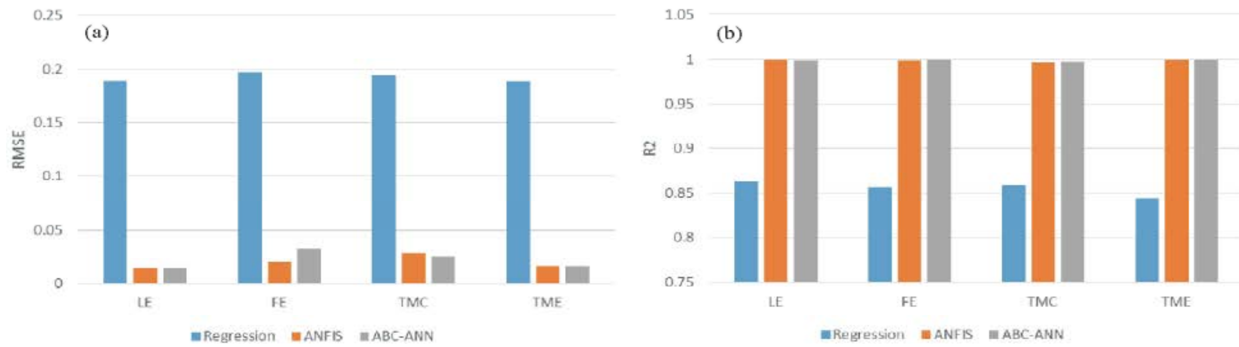

Fig. 14: RMSE (a) and R^2 (b) of four prediction algorithms.

Table 5: Comparison of sensitivity analysis and ANN and ICA-ANN models.

	Regression		ANFIS		ABC-ANN	
Responce	RMSE	R^2	RMSE	R^2	RMSE	R^2
LE	0.1899	0.8631	0.0143	0.9990	0.0146	0.9983
FE	0.1971	0.8562	0.0206	0.9983	0.0322	0.9987
TMC	0.1946	0.8581	0.0287	0.9966	0.0248	0.9972
TME	0.1892	0.8437	0.0157	0.9990	0.0161	0.9994

respectively. While in back propagation model it was calculated as 0.9925 and 0.9926, respectively. The measured and ANFIS forecasted total machinery, energy for back propagation is shown in Fig. 13. Fig. 12 Presents the regression analysis of rolling resistance (with R=0.9976) calculated from the ANFIS model. The data points occur around a 1:1 line and it is evident that the selected ANFIS model has an acceptable estimation power. The selected ANFIS model performs very well compared to fuel energy, labor energy, total machinery cost

Results of ABC-ANN: Table 5 shows the RMSE and R^2 of three applied methods. As it is shown in this table, regression is the least ability in energy production compared to the two other methods because of the highest RMSE and the least R^2. The other methods have more ability to predict the environmental, energy parameters in which ABC-ANN has the most capability in prediction according to least RMSE and the highest R^2 for TMC, FE and TME. For LE the appropriate algorithms which are almost better compared to others, are ANFIS, respectively. As it is shown in (Fig. 14), among three applied methods to predict (LE), (FE), (TMC) and (TME) according to three selected input parameters (soil cut/fill volume, specific gravity and soil compressibility factor) the mean square error (RMSE) of (LE) and (TME) are less than (FE) and (TMC). In fact, using adaptive neuro-fuzzy inference system (ANFIS) based prediction methods regression and ABC-ANN have a more accurate prediction for (LE) and (TME) in comparison to (FE) and (TMC). On the other hand, as it is shown in (Fig.14b) correlation coefficient (R^2) of (LE) and (TME) is more than (LE) and (TME). According to the comparison of the correlation coefficient (R^2) for three methods, it is revealed that among these methods, ABC-ANN has the maximum (R^2) value in (TME), (FE) and (TMC).Also it is revealed that among these methods, ANFIS has the maximum (R^2) value in LE. Fig.14a shows the RMSE value of all methods. As it is shown in this diagram, the regression algorithm has the maximum RMSE value between all methods. It must be considered that the smaller R^2 value and on the other hand the bigger RMSE value the worst result will be expected for the output prediction. The results show that although the output values are acceptable by applying these three methods but, It is noted that as the neural networks were run 1000 times, regression has definitely the least prediction capability in LE, FE, TMC and TME. Although the ABC-ANN has good prediction in (TME), (FE) and (TMC) but ANFIS is also a good predicting method between mentioned methods regarding that this method has the least predicting capability for (LE). Table 5 illustrates the best results obtained from regression, ABC-ANN models and ANFIS models for studying parameters in this research with statistical criteria (RMSE and R^2). Artificial intelligent models ABC-ANN and ANFIS outperformed regression model for predicting energy consumption LE, FE, TMC and TME. Hence, similarly, the best model for prognostication of LE is ANFIS model with small difference from (ABC-ANN) model. RMSE and R^2 were 0.0143 and 0.9990, respectively. ABC- ANN technique produced a best model for predicting FE, TMC and TME. While these parameters for multivariate ABC-ANN model was for FE, with RMSE of 0.0322 and R^2 of 0.9987. While these parameters for multivariate ABC-ANN model here, for TMC, with RMSE of 0.0248 and R^2 of 0.9972. On the other hand these parameters for multivariate ABC-ANN model were, for TME, with RMSE of 0.0161 and R^2 of 0.9994.

DISCUSSIONS

Analysis of the Effects of Parameters on Energy Consumption in Land Leveling: Soil cut-fill volume, slope of land and specific soil gravity had effect on energy consumption of land leveling but, on the other hand moisture content, swelling index, soil compressibility factor and type of soil showed low effect on cost and energy consumption. Whatever slope of the farm becomes greater, machine work hours for clearing specific surface is increasing and subsequently much fuel will be consumed. By increasing soil cut/fill volume, work hours of machine and a number of laborers are being increased and again much fuel is necessary. Whatever swelling factor of the ground becomes greater, volume of the soil is getting greater too and work hours of machine for clearing specific surface is becoming increasing and subsequently much fuel will be consumed. Soil moisture content, soil type, soil compressibility factor and specific gravity in fine-textured soils like clays with high organic materials leads to resistance against machine movement, increase machine work hour, labor work and fuel consumption. On the other hand soft structure of soil, gross form of it, low organic materials caused no effect on energy consumption. In course-texture soils like sand these parameters in energy consumption didn't affect because of low organic materials. Similarly Soil moisture had a little effect on the work hours of machine and also fuel and energy showed slight increase too. Perhaps this is because of the sandy and loamy soils that have been tested for this research. These results are in agreement with the findings of other researchers [34,35,36]. Also the obtained results demonstrated that the interaction between cut-fill volume (V) and slope had the biggest effect on LE from the rest of the parameters.

Regression result for RMSE of all epochs is shown in Table 5. The results are in agreement with result of Aboukarima [37]. He developed Regression model to predict drawbar pull of chisel plow using forward speed, plowing depth, nominal Soil Swelling Index, cut-fill Volume, soil texture index, slope, initial soil moisture content and initial soil specific weight as independent variables. He reported the R^2 value of the developed model was more than 0.87. Slippage increased by 100% when tillage depth increased from 10 to 20 cm. Increase of tillage depth brings out increase of fuel consumption. Increase of drawbar pull increases gross traction which leads to increment of displacement of soil. Similar results have been reported by researchers which confirm the results of the present study [38]. Furthermore, the results demonstrated that slippage increased by 96% by rising of forward speed from 0.39 to 1.56 m/s.

Nikoo *et al*. [39] used ICA-ANN to predict the flood-routing problem. The results were proved that using this technique on flood-routing problem is a valid approach, which is not only simple but also reliable [39]. In another study, [40] applied ICA- ANN for prediction of flyrock induced by blasting and parameters of 113 blasting operations were accurately recorded. The results were clearly illustrated the superiority of the proposed ICA-ANN model in comparison with the proposed BP-ANN model and empirical approaches [40]. Although there were some research which applied the ABC-ANN, but their fields of study was not about energy of machine and labor and together with environmental pollution. As it was revealed in results, this method showed the most capability in prediction according to least RMSE and the highest R^2 for TMC, FE and TME.

ANFIS with a hybrid method of the gradient descent and the least-squares method was applied to find the optimal learning parameters using various membership functions (MFs).The implementations divulged that Gaussian membership function (gaussmf) and Trapezoidal membership function (tramf) configurations were found to denote MSE of 0.0166 and R^2 of 0.98 for traction coefficient while MSE equal to 1.5676 and R^2 equal to 0.97 for the tractive power efficiency were obtained. The ANFIS with different MFs was used to model the drawbar pull energy as affected by the tire parameters of velocity at three levels of 0.8, 1 and 1.2 m/s, wheel load at three levels of 2, 3 and 4 kN and slip at three levels of 8, 12 and 15% indicating that drawbar pull energy is a direct function of wheel load, velocity and slippage. Hence, the greatest value of 1.056 kJ corresponded to the wheel load of kN, slip of 15% and velocity of 1.2 m/s [41]. Fig. 6 shows the predicted values by ANFIS versus experimental values. Close scattering around unity slope line confirms the satisfactory performance of developed model. The obtained results are better than the other studies in term of RMSE and R^2 like [32] and [33] who used ANN. The selected ANFIS model performs very well compared to measured machinery energy. Comparison between these study andother similar researchers reveals that the obtained model in terms of statistical criteria is more accurate. For example, the RMSE and R^2 values for the best ANFIS model (Table 5) are better than those obtained by [42] who used ANN.

The results also revealed that Machinery power increased by 4% by increasing moisture content from 6 to 23%. Also, by increasing soil moisture content, drawbar pull considerably increased. These results are in agreement with the findings of other researchers [34,35,36]. The results demonstrated a linear relationship between TFC with depth of tillage and engine speed. TFC increased by increased by 44% when the depth of cut-fill increased from 10 to 20 cm, while increasing the engine speed from 1200 to 2000 rpm increased fuel consumption by 56%. In other hands, the greatest TFC was reached at a depth of 20 cm and engine speed 2000 rpm. The findings were in agreement with other researches [43].

CONCLUSIONS

In this research, a holistic approach was proposed to find the correlation between energy and cost of land leveling that are dependent on other properties of the land including the slope, coefficient of swelling, soil density, soil moisture. For uniform distribution of water on field irrigation it is necessary to ensure the optimal slope for water movement across a field. The designed slope for graded irrigation methods should be equal to or less than the maximum recommended irrigation grade of the particular soil to model and predict the environmental indicators for land leveling and to analysis the sensitivity of these parameters under various field conditions. Finally, to perform a comparison among ANFIS, regression and integrating artificial neural network and artificial bee colony algorithm (ABC-ANN), to choose the optimum and most suitable model. Field data were used to elicit an accurate model for LE, FE, TMC and TME. Using artificial intelligence techniques ANFIS, Regression and ABC-ANN Have shown acceptable performance with statistical criteria (MSE and R^2) for predicting all parameters studied in this work. The results showed that using regression method for final LE, TMC and TME models only three variables including of slope, cut-fill volume (V) and soil swelling index (SSI) had significant effects on environmental indicators. Although in FE model the effect of soil swelling index (SSI) is not significant and has been replaced by percentage of soil sand. The results showed that using adaptive neural-fuzzy inference system for prediction of labor, fuel, energy, total machinery cost and total machinery energy can be successfully demonstrated. The results revealed that using adaptive neural-fuzzy inference system for prediction of labor, energy, fuel, energy, total machinery cost and total machinery energy can be demonstrated successfully. The ANFIS models with hybrid optimization method and Sugeno FIS type shows better performance than the back propagation and Mamdani ones. ANFIS model has the most capability in prediction according to least RMSE and the highest R^2 for LE. The other methods have more ability to predict the environmental and energy parameters in which ABC-ANN has the most capability in prediction according to least RMSE and the highest R^2 for TMC, FE and TME which these mentioned appropriate algorithms can be used for energy consumption prediction in land leveling. Using ABC-ANN and ANFIS will lead to an economical land leveling operations in farm lands. Furthermore, implementing these techniques on heavy operations such as land leveling will help in protecting the environment which in turn increases the life quality. These implications are consistent with the findings and conclusions of this study.

Symbols Used:

FE: Fuel energy
LE: Labour Energy
TMC: Total Machinery Cost
TME: Total Machinery Energy
ABC-ANN: Integrating Artificial Neural Network and; artificial bee colony algorithm.
ANN:Artificial Neural Network
MAE:Mean absolute error
ME: mean Error
MSE: mean square error
R^2: correlation coefficient
RMSE: Root mean square error

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