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RESEARCH ARTICLE

Prediction of environmental indicators in land leveling using artificial intelligence techniques

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Abstract

Background Land leveling is one of the most important steps in soil preparation and cultivation. Although land leveling with machines require considerable amount of energy, it delivers a suitable surface slope with minimal deterioration of the soil and damage to plants and other organisms in the soil. Notwithstanding, researchers during recent years have tried to reduce fossil fuel consumption and its deleterious side effects. The aim of this work was to determine best linear model using artificial neural network (ANN), imperialist competitive algorithm and ANN and regression and adaptive neural fuzzy inference system (ANFIS) in order to predict the environmental indicators for land leveling.

Methods New techniques such as; ANN, imperialist competitive algorithm and ANN and sensitivity analysis and regression and ANFIS that will lead to a noticeable improvement in the environment. In this research effects of various soil properties such as embankment volume, soil compressibility factor, specific gravity, moisture content, slope, sand percent, and soil swelling index in energy consumption were investigated. The study was consisted of 90 samples were collected from 3 different regions. The grid size was set 20 m in 20 m (20×20) from a farmland in Karaj province of Iran.

Results According to the results of sensitivity analysis, only three parameters; density, soil compressibility factor and, embankment volume index had significant effect on fuel consumption. In comparison with ANN, all ICA-ANN models had higher accuracy in prediction according to their higher R^2 value and lower RMSE value. Statistical factors of RMSE and R^2 illustrate the superiority of ICA-ANN over other methods by values about 0.02 and 0.99, respectively.

Conclusion Results extracted and statistical analysis was performed and RMSE as well as coefficient of determination, R^2, of the models were determined as a criterion to compare selected models. According to the results, 10–8–3-1, 10–8–2-5-1, 10–5–8-10-1, and 10–6–4-1 MLP network structures were chosen as the best arrangements and were trained using Levenberg-Marquet as NTF. Integrating ANN and imperialist competitive algorithm (ICA-ANN) had better performance in prediction of output parameters in comparison with conventional methods such.

Keywords Artificial neural network · Energy · Environmental research · Imperialist Competitive Algorithm · ANFIS

Introduction

During the last century due to increasing human population, demands for agricultural commodities have been enormously increased. Nowadays, one of the cardinal environmental challenges in the world is energy production and consumption. Despite using modern types of energy such as solar energy, inappropriate use and lack of proper

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management have led to an intensive rise in energy consumption in this field. It also should be taken into account that environmental conservation and market globalization will be dependent on food security in the future agriculture [1]. Regarding this, some special policies should be addressed to consider energy viewpoint in conjunction with the environmental issues to solve the problem. Land levelling is one of the heavy and costly operations among agricultural practices that consumes considerable amount of energy. In addition, moving heavy machines on the ground makes the soil denser, particularly in the wet regions which the moisture content of the soil is high and it makes a situation that is not easily recoverable [2]. On the other hand, land levelling simplifies the irrigation, improves field situations in other practices related to agriculture and regulates the soil surface and normalizes its slope [3]. Reportedly, there are three significant factors which have effect on grain yield including the effects of land levelling, methods of water application and the interaction between land levelling and water applied. Okasha et al. observed a noteworthy connection between slope and diverse irrigation scheme in different seasons [4]. Diverse methods of land levelling can affect the physical and chemical properties of the soil and hence can make differences in plant establishment, root growth, aerial cover and eventually crop yield. As a direct result, one of the most important steps in soil preparation and a key factor in food production that should be optimized is land levelling [5]. Besides, decreasing fossil fuel consumption for land leveling diminishes air contaminants and improves the environmental condition. There is a growing understanding of importance and effects of water and soil management which in turn reveals the significance of optimized laser land levelling from social, financial and agronomic points of view. [6]. Even though some improving strategies have been proposed for the enhancement of operations related to the environment, they have diverse undesirable effects [7]. ANN is a conceptual technique which its output or inferred variable can be modelled in terms of other parameters that are relevant to the same process [8]. This technique has been widely used in engineering field for optimization and prediction. Ahmadi et al. proposed ANNs trained with particle swarm optimization (PSO) and Back-Propagation (BP) algorithm to estimate the equilibrium water dew point of a natural gas stream with a TEG solution at different TEG concentrations and temperatures. They reported that this approach, PSO-ANN, can aid in better understanding of fluid reservoirs' behaviour through simulation scenarios and statistical result were quiet notable [9]. In another research a feed-forward ANN optimized by PSO was used as an artificial intelligence modelling tool to predict asphalting precipitation due natural depletion [10]. They also proposed another network based on feed-forward ANN optimized by hybrid genetic algorithm and practical swarm optimization (HGAPSO) and compared it with conventional BP-ANNs. They reported that results of this approach were better than conventional methods, based on statistical analysis [11, 12]. This techniques have been also used for predicting parameters with reducing uncertainties. In a research, Ahmadi et al. Used artificial intelligence techniques to accurately determination of the amount of Dissolved Calcium Carbonate Concentration in oil field brines with minimum uncertainty [13]. In another study, Multi-Layer Perceptron (MLP)-ANN models and adaptive network-based fuzzy inference system (ANFIS) models were adopted in order to predict and simulate the groundwater level of Lamerd plain; the required results were obtained by emphasis on higher accuracy and lower scattering for modelling ANFIS with RMSE of 0.9987 and R2 of 0.0163 in training stage, and RMSE of 0.9753 and R2 of 0.0694 in test stage [14]. ANN and ANFIS were also used to predict the subsurface water level in paddy fields of Plain Areas between Trajan and Nectarous Rivers. The correlation coefficient of proposed models were 0.8416 and 0.8593 and RMSE of them were 0.2667 and 0.249, respectively [15]. Likewise, ICA is a new evolutionary algorithm in the Evolutionary Computation field based on the human's socio-political evolution. This algorithm has been proposed by Atashpaz-Gargari and lucas in 2007. It simulates an optimization problem by analogizing variables to colony and imperial countries. This method has been widely used in solving engineering problems [16] such as data clustering [17], Nash balance point attainment [18], ANNs training [19] composite constructions [20], production administration complications [21], and optimization complications [22]. Environmental Impact Assessment (EIA) were also addressed in literature which involves the investigation and estimation of scheduled events with a view to ensure environmentally sound and sustainable improvements [23]. Since, land levelling with machines requires considerable energy. Thus, optimizing energy consumption in the levelling operation is expected. As a result, here, Five approaches including Integrating Artificial Neural Network (ANN), Integrating Artificial Neural Network and Imperialist competitive algorithm (ICA-ANN) and Sensitivity Analysis and Regression and adaptive neural fuzzy inference system (ANFIS) models have been tested and evaluated in prediction of environmental indicators for land levelling. Moreover, since a limited number of studies associated with the energy consumption in land levelling have been done, the objective of current energy and cost research is to find a function for all the indices of the land levelling including the slope, coefficient of swelling, the density of the soil, soil moisture, special weight dirt and the swelling.

Materials and methods

Case study region

In order to verify the accuracy and applicability of the proposed linear model, a case study was carried out based on requirements of the project in a farmland at Karaj, Iran. The farm area was 70 ha and was located in west of Karaj, 31° 28′ 42″ north latitude and 48° 53′ 29″ east longitude. Topographic maps of the farm were plotted at scale of 1:500. Length, width and height of points from a reference point (coordinates of x, y and z) were considered as outputs. The grid size in the case study region was 20 × 20 m during topography operations. Samples were collected from two different sites within the region and two different depths; Surface soil (0–10 cm) and subsurface soil (10–30 cm). Totally 90 samples (30 from each location and 15 from each depth) were collected from 3 lands. At the next step, every five samples were mixed to create one sample. In this way total 90 samples were converted into 18 composite soil samples for convenient laboratory analysis. In the laboratory, collected moist soil samples were firstly sieved through 10 mm mesh sieve to remove gravel, small stones and coarse roots and plant remnants then passed through 2 mm sieve. Then the sieved samples were dried at room temperature and moisture content of the samples as well as texture, bulk density, land slope and soil optimum density were determined.

Development of the ANN model

ANNs are massively parallel-distributed information processors that have certain performance characteristics resembling biological neural networks of human brain [24]. They have been developed as a generalization of mathematical models of human biological neural system [15]. There are a lot of structure types of ANN models. In this study, a typical feed forward back propagation (BP) MLP structure was used. The main advantage of MLP structures over other types is that they have the ability to learn complex relationships between input and output patterns, which would be difficult to model with conventional algorithmic methods [25]. An ANN structure usually consists of an input layer, followed by one or more hidden layers and an output layer. The input nodes are the previous lagged observations, while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. The model can be written as follows [25]:

$$y_t = \alpha_0 + \sum_{j-1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_{0j}\right) + \varepsilon_t, j = 0, 1, \dots, n \text{ and } i = 0, 1, \dots, m \tag{1}$$

Where m is the number of input nodes, n is the number of hidden nodes, α_j denotes the vector of weights from the hidden to output nodes and β_{ij} denote the weights from the input to hidden nodes. α_0 and β_{0j} represent weights of arcs leading from the bias terms which have values always equal to 1 and f is a sigmoid transfer function [26]. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output parameters [27]. The linear output layer lets the network to take any values even outside the range of −1 to +1; while if the last layer of a multilayer network has sigmoid neurons, then the outputs of the network will be only in a limited range [27]. Input variables were specific gravity, density, moisture content, slope, inflation rate and type of the cut soil. Relevantly, output variables were fuel energy, machinery energy, labor power, total cost and energy consumption. In this study, all available data sets were used for regression modelling, but for ANN model development, data were randomly divided into two groups of training 70% of the dataset for training, (II) 15% for model cross validation and (III) 15% for testing [28]. Several architectures of MLP type have been investigated to find the one that could result in the best overall performance. The learning rules of Momentum and Levenberg Marquart were considered and also no transfer function for the first layer was used. For the hidden layers, the sigmoid and hyperbolic tangent transfer functions were applied, and for the last one a linear transfer function was set. Also, a number of different network sizes and learning parameters have been tried.

The ANN system applied for the predictor models had seven inputs and a single output. These inputs were soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, % sand, and soil swelling index. The outputs of each model were labor energy, fuel energy, total machinery cost, total machinery energy. The schematic architecture of the used ANN is shown in Fig. 1.

As mentioned earlier, the main elements of ANNs are constituted by artificial neurons. The input model consists of dendritic nodes similar to a biological cell that could be represented as a vector with N items $X = (X_1, X_2, \dots, X_n)$; the summation of inputs multiplied by their corresponding weights could be represented by scalar quantity S.

$$S = \sum_{n=1}^{n} W_n X_n \tag{2}$$

where $W = (W_1, W_2, \dots, W_N)$ is the weight vector of associations among neurons. The S quantity is then passed to a non-linear activation function f, yielding the following output:

$$y = f(s) \tag{3}$$

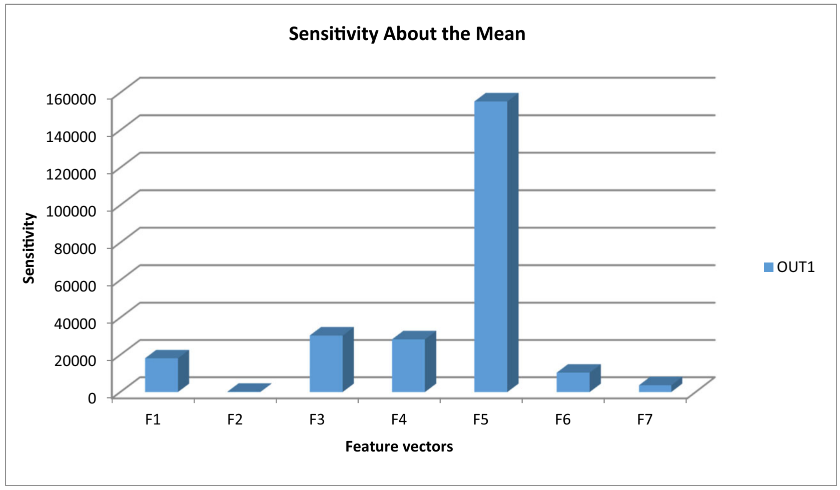

Fig. 1 Sensitivity analysis for Labor Energy (LE), Fuel energy (FE), Total Machinery Cost (TMC), Total Machinery Energy (TME)

Non-linear transfer function is usually represented as sigmoid functions and is defined via:

$$f(s) = \frac{1}{1+e^{-s}} \tag{4}$$

The output of y can be as a result of the model or that of the next layer (in multilayer networks). In the design of an ANN, certain elements should be taken into account including type of input parameters. In this research, the three-layer perceptron network was used which is composed of an input layer, one hidden layer of computational modes, and an output layer. In each layer, a number of neurons were considered which were connected to the neurons of neighboring neurons via some associations. In these networks, the effective input of each neuron was as a result of the multiplication of the outputs of the previous neurons by the weights of those neurons. Neurons in the first layer receive the input information and transfer it to hidden neurons through related connections. The input signal in such networks is only expanded in a forward direction. The main advantage of such a network is the simplicity in implementing the model and estimating input/output data. Some of the major shortcomings of this model are the low training rate and need for a huge set of data.

Imperialist competitive algorithm (ICA)

ICA is a novel swarm-intelligence method that has been developed by mimicking the human being's socio-political evolution strategies. ICA optimization process starts with initialization of random populations and some incipient empires. In each stage of ICA, a union of sub groups, colonies, and imperialists assemble the empires. ICA breaks the early population into the subpopulations, and then it searches the solution space for the best point by using two main operators: competition and assimilation. During algorithm proceedings empires can interact with the members of the swarm. Throughout the assimilation procedure, colonies move towards the relevant imperialist progressively. Imperialistic competition among the empires is the momentous procedure of the ICA [29, 30]. In competition stage powerless empires collapse, whereas the dominant ones gain further control over their colonies. This operation is stopped whenever one empire controls the entire countries. In termination condition, empire has equal cost with its colonies, which can be regarded as a satisfactory solution for the problem. To explain the algorithm more practically, the required steps are as follows:

Step 1: Initializing phase. Scattering the early population randomly over the search space and composing the basic solutions in the format of a $1 \times N_{var}$ array via Eq. (5):

$$country = \left[p_1, p_2, p_3, \ldots, p_{N_{var}}\right] \tag{5}$$

Where p_i represents variables that are fundamentally related to socio-political characteristics of the countries such as culture, language, religion, and economic policy. N_{var} shows the total variables of the target problem.

Step 2: computing the cost of every country using Eq. (6):

$$C = f(country) = f(p_1, p_2, \ldots, p_{N\mathrm{var}}) \tag{6}$$

Step 3: Initializing the empires. The normalized cost of an imperialist is obtained via Eq. (7)

$$NC_n = f_{\mathrm{cost}}^{(imp,n)} - \max_i\left(f_{\mathrm{cost}}^{(imp,i)}\right) \tag{7}$$

Where $f_{\mathrm{cost}}^{(imp,n)}$ stands for the cost of n^{th} imperialist, and NC_n indicates its normalized cost.

p 4: Dividing the colonies among imperialists. This process is based on the power of imperialist and relationships between the countries and their interdependent empires (i.e., the countries should be possessed by their imperialist based on the power). This step is completed using Eqs. (8)–(10), respectively:

$$Power_n = \left| \frac{NC_n}{\sum_{i=1}^{N_{imp}} NC_i} \right| \tag{8}$$

$$NOC_n = round\{Power_n, N_{col}\} \tag{9}$$

$$N_{col} = N_{pop} - N_{imp} \tag{10}$$

Where $Power_n$ is the normalized power of each imperialist, N_{col} and N_{imp} are the given number of colonies and imperialists, respectively, and NOC_n represents the total number of colonies that are possessed by n^{th} empire.

Step 5: Assimilation strategy. The purpose of the assimilation procedure can be expressed as the movement of the colonies towards their interdependent imperialist. Based on this stage, each movement is performed according to Eq. (11):

$$x \approx U(0, \beta \times d) \quad \beta > 1 \tag{11}$$

Where x is a random number with uniform (or any proper) distribution, β is a number greater than 1, and d is the distance between a colony and related imperialist.

Step 6: Revolution strategy. In this strategy, a random amount of deviation is added to direct the colonies movement via Eq. (12):

$$\theta \approx U(-\gamma, \gamma) \tag{12}$$

Where θ is a random variable with uniform distribution, and γ shows a parameter for adjusting the deviation from the initial movement direction.

Step 7: Exchanging phase. During assimilation, whenever a colony reaches to a position with lower (better) cost compared with the imperialist, the imperialist and the colony exchange their positions, and the colony becomes new imperialist and vice versa.

Step 8: Imperialistic competition phase. Calculating the overall power of an empire that is mainly affected by the power of empire and its colonies as Eq. (13):

$$TC_n = f_{\text{cost}}^{(imp,n)} + \xi . \frac{\sum_{i=1}^{NC_n} f_{\text{cost}}^{(col,i)}}{NC_n} \tag{13}$$

Where TC_n represents the total cost of the n^{th} empire, and ζ is a coefficient between 0 and 1 for decreasing the effect of colonies cost.

Step 9: Imperialistic competition strategy. Based on this process, each empire tries to extend its power to possess more colonies compared with other empires. Throughout the competition, weakest colony from the weakest empire is selected to be governed by the strongest empire. Imperialistic competition conducts a searching procedure towards a peak solutions. The competition operator is designed to dedicate the colonies of the weakest empires to other empires. Based on TC_n, the normalized total cost is evaluated using Eq. (14):

$$NTC_n = TC_n - \max_i\{TC_i\} \tag{14}$$

Where NTC_n is the total normalized cost of nth empire. According to NTC_n, the possession probability of each empire is computed with Eq. (15):

$$P_{pn} = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \tag{15}$$

To find out the winner of competition with less computational effort, the vectors P, R, and D are formed via Eqs. (16)–(17)-(18):

$$P = \left[P_{P1}, P_{P2}, \dots, P_{PNimp}\right] \tag{16}$$

$$R = \left[r_1, r_2, \dots, r_{N_{imp}}\right] \quad r_1, r_2, r_3, \dots, r_{Nimp} \approx U(0,1) \tag{17}$$

$$D = P - R = [P_R] = \left[D_1, D_2, \dots, D_{N_{imp}}\right]$$
$$= \left[P_{P1} - r_1, P_{P2} - r_2, \dots, P_{PNimp} - r_{Nimp}\right] \tag{18}$$

Where P is the vector of possession probability of the imperialists and R represents a vector with uniformly distributed random values. Maximum index of D determines the winner empire of the competition.

Step 10: Eliminating phase. When a powerless empire loses all of its controlled colonies, it should be removed from the competition.

Step 11: Convergence phase. Finally, the most powerful imperialist controls all the remained colonies. In such a condition, the algorithm is stopped.

Training of ANNs can be done using the ICA. For this purpose, the algorithm should be able to adjust the weights and bias, so that the difference between the output of ICA and real output be minimized. Mean squared error (MSE) was considered to determine the error.

Integrating Artificial Neural Network and Imperialist competitive algorithm (ICA-ANN)

In this study, after writing commands of ANNs in MATLAB software, the number of neurons in the input layer considered the same as the number of effective parameters; Cut-Fill Volume (V) (embankment volume), soil compressibility factor, specific gravity, moisture content, slope, sand percent, and soil swelling index. Similarly, the number of neurons in the output layer should be equal to the number of desired parameters for modeling. Instead of the default commands for network training, ICA was used. For running ANNs 70% of the data were used for training, 15% for evaluation, and the remained 15% were used for test.

Data availability The dataset supporting the conclusions of this article will not be shared due to performing our next projects with this software.

Results

Sensitivity analysis model

The outputs that are shown in the Table 1, are the results of the model after running it 500 times. Table 1 indicates F-values and a great significance ($\alpha < 0.0001$) for all developed sensitivity analysis models in rejecting the null hypothesis was obvious.

Figure 1 shows the sensitivity analysis for Labour Energy. In this fig. F1 to F7 represent land slope, moisture content, density, soil compressibility factor, embankment volume, Soil Swelling Index and sand percent, respectively. The results revealed that F3 (density), F4 (soil compressibility factor), and F5 (embankment volume) had the highest sensitivities on LE.

Sensitivity analysis showed that three soil parameters including; volume of soil, specific gravity and soil compaction had the greatest impact on the amount of energy required for land-leveling. These parameters had direct relation with the required energy. In other words, more density of the soil leads to more required energy for constant volume of the soil. For a soil with higher densities, in addition to its weight, handling it also requires more energy consumption. It is obvious that more working time of the machine leads to higher energy consumptions. In the same manner, the higher the excavation volume, the greater the energy consumption. It can be interpreted in this way that more soil volume needs more time of machine and leads to more fuel consumption. Table 1 shows that soil volume is the most important parameter between all input variables for energy consumption including LE, FE, TMC and TME. It is clear that by increasing cut soil volume, needed time of machinery used increases, and consequently fuel energy increases as well. Furthermore, prolonged working time of machinery increases labour requirement for operation which in turn, rises the energy consumption by the labours. On the other hand by decreasing the cut soil volume, required human labour also decreases. Therefore, on of the most important ways for decresing energy consumption is to reduce soil cut/fill.In addition, in each table if the F value of a variable is higher than others, it can be indicate the higher impact of that variable in the final model. This situation is occurred for cut-fill volume as a variable with most effect on all response of interest. The lower F value of a variable show lower effect of that variable on response.

Regression model

All model F-values in Tables 2 indicated a great significance ($\alpha < 0.0001$) for all developed regression models in rejecting the null hypothesis. All models have significant p-value.

Of the seven parameters of soil and land characteristics (moisture, density, soil compressibility factor, land slope, soil type, embankment volume), three factors of slope, embankment volume and soil compressibility have the most significant effect on labor energy (LE) in land leveling. The factors of slope, embankment volume (V) and soil type (sand) have significant effects on fuel energy. Embankment volume (V), soil compressibility factor (cf) and slope have significant effects on total machinery cost in land leveling (Table 2).

So that the results show the relationship of land levelling in the energy with the slope of the land, swelling coefficient and

Table 1 Analysis of variance for (Labor Energy (LE), Fuel energy (FE), Total Machinery Cost (TMC), Total Machinery Energy (TME))

Model	Source	Sum of squares	df	Mean square	F value	p-value prob. > F
LE model	Model	2.858^{7}	1	2.858^{7}	4277.61	< 0.0001
	Cut-Fill Volume (V)	2.858^{7}	1	2.858^{7}	4277.61	< 0.0001
FE model	Model	6.478^{8}	1	6.478^{8}	3931.00	< 0.0001
	Cut-Fill Volume (V)	6.478^{8}	1	6.478^{8}	3931.00	< 0.0001
TMC model	Model	2.737^{12}	1	2.737^{12}	4023.17	< 0.0001
	Cut-Fill Volume (V)	2.737^{12}	1	2.737^{12}	4023.17	< 0.0001
TME model	Model	1.086^{11}	1	1.086^{11}	4311.77	< 0.0001
	Cut-Fill Volume (V)	1.086^{11}	1	1.086^{11}	4311.77	< 0.0001

Table 2 Analysis of variance for Labor Energy (LE), Fuel energy (FE), Total Machinery Cost (TMC), 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}	16,149.7	< 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}	13,457.37208	< 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}	13,881.29	< 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}	16,537.35	< 0.0001
	SSI	1.44^{14}	1	1.44^{14}	36.87527	< 0.0001

soil type is significant. By increasing land slope, volume of excavation and embankment increases and the number of sweep and distance travelled levelling machines also increases and fuel consumption will increase. Increase in soil swelling factor, increases the volume of the embankment and increase in volume of the embankment also increases the demand on fuel and energy. The fitted nonlinear equations for the all response of interest including LE, FE, TMC, and TME are represented in Eqs. 19–22, 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, V, and SSI have significant effects. Although, in FE model the effect of 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 (Eq. 19). Energy consumption in land leveling (fuel energy) is a nonlinear function of the soil compressibility factor and slope (Eq. 20). Energy consumption in land leveling (total machinery cost) is a nonlinear function of the soil compressibility factor and slope (Eq. 21). Energy consumption in land leveling (total machinery cost) is a nonlinear function of the soil compressibility factor and slope (Eq. 22). The value of each coefficient variable in the equation represents the effect of variable on the function.

$$(\mathrm{LE})^{0.8} = 34161.36 + 3639.90^{*}\,\mathrm{Slope} + 31173.94^{*}\,\mathrm{V} + 911.96^{*}\,\mathrm{SSI} \tag{19}$$

$$(\mathrm{FE})^{0.8} = 4.148^{5} + 49590.44^{*}\,\mathrm{Slope} + 3.782^{5*}\,\mathrm{V} - 10008.33^{*}\,\mathrm{Sand} \tag{20}$$

$$(\mathrm{TMC})^{0.8} = 3.319^{8} + 3.587^{7*}\,\mathrm{Slope} + 3.015^{8*}\,\mathrm{V} + 8.393^{6*}\,\mathrm{SSI} \tag{21}$$

$$(\mathrm{TME})^{0.8} = 2.494^{7} + 2.621^{6*}\,\mathrm{Slope} + 2.277^{7*}\,\mathrm{V} + 6.787^{5*}\,\mathrm{SSI} \tag{22}$$

A relatively flat line shows insensitivity to change in that particular factor. The response trace plot for the LE, FE, TMC and TME are shown in Fig. 2a to d. 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 response of interest vs. predicted values using final models are displayed in Fig. 3a to d. The strong nonlinear effect of cut-fill volume on the all response of interest is conspicuous (Fig. 2a to d). As appreciated from the Fig. 3 a to d, energy and cost increase with increased cut-fill volume as the major effect. All response of interest are moderately affected by 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. 2a). Scatter plots of Actual vs. Predicted for regression model (Fig. 3a-d).

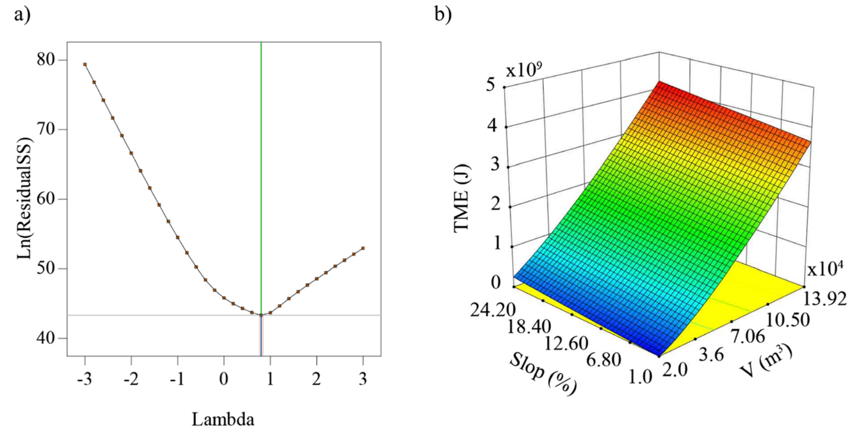

Fig. 2 **a** Box-Cox plot of **b**) surface plot of Total machines energy versus slop and volume

Results of ANFIS model prediction

In this section the results of ANFIS models for prediction of labour energy (LE), fuel energy (FE), total machinery cost (TMC) and total machinery energy (TME) are presented. A code was written in MATLAB programming language for ANFIS simulations. Different ANFIS structures were tried using the programming code and the appropriate representations were determined. Each structure for correspond combination has been evaluated using 100 independent runs and the statistical criteria (R^2 and MSE) of the output models have been calculated for responses of interest. In Tables 3 and 4 the minimum, average and maximum values of R^2 and MSE for various combination of developed ANFIS-based models are presented. Calculated R^2 and MSE values of different developed models of labour energy vs. number of clusters are illustrated. Other outputs have similar behaviour. As presented in Table 3, statistical criteria for prediction of labour

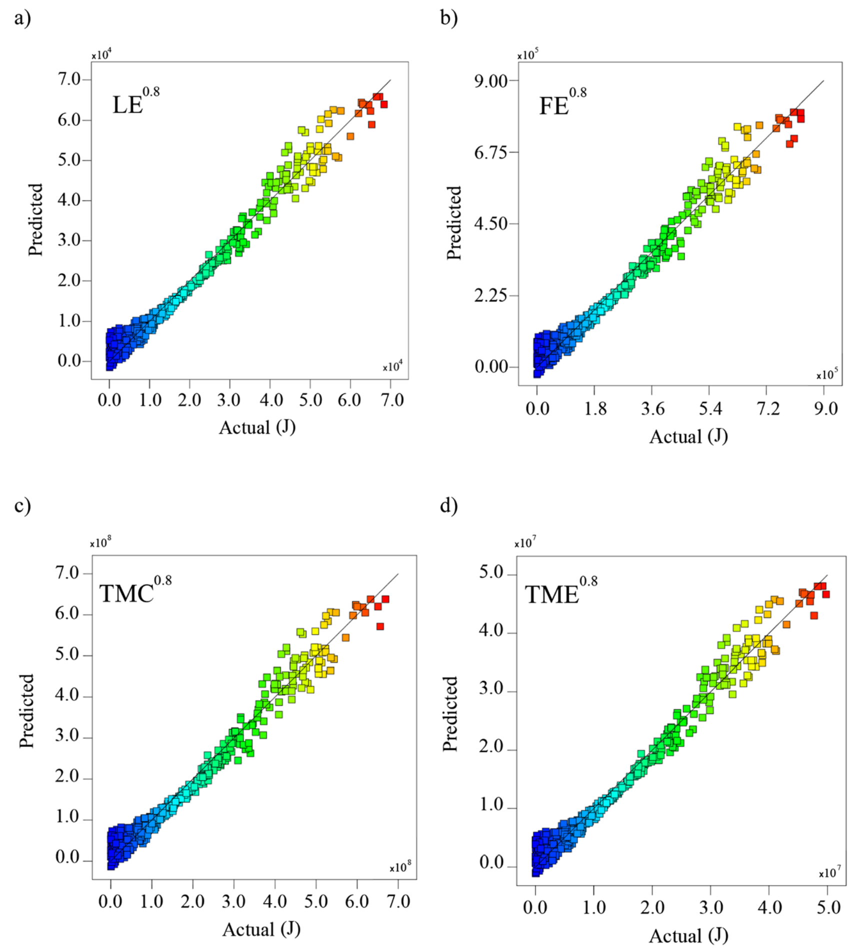

Fig. 3 Scatter plots of Actual vs. Predicted using regression models for (**a**) Labor energy, **b** Fuel energy, **c** Total Machines cost, and **d** Total machines energy

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	0.00063	0.00130	0.00329	0.9856	0.9948	0.9971
		Sugeno	0.00058	0.00126	0.00326	0.9865	0.9944	0.9974
	Backpropagation	Mamdani	0.00083	0.00102	0.00412	0.9831	0.9921	0.9965
		Sugeno	0.00088	0.00154	0.00407	0.9831	0.9921	0.9964
Fuel E.	Hybrid	Mamdani	0.00119	0.00181	0.00371	0.9851	0.9927	0.9952
		Sugeno	0.00111	0.00173	0.00390	0.9843	0.9922	0.9955
	Backpropagation	Mamdani	0.00119	0.00270	0.00560	0.9775	0.9891	0.9952
		Sugeno	0.00123	0.00268	0.00560	0.9775	0.9892	0.9950

energy reveals that FIS model is superior to ANN back propagation model. Average R^2 value in FIS model for prediction of Labor energy was found to be 0.9948 and 0.9944 in Mamdani and Sugeno models, respectively. While in in back propagation model it was calculated as 0.9921 and 0.9921, respectively.

Moreover, as presented in Tables 3 and 4, statistical criteria for prediction of fuel energy reveal that FIS model is superior to ANN back propagation model. Average R^2 value in 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 R^2 value was calculated as 0.9891 and 0.9892, respectively.

As presented in Table 4, statistical criteria for prediction of total machinery cost reveals that FIS model is superior to ANN back propagation model. Average R^2 value in FIS model for 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 R^2 value was calculated as 0.9894 and 0.9895, respectively. As presented in Table 4, statistical criteria for prediction of total machinery energy reveals that FIS model is superior to back propagation model. Average R^2 value in FIS model for prediction of total machinery energy was found to be 0.9950 and 0.9952 in Mamdani and Sugeno models, respectively. While in in back propagation model it was calculated as 0.9925 and 0.9926, respectively.

Determining the effect of number of clusters on the all developed models is feasible (Fig. 4). Moreover, comparison between different optimization methods and FIS types can also be done. For the ANFIS based model, in both training methods the MSE (R^2) value decreases (increases) and also the prediction performance of developed ANFIS-based models improve gradually with the number of clusters. In addition, comparison of the results indicates that the Hybrid method has a higher value of R^2 and a lower value of MSE, so that its performance is more accurate. Also, the performance of the Sugeno FIS type is better than the Mamdani. Noteworthy, models having low MSE values have more R^2 values and vice versa.

Comparison results of the predicted values of ANFIS models with actual data are shown in Fig. 5a-d. These predicted values are compared with actual data to show the performance of the ANFIS models for the prediction of each response. Results from these figures reveal that FIS model is superior to ANN model in predicting labour energy, fuel energy, total machinery energy and total machinery cost.

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			R^2		
			Min.	Ave.	Max.	Min.	Ave.	Max.
Cost	Hybrid	Mamdani	0.00122	0.00188	0.00387	0.9837	0.9921	0.9949
		Sugeno	0.00119	0.00185	0.00394	0.9834	0.9922	0.9950
	Backpropagation	Mamdani	0.00140	0.00251	0.00465	0.9805	0.9894	0.9941
		Sugeno	0.00141	0.00250	0.00465	0.9805	0.9895	0.9940
Energy	Hybrid	Mamdani	0.00059	0.00121	0.00353	0.9856	0.9950	0.9975
		Sugeno	0.00058	0.00120	0.00356	0.9855	0.9952	0.9976
	Backpropagation	Mamdani	0.00077	0.00183	0.00395	0.9839	0.9925	0.9968
		Sugeno	0.00080	0.00182	0.00395	0.9839	0.9926	0.9967

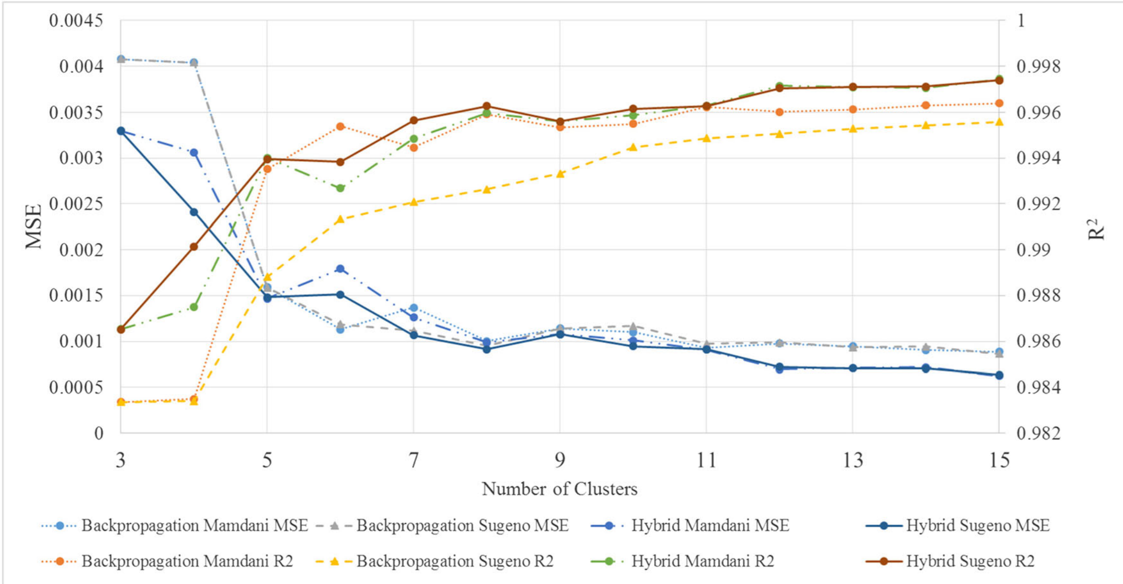

Fig. 4 Statistical performance criteria of LE

ANN model

The results of regression models and training various networks with different structures are presented in this section. The ANN models were developed by training the networks with various combination of Network Training Functions (NTF), number of hidden layers and number of neurons in the each hidden layer. For selecting the best Network topology, totally 20,678 different ANN models were evaluated and the RMSE and coefficient of determination (R^2) values were calculated. For a full comparison between the performances of the trained structures, Tables 5 and 6 represent results obtained from ANN of feed forward BP type with 7 different network training algorithms. These methods of training are available in the Neural Network Toolbox software and they use gradient- or Jacobian-based methods including Levenberg-Marquet (trainlm), Bayesian regularization (trainbr), scaled conjugate gradient (trainscg), resilient BP (trainrp), Gradient descent with momentum and adaptive learning rate BP (traingdx), Gradient descent with adaptive learning rate BP (traingda), Gradient descent with momentum BP (traingdm) and conjugate gradient function (traincgf). These networks use 10 input data in the input layer to predict the outputs and utilize a linear function in their output layer to transfer the data to the output. The outputs of the model represented in Tables 2 and 3, are the results of 500 thousand runs of the model. The selected NTFs for LE in land leveling, as shown in the first row of the Table 5, was the best because it had the highest correlation coefficient and lowest RMSE. These functions had 8 neurons in the first layer, and three neurons in the second. Details of the best trained networks for prediction of LE are shown in Table 5. The NTF of trainlm had higher RMSE and lower R2 for 2 (8–3) and 3 (2–7-6) hidden layers but NTF of trainbr for 1 hidden layer had the best statistical interpretation. The NTF of trainlm including 2 neurons in one hidden layer is the most simple ANN for forecasting the LE with RMSE lower than 0.021 and R2 higher than 0.996. Details of the selected networks for prediction of FE are presented in Table 5. The NTF of trainlm had higher RMSE and lower R^2 for 2 (4–2) and 3 (8–2-5) hidden layers but NTF of trainscg for 1 hidden layer has the best statistical output. The NTF of trainlm including 2 neurons in one hidden layer is the simplest ANN for predicting the FE with RMSE of lower than 0.033 and R^2 higher than 0.995. As it is shown in the Table 6, the first model consisting of three hidden layers (5–8-10 topology) had the highest coefficient of determination (0.9966) and the lowest values of RMSE (0.0287) indicating that this model can predict the TMC accurately. So this model was given as the best solution for estimating the TMC. The detail of the selected networks for prediction of TME is presented in Table 6. The NTF of trainlm had higher RMSE and lower R^2 for 2 (6–4) and 3 (4–5-3) hidden layers but NTF of trainscg for 1 hidden layer had the best statistical results. The NTF of traingdx including 2 neurons in one hidden layer was the simplest ANN for forecasting the FE. The RMSE for this model was found to be 0.225 which was very low.

ANN Models shown in the Fig. 6 shows the actual responses versus the predicted ones. As the predicted values come closer to the actual values, the points on the scatterplot come closer to the diagonal line which is the regression result. Closeness of the points to the line is an evidence of satisfactory performance of the models in prediction of the targets. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the targets. The

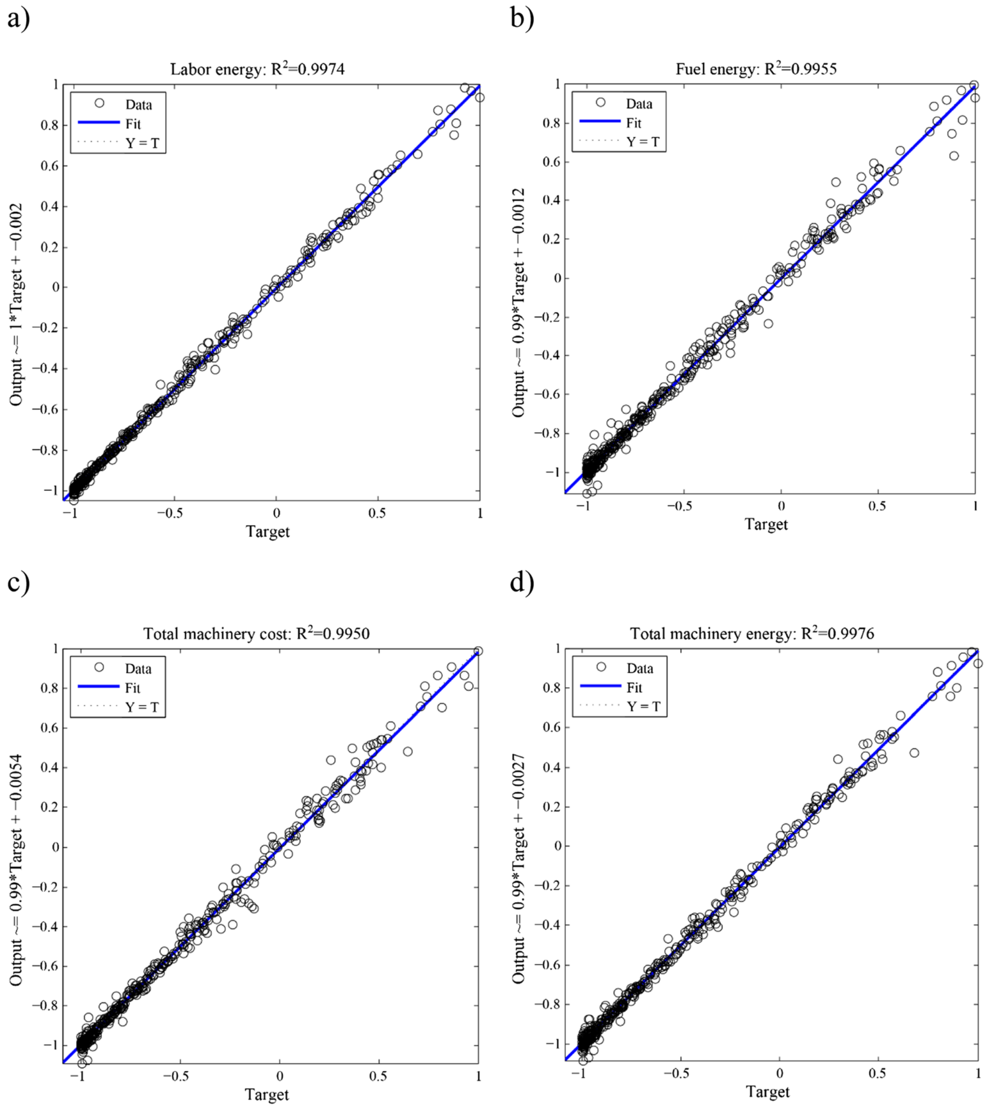

Fig. 5 Scatter plot for the predicted model and actual values of (**a**) Labor energy, **b** Fuel energy, **c** Total machinery cost, **d** Total machinery energy

training record was used to plot the training, validation, and test performance of the training progress (error vs. number of training epochs).

Integrating Artificial Neural Network and Imperialist competitive algorithm (ICA-ANN) model

The results of training various networks with different structures are presented in this section. By training the networks with different number of neurons (3–11) in the hidden layer using ICA with presented parameters in Table 7, the ANN models were developed. For each response totally 18,000 networks were trained and evaluated. After several repetitions, the RMSE and coefficient of determination (R^2) values were calculated. The network utilized a tansig function in its output layer to transfer the data to the output. The results obtained from the best trained models and their characteristics are illustrated in Table 8. R^2 value for prediction of LE was found to be 0.9987. FE was predicted by R^2 value of 0.9975. By using a Network topology of 2 structure, TMC was predicted by R^2 value of 0.9963. R^2 value for prediction of TME was found to be 0.9987. Scatter plots of Actual versus Predicted results of the ANN Models are shown in the Fig. 7a,b,c and d. As the predicted values come closer to the actual values, the points on the scatterplot fall closer around the regression result (the diagonal line). These models can predict the target accurately and that is evident from closeness of the points to the line. For a perfect fit, the data should fall along a 45 degree line, where the network outputs are equal to the actual data. Figure 7a shows the scatter plot of output data versus actual data using ICA-ANN models for prediction of LE. It is clear that the predicted outputs are very close to the target values. Figure 7b is related to the scatter plot of the output data in contrast with target data using ICA-ANN models for

Table 5 Selected ANN for prediction of Labor Energy (LE), Fuel energy (FE)

Selected ANN for prediction of Labor Energy (LE)				Selected ANN for prediction of Fuel energy (FE)			
NTF	Network topology	RMSE	R^2	NTF	Network topology	RMSE	R^2
trainlm	8–3	0.0159	0.9990	trainlm	8–2-5	0.0206	0.9983
trainlm	4–9	0.0159	0.9990	trainlm	10–4-10	0.0224	0.9980
trainlm	2–7-6	0.0164	0.9989	trainlm	4–2	0.0238	0.9977
trainlm	7–10	0.0164	0.9989	trainlm	9–2-3	0.0241	0.9977
trainlm	5–3	0.0165	0.9989	trainlm	5–2-9	0.0248	0.9976
trainlm	9–5-6	0.0166	0.9989	trainlm	3–2	0.0253	0.9974
trainlm	6–2-3	0.0167	0.9989	trainlm	2–2-2	0.0269	0.9971
trainlm	7–2-3	0.0171	0.9988	trainlm	2–2	0.0271	0.9971
trainbr	3–2	0.0174	0.9988	trainbr	2–6	0.0279	0.9969
trainbr	10–7	0.0179	0.9987	trainlm	6–2-2	0.0310	0.9962
trainbr	4	0.0171	0.9988	trainbr	5	0.0249	0.9975
trainlm	2	0.0209	0.9982	trainlm	6	0.0255	0.9980
traincg	6	0.0217	0.9981	trainscg	11	0.0261	0.9973
trainrp	7	0.0254	0.9974	traingdx	3	0.0329	0.9957
traingdx	2	0.0298	0.9964				

prediction of FE. It is also evident for the FE values that the predicted results are very close to the target values. Figure 7c illustrates the scatter plot of output in comparison with target using ICA-ANN models for prediction of TMC. This figure clearly demonstrates that the predicted TMC values are very close to the target values. The scatter plot of output vs. target values for TME is presented in Fig. 7d. As it is evident, the predicted TME values are approximately fitting to the target values. By and large, the results show good performance of ICA-ANN to predict LE, FE, TMC, and TME.

Utilizing ICA-ANN for this types of optimization problems are broadly reported in engineering and the researchers acknowledged the superiority of ICA-ANN over conventional approaches. Taghavifar et al. were used a meta-heuristic optimization algorithm for prediction of soil compaction indices. ANN trials were developed and then merged with the evolutionary optimization technique of ICA. The results were compared on the basis of a modified performance function (MSE-REG) and coefficient of determination (R2). Their results elucidated that hybrid ICA–ANN

Table 6 Selected ANN for prediction of Total Machinery Cost (TMC), Total Machinery Energy (TME)

Selected ANN for prediction of Total Machinery Cost (TMC)				Selected ANN for prediction of Total Machinery Energy (TME)			
NTF	Network topology	RMSE	R^2	NTF	Network topology	RMSE	R^2
trainlm	5–8-10	0.0287	0.9966	trainlm	6–4	0.0157	0.9990
trainlm	7–9-2	0.0298	0.9963	trainlm	4–5-3	0.0158	0.9990
trainlm	4–5-7	0.0304	0.9961	trainlm	6–2-4	0.0160	0.9990
trainlm	7–8	0.0329	0.9957	trainlm	2–7	0.0163	0.9989
trainlm	7–2-2	0.0332	0.9954	trainlm	3–2	0.0164	0.9989
trainlm	3–2-3	0.0332	0.9954	trainbr	5–6	0.0167	0.9989
trainlm	2–4-10	0.0343	0.9951	trainlm	3–2-8	0.0168	0.9989
trainlm	2–2-5	0.0345	0.9951	trainlm	9–2-10	0.0171	0.9989
trainbr	3–9	0.0345	0.9950	trainlm	2–4-2	0.0192	0.9985
trainbr	5–8	0.0349	0.9950	trainlm	2–2-2	0.0199	0.9984
trainscg	7	0.0321	0.9958	trainscg	8	0.0164	0.9989
trainlm	2	0.0325	0.9948	trainlm	3	0.0176	0.9987
trainbr	5	0.0328	0.9955	traingdx	2	0.0300	0.9964
trainrp	4	0.0368	0.9944				
traingdx	2	0.0433	0.9922				

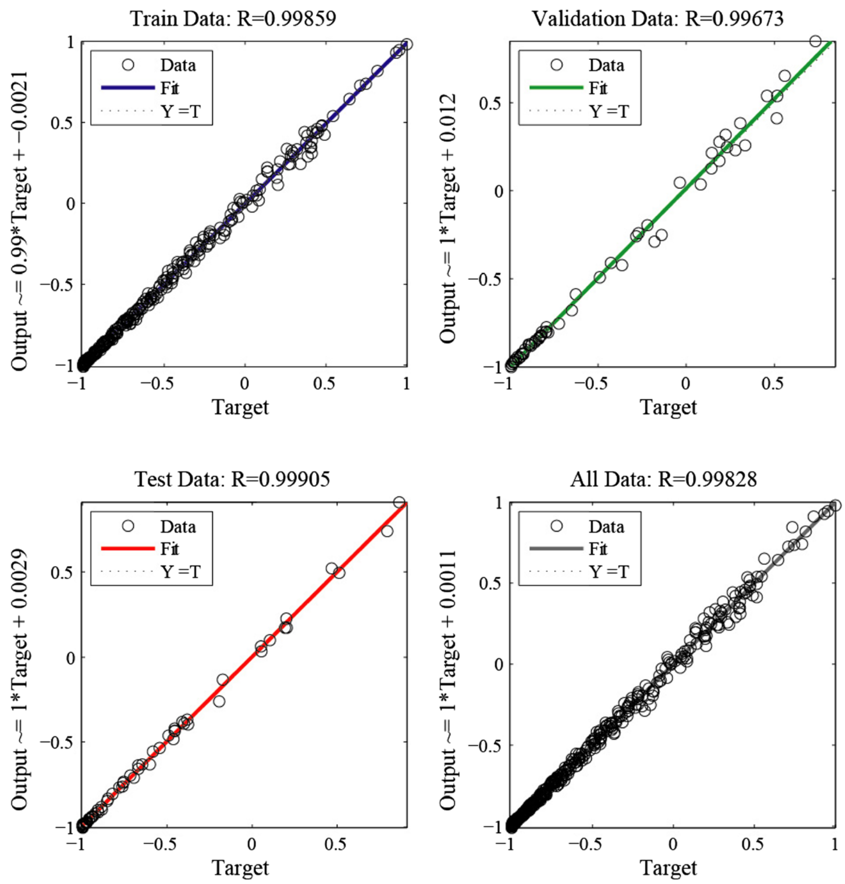

Fig. 6 Scatter plots of output vs. target using ANN models for prediction of LE

succeeded to denote lower modeling error than other methods [31]. In another study, Marto et al. 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 [32]. Nikoo et al. 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 [33].

Table 7- Algorithm Parameters

Algorithm parameter	value
Number of Countries	250
Number of initial imperialists	25
Number of decades	500
Revolution rate	0.3
Assimilation coefficient	2
Assimilation angle coefficient	0.5
Zeta	0.02
Damp ratio	0.99
Uniting threshold	0.02

Discussion

Comparison of models

The comparison of statistical results of ICA-ANN and ANN and sensitivity analysis and regression and ANFIS models and Sensitivity analysis are tabulated in Table 8. As it can be seen from the Table 8, among the ICA-ANN models and ANN models and Sensitivity analysis and ANFIS and Regression, ICA-ANN models provide better results with regards to higher R^2 values and lower RMSE values for them.

Why did moisture content, swelling index, soil compressibility factor and type of soil have low effect on cost and energy consumption?

In the case of specific gravity: whatever specific gravity of ground becomes greater, weight of determined volume of the soil is getting greater too and work hours of machine for clearing specific surface is becoming increased and subsequently much fuel will be consumed.

About soil cut/fill volume: whatever soil cut/fill volume is getting increased, work hours of machine and number of laborers is being increased and again much fuel is necessary.

Table 8 Comparison of Integrating Artificial Neural Network and Imperialist competitive algorithm (ICA-ANN) and ANFIS and regression and ANN and Sensitivity Analysis models

Responce	Sensivity analysis		Regression		ICA-ANN		ANFIS		ANN	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
LE	0.1899	0.8631	0.1394	0.9008	0.0146	0.9987	0.0159	0.9990	0.0159	0.9990
FE	0.1971	0.8562	0.1514	0.8913	0.0322	0.9975	0.0206	0.9983	0.0206	0.9983
TMC	0.1946	0.8581	0.1492	0.9128	0.0248	0.9963	0.0287	0.9966	0.0287	0.9966
TME	0.1892	0.8437	0.1378	0.9103	0.0161	0.9987	0.0157	0.9990	0.0157	0.9990

About moisture content, swelling factor and type of soil: moisture, soil compressibility factor and specific gravity in fine-textured soils like clays and with high organic materials leading to stability against machine movement and slowness movement of it, increasing of work hours of machine following laborers and fuel will be increased and because of lacking light structure of region soil form (gross), low organic materials, these parameters in energy consumption didn't affect.

Conclusion

A limited number of research related to energy consumption in land leveling have done that energy the function of the volume of excavation and embankment have presented. But, in this research, energy and cost of land leveling are function of all the properties of the land including the slope, coefficient of swelling, and the density of the soil, soil moisture special weight dirt. The paper's argument built on an appropriate base

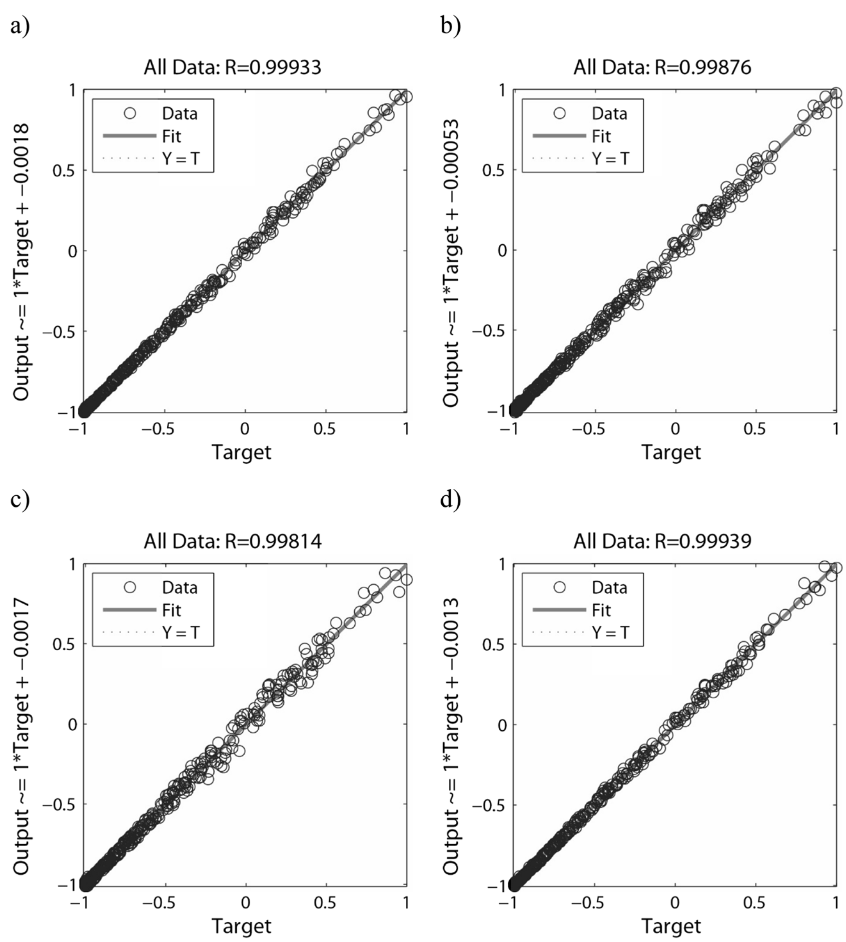

Fig. 7 Scatter plot of output vs. target using ICA-ANN models for prediction of (**a**) LE, **b** FE, **c** TMC, and **d** TME

of theory, concepts, and other ideas. And the methods are employed appropriate. In this study, the ability of Artificial Neural Network (ANN), Imperialist Competitive Algorithm and artificial neural network (ANN) and Sensitivity Analysis and Regression and adaptive neural fuzzy inference system (ANFIS) for prediction of environmental indicators, LE, FE, TMC, and TME during land leveling were investigated. Results extracted and statistical analysis was performed and RMSE as well as coefficient of determination, $R^{2,}$ of the models were determined as a criterion to compare selected models. According to the results, 10–8–3-1, 10–8–2-5-1, 10–5–8-10-1, and 10–6–4-1 MLP network structures were chosen as the best arrangements and were trained using Levenberg-Marquet as NTF. Sensitivity analysis revealed that only three variables including (density, soil compressibility factor, and Cut-Fill Volume (V)) had the highest sensitivity on the output parameters including LE, FE, TMC and TME. Using regression method only three variables including Slope, Cut-Fill Volume (V), and Soil Swelling Index (SSI). In FE model the effect of SSI is not significant and has been replaced by the percentage of Sand. The ANFIS models with hybrid optimization method and Sugeno FIS type shows better performance than the backpropagation and Mamdani ones. All ANFIS-based models have R^2 values above 0.995 and MSE values below 0.002. Based on the results, ICA-ANN had better performance in prediction of output parameters in comparison with conventional methods such as ANN or PSO-ANN. Statistical factors of RMSE and R^2 illustrate the superiority of ICA-ANN over other methods by values about 0.02 and 0.99, respectively. Moreover, using ANFIS for prediction of output variables, LE, FE, TMC and TME were successfully demonstrated. The result of this research is used for surface irrigation on agricultural lands. The results of this research could be used in economic project on agricultural lands. The results of this research could be used as a tools by the managers and consultants, researchers and etc. The results of this research impact upon agricultural society and affecting quality of theirs life. These implications are consistent with the findings and conclusions of this paper.

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Authors' contributions AI carried out all studies about the work and cultivated the data which were necessary to be analyzed. DM helped in statistical analysis. MF participated in land leveling studies results acquisition. A.N B helped in design and studying of artificial neural network. All authors read manuscript and approved it.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no competing interests.

Consent for publication Not applicable.

Ethics approval and consent to participate Not applicable.

Abbreviations ICAANN, Integrating Artificial Neural Network and Imperialist competitive algorithm; ANN, Artificial Neural Network.; LE, environmental indicators: Labor Energy; FE, environmental indicators: Fuel energy; TMC, Total Machinery Cost; TME, environmental indicators: Total Machinery Energy

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