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Abstract

Purpose – This work aims to determine the best linear model using an artificial neural network (ANN) with the imperialist competitive algorithm (ICA-ANN) and ANN to predict the energy consumption for land leveling.

Design/methodology/approach – Using ANN, integrating artificial neural network and imperialist competitive algorithm (ICA-ANN) and sensitivity analysis (SA) can 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 per cent and soil swelling index on energy consumption were investigated.

Findings – According to the results, 10-8-3-1, 10-8-2-5-1, 10-5-8-10-1 and 10-6-4-1 multilayer perceptron network structures were chosen as the best arrangements and were trained using the Levenberg–Marquardt method as the network training function. Sensitivity analysis revealed that only three variables, namely, density, soil compressibility factor and cut-fill volume (V), had the highest sensitivity on the output parameters, including labor energy, fuel energy, total machinery cost and total machinery energy. Based on the results, ICA-ANN had a better performance in the prediction of output parameters in comparison with conventional methods such as ANN or particle swarm optimization (PSO)-ANN. Statistical factors of root mean square error (RMSE) and correlation coefficient (R^2) illustrate the superiority of ICA-ANN over other methods by values of about 0.02 and 0.99, respectively.

Originality/value – A limited number of research studies related to energy consumption in land leveling have been done on energy as a function of volume of excavation and embankment. However, in this research, energy and cost of land leveling are shown to be functions of all the properties of the land, including the slope, coefficient of swelling, density of the soil, soil moisture and special weight dirt. Therefore, the authors believe that this paper contains new and significant information adequate for justifying publication in an international journal.

Keywords Energy sector, Optimization, Particle swarm optimization (PSO), Neural networks, Fossil fuel, ANFIS, Land levelling, Energy, Environmental research, ANN, Sensitivity analysis, Fuzzy adaptive PSO

Paper type Research paper

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Introduction

During the past century, owing to an increase in the human population, demands for agricultural commodities have 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 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 agriculture in the future (Jat *et al.*, 2006). Regarding this, some special policies should be addressed to consider the energy viewpoint in conjunction with the environmental issues to solve the problem. Land leveling is one of the heavy and costly operations among agricultural practices that consume considerable amount of energy. In addition, moving heavy machines on the ground makes the soil denser, particularly in the wet regions where the moisture content of the soil is high, and thus creates a situation that is not easily remedied (Khan *et al.*, 2007). On the other hand, land leveling simplifies the irrigation process, improves field situations in other practices related to agriculture and regulates the soil surface and normalizes its slope (Brye *et al.*, 2006). Reportedly, there are three significant factors which have an effect on grain yield, including the effects of land leveling, methods of water application and the interaction between land leveling and water applied. Okasha *et al.* (2013) observed a noteworthy connection between slope and diverse irrigation schemes in different seasons. Diverse methods of land leveling 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 leveling (Cassel *et al.*, 1982). 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 leveling from social, financial and agronomic points of view. (McFarlane *et al.*, 2006). Even though some improvisation strategies have been proposed for the enhancement of operations related to the environment, they have diverse undesirable effects (Moghaddam and Far, 2015). Artificial neural network (ANN) is a conceptual technique in which the output or inferred variable can be modeled in terms of other parameters that are relevant to the same process (Rallo *et al.*, 2002). This technique has been widely used in the engineering field for optimization and prediction. Ahmadi *et al.* proposed ANNs trained with particle swarm optimization (PSO) and the back-propagation (BP) algorithm to estimate the equilibrium water dew point of a natural gas stream with a minimum triethylene glycol (TEG) solution at different TEG concentrations and temperatures. They reported that this approach, integrating artificial neural network and particle swarm optimization (PSO-ANN), can aid in better understanding of fluid reservoirs' behavior through simulation scenarios, and statistical results were quiet notable (Ahmadi *et al.*, 2014). In other research, a feed-forward ANN optimized by PSO was used as an artificial intelligence modeling tool to predict asphalting precipitation owing to natural depletion (Ahmadi and Golshadi, 2012). They also proposed another network based on feed-forward ANN optimized by hybrid genetic algorithm and particle 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 (Ahmadi and Shadizadeh, 2012). These techniques have also been used for predicting parameters with reducing uncertainties. In research, Ahmadi *et al.* (2015) used artificial intelligence techniques to accurately determine the amount of dissolved calcium carbonate concentration in oil field brines with minimum uncertainty. In another study, multilayer perceptron (MLP)-ANN models and adaptive network-based fuzzy inference system (ANFIS) models were adopted to predict and simulate the groundwater level of the Lamerd Plain; the required results were obtained by emphasis on higher accuracy and lower scattering for modeling ANFIS with RMSE of 0.9987 and correlation coefficient (R^2) of 0.0163 in the training stage and RMSE of 0.9753 and R^2 of 0.0694 in the test stage (Fereydooni and Mansoori, 2015). ANN and ANFIS were also used to predict the subsurface water level in paddy fields of plain areas between the rivers Trajan and Nectarous. The correlation coefficient of the proposed models was 0.8416 and 0.8593 and RMSE was 0.2667 and 0.249, respectively (Mohammadi *et al.*, 2009). Likewise, imperialist competitive algorithm (ICA) is a new evolutionary algorithm in the evolutionary computation field based on the socio-political evolution of humans. This algorithm was proposed by Atashpaz-Gargari and Lucas in 2007 (Lei *et al.*, 2006). It simulates an optimization problem by analogizing variables to colony and imperial countries. This method has been widely used in solving engineering problems (Abdechiri *et al.*, 2010) such as data clustering (Ebrahimzadeh *et al.*, 2012), Nash balance point attainment (Rajabioun *et al.*, 2008), ANN training (Zhang, 2012) composite constructions (Abdi *et al.*, 2011), production administration complications (Nazari-Shirkouhi *et al.*, 2010) and optimization complications (Ahmadi *et al.*, 2013). Environmental impact assessment was also addressed in literature which involves the investigation and estimation of scheduled events with a view to ensure environmentally sound and sustainable improvements (Toro *et al.*, 2010). As land leveling with machines requires considerable energy, optimizing energy consumption in the leveling operation is expected. As a result, here, two approaches including integrating ANN and ICA, sensitivity analysis (SA) and ANN models have been tested and evaluated in the prediction of environmental indicators for land leveling. Moreover, as a limited number of studies associated with the energy consumption in land leveling has been done, the objective of current energy and cost research is to find a function for all the indices of land leveling, including slope, coefficient of swelling, density of the soil, soil moisture, special weight dirt and swelling.

Materials and methods

Case study region

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 the 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). In total, 90 samples (30 from each location and 15 from each depth) were collected from three lands. At the next step, every five samples were mixed to create one sample. In this way, 90 samples were converted into 18 composite soil samples for convenient laboratory analysis. In the laboratory, the collected moist soil samples were first sieved through a 10-mm mesh sieve to remove gravel, small stones and coarse roots and plant remnants and then passed through a 2-mm sieve. The sieved samples were then 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 the human brain (Movagharnejad and Nikzad, 2007). They have been developed as a generalization of mathematical models of the human biological neural system (Mohammadi *et al.*, 2009).

There are a lot of structure types of ANN models. In this study, a typical feed-forward 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 (Azadeh *et al.*, 2008). 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 (Azadeh *et al.*, 2008):

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

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} denotes 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 (Shakibai and Koochekzadeh, 2009). Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output parameters (Tiryaki, 2008). The linear output layer lets the network to take any values even outside the range of -1 to $+1$, whereas if the last layer of a multilayer network has sigmoid neurons, then the outputs of the network will be only in a limited range (Tiryaki, 2008). Input variables were specific gravity, density, moisture content, slope, inflation rate and type of the cut soil. Relevantly, output variables were fuel energy (FE), machinery energy, labor power, total cost and energy consumption. In this study, all available data sets were used for regression modeling, but for ANN model development, data were randomly divided into three groups of training: 70 per cent of the data set for training, 15 per cent for model cross validation and 15 per cent for testing. (Diamantopoulou, 2005). 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–Marquardt 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, per cent sand and soil swelling index. The outputs of each model were labor energy (LE), FE, total machinery cost (TMC) and total machinery energy (TME). The schematic architecture of the used ANN is shown in Figure 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 $X = (X_1, X_2, \ldots, X_n)$; 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 $W = (W_1, W_2, \ldots, W_N)$ is the weight vector of associations among neurons. The S quantity is then passed to a nonlinear activation function f, yielding the following output:

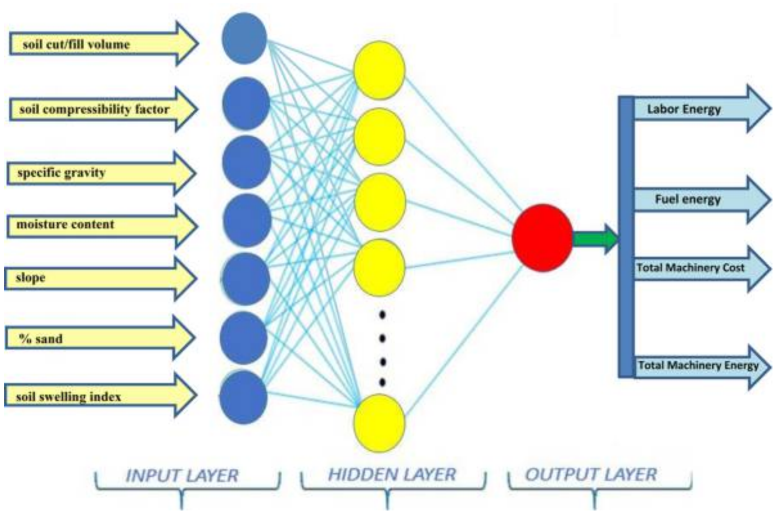

Figure 1.
A schematic representation of a three-layer ANN

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

Nonlinear 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

The ICA is a novel swarm-intelligence method that has been developed by mimicking the socio-political evolution strategies of human beings. The ICA optimization process starts with initialization of random populations and some incipient empires. In each stage of the ICA, a union of subgroups, colonies and imperialists assemble the empires. The 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 toward the relevant imperialist progressively. Imperialistic competition among the empires is the momentous procedure of the ICA (Kaveh and Talatahari, 2010; Talatahari *et al.*, 2012). In competition stage, powerless empires collapse, whereas the dominant ones gain further control over their colonies. This operation is stopped whenever one empire controls all the countries. In the termination condition, the 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 equation (5):

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

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 equation (6):

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

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

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

where $f_{\text{cost}}^{(imp,n)}$ stands for the cost of nth imperialist, and NC_n indicates its normalized cost.

Step 4: Dividing the colonies among imperialists. This process is based on the power of imperialists 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 equations (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 nth empire.

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

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

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 equation (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 a 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 equation (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, the weakest colony from the weakest empire is selected to be governed by the strongest empire. Imperialistic competition conducts a searching procedure toward 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 equation (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 equation (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 equations (16)-(18):

$$P = [P_{P1}, P_{P2}, \ldots, P_{PNimp}] \tag{16}$$

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

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

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 remaining 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 the ICA and real output is minimized. Mean squared error (MSE) was considered to determine the error.

ICA-ANN

In this study, after writing commands of ANNs in MATLAB software, the number of neurons in the input layer was considered the same as the number of effective parameters: cut-fill volume (V) (embankment volume), soil compressibility factor, specific gravity, moisture content, slope, sand per cent 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, the ICA was used. For running ANNs, 70 per cent of the data were used for training, 15 per cent for evaluation and the remained 15 per cent for testing.

The pseudo code of the basic ICA is:

(1) Select some random points on the function and initialize the empires.
(2) Move colonies to the relevant imperialist (assimilation).
(3) Select some colonies, then replace them with equal number of new generated countries (revolution).
(4) If a colony is better than the relevant imperialist, exchange the roles of the colony and the imperialist.
(5) Compute the total cost of every empire.
(6) Pick the weakest colony out from the weakest empire and give its control to the most powerful imperialist.
(7) If an empire loses all colonies, collapse it.
(8) If the stop condition is satisfied, stop, if not, go to Step 2.

Results

Sensitivity analysis model

The outputs that are shown in Table I are the results of the model after running it 500 times. Table I indicates F-values, and a great significance ($\alpha < 0.0001$) for all developed sensitivity analysis models in rejecting the null hypothesis was obvious. All models which had a significant p-value are represented in equations (19)-(22), and the coefficients are provided in coded units. The coded equation can be interpreted more easily. 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 LE, TMC, FE and TME models, only three variables, namely, soil compressibility factor, density and cut-fill volume (V), were applied.

In each equation, if the coefficient of a variable is lower than others, it can indicate the lower effect of that variable in the final model and vice versa (a sharp line in the trace plot). In all equations, the coefficient of the cut-fill volume term is maximum:

$$\mathrm{Sqrt(LE)} = +651.47 + 477.91 \times \mathrm{V} \tag{19}$$

$$\mathrm{Sqrt(FE)} = +3112.34 + 2275.41 \times \mathrm{V} \tag{20}$$

$$\mathrm{Sqrt(TMC)} = +2.024\mathrm{E} + 005 + 1.479\mathrm{E} + 005 \times \mathrm{V} \tag{21}$$

$$\mathrm{Sqrt(TME)} = +40138.00 + 29455.50 \times \mathrm{V} \tag{22}$$

Figure 2 shows the sensitivity analysis for LE. In this figure, F1 to F7 represent land slope, moisture content, density, soil compressibility factor, embankment volume, soil swelling

Table I.
Analysis of variance for LE, FE, TMC and TME

Model	Source	Sum of squares	df	Mean square	*F* value	*p*-value Probability > *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

Note: The same superscript numbers have no significant difference ($a < 0.0001$)

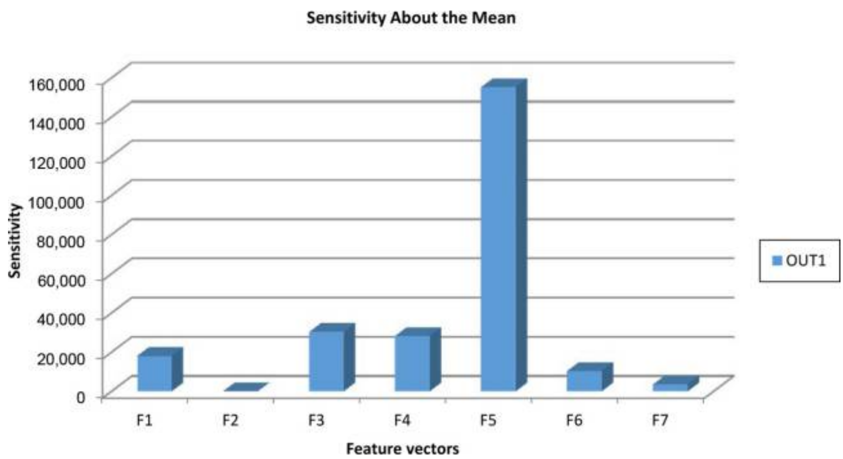

Figure 2.
Sensitivity analysis for LE

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.

Figure 3 shows the sensitivity analysis for FE. In this figure, F1 to F7 stand for the 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 sensitivity on FE, same as LE.

Figure 4 shows the sensitivity analysis for TMC. In this figure, legends are the same as Figure 2. Sensitivity analysis illustrated that F3 (density), F4 (soil compressibility factor) and F5 (embankment volume) were the most effective parameters on TMC, too.

Figure 5 shows the sensitivity analysis for TME. Legends of this figure are the same as Figure 3. Based on the results, the F3 (density), F4 (soil compressibility factor) and F5 (embankment volume) played the main role in TME and had the highest sensitivities. Sensitivity analysis showed that three soil parameters, namely, volume of soil, specific

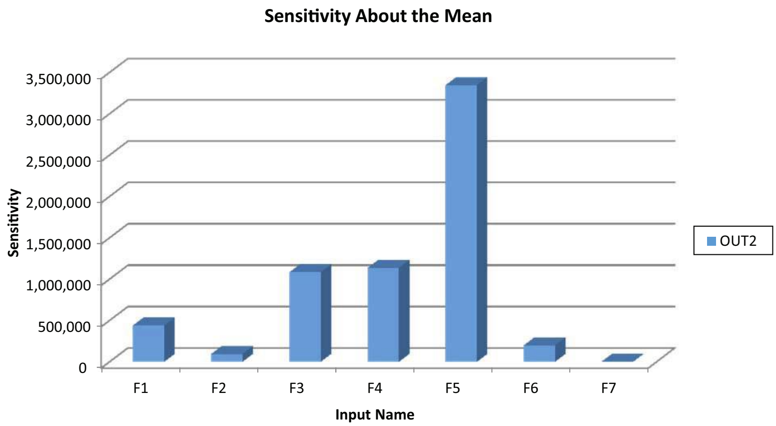

Figure 3. Sensitivity analysis for FE

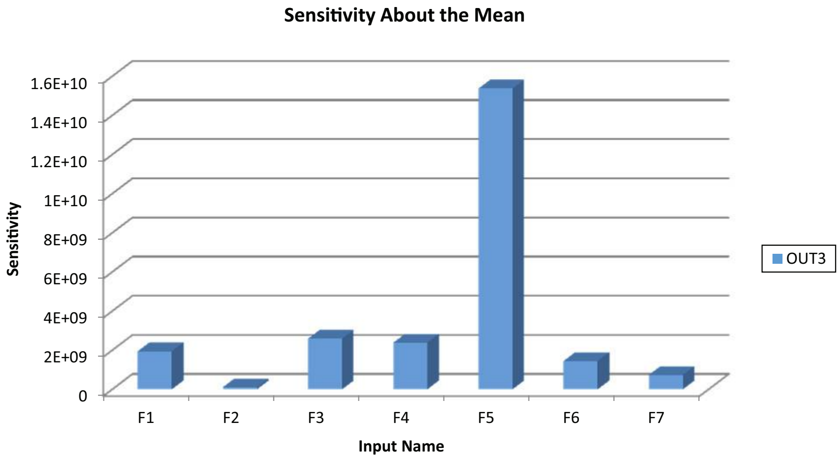

Figure 4. Sensitivity analysis for TMC

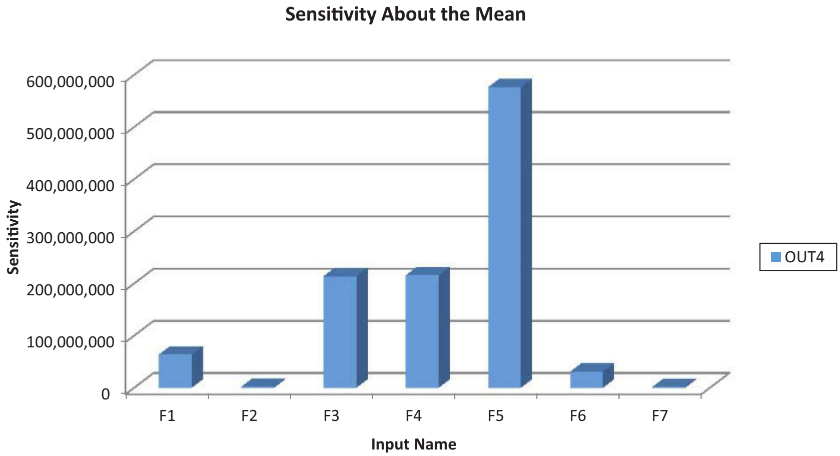

Figure 5.
Sensitivity analysis for TME

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 I 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, FE increases as well. Furthermore, prolonged working time of machinery increases labor requirement for operation, which in turn raises the energy consumption by the laborers. On the other hand, by decreasing the cut soil volume, required human labor also decreases. Therefore, one of the most important ways for decreasing 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 indicates 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 responses of interest. The lower F value of a variable indicates lower effect of that variable on responses.

Artificial neural network 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 combinations of network training functions (NTFs), number of hidden layers and number of neurons in each hidden layer. For selecting the best network topology, in total, 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 II and III represent results obtained from ANN of feed-forward BP type with seven 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–Marquardt (trainlm), Bayesian regularization (trainbr), scaled

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

Table II. Selected ANN for prediction of LE and FE

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 Table II and III, are the results of 500 thousand runs of the model. The selected NTF for LE in land leveling, as shown in the first row of the Table II, was the best because it had the highest correlation coefficient and lowest RMSE. These functions had eight 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 II. The NTF of trainlm had higher RMSE and lower R^2 for two (8-3) and three (2-7-6) hidden layers, but NTF of trainbr for one hidden layer had the best statistical interpretation. The NTF of trainlm including two neurons in one hidden layer is the most simple ANN for forecasting the LE with RMSE lower than 0.021 and R^2 higher than 0.996. Details of the selected networks for prediction of FE are presented in Table II. The NTF of trainlm had higher RMSE and lower R^2 for two (4-2) and three (8-2-5) hidden layers, but NTF of trainscg for one hidden layer has the best statistical output. The NTF of trainlm including two neurons in one hidden layer is the

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

Table III.
Selected ANN for prediction of TMC and TME

simplest ANN for predicting the FE with RMSE of lower than 0.033 and R^2 higher than 0.995. As shown in Table III, 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 details of the selected networks for prediction of TME are presented in Table III. The NTF of trainlm had higher RMSE and lower R^2 for two (6-4) and three (4-5-3) hidden layers, but NTF of trainscg for one hidden layer had the best statistical results. The NTF of traingdx including two 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 Figure 6 show 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 training record was used to plot the training, validation and test performance of the training progress (error vs number of training epochs).

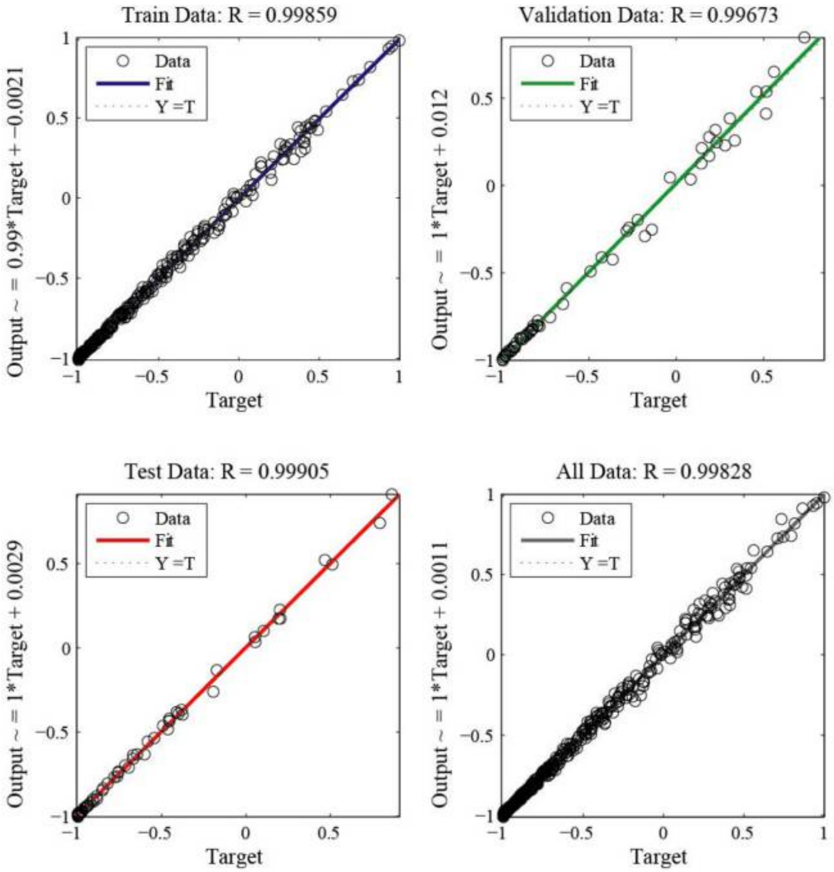

Figure 6.
Scatterplots of output versus target using ANN models for prediction of LE

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 the ICA with presented parameters in Table IV, the ANN models were developed. For each response, 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 V. 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 two structures, TMC was predicted by R^2 value of 0.9963. R^2 value for prediction of TME was found to be 0.9987. Scatterplots of actual versus predicted results of the ANN models are shown in Figure 7(a) to (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, which is evident from the 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 7(a) shows the scatterplot 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 7(b) is related to the scatterplot of the output data in contrast with target data using ICA-ANN models for prediction of FE. It is also evident for the FE values that the predicted results are very close to the target values. Figure 7(c) illustrates the scatterplot 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 scatterplot of output versus target values for TME is presented in Figure 7(d). 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 type of optimization problems is broadly reported in engineering, and the researchers acknowledged the superiority of ICA-ANN over conventional approaches. Taghavifar *et al.* 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 the ICA. The results were compared on the basis of a modified performance function (MSE-REG) and coefficient of determination (R^2).Their results elucidated that hybrid ICA-ANN succeeded to denote lower modeling error than other methods (Taghavifar *et al.*, 2014). 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 clearly illustrated the superiority of the proposed ICA-ANN model in comparison with the proposed BP-ANN model and empirical approaches (Marto *et al.*, 2014). Nikoo *et al.* used ICA-ANN to predict the flood-routing problem. The results proved that using this technique on the flood-routing problem is a valid approach, which is not only simple but also reliable (Nikoo *et al.*, 2016).

Table IV. 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

Table V. Comparison of ICA-ANN models and sensitivity analysis models and ANN models

	Sensitivity analysis		ANN		ICA-ANN	
Responce	RMSE	R^2	RMSE	R^2	RMSE	R^2
LE	0.1899	0.8631	0.0159	0.9990	0.0146	0.9987
FE	0.1971	0.8562	0.0206	0.9983	0.0322	0.9975
TMC	0.1946	0.8581	0.0287	0.9966	0.0248	0.9963
TME	0.1892	0.8437	0.0157	0.9990	0.0161	0.9987

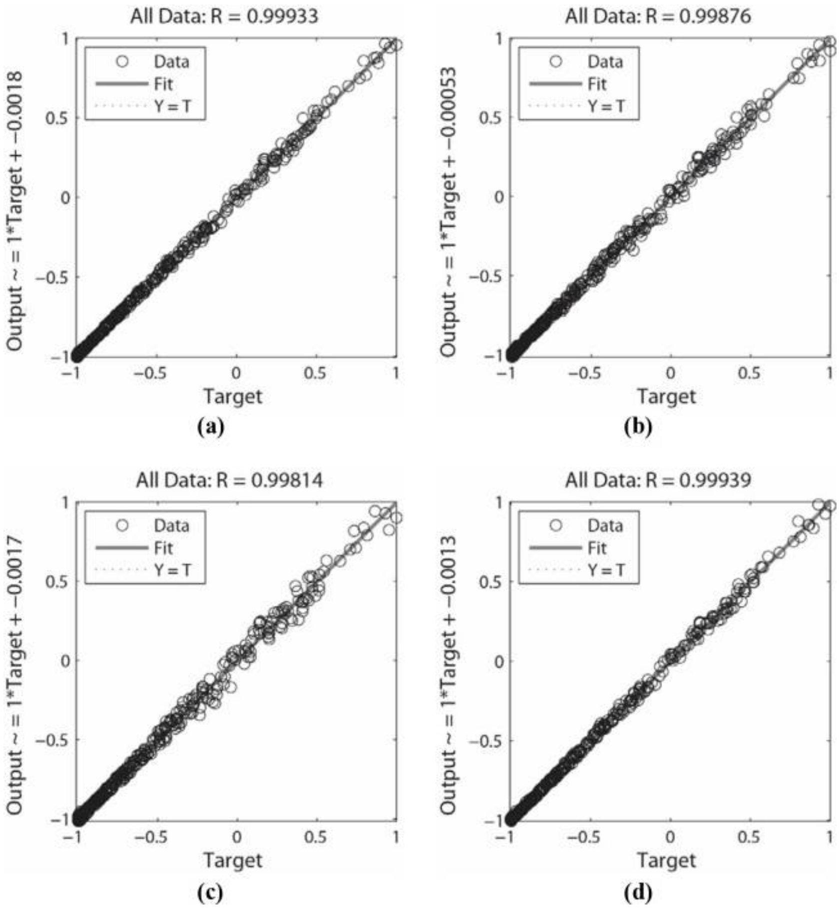

Figure 7.
Scatterplot of output versus target using ICA-ANN models for prediction of (a) LE, (b) FE, (c) TMC and (d) TME

Discussion

Comparison of models

The comparison of statistical results of ICA-ANN models and ANN models and sensitivity analysis is tabulated in Table V. As it can be seen from Table V, among the ICA-ANN models and ANN models and sensitivity analysis, 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 a low effect on cost and energy consumption?

In the case of specific gravity: if specific gravity of the ground becomes greater, the weight of a determined volume of the soil becomes greater too and work hours of the machine for clearing that specific surface increase and, subsequently, much fuel will be consumed.

In the case of soil cut/fill volume: if the soil cut/fill volume increases, work hours of the machine and the number of laborers increase and again much fuel is necessary.

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.

Conclusion

A limited number of research studies related to energy consumption in land leveling on energy as a function of the volume of excavation and embankment have been presented. But, 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 and special weight dirt. The paper's argument was built on an appropriate base of theory, concepts and other ideas. And, the methods used are appropriate. In this study, the ability of ICA-ANN models, ANN models and sensitivity analysis for prediction of environmental indicators, LE, FE, TMC and TME, during land leveling was investigated. Results were 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–Marquardt as the NTF. Sensitivity analysis revealed that only three variables, namely, density, soil compressibility factor and cut-fill volume (V), had the highest sensitivity on the output parameters, including LE, FE, TMC and TME. 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 of about 0.02 and 0.99, respectively. Moreover, using ANFIS for prediction of output variables, LE, FE, TMC and TME, was 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 projects on agricultural lands and as a tool by managers, consultants, researchers, etc. The results of this research impact upon the agricultural society, affecting quality of their life. These implications are consistent with the findings and conclusions of this paper.

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