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Modeling And Sensitivity Analysis Of Environmental Indicators For Land Leveling Using Integrating Artificial Neural Network And Genetic Algorithm (GA-ANN)

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1. Abstract

Land leveling is one of the most important steps in soil preparation for consequent objectives. Parallel policies need to take both energy and environmental subjects into the account as well as certain financial development and eco-friendly protection. Energy is regarded as one of the most important elements in agricultural sector nevertheless; pollution is linked with usage of fossil fuels (particularly gasoline) as energy source. New techniques based on artificial intelligence, such as Artificial Neural Network (ANN), Integrating Artificial Neural Network and Genetic algorithm (GA-ANN) and Sensitivity Analysis (SA), have been employed for developing of predictive models to estimate the energy related and other parameters. In this study, several soil properties such as soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, sand percent, and soil swelling index in energy consumption were investigated. Total of 100 samples were collected from 2 land areas. The grid size was (20m×20m). The aim of this work was to develop predictive models based on artificial intelligence techniques to predict the environmental indicators for land leveling and to analysis the sensitivity of these parameters. Results of sensitivity analysis showed that only three parameters of soil density, soil compressibility and soil cut/fill volume had significant effects on energy consumption. R^2 and RMSE results revealed that GA-ANN models have higher accuracy to predict targets.

2. Keywords:
Energy; Genetic algorithm; Sensitivity analysis; ANN; Land levelling; Environmental indicators

3. 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 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 [8]. Energy supply for land levelling and agricultural water supply is one of the important factors. It is necessary to protect the environment in energy supply and consumption. 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 [118]. 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 [31].

ANN is a conceptual technique which its outputor inferred variable can be modelled in terms of other parameters that are relevant to the same process [129]. 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' behavior through simulation scenarios and statistical result were quiet notable [2] and optimization complications [1]. 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 [1310]. Since, land leveling with machines requires considerable energy.

Thus, optimizing energy consumption in the leveling operation is expected. As a result, here, three approaches including Artificial Neural Network (ANN), Integrating Artificial Neural Network and Genetic algorithm (GA-ANN), and Sensitivity Analysis (SA) have been tested and evaluated in prediction of environmental indicators for land leveling. Moreover, since a limited number of studies associated with the energy consumption in land leveling have been done, the objective of current energy and cost research is to find a function for all the indices of the land leveling including the slope, coefficient of swelling, the density of the soil, soil moisture, special weight dirt and the swelling.

4. Materials And Methods

4.1. 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. 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 city of Karaj is located between longitude 35° 50' 24'' N and latitude 50° 56' 20'' E. For the present research, data was collected from agricultural land in Karaj.

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 4 lands. At the next step, every five samples were mixed to create one sample. In this way total 100 samples were converted into 20 composite soil samples for convenient laboratory analysis. In the laboratory, collected moist soil samples were firstly sieved through 10mm 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. In the laboratory, soil samples were firstly sieved through 10mm mesh then passed through 2 mm sieve. Then the sieved samples were dried at room temperature. Parameters moisture content, soil texture, bulk density, and soil optimum density were measured.

4.2. Conceptual Foundations And The Artificial Neural Network (ANN) Theory

To predict performance of Energy Consumption for land leveling, the ANN models with back-propagation algorithm have been developed using MATLAB software. Generally, the ANN is characterized by three layers: an input layer, a hidden layer, and an output layer. The available data are usually divided into three randomly selected subsets which include: (data were randomly divided into two groups of training (80% of all data) and test (the remaining 20%) for testing. ANN of feed forward back-propagate type with 8 different network training algorithms that are available in the Neural Network Toolbox software and that use gradient- or Jacobian-based methods, including [1613],

Bayesian regularization (trainbr) has been proven to have appropriate generalization properties when used in the training of the NN [1714], scaled conjugate gradient (trainscg) is one of the most popular second-order gradient supervised procedure [1815] , conjugate gradient function (traincgf) which is a network training function that updates related values of weight and bias based on conjugate gradient back propagation with Fletcher-Reeves updates [1916], resilient back-propagation (trainrp) in which the ordinary gradient descent back-propagation modification is applied in order to omit the harmful effects of the magnitudes related to the partial derivatives [2017] Gradient descent with momentum and adaptive learning rate back propagation (traingdx) is a network training function to update bias and weight values according to gradient descent momentum and adaptive learning rate [1916] Were used for network training. The Neural Network Toolbox for MATLAB, provides a clear and detailed coverage of fundamental neural network architectures and learning rules. In it, is emphasized a coherent presentation of the principal neural networks, methods for training them and their applications to practical problems. In addition to conjugate gradient and Levenberg-Marquardt variations of the back propagation algorithm, the text also covers Bayesian regularization and early stopping, which ensure the generalization ability of trained networks. Associative and competitive networks, including feature maps and learning vector quantization, are explained with simple building blocks [2118].

In general, there is not a specific method for defining the number of hidden layers and also the number of neurons in the hidden layer; so these factors were obtained by trial and error method. In this research, the number of hidden layers and neurons in the hidden layer (or layers) were chosen by comparing the networks performance.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 as the performance parameters. Output The schematic architecture of the used ANN is shown

As mentioned earlier, the main elements of ANNs are constituted by artificial neurons. The input model be represented as a vector with N items X= (X1, X2,… ,Xn).The summation of inputs multiplied by their corresponding weights could be represented by scalar quantity S. 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,… ,X_n); the summation of inputs multiplied by their corresponding weights could be represented by scalar quantity S.

$$S = \sum_{n=1}^{n} W_n X_n \quad (1)$$

Where W=(W_1 ,W_2 ,… ,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:

$$y = f(s) \quad (2)$$

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

$$f(s) = \frac{1}{1+e^{-s}} \quad (3)$$

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.

4.3. Genetic Algorithms

Many researchers have widely used the BPA for the training performance of the neural networks model. It is a first-order method based on the steepest gradient descent, with the direction vector being set equal to the negative of the gradient vector. It is also possible for the training performance to be trapped at the local minimum despite the use of a learning rate [53]. Therefore, the various methodologies have been suggested to overcome the weakness of the BPA application for the training performance of the neural networks model. The training performance of the neural networks model using the genetic algorithm (GA) starts by initializing the connection weights and the input layer nodes. The global error at the output layer of the neural networks model is then calculated as the fitness value of the objective function.

These procedures are repeated from one generation to the next with the objective of reaching the global optimal solution after a sufficient number of generations. It is to be noted that a generation in the GA is highly analogous to iteration in the BPA, and the goal in both algorithms is to update the connection weights.nice the connection weights are updated at the end of a generation, the fitness value of the objective function can be calculated [75]. In this study, it was determined that the procedure of updating the connection weights is repeated from one generation to the next until convergence is reached in terms of a certain acceptable error or within the training tolerance at the output layer of the neural networks model. .The concept of genetic algorithm (GA) was first introduced by [64]. These algorithms are a particular group of evolutionary algorithms, which working principle is the same of Darwinian selection and evolution [96]. The principle of GA is to create new generations by using strong individuals, and eliminating weak individuals, to obtain better solutions. Individuals are modified by crossover and mutation operations in the same way as biological evolution [42]. The GA algorithm gets rid of minima by using a waste range of population. In this research input parameters are soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, % sand and soil swelling index.

The output parameters are Labor Energy, Fuel energy, Total Machinery Cost and Total Machinery Energy (TME). Many researchers have widely used the BPA for the training performance of the neural networks model. It is a first-order method based on the steepest gradient descent, with the direction vector being set equal to the negative of the gradient vector. It is also possible for the training performance to be trapped at the local minimum despite the use of a learning rate (Haykin, 1994). Therefore, the various methodologies have been suggested to overcome the weakness of the BPA application for the training performance The training performance study is to develop and apply the generalized regression neural networks model (GRNNM) embedding the genetic algorithm (GA) using the GA progresses largely in two parts. The first part uses training data to train the GRNNM. The second part uses the developed GRNNM in the first part to test the entire range of the smoothing factor for the optimal operation over the testing data. And, the GA can produce the GRNNM which can be operated best over the testing data. When the neural networks model is trained using the GA, however, it requires much time than the BPA is used as a search method. All calculations for the training, the testing and the reproduction performances of the GRNNMGA are carried out using Neuroshell 2 software provided by Ward Systems Group, Inc. [107].

4.4. GA-ANN

GA--ANN method was one of the applied methods to predict the prospective environmental indicators. The algorithm required for this model was compiled in MATLAB software in a way that in the first layer 7 neurons were considered which are correspond of effective parameters (Cut-Fill Volume (V-embankment volume), soil compressibility factor, specific gravity, moisture, slope, sand percent, and soil swelling index) and in the output layer 4 neurons were responsible for desired parameters of the problem, LE, FE, TMC, and TME. In training section, 70% of the data were used data were randomly divided into two groups of training (80% of all data) and test (the remaining 20%) g GA approach.

5. Results

5.1. Results of Sensitivity Analysis

The results of the model are shown in (Table 1) which are derived from 400 thousand run of the model. All F-values shown in)Table 1(were indicated a great significance ($\alpha<0.0001$) for all developed sensitivity analysis which refutes the null hypothesis. All models have significant p-values too. Of the seven parameters of soil and land characteristics (moisture, density, soil compressibility factor, land slope, soil type, embankment volume), three factors of slope, Cut-Fill Volume (V) and soil density have the most significant effect on labor energy (LE) in land leveling (Table 1).And three factors of slope, Cut-Fill Volume (V) and soil compressibility have significant effects on fuel energy (Table 1).And embankment volume (v), soil density and slope have significant effects on total machinery cost in land leveling (Table 1).

Table 1: Analysis of variance for models studied.

Model	Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F
LE Model	Model	1.24^{11}	3	4.15^{10}	5523.9	< 0.0001
	Slope	1.85^{9}	1	1.85^{9}	246.77	< 0.0001
	Cut-Fill Volume (V)	1.21^{11}	1	1.21^{11}	16149.3	< 0.0001
	soil density	2.61^{8}	1	2.61^{8}	34.702	< 0.0001
FE Model	Model	1.84^{13}	3	6.15^{12}	4632.446	< 0.0001
	Slope	3.43^{11}	1	3.43^{11}	258.640	< 0.0001
	V	1.78^{13}	1	1.78^{13}	13457.37	< 0.0001
	soil compressibility	3.28^{10}	1	3.28^{10}	24.73922	< 0.0001
TMC Model	Model	1.16^{19}	3	3.88^{18}	4751.32	< 0.0001
	Slope	1.8^{17}	1	1.8^{17}	220.26	< 0.0001
	V	1.13^{19}	1	1.13^{19}	13881.2	< 0.0001
	soil density	2.21^{16}	1	2.21^{16}	27.006	< 0.0001
TME Model	Model	6.64^{16}	3	2.21^{16}	5653.4	< 0.0001
	Slope	9.6^{14}	1	9.6^{14}	245.44	< 0.0001
	V	6.47^{16}	1	6.47^{16}	16537.3	< 0.0001
	soil density	1.44^{14}	1	1.44^{14}	36.8753	< 0.0001

The fitted nonlinear equations for the all response of interest including LE, FE, TMC, and TME are represented in Eqs. 4-7, 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 soil density have significant effects. Although, in FE model the effect of SSI is not significant and has been replaced by the percentage of soil compressibility.

.(LE)0.8 = 34161.36 + 3639.90 * Slope + 31173.94 * V+911.96 * soil density (4)

(FE)0.8 = 4.1485 + 49590.44 * Slope + 3.7825 * V -10008.33 * soil compressibility (5)

(TMC)0.8 = 3.3198 + 3.5877 * Slope + 3.0158 * V+ 8.3936 * soil density (6)

(TME)0.8 = 2.4947 +2.6216 * Slope +2.2777 * V+6.7875 * soil density (7)

5.2. Results Of ANN Model Prediction

The detail of the best trained networks for prediction of LE is shown in (Table 2). The NTF of trainlm has higher RMSE and lower R2 for 2 (8-3) and 3 (2-7-6) hidden layers but NTF of trainbr for 1 hidden layer has best statistical criteria. The NTF of trainlm including 2 neurons in one hidden layer is the most simple ANN for forecasting the LE having RMSE lower than 0.021 and R2 higher than 0.996 (Table 2).

Table 2: Selected ANN for prediction of Labor Energy (LE) Selected NTF and Network topology for prediction of (LE)

NTF	Network topology	RMSE	R^2
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

The detail of the selected networks for prediction of FE is presented in (Table 3). The NTF of trainlm has 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 best statistical criteria. The NTF of trainlm including 2 neurons in one hidden layer is the most simple ANN for forecasting the FE having RMSE lower than 0.033 and R^2 higher than 0.995 (Table 3).

Table 3: Selected ANN for prediction of Fuel energy (FE) Selected NTF and Network topology for prediction of (FE)

NTF	Network topology	RMSE	R^2
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

As can be seen from the (Table 4), the first model consisting of three hidden layers (5-8-10 topology) has the highest coefficient of determination (0.997) and the lowest values of RMSE (0.029) indicating that this ANN can predict the TMC accurately. So this model was given as the best solution for estimating the TMC. According to table 4 three hidden layers (5-8-10 topology) was given as the best solution for estimating the TMC (Table 4).

Table 4: Selected ANN for prediction of Total Machinery Cost (TMC) Selected NTF and Network topology for prediction of (TMC)

NTF	Network topology	RMSE	R^2
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

The detail of the selected networks for prediction of TME is presented in (Table 5). The NTF of trainlm has 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 has best statistical criteria. The NTF of traingdx including 2 neurons in one hidden layer is the simplest ANN for forecasting the FE. The RMSE for this model was found to be 0.225 which was very low (Table 5).

Table 5: Selected ANN for prediction of Total Machinery Energy (TME)

NTF	Network topology	RMSE	R^2
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

Result of ANN-ICA model for LE is presented in Fig. 1. The model reliably predicted LE based on input parameters (soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, sand percent, and soil swelling index). At the test stage, the model predicted LE with R value of 0.999 (Figure 1).

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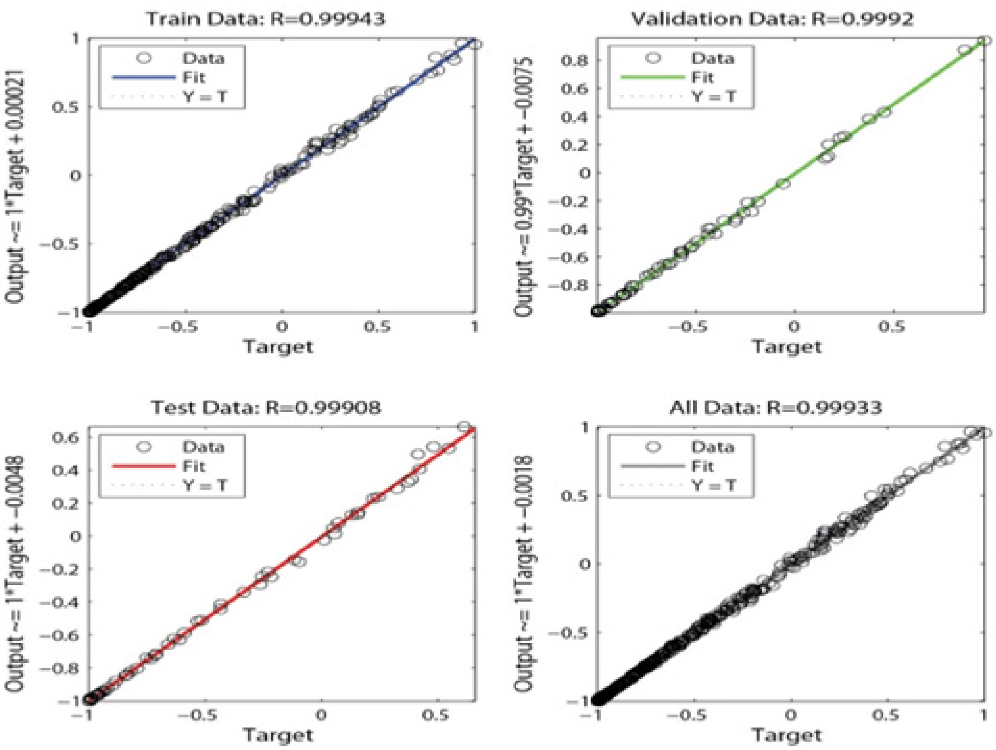

Figure 1. Scatter plots of output vs. target using ANN-ICA models for prediction of LE. Figure 1. Displaying the outputs vs the target in ANN-ICA model in labor energy estimation.

5.3. Results Of GA-ANN Model

Comparative results for sensitivity analysis, GA-ANN for prediction of LE, FE, TMC and TME parameters presented in (Table 6). For the error analysis R2 and RMSE parameters were considered. The results of LE prediction revealed that GA-NN model can predict LE by a relatively high R^2 and lowest RMSE. So, this model is considered as the best one for the prediction of LE.. On the other hand, sensitivity analysis model showed the highest error and lowest R^2 value in prediction of LE. The results of FE prediction revealed that ANN model can predict FE by a relatively high R2 and lowest RMSE. So,The results of TMC and TME predictions also revealed that GA-ANN model can predict TMC and TME by a relatively high R2 and lowest RMSE. So, this model is considered as the best one for the prediction of TMC and TME. On the other hand, sensitivity analysis model showed the highest error and lowest R^2 value in prediction of TMC and TME (Table 6).

Table 6: Comparison of sensitivity analysis and ANN and GA-ANN models

Responce	sensitivity analysis		ANN			GA-ANN	
	RMSE	R^2	RMSE	R^2		RMSE	R^2
LE	0.181	0.863	0.016	0.999		0.015	0.998
FE	0.197	0.856	0.021	0.998		0.026	0.996
TMC	0.195	0.858	0.029	0.997		0.019	0.997
TME	0.189	0.844	0.016	0.999		0.012	0.999

As it is shown in Fig3 (a), among four applied methods to predict (LE), (FE), (TMC) and (TME) accroding to three selected input parameters (soil cut/fill volume, specific gravity and soil compressibility factor) the mean square error (RMSE) of (LE) and (TME)

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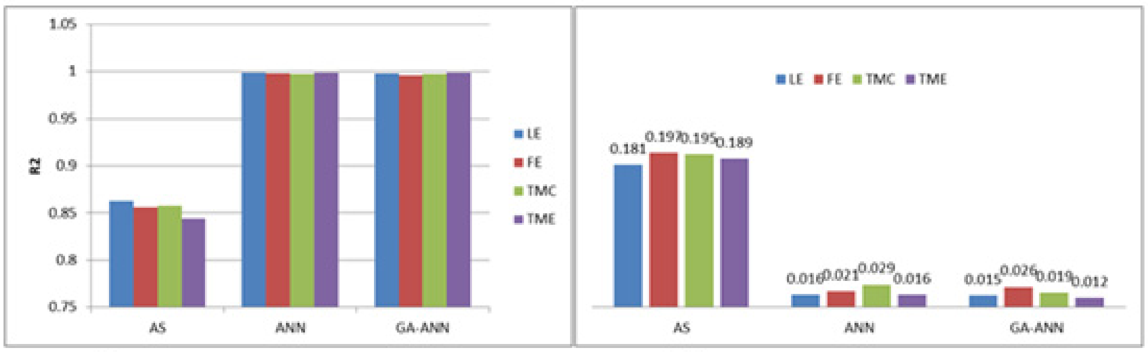
are less than (FE) and (TMC). In fact using artificial neural network based prediction methods (ANN, GA-ANN, Sensitivity Analysis SA) have more accurate prediction for (LE) and (TME) in comparison to (FE) and (TMC). On the other hand as it is shown in figure (b) correlation coefficient (R^2) of (LE) and (TME) are more than (LE) and (TME) (Figure 2).



(a) (b)

Figure 2: RMSE (a) and R^2 (b) of four prediction algorithms

As shown in (Fig. 3), among four applied methods to predict (LE), (FE), (TMC), and (TME) according to three selected input parameters (soil cut/ fill volume, specific gravity, and soil compressibility factor) RMSE of LE and TME were less than that of FE and TMC. In fact using ANN-based prediction methods (ANN, AG-ANN,) Sensitivity Analysis were predicted LE and TME more accurately than FE and TMC. On the other hand, as it is evident in (Fig.2 (a) R2 of prediction of LE and TME were higher than LE and TME. According to the comparison of the R2 between four ANN methods, it is revealed that among these methods, GA-ANN had the maximum R2 value in in prediction of TME, FE, It is noticeable that the R2 value of LE, and TMC. resulted from GA-ANN, are equal, (GA-ANN) algorithms. on the other hand, as it is shown in (Fig.2 (b)) , the RMSE of FE using ANN algorithm was the least value between three mentioned algorithms. (Fig2 (b)) shows the RMSE value of all methods. As it is shown in this diagram, the ANN algorithm has the maximum RMSE value among all methods. It is considerable that the smaller R^2 value and higher RMSE value will lead to the worst result in the prediction. The results show that although the output values were acceptable by applying these four methods, it should be considered that ANN algorithm was the weakest algorithm for prediction of TMC,LE,TME as the neural networks were run 1000 times. Although GA-ANN had the best performance in prediction of FE, AG-ANN was also a good prediction method regardless of its weakness in prediction of FE.

6. Discussion

Analysing the statistical results of artificial intelligence techniques (GA-ANN, ANN, and Sensitivity analysis) are in Table 4. As it can be seen from the Table 4, among GA-ANN, ANN and Sensitivity analysis, GA-ANN models had significantly better performance according to R2 and RMSE values for them.

So that the results show the relationship of land leveling in the energy with the slop of the land, swelling coefficient and soil type is significant. By increasing land slope, volume of excavation and embankment increases and the number of sweep and distance traveled leveling machines also increases and fuel consumption 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. Heavy clay soils and soil adhesion on wet mode with more machines and move the car to be faced with a larger resistance leveling and cause more consumption of fuel and energy.

In another research, Artificial Neural Network (ANN) and Neuro-Fuzzy inference system (ANFIS) were used to predict the subsurface water level in paddy fields of Plain Areas between Trajan and Nectarous Rivers. The correlation coefficient of these two respective models are 0.8416 and 0.8593 and RMSE of them is 0.2667 and 0.2491 (Mohammadi et al., 2009)[14].

In another study , MLP-ANN models and 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 R^2 of 0.0163 in training stage, and RMSE of 0.9753 and R^2 of 0.0694 in test stage (Fereydooni and Mansoori, 2015) [15].

MLP-ANN models and ANFIS models were used in order to predict and simulate the groundwater level of Lamerd plain.The results showed on high accuracy for modes ANFIS and MLP-ANN models (Fereydooni and Mansoori, 2015)[15].

7. Conclusion

A limited number of research related to energy consumption in land leveling have been done that study the function of the volume of excavation and embankment on energy consumption. But, in this research, a holistic approach was proposed to find the correlation between energy and cost of land leveling that are dependent on other properties of the land including the slope, coefficient of swelling, soil density, soil moisture. In this study, the ability of Integrating artificial intelligence techniques (GA-ANN), -ANN and Sensitivity analysis) for prediction of LE, FE, TMC, and TME values were used. These methods were compared based on the statistical criteria, RMSE, MEA and R2. According to the results, networks with 10-8-3-1, 10-8-2-5-1, 10-5-8-10-1, and 10-6-4-1 structures were chosen as the best MLP networks.

Levenberg-Marquetwere used as network training function for prediction of all LE, TE, TMC, and TME. Using sensitivity analysis method revealed that only three parameters of soil density, Slope and soil cut/fill volume had significant effects on environmental indicators. The results shows the RMSE and R^2 of five applied methods. As it is shown, sensitivity analysis has the least ability in energy prediction compare to the two other methods because of the highest RMSE and the least R^2. The other methods have more ability to predict the environmental energy parameters in which GA-ANN has the most capability in prediction according to least RMSE and the highest R^2 for FE. accurate one. Ability of GA-ANN models in prediction of sophisticated problems with high accuracy makes it a powerful tool for engineers and researchers to use it not only in agricultural operations, but also in other fields such as finance, mining, infrastructures, etc. Using this tool will lead to an economical land leveling operations in farm lands. The results of GA-ANN models shows that using this tool will lead to an economical land leveling operations in farm lands.

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