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Modeling environmental indicators for land leveling, using Artificial Neural Networks and Adaptive Neuron-Fuzzy Inference System

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ABSTRACT: Land leveling is one of the most important steps in soil preparation and cultivation. Although land leveling with machines requires considerable amount of energy, it delivers a suitable surface slope with minimal soil deterioration as well as damage to plants and other organisms in the soil. Notwithstanding, in recent years researchers have tried to reduce fossil fuel consumption and its deleterious side effects, using new techniques such as Artificial Neural Networks (ANNs) and Adaptive Neuron-Fuzzy Inference System (Fuzzy shell-clustering algorithm) models that will lead to a noticeable improvement in the environment. The present research investigates the 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. The study consists of 90 samples, collected from three different regions. The grid size has been set on 20 m * 20 m from a farmland in Karaj Province, Iran. The aim is to determine the best linear model, using ANNs and ANFIS model to predict environmental indicators and find the best model for land leveling in terms of its output (i.e. Labor Energy, Fuel energy, Total Machinery Cost, and Total Machinery Energy). Results show that ANFIS can successfully predict labor energy, fuel energy, total machinery cost, and total machinery energy. All ANFIS-based models have R^2 values above 0.995 and MSE values below 0.002 with higher accuracy in prediction, given their higher R^2 value and lower RMSE value.

Keywords: ANFIS, artificial neural network, energy, environmental research, land levelling.

INTRODUCTION

During the last century due to increasing human population, demands for agricultural commodities have risen enormously. In addition, currently one of the cardinal environmental challenges in the world is production and consumption of energy. 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 should be taken into account that environmental conservation and market globalization will depend on food security in future agriculture (Jat et al., 2006). Accordingly, some special policies ought to

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be addressed so that an energy viewpoint can be considered in conjunction with environmental issues to solve the problem. Land leveling is one of the heavy and costly operations among agricultural practices that consumes considerable amount of energy. What is more, moving heavy machines on the ground makes the soil denser, particularly in wet regions where the moisture contents of the soil is higher, leading to a situation, not easily recoverable (Khan et al., 2007).

On the other hand, land leveling simplifies irrigation and improves field situations in other practices, related to agriculture, regulating the soil surface and normalizing its slope (Brye et al., 2006). Reportedly, there are three significant factors, having effect on grain yield, including the effects of land leveling, methods of water application, and the interaction between the two. Okasha et al. (2013) observed a noteworthy connection between slope and diverse irrigation scheme in different seasons. Diverse methods of land leveling can affect the physical and chemical properties of the soil, hence they 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, to be optimized, is land leveling (Cassel et al., 1982). Besides, decreasing consumption of fossil fuel for land leveling diminishes air contaminants and improves the environmental condition. There is growing understanding about the importance and impacts of water and soil management which in turn reveals the significance of optimized laser land levelling from social, financial, and agronomic points of view (McFarlane et al., 2006).

An artificial neural network paradigm, known as the temporal back propagation neural network (TBP-NN), is successfully demonstrated as a monthly rainfall –runoff model (Sajikumar & Thandaveswara, 1999). An ANN with sufficient complexity is capable of approximating any smooth function to any desired degree of accuracy. In addition, ANNs are computationally robust, capable of learning and generalizing from examples to give meaningful solutions to problems even when the input data are either erroneous or incomplete (Luk et al., 2000). ANN is a conceptual technique, the output or inferred variable of which can be modeled in terms of other parameters, relevant to the same process (Rallo et al., 2002). It has been widely used in the field of engineering for optimization and prediction. Ahmadi et al. (2014) 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, namely PSO-ANN, can help better understand fluid reservoirs' behavior through simulation scenarios, giving statistical results that were quite considerable.

In another research a feed-forward ANN, optimized by PSO, was used as an artificial intelligence modeling tool to predict asphalting precipitation due natural depletion (Ahmadi & Golshadi, 2012). They also proposed another network, based on feed-forward ANN and optimized by (HGAPSO), comparing it with conventional BP-ANNs. They reported that results of this approach were better than conventional methods, based on statistical analysis (Ahmadi et al., 2013). These techniques have been also used to predict parameters with declining uncertainty. In a 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 research Gautam and Holz (2001) explored the effectiveness and applicability of adaptive neuron-fuzzy-system-based on rainfall-runoff models for simulation and forecasting. Therefore, they proposed an adaptive neuron-fuzzy system with autoregressive exogenous input (ARX) structure, presenting an application for modeling rainfall-runoff processes in the Sieve basin, Italy.

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 Lammed plain. The results were obtained by emphasizing higher accuracy and lower scattering for modeling ANFIS, where RMSE and R2 turned out to be 0.9987 and 0.0163 in training stage, and 0.9753 and 0.0694 in test stage, respectively (Fereydooni & Mansoori, 2015). 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 the proposed models were 0.8416 and 0.8593, with their RMSE being 0.2667 and 0.249, respectively (Mohammadi et al., 2009; Lei et al., 2006).

Imperialist competitive algorithm 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., 2011) such as data clustering (Ebrahimzadeh et al., 2012), Nash balance point attainment (Rajabioun et al., 2008), ANNs training (Zhang, 2012) composite constructions (Abdi et al., 2011), production administration complications (Nazari-Shirkouhi et al., 2010), and optimization complications (Ahmadi and Golshadi, 2012). Environmental Impact Assessment (EIA) has been also addressed in the literature, involving the investigation and estimation of scheduled events with an eye on ensuring environmentally-sound and sustainable improvements (Toro et al., 2010).

In another study, Akbarzadeh et al. (2009) developed an ANFIS model to estimate soil erosion, while a further research (Krueger et al., 2011) evaluated characterization of root distribution patterns under field conditions with ANFIS model. Zhu and Fujitha (1994) compared a feed-forward ANN model to predict a 3-hour lead-runoff, employing a fuzzy reasoning in rainfall–runoff modelling performance. They took into account the phenomenon's dependence on time by using a window of rainfall inputs. Recently, neural networks based researches have implemented semantic-based fuzzy neural architecture, instead of black box approach (Ang & Quek, 2005). Since, land levelling with machines requires considerable energy, it is expected to optimize energy consumption in the levelling operation. As a result, this paper tests two approaches, namely Integrating Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (Fuzzy shell clustering algorithm) models and evaluates them in terms of their prediction of environmental indicators for land leveling. Moreover, since there has been a limited number of studies, associated with energy consumption in land leveling, the objective of the current energy and cost research is to find a function for all indices of land leveling, including the slope, coefficient of swelling, soil density, soil moisture, special weight dirt, and the swelling.

MATERIALS AND METHODS

The region of the case study

In order to verify the accuracy and applicability of the proposed linear model, a case study was carried out based on the project's requirements in a farmland in Karaj, Iran. The farm area was 70 hectare big and was located 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. The length, width, and height of the points, from a reference point (coordinates of x, y, and z), were considered the outputs. The grid size in the case study region was 20*20 m, during the topographical operations. Samples were collected from two different sites inside the region at 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 3 lands. In the next step, every five samples were mixed to create one sample. In this way, the 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 10mm mesh sieve to remove gravel, small stones, coarse roots, and plant remnants, then to be passed through 2 mm sieve. Afterwards, the sieved samples were dried at room temperature and their moisture content, texture, bulk density, land slope, and soil optimum density were determined.

Intelligent techniques

This research applied ANN and ANFIS (Fuzzy shell clustering algorithm) techniques as two methods of Computational Intelligence (CI) to predict the energy consumption of land leveling at various field conditions (two levels of moisture contents, three levels of inflation pressure, three tillage depths) and finally their performances were evaluated and compared, and the optimal models, identified. The ANN model with back-propagation algorithm was developed, using MATLAB software (Mathworks, Inc). The developed ANN in the present study was characterized by three layers: an input layer, a hidden layer, and an output layer. The obtained data was divided into three randomly-selected subsets: the training set, the testing set, and the validation set. Some papers use 70% of the dataset for training purposes with the remaining 30% for model validation and testing. Training set (input vectors and the corresponding target vectors) were used to train the network to find a function, associating input vectors with the specific output vector. Within the development of the ANFIS prediction models, the available data were divided, similar to ANN modeling, into two randomly-selected subsets: training and testing datasets with the former used to develop and calibrate the model, while the latter (also known as the validation dataset), not used in the development of the model, was utilized to validate the trained model. The ANFIS and ANN were applied to perform prediction models with seven inputs and four single outputs. The input parameters were soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, percentage of sand, and soil swelling index. The output of each model included labor energy, fuel energy, total machinery cost, and total machinery energy. Prior to utilization of the dataset for modeling, the inputs and target output were normalized or scaled linearly between -1 and 1, in order to increase the performance and speed of ANN and ANFIS models (Luk et al., 2000):

$$x_n = 2\frac{x_r - x_{rmin}}{x_{rmax} - x_{rmin}} - 1 \qquad (1)$$

where x_n is the normalized input variable; x_r, the raw input variable; and x_{rmin} and x_{rmax}, the minimum and maximum rates of the input variable, respectively.

Development of ANN model

ANNs are massively parallel-distributed information processors that have certain performance characteristics, resembling biological neural networks of human brain (Movagharnejad & Nikzad, 2007). They have been developed as a generalization of mathematical models of human biological neural system (Mohammadi et al., 2009). There are a lot of structure types of ANN models. This study used a typical feed forward back propagation (BP) MLP structure. The main advantage of MLP structures over other types is that they have the ability to learn complex relations 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 as well as an output layer. The input nodes are the previous lagged observations, while the output provides the forecast for future values. Hidden nodes with appropriate nonlinear transfer functions were used to process the information, received by the input nodes. The model can be written as follows (Azadeh et al., 2008):

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j f(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j}) + \varepsilon_t \tag{2}$$

$$j = 0,1,\ldots,n \quad and \quad i = 0,1,\ldots,m$$

where m is the number of input nodes; n, the number of hidden nodes; α_j, the vector of the weights from hidden to output nodes; and β_{ij}, the weights from the input to hidden nodes The weights of the arcs, leading from the bias terms, are represented by α_0 and $\beta_{0j,}$ whose values are always equal to 1, while 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 relations between the 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, while if the last layer of a multilayer network has sigmoid neurons, the network outputs will be only in a limited range (Tiryaki, 2008). Input variables included 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 datasets were used for regression modeling; however, for development of ANN model, the data were randomly divided into two groups of training (consisted of 80% of all data) and testing (the remaining 20%) datasets (Diamantopoulou, 2005). Several architectures of MLP type became the subject of investigation in order to find the one that could result in the best overall performance.

The learning rules of Momentum and Levenberg Mar quart were taken into consideration and also no transfer function was used for the first layer. For the hidden layers, the sigmoid and hyperbolic tangent transfer functions were applied, while for the last one a linear transfer function was set. Also, a number of different network sizes and learning parameters were tried. The ANN system, applied for the predictor models, had seven inputs and four outputs. These inputs included soil cut/fill volume, soil compressibility factor, specific gravity, moisture content, slope, percentage of sand, and soil swelling index, whereas the outputs of each model were labor energy, fuel energy, total machinery cost, and total machinery energy. Fig.1 shows the schematic architecture of the used ANN. As aforementioned, the main elements of ANNs are constituted by artificial neurons. The input model consisted 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.

$$S = \sum_{n=1}^{n} W_n X_n \tag{3}$$

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 non-linear activation function f, yielding the following output:

$$y = f(s) \tag{4}$$

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

$$f(s) = \frac{1}{1+e^{-s}} \tag{5}$$

The output of y can be produced 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, such as the type of input parameters.

This research has used the three-layer perceptron network, 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 that were connected to the neighboring neurons via some associations. In these networks, the effective input of each neuron was obtained from the multiplication of the outputs of the previous neurons by the weights of those neurons. The neurons in the first layer received the input information and transferred it to hidden neurons through related connections. The input signal in such networks can only be expanded in a forward direction. The main advantage of such a network is its simplicity of model implementation as well as input/output data estimation. Yet, some of its major shortcomings are the low training rate and need for a huge set of data.

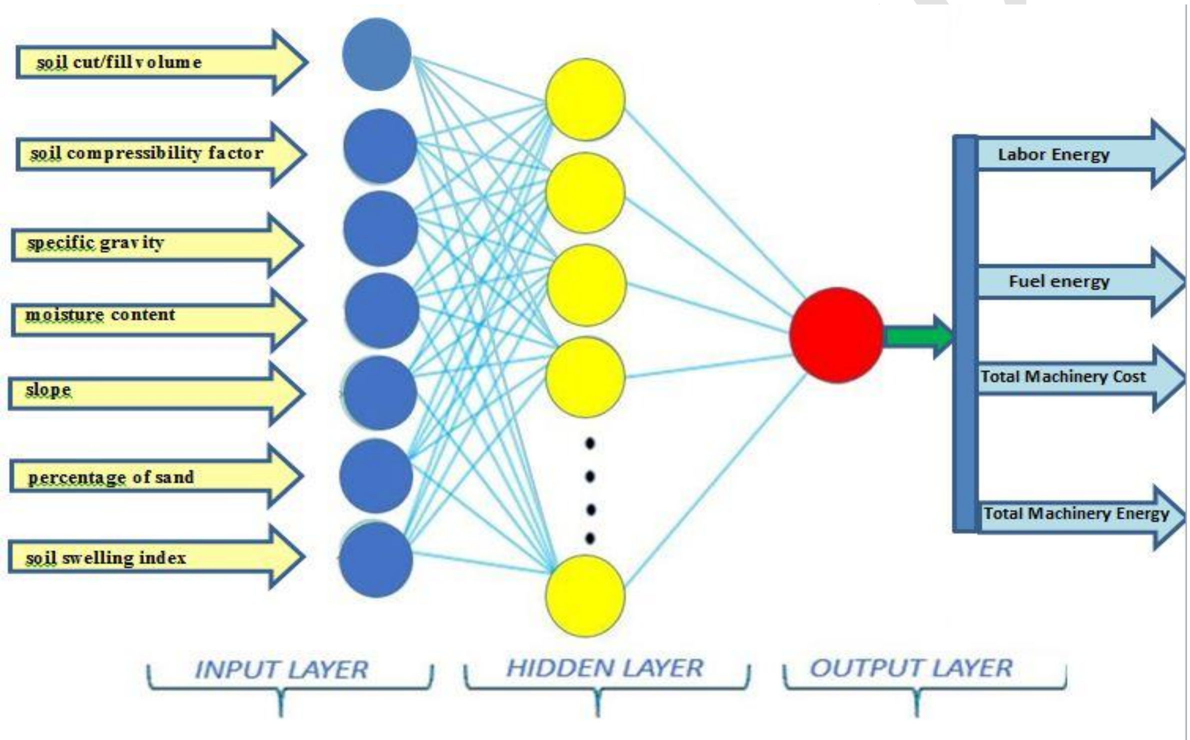


Fig. 1. A schematic representation of a three-layer ANN

Adaptive Neuron-Fuzzy Inference System (ANFIS)

ANFIS is a suitable and well-known technique for modeling complex systems that face uncertainty (Buragohain & Mahanta, 2008). It uses a learning algorithm, derived from or inspired by neural network theory, to determine fuzzy sets and fuzzy rules by processing data samples (Lin & Lee, 1996). Fuzzy sets provide a framework to incorporate human knowledge in problems' solution, being the basis of adaptive network-based fuzzy inference system (ANFIS). In fuzzy logic theory, the sets are associated with set membership. Compared to traditional binary sets or "crisp sets" where membership is either '1', typically indicating true, or '0', indicating false, fuzzy logic variables range between 0 and 1. Thus, fuzzy logic deals with approximate reasoning rather than fixed and exact one (Gonzalez & Woods, 2008). By using hybrid learning methodology, it gives the mapping relation between the input and output data, specifying the best distribution of membership functions (Ying & Pan 2008). By combining ANN and fuzzy logic, ANFIS has many advantages of fuzziness (Avci, 2008). Combination of these two techniques makes ANFIS modeling more systematic and less dependent on expert knowledge (Sengur, 2008a; Ubeyli, 2008). In order to arrange this inference system, five layers are used, each containing several nodes, with the outputs from one layer used as the inputs of the next. To easily specify ANFIS function, a system with two inputs (x, y) and one output (f_i) is assumed. ANFIS is based on fuzzy if-then rules (Buragohain & Mahanta, 2008). In a Surgeon type fuzzy inference system (FIS) the two rules may be as follows (Sengur, 2008a; Ying & Pan, 2008; Ubeyli, 2008):

Rule 1. IF x is A_1 and y is B_1, then z is $f_1(x,y)$, and

Rule 2. IF y is A_2 and y is B_2, then z is $f_2(x,y)$,

In these rules, the inputs to ANFIS model are specified by x and y and the fuzzy sets are specified by A and B, in which case $f_i(x,y)$ represents the outputs of FIS. The structure of ANFIS and the node function in each layer is described in details, below. Adaptive nodes denote the parameter sets, adjustable in these nodes, while, fixed nodes show the parameter sets that are fixed in the system (Buragohain & Mahanta, 2008).

Layer 1. Each node *i* in this layer produces a membership grade of a linguistic label. Assuming that node *i* input is presented by *x*; the linguistic label (small, large, etc.), associated with node *I* is represented by A_i; and the parameter set that changes the shapes of the membership function is denoted by {a_i; b_i; c_i} (or {a_i; c_i} in the latter case). The node function of the i^{th} node is presented as follows:

$$O_i^1 = \mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (6)$$

Layer 2. By means of multiplication, the 'firing strength' of each rule is computed by each node in this layer as follows:

$$O_i^1 = w_i = \mu A_i(x) x \mu B_i(y), i = 1,2 \quad (7)$$

Layer 3. The i^{th} node of this layer computes the i^{th} rule's firing strength to the sum of all rules' firing strengths ratio and it is presented as follows:

$$O_i^5 = overall\ output = \sum_i \overline{wf_i} = \frac{\sum_i wf_i}{\sum_i w_i} \quad (8)$$

Back-propagation gradient descent is the basic learning rule of ANFIS. Error signals are defined as the derivative of the squared error, compared to each node's output. Back-propagation gradient descent rule computes error signals from the output layer backward to the input layer, and is similar to the back-propagation learning rule, applied in the common feed-forward neural-networks (Rumelhart et al., 1986). The present study has used a hybrid-learning rule, combining the least-squares and gradient descent methods to find a feasible set of antecedent and consequent parameters (Jang, 1991). There are two passes in the hybrid learning methodology for ANFIS. In the backward pass, the error rates propagate backward from output layer to input one, and the premise parameters are updated by the gradient descent approach. In the forward pass the functional signals go forward until layer 4 and the consequent parameters are identified by the least squares estimate. Assuming fixed values for the premise parameters, the overall output can be presented as a linear combination of the consequent parameters as follows (Ying & Pan, 2008):

$$f = \overline{w} f_1 + \overline{w} f_2 \frac{w_i}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w_1} f_1 + \overline{w_1} f_2$$
$$= \left(\overline{w_1} x\right) p_1 + \left(\overline{w_1} y\right) q_1 + \left(\overline{w}\right) r_1 + \left(\overline{w_2} x\right) p_2 + \left(\overline{w_1} y\right) q_2 + \left(\overline{w}\right) r_2 \quad (9)$$

In hybrid learning algorithm the gradient approach is combined by the least squares approach (Ying & Pan 2008). In the forward pass, consequent parameters are recognized by the least squares estimate (Sengur, 2008a; Ubeyli, 2008). In this study, the inputs have been considered to be moisture, density, soil compressibility factor, Soil Swelling Index (SSI), land slope, percentage of sand, and embankment volume. On the other hand, the outputs have been considered to involve environmental indicators associated with land levelling, i.e. fuel energy, labor energy, machinery energy, and cost of total energy.

RESULTS

Results of ANFIS model prediction

In order to predict the energy, consumed for land leveling, fuzzy shell clustering algorithm was applied. This section presents the results of ANFIS models for prediction of Labor Energy (LE), Fuel Energy (FE), Total Machinery Cost (TMC), and Total Machinery Energy (TME). 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 the corresponding combination was evaluated, using 100 independent runs, and the statistical criteria (R^2 and MSE) of the output models were calculated for responses of interest.

Tables 1 and 2 present the minimum, average, and maximum values of R^2 and MSE for various combination of developed ANFIS-based models, illustrating the calculated values of R^2 and MSE for different developed models of labor energy against the number of clusters, with other outputs showing similar behavior.

As presented in Table 1, statistical criteria for prediction of labor energy reveals that FIS model was 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, whereas in back propagation model they turned out to be 0.9921 and 0.9921, respectively. Moreover, as presented in Table 1, statistical criteria for prediction of fuel energy reveal that FIS model was superior to ANN back propagation model .Average R^2 value in FIS model for prediction of fuel energy was 0.9927 and 0.9922 in Mamdani and Sugeno models ,respectively, while, in back propagation model R^2 value was 0.9891 and 0.9892, respectively.

As presented in Table 2, statistical criteria for prediction of total machinery cost reveals that FIS model was superior to ANN back propagation model .Average R^2 value in FIS model for prediction of total machinery cost was 0.9921 and 0.9922 in Mamdani and Sugeno models, respectively. In back propagation model, however, R^2 gave the values of 0.9894 and 0.9895, respectively. As presented in Table 2, statistical criteria for prediction of total machinery energy reveals that FIS model was superior to back propagation model, for average R^2 value in FIS model for this criterion turned out to be 0.9950 and 0.9952 in Mamdani and Sugeno models , respectively, while in back propagation model it was calculated as 0.9925 and 0.9926, respectively.

Table 6 compares statistical criteria of sensitivity analysis and neural network models and ANFIS models. As it can be seen from Table 6, the ANFIS model performed, providing better results than the ANN models ,based on its higher R^2 and lower RMSE values.

Table 1. Calculated statistical criteria for prediction of labor energy/fuel energy with different combinations 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

Table 2. Calculated statistical criteria for prediction of total machinery cost /energy, using different combinations 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

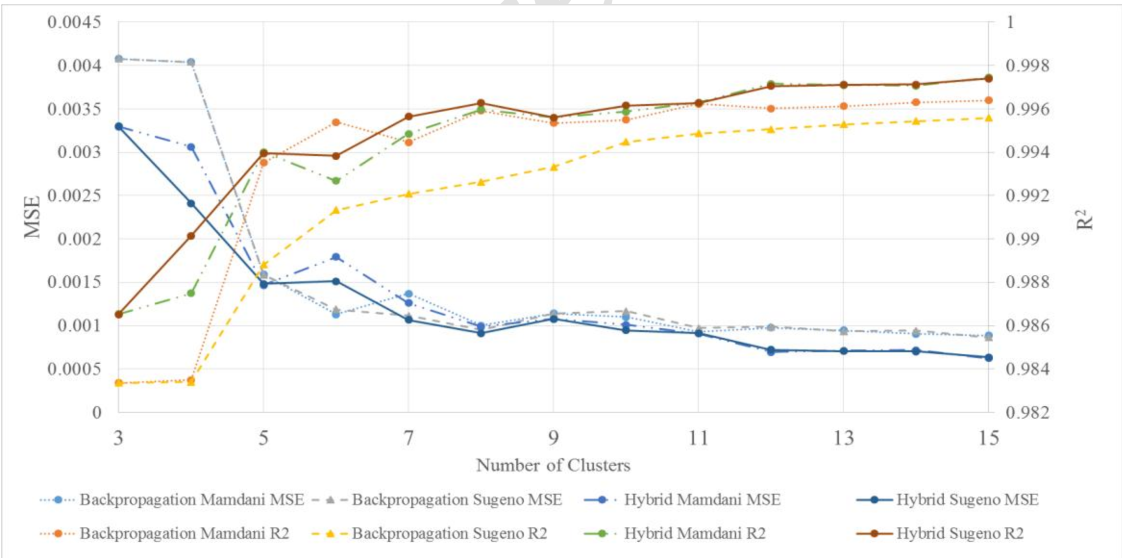
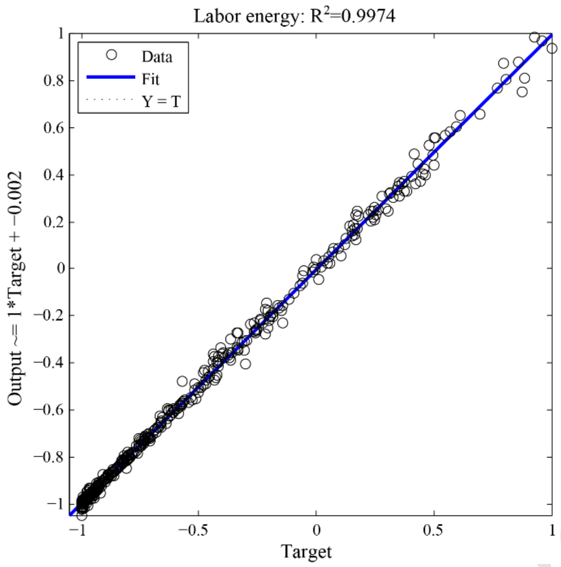


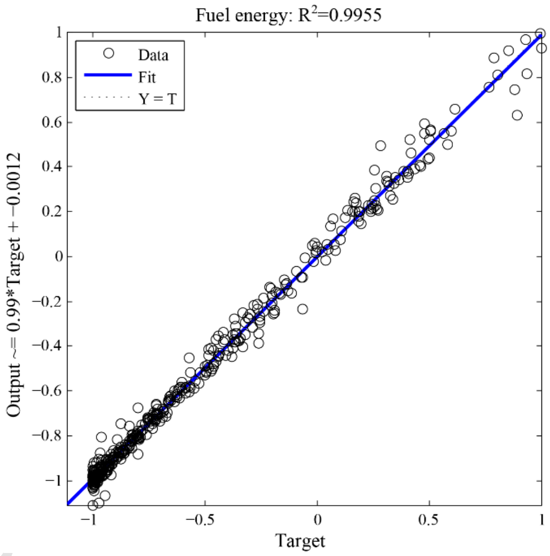
Fig. 2. Statistical performance criteria of LE

Determining the impact of number of clusters on all developed models is feasible (Fig. 2). Moreover, different optimization methods and FIS types can be easily compared. 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, thus its performance is more accurate. Also, the performance of the sugeno FIS type is better than the Mandeni. It is noteworthy that the models with low MSE values, have more R^2 values, and vice versa. Figure 3 a-d shows the results from the comparison of the predicted values of ANFIS models with the actual data. 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 was superior to ANN model in predicting labour energy, fuel energy, total machinery energy, and total machinery cost.

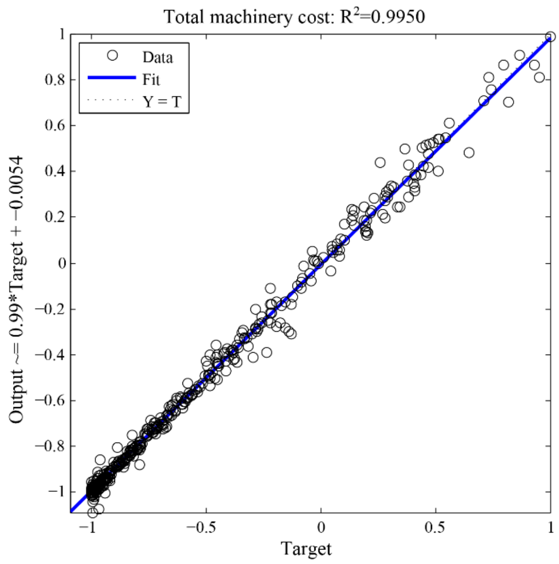
a)



b)



c)



d)

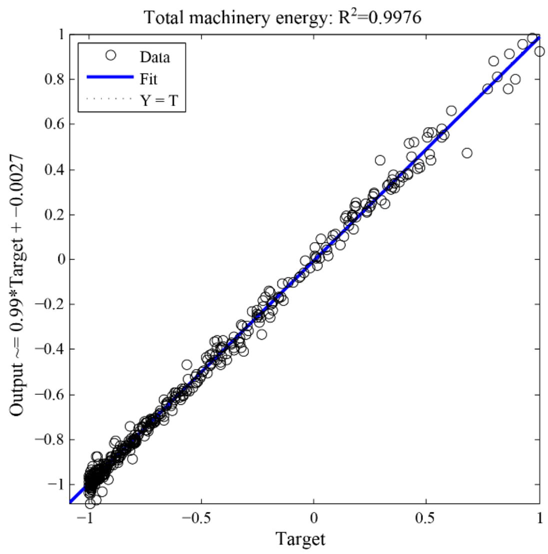


Fig. 3. Scatter plot for the predicted model and actual values of a) labor energy, b) fuel energy, c) total machinery cost, and d) total machinery energy.

Artificial neural network model

This section gives the results of regression models and training various networks with different structures. The ANN models were developed by training the networks with various combinations of Network Training Functions (NTF), number of hidden layers, and number of neurons in the each hidden layer. To select the best network topology, in total 20678 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 3 and 4 show the 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 use gradient- or Jacobian-based methods, such as Levenberg-Marquet (trainlm), (Levenberg, 1944; Marquardt, 1963).

It has been proven that Bayesian regularization has appropriate generalization properties, when used in the training of the NN (Mahersia & Hamrouni, 2015). Scaled conjugate gradient (trainscg) is one of the most popular second-order gradient supervised procedure (Møller, 1993), along with 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 (Pandey et al., 2012). 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 (Shiblee et al., 2010). 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 (Pandey et al., 2012). Gradient descent with adaptive learning rate back propagation (traingda) is a batch gradient descent that runs with variable learning rate (Hagan et al., 1996), and finally gradient descent with momentum back propagation (traingdm) is a network training function, used to update weight and bias values, according to gradient descent with momentum (Pandey et al., 2012).

These networks use 10 input data in the input layer to predict the outputs, utilizing a linear function in their output layer to transfer the data to the output. Tables 3 and 4 demonstrate the model outputs, which are the result of 500 thousand runs of the model. The selected NTFs for LE in land leveling, as shown in the first row of Table 3, was the best, as 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 2. The NTF of trainlm had higher RMSE and lower R2 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 simplest ANN for forecasting the LE with RMSE, below 0.021 as well as R2 above 0.996.

Table 3 gives the details of the selected networks for prediction of FE. The NTF of trainlm had higher RMSE and lower R^2 for two (4-2) and three (8-2-5) hidden layers; however, NTF of trainscg for one hidden layer had the best statistical output. The NTF of trainlm, including two neurons in one hidden layer, was the simplest ANN for predicting the FE with RMSE below 0.033 and R^2 above 0.995. As it is shown in Table 4, 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 could predict the TMC accurately. So this model was given as the best solution to estimate TMC. Table 4 demonstrates the details of the selected networks for prediction of

TME. The NTF of trainlm had higher RMSE and lower R^2 for two (6-4) and three (4-5-3) hidden layers, though 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 Figure 4, 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 against the number of training epochs).

Table 3. 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				

Table 4. 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				

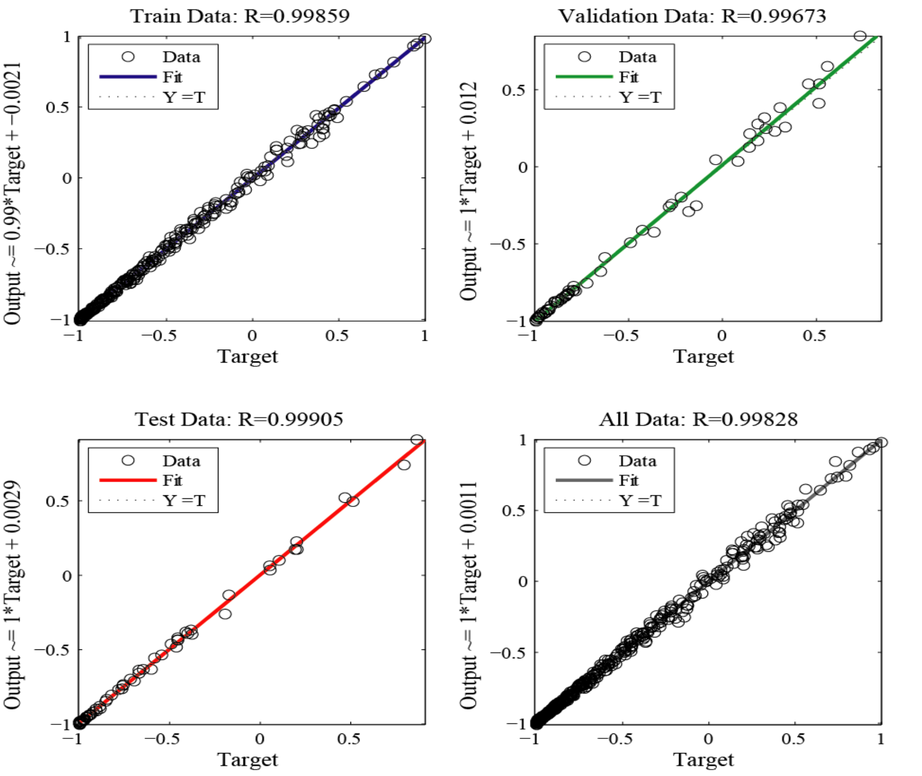


Fig. 4. Scatter plots of output vs. target, using ANN models for prediction of LE

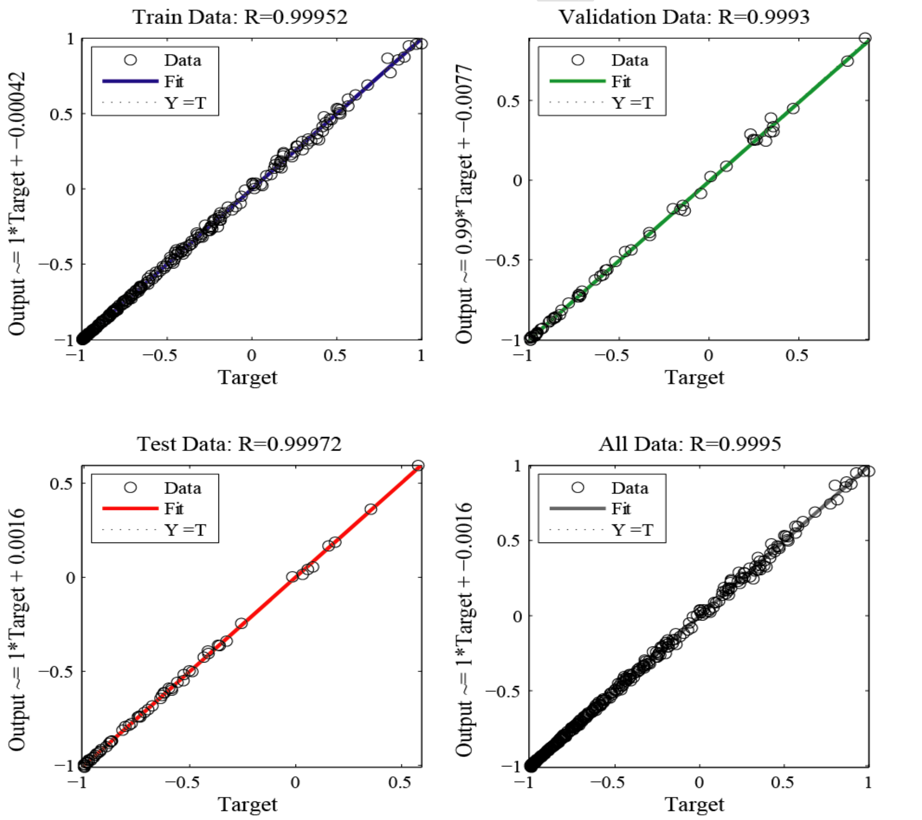


Fig. 5. Scatter plots of output vs. target, using ANN models for prediction of FE

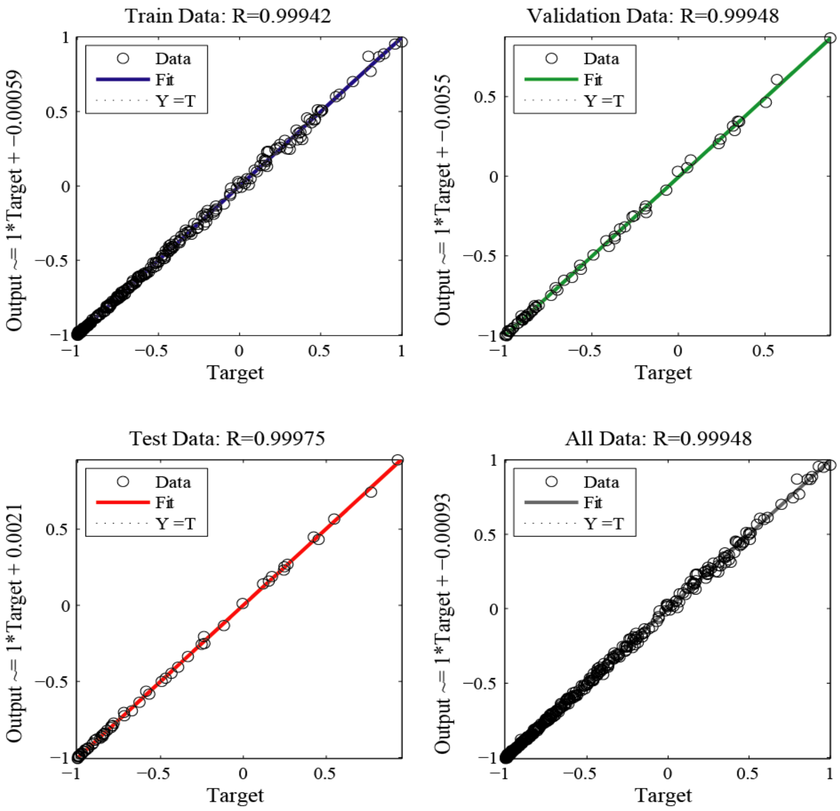


Fig. 6. Scatter plots of output vs. target, using ANN models for prediction of TMC

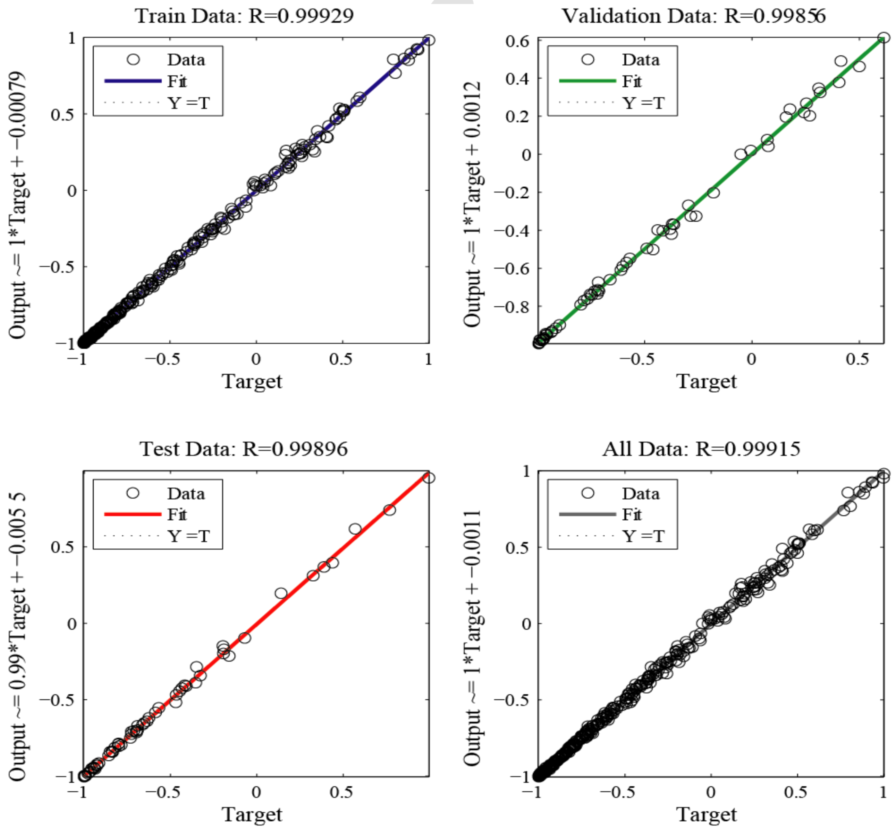


Fig. 7. Scatter plots of output vs. target, using ANN models for prediction of TME

Table 5. Comparison of ANFIS and ANN models

Responce	ANFIS		ANN	
	RMSE	**R^2**	**RMSE**	**R^2**
LE	0.00058	0.9974	0.0159	0.9990
FE	0.00111	0.9955	0.0206	0.9983
TMC	0.00119	0.9950	0.0287	0.9966
TME	0.00058	0.9976	0.0157	0.9990

Table 5 compares the statistical criteria of neural network models and ANFIS models. As it can be seen in this table, ANFIS models perform and provide better results than the ANN models, thanks to their higher R^2 and lower RMSE values.

When evaluating the predictive capabilities of ANNs and ANFIS in terms of estimating soil shear strength from measured particle size distribution (clay and fine sand), Calcium Carbonate Equivalent (CCE), results showed that the ANN model was more feasible in predicting the soil shear strength than the ANFIS model. The root mean square error (RMSE), mean estimation error (MEE), and correlation coefficient (R) between the measured soil shear strength and the estimated values, using the ANN model, were 0.05, 0.01, and 0.86, respectively (Besalatpour et al., 2012).

Khoshnevisan et al. (2014) used several ANFIS models to predict wheat grain yield on the basis of energy inputs. Moreover, ANNs were developed and the obtained results were compared with ANFIS models. The results illustrated that ANFIS model can predict the yield more precisely than ANN.

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 emphasizing higher accuracy and lower scattering for modelling ANFIS, with RMSE value of 0.9987 and R^2 value of 0.0163 in the training stage, and RMSE of 0.9753 and R^2 of 0.0694 in testing stage (Fereydooni & Mansoori, 2015).

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 were 0.8416 and 0.8593, and their RMSE was 0.2667 and 0.2491 (Mohammadi et al., 2009).

Kisi and Shiri (2013) compared ANN and ANFIS models for prediction of long-term monthly air temperature, using geographical inputs. They illustrated that the maximum and minimum $R^{٢}$ values were 0.995 and 0.921 for ANN model, computed to the values of 0.999 and 0.876 for ANFIS model.

CONCLUSION

There have been a limited number of researches, related to energy consumption in land leveling, which presented the function of the volume of excavation and embankment. In the present research, however, energy and cost of land leveling were function of all land properties, including the slope, coefficient of swelling, soil density, soil moisture, and special weight dirt. The paper's argument was built on an appropriate theoretical foundation, concepts, and other ideas, and the methods were employed appropriately. This study investigated the ability of Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for prediction of environmental indicators, namely LE, FE, TMC, and TME, during land leveling. Results were extracted and the statistical analysis was performed, enabling the determination of RMSE and coefficient of determination, $R^{2,}$ of the models, as a criterion to compare the 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. Results showed that adaptive neuro-fuzzy inference system could be successfully used for prediction of labor energy, fuel energy, total machinery cost, and total machinery energy. The ANFIS models with hybrid optimization method and Sugeno FIS type showed better performance than the backpropagation and Mamdani ones. All ANFIS-based models had R^2 values above 0.995 and MSE values below 0.002. Moreover, ANFIS was shown to be capable of predicting output variables (i.e. LE, FE, TMC, and TME). The result of this research was used for surface irrigation on agricultural lands and can be employed in economic projects on agricultural lands. They can be further used as a set of tools for the managers, consultants, researchers, etc. The present study's results may have an impact on agricultural society, affecting their life quality. These implications are consistent with the findings and conclusions of the paper.

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