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Using new computer based techniques to optimise energy consumption in agricultural land levelling

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Abstract: Land levelling is one of the most energy-demanding steps in soil preparation. There are many limiting factors for a specific land levelling operation, such as fertile topsoil conservation, limited allowed slope, specific cut to fill ratio, etc. These limitations make optimisation problems of land levelling even more complicated. In this research, three computational and evolutionary methods including ICA, PSO, GA along with MLS were utilised as optimisation methods to minimise the soil cut and fill volumes and to determine the preferred levelling plane. The results indicated that ICA had the most efficient solution for the energy optimisation in the land levelling among the other investigated methods by saving 29% (17 GJ) of the total energy consumption compared with MLS. This study deals with optimising the energy consumption during land levelling projects using new computer-based techniques and compares them to the MLS method as a benchmark. All in all, ICA, PSO, and GA performed much better than MLS by saving 29, 17, and 10% of the total energy consumption in their best model (number 1 models), respectively. Nonetheless, with these great capacities for saving energy in developing countries, unfortunately, the lack of education and excess subsidies on fossil fuels nullify these potentials.

Keywords: genetic algorithm; imperialistic competitive algorithm; particle swarm optimisation; sustainable agriculture

Nowadays, the sustainable supply of energy is one of the most challenging and widely considered research areas. It has gained scholarly attention more than ever due to the increasing human population over the current century, globally emerging issues such as air pollution and global warming, the daily increasing fuel costs, and the limited amount of fossil fuels. As a result, harnessing energy from sources such as the sun, wind, waves, etc., has continuously been improved over the past several decades. However, in some sectors, such as the agricultural sector, the vast majority of required energy comes from internal combustion engines that use fossil fuels. In this regard, some managerial methods are necessary to control and optimise the energy consumption in these areas. Although energy management and optimisation are indispensable to overcome the energy crisis of the world, it is more significant for fossil fuels than other sources due to the costs of fossil fuels both on the environment and on the economy (Tieppo et al. 2019). Moreover, based on international organisations such as the Food and Agriculture Organization (FAO) of the United Nations, there is justifiable concern that the current dependence of the food sector on fossil fuels may limit the sector's ability to meet global food demands. So, food prices should be decoupled from the fluctuating and rising fossil fuel prices (FAO 2011).

There is a great number of research studies focused on energy consumption and management

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in agriculture, even in countries such as Iran and Iraq that possess huge resources of fossil fuels (Farajian et al. 2018). These studies mainly focus on greenhouse gas (GHG) emissions, renewable energy usage, and sustainable agriculture (Fei and Lin 2017; Khan et al. 2018). According to the Intergovernmental Panel on Climate Change (IPCC), in the year 2014, about 24% of the total GHG emissions were related to Agriculture, Forestry and Other Land Use (AFOLU) where fossil fuels accounted for 78% of the total GHG emissions increase between 1970 to 2000 and approximately the same amount between 2000 to 2010 (Change 2014).

Based on the Energy Information Agency, the Department of Energy of the United States, within the agricultural sector, changes in the supply and demand of energy can have significant implications for the profitability of U.S. agriculture as well as to the mix of output and management practices (Schnepf 2004). As a result, there is a growing consensus among researchers that sustainable agriculture needs the separation of required energy sources from fossil fuels since fluctuating oil prices have an inflationary impact on societies and endangers the food security (FAO 2011; Anand 2014).

The total oil energy use of agriculture in the U.S. has declined by approximately 30% from 1970 to 2004 due to the increasing efficiency of machinery and adopting conservation tillage practices (Robertson et al. 2004). Conversely, based on the statistics issued by the Ministry of Energy of Iran, during the period of 1975–2005, the energy used in Iran's agricultural sector has experienced a forty-five-fold increase (M.o.E.o. 2018). These data are in accordance with the International Energy Agency statistics that show that the agricultural and forestry sectors in Iran consumed more than 4 million tonnes of an oil equivalent of oil products and natural gas in the year 2015 (IEA 2017). This is partly due to a shift from conventional ways of farming based on human and animal power to a fuel-based agriculture and mostly due to the low cost of fuels in this country that has led to the lower efficiency of agricultural production from an energy viewpoint. Regarding the mentioned facts, this paper brings land levelling, which is one of the heaviest and most energy-consuming practices in agriculture, especially in developing countries, into focus from an energy perspective. In the following, the energy issue in agricultural land levelling based on the literature will be briefly discussed and then the implementation procedures of computational techniques will be explained in the material and methods section and, finally, the results and discussion, as well as conclusion, will be explicated upon.

Land levelling, with a scholarly history of more than 60 years (Whitney et al. 1950), is a practice that is used to create a uniform land surface which is undertaken by cutting the higher elevations of the soil and filling the lower elevations with the cut soil (Jat et al. 2006). Although some researchers have studied the detrimental effects of land levelling, such as disturbances on the biological, chemical and physical balances of the topsoil (Unger et al. 1990; Walker et al. 2003; Brye et al. 2006), most of them looked at the bright side and considered the benefits of this practice. The most important advantages of land levelling are related to the water saving capacity (Sattar et al. 2003; Abdullaev et al. 2007; Jat et al. 2009), economic production of a higher yield (Rickman 2002; Jat et al. 2009; Ali 2018), and protection of the topsoil from erosion by runoff water in an uneven terrain (Gagnon et al. 2017). Based on the fact that land levelling ranges from major landscape modifications to the removal of minor undulations in the field, this large spectrum of work may contribute to the contradictory results found in the scientific literature about the environmental impacts of land levelling. However, major landscape modifications seem to result in more negative aspects (Peter et al. 2014). Nevertheless, some researchers have tried to optimise the levelling problems with major landscape wackiness through computational and computer-based techniques.

Gebre-Selassie and Willardson (1991) introduced a computer program based on the minimum least squares (MLS) to minimise the time and energy consumption during land levelling (Gebre-Selassie and Willardson 1991). In 2001, Modarres and Shams suggested a new model to optimise land levelling using the idea of an optimum surface concept with different longitudinal and transverse slopes. Using their model, the average cut : fill depth as well as total earthwork could be optimised. Their method was better than other analysis methods, such as linear and nonlinear programming methods (Modarres and Shams 2001). In 2010, Cazanescu et al. simultaneously utilised a laser land scan, computer-aided design (CAD), and a geographic information system (GIS) technique to optimise the land levelling process. Based on their reports, this

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approach resulted in a low cost, accurate, and fuel-saving method of land levelling (Cazanescu et al. 2010). To determine the optimum farm slope, some researchers used the least-squares method and GIS technique to minimise the amount of soil, cut and fill (Dauda and Baiyeri 2001; Demİrtaş and Demİr 2011). Some others combined GPS (global positioning system), CAD, and GIS data to optimise the levelling practice and thus reduce the energy consumption (Zhang and Wright 2004). Wang et al. (2010) focused on hauling distance and tried to optimise the distance using GIS to diminish the costs.

Besides agriculture, earthwork costs lead researchers to consider optimum levelling methods and approaches on highway projects as well. In this regard, Goktepe and Lav suggested a hypothetical weighted ground elevation concept to balance cut-fill volumes to minimise the total amount of earthwork. This method minimises the errors that resulted from the assumption of the centre line as a representative of whole road (Goktepe and Lav 2003). Most of the optimisation problems in this area deal with balancing the cut-fill volume and minimising the total earthwork. With advances in technology, computer-aided earthwork systems have been developed to optimise land levelling problems. Previously developed software packages include: earthwork control systems (Askew et al. 2002), earthwork modelling and simulation systems (Ji et al. 2010), and 4D virtual road construction frameworks (Askew et al. 2002). However, some special considerations have brought new factors to earthwork and land levelling optimisation problems, such as an ecological criterion in forest roads (Macku 1996). Using computers can solve problems with a myriad of restrictions that were previously impossible to solve.

In this paper, approaches including the imperialistic competitive algorithm (ICA), genetic algorithm (GA), particle swarm optimisation (PSO), and minimum least squares (MLS) were used to optimise the land levelling formulated problem considering specific constraints. Then, the energy consumption resulting from implementing each method was analysed and compared. Since MLS has long been used for levelling and grading problems, this method is a benchmark to compare different methods. Moreover, since there a limited number of studies associated with the energy consumption in land levelling, the other objective of the current research is to find a function for all the land levelling indices used in energy consumption.

MATERIAL AND METHODS

The material and methods section has been divided in four separate subsections. The first subsection deals with the formulation of the optimisation problem followed by subsection focused on optimisation methods. In the third subsection, energy-related parameters, definitions, and equations are presented. In the last subsection, the study field area as a case study region, the data acquisition, and the specific characteristics of this case study are illustrated.

Formulation. Any irregularly shaped plot of land, like the one shown in Figure 1, can be represented as:

$$h_{ij} = C_1 + C_2 x_{ij}^m + C y_{ij}^n \tag{1}$$

where: h_{ij} – elevation of the curved surface in metres at any point (i, j) whose coordinates are (x_{ij}, y_{ij}), i.e. z at each point; i – grid point location along the X-axis; j – grid point location along the Y-axis; x_{ij} – X-coordinate of point (i, j); y_{ij} – Y-coordinate of point (i, j); C_1 – elevation of the graded surface at the origin of the coordinate axes; C_2 and C_3 – coefficients; and m and n – exponents. If C_1, C_2, C_3, m, and n are known, then the elevation at any point (i, j) may be computed using (1). As a special case for $n = m = 1$, (1) represents a simple plane surface with C_2 and C_3 as slopes in the X- and Y-direction, respectively.

If h'_{ij} is the elevation of the natural surface, the vertical distance z_{ij} between the natural and the graded surface may be computed using:

$$z_{ij} = h_{ij} - h'_{ij} \tag{2}$$

where: a positive value for z (in metres) – a cut; a negative value for z – a fill.

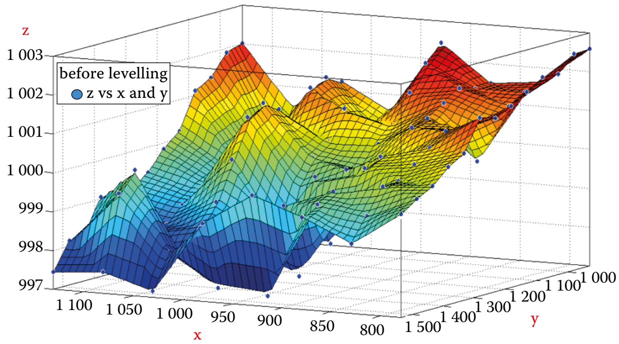

Figure 1. Sample topography of a part of the region before the levelling experiment

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Since inland levelling projects are high in energy consumption whose most expensive part relates-to the excavation and filling, the aim of all optimisation algorithms should be to minimise either the cut soil or both the cut and fill. However, certain design constraints should also be taken into the account. Hence, the objective function of this optimisation problem is to minimise the total volume of earth in the cut and fill while satisfying certain design constraints. This objective function can be written mathematically as:

$$\text{Minimise } V = f(C_1, C_2, C_3, m, n) \quad (3)$$

where: V – total volume of the cut plus fill which is a non-linear function of C_1, C_2, C_3, m; n – the graded surface.

There are several methods that can be used to calculate the volumes of the cut and fill. In the three-point method, the surface of the land is meshed as rectangular and triangular grids and the average of the elevation on the corners of the grids are used as a factor to be multiplied in the area of the grid to calculate the excavation or fill volume (Easa 1989). In another method, called the four point method, the surface of the land needs to be meshed in a rectangular shape only, and the average of the elevation on the corners determines the factor by which the volume of the soil on that grid can be calculated (Anderson et al. 1980). However, these methods require excess computation when the grid size is small and the total area is comparatively large. In this situation, the summation method results in a simpler computation and reasonable approximation. Based on this method, the elevation of the original ground surface in each grid is assumed to be constant and, as a result, the cut or fill volume is computed simply by multiplying the area of the grid by the cut or fill depth at the midpoint of the grid. The method is applicable to square and non-square grids and the smaller the grid size, the higher the precision (USDA 1970). This method was used in this research as:

$$V_{ij} = A_{ij} \times z_{ij} \quad (4)$$

where: V_{ij} – the cut or fill volume of a grid at point (i, j); A_{ij} – the area of each grid.

To avoid the negation of a cut and fill in the calculation of the total earthwork, the absolute value for z should be used.

As a result, the total earthwork may be compute using:

$$V = \sum_{i=1}^{nx} \sum_{j=1}^{ny} A_{ij} \times \left| z_{ij} \right| \quad (5)$$

The constraints of this problem consist of:

The maximum elevation at the origin, i.e. C_1. Hence,

$$ll < C_1 < ul \quad (6)$$

where: ll and ul – the lower limit and upper limit for C_1, respectively.

This guarantees that the elevation of the land after the levelling process remains within a range that allows irrigation water to flow into the land or below the pump's head power.

The cut depth should be curtailed in order to avoid loss of the fertile topsoil. Therefore,

$$z < \text{max\_}depth \quad (7)$$

This limit varies for diverse land situations and should be determined by soil experts.

The slope of the surface in the x and y direction should remain in a specific bound. Hence, the upper and lower limits for these slopes must be applied. To calculate these slopes from Equation (1), differentiation with respect to x and y will result in:

$$S_{x_{ij}} \frac{\delta h}{\delta x} = C_2 m x_{ij}^{m-1} \quad (8)$$

$$S_{y_{ij}} \frac{\delta h}{\delta y} = C_3 m y_{ij}^{n-1} \quad (9)$$

$$min\_S_x < S_{x_{ij}} < max\_S_x \quad (10)$$

$$min\_S_y < S_{y_{ij}} < max\_S_y \quad (11)$$

By calculating the cut and fill volumes, the all cut to fill ratio must comply with some standards and should lie within the acceptable range reported in the literature. The first point about the cut to fill ratio (R) refers to the topsoil conservation; Due to special characteristics and the limited depth of fertile topsoil, during levelling practices, the cut depth should remain as low as possible, which was applied in the 2nd constraint. If the cut depth exceeds the optimum range of the fertile soil, plants will face difficulty in growing both on the cut and

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fill areas. As a result, an equal amount of cut and fill would be the best scenario in land levelling projects. However, based on the literature, after the levelling practice, in most cases, the filled ditches subside after moisture absorption. Therefore, it is necessary that the amount of cutting be more than the filling (Mobtaker et al. 2010). Thus, in many projects, the ratio of cut to fill lies between 1.15 to 1.25 according to the soil characteristics and composition. Based on the aforementioned discussion, cut to fill ratio has upper and lower limits that may be applied as a constrain as follows:

$$min\_R < R < max\_R \tag{13}$$

Where R can be calculated using Equation (14) and the following formula:

$$R = \frac{V_c}{V_f} = \frac{\sum A_{ij} \times z_{ij} \rightarrow if(z > 0)}{\sum A_{ij} \times z_{ij} \rightarrow if(z < 0)} \tag{14}$$

It is clear that land levelling design is a nonlinear problem with linear and nonlinear constraints and several techniques were used to minimize the energy consumption at this operation which are is described in optimisation methods section.

Energy balance analysis. Based on the literature related to energy estimation and consumption in agriculture, input energies can be classified as direct and indirect inputs where the energy of human labour and diesel are among the direct energy inputs while machinery energy is considered as an indirect input (Samavatean et al. 2011) and these inputs typically account for the bigger share of energy consumption in agricultural operations without taking chemical fertilisers into account (Mobtaker et al. 2010).

Since there is no use for chemicals, irrigation, seeds, etc., in land levelling operations, only the machinery energy, labour energy, and fuel energy were inspected in this study. Because no study to calculate the energy equivalents of inputs in the conditions of Iran were available; therefore, in this study, approximate coefficients were obtained from previous studies conducted in similar conditions as presented in Table 1. It is worthwhile mentioning that due to the application of the same coefficients for all the methods, there would not be any statistical inconsistency in the results, and the approximation of the energy coefficients will not affect the comparison results.

Table 1. Energy equivalent of the inputs and output

Input	Unit	Energy equivalent (MJ·Unit^{-1})	Reference
Human labour	h	2	Moore 2010
Diesel fuel	L	50	Mousavi-Avval et al. 2011
Machinery	h	60	Beheshti Tabar et al. 2010

Machinery energy. For estimating the total energy embodied in the machinery, the model introduced by Beheshti et al. (2010) was used. In this model, the total machinery energy includes; energy for the raw materials, manufacturing, repairs and maintenance as well as the transportation energy (Beheshti et al. 2010). Moreover, based on previous research, the total weight and life of the machinery, and the energy required for the land levelling operation were calculated assuming that the embodied energy of the machinery is depreciated during its economic lifetime. As a result, the embodied energy was calculated by multiplying the depreciated weight of the machinery (kg·ha^{-1}) by its energy coefficient (MJ·kg^{-1}). Furthermore, the weight of the machinery depreciated per hectare of land levelling was calculated using the following Equation (15) (Mousavi-Avval et al. 2011):

$$TW = \frac{G \times W_h}{T} \times t \tag{15}$$

where: TW – the machinery energy per unit area (MJ·ha^{-1}); G – the machine mass (kg); W_h – the production energy of the machine (MJ·kg^{-1}); t – the time that the machine is used per unit area (h·ha^{-1}); T – the economic lifetime of the machine (h).

Fuel energy. The following functions were used to calculate the total fuel energy equivalent using the amount of the required fuel consumption rate, a number of graders, as well as the heat value of the fuel (approximately 50 MJ·L^{-1}) (Yilmaz et al. 2005):

$$f_2(x) = \sum_{i=1}^{n} (q_i \times E_{fuel} \times N_i \times t) \tag{16}$$

where: f_2 – the total fuel energy (MJ); q_i – the fuel consumption rate (L); E_{fuel} – the energy value of the fuel (MJ·L^{-1}); N_i – the number of machines in the operation; t – the operation time. This is equal to the total fuel consumed multiplied by the heat value of the fuel.

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Labour energy. The energy equivalent of the human labour is the muscle power used during the levelling operations. The labour energy was estimated considering the total number of people involved in the operation. In the calculation of the human energy for each grader, one full-time driver plus one driver assistant, and one serviceman with 1.5 work hours per day were determined. The energy equivalent, thus, was defined using reports from the literature for the energy equivalent of the labour energy. Although there are very different interpretations of the labour energy equivalent, an estimation of 2 MJ·h^{-1} (Yilmaz et al. 2005) would be a fair approximation for our study. As a result, the total labour energy was calculated using the following Equation (17):

$$f_3(x) = \sum_{i=1}^{n}(n_1 \times E_1 \times t_1) \quad (17)$$

where: f_3 – the total labour energy (MJ); E_1 – the energy equivalent of the labour work (MJ·h^{-1}); n_1 – the number of labourers; t_1 – the labour activity hours (h).

The considered inputs for this energy system are shown in Table 1. However, as it is evident from this table, due to the large amount of energy consumption as fuel energy and machinery energy compared to the human factor, this input value is almost negligible. Nevertheless, this factor has been taken into the account.

Optimisation methods

Three computational techniques along with MLS were used in this research. Among the computational algorithms that consisted of ICA, PSO, and GA, ten models were extracted for each solution and only four of the best answers are represented here. The MLS was also calculated as a criterion to compare the results of the other three algorithms. In addition to the MLS, the success rate (SR) was deployed as another means of comparison among the different methods.

The SR is a parameter in the realm of artificial intelligence algorithms that demonstrates the number of times that a known optimal solution was found after 100 runs and it has different interpretations in different algorithms (Rafiee et al. 2010). For example, in the case of ICA, it indicates the portion of colonies that are moving toward a better position. As a result, a higher SR will result in a better final answer.

Imperialist competitive algorithm (ICA). The imperialist competitive algorithm (ICA) is a new swarm-intelligence approach that is inspired by the human socio-political evolution process and could be applied to optimise different types of problems (Xing and Gao 2014). This approach was introduced by Atashpaz-Gargari and Lucas (2007) to mimic the behaviour of countries and empires to find the most powerful empire. However, this method is widely used to find the minimums of a function and to avoid local minima (Atashpaz-Gargari and Lucas 2007). The steps of ICA and its implementation in the land levelling problem are explained below. The ICA for the optimisation starts with generating some set of random solutions in the search pool (in this research, the best plane that has the minimum cost for the land levelling). In each step, a union of subgroups, colonies and imperialists assembles the empires. The first population is broken into some subpopulations. Consequently, the ICA searches the solution area again to find the best solution by considering the competition and assimilation operators. During the competition and assimilation, empires have interactions with the swarm members. By using assimilation, colonies might reach a better position and it might take control of the entire empire (Atashpaz-Gargari and Lucas 2007; Kaveh and Talatahari 2010). In the competition part of the algorithm, all the empires try to take control of the other empires and be the dominant one. The algorithm continues with the mentioned steps until one empire controls all of the other countries. At this time, the stop condition is satisfied. The formulation of the aforementioned steps is explained in the following equation.

For the preparation of initial populations, each country can be defined in the form of an array by Equation (18) (Xing and Gao 2014).

$$country = [p_1, p_2, p_3, ..., p_{N_{var}}] \quad (18)$$

where: p_i – the different variables based on various socio-political characteristics (such as culture, language, and economical policy); N_{var} – total number of the characteristics (i.e. n – dimensions of the problems) to be optimised.

Creating the cost function is the next step. In order to evaluate the cost of the countries, the cost function can be defined via Equation (19):

$$C = f(country) = f(p_1, p_2, ..., p_{N_{var}}) \quad (19)$$

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In the next step, the costs of the imperialist are normalised as follows (Kaveh and Talatahari 2010):

$$NC_n = f_{cost}^{(imp,\,n)} - \max_i \left(f_{cost}^{(imp,\,i)} \right) \tag{20}$$

where: $f_{cost}^{(imp,\,n)}$ – the cost of the n^{th} imperialist; NC_n – the normalised cost.

In this step, the colonies are divided among the imperialists. This process is performed by considering the power of the imperialism and the relationships between the countries and their interdependent empires. This operation is completed using the following respective Equations (21–23):

$$Power_n = \left| \frac{NC_n}{\sum_{i=1}^{N_{imp}} NC_i} \right| \tag{21}$$

$$NOC_n = round\{Power_n, N_{col}\} \tag{22}$$

$$N_{col} = N_{pop} - N_{imp} \tag{23}$$

where: $Power_n$ – the normalised power of each imperialist; N_{col}; N_{imp} – the given number of colonies and imperialists, respectively; NOC_n – the total number of colonies possessed by the n^{th} empire.

Assimilation strategy: in this process, the colonies move towards their independent imperialist using the following Equation (24):

$$x \approx U(0, \beta \times d) \qquad \beta > 1 \tag{24}$$

where: x – a uniformly distributed random number; β – a number greater than one; d – the distance of a colony from its related imperialist.

Revolution strategy: Based on this strategy, the colonies' movement is directed by adding a random amount of deviation using the following Equation (25):

$$\theta \approx U(-\gamma, \gamma) \tag{25}$$

where: θ – a uniformly distributed random number; γ – an adjusting parameter for the deviation from the initial movement direction.

Exchanging step: Based on the cost function, a colony with a lower cost than that of the corresponding imperialist taking over the position of the imperialist becomes the imperialist. The revolution function brings about sudden random changes in the position of some countries in the search space which helps the algorithm to avoid local minima. During assimilation and revolution, a colony might reach a better position and has the chance to take control of the empire.

Imperialistic competition: Calculating the overall power of an empire that is mainly influenced by the power of the empire and its colonies according to the following Equation (26):

$$TC_n = f_{cost}^{(imp,n)} + \xi \times \frac{\sum_{i=1}^{NC_n} f_{cost}^{(col,i)}}{NC_n} \tag{26}$$

where: TC_n – the total cost of the n^{th} empire; ζ – a positive coefficient less than 1.

The imperialistic competition induces each empire to extend its power for controlling more colonies. So, the strongest empire controls the weakest colony from the weakest empire. The competition operator is designed to dedicate the colonies of the weakest empires to the other empires. Based on TC_n, the normalised total cost is evaluated using the following Equation (27):

$$NTC_n = TC_n - \max_i \{TC_i\} \tag{27}$$

where: NTC_n – the total normalised cost for the n^{th} empire.

According to NTC_n, the possession probability of each empire is computed using the following Equation (28):

$$P_{pn} = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \tag{28}$$

The eliminating strategy removes powerless empires (an empire with no colonies) from the competition. Finally, the stop condition will be satisfied when all the remaining colonies are governed by the most powerful imperialist. It means that all the colonies and the imperialist itself have the same cost. The countries in this algorithm are the counterpart of chromosomes in GAs and particles in PSO that form an array of values of candidate solutions of an optimisation problem. Figure 2 shows the ICA flowchart.

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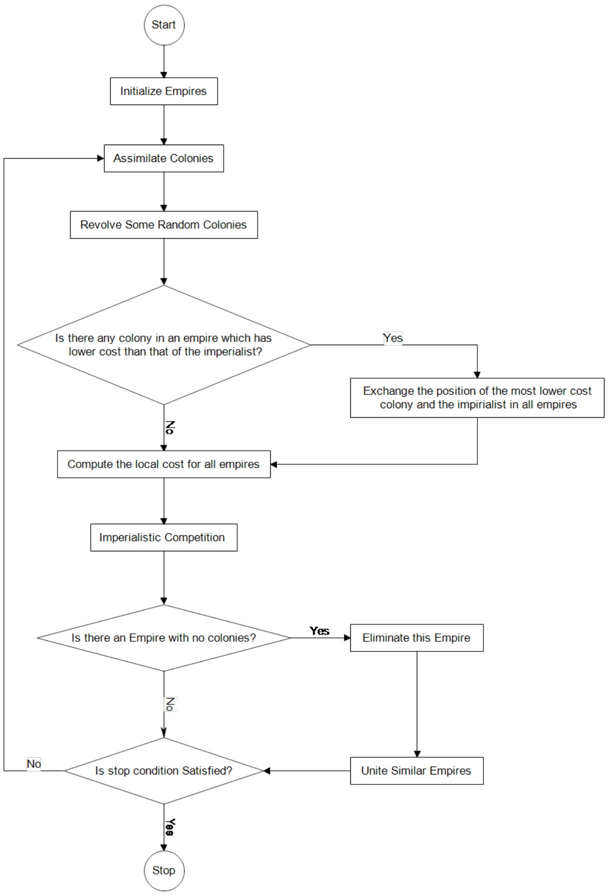

Figure 2. Flowchart of the imperialist competitive algorithm

Genetic algorithm. The genetic algorithm (GA) concept was first introduced by Holland (1962). This algorithm is a particular type of evolutionary algorithm which works based on Darwinian selection and the evolution principle (Holland 1962). The idea of GA is to create strong descendants by using stronger individuals of a society and eliminating weaker individuals. Offspring are produced by crossover and mutation operations on their parents in the same way as biological evolution (Reddy 1996; Anderson-Cook 2005). The GA algorithm gets rid of the local minima using a waste range of the population.

Similar to ICA, GAs start with an initial set of randomly generated solution vectors that may be either feasible or infeasible within the search pool. Since GAs work with the coding of the parameters' set rather than the parameters themselves, each decision variable in a decision vector is coded into a string of binary numbers (0, 1). Starting with a randomly generated initial set of decision vectors, the GAs select a few best decision vectors based on their fitness value and perform crossover and mutation (like revolution and assimilation in ICA) operations to generate a new set of decision vectors. Detailed information on GAs can be found in Golberg and Holland (1988). In this research, MATLAB software was used to implement the GA.

Particle swarm optimisation (PSO) algorithm. The PSO technique was introduced by Eberhart and Kennedy (1995) when they found that the synchrony of flocking behaviour was through maintaining optimal distances between individual members and their neighbours. Thus, velocity plays an important role in adjusting each bird for an optimal distance from the others. Furthermore, simulated scenarios in which birds search for food illustrated that, in order to find food, the individual members determined their velocities by two factors; their own best previous experience and the best experience of all the other members (Eberhart and Kennedy 1995). This technique can be used for training artificial neural networks and it has demonstrated good performance as a benchmark function for GAs (Shi and Eberhart 1998). Since the PSO algorithm can be used for solving complicated optimisation problems, in this study, the PSO algorithm was used to optimise the volume of the soil operation and energy consumption; i.e. to find the optimum levelling plane. By determining the best plane for levelling, the obtained data were exported to GIS software for further analysis and calculation of the fill : cut volumes, area, ratios, etc. For all the possible results, when the cut to fill ratio was reasonable, the aforementioned energy parameters were calculated.

Minimum least squares (MLS). The least squares technique is one of the oldest methods that has been widely used for optimisation problems and land levelling is not an exception. Scaloppi and Willardson first described the use of MLS in land levelling projects in 1986 (Scaloppi and Willardson 1986) and then MLS was used in 1991 in a computer program to optimise land levelling projects based on MLS (Gebre-Salassie and Willardson 1991). Based on this method, the optimal plane surface is obtained by minimising the sum of the squares of the vertical deviation between the graded-plane surface and the natural surface. Mathematically, this may be expressed as:

$$\sum_{i=1}^{nx}\sum_{j=1}^{ny}(h_{ij} - C_1 - C_2 x_{ij}^{1} - C_3 y_{ij}^{1})^2 \tag{29}$$

However, the cut to fill ratio must be applied by trial and error and cannot be determined by this method.

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In some research studies, the determined optimum plane resulted in an out of range cut to fill ratio (Gebre-Salassie and Willardson 1991) which means extra soil must be transferred outside of the field or *vice versa* and, from an energy viewpoint, it would not be reasonable. Anyway, this method has been used in this research as a benchmark to analyse the results of the other methods.

Case study field. In order to acquire the data needed to test and verify the proposed model, a case study region was specified in the district of Qazvin, Iran. The study farm was 2 ha in area that was located in the mid-west of Iran in a mountainous terrain. The topography of the farm was captured using a drone equipped with a laser range finder and RTK-GPS. Finally, the plan was produced by the length, width and height coordinates of the points (as x, y and z) with a grid size of 2 × 2 m. The study region had multiple local concave and convex places. A schematic of the topography of part of the land surface before the levelling task can be seen in Figures 1 and 3.

The total volume of the soil that needed to be displaced and the cut-fill volumes were obtained by creating models (TIN, Raster) in GIS. If the cut to fill ratio is within an allowable range, as was described in formulation section, the amount of energy consumption will be calculated based on the estimated volumes. Figure 4 shows a holistic flowchart for determining the optimum cut-fill volume (V) by GIS. Per this flowchart, after reaching an acceptable *R*-value, the required slopes will be checked as well. After reaching an optimum slope, all of the data including the machinery weight, human labour and work time were exported to MATLAB software for estimation of the machinery, fuel and labour energy.

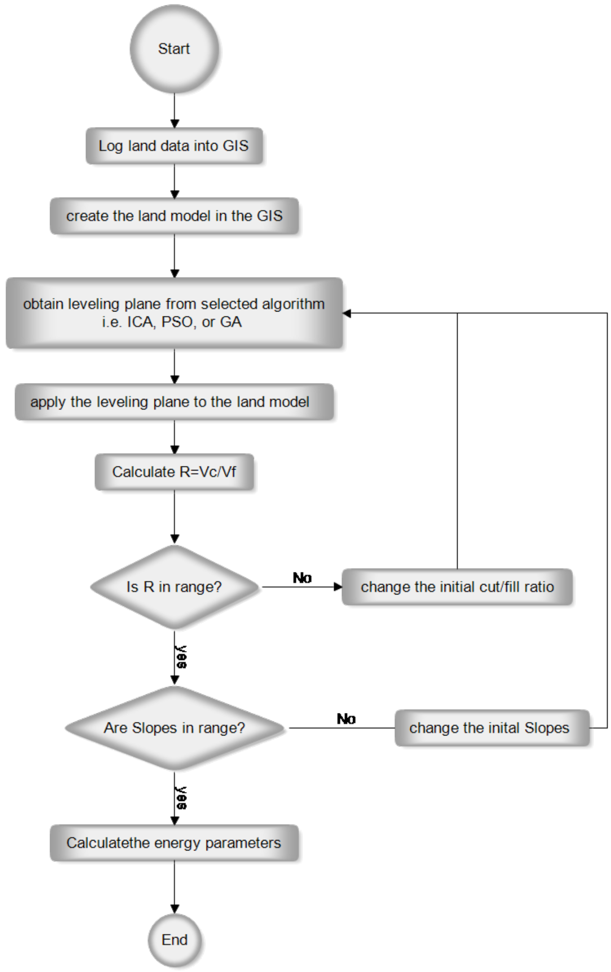

Figure 4. Suggested flowchart for reaching the optimum *R* in GIS

ICA – imperialist competitive algorithm; GA – genetic algorithm; GIS – geographic information system; PSO – particle swarm optimisation; *R* – cut : fill ratio

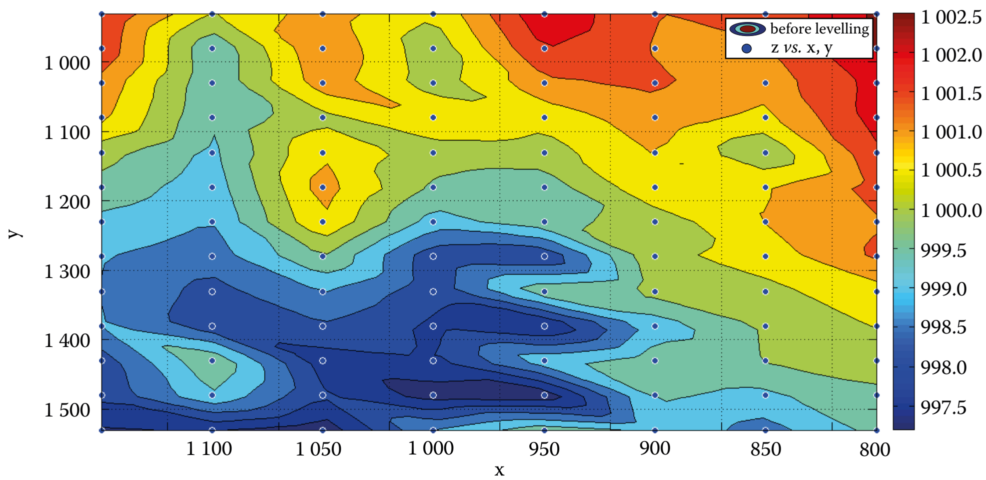

Figure 3. Contour map of part of the study region before levelling

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RESULTS AND DISCUSSION

Imperialist competitive algorithm model. The results of the applied ICAs are shown in Table 2. In the application of the ICA models, the cut volume was calculated so that they were extended from 5 344 m^3 to 6 183 m^3. This difference refers to R which is computed to be between 1.15 to 1.19 with these models. The energy parameters that are in direct relation to the earthwork volume are approximately between 41 and 51 GJ. Expectedly, the largest portion of the energy usage relates to the fuel energy which consumes about 87% of the total energy with the different models, which are shown in the Table 2. Although this portion of fuel usage can be amended using machinery with a higher efficiency and lower fuel consumption rates, considering the same condition for all other methods, a comparison of the different methods is logical. On the other hand, the smallest energy portion belongs to the labour energy which accounts for less than 1% of the total energy consumption, while the machinery energy is approximately responsible for 13% of the total energy consumption. Based on Table 2, it is evident that the SRs among the ICA models are higher than the other methods, which indicates the reliability of the solutions. The levelled surface by ICA and a counter map of the ground is shown in Figures 5 and 6, respectively. It is noticeable that the blue dots in Figure 5 represent the elevation of the grid before the levelling process.

PSO model. Table 3 summarises the results of the deployed PSO models. As is shown in the table, the cut to fill ratio in these models ranges from 1.117 to 1.20, which is close to the results of the ICA. It is clear that when the cut to fill ratio approaches unity, the total energy consumption diminishes and the results of these models confirm this fact. However, when the constraints of the problem take effect, algorithms try to minimise the objective function considering those constraints. Although the enforced constraints may increase the total energy consumption at first glance, they actually reduce it and this fact will be discussed in the MLS results. For the PSO models, the portions of energy consumption, from the largest portion to the smallest portion, are roughly the same as the ICA, nevertheless, the average total energy consumption for the PSO models is higher than the ICA models. In the same manner, the SR for the PSO algorithms is lower than that of the ICAs.

Genetic algorithm model. Table 4 represents the results of the GA models. Based on this table, the soil cut to fill ratio from the most energy efficient to the most energy-consuming method increases from 1.15 to 1.19. The total energy consumption average with this method is also greater than that of the ICAs. In addition, the SR for the dif-

Table 2. Volume of the earthwork and energy consumption in ICA

No.	SR	Cut (m^3)	Fill (m^3)	Cut : fill	Energy (MJ)			
					machinery × 10^3	fuel × 10^3	labour	total × 10^3
1	28	5 344	4 647	1.15	5.40	36	0.3960	41.40
2	30	5 543	4 778	1.16	5.88	39.2	0.4312	45.08
3	29	6 043	5 165	1.17	6.60	44.0	0.4840	50.60
4	30	6 183	5 196	1.19	6.72	44.8	0.4928	51.52

ICA – imperialist competitive algorithm; SR – success rate

Table 3. Summary of the results obtained from the PSO algorithm for the curve model

No.	SR	Cut (m^3)	Fill (m^3)	Cut : fill	Energy (MJ)			
					machinery × 10^3	fuel × 10^3	labour	total × 10^3
1	15	5 913	5 054	1.17	6.36	42.4	0.4664	48.76
2	19	6 214	5 266	1.18	6.84	45.6	0.5016	52.44
3	20	6 355	5 340	1.19	7.32	48.8	0.5368	56.12
4	21	6 471	5 393	1.20	7.56	50.4	0.5544	57.96

PSO – particle swarm optimisation; SR – success rate

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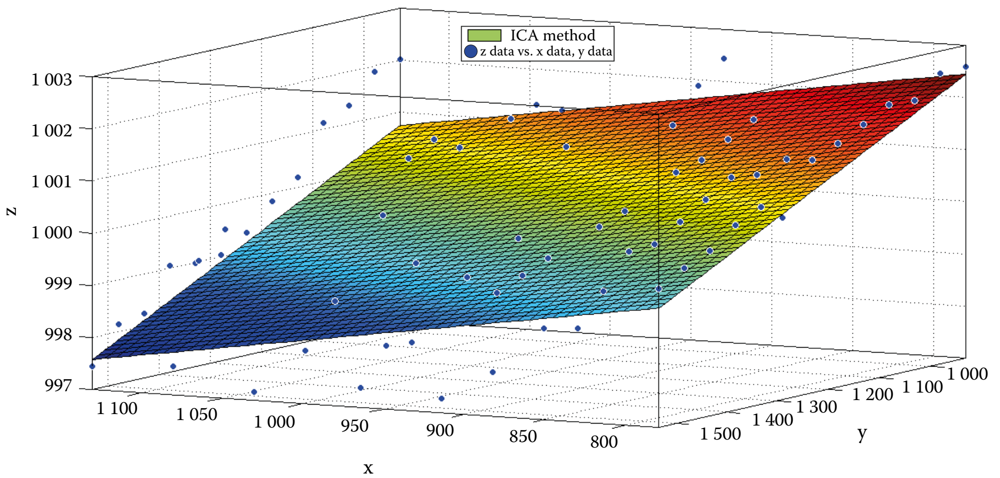

Figure 5. Levelled surface using ICA

ICA – imperialist competitive algorithm

ferent models with this method is more alike to the GAs than the ICA. There is also a slight increase in the amount of the cut volume, which is the based on the factor for the intensification of the energy consumption factors from ICA to GA. The results of these methods are juxtaposed in the charts, which illustrates the superiority of the methods.

Least squares method. Table 5 contains the results of the MLS method. The volumes of the earthworks and energy consumption in this method is higher than all the other methods tested in this research. This is directly connected with the R (cut to fill ratio). Since the R range cannot be enforced as a constraint for solving the problem, after determining the optimum plane, R can be changed by trial and error. In other words, MLS determines the best-fitted plane using the equations described in MLS section. However, this plane may not satisfy the R condition and R will either be less than 1 or more than 1.25. In either case, much more energy is required to transfer extra soil from the field to outside the field or *vice versa*. The former case frequently happens in Iranian agriculture and most farmers spend hundreds of litres of oil and transfer fertile soil from the fields to other places or, at best, to the field margins. This action extends the operation time significantly and because all the energy-related parameters are connected to the time, the total energy consumption rises drastically. For optimising the energy-related measures in the MLS method, the optimised plane may be moved vertically to reach a favourable ratio by trial and error. However, this will violate the constraint associated with the origin elevation, C_1. C_1 obtains its value when the most important goal of levelling is irrigation. In this case, the origin elevation is used to calculate the head of the pipeline systems which is a strict constraint that should be satisfied.

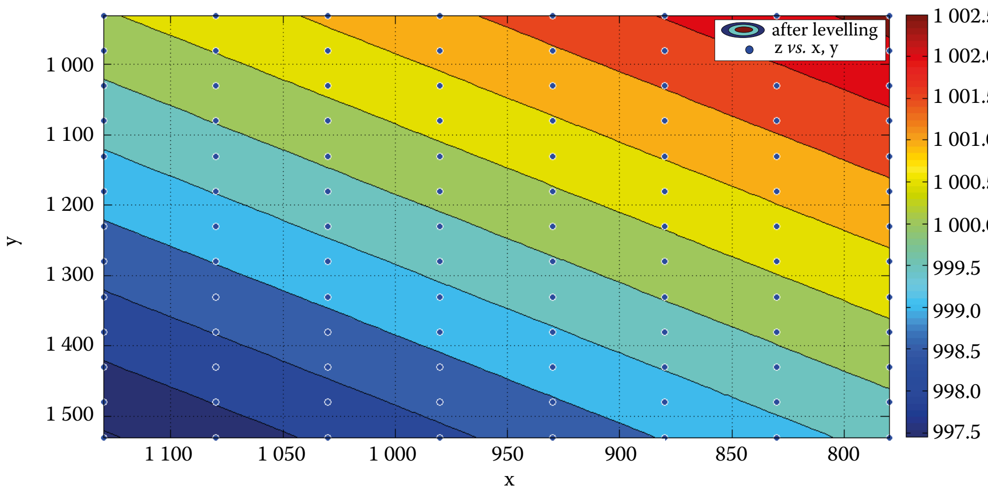

Figure 6. Counter map of the levelled ground by ICA

ICA – imperialist competitive algorithm

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Table 4. Volume of the earthwork and energy consumption for GA

No.	SR	Cut (m^3)	Fill (m^3)	Cut : fill	Energy (MJ)			
					machinery × 10^4	fuel × 10^4	labour	total × 10^4
1	15	5 932	5 158	1.15	6.84	45.6	0.5016	52.44
2	18	6 326	5 361	1.18	7.08	47.2	0.5192	54.28
3	17	6 348	5 334	1.19	7.20	48.0	0.528	55.20
4	20	6 406	5 383	1.19	7.44	49.6	0.5456	57.04

GA – genetic algorithm; SR – success rate

Table 5. Volume of the earthwork and energy consumption in the least squares method

Model	Cut (m^3)	Fill (m^3)	Cut : fill	Energy (MJ)			
				machinery × 10^4	fuel × 10^4	labour	total × 10^4
MLS	6 575	5 177	1.27	7.56	50.4	0.5544	58.51

MLS – minimum least squares

Comparison of different methods. Figure 7 poses the total energy consumption estimated by the different methods in this research. It is obvious that model number one in ICA outperforms all the other models not only in the ICA method, but in the GA, PSO and MLS methods. Considering MLS as a criterion reveals the superiority of computational algorithms for saving energy in land levelling practices. This is due to the treatment of these algorithms by a set of codes and numbers instead of variables themselves and their independence from the derivatives of functions that are quite difficult to perform sometimes. These advantages make these algorithms more robust for nonlinear optimisation problems, such as land grading, over their conventional rivals.

The percent of energy that can be saved using each model in comparison with MLS is shown in Figure 8. Although all of these algorithms are potentially capable of saving energy over the MLS method, the ICA shows the most promising results. Model number 1 in the ICA can save 29% in the energy consumption, equal to 17 MJ, which is considerably high for such a relatively small project. The PSO and GA methods also showed better performance than MLS by saving 17 and 10% of the total energy consumption in their best model (number 1 models), respectively. However, in countries like Iran and Iraq that are producers of fossil fuels in which farmers receive fuels with substantial governmental subsidies, this savings will not induce farmers to reconsider their fuel consumption either from a financial or environmental viewpoint. The former is because of the low price of fuels in these countries which allows customers to burn as much fuel as they wish,

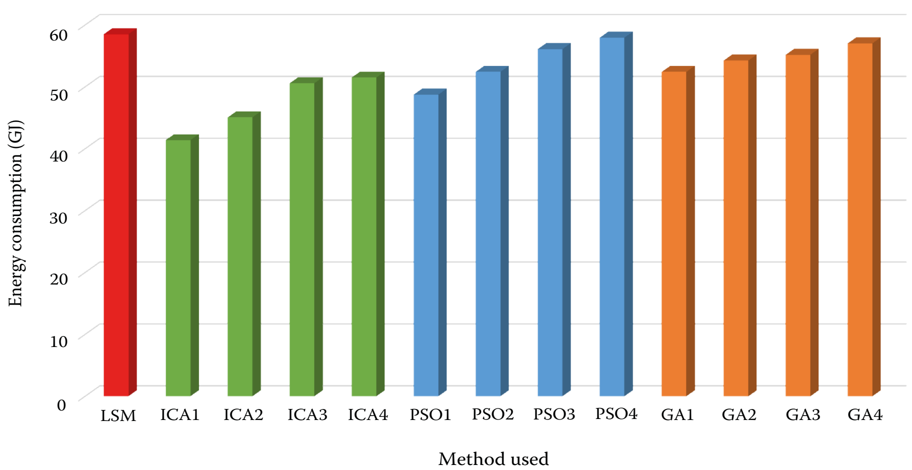

Figure 7. Total energy consumption for the levelling in the study region based on the different models (GJ)

ICA – imperialist competitive algorithm; PSO – particle swarm optimisation; GA – genetic algorithm

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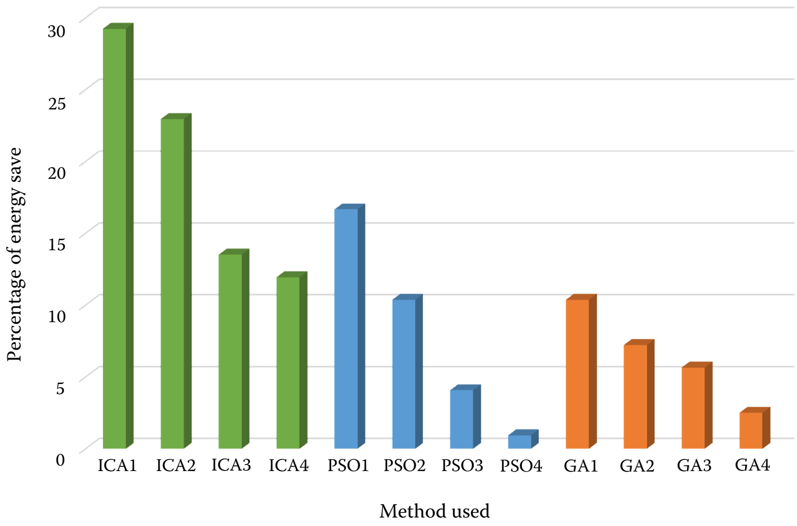

Figure 8. Percentage of energy saving capacity of each model compared with MLS

ICA – imperialist competitive algorithm; PSO – particle swarm optimisation; GA – genetic algorithm; MLS – minimum least squares

while the latter stems from a lack of environmental and ecosystem-related knowledge among farmers of developing countries.

Although it is evident that new methods are much more effective in saving energy and reducing the price of production, unfortunately, farmers in developing countries pay no heed to these concerns, and even conventional methods such as MLS are barely used, let alone new methods.

The total energy consumption in land levelling projects can differ based on the physical and mechanical characteristics of the soil (such as the sand percent), required final slopes, types of machinery used, etc. However, most of these factors are far less important than the amount of cut and fill or cut to fill ratio (Alzoubi et al. 2018). Moreover, these parameters can be treated in a way to reduce energy usage. For example, soil moisture is an effective factor in land levelling projects that can be controlled to a great extent. On the other hand, the volume of the cut or fill, which is the most effective factor in the energy consumption during a land levelling project, is highly constrained. As a result, using a technique to determine the best methodology and procedure for land levelling prior to operation is inevitable.

CONCLUSION

In conclusion, this study deals with optimising the energy consumption during land levelling projects using new computer-based techniques and compares the results to the MLS method as a benchmark. The three energy inputs in the land levelling project were machinery energy, fuel energy, and human labour energy. Although human labour energy is negligible compared to fuel energy and machinery energy, it was nevertheless taken into account. For minimising the amount of input energy, the land levelling problems were modelled as nonlinear problems with linear and nonlinear constraints and solved using ICA, PSO, GA, and MLS techniques. For optimising the amount of energy, the volume of the cut and fill, which is the paramount factor affecting the energy consumption, was minimised. For this purpose, the coordinates of a 2-ha field were extracted and the data were proceeded by the proposed algorithms as well as MATLAB and ArcGIS software programs. Based on the results, ICA has the capacity to save approximately 30% of the required energy for land levelling projects. Not only does this model result in higher SRs, but also in a lower total energy consumption. Moreover, all of the problem constraints can be enforced directly to the algorithm to avoid extra computations using trial and error. All in all, ICA, PSO, and GA performed much better than MLS by saving 29, 17, and 10% of the total energy consumption in their best model (number 1 models), respectively. Nonetheless, with the great capacity for saving energy in developing countries, a lack of education and excess subsidies on fossil fuels unfortunately nullifies the potential.

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