International Journal of Mining Science and Technology 27 (2017) 491–498

Contents lists available at ScienceDirect

International Journal of Mining Science and Technology

journal homepage: www.elsevier.com/locate/ijmst

Selection of optimal land uses for the reclamation of surface mines by using evolutionary algorithms

Palogos Ioannis [a], Galetakis Michael [a,*], Roumpos Christos [b], Pavloudakis Francis [b]

[a] School of Mineral Resources Engineering, Technical University of Crete, 73100 Chania, Greece
[b] Public Power Corporation of Greece-Mines Division, 104 42 Athens, Greece

ARTICLE INFO

Article history:
Available online 6 April 2017

Keywords:
Reclamation
Land uses
Optimization
Evolutionary algorithms
Desirability functions

ABSTRACT

A methodology for the selection of the optimal land uses of the reclamation of mined areas is proposed. It takes into consideration several multi-nature criteria and constraints, including spatial constrains related to the permissible land uses in certain parts of the mined area. The methodology combines desirability functions and evolution searching algorithms for selection of the optimal reclamation scheme. Its application for the reclamation planning of the Amynteon lignite surface mine in Greece indicated that it handles effectively spatial and non-spatial constraints and incorporates easily the decision-makers preferences regarding the reclamation strategy in the optimization procedure.

1. Introduction

Land reclamation and the related post-mining activities play a vital role in every mining project. The selection of the most appropriate land uses of the reclaimed mined area is a key point in the overall process. However the selection of the most appropriate land uses is a complicated multi-criteria decision problem because of the variety of the criteria and parameters (geotechnical, environmental, legal, economic, social) which are taken into consideration and the necessity to attain the acceptance of the reclamation plan by local communities [1–5]. The complexity of the problem is further increased due to nature of social and environmental constraints and to subjectivity that characterize the decision makers, like local authorities or local communities [1,3,6].

Many studies have been published for land reclamation and land use selection in mining industry. The majority of them focus in ranking or prioritizing a number of potential land uses (alternatives) leading to the selection of a single land use for the whole mined area. Such a selection is achieved by applying multi-criteria decision-making (MCDM) approaches [1,3,7–9]. An example of the MCDM approach is the development of the analytical hierarchy process (AHP) methodology that assesses the priorities based on the inputs of specialists in mining industry activities. AHP handles the qualitative and quantitative criteria that are related with reclamation problems and allow the decision team to examine systematically, compare and determine the priorities of the relevant criteria and sub-criteria. Based on this information, the reclamation alternatives can be compared effectively and the optimum one can be selected [3,10,11].

Mined land suitability analysis (MLSA) combines analytical hierarchy process methodology (AHP) and the ELECTRE multi-criteria decision analysis methods. The abbreviation ELECTRE denotes ELimination Et Choix Traduisant la REalité (Elimination and Choice Expressing Reality). This combination is used for the evaluation of the mined land suitability for the various alternatives. The AHP estimates the global calculated weights of the attributes evaluated by decision maker's subjective judgments and then, the weights passed to the ELECTRE method so that the most efficient post mining land uses could be appointed through comparisons of pair-wise dominance relationships between alternatives [12].

Fuzzy comprehensive method, and more specifically the multi-level comprehensive evaluation method combined with GIS, is another MCDM technique that has been suggested for selecting the most appropriate land use among various alternatives. The main advantage of this method is that it can be adjusted in an easy manner and it can objectively determine pros and cons of complicated models with multi-attributes, multi-factors in which quantitative and qualitative methods co-exist. It can also classifies different reclamation programs based on the comprehensive evaluation values which are suitable for the problems with large amounts of information, more evaluation indicators and more complicated reclamation programs [7].

However, few methods, in terms of optimization of land reclamation, have been issued taking into consideration the spatial

* Corresponding author.
E-mail address: galetaki@mred.tuc.gr (M. Galetakis).

http://dx.doi.org/10.1016/j.ijmst.2017.03.008
2095-2686/

variation of the decision-making parameters in a mining area [1,13]. According to the reclamation of each different parts of the post-mining area is to be provided, thus a spatial decision support system must be developed and implemented [1]. The proposed spatial decision support system (SDSS) involves two main steps: at the first stage the elaboration of the qualitative information is taking place. This information includes the negotiation conclusions among stakeholders, the existing legal framework regarding land reclamation and uses, as well as, the economic prospects. Based on this information a set of possible land uses are initially determined. In the next step the spatial analysis is performed. The mined area under reclamation is divided into several smaller parts (squares) and the decision criteria with spatial character are considered in order to select the most appropriate land use for each square. All the alternatives suggested are resulted from the previous stage. A number of technical and social criteria are considered for the characterization of land suitability for each of the possible alternatives. Hence, the second step is the heart of the decision model. Binary linear programming procedure (branch and bound algorithm) is applied for the determination of specific land uses. The applied constrains referred to the maximum and minimum area allowed for each specific land use.

However, it is well known that numerous additional constraints, mainly of spatial nature, are considered during the selection of the land uses. These constraints usually refer to compatibility of specific land uses of adjacent areas, to exclusion or inclusion of specified mined areas for a particular land use and to the number and shape of created sub-areas for each land use. The existing methods are not capable in handling efficiently such constraints considered during reclamation planning, thus the derived land use maps must be corrected manually by the reclamation planning team. This is a time-consuming procedure and do not always lead to optimal solutions, thus the need for developing a more sophisticated SDSS for the selection of the optimal land uses is necessary.

In this work an advanced SDSS as a tool for selecting the most suitable land uses is developed. Constraints regarding the proximity between the potential land-use alternatives, as well as, constrains regarding the area of each alternative land use are considered. Because of the complexity in structure and the spatial nature of these constraints, the optimization problem cannot be handled effectively by classic linear programming algorithms. Thus, the proposed advanced methodology incorporates evolutionary algorithms and desirability functions to overcome such optimization complexities.

The structure of this study is as follows: first the problem for the selection of the optimal land uses of reclaimed mined areas is described, next the methodology for the selection of the optimal land uses is presented and finally the proposed methodology is applied for the planning of the reclamation of the Amynteon surface lignite mine in Greece.

2. Reclamation of mined areas-criteria for selection of the appropriate land uses and related constraints

The main outcome of the planning of land reclamation in an area that is affected by surface mining is a thematic map which indicates the specific land uses for every part of the area.

The decision for the most suitable land use for each part of the mined area is based on the findings obtained from the area's characteristics, the opinions of experts, the development plans of local communities and authorities, the legal environmental framework and the environmental restrictions. The resulting map illustrates the reclaimed area divided into coloured squares, where each colour corresponds to a specific land use. The most common land uses of the reclaimed mined areas include agricultural land, forest, residential area, recreational area and industrial zone. The deepest part of the mined area is usually reclaimed to form a lake.

For the selection of the most appropriate land use for each square of the reclaimed area, a number of criteria, mainly of spatial nature, are considered. Experts in field of land reclamation select the decision parameters and their optimum values for each land use. A typical set of such criteria with the considered as optimum values is shown in Table 1. The values of these parameters represent the suitability of a square of the area for a specific land use according to the corresponding criterion. The land use suitability is usually expressed by applying a three-level scale: 0 for low, 1 for medium and 2 for high suitability. The most desirable (optimal) land uses for the area are those with the minimum deviation from the optimum values while at the same time satisfies numerous general (with non-spatial character) and spatial constraints.

The non-spatial constraints refer to the expressed preferences regarding the total area covered by a specific land use. Such a preference can be expressed as: 'the agricultural land must be at least 1×10^7 m^2, or 'the industrial area must be less than 4×10^6 m^2, or in a more complicated form such as: 'the desirable forestry land is 4×10^7 m^2, however it should be at least 3.5×10^7 m^2 (1 ha = 10,000 m^2).

The spatial constraints are classified into those related to the compatibility of specific land uses of adjacent land squares (proximity constraints) and into those related to obligatory exclusion or inclusion of pre-determined mined areas for a particular land use. Such constraints can be expressed as: 'recreational area must not be adjacent to industrial area' or 'the bottom of the mined area must form a lake', or 'a zone of forest must be created around the lake'.

The simultaneous fulfillment of general and spatial constraints during the selection of the optimal land uses for each square is not always attainable. To overcome this problem in the developed methodology, the general constraints referring to the area of each land use were transformed to additional optimization functions, where the preferable area of each land use was considered as the target value. Hence, the single optimization problem is transformed to multi-objective optimization problem and the only remaining constraints were those with spatial nature.

Spatial constraints were considered more important than general constraints since the first is almost exclusively related to legal end environmental regulations and their fulfillment is essential. Therefore an algorithm to examine the accomplishment of spatial constraints in the generated land use maps during the reclamation planning process was developed. If spatial constraints are not met in a square of the map then the land use of the square changes according to certain rules embedded in the algorithm. A typical example of such a case is shown in Fig. 1, where the restriction regarding the proximity of recreational and industrial zone areas is violated.

3. Methodology for selection of optimal land uses

3.1. Model development and mathematical notations

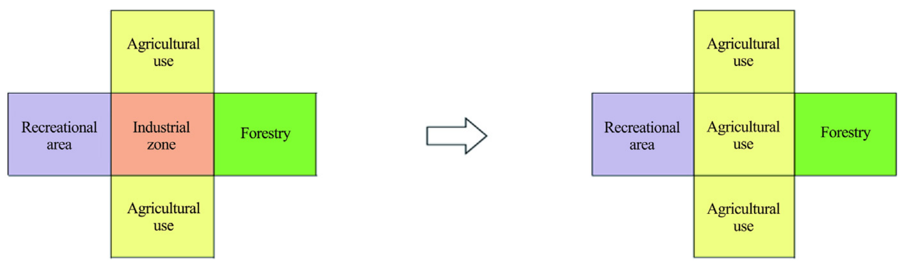
The development of the model for the selection of the most suitable land uses in the reclamation planning includes the following steps:

(1) The L different permissible land uses and the K evaluation criteria (decision parameters) are defined.
(2) The optimum value for each decision parameter corresponding to a specific land use is determined (Table 1). These optimum values form matrix $B \in R^{K \times L}$.

Table 1
Optimum decision parameters (criteria) values for the selection of the alternative land use [1].

Decision parameter (criteria) k	Land uses l			
	1 = Agriculture	2 = Forestry	3 = Recreational	4 = Industrial
1 = Terrain slope	0	1 or 2	0	0
2 = Fertility of the soil	2	0 or 1	1 or 2	0
3 = Proximity to lakes	0 or 1	0 or 1 or 2	2	0
4 = Proximity to archaeological sites	0 or 1	0 or 1 or 2	2	0
5 = Proximity to villages	0 or 1	0 or 1 or 2	2	0

Note: rating scale for the decision parameters is as follows: 0 = low, 1 = medium, and 2 = high.



(a) Land use pattern before the application of the algorithm for ensuring the fulfilment of squares proximity constraints

(b) Land use pattern after the application of the algorithm for ensuring the fulfilment of squares proximity constraints

Fig. 1. Application of neighbourhood spatial constraints (a square marked "recreational use" must not be adjacent to a square marked "industrial zone").

(3) The study area is divided into $D = m \times n$ squares and in each square are assigned the values of the K decision parameters (i.e. terrain slope, proximity to villages, soil fertility, etc.). The terrain slope and the proximity to villages, lakes, archaeological sites etc., were measured by using a GIS while other parameters, like the soil fertility, were estimated from existing analytical data. The obtained values were ranked according to a three-level scale as low (0), medium (1) and high (2). These assigned values form the matrix $S \in R^{m \times n \times K}$.
(4) Every square (i, j) of the study area is rated for each specific land use l according to K decision parameters. The rating is performed by estimating first the absolute difference, $dev_{partial}$, from the optimum value for each decision parameter k as it is shown in Eq. (1) and by following Eq. (2) the overall deviation dev_{total} is calculated.

$$dev_{partial}(i,j,k,l) = \min\{|S(i,j,k) - B(k,l)|\} \quad (1)$$

$$dev_{total}(i,j,l) = \sum_{k=1}^{K} dev_{partial}(i,j,k,l) \quad (2)$$

(5) The general constraints related to the preferable area for each selected land use are transformed into objectives functions.
(6) The multiple objective optimization problem is turned to single optimization problem by using the desirability functions.
(7) The optimal land uses are estimated by applying a genetic algorithm in conjunction with the procedure of spatial constraints fulfillment.

The last three steps referring to the optimization are described in detail below.

3.2. Definition of objective and desirability functions

The first goal of the optimization is to select these land uses, at each square, that minimize the total sum of deviations, dev_{total} of the decision parameters from their optimum values for the entire study area. Considering that in each square only one land use can be assigned, the objective function y_0 to be minimized is

$$\min\ y_0 = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{l=1}^{L} dev_{total}(i,j,l), \quad \forall i = 1,\ldots,m,$$
$$j = 1,\ldots,n,\ l = 1,\ldots,L \quad (3)$$

The second goal of the optimization is related to the expressed preferences regarding the area A_l covered by each specific land use l. The desirable values were set as targets ($A_{target,l}$) thus the deviations y_l of the resulting areas from target values must be minimized. The area A_l of each land use l is calculated as the sum of the corresponding squares according to Eq. (4), while its deviation y_l from the target area A_{target} is calculated as shown in Eq. (5). Therefore the second goal refers to the minimization of L objective functions $y_1, y_2, \ldots, y_L$.

$$A_l = \sum_{i=1}^{m}\sum_{j=1}^{n}((i,j) = l) \quad (4)$$

$$y_l = |A_l - A_{target,l}|, \ \forall l = 1,\ldots,L \quad (5)$$

Consequently, after the transformation of the general restrictions to objective functions, the goal is to minimize simultaneously the $L + 1$ objective functions, $y_0, y_1, y_2, \ldots, y_L$. One of the most popular methods used in multi-objective optimization is that based on the desirability functions. The method finds the values of the decision parameters that provide the "most desirable" solution. The basic idea of desirability function approach is to transform a multi-response problem into a single response problem by means of mathematical transformations [10]. For each y_t, with $t = 0, 1, \ldots,$ L, a desirability function $des_t(y_t)$ assigns numbers between 0 and 1 to the possible values of y_t with $des_t(y_t) = 0$ representing a completely undesirable value of y_t and $des_y(y_t) = 1$ representing a completely desirable or ideal value. The overall objective function, referred as total desirability f_{des}, is defined as the geometric mean of the n individual desirabilities $des_t(y_t)$. If some individual desirabilities are considered more important than others, an impact coefficient w_t can be assigned for each response $des_t(y_t)$. In this case the total desirability is [14]:

$$f_{des} = \left(\prod_{t=0}^{t=L} des_t^{w_t}(y_t) \right)^{\frac{1}{\sum_{t=0}^{L} w_t}} \quad (6)$$

Using the geometric mean of the individual desirability functions guarantees that if any single desirability is zero (complete undesirable), the overall desirability f_{des} is zero. In contrast the overall desirability is 1 if all individual desirabilities are 1 (complete desirable). Thus, the simultaneous optimization of several responses has been transformed to optimization of a single response, the overall desirability. Derringer and Suich proposed three different forms for the desirability function, depending upon whether y_t is to be maximized, minimized, or attain a target value [14]. When y_t is to be minimized (as in this case) the form of the desirability $des_t(y_t)$ function is

$$des_t(y_t) = \begin{cases} 1 & y_t < L_b \\ \left(\frac{U_b - y_t}{U_b - L_b}\right)^h & L_b \leqslant y_t \leqslant U_b \\ 0 & y_t > U_b \end{cases} \quad (7)$$

where U_b is the upper value above which the response y_t is considered as unacceptable; and L_b the lower value below which the response y_t is fully acceptable. The parameter h defines the desirability function's shape in the interval $[L_b, U_b]$ [15].

In this study $L+1$ objectives functions, and eventually $L+1$ desirability functions, were defined. The first one, presented in Eq. (3), corresponds to the objective y_0, whereas the remaining L objectives refer to the deviation of the area covered by each land use from the defined target area, according to Eq. (5). Thus the optimal land uses of the study area are those with the maximum value of the total desirability.

3.3. Genetic evolution algorithm

Since 1950s, many computer researchers studied the application of evolutionary systems as an optimization tool for engineering problems because of their ability to solve problems that could not be solved by conventional optimization methods [16,17]. These systems evolve a population of candidate solutions to a given problem, using processes inspired by natural genetic variation and natural selection [16]. Genetic evolution algorithm (GA) is a stochastic, population-based optimization algorithm introduced by Holland in 1975 [18]. The optimization process is carried out by evolving populations by means of mutation, crossover and selection operations. The steps for the development of the GA algorithm, described below, include the creation of the initial population (initialization), the mutation, and crossover and selection operations. GA optimizations methods have found several applications in mining industry such as for the optimal equipment selection in opencast mining, or, as a tool to predict the failure of mining equipment over the time [17,19].

3.3.1. Initialization

As initial population in this study a set of N_p matrices of dimension $m \times n$ was created. Each matrix $m \times n$ represents a candidate reclamation solution (land use matrix) and is called individual p at a generation G. Each individual p of the population at a generation G, with $p \in [1, N_p]$, is denoted as a target matrix $X_{p,G}$ and is expressed as

$$X_{p,G} = \begin{bmatrix} x_{p,G}(1,1) & x_{p,G}(1,2) & \ldots & x_{p,G}(1,n) \\ \vdots & \vdots & \vdots & \vdots \\ x_{p,G}(m,1) & x_{p,G}(m,2) & \ldots & x_{p,G}(m,n) \end{bmatrix}, \text{ for } p = 1, 2, \ldots, N_p \quad (8)$$

The size of the population does not change through the optimization procedure. The initial population at the start, $G = 0$, should cover the entire search space of the alternatives, by selecting each individual from an empirical distribution from the range of $[1, L]$. The empirical distribution was selected instead of the uniform distribution, which is the most common, to increase the efficiency of the evolution process. Considering the probability p_l of selecting an alternative l at a square $x(i, j)$ is equal to the predetermined percentage of the area for this specific land use l, then the cumulative probability q_l of the empirical distribution is

$$q_i = \sum_{j=1}^{i} p_j, \quad i = 1, 2 \ldots, L \quad (9)$$

Assigning a land use value l to a square from the empirical distribution involves the steps indicated in Eq. (10). A number r is randomly selected from the uniform distribution [0, 1]. If r is within the interval $[0, q_1]$ then the land use 1 is selected, if r is within the interval $(q_1, q_2]$ the land use 2 and so on.

$$l = \begin{cases} 1 & \text{if} \quad r \in [0, q_1] \\ 2 & \text{if} \quad r \in (q_1, q_2] \\ & \quad \ldots\ldots. \\ L & \text{if} \quad r \in (q_{L-1}, q_L] \end{cases} \quad (10)$$

3.3.2. Mutation step

After initializing the population of the candidate solutions, an evolution process is taking place at each generation for a predetermined number of generations G_{max}. The first step of the evolution process is the mutation step. A mutant solution matrix $V_{p,G}$ is created with respect to each target matrix $X_{p,G}$ following a mutation strategy.

$$V_{p,G} = \begin{bmatrix} v_{p,G}(1,1) & v_{p,G}(1,2) & \ldots & v_{p,G}(1,n) \\ \vdots & \vdots & \vdots & \vdots \\ v_{p,G}(m,1) & v_{p,G}(m,2) & \ldots & v_{p,G}(m,n) \end{bmatrix} \quad (11)$$

In this study the single point mutation method was selected. The mutation probability F of the land use of a square is first defined. This probability is set low, usually 1%–5%, since if it is set too high, the search will turn into a simple random search [20,21]. During the mutation step at each square, a random number p_{mut} is randomly selected from a uniform distribution with $p_{mut} \sim U$ [0,1]. If $p_{mut} \leq F$, then the land use l in the square is changed else it remains the same. The new land use l (mutated value) is derived from the empirical distribution used in the initialization step according to Eqs. (9) and (10). If the new land use (mutated) is identical to the initial, the mutation procedure is repeated until the mutated value become different from the initial one.

3.3.3. Crossover step

The succeeding crossover step applied to each pair of $X_{p,G}$ and $V_{p,G}$, is used to increase the diversity of the perturbed solutions. The crossover operation generates a new matrix, called trial matrix, by mixing the elements of the mutant matrix with those of the target matrix. If the trial matrix obtains a higher desirability value than the target matrix, then the trial matrix replaces the target matrix in the next generation. The trial matrix is denoted as:

$$U_{p,G+1} = \begin{bmatrix} u_{p,G+1}(1,1) & u_{p,G+1}(1,2) & \ldots & u_{p,G+1}(1,n) \\ \vdots & \vdots & \vdots & \vdots \\ u_{p,G+1}(m,1) & u_{p,G+1}(m,2) & \ldots & u_{p,G+1}(m,n) \end{bmatrix} \quad (12)$$

Initially the crossover probability CR of a matrix element is defined. Crossover probability is generally chosen from the interval [0.5, 1) [20,21]. For $\tau = i \times j$, where $\tau \in [1, D]$, each element of the trial matrix is estimated by

$$u_{p,G+1}(i,j) = \begin{cases} v_{p,G}(i,j), & \text{if } rand_\tau \leqslant CR \text{ or } \tau = \tau_{rand} \\ x_{p,G}(i,j), & \text{if } rand_\tau > CR \text{ or } \tau \neq \tau_{rand} \end{cases} \quad (13)$$

where $rand_\tau \sim U\,[0, 1)$; and τ_{rand} is an integer randomly chosen in the interval [1, D].

3.3.4. Selection step

The final stage of the evolution process is the selection step. The value of the objective function for the target solution $f_{des,G}\ (X_{p,G})$ is compared to the value of the objective function corresponding to the trial solution $f_{des,G}\ (U_{p,G+1})$. In minimization problems, if $f_{des,G}(U_{p,\ G+1}) \leq f_{des,G}(X_{p,G})$ then the trial $U_{p,G+1}$ passes to the next generation. Otherwise, the target solution $X_{p,G}$ is retained in the next generation.

The total desirability functions $f_{des,G,p,G}\ (X_{p,G} = 0)$ and $f_{des,G,p,G}\ (U_{p,G} = 1)$ are calculated for the target and the trial matrix respectively, and the population of candidate matrices, to pass at the next generation, are formed $\forall i \in [1, N_p]$. If $f_{des,G,p,G}\ (U_{p,G} = 1) \leq f_{des,G,p,G}(X_{p,G} = 0)$, then the target vector is retained, otherwise trial matrix is winner. The overall developed optimization process is shown schematically in Fig. 2.

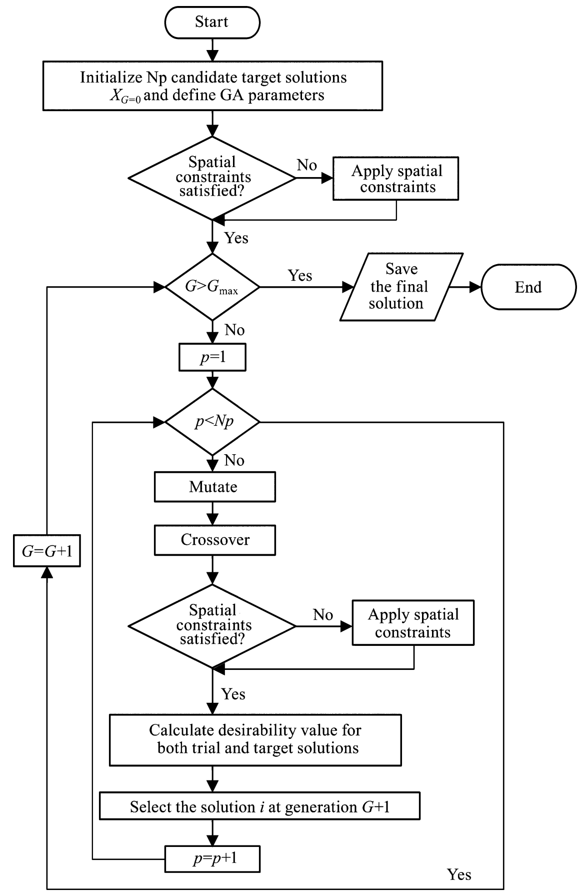


Fig. 2. Flow chart diagram of developed optimization process.

4. Application of the methodology–results and discussion

The above described methodology was developed in Matlab R2014a environment and was applied for the planning the land reclamation activities and specifically the post-mining land use of Anynteon open pit lignite mine The Amynteon lignite mine is located in Ptolemais lignite-bearing basin, in the Region of West Macedonia, Northern Greece. The lignite mine that has been developed and operates in this area during the last 30 years occupies currently approximately 6×10^7 m^2 and supplies with lignite a thermal power plant with an installed capacity of 600 MW. The Amynteon mine pit is developed from a depth of 40–50 m, in the eastern boxcut area, and reaches the depth of 250 m in the central section of the western rim slope and the depth of 180 m in the area of the southern rim slope. The mine and the power plant are surrounded by a relatively flat agricultural area, with an extensive network of irrigation channels lakes. Some areas nearby the water bodies are controlled by laws and regulations relevant to the preservation of wildlife and of sensitive environmental components, which set specific restrictions regarding the development of human activities. Moreover, in the vicinity of the mine there are several villages. According to *the National Regulation of Mining and Quarries Works*, mining activities must keep a clearance of 250 m from residential areas [1].

The wider region, including the mined area for reclamation as shown in Fig. 3, was divided into $D = 20 \times 24 = 480$ squares. The dimension of each square is 300 m × 300 m squares with an area of 90,000 m^2. The overall studied mined area contains 370 squares with a total area of 3.33×10^7 m^2.

The optimum values of decision variables for each land use are shown in Table 1. As shown in Table 1 four possible alternative land uses ($L = 4$) and five decision criteria ($K = 5$) were used for the selection of the most appropriate land use for each square.

At first, the absolute minimum partial deviations $dev_{partial}$ of decision parameters from the optimum values for each land use are calculated in each square according to Eq. (1). Then the overall deviation dev_{total} for each land use is estimated in every square according to Eq. (2). Table 2 shows in detail the calculation of dev_{total} for a square (i, j) when the considered land use is agriculture. The decision parameters values of the square (i, j) were assumed: terrain slope = 1, fertility of soil = 0, proximity to lakes = 1, proximity to archaeological sites = 2 and proximity to villages = 2.

Thus the first minimization function is $y_0 = \sum_{i=1}^{20}\sum_{j=1}^{24}\sum_{l=1}^{4} \mathrm{dev}_{\mathrm{total}}(i,j,l)$. The other minimization functions referring to the total area A_l covered by each land use l are: $y_1 = |A_1 - A_{1,target}|$, $y_2 = |A_2 - A_{2,target}|$, $y_3 = |A_3 - A_{3,target}|$ and $y_4 = |A_4 - A_{4,target}|$. The desirable areas $A_{l,target}$ to be covered area by each land use are given in Table 3.

For the estimation of the individual desirabilities of the objective functions y_0, y_1, y_2, y_3, y_4 the shape parameter h was selected to reflect the tolerance of the decision makers regarding the fulfillment of the predefined targets. Fig. 3 indicate the effect of shape parameter h on the value of the resulting desirability. For $h > 1$ the desirability falls rapidly as the deviation of an objective function from its target value increases. For $h = 1$ the decrease is linear while for $h < 1$ the decrease is slow. Selection of $h > 1$ for a specific objective function indicates that it is crucial to maintain the obtained optimal value as close as possible to the target. In contrast, $h < 1$ indicates a relatively high tolerance to this deviation, while $h = 1$ signifies a moderate tolerance.

As noted in Fig. 4, X-axis represents the absolute deviation of the objective function from the pre-defined target value, whereas y-axis denotes the value of the desirability function.

To involve the above approaches for the selection of the optimal land uses of the studied area, four different scenarios, shown in Table 4, were examined. Scenarios 1–3 were created to examine the effect of desirability parameter h on reclamation results, while the fourth to investigate the influence of spatial constraints. The

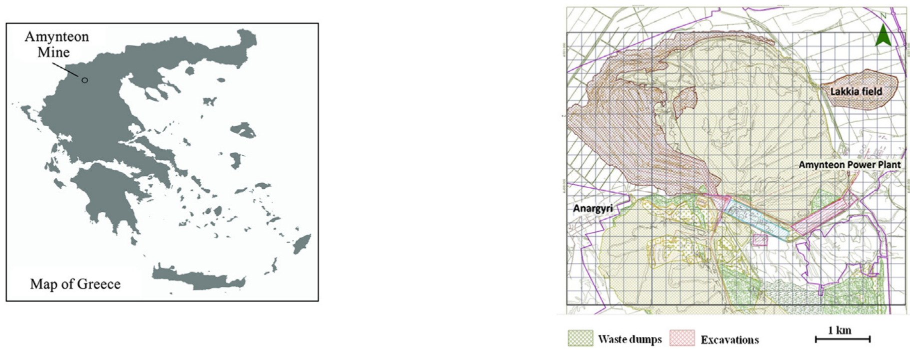


Fig. 3. Location of the area of Amynteon in Northern Greece (left) and map of the studied area of the Amynteon lignite mine (right).

Table 2
Estimation of partial and total deviation of square (i, j) when the agriculture land use is considered.

Value of decision parameter for square (i, j)	Optimum value for agriculture use	Difference from the optimum values $\mathrm{dev}_{\mathrm{partial}}$
Terrain slope = 1	0	|0–1| = 1
Fertility of the soil = 0	2	|2–0| = 2
Proximity to lakes = 1	0 or 1	min{|0–1|, |1–1|} = 0
Proximity to archaeological sites = 2	0 or 1	min{|0–2|, |1–2|} = 1
Proximity to villages = 2	0 or 1	min{|0–2|, |1–2|} = 1
Overall difference for agricultural use (l = 1) $dev_{total}(i, j, 1) = 1 + 2 + 0 + 1 + 1 = 5$		

Table 3
Optimal land uses according to the examined scenarios.

Land use	A_{target}	Obtained result for each examined scenario			
		1	2	3	4
Lake (l = 0)	4.05	4.05	4.05	4.05	4.05
Agricultural (l = 1)	54.05	53.24	53.24	54.05	47.30
Forestation (l = 2)	33.78	34.59	34.59	33.78	40.54
Recreational (l = 3)	5.41	5.41	5.41	5.41	5.41
Industrial zone(l = 4)	2.70	2.70	2.70	2.70	2.70
Mean deviation from the optimum values of Table 2 (per square)	Minimum	1.16	1.27	1.35	1.35
Overall desirability		0.82	0.81	0.81	0.75

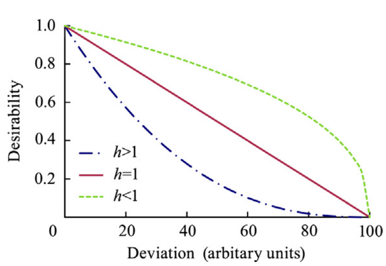


Fig. 4. Shape of desirability functions for different values of h.

parameters of evolutionary algorithm were kept identical in all scenarios. The size of the population, N_p, the number of iterations and the mutation probability F, were selected respectively to 100, 500 and 5%. These values were found, during the trial application of the developed methodology, to ensure the satisfactory convergence of the evolutionary searching algorithm in a reasonable time (the required execution time for the optimization was approximately one hour for each case, when a modern desktop computer with a multiple-core processor was used).

The results of the developed methodology for the selection of the optimal land uses for the examined scenarios are summarized in Table 3. The resulting maps indicating the proposed land use for each square of the mined area are shown in Figs. 5 and 6.

Blank squares, shown in Figs. 5 and 6 belong to the surrounding area which has not been affected by the mining activities.

Results, shown in Table 3, indicate that scenarios 1–3 lead to similar results. The proposed areas for residential and industrial zones coincide with the pre-defined areas (target) for all scenarios (1–4). The difference between the target and obtained values for agriculture use and forestation are small for scenarios 1 and 2, while for the scenario 3 these differences became zero. However

Table 4
Description and parameters of the examined scenarios.

No.	Description of the scenario (Express decision makers tolerance to expected deviations)	Desirability parameter				
		h_0	h_1	h_2	h_3	h_4
1	Moderate tolerant to all deviations	1.0	1.0	1.0	1.0	1.0
2	Stringent to deviation regarding the industrial area and moderate tolerant to the remaining	1.0	1.0	1.0	1.0	1.5
3	Stringent to deviations regarding the industrial and forest area and moderate tolerant to the others	1.0	1.0	1.5	1.0	1.5
4	Moderate tolerant to all deviations, and do not consider spatial constraints regarding compatibility of adjacent squares	1.0	1.0	1.0	1.0	1.0

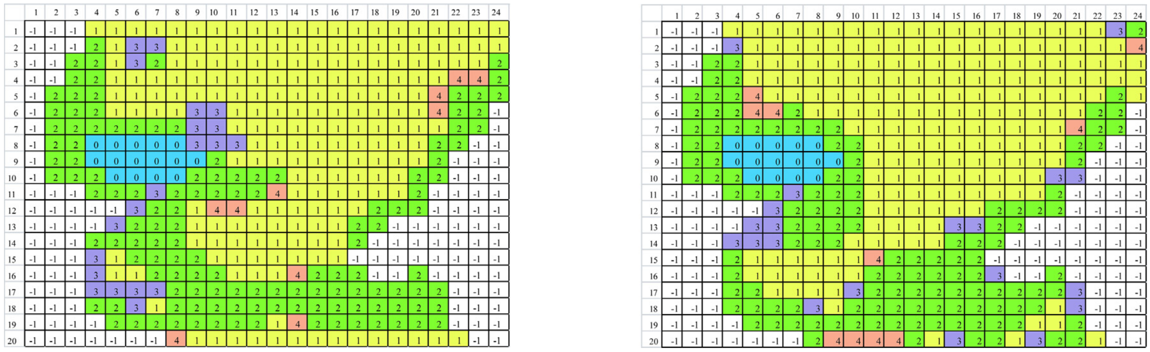


Fig. 5. Generated maps of optimal land uses for scenario 1 (left) and 2 (right) after 500 iterations of the evolutionary algorithm (0 = Lake, 1 = Agricultural, 2 = Forestation, 3 = Recreational, and 4 = Industrial zone).

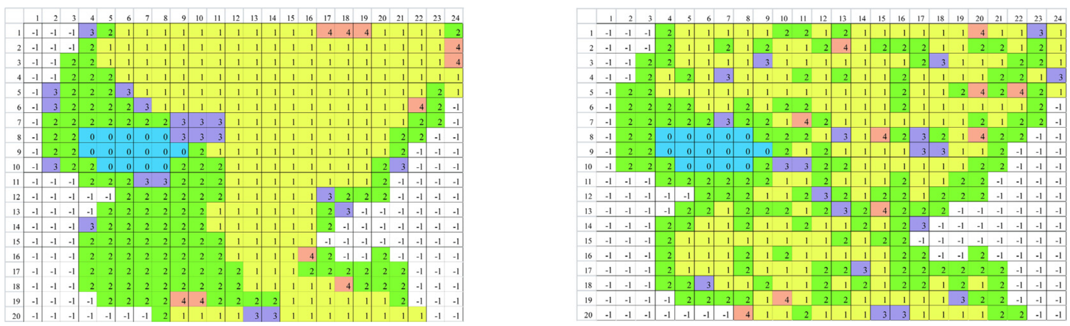


Fig. 6. Generated maps of optimal land uses for scenario 3 (left) and 4 (right) after 500 iterations of the evolutionary algorithm (0 = Lake, 1 = Agricultural, 2 = Forestation, 3 = Recreational, 4 = Industrial zone).

in the third scenario the deviations of the proposed land uses, regarding the criteria defined in Table 2, are increased. This results in slightly lower values of the overall desirability. Results obtained in scenario 4, where no spatial constraints were applied, are fairly inferior to those of 1–3.

The impact of the spatial constraints is evident in the produced maps affecting significantly the spatial distribution of the proposed land uses. In the map produced according to scenario 4 the proposed areas for all land uses are fragmented into several small sub-areas. In contrast the proposed areas according to scenario 1–3 consist of few large sub-areas. Such a spatial distribution is preferable since it has a lower reclamation cost and additionally eliminates the probability of assigning incompatible land uses in adjacent squares.

5. Conclusions

In this study an advanced methodology for the selection of the optimal land uses for the reclamation of mined areas was proposed. It incorporates the genetic evolutionary searching algorithm and the desirability functions to overcome the complexity of spatial constraints and to accomplish the multi-objective nature of the optimization. It has the capability to incorporates the decision makers attitudes and thus to determine the optimal land uses representing different reclamation strategies. The application of the developed methodology in the selection of the optimal landscape reclamation strategy of the Amynteon lignite surface mine located at West Macedonia Lignite Centre, Northern Greece, indicated that it is a valuable tool enabling mining companies to evaluate different reclamation strategies maximizing thus the long-term sustainability of the broader mining area.

The developed methodology can be easily extended with the incorporation of an economic objective function, by introducing the benefit per area unit for the alternative land uses in relation to the life cycle of the project. Finally a more sensitive scale to describe the characteristics (slope, soil fertility, etc.) of every square of the reclaimed mine land instead of the used three level scale (0 = low, 1 = medium, 2 = high) could increase the accuracy of the obtained results.

Acknowledgments

The authors wish to thank the Division of Mines of the Public Power Corporation of Greece (PPC) for providing the data about the reclamation of Amynteon Mine. The presented results reflect only the authors' view and the PPC is not liable for any use that may be made of the information contained therein.

References

[1] Pavloudakis F, Galetakis M, Roumpos C. A spatial decision support system for the optimal environmental reclamation of open-pit coal mines in Greece. Int J Min Reclam Environ 2009;23:291–303.

[2] Pavloudakis F, Roumpos C, Galetakis M. Public acceptance of surface mining projects and the determination of the marginal environmental cost. Int J Min Reclam Environ 2012;26:292–308.

[3] Bascetin A. A decision support system using analytical hierarchy process (AHP) for the optimal environmental reclamation of an open-pit mine. Environ Geol 2007;52:663–72.

[4] Bian Z, Inyang HI, Daniels JL, Frank O, Struthers S. Environmental issues from coal mining and their solutions. Min Sci Technol 2010;20(2):215–23.

[5] Ma J, Cai Q, Liu F, Chen S. Calculation of slope-cover height under price fluctuation in open-pit mines. Int J Min Sci Technol 2014;24:293–7.

[6] Frank O. Aspects of surface and environment protection in German mining areas. Min Sci Technol 2009;19:615–9.

[7] Guo L, Zhou L, Yang C, Fecko P. Fuzzy comprehensive evaluation of land reclamation suitability in mining subsidence based on GIS. In: Proceedings of IEEES'10: sixth international conference on natural computation (ICNC), Yantai, China; 2010.

[8] Narrei S, Osanloo M. Post-mining land-use methods optimum ranking, using multi attribute decision techniques with regard to sustainable resources management. OIDA Int J Sustain Dev 2011;2:65–76.

[9] Dimitrijevic B, Vujic S, Matic I, Majianac S, Praštalo J, Radosavljevic M, et al. Multi-criterion analysis of land reclamation methods at Klenovnik open pit mine, Kostolac coal basin. J Min Sci 2014;50(2):319–25.

[10] Uberman R, Ostrega A. Applying the analytic hierarchy process in the revitalization of post-mining areas field. In: ISAHP'05: eighth international symposium on the analytic hierarchy process (ISAHP), Honolulu, Hawai; 2005.

[11] Rahimdel MJ, Ataei M. Application of analytical hierarchy process to selection of primary crusher. Int J Min Sci Technol 2014;24(4):519–23.

[12] Soltanmohammadi H, Osanloo M, Bazzazi AA. An analytical approach with a reliable logic and a ranking policy for post-mining land-use determination. Land Use Policy 2010;27:364–72.

[13] Bangian AH, Ataei M, Sayadi A, Gholinejad A. The application of fuzzy MADM modeling to define optimum post mining land use for pit area to recognize reclamation costs in open pit mining. Arc Min Sci 2011;56:93–118.

[14] Derringer G. Simultaneous optimization of several response variables. J Qual Technol 1980;12:214–9.

[15] Galetakis M, Roumpos C. A Multi-objective response surface analysis for the determination of the optimal cut-off quality and minimum thickness for selective mining of multiple-layered lignite deposits. Energy Sources Recov Util Environ Eff 2015;37:428–39.

[16] Mitchell M. An introduction to genetic algorithms. USA: MIT Press Cambridge; 1996.

[17] Haidar A, Naoum S. Opencast mine equipment selection using genetic algorithms. Int J Surf Min Reclam 1996;10:61–7.

[18] Holland JH. Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control and artificial intelligence. USA: MIT Press Cambridge; 1992.

[19] Vayenas N, Yuriy G. GenRel—a computer model for prediction of mining equipment failures based on genetic algorithms (GAs). Int J Surf Min Reclam Environ 2005;19:3–11.

[20] Gämperle R, Müller SD, Koumoutsakos P. A parameter study for differential evolution. Adv Intel Syst Fuzzy Syst Evol Comp 2002;10:293–8.

[21] Zaharie D. Critical values for the control parameters of differential evolution algorithms. In: Proceedings of MENDEL, vol. 2; 2002. p. 6267.