Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

A New Technical and Economic Approach to Aptimal Plant Species Selection for Open-pit Mine Reclamation Process

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Article Info

Received 10 September 2022

Received in Revised form 27 December 2022

Accepted 30 December 2022

Published online 30 December 2022

DOI:10.22044/jme.2023.12267.2226

Keywords

Cost Estimation

Mine Reclamation

Statistical Analysis

Sungun Copper Mine

PROMETHEE Method

Abstract

Estimating the costs of mine reclamation is a significant part of mine closure projects. One approach to mine reclamation is planting mine areas. In this approach, the optimum selection of plant types is cosidered a multiple-criteria decision-making (MCDM) problem. Once proper plant species are identified, it is required to estminate planting costs through statistical analysis. This work aims to introduce an algorithm for optimal plant type selection and a reclamation cost estimation model for open-pit mines. To this end, the plant species compatible with the sorrounding areas of Sungun copper mine are identified and ranked using the PROMETHEE technique. In this analysis, the main criteria are local landscape, pest resistance, plant growth ability, availability, economic issues, soil protection, water storage ability, and pollution prevention. Among the six plant types, Maple trees have the highest score (4.34). After that, to develop the reclamation cost estimation model, the data (99 datasets) is collected from the Sungun copper mine, Sarcheshmeh copper mine, and Chadormaloo iron mine. The variables in the database include soil gradation by graders, slope trimming and topography by bulldozers, the ripping and softening of the compacted soil, chemical fertilizers, natural fertilizers and mulch and biosolid, lime soil pH adjustment, herbicide, seedling, tree planting, workers and drivers, and fuel and maintenance. Regression analysis is performed to analyze the data, and a reclamation cost estimation model is developed with high accuracy (R2 = 0.78). On the whole, this study proposes an innovative, step-by-step, technical, and economic approach to the optimal selection of plant species, and presents a reclamation cost estimation model so as to promote the open-pit mine reclamation process.

1. Introduction

Reclamation generally refers to the preparation of post-mining land use (PMLU). Today, mine reclamation is regarded as the most important stage of mining since it contributes to a sustainable development (SD) [1-2]. Mine closure occurs when the operational stage of a mine has permanently ceased due to economic, social, and environmental factors [3-10]. The primary objectives of reclamation are backfilling, regrading specified landforms, replacing topsoil, and establishing new vegetation covers in order to attain the land use goals of landowners. The regulatory authority issues mining permits based on the mining and reclamation plans to mitigate mining impacts on land and water [11]. The major reclamation criteria and performance standards are as follows: rebuilding approved Post-Mining Topography (PMT) and drainage systems, reconstructing stream channels, using soil application methods, establishing vegetation, restoring approved post-mining land use, and evaluating the quantity and quality of post-mining groundwater and surface water to support land use [12]. In order to improve mine reclamation and reach sustainable development goals in mines, it is essential to determine the available financial resources. Nonetheless, to identify these resources, it is required to estimate mine reclamation costs first

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[13-17]. In this regard, regression analysis is deemed to be a useful statistical technique since it provides satisfactory results with a fairly small dataset [18, 19]. Implementing reclamation from the initial stages of mining generally reduces the reclamation-related costs. The main reclamation costs consist of costs associated with transportation, project management, monitoring and control, contingency, and inflation [20]. An accurate estimation of reclamation costs is required to determine reclamation bond amounts. Predicting minimum and maximum reclamation costs is much simpler than calculating the exact costs [21]. The major purpose of estimating closure costs by the mining industry is to plan, provide the budget for, and carry out actual closure activities [22], and raise the reclamation financial guarantee. This financial guarantee is also called reclamation financial commitment, financial security, financial guarantor or closure bonds. Governments attempt to assure that mine operators can manage to close and restore their mine lands [23]. The goal of providing financial assurance is to make certain that sufficient funds are available for site reclamation and post-closure monitoring and maintenance at any stage of a project life [13].

Catlett and Boehlje in 1979 [24] developed a multivariate regression model to compute the reclamation costs of surface coal mines. The US OSMRE [25] introduced a handbook as a guide for calculating the amounts of reclamation bonds. In 2001, McHaina presented environmental design considerations for abandoning a mining project and closing and reclaiming mine sites [26]. In 2007, Carrick and Kruger evaluated the limiting factors to plant growth on mined soil [27]. In their study, Akbari et al. utilized the hierarchical analysis method to rank various possible types of post-mining land use in the Sungun copper mine [28]. Emilsson and Freshman in 2008 estimated the reclamation costs of large metal mines [1]. In 2010, Sheoran et al. investigated the reclamation of abandoned mines using vegetation covers [29]. Sullivan and Amacher in 2010 computed the social and personal costs of reforestation in open-pit mines [30]. In 2011, Alavi and Rokni selected the best plant species (i.e. Maple trees) for the reclamation of the Sungun copper mine using the fuzzy AHP and fuzzy TOPSIS methods [31]. Ebrahimabadi and Alavi, in 2013, identified Amygdalus scoparia as the most appropriate plant type for the reclamation of the Sarcheshemeh copper mine in the Kerman Province through the fuzzy TOPSIS method [32]. In 2013, in an attempt to compute the costs of mine reclamation, Brodie underscored the uncertainty of cost estimates [24]. Mhlongoa and Dacostaa in 2016 reviewed the general problems and legal issues of abandoned mines in South Africa and the proposed solutions for their reclamation, and then estimated their reclamation costs [33]. In 2016, Nehring and Cheng investigated the effects of mine closure and its related costs on the life of mine planning process and resource recovery [34]. In 2017, Palogos et al. conducted a study to identify the best PMLU for mine reclamation using an evolutionary algorithm [35] because mine reclamation, as a risk treatment option, requires the optimal choice of PMLU [9]. In 2017, Mavrommatis and Menegaki examined the reclamation of abandoned mines using the visual effects [36]. In 2017, Paricheh and Osanloo proposed a simulation-based estimate to determine the times and costs of open-pit mine closure [37]. In 2018, Amirshenava and Osanloo propounded a general procedure for mine closure risk management [8]. In 2018, Ebrahimabadi et al. used the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) and fuzzy TOPSIS methods to select the best plant type for the reclamation of the Sarcheshmeh copper mine, and compared the results obtained from these two methods. The results of both the PROMETHEE and fuzzy TOPSIS methods indicated that Amygdalus scoparia was the best choice [38]. In another study, Alavi and Alinejad also came to the same conclusion [31]. In 2018, Ebrahimabadi, Alavi et al. undertook a study on the selection of plant species for mine reclamation using the PROMETHEE and TOPSIS methods in the Choghart iron mine [39]. Kaźmierczak et al. [16] and Ignatyeva et al. [40] proposed an approach for the cost estimation of mine reclamation activities based on the unit cost method. Amirshenava et al., in 2021, introduced predictor models for the estimation of mine reclamation costs based on regression analysis [41]. In their study carried out in 2021, Halecki and Klatka demonstrated that an effective method of managing waste materials in post-mining areas and reclaiming the soil's quality was the use of sewage sludge [42]. As for application of regression models, Pujari and Majumdar, in 2022, examined the use of mobile banking applications among active users in the United Arab Emirates using the categorical regression model [43]. To enhance the utilization value of wetlands and protect them effectively, Yan et al., in 2022, scrutinized the comprehensive ecological management of coastal areas [44]. Tang et al., in 2022, used Regression modeling to analyze the laminar flow of Herschel-Barkley fluids in the concentric elliptical annulus [45]. Krzyszowska Waitkus, in 2022, investigated the sustainable reclamation practices for a large surface coal mine in the semiarid environment of the shortgrass prairie in Wyoming, USA [12]. As another example for regression models, Tomal et al., in 2022, proposed a likelihood-based Bayesian Poisson regression model. In this model, the likelihood contribution from observations is adjusted by its weight in order to model the number of Children Ever Born (CEB) to married women of reproductive age in Bangladesh [46].

Despite the importance of reclamation cost estimation, no model has been proposed to compute the reclamation costs of abandoned or active mines in Iran. Therefore, it is required to perform research on the reclamation of mines in Iran and determine the costs of reconstructing them by considering various influential parameters and financial guarantees. To bridge this gap, the present study aims to establish and evaluate a model and a technical and economic algorithm for predicting the costs of planting mine areas in Iran. This model has a good application potential for mine reclamation planning and management in Iran.

In this study, initially, the most appropriate plant species is detected through the PROMETHEE method. The costs related to the preparation, planting, and maintenance of the selected trees are then estimated for the Sungun copper mine in Iran in the form of a reclamation plan. Afterward, a comprehensive model is proposed to forecast the costs of reclamation and planting. The distribution and matching graphs of the costs predicted by the developed model and the actual costs are also provided.

2. Materials and methods

2.1. PROMETHEE

The structured method of preference ranking for enriching evaluations is part of MADM methods and as an efficient method, it seeks to choose the best option by using two words, preference and indifference. This method is used in various fields such as banking, industrial areas, workforce planning, water resources, investments, medicine, chemistry, medical care, operations research, and dynamic management [26]. This method is one of the popular methods due to its mathematical properties and ease of use. This method was presented by two Belgian professors named Jean-Pierre Burns and Bertrand Marschal in the 1980s. In fact, after this beginning, Prometheus was developed, and there were versions of it in different conditions, and they could be referred to as the Prometheus family. PROMETHEE is one of the multi-indicator decision-making methods for choosing the optimal option, which measures the superiority of the options by detecting the type of function. This method was presented by two Belgian professors named Japan Pierre Burns and Bertrand Marschal in the 1980s. PROMETHEE is the keyword of Preference Ranking Organization method for Enrichment Evaluations [30, 31]. In evaluating a number of options based on a number of criteria, the type of index, superiority function, indifference threshold, and superiority threshold should be determined. This method uses two types of information: superior information and inferior information based on which options are better and worse, i.e. the options are ranked once based on the degree of being better, and once based on the degree of being worse. The Prometheus method is one of the most complex multi-criteria decision-making methods, the results of which are highly accurate [32].

2.2. Regression

In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome' or 'response' variable or a 'label' in machine learning parlance) and one or more independent variables (often called 'predictors', 'covariates', 'explanatory variables' or 'features'). The most common form of regression analysis is linear regression, in which one finds the line (or a more complex linear combination) that most closely fits the data according to a specific mathematical criterion. For example, the method of ordinary least squares computes the unique line (or hyperplane) that minimizes the sum of squared differences between the true data and that line (or hyperplane). For specific mathematical reasons (see linear regression), this allows the researcher to estimate the conditional expectation (or population average value) of the dependent variable when the independent variables take on a given set of values. Less common forms of regression use slightly different procedures to estimate alternative location parameters (e.g. quantile regression or Necessary Condition Analysis) or estimate the conditional expectation across a broader collection of non-linear models (e.g. non-parametric regression .Regression analysis is primarily used for two conceptually distinct purposes. First, regression analysis is widely used for prediction and forecasting, where its use has substantial overlap with the field of machine learning. Secondly, in some situation's regression analysis can be used to infer causal relationships between the independent and dependent variables. Importantly, regressions by themselves only reveal relationships between a dependent variable and a collection of independent variables in a fixed dataset [17]. To use regressions for prediction or to infer causal relationships, respectively, a researcher must carefully justify why existing relationships have predictive power for a new context or why a relationship between two variables has a causal interpretation. The latter is especially important when the researchers hope to estimate causal relationships using observational data [18].

2.3. Case study

The Sungun copper mine has a copper-molybdenum deposit, and is the second largest producer of copper in Iran. The distances of this deposit from the cities of Tabriz and Varzghan are 130 km and 30 km, respectively. Figure 1 illustrates the location of the Sungun copper mine. This mine is placed in a mountainous area with a height of 2000 m above the sea level, ranging from 1700 to 2460 m. Apart from valuable metals, like copper, molybdenum, gold, and silver, it possesses other critical elements associated with these metals. The temperature of this area varies from -5.5 to 29.3 $^{\circ}$C [25]. In the proven, probable, and possible reserves in the areas of Sungun and Varzeghan deposits, approximately 1.7 billion tons of copper ore with a grade of 0.61% are found [47].

Figure 1. Location of Sungun copper mine in Iran.

3. Methodology Results

Mine reclamation is an efficient way to tackle the problems of pre-mature mine closure. To improve mine reclamation planning, the multiple-criteria decision-making (MCDM) method is usually employed [48-50]. The parameters (criteria) of these methods are as follows: local landscape, pest resistance, plant growth, availability, economic issues, soil protection, water storage capacity, and pollution prevention. Different approaches and techniques have been introduced to analyze these parameters through the MCDM methods. Previous studies have utilized MCDM approaches such as Fuzzy TOPSIS or Fuzzy AHP to determine the most suitable plant species for the Sungun copper mine. Since no study has used the PROMETHEE methods for the reclamation of this mine, this study adopted this method with preference functions to choose the best plant type for this mine. Moreover, the Fuzzy Analytic Hierarchy Process (F-AHP) method was employed to weigh the parameters. Also a hybrid approach using F-AHP and PROMETHEE has not yet been applied for the mine as well as such cases.

Selecting suitable plant species is one of the key stages in attaining the objectives of mine reclamation [47]. Mined lands can be planted with native plants to restore the ecosystems of mined areas and surrounding areas or with non-native plants to stabilize the soil effectively. The first step in planting a mine area is to remove the surface soil and transfer it to a suitable location. This biologically active and rich soil can be returned to the mined sites once mine operations end. After that, proper plant species are selected based on the major parameters of Post-Mining Land-Use (PMLU). These parameters include the economic, technical, environmental and panorama, social, and mine site factors that are in accordance with sustainable mining [8]. The compatibility of the selected plant types with the climate of the mining areas is then examined, and the inappropriate species are excluded. Soil characteristics, as another significant parameter, are also considered to omit improper options. In this study, based on these major factors (i.e. post-mining land use, climate conditions, and soil properties), six plant species are selected: Maple, Fraxinus excelsior, Paliurus spina-christi, Berberis vulgaris, Prunus divaricate ledeb, and Quercus macranthera.

3.1. Choosing plant types in Sungun copper mine through PROMETHEE method

To select the proper plant species for the Sungun copper mine, first, following previous studies, the weights of parameters were calculated via the F-AHP method [31]. To this end, the following steps (weights) were taken: (0.187, 0.166, 0.088, 0.138, 0.088, 0.166, 0.166).

Step 1: Creating an assessment table

Several experts (including mining, environmental, and natural resource engineers) qualitatively assessed the alternatives (six plant types) in terms of the selection criteria using the 5-point Likert scale. Then quantitative values were assigned to their qualitative evaluation, as presented in Table 1.

The criteria-alternatives evaluation matrix was generated based on the responses of experts to the 5-point Likert scale questionnaire [52]. This matrix is indicated in Table 2.

Table 1. Assigning numerical values to oral descriptions using 5-point Likert scale [51].

Oral descriptions	Numeral values
Extremely low	1
Low	2
Mediocre	3
Excellent	4
Extremely excellent	5

Table 2. Criteria-alternative evaluation matrix.

	Criteria						
Alternatives	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**
A	5	5	5	5	5	5	5
B	4	4	3	3	3	3	2
C	5	5	3	4	4	5	4
D	4	4	2	4	2	2	4
E	4	4	2	5	2	2	3
F	3	3	2	3	2	2	3

Note: C1-C7 denote selection criteria, A-F are plant types.

Step 2: Calculating preference functions

The preference function (PF) compares the quantitative values of two alternatives concerning each criterion and generates a preference grade, ranging from 0 to 1, for each pair of alternatives [53, 54].

$$\begin{aligned} & Pj\ (a,b) = Fj\ [dj(a,b)] \\ & a,b \in A \\ & dj\ (a,b) = fj(a) - fj(b) \\ & 0 <= Pj\ (a,b) <= 1 \end{aligned} \tag{1}$$

Pj is the value obtained from the paired comparison of two alternatives. Since all the criteria in this study were affirmative, the Pj values close or equal to one were scored 1, and the values close or equal to zero were scored 0 [55]. Table 3 reports the paired comparisons of alternatives.

Table 3. Matrix of paired comparisons of alternatives.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
A-B	1	1	1	1	1	1	1
B-A	0	0	0	0	0	0	0
A-C	0	0	1	1	1	0	1
C-A	0	0	0	0	0	0	0
A-D	1	1	1	1	1	1	1
D-A	0	0	0	0	0	0	0
A-E	1	1	1	0	1	1	1
E-A	0	0	0	0	0	0	0
A-F	1	1	1	1	1	1	1
F-A	0	0	0	0	0	0	0
B-C	0	0	0	0	0	0	0
C-B	1	1	0	1	1	1	1
B-D	0	0	1	0	1	1	0
D-B	0	0	0	1	0	0	1
B-E	0	0	1	0	1	1	0
E-B	0	0	0	1	0	0	1
B-F	1	1	1	0	1	0	0
F-B	0	0	0	0	0	0	1
C-D	1	1	1	0	1	1	0
D-C	0	0	0	0	0	0	0
C-E	1	1	1	0	1	1	1
E-C	0	0	0	1	0	0	0
C-F	1	1	1	1	1	1	1
F-C	0	0	0	0	0	0	0
D-E	0	0	0	0	0	0	1
E-D	0	0	0	1	0	0	0
D-F	1	1	0	1	0	0	1
F-D	0	0	0	0	0	1	0
E-F	1	1	0	1	0	0	0
F-E	0	0	0	0	0	1	0

Step 3: Calculating total preference function

To compute the total preference function [54], the following cumulative preference index was used:

$$\pi\ (a\ ,b) = \sum_{k=1}^{k} p_j(a\ ,b) w_j \tag{2}$$

The results of the total preference functions for each pair of alternatives are provided in Table 4.

Step 4: Computing affirmative and non-positive currents for every alternative

To compute the affirmative outranking currents, the following equation was used [56]:

$$\phi^+(a) = \frac{1}{n-1} \sum_{x \in A}^{\infty} \pi(a\ ,x) \tag{3}$$

The higher the value of $\Phi^+(a)$, the better the alternative is [57]. The non-affirmative outranking currents were obtained as follows [56]:

$$\phi^-(a) = \frac{1}{n-1} \sum_{x \in A}^{\infty} \pi(x\ ,a) \tag{4}$$

The lower the value of $\Phi^-(a)$, the better the alternative is [57].

The alternative-preference matrix achieved from these equations is demonstrated in Table 5. This matrix provides partial ranking as it separately examines the two currents of $\Phi^{+}(a)$ and $\Phi^{-}(a)$ (partial ranking or ranking 1) [57]. The PROMETHEE I method has some drawbacks, as illustrated in Figure 2. For instance, because the D affirmative current is lower than B, D seems to be more desirable. However, the D non-positive current is lower than B, which indicates the superiority of B over D. Thus this method cannot clearly specify which alternative is more favorable.

Table 4. Matrix of total preference functions of alternatives associated with specified criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	Total preference index
A-B	0.187	0.166	0.088	0.138	0.088	0.166	0.166	0.999
B-A	0	0	0	0	0	0	0	0
A-C	0	0	0.088	0.138	0.088	0	0.166	0.48
C-A	0	0	0	0	0	0	0	0
A-D	0.187	0.166	0.088	0.138	0.088	0.166	0.166	0.999
D-A	0	0	0	0	0	0	0	0
A-E	0.187	0.166	0.088	0	0.088	0.166	0.166	0.861
E-A	0	0	0	0	0	0	0	0
A-F	0.187	0.166	0.088	0.138	0.088	0.166	0.166	0.999
F-A	0	0	0	0	0	0	0	0
B-C	0	0	0	0	0	0	0	0
C-B	0.187	0.166	0	0.138	0.088	0.166	0.166	0.911
B-D	0	0	0.088	0	0.088	0.166	0	0.342
D-B	0	0	0	0.138	0	0	0.166	0.304
B-E	0	0	0.088	0	0.088	0.166	0	0.342
E-B	0	0	0	0.138	0	0	0.166	0.304
B-F	0.187	0.166	0.088	0	0.088	0	0	0.529
F-B	0	0	0	0	0	0	0.166	0.166
C-D	0.187	0.166	0.088	0	0.088	0.166	0	0.695
D-C	0	0	0	0	0	0	0	0
C-E	0.187	0.166	0.088	0	0.088	0.166	0.166	0.861
E-C	0	0	0	0.138	0	0	0	0.138
C-F	0.187	0.166	0.088	0.138	0.088	0.166	0.166	0.999
F-C	0	0	0	0	0	0	0	0
D-E	0	0	0	0	0	0	0.166	0.166
E-D	0	0	0	0.138	0	0	0	0.138
D-F	0.187	0.166	0	0.138	0	0	0.166	0.657
F-D	0	0	0	0	0	0.166	0	0.166
E-F	0.187	0.166	0	0.138	0	0	0	0.491
F-E	0	0	0	0	0	0.166	0	0.166

Table 5. Alternative-preference matrix.

	A	B	C	D	E	F	output flow Φ +
A	0	0.999	0.48	0.999	0.861	0.999	4.338
B	0	0	0	0.342	0.342	0.529	1.213
C	0	0.911	0	0.695	0.861	0.999	3.466
D	0	0.304	0	0	0.166	0.657	1.127
E	0	0.304	0.138	0.138	0	0.491	1.071
F	0	0.166	0	0.166	0.166	0	0.498
input flow Φ -	0	2.684	0.618	2.34	2.396	3.675	**output flow Φ +**

1	A	3	D	5	B
Q+	4.338	Q+	1.127	Q+	1.213
Q-	0	Q-	2.34	Q-	2.684
2	C	4	E	6	F
Q+	3.466	Q+	1.071	Q+	0.498
Q-	0.618	Q-	2.396	Q-	3.675

Figure 2. Partial ranking of PROMETHEE I method.

Step 5: Calculating net flow

To complete the alternative rating process, the net currents were computed for each alternative using the following equation [56]:

$$\phi(a) = \phi^{+}(a) - \phi^{-}(a) \quad (5)$$

After the net currents ((Φ^{+})-(Φ)) were computed for the alternatives, they were ranked (overall ranking or ranking 2) (Table 6 and Figure 3). The alternative with the highest value of the net current was considered the best option [57, 58].

Table 6. PROMETHEE II method currents and overall rating.

Alternative	Φ +	Φ -	(Φ +)-(Φ -)	Rank
A	4.338	0	4.34	1
B	1.213	2.684	-1.47	5
C	3.466	0.618	2.85	2
D	1.127	2.34	-1.21	3
E	1.071	2.396	-1.33	4
F	0.498	3.675	-3.18	6

1	A	3	D	5	B
Q	4.34	Q	-1.21	Q	-1.47
2	C	4	E	6	F
Q	2.85	Q	-1.33	Q	-3.18

Figure 3. Overall ranking of PROMETHEE II method.

As indicated in Table 6 and Figure 3, alternative A (Maple trees) was the best choice for promoting the reclamation of the Sungun copper mine. Figure 4 depicts planting these trees in the surrounding areas of this mine.

The next step was to establish a cost estimation model for predicting the costs of planting these trees around the Sungun mine. In doing so, the costs of land preparation, planting processes, and plant maintenance were estimated by agricultural, environmental, and mining experts for 670 hectares of the Sungun copper mine, 2000 hectares of the Sarcheshmeh copper mine, and 86 hectares of the Chadormaloo iron mine. Eleven cost factors were included as follows: costs associated with soil gradation by graders (S.G), slope trimming and topography by bulldozers (S.T & T), the ripping and softening of the compacted soil (R&S), chemical fertilizers (Ch.F), natural fertilizers, mulches, and biosolids (N.F & M & B), lime for soil pH adjustment (L), herbicides (H), seedling (S), tree planting (T.P), workers and drivers (W&D), and fuel and maintenance (F & M). Ninety-nine datasets with rich information on these cost factors were collected (Table 7).

Figure 4. Planting Maple trees in Sungun copper as part of mine reclamation planning.

Table 7. Data obtained for cost factors.

	S.G	S.T & T	R & S	CH.F	N.F & M &B	L	H	S	T.P	W&D	F & M	Total cost
Mean	63.32	142.55	107.16	23.38	26.09	148.87	24.75	125.81	294.0	43.83	420.00	1419.93
N	99	99	99	99	99	99	99	99	99	99	99	99
Std. Deviation	3.219	1.716	5.799	1.978	3.698	1.946	3.268	8.848	3.081	3.159	15.403	33.686
Min	60	140	100	20	20	145	20	120	290	40	400	1363
Max	70	145	115	26	30	151	30	145	300	50	450	1468
Variance	10.364	2.944	33.627	3.912	13.675	3.789	10.680	78.279	9.490	9.980	237.245	1134.740
Std. error of mean	0.324	0.172	0.583	0.199	0.372	0.196	0.328	0.889	0.310	0.318	1.548	3.386

To develop a predictive model for reclamation cost estimation, the collected data was analyzed via linear regression, as an experimental and simple statistical method, using the SPSS and MATLAB software. In the regression analysis, the relationships between a dependent variable and one or more independent (explanatory) variables are determined. A regression model reveals whether changes observed in the dependent variable are associated with changes in one or more of the explanatory variables [59, 60]. The results of the regression analysis are reported in Tables 8 and 9.

Table 8. Results of linear regression analysis for reclamation cost estimation model.

Model	R	R Square	Adjusted R Square	Std. Error of the estimate
1	0.888[a]	0.78	0.76	16.41
a. Predictors: (constant)				

Table 9. Regression coefficients of predictive linear regression model.

Model	Unstandardized coefficients		Standardized coefficients	t	sig
	B	Std. Error	Beta		
(constant)	693.713	48.573		14.282	0
S.G	6.556	0.604	0.627	10.855	0
S.T & T	0.058	0.074	0.040	0.784	0.435
R & S	0.303	0.127	0.133	2.382	0.19
Ch.F	0.174	0.132	0.066	1.315	0.192
N.F & M & B	0.337	0.203	0.094	1.662	0.01
L	-.035	0.253	-0.008	-0.138	0.891
H	0.197	0.205	0.055	0.959	0.340
S	1.894	0.219	0.516	8.636	0
T.P	0.039	0.044	0.049	0.900	0.371
W & D	0.248	0.164	0.088	1.510	0.135
F & M	-0.004	0.041	-0.005	-0.089	0.929

As Table 8 demonstrates, the coefficient correlation (R) is 0.888, which is a high degree of correlation. The coefficient of determination (R^2) is 0.789, which is very large. This R^2 value indicates that all the cost factors account for 78.9% of variations in reclamation costs. Table 9 reports the regression coefficients of the cost factors and provides information on cost prediction modeling. This table shows whether each cost factor contributes statistically significantly to the model or not. It should be noted that due to sig (= p-value), the parameters lower than 0.05 (G.S., N.F & M & B, and S) are significant in regression. Thus there is no need to input all parameters. Based on the results, the predictive model for reclamation cost estimation is obtained via Equation (6):

$$Total\ cost = \left(693.713 + 6.556(\mathrm{S.G}) + 0.337(\mathrm{N.F\&M\&B}) + 1.894(\mathrm{S})\right) \tag{6}$$

This model can be used to predict the reclamation costs of various mines in Iran. The costs of the main cost-bearing factors in mine reclamation were estimated for different mines by the experts. The minimum and maximum costs in terms of million rials per hectare are given in Table 7. Moreover, the distribution and matching graphs of the actual (or target) costs versus the predicted costs (obtained from the predictive model) are depicted in Figures 5 and 6, respectively.

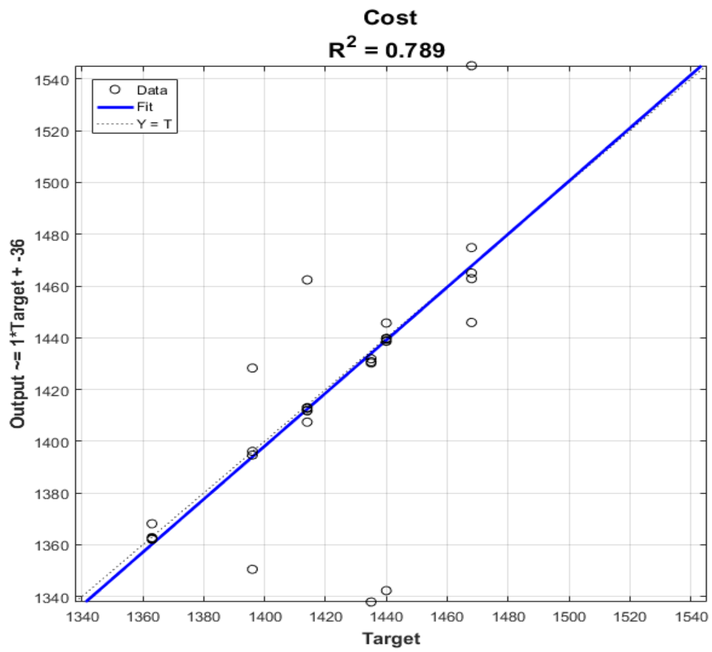

Figure 5. Distribution graph of actual and predicted costs.

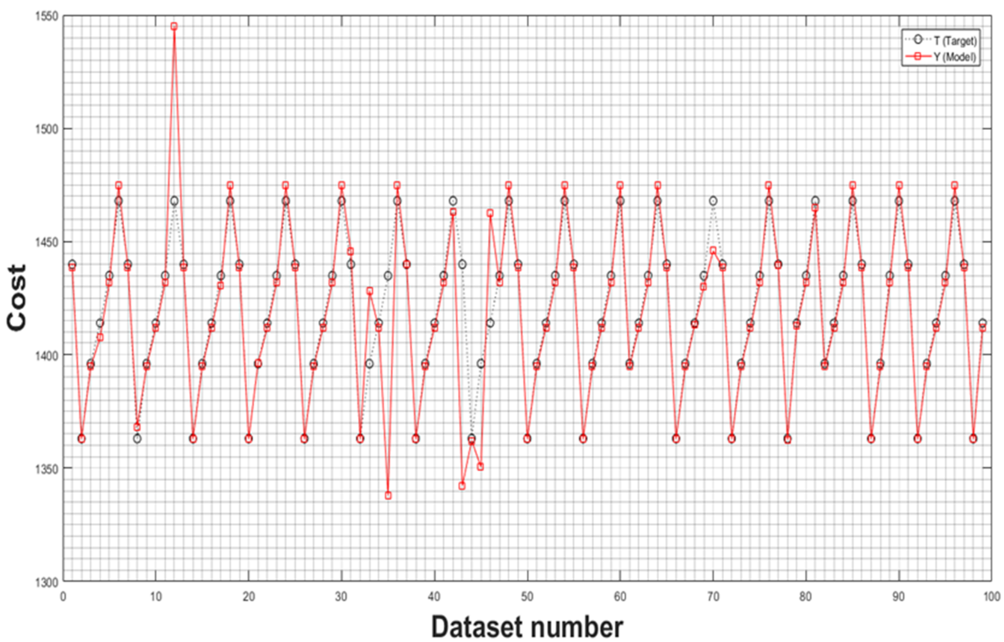

Figure 6. Matching graph of actual and predicted costs.

On the whole, in this study, to develop a cost estimation model, the PROMETHEE I and II methods were utilized since they were effective techniques for evaluating alternatives in terms of pre-specified criteria and treating multicriteria problems in the MCDM method. In the PROMETHEE methods, many types of preference functions are used to assign the difference between alternatives and select the superior option. As for statistical analysis, the regression model was run to determine how much variations in costs were explained by the cost variables and develop the cost estimation model. The flowchart of the technical and economic evaluation process of optimal plant selection for open-pit mine reclamation is presented in Figure 7.

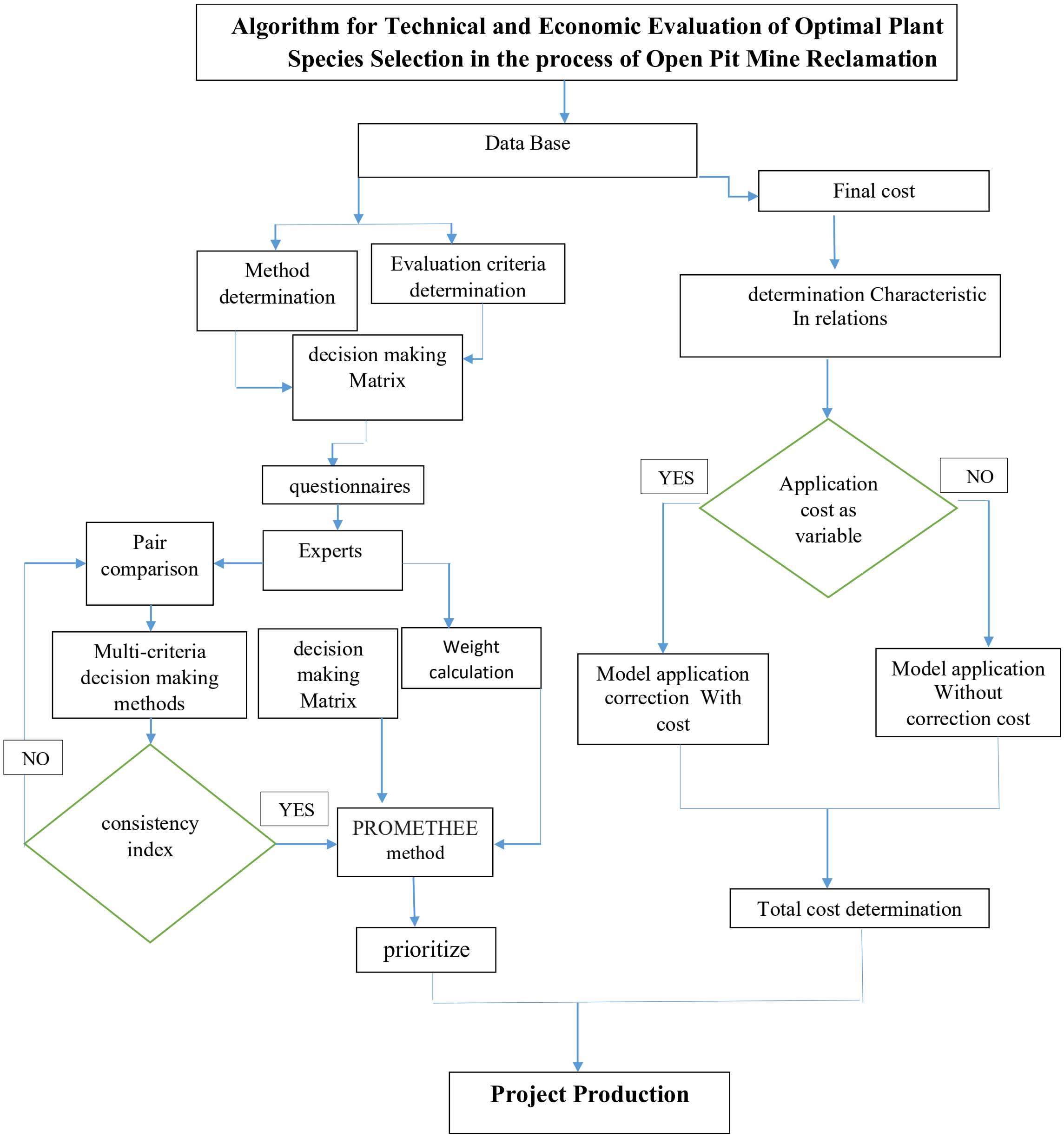

Figure 7. Flowchart of technical and economic approach to optimal plant species selection in open-pit mine reclamation process.

4. Conclusions

The purpose of this work was to promote the reclamation of the Sungun copper mine by choosing proper plant types through the multiple-criteria decision-making method. Mine reclamation planning is one of the most vital parts of mining plans. One way to enhance mine reclamation is to select and plant suitable plant species. The results of this work demonstrate that the multi-criteria decision-making methods, especially the PROMETHEE I and II methods, are efficient approaches to appropriate plant species selection in mine reclamation planning.

In the previous studies, to weight the criteria, coefficients have been normalized into a range between 1 and 9. However, in this work, the weights of the criteria were obtained through the F-AHP method, which is a more robust and accurate technique. Furthermore, the PROMETHEE I and II methods were used to rank the options. In the soil of the Sungun copper mine, the levels of potassium, phosphorus, and micronutrients are quite low; consequently, the soil requires fertilization. Because of being native plants and adapting well to the environment, all six plant species (Maple, Fraxinus excelsior, Berberis vulgaris, Paliurus spina-christi, Quercus macranthera, Prunus divaricate ledeb) are proven to be suitable when fully planted in the mining areas. Based on the results of the PROMETHEE methods, no considerable difference was found between their net currents: Maple (4.34), Fraxinus excelsior (2.85), Berberis vulgaris (-1.21), Paliurus spina-christi (-1.33), Quercus macranthera (-1.47), and Prunus divaricate ledeb (-3.18). As the results suggest, planting Maple trees is the top priority.

Estimating mine reclamation costs and considering them in mine planning and design are prerequisites for the successful implementation of mine reclamation projects and sustainable mining. In this work, to determine reclamation costs in mines, the data was collected from three big mines. The costs of all the planting stages, from soil preparation to plant cultivation, were recorded and statistically analyzed by linear regression. Based on the results, the total planting cost formula (the cost model) was established. The goodness of fit of this model was then assessed via the R^2 coefficient as a good measure to explain the capability of the model. R^2 values greater than 0.5 are at an acceptable level, and values greater than 0.75 show large predictive accuracy. The R^2 value obtained for the developed model was high (0.789), indicating that the proposed cost model accurately estimates mine reclamation costs. This cost model is not developed for specific plant species and can be utilized to determine costs at all stages of reclamation and planting in different mines.

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ارائه یک رویکرد جدید فنی و اقتصادی برای انتخاب بهینه گونه‌های گیاهی در فرآیند بازسازی معادن روباز

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ارسال ۲۰۲۲/۰۹/۱۰، پذیرش ۲۰۲۳/۱۲/۳۰

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چکیده:

تخمین هزینه‌های بازسازی معدن، بخشی حیاتی از پروژه بستن معدن می‌باشد. یکی از روش‌های بازسازی معدن، گیاه‌کاری نواحی تحت تاثیر معدن‌کاری است. با این رویکرد، انتخاب بهینه گونه‌های گیاهی به منظور بازسازی معدن با روش‌های تصمیم‌گیری چندمعیاره انجام شد. در این راستا، ابتدا گونه‌های گیاهی مناسب، مشخص شده و سپس تخمین هزینه‌های کاشت گیاه از طریق تحلیل آماری انجام پذیرفت. هدف از این تحقیق، معرفی الگوریتمی برای انتخاب گونه‌های گیاهی و ارائه مدلی برای تخمین هزینه بازسازی در معادن روباز می‌باشد. بدین منظور و در مطالعه موردی در معدن مس سونگون، گونه‌های گیاهی سازگار با مناطق معدن مس سونگون مشخص شده و با استفاده از روش پرامیتی اولویت‌بندی شدند. در این تحلیل، معیارهای اصلی شامل چشم‌انداز منطقه، مقاومت در برابر بیماری و حشرات، نحوه و قدرت رشد گیاه، دسترسی به گونه گیاهی، بازدهی اقتصادی، حفاظت از خاک و ذخیره آب و جلوگیری از آلودگی‌ها بوده است. از میان شش گونه گیاهی، درخت افرا بالاترین امتیاز(۴,۳۴) را بدست آورد. بعد از آن، برای توسعه مدل تخمین هزینه بازسازی، تعداد ۹۹ داده از معادن مس سونگون، مس سرچشمه و معدن سنگ آهن چادرملو جمع آوری شدند. متغیرها در این داده‌ها شامل هزینه‌های درجه‌بندی و تسطیح خاک توسط گریدر، اصلاح شیب و توپوگرافی توسط بولدزر، ریپر زدن و نرم کردن خاک متراکم شده، کود شیمیایی، کود طبیعی، آهک برای تعدیل خاک، علف‌کش، بذرکاری، نهال‌کاری، کارگر و راننده، سوخت و تعمیر و نگهداری بود. تحلیل رگرسیونی و آنالیز داده‌ها انجام شد و نهایتا مدلی برای تخمین هزینه بازسازی معادن روباز با ضریب تعیین ۰,۷۸ توسعه داده شد. به طور کلی در این مطالعه، یک رویکرد نوآورانه و گام به گام در ارزیابی فنی و اقتصادی انتخاب بهینه گونه‌های گیاهی پیشنهاد و مدلی برای تخمین هزینه بازسازی برای ارتقاء بهره وری و اثربخشی در فرآیند بازسازی معادن روباز ارائه شد.

کلمات کلیدی: تخمین هزینه، بازسازی معدن، تحلیل آماری، ناحیه معدن مس سونگون، روش پرامیتی.