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An Efficient and Simple Multiple Criteria Model for a Grinding Circuit Selection Based on MOORA Method

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Abstract. The comminution process, particularly grinding, is very important in the mineral processing industry. Some characteristics of ore particles, which occur as a product of grinding process, have a significant impact on the effects of further ore processing. At the same time, this process requires a significant amount of energy which significantly affects the overall processing costs. Therefore, in this paper, we propose new multiple criteria decision making model, based on the Ratio system part of the MOORA method, which should enable an efficient selection of the adequate comminution circuit design.

Key words: MCDM, interval grey number, grinding circuit selection, mineral processing, flotation, grinding, MOORA, ratio system.

1. Introduction

Metallic ores mined in the 21st century generally have a low content of valuable minerals. For example, a typical copper ores that are now mined usually contain less than 0.5% Cu from surface mining and 2% from underground mining (Davenport *et al.*, 2002).

The low content of valuable minerals in ores does not provide any economic justification for direct ore smelting. Valuable minerals in mined ores are inter-grown with gangue materials. Therefore, ores are crushed and ground into fine particles to allow liberation of commercially valuable minerals. Crushing and grinding are very important operations in the process of separating commercially valuable minerals from ores. These operations are also very expensive due to costs of comminution equipments, used energy and maintenance.

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The grinding process determines the proper choice of valuable materials separation, and it can be considered as trade-off between the ore recovery and plant throughput. Ore over-grinding limits the throughput and can produce a significant amount of very fine particles, so fine, that they do not allow the adequate liberation of valuable minerals. Over-grinding also causes higher energy consumption and higher running costs. Ore under-grinding produces a significant amount of too-large ore particles, which have a negative effect on the utilization of valuable minerals. Therefore, the largest particles are separated and send to secondary grinding. The separation of such particles also requires additional equipment, or even additional grinding circuits. Therefore, adequate crushing and grinding, i.e. obtaining a proper size range of ground ore particles with minimal costs, is the key for a successful mineral processing.

In the meantime, many types of grinding mills and related equipment are designed. As a result, many grinding circuit (GC) designs also are formed. These GC designs have their own characteristics and specificities. Therefore, in selection process their characteristics and specificities should be take into account, as well as the importance that their characteristics and specificities have.

Multiple criteria decision making (MCDM) provides the opportunity for selecting the most acceptable alternative based on conditions that are stated using the criteria. MCDM is a very popular and commonly used approach for selecting the most acceptable alternative among the sets of available alternatives. This approach has been used to solve various problems in many fields, which has also been published in numerous professional and scientific journals. Some of them cover the supplier selection (Chen *et al.*, 2006), a new product launch strategy evaluation (Chiu *et al.*, 2006), the training aircraft evaluation (Wang and Chang, 2007), the banking performances evaluation (Wu *et al.*, 2009), the pant layout selection (Yang and Hung, 2007), and so on.

A number of methods have been proposed in the field of MCDM, such as TOPSIS (Hwang and Yoon, 1981), AHP (Saaty, 1980), ELECTRE (Roy, 1991), VIKOR (Opricovic, 1998), COPRAS (Zavadskas *et al.*, 1994) and ARAS (Zavadskas and Turskis, 2010).

A comprehensive review of MCDM methods and their application in the field of economics is given in Zavadskas and Turskis (2011).

The Multi-Objective Optimization by Ratio Analysis (MOORA) method was introduced by Brauers and Zavadskas (2006). Later, Brauers and Zavadskas (2010) further developed this method under the name MULTIMOORA (MOORA plus the full multiplicative form). These methods have been applied in numerous studies (Brauers and Zavadskas, 2012, 2011a, 2011b, 2010, 2008; Brauers and Ginevicius, 2009, 2010; Brauers *et al.*, 2010; Balezentis and Balezentis, 2011b, 2011c, 2011d; Baležentis *et al.*, 2011a; Balezentis, 2011; Chakraborty, 2010; Kracka *et al.*, 2010) for solving a wide range of different problems in the field of economy, management, construction, regional development, sustainability, estimation of farming efficiency, personnel selection, and so on.

In order to obtain applicability for solving complex real-world decision making problems Balezentis and Balezentis (2011a) and Balezentis *et al.* (2012a, 2012b) extended MULTIMOORA method for fuzzy linguistic reasoning and group decision making.

Also, to use MOORA method under uncertainty Stanujkic *et al.* (2012a, 2012b) proposed a Grey extension of MOORA method.

The MOORA method, as well as its extension MULTIMOORA method, can be mentioned as the prominent and often used MCDM methods. This is proven by a number of newly published papers, which consider solving of many currently actual problems in various areas. From them, as the most significant can be listed the following: Karande and Chakraborty (2012) used MOORA method for material selection; Brauers *et al.* (2012a) also considered the problem of material selection. However, they focused on the selection of elements for building renovation important for energy saving in buildings; Brauers and Zavadskas (2012) use the MOORA and MULTIMOORA as the basis for the formation of multi-objective decision support system. This multi-objective decision support system is intended for the selection of projects, and it is tested on the Tunisian textile industry; Balezentis *et al.* (2012b) used MULTIMOORA to solve personnel selection problem; Baležentis *et al.* (2011b) and Brauers *et al.* (2012b) used MULTIMOORA method to evaluate the implementation of the EU strategies; Streimikiene *et al.* (2012) used MULTIMOORA method to develop the multi-criteria decision support framework for choosing the most sustainable electricity production technologies.

Proper machine selection is a well-known and still actual problem which is often solved by using MCDM method. Only a few papers from many written are mentioned here, such as: Ayag and Ozdemir (2011) proposed an intelligent approach to machine tool selection problem through based on fuzzy ANP process; Lashgari *et al.* (2011) used TOPSIS methods under fuzzy environment in order to select a proper shaft sinking method; Yazdani-Chamzini and Yakhchali (2012) used fuzzy AHP and fuzzy TOPSIS for Tunnel Boring Machine selection. Samvedi *et al.* (2012) used fuzzy AHP and grey relational analysis approaches for the selection of a machine tool from a given set of alternatives.

Due to the above, the use of MCDM approach for the GC design selection is proposed, based on Ratio system part of the MOORA method. To verify the proposed approach, this paper discusses the major characteristics of the grinding process and then proposes a simple and effective MCDM for the most appropriate GC design selection.

Therefore, the rest of this paper is organized as follows. In Section 2, some basic GC designs, as well as their significant characteristics are considered. In Section 3, some basic elements of MCDM are considered. In this section, a simple MCDM model is proposed, which allows a simple and effective selection of appropriate GC design. In Section 4, a numerical example is considered in order to perform the verification of the proposed model and highlight its efficiency and simplicity. Finally, Section 5 presents conclusions.

2. Typical Grinding Circuit Designs

After excavation, the size of run of-mine ores can vary a lot, starting from fine powders to big rocks. Therefore, the first stage in the ore processing is crushing, and it is usually performed in two or three stages.

Fine ore particles, necessary for efficient extraction of valuable minerals from the ore, are obtained by grinding. Similar to crushing, grinding is done in several stages, usually

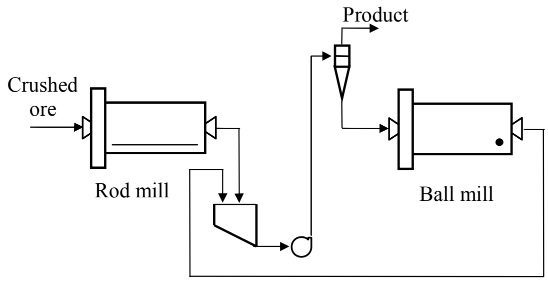

Fig. 1. Schematic overview of a typical two-stage grinding process, based on the use of rod and ball mills.

through the primary and secondary grinding. Therefore, for these has been also developed various equipment such as rod mills, ball mills and autogenous (AG) mills.

These mills, among many others, differ in the media used for ore grinding. However, one type of mills stands out as a specific one, and these are AG mills. Unlike the rod and ball mills, these mills do not require the use of grinding media because they use larger particles of ore for grinding.

As a result, these mills also have some advantages, as they can be also used for crushing and for grinding. However, the application of these mills has certain limitations, which are primarily associated with some characteristics of ground ore. The area of the use of these mills may be extended, and their characteristics improved by adding small amounts of grinding media, i.e. grinding balls. This subtype of AG mills is often considered as a separate type of mills, i.e. semi-autogenous (SAG) mills.

Due to the variety of equipment that can be used for crushing and grinding, a few GC designs were formed. In the following short analysis, three general GC designs are highlighted.

The first typical grinding circuit design. As first, or typical, we highlight the GC design in which:

(i) ore crushing is done in three phases, as primary, secondary and tertiary; and
(ii) ore grinding is done in two phases; whereby, the primary grinding is done by using the rod mills, while the secondary grinding is done by using ball mills.

The rod mills usually require less speed versus the similar ball mills, which has a positive effect on energy consumption. A smaller number of rpm is achieved through the use of grinding rods. Furthermore, due to use of rods, a possibility of over-grinding is also reduced. The larger ore particles, formed during primary grinding, are separated using some type of classifiers, usually with hydro-cyclones, and sent to secondary grinding. In this comminution circuit design, secondary grinding is carried out using ball mills because they allow a more efficient grinding of small ore particles. This GC design provides a high technological efficiency. However, a large amount of equipment, required in these comminution circuits, is associated with a significantly large investment and maintenance costs.

Second typical grinding circuit design. Contrary to what was previously said, this GC design uses one stage grinding process, where the grinding is done by using a ball mill.

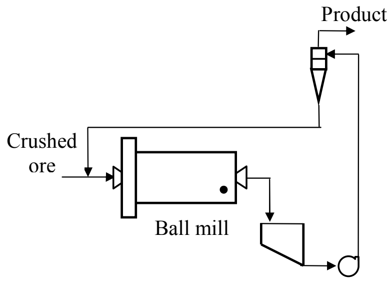

Fig. 2. Schematic overview of one-stage grinding process, based on the use of ball mills.

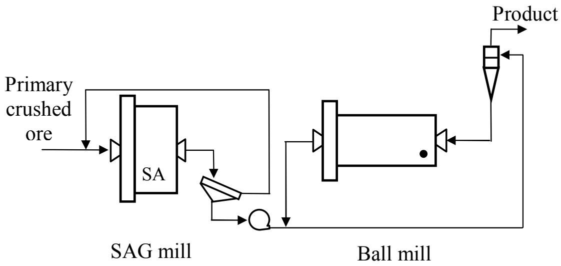

Fig. 3. Schematic overview of a two-stage grinding process, based on the use of SAG and ball mills.

Third typical grinding circuit design. The third GC design has been more specific. Its most important feature is the use of SAG mills, and rarer AG mills.

Because of its characteristics and specificities, these mills are also used for crushing (secondary and tertiary) and grinding (primary). As for grinding part, this comminution circuit design has been similar to the first GC design.

2.1. *Basic Criteria for Grinding Circuit Design Selection*

Evaluation criteria have great significance in MCDM models. Keeney and Raiffa (1976) state that selected evaluation criteria should satisfy the following five principles: completeness, decomposability, non-redundancy, operational feasibility, and minimum size. Then, Pomerol and Barba-Romero (2000) emphasize the importance of two principles: completeness, i.e. all criteria necessary for particular decision making problems have been identified, and non-redundancy, i.e. if one of the evaluation criteria is removed from the list, the rest of the set no longer satisfy the requirements of completeness.

To create an efficient and also simple to use the MCDM model for GC design selection, the following criteria are proposed to be met: completeness, non-redundancy and minimum size. Therefore, based on ideas of Daniel *et al.* (2010), Putland (2006), Magdalinovic *et al.* (2011) and Stanujkic *et al.* (2011), the use of the following evaluation criteria is proposed: grinding efficiency, economic efficiency, capital investment costs and environmental impact.

Grinding efficiency. The comminution process is carried out in order to obtain ore particles which enable efficient recovery of commercially valuable minerals. In addition, it is necessary to do this with lower costs.

Economic efficiency. From economic point of view, the main goals are minimization of operating and maintenance costs. The capital investment costs, which can be subsumed under the economic efficiency, is considered as a separate criterion.

Capital investment costs. Grinding require a significant amount of heavy equipment and corresponding installations. As a result, building of GC is strongly associated with high investment costs. By applying this criterion the GC design, which requires lower investment cost, is more acceptable.

Environmental impact. Ore grinding requires spending a significant amount of energy, which is partly obtained by consuming fossil fuels. Production of grinding media also requires the expenditure of energy and natural resources, such as iron ore.

It would be fine if the energy consumption for grinding could be reduced significantly, however particle size distribution of ground ore has a significant impact on the utilization of valuable minerals.

A very small ore reserves, the mainly with low content of commercially valuable minerals, do not allow their unsustainable exploitation. Therefore, by using the criterion named Environmental impact, decision makers can express their attitudes about the ratio between the benefits and consequences that arise as a result of excavation and processing of ores. Besides, the GC design, which provides a better separation of valuable minerals with fewer negative impacts on the environment, has a higher rating.

3. Multiple Criteria Decision Making Model for Grinding Circuit Design Selection

The multiple criteria decision making can be defined as the process of selecting one from a set of possible alternatives. In addition, the selected alternative should, as much as possible, meet decision maker requirements or preferences, which are expressed by using evaluation criteria. A MCDM can be simply represented as follows:

$$D = [x_{ij}]_{m \times n}, \tag{1}$$

where D is a decision matrix; x_{ij} is the performance rating of i-th alternative to the j-th criterion; $i = 1, 2, \dots, m$; m is a number of alternatives; $j = 1, 2, \dots, n$; n is a number of criteria.

In the MCDM, evaluation criteria usually have a different importance. To express their importance, the MCDM models also include criteria weights, as shown:

$$W = [w_j], \tag{2}$$

where W is a weight vector; w_j is the weight of j-th criterion; $j = 1, 2, \dots, n$; n is a number of criteria.

The relative criteria weights and performance ratings are very important in MCDM models. To ensure its more realistic determination, a multiple criteria group decision making (MCGDM) approach is often used. In this approach, more decision makers and/or more experts have the ability to express their attitudes about the weights of criteria and performance ratings of alternatives with respect to the criteria. A MCGDM can be represented as follows:

$$D^k = [x_{ij}^k]_{m\times n}, \tag{3}$$

where D^k is a group decision making matrix; x_{ij}^k is the performance rating of i-th alternative to the j-th criterion given by k-th decision maker; $i = 1, 2, \ldots, m$; m is a number of alternatives; $j = 1, 2, \ldots, n$; n is a number of criteria; $k = 1, 2, \ldots, K$; K is number of decision makers and/or experts involved in group multiple criteria decision making.

Problem solving, or a more precisely, selection of the most acceptable alternative by using MCDM methods contains a number of steps, from which the following are highlighted:

(i) Determine usable alternatives and select the relevant evaluation criteria;
(ii) Determine the weight of each criterion;
(iii) Determine performance ratings of each alternative to the criteria;
(iv) Transform performance ratings to dimensionless values;
(v) Perform aggregation procedure; and
(vi) Choose the most acceptable alternative.

In the previous section of this paper, some characteristic alternatives, i.e. GC designs, and criteria relevant for their evaluation have already been identified. Because of that, further continue the review of the remaining steps of an MCDM procedure.

3.1. *Determination of Criteria Weights*

In MCDM, several methods are often used to determine the relative criteria weights (Ma *et al.*, 1999; Ustinovichius *et al.*, 2007). Besides different approaches that can be used to determine the relative criteria weights, such as pairwise comparison and entropy method, depending on the number of participants involved in determining criteria weights it is also possible to identify individual and group approach.

3.1.1. *Determination of Criteria Weights by Using Pairwise Comparisons*

In this paper, the use of pairwise comparisons for determining the criteria weights is proposed. To calculate criteria weights the following procedure can be used:

***Step* 1: *Construct a pairwise comparison matrix*.** For a decision making problem that contains criteria, the process of determining the criteria weights begins by forming a reciprocal square matrix

$$A = [a_{ij}]_{n\times n}, \tag{4}$$

Table 1
Scale of relative importance for pairwise comparison.

Intensity of importance	Definition
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	For interpolation between the above values

where a_{ij} is a relative importance of i-th in relation to j-th criterion, $i = 1, 2, \dots, n$, $j = 1, 2, \dots, n$, and n is the number of criteria. In the matrix A, $a_{ij} = 1$ when $i = j$ and $a_{ji} = 1/a_{ij}$.

The values of a_{ij} are chosen from nine point scale, for any $i > j$. Table 1 shows the nine point pairwise comparison scale (Saaty, 1980, 2008), used for pairwise comparisons and translation from linguistic terms into corresponding numerical values.

Step* 2: *Calculate the criteria weights. To calculate the criteria weights, the Arithmetic Mean over the Normalized Columns (AMNC) method is used, due to simplicity of its calculation procedure. The process of determining the relative criteria weights can be expressed using the following formula:

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}. \tag{5}$$

***Step* 3: *Check the consistency of pairwise comparison*.** During the pairwise comparison, it is very important that the decision maker performs a consistent comparison. The decision about acceptability of performed pairwise comparisons is made on the basis of the Consistency ratio. Pairwise comparisons from a pairwise comparison matrix are acceptable if the Consistency ratio is less than or equal to 0.1. Otherwise, comparisons are not acceptable and should be revised.

To calculate the Consistency ratio, the following simple three-step procedure can be used:

***Step* 3.1:** Calculate the maximum eigenvalue $\lambda_{\max}$ of the pairwise comparison matrix A, as follows:

$$\lambda_{\max} = \frac{1}{n} \sum_{i=1}^{n} \frac{\sum_{j=1}^{n} a_{ij} w_j}{w_i}. \tag{6}$$

***Step* 3.2:** Calculate the Consistency index *CI*, as follows:

$$CI = (\lambda_{\max} - n)/(n - 1). \tag{7}$$

Table 2
Random consistency index for different matrix sizes.

Matrix size (n)	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

***Step* 3.3:** Calculate the Consistency ratio *CR*, by using the following formula:

$$CR = CI/RI, \tag{8}$$

where *RI* is the random consistency index, and its value is determined on the basis of the matrix size n. Table 2 shows the value of the random consistency index for different matrix sizes (Saaty, 1980, 1994).

3.1.2. *The Group Approach Based on the Pairwise Comparison for Determining the Criteria Weights*

When solving some real-world decision problems it can be important to take into account attitudes of more experts, or decision makers, when determine the relative criteria weights. Then, the group decision making approach, for determining the criteria weights, can be used.

A simple procedure to determine criteria weights can be expressed by the following steeps:

Step* 1**: ***Construct a pairwise comparison matrix, for each decision maker. In the first step, each decision maker forms his own pairwise comparison matrix.

Step* 2**: ***Calculate the criteria weights, for each decision maker. After that, using steps 2 and 3 of the procedure described in Section 3.1.1, the criteria weights are determined, for each decision maker.

Step 3: ***Determine the resulting criteria weights.*** For a group that contains K decision makers, as a consequence of performing the above-mentioned activities, for each criterion are obtained k weights. After that, the resulting criteria weight of each criterion w_j can be easily determined using the arithmetic mean, as shown in the following formula:

$$w_j = \frac{1}{K} \sum_{k=1}^{K} w_j^k, \tag{9}$$

or using the geometric mean, as shown in the following formula:

$$w_j = \left(\prod_{k=1}^{K} w_j^k \right)^{\frac{1}{K}}, \tag{10}$$

where w_j^k is the relative criteria weight of j-th criterion, obtained on the basis of pairwise comparisons of the k-th decision maker.

3.2. *Determine Performance Ratings of Evaluated Alternatives*

Determining performance ratings of alternatives in relation to the criteria is also a very important stage in a MCGDM process. For the MCGDM model creation, which allows simple and efficient evaluation of alternatives, and also ensures that decision makers, and/or experts, can easily express their preferences, often based on their empirical knowledge, the use of relative performance ratings is suggested. As for our approach, the relative performance ratings are ratios between performance ratings of considered and standard alternative, obtained in relation to each criterion.

The simple procedure for assigning relative performance ratings can be expressed as follows:

Step* 1: *Determine the standard performance level, for each criterion. In the first step, decision makers and/or experts choose one alternative, and declare it as a standard one. Due to a simpler evaluation, to this alternative is assigned index $i = 1$.

The performance ratings of the selected alternative for the evaluation criteria then become the standard performance levels for these criteria.

Step* 2: *Determine the performance ratings of remaining alternatives, for each decision maker. In the next step, decision makers and/or experts evaluate the remaining alternatives by comparing their performances with the standard performance level, for each criterion. According to this approach, relative performance ratings $\dot{x}_{ij}^{k}$ are ratios between the performances of the i-th alternatives compared to the performance rating of standard alternative according to the k-th decision maker or expert.

The relative performance ratings can be represented by the following formula:

$$\dot{x}_{ij}^{k} = \vartheta_{ij}^{k} / \vartheta_{1j}^{k}, \tag{11}$$

where ϑ_{ij}^{k} is a performance rating of i-th alternative to the j-th criterion given by the k-th decision maker; and ϑ_{1j}^{k} denotes the performance rating of standard alternative to the j-th criterion given by the k-th decision maker.

The usage of ratios instead of real performance rating, makes it an easier evaluation of alternatives in relation to criteria based on experts' empirical knowledge.

But when solving complex problems by using MCDM methods, the exclusive use of exact values, i.e. the use of crisp numbers, does not always allow adequate evaluation of alternatives in relation to the criteria. This problem is particularly evident when performance ratings of alternatives are determined on the basis of given estimates and assumptions. In such cases, the use of fuzzy numbers (Bellman and Zadeh, 1970) or interval grey numbers (Deng, 1982) may be more appropriate.

The Grey systems theory, proposed by Deng (1982), is an effective methodology that can be used to solve problems with partially known information. The basic concept of grey system theory is that all information can be classified into three categories that are labeled with corresponding colors: known information is white, unknown information is black, and the uncertain information is grey.

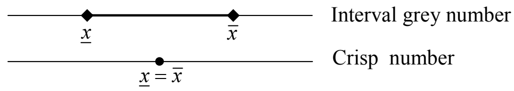

Fig. 4. The interval grey number and the crisp number.

The Grey system theory also introduces a concept of a grey numbers. A grey number, denoted as $\otimes x$, is such a number whose exact value is unknown, but a range within which the value lies is known. There are several types of grey numbers such as: grey numbers with only an upper bound, grey numbers with only a lower bound, black and white numbers and so on, but we will focus below on the interval grey numbers.

A grey number with known upper, $\bar{x}$, and lower, $\underline{x}$, bounds but with unknown distribution information for x is called the interval grey number.

$$\otimes x = [\underline{x}, \bar{x}] = \left[x' \in x \mid \underline{x} \leqslant x' \leqslant \bar{x}\right]. \tag{12}$$

When upper and lower bounds are equal, $\underline{x} = \bar{x}$, interval grey number becomes a white number, i.e. crisp number.

The use of interval grey numbers, or more precise the combined use of crisp and interval gray numbers allow forming of more realistic models of complex real-world problems and their more efficient solving by using MCDM methods.

3.3. *Defining a Simple and Efficient Aggregation Procedure*

Aggregation procedures, used in a MCDM and MCGDM methods, perform a transformation of all performance ratings of considered alternatives into the overall performance ratings. In this way, the multiple criteria decision making problems are converted to single criterion decision making problems.

A different MCDM and MCGDM methods also use the different aggregation procedures, which differ in their complexity. Simple aggregation procedures, as the procedure applied in the Simple Additive Weight method, do not make any difference between benefit and cost criteria. Therefore, the cost criteria must be transformed into the benefit criteria, usually during the normalization stage. This kind of transformation usually is not comfortable. More complex aggregation procedures make a distinction between the cost and benefit criteria, and therefore, there is no need for transformation of the cost into benefit criteria, during the normalization stage.

In this search for the simplest aggregation procedure, start point is from the formula[2] proposed by Brauers and Zavadskas (2009):

$$\ddot{y}_i^* = \sum_{j=1}^{g} s_j x_{ij}^* - \sum_{j=g+1}^{n} s_j x_{ij}^*, \tag{13}$$

[2]In the originally proposed formula, the authors of the MOORA method have used index j to denote alternatives and index i to denote criteria, i.e. objectives. In this paper the index i is used to denotes alternatives and index j to denotes criteria.

where s_j is a significance coefficient, i.e. the criteria weight, of j-th criterion; x^*_{ij} is the normalized performance of i-th alternative with respect to j-th criterion, g is the number of benefit criteria, n is the number of criteria and $\ddot{y}^*_i$ is the overall performance rating of i-th alternative with respect to all criteria, $\ddot{y}_i \in [-1, 1]$.

The formula (13) was, for the first time, proposed by Brauers and Zavadskas (2006), in the Ratio system part of the MOORA method, and there it is used without the significance coefficients.

After adjusting to the form of formulae used in this paper, and slight modification, the formula (13) gets the following form:

$$S_i = \sum_{j\in\Omega_{\max}} w_j \dot{x}_{ij} - \sum_{j\in\Omega_{\min}} w_j \dot{x}_{ij}, \tag{14}$$

where $\dot{x}_{ij}$ is relative performance rating of the i-th alternatives compared to the performance rating of standard alternative to the j-th criterion, S_i is overall performance ratings of the i-th alternative, $S_i \in [-1,\ 1]$, $\Omega_{\max}$ and $\Omega_{\min}$ are sets of the benefit and cost criteria, respectively.

The aggregation procedure, shown by the formula (14), allows solving problems that include the cost and benefit criteria, without need for any kind of transformation.

Brauers and Zavadskas (2006) also state the reasons why the normalized values in the formula (13) should be obtained by using the vector normalization procedure. Compared with other normalization methods, the vector normalization method is more complex, and its use does not lead to the creation of a simple procedure for evaluating alternatives. However, the proposed procedure for assigning performance ratings, i.e. the use of relative instead absolute performance ratings, eliminates the need of using the normalization procedure, which makes our approach simple and efficient.

The formula (14) does not allow a group decision making approach. To extend its usage for a group decision making, following form is proposed:

$$S_i = \frac{1}{K}\sum_{k=1}^{K}\left(\sum_{j\in\Omega_{\max}} w_j \dot{x}^k_{ij} - \sum_{j\in\Omega_{\min}} w_j \dot{x}^k_{ij}\right), \tag{15}$$

Formula (14) also requires the use of only precise information, i.e. performance ratings must be expressed by using crisp numbers. To extend its usage for solving problems characterized by imprecise information, the following formula is suggested:

$$\otimes S_i = \sum_{j\in\Omega_{\max}} w_j \otimes \dot{x}_{ij} - \sum_{j\in\Omega_{\min}} w_j \otimes \dot{x}_{ij}, \tag{16}$$

where $\otimes S_i$ is a grey overall performance index of the i-th alternative, $\otimes\dot{x}_{ij}$ is a relative grey performance rating of i-th alternative to the j-th criterion.

In formula (16) its parts $\sum_{j\in\Omega_{\max}} w_j \otimes \dot{x}_{ij}$ and $\sum_{j\in\Omega_{\min}} w_j \otimes \dot{x}_{ij}$ represent a grey overall performance of i-th alternative obtained on the basis the benefit $\otimes S^+$ and cost $\otimes S^-$ criteria, respectively.

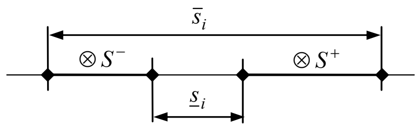

Fig. 5. The simplified meaning of overall grey performance ratings.

Finally, finding out that process of solving many complex real-world problems require the use of imprecise information, as well as the application of group decision making process, the use of the following formula is proposed:

$$\otimes S_i = \frac{1}{K}\sum_{k=1}^{K}\left(\sum_{j\in\Omega_{\max}} w_j \otimes x_{ij}^k - \sum_{j\in\Omega_{\min}} w_j \otimes x_{ij}^k\right), \tag{17}$$

where $\otimes\dot{x}_{ij}^k$ is a relative grey performance rating of the i-th alternative to the j-th criterion given by the k-th decision maker.

The formula (16) and (17) use arithmetic operations on interval grey numbers instead of operations on crisp numbers, and they are somewhat different. In these formulae the operations of addition and subtraction of interval grey numbers are used, as well as the multiplication of interval grey number with a real number. For a given two interval grey numbers $\otimes x_1 = [\underline{x}_1, \bar{x}_1]$ and $\otimes x_2 = [\underline{x}_2, \bar{x}_2]$ these operations are as follow:

$$\otimes x_1 + \otimes x_2 = [\underline{x}_1 + \underline{x}_2, \bar{x}_1 + \bar{x}_2], \tag{18}$$

$$\otimes x_1 - \otimes x_2 = [\underline{x}_1 - \bar{x}_2, \bar{x}_1 - \underline{x}_2], \quad \text{and} \tag{19}$$

$$k \times \otimes x_1 = [k\underline{x}_1, k\bar{x}_2]. \tag{20}$$

As a result of the use of the formula (17), or (16), and formula (19), obtained overall performance indexes are also interval grey numbers $\otimes S_i = [\underline{s}_i, \bar{s}]$ where $\bar{s}_i$ represents the best possible situation for the i-th alternative, or a hypothetical case where the performance ratings of all benefit criteria tend to reach their maximum values and the performance ratings of all cost criteria tend to reach their minimum values, and $\underline{s}_i$ represents the opposite situation, or the least desirable situation when performance ratings of all benefit criteria tend to reach their minimum values and performance ratings of all cost criteria tend to reach their maximum values.

The simplified meaning of lower $\underline{s}_i$ and upper $\bar{s}_i$ bound of the grey overall performance index for the i-th alternative is shown in the Fig. 5.

When solving the real-world problems, the overall performance ratings of the considered alternatives lie between these extreme values. To make a selection or rank alternatives, it is necessary to transform these interval grey numbers into corresponding crisp numbers. For such transformation, we propose the usage of the following formula:

$$S_{i(\lambda)} = (1-\lambda)\underline{s}_i + \lambda\bar{s}_i, \tag{21}$$

where $S_{i(\lambda)}$ is overall performance index of the i-th alternative for a given value of the coefficient λ, and $\lambda \in [0, 1]$.

By varying the values of a coefficient λ in the formula (21), from 0 to 1, solutions that lie between pronounced pessimism ($\lambda = 0$) and pronounced optimism ($\lambda = 1$) are obtained. For $\lambda = 0.5$ the solution that represents the compromise between the pronounced pessimistic and pronounced optimistic solutions is obtained, and then the formula (21) gets the following form:

$$S_{i(0.5)} = \frac{1}{2}(\underline{s}_i + \bar{s}_i). \tag{22}$$

Finally, the selection of the most acceptable alternative A^* is based on overall performance indexes, where the alternative with the highest crisp value of the overall performance index S_i is the most acceptable, as shown by the following formula:

$$A^* = \left\{A_i \mid \max_i S_i\right\}. \tag{23}$$

4. Case Study

To demonstrate the simplicity and efficiency of the proposed approach, in this section is shown its use to solve a particular problem.

The mining company XYZ from Serbia plans to start exploitation of a new mine with surface mining. Its geographic location, i.e. distance of the new mine to the existing flotation, does not provide a cost-effective transportation of the excavated ore. Therefore, the team of experts was formed with the aim to evaluate the comminution circuit design and propose the most appropriate one.

At the beginning of the evaluation, each expert, using the procedure previously proposed in Section 3.1, performed an assignment of the criteria weights. The results of pairwise comparisons, for each expert, are given in Tables 3, 4 and 5.

By using the proposed approach, experts involved in the evaluation of GC design had the opportunity to express their attitudes related to the criteria weights. The set of selected evaluation criteria allowed consistent pairwise comparisons, even to experts who are not familiar with the use of pairwise comparison method. Although the proposed set of evaluation criteria did not contain a large number of criteria, it was flexible enough to allow the

Table 3
The pairwise comparisons matrix and the relative criteria weights obtained from the first decision maker.

Criteria		C_1	C_2	C_3	C_4	w_i
Grinding efficiency	C_1	1	3	5	7	0.540
Economic efficiency	C_2	1/3	1	3	7	0.273
Capital investment costs	C_3	1/5	1/3	1	5	0.138
Environmental impact	C_4	1/7	1/7	1/5	1	0.047
		$CR = 0.091$				

Table 4
The pairwise comparisons matrix and the relative criteria weights obtained from the second decision maker.

Criteria		C_1	C_2	C_3	C_4	w_i
Grinding efficiency	C_1	1	3	4	5	0.515
Economic efficiency	C_2	1/3	1	3	5	0.281
Capital investment costs	C_3	1/4	1/3	1	3	0.137
Environmental impact	C_4	1/5	1/5	1/3	1	0.067
		$CR = 0.071$				

Table 5
The pairwise comparisons matrix and the relative criteria weights obtained from third the decision maker.

Criteria		C_1	C_2	C_3	C_4	w_i
Grinding efficiency	C_1	1	7	5	3	0.558
Economic efficiency	C_2	1/7	1	5	3	0.263
Capital investment costs	C_3	1/5	1/5	1	3	0.122
Environmental impact	C_4	1/3	1/3	1/3	1	0.057
		$CR = 0.044$				

Table 6
Performance ratings of alternatives assigned by three experts.

	Criteria	G_E	E_E	C_{IC}	E_I
	CCD	C_1	C_2	C_3	C_4
	A_1	1.00	1.00	1.00	1.00
Expert 1	A_2	0.90–0.95	1.00–1.03	0.90–0.95	1.00–1.03
	A_3	1.05–1.10	1.05–1.10	1.00–1.20	0.90–0.95
Expert 2	A_2	0.90–1.00	1.05–1.10	0.80–0.85	1.00
	A_3	1.00–1.05	1.00	1.10	1.10
Expert 3	A_2	0.90–0.95	1.02–1.04	0.80–0.90	1.00–1.03
	A_3	1.02–1.07	1.03–1.10	1.15–1.20	0.90–1.00

formation of a balance between short and long-term objectives and the balance between the benefits and consequences of ore exploitation.

In the next step, experts estimated performance ratings of three GC designs in relation to the criteria, using the procedure described in the Section 3.2.

Three available alternatives, previously discussed in this paper, have been evaluated in relation to conditions that will exist in the case of ore exploitation from the ore body Cerovo. The results of evaluation are shown in Table 6.

After determining the criteria weights and estimating relative performance ratings of considered alternatives in relation to the criteria, the resulting decision table is formed, as shown in Table 7.

The resulting relative criteria weights w_j, presented in Table 7, are calculated by using the formula (9).

The performance ratings are also determined as the arithmetic means of the performances given by the experts. In doing so, in order to form a unified approach, exact per-

Table 7
The resulting decision matrix.

Criteria	G_E	E_E	C_{IC}	E_I
Optimization	max	max	min	min
w_j	0.538	0.273	0.132	0.057
CCD	C_1	C_2	C_3	C_4
A_1	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
A_2	[0.900, 0.967]	[1.023, 1.057]	[0.833, 0.900]	[1.000, 1.020]
A_3	[1.017, 1.073]	[1.027, 1.067]	[1.083, 1.167]	[0.967, 1.017]

Table 8
The results of the comminution circuit design evaluation.

CCD	Criteria					
	G_E	E_E	C_{IC}	E_I	$\Omega_{\max}$	$\Omega_{\min}$
	max	max	min	min	$\otimes S^+$	$\otimes S^-$
A_1	[0.538, 0.538]	[0.273, 0.273]	[0.132, 0.132]	[0.057, 0.057]	[0.811, 0.811]	[0.189, 0.189]
A_2	[0.484, 0.520]	[0.279, 0.289]	[0.110, 0.119]	[0.057, 0.058]	[0.763, 0.808]	[0.167, 0.117]
A_3	[0.547, 0.577]	[0.280, 0.291]	[0.143, 0.154]	[0.055, 0.058]	[0.827, 0.868]	[0.198, 0.212]

formance rating values have been transformed to the interval grey numbers. Then the calculation of the lower and upper bounds of the interval is performed by using the following formulae:

$$\underline{x}_{ij} = \frac{1}{K}\sum_{k=1}^{K}\underline{x}_{ij}^{k}, \quad \text{and} \tag{24}$$

$$\bar{x}_{ij} = \frac{1}{K}\sum_{k=1}^{K}\bar{x}_{ij}^{k}. \tag{25}$$

Further, by multiplying weights and performance ratings finally the weighted decision making matrix has been formed. At the same time, the grey overall performances of each alternative, obtained on the basis the cost $\otimes S^-$ and benefit $\otimes S^+$ criteria, has been calculated. The weighted decision making matrix and grey overall performances are shown in Table 8.

As it can be seen from Table 8, the overall performances of each alternative obtained on the base of the cost and benefit criteria are expressed by using the grey interval numbers. To select the most appropriate alternative, or the rank alternatives, these intervals must be transformed into the corresponding crisp numbers, using the formula (21). The ranking results obtained using formula (21) for some characteristic values of the coefficient λ, are shown in Table 9.

As shown in Table 9, the alternative A_3, i.e. a two-stage grinding process based on the use of SAG and ball mils, is probably the most acceptable solution for the ore processing

Table 9
Ranking results obtained using proposed approach for different values of λ.

	$\lambda = 0$		$\lambda = 0.5$		$\lambda = 1$	
	S_i	Rank	S_i	Rank	S_i	Rank
A_1	0.621	1	0.621	2	0.621	3
A_2	0.586	3	0.613	3	0.641	2
A_3	0.615	2	0.642	1	0.670	1

from the ore body Cerovo. For a moderate and optimistic decision maker altitude this alternative has the highest rank, but when the decision maker has a very pessimistic attitude this alternative has the second position.

The importance of the use of interval grey numbers and the coefficient λ to solve real-world problems can be clearly seen from this example. By changing the value of the λ coefficient, decision makers can more realistically examine the applicability of the available alternatives and choose the most acceptable one.

For a moderate decision makers' attitude, $\lambda = 0.5$, the considered GC designs have the following ranking order $A_3 \succ A_1 \succ A_2$. According to experts' opinions who were involved in selection of the most appropriate one GC design, the obtained ranking order realistically reflects their applicability.

5. Conclusion

The selection of a grinding circuit design is very important and it is also a very complex problem. Therefore, with a combined use of verified and effective procedures and approaches such as: the pairwise comparison, the group decision making, the interval grey numbers and the Ratio system approach of the MOORA method, a new simple, but also effective and flexible, MCGDM model for grinding circuit design selection is proposed.

In the MCDM models, the criteria weights have a significant influence on the selection of the most acceptable solutions. Therefore, the proposed procedure for determining the relative criteria weights should provide a respect for attitudes of all decision makers. In the proposed model, all decision makers have the equal importance, but this model can be easily modified so that various decision makers have a different importance, i.e. they have different impacts on the criteria weights and thus actually on the selection of the most acceptable alternative.

The performance ratings, as well as the procedure used for their determination, also have significant impact on the ranking order of alternatives. This is particularly evident when the performance ratings are obtained on the base of the estimations or experts experience. The proposed procedure allows experts to determine the performance ratings easier and more accurately. The usage of interval grey numbers for expressing performance ratings also significantly contribute to this fact.

The use of interval grey numbers also allows the consideration of various strategies. By using the different values of the coefficient λ decision makers can consider a various scenarios, such as pessimistic, realistic or optimistic.

And finally, in proposed model a small number of evaluation criteria are used to enable a creation of simple and efficient model. It is considered that they are sufficient to ensure the achievement of the objectives of the selection. It is also emphasized that the existing set of criteria can be easily expanded, and that the proposed evaluation criteria also can be divided into sub-criteria.

With respect to all these reasons, the key aspect of the proposed model is that it is easy to use, and it also allows the efficient selection of the proper comminution circuit design.

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Efektyvus ir paprastas daugiakriterinis modelis šlifavimo schemoms parinkti taikant MOORA metodą

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Smulkinimo procesas, specifinis šlifavimas yra labai svarbus mineralų apdirbimo industrijoje. Kai kurios dalelių charakteristikos, kurios pasitaiko gaminiuose šlifavimo proceso metu, turi reikšmingą įtaką rūdos gamybos rezultatui. Tuo pat metu, šis procesas reikalauja žymiai didesnio kiekio energijos įvertinant visos gamybos kaštus. Todėl, šiame straipsnyje, autoriai pateikia naują sprendimų priėmimo modelį, kurio pagrindas racionalumo sistema yra MOORA metodo dalis. Metodas taikomas atitinkamo smulkumo šlifavimo schemoms projektuoti.